

Behavioral Perspectives on Organizational Change: Practice Adoption, Product Culling,
and Technological Search
by

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Dissertation submitted in partial fulfillment of
the requirements for the degree of Doctor
of Philosophy in the Department of
Business Administration in the Graduate School
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ABSTRACT

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Abstract

This dissertation explores the complex process of organizational change, applying a behavioral lens to understand change in processes, products, and search behaviors. Chapter 1 examines new practice adoption, exploring factors that predict the extent to which routines are adopted “as designed” within the organization. Using medical record data obtained from the hospital’s Electronic Health Record (EHR) system I develop a novel measure of the “gap” between routine “as designed” and routine “as realized.” I link this to a survey administered to the hospital’s professional staff following the adoption of a new EHR system and find that beliefs about the expected impact of the change shape fidelity of the adopted practice to its design. This relationship is more pronounced in care units with experienced professionals and less pronounced when the care unit includes departmental leadership. This research offers new insights into the determinants of routine change in organizations, in particular suggesting the beliefs held by rank-and-file members of an organization are critical in new routine adoption. Chapter 2 explores changes to products, specifically examining culling behaviors in the mobile device industry. Using a panel of quarterly mobile device sales in Germany from 2004-2009, this chapter suggests that the organization’s response to performance feedback is conditional upon the degree to which decisions are centralized. While much of the research on product exit has pointed to economic drivers

or prior experience, these central finding of this chapter—that performance below aspirations decreases the rate of phase-out—suggests that firms seek local solutions when doing poorly, which is consistent with behavioral explanations of organizational action. Chapter 3 uses a novel text analysis approach to examine how the allocation of attention within organizational subunits shapes adaptation in the form of search behaviors in Motorola from 1974-1997. It develops a theory that links organizational attention to search, and the results suggest a trade-off between both attentional specialization and coupling on search scope and depth. Specifically, specialized unit attention to a more narrow set of problems increases search scope but reduces search depth; increased attentional coupling also increases search scope at the cost of depth. This novel approach and these findings help clarify extant research on the behavioral outcomes of attention allocation, which have offered mixed results.

Dedication

To Alison, my wife, and to the memory of Wally Wilson and Ray Lotkowitz.

Contents

Abstract	iv
List of Tables	xi
List of Figures	xii
Acknowledgements	xiii
1. New Practice Adoption: Predicting the Gap Between Routine as Designed and Routine as Realized.....	1
1.1 Introduction.....	2
1.2 Routines “As Designed” and “As Realized”	5
1.2.1 Professional Norms and Shared Beliefs About the Expected Impact of the Change	7
1.2.2 Professional Experience as a Moderator of the Belief-Gap Relationship	11
1.2.3 Departmental Leadership as a Moderator of the Belief-Gap Relationship	12
1.3 Methods	13
1.3.1 Description of the Data.....	13
1.3.2 EHR Installation as a Change to Organizational Routines “as Designed”	15
1.3.3 Identifying the Routine “as Designed”	17
1.3.4 Quantitative Analysis of Organizational Routines.....	20
1.3.5 Calculation of Shared Beliefs about the Expected Impact of the Change	26
1.3.6 Professional Experience.....	32
1.3.7 Departmental Leadership Position	33
1.3.8 Other Controls	33

1.3.8.1 Care Unit Controls	33
1.3.8.2 Patient Controls.....	35
1.3.9 Empirical Specification	35
1.4 Results	36
1.5 Robustness.....	43
1.5.1 Alternative DV.....	43
1.5.2 Composite Measure of Belief.....	46
1.6 Discussion and Conclusions	48
2. Organizational Structure and Performance Feedback: Centralization, Aspirations, and Termination Decisions.....	54
2.1 Introduction.....	55
2.2 Performance Feedback and Termination Decisions	60
2.3 Organizational Structure and Termination Decisions.....	65
2.3.1 Centralization and Information Processing.....	66
2.3.2 Centralization and Performance Feedback.....	69
2.4 Methods	73
2.4.1 Dependent Variable	78
2.4.2 Aspiration Levels and Performance Feedback.....	79
2.4.3 Centralization.....	83
2.4.4 Alternative Measure of Centralization.....	87
2.4.5 Phone Replacement.....	90
2.4.6 Other Controls	92

2.4.7 Empirical Specification	94
2.5 Results	97
2.6 Robustness	108
2.7 Discussion.....	113
2.8 Conclusion.....	122
3. Organizational Attention and Technological Search in the Multibusiness Firm: Motorola from 1974-1997	124
3.1 Introduction.....	124
3.2 Attentional Structure in the Multibusiness Firm	128
3.2.1 Attention Specialization and Technological Search	130
3.2.2 Attentional Coupling and Technological Search	132
3.3 Methods	135
3.3.1 Research Setting.....	135
3.3.2 Sample.....	136
3.3.3 Dependent Variables: Search Scope and Depth	137
3.3.4 Topic Modeling: Text as a Measure of Attention to Technological Problems	139
3.3.5 Attentional Specialization	145
3.3.6 Attentional Coupling	146
3.3.7 Controls.....	150
3.3.8 Empirical Specification	152
3.4 Results	152
3.5 Discussion and Conclusions	156

References	162
Biography	180

List of Tables

Table 1: Summary Statistics and Cross-Correlations	14
Table 2: OLS Regression Models Predicting Gap Size.....	37
Table 3: OLS Regression Models Predicting Compliance (Using Internal Tracking Data)	45
Table 4: OLS Regression Models Predicting Gap Size (Composite Belief Measure).....	47
Table 5: Summary Statistics and Cross-Correlations ($N = 3,192$ product-quarters)	77
Table 6: Piecewise Exponential Hazard Rate Models for Phase-Out	99
Table 7: Robustness Tests of Piecewise Exponential Hazard Rate Models for Phase-out	109
Table 8: Summary Statistics	137
Table 9: Tobit Regression Results	154

List of Figures

Figure 1: Relationship between Care unit, particular orders associated with the patient-encounter, and compliance as measured by the internal tracking (“pulsemetric”) system	19
Figure 2: Example of Sequence Analysis as Applied to all Cesarean Sections Without Complications at Duke University	26
Figure 3: 2x2 Showing Proportion of Respondents for Beliefs about Quality of Care and Hospital Revenue, Respectively	29
Figure 4: Quality of Care Beliefs by Key Demographics in Hospital (Experience, Satisfaction, Department)	30
Figure 5: Interaction Between Belief that the Change will Improve Quality of Care and Professional Experience	40
Figure 6: Interaction Between Belief that the Change Will Improve Quality of Care, Presence of Departmental Leader.....	42
Figure 7: Kaplan-Meier Survival Graph (each discontinuity is one quarter)	96
Figure 8: The Effect on Product Phase-out of Centralization and of Performance Relative to Aspirations; Dashed and Solid Plots Indicate where Centralization Equals 2 and 4, Respectively (These Results Correspond to Table 6, Model 10).....	106
Figure 9: Sample Mapping from Patent Background to Topic.....	141
Figure 10: Multidimensional Scaling Applied to Measures of Attentional Coupling at Motorola in 1975, 1985, and 1995.....	150

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1. New Practice Adoption: Predicting the Gap Between Routine as Designed and Routine as Realized

This chapter addresses the question of what drives the adoption of new routines. The adoption of new routines is described in the literature as difficult or imperfect, and the degree to which firms are successful in adopting new or changing existing routines varies considerably. In this study, to explain new routine adoption, I consider how beliefs about the impact of the new practices will shape the extent to which change is perceived as aligned with professional norms, and subsequently, degree of adoption. My empirical analysis employs a sample consisting of a survey to 1,248 healthcare professionals about their beliefs regarding the expected impact of a new EHR system and 32,460 patient encounters following the launch of the system, where each encounter reflects the set of medical activities undertaken by a care unit (i.e., physicians and nurses) responsible for the care of a patient for a given admission. I find that belief that the EHR system will improve patient care, an outcome aligned with professional norms, will reduce the size of the gap between routine as designed and routine as realized. My results also indicate that this relationship is strongest for highly experienced units without a departmental leader present on the care team. This study contributes to literature in organizational routines by providing insight into how beliefs shape the interpretation and realization of particular routines and the ultimate impacts of these beliefs on the firm's ability to engage in change.

1.1 Introduction

This chapter addresses the question of what drives the adoption of new practices and the change in corresponding routines, a key question in behavioral and evolutionary theories of strategy (Cyert & March, 1963; Nelson & Winter, 1982). Though it is critical that firms develop the capacity and motivation to change (Feldman, 2000; Pisano, Bohmer, & Edmondson, 2001; Zollo & Winter, 2002), organizations often find it difficult to do so. Changing routines is challenging, costly, time-consuming, and expected benefits often fail to materialize (Szulanski, 1996). In explaining routine change, prior research has primarily focused on the role of learning (Edmondson, 1999; Edmondson, Bohmer, & Pisano, 2001), transferability (Knott, 2003; Winter & Szulanski, 2002), and replication (Feldman & Pentland, 2003; Knott, Gupta, & Hoopes, 2008). Largely missing from these accounts is role of the beliefs of those responsible for implementing routine change, despite a growing recognition of the role that cognitive drivers play in explaining performance heterogeneity (Helfat & Peteraf, 2015). In addition, new routine adoption is often assumed to be a discrete change. Scholars still do not view the adoption of new organizational practices as a question of degree, despite recognition that particular realizations of the underlying routines may be quite different from each other (Cohen et al., 1996; Pentland, Hærem, & Hillison, 2011).

To address these gaps, this chapter examines the relationship between the beliefs held by decision makers and the “gap” between routine “as designed” versus routine “as realized.” To do so, I draw upon literature that examines the role of professional norms in guiding behavior (Haas & Park, 2010; Merton, 1973; Merton, Reader, & Kendall, 1957). An unexplored implication of this literature is that new routines that are perceived to be aligned with professional norms will be seen as legitimate, increasing motivation and capacity to change. Consequently, belief that the change aligns with professional norms will reduce the size of the gap between routine “as designed” and routine “as realized.” I then explore the moderating role of professional experience on this relationship.

The context for this study is the implementation of a new electronic health record (EHR) system at Duke University Hospital in 2013. This was an extensive change initiative which prompted a nearly complete redesign of all major clinical workflows. Duke University Health System launched this new system for two reasons. The HITECH Act tied future reimbursement rates to the “meaningful use” of an appropriately advanced EHR system. It was deemed more desirable to adopt a 3rd party EHR system (EPIC) over bringing the dozens of legacy systems to the standard that would be required under this new regime. Furthermore, the organization embraced this new EHR 3rd party system in the hopes of creating a single, comprehensive electronic health record for each patient. It was hoped that “The seamless, real-time access to a

patient's complete medical record will provide valuable information to Duke clinicians and will advance the already high quality of care provided to patients. The breadth of functionality offered by the new health record system will also revolutionize the way Duke providers exchange information about a patient's care across all care settings – improving quality, safety, speed and efficiency.”

A hospital setting provides insight into the nature of organizational routine change, as all activities are individually and meticulously tracked. Furthermore, professional norms are strong in the healthcare profession and provide guidance on roles and beliefs. I argue that belief that the EHR system will improve patient care, an outcome aligned with professional norms, will reduce the size of the gap between routine as designed and routine as realized, and that belief that the EHR system will improve hospital revenue, a belief that may be considered contrary to professional norms in medicine, will increase the size of the gap.

To prefigure my main empirical results, I find that belief that the EHR system will improve patient care, an outcome aligned with professional norms, reduces the size of the gap between routine “as designed” and routine “as realized.” The magnitude of this effect is large – a one standard deviation change in belief has approximately 12.5 times the impact of a standard deviation increase in experiential learning (operationalized as time since go live). This relationship is strongest for units with a high degree of professional experience, the effect size increasing to 20 times that of

experiential learning at the 90th percentile of professional experience. This relationship, however, is weakened when a departmental leader is present on the care team.

This study makes two contributions to the literature. First, I apply a new theoretical lens to the important issue of routine change in organizations, articulating the critical role of beliefs about the expected impact of the change. This compliments literature that has focused on a variety of factors that predict the success of routine change in firms, including those that condition the motivation, opportunity, and capacity to engage in change. Second, I frame top-down routine change as a question of degree rather than as a discrete outcome by introducing the notion of a gap between routine “as designed” versus routine “as realized.” In doing so, I examine practice adoption (Szulanski 1996) in the light of advances in the study of organizational routines (Cohen et al., 1996; Pentland et al., 2011; Salvato, 2009; Winter, 1994).

1.2 Routines “As Designed” and “As Realized”

A routine “as designed” refers to the intended practice that upper management seeks to impose on the organization (Winter 1994). A routine “as realized” refers to a particular performance of that organizational routine, at a particular time, by a particular organizational unit/group of individuals. A routine as realized may reflect the underlying design (what Nelson and Winter (1982) refer to as the “target”), as well as variations specific to a particular performance of the routine (Feldman and Pentland 2003). The gap between designed and realized routine can take many forms, including

differences in the set of activities that comprise the routine, the number of components to the routine and the sequence in which those components are carried out (Pentland et al., 2011; Salvato, 2009).

Recent research has recognized the role of deliberate or purpose-driven change efforts in new practice adoption (Becker & Lazaric, 2003; Levinthal & Rerup, 2006; Winter, 1994, 2000). Organizations often initiate such efforts to improve the quality of outcomes, lower cost, increase responsiveness to environmental signals, transfer capabilities from one part of an organization to another, or exploit benefits to knowledge sharing within the organization (Szulanski, 1996; Winter & Szulanski, 2001; Zollo & Winter, 2002). In this chapter, I consider changes to common practices as changes to organizational routines.

A variety of studies have documented the difficulty that firms have in changing routines, despite organizational intentions and efforts to do so. Much literature characterizes routines as highly path-dependent, in that it is difficult to break out of established patterns of behavior (Cohen, 2007; Nelson & Winter, 1982). Organizational attempts to design new organizational routines often fail due to the difficulty of predicting human response to change. Pentland and Feldman (2008) suggest that organizations overinvest in designing new systems, protocols, and procedures at the expense of considering how individuals will react to the change. This stream of research, much of which has taken place in the context of service industry (e.g.,

healthcare), has generally overlooked the guiding role of professional norms and role of shared beliefs concerning the change effort. In addition, much of the research examines the adoption of new routines as a discrete outcome (i.e. the routine is either adopted or it is not), though work such as Szulanski (1996) and Edmondson et al (2001) consider cost and time as dimensions that might vary between implementations. Yet, routines “as designed” may be only partially adopted in this form and “in practice” may be altered to accommodate differences in the shared beliefs underlying the capacity and motivation to change.

In the sections that follow, I discuss how a particular set of beliefs – specifically, beliefs regarding the expected impact of a change, will affect the capacity and motivation for individuals to accept and expedite change, affecting the gap between organizational routines as designed vs. organizational routines as realized. I argue that the degree to which the change is believed to align with professional norms will affect the size of the gap between routine “as designed” vs. “as realized.”

1.2.1 Professional Norms and Shared Beliefs About the Expected Impact of the Change

Professional norms provide clear role expectations that guide individual behavior (Haas and Park, 2010). For example, in scientific professions, the importance of information sharing provides the basis for the norm of open communication within the scientific community (Merton 1973). In the medical community, the uncertain nature of outcomes and the need to maintain legitimacy provide the basis for professional codes

of conduct, such as the Hippocratic Oath (Ruef & Scott, 1998). Norms are reinforced among professionals through a process of professional training and socialization that occurs early in and continues throughout a career. Individuals that violate professional norms may be sanctioned or cast out of the profession, while individuals that uphold norms may receive status or recognition (Merton et al. 1957). Thus, professionals develop a sense about what activities are considered appropriate or inappropriate that is derived from the values of the profession (Abbott, 2014; Pratt, Rockmann, & Kaufmann, 2006).

These professional norms will provide a basis by which organizational change, such as the implementation of an EHR system, are evaluated. Take the following quotation from an affected Urologist, regarding the EHR implementation: *"The [change] has one main goal: help an institution maximize billing revenue. It is designed by hospital administrators for hospital administrators. It is not designed to improved patient point of care. It was not designed by clinicians for clinicians. This is a sad moment in the history of health care."* Similar norm-based judgments occur in individuals with different roles, for example, this Cardiology nurse: *"This [The organizational change in question] is not living the values of caring for our patients, families and each other."* Yet, beliefs about the expected impact of the system were heterogeneous, even *within* units and roles, as evidence by another Cardiology nurse: *"I do have high hopes for [the new system] and look forward to using it. A lot of hype is attached to this new system, but it is a system a lot of hospitals around the country*

are adopting. I am encouraged by that, and believe, in the end, the system, once configured and customized to the needs of each particular unit, will be much better than the present system." In all three of these quotations, the change (implementation of EHR) is being evaluated in terms of its expected impact on patients. The change is perceived either as reinforcing or threatening the behavior of patient care, which is aligned with professional norms.

Shared beliefs about the expected impact of the change can either galvanize or hinder the motivation to change. When a change is perceived to improve an outcome that aligns with professional norms, it legitimizes the change and provides motivation to adopt the new set of procedures. Motivated groups may be willing to expend extra effort to engage in the change initiative, thus improving capacity to change. They may spend time and energy attending optional training sessions, more readily seek out counsel should questions arise, or more actively engage with materials such as handbooks and manuals. High levels of motivation can also spur the emergence of "champions for change" within the organization (Pisano et al. 2001). These "champions for change" in addition to advocating the positive impact of the initiative, will help others in the organization learn the new practice.

Shared beliefs about the expected impact of the change may also facilitate cooperation in the organization. Rather than perceiving others in the organization as a threat to action in accordance with norms, positive views about the change can provide the basis for positive interactions, facilitating the "mutual execution" of new procedures.

Barley (1986) describes a breakdown in this process in the context of the adoption of CT scanning technology. When physicians perceived technicians as a threat to their professional authority, they engaged in many maladaptive behaviors, critiquing and accusing the technicians. In turn, the technicians began to be reluctant to share their technical expertise with the physician group. This will ultimately result in greater fidelity to the routine “as designed.” Consequently, I hypothesize the following:

***Hypothesis 1a (H1a):** Beliefs about the expected impact of a change that align with professional norms (e.g. the change is expected to improve quality of care) will decrease the gap between routine “as designed” and routine “as realized.”*

When there is perceived misalignment between professional norms and the change initiative (take, for example, the quotations from the Nurse and Urologist above), both motivation and capacity to change will be reduced. The change may be perceived as unnecessary, harmful, or a “waste of time.” This may result in change by the minimum amount that does not result in punishment by superiors. Capacity to engage in change may be reduced to the extent that training resources are not sought out, units may be less engaged during mandatory training.

Consequently, I also hypothesize the converse:

***Hypothesis 1b (H1b):** Beliefs about the expected impact of a change that conflict with professional norms (e.g. the change is expected to improve hospital revenue) will increase the gap between routine “as designed” and routine “as realized.”*

Having established the relationship between beliefs about the expected impact of a change and size of the gap between routine “as designed” and routine “as realized,” I explore some additional factors that affect this relationship in the following sections. In particular, I examine the moderating role of experience and face-to-face interactions. I then examine the role of the presence of a departmental leader within a care unit.

1.2.2 Professional Experience as a Moderator of the Belief-Gap Relationship

Early in a professional’s career, the influence of norms on judgment is still nascent, relatively adaptable and mutable (Schein, 1978). As experience is gained, professional norms are reinforced, and the values associated with the profession become further internalized. Experienced members of a profession often have a role in training and socializing new members, thus continually reaffirming their commitment to established professional norms. Violation of professional norms can lead to loss of reputation (Merton et al. 1957), an outcome worse than material penalty (Das & Teng, 2002). Consequently, as experience builds, the motivational aspects of beliefs on change become more critical, and these physicians adjust their behavior to preserve their reputations. For example, Quinn (1998) found that more experienced physicians are more likely to order diagnostic tests as a safeguard against loss of reputation due to malpractice litigation.

Professional experience will also shape how beliefs about expected impact of change shape organizational capacity to change. More junior professionals seek

behavioral cues from more established colleagues (Ibarra, 1999). If their senior colleagues believe that a change is consistent with professional norms, it can help legitimize the change in the organization as a whole. However, if senior members believe the change is counter to professional norms, it will send a signal that delegitimizes the change in the broader organization. More senior professionals may also be to provide guidance to facilitate the implementation of the new organizational routines by giving management greater insight into tacit aspects of their occupation (Winter 1994; Zollo and Winter, 2001), as they understand and can articulate these better than junior colleagues. Similarly, they will also resist more strongly when these norms are challenged. Relative to junior professionals, they are able to be more openly vocal in their criticisms and reservations about the change, making effective collaboration more difficult. Consequently, I hypothesize the following:

Hypothesis 2 (H2): Professional experience will strengthen the impact of beliefs about the expected impact of a change initiative on the gap between routine “as designed” and routine “as realized.”

1.2.3 Departmental Leadership as a Moderator of the Belief-Gap Relationship

The influence of beliefs that run counter to professional norms may be less when care units include departmental leadership, as their role causes them to evaluate the change differently. More senior leaders are, by design, more sensitive to a broader array of organizational goals (March & Simon, 1958). In the case of a hospital, this means that

leadership has to develop a view of the hospital that considers not just the merits of providing healthcare, but also in operating a sustainable business enterprise.

Departmental leadership may thus clue the broader team into the interests and realities of the hospital as a revenue generating entity, helping to legitimize beliefs initially viewed as counter normative.

Presence of a departmental leader on a routine team also clarifies the authority structure in the care unit – if an ambiguous situation arises in the performance of a routine, then their authority will enable them to resolve any potential misalignments within the unit (Denis, Langley, & Cazale, 1996). Finally, direct involvement of departmental leadership facilitates the active monitoring of the behavior of their colleagues (Knott, 2003), ensuring that the routine is executed more closely to the design, regardless of whether or not the change is perceived as legitimate. For these reasons, I expect the following:

Hypothesis 3 (H3): Presence of a departmental leader on a care team will weaken the impact of beliefs about the expected impact of a change initiative on the gap between routine “as designed” and routine “as realized.”

1.3 Methods

1.3.1 Description of the Data

This study uses two primary sources of data to examine the hypotheses relating routine change to beliefs. The first source is a set of sequences of activity data generated

in the course of healthcare provision, which is used to recreate various organizational routines at Duke University Hospital. The second source of data is a pre-implementation survey that captured physician and nurse beliefs about the upcoming change to the new electronic health record (EHR) platform.

The sample covers most major procedures performed at clinical departments at Duke University Hospital in the year following the “go live” on the new electronic health record system (July 2013-July 2014). I observe 32,640 sequences of activities over a year period following implementation. Each sequence, or *patient-encounter*, consists of all orders performed by doctors and nurses from admission to discharge. They capture substantively all activity involved with the treatment of an individual for a particular hospital stay. These detailed records are aligned with a pre-implementation survey that asked 1,248 doctors and nurses across a variety of specialties about their perceptions of the new EHR system and their experience with this and other similar systems. Order records and the pre-implementation survey were linked by the doctor or nurse name. Descriptive statistics and correlations for all predictor variables are given in Table 1.

Table 1: Summary Statistics and Cross-Correlations

	Mean	Std. dev.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
1 Gap Size (Routine as Intended v. Realized)	0.19	0.09	1.00												
2 Pulsemetric Compliance	0.81	0.12	-0.59	1.00											
3 Belief: Quality of Care	53.06	8.28	-0.52	0.26	1.00										
4 Belief: Hospital Revenue	59.47	4.13	0.30	-0.25	-0.55	1.00									
5 Professional Experience	21.37	8.93	0.43	-0.27	-0.56	0.54	1.00								
6 Experiential Learning: Time Since Go Live	6.88	2.63	-0.06	0.05	0.04	0.02	-0.02	1.00							
7 Doctor: Nurse Ratio on care unit	0.46	0.20	-0.07	0.05	0.02	-0.06	-0.04	-0.04	1.00						
8 Care unit has departmental leader	0.22	0.41	-0.05	0.04	0.03	-0.01	-0.02	0.00	0.00	1.00					
9 Average IT Comfort	3.49	1.07	-0.41	0.55	0.09	0.06	0.07	0.02	0.03	0.02	1.00				
10 Care unit has fellowship physician	0.28	0.35	0.03	-0.02	-0.02	0.02	0.01	-0.04	-0.07	0.01	-0.02	1.00			
11 Belief of departmental leader	55.91	7.13	-0.57	0.28	0.61	-0.58	0.13	0.03	0.04	0.57	0.04	0.03	1.00		
12 Patient Gender	0.58	0.49	-0.01	0.01	0.00	0.00	0.00	0.01	0.00	-0.01	0.00	-0.01	0.00	1.00	
13 Patient Age	47.52	16.23	-0.01	0.01	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	0.01	0.00	0.00	1.00

All bolded correlations significant ($p < .05$)

1.3.2 EHR Installation as a Change to Organizational Routines “as Designed”

For numerous reasons, Duke University Hospital’s transition to a new EHR system is an ideal setting in which to study the role of belief in driving the gap between routine as designed vs. routine as realized. First, regulatory requirements regarding billing require extensive documentation to support charges on a patient’s account. This makes it possible to track all activities that occur in a particular patient-encounter as well as the individual responsible for said activities. The activities in a patient-encounter constitute one realization of an organizational routine.

Second, major procedure types have well-documented standard operating procedures and “ideal” types that are well-tracked. Built into the EHR system itself is the notion of the routine “as designed,” because as all clinical workflows are changed, the hospital must incorporate these new clinical workflows into the logic of the system’s programming. The process of “discovering” the organization’s clinical workflows begins before any “customization” of the software tool is begun. Because the implementation of an EHR system requires an in-depth understanding of clinical workflows for nearly all care activities, it is possible to track how most activities are “supposed” to be performed in an electronic health record system. Though compliance information was not yet systematically shared with healthcare providers, the electronic health record system enables hospital management to monitor compliance with designed clinical workflows.

Third, using the new electronic health record system was required by all nurses and physicians. Following a substantial training initiative, the old electronic health record system was replaced overnight. Only two physicians opted to retire rather than to learn the new set of practices and system. Consequently, all organizational members faced a new set of routines “as designed” simultaneously. At the time, Duke’s “go live” process represented the largest simultaneous launch to date for the company that provided the EHR system, EPIC, which at the time of writing was the largest provider of such systems.

Finally, Duke University Hospital’s experience switching to a new electronic record system was not an instance in which a hospital switched from paper records to electronic. Duke had already been using an in-house EHR system for several years. With “meaningful use” requirements mandated by the HITECH Act, hospital management was forced to decide whether or not to switch to a major provider of EHR systems or to attempt to bring their own solution up to governmental standards, compliance with which would eventually affect reimbursement rates for the hospital. Ultimately, it was deemed more tractable to perform a single installation of a new system rather than to replace the dozens of legacy systems that had been built in-house. Each department in the hospital faced its own set of challenges with the new electronic health record system, as the specific tools and capabilities required by each different medical specialty had to be incorporated into the new system.

Finally, though the study is focused on the experience of a single organization (Duke University Hospital), this is ideal for many reasons. A single-firm setting provides for variation in the conditions of interest (beliefs, gap between routine as designed and realized), while ensuring that the procedures associated with patient care are documented consistently within the organization and ensuring consistency in many factors, such as physician incentives and executive leadership.

1.3.3 Identifying the Routine “as Designed”

My data consist of 32,460 realizations of 166 particular organizational routines. Each routine corresponds to a particular procedure type (DRG, or diagnosis related group). Each *patient-encounter*, or all medical activities that took place in the course of care, reflects a single realization of one routine. To effectively monitor behavioral compliance with the new set of practices, the hospital system put in place an internal tracking system to identify behaviors that did not comply with the workflow as it was intended to be performed in the new system. I use data from this internal tracking system to identify particular patient-encounters that embody the realizations that reflect the routine “*as designed*.”¹

¹ These data, while available to hospital administration, were not yet widely shared within the organization – it was deemed more imperative to first work out any issues with the system itself rather than monitor compliance or overwhelm doctors and nurses with a suite of new metrics.

In particular, I use six goals to identify instances where the routine was performed “as designed.” A description of these goals and the rationale for why these goals are tracked follows:

1. Did the care team chart the encounter quickly (within a certain time limit) and correctly? (ensuring workflows followed, timeliness, and accuracy of order information)
2. Was most charting completed within an hour of arrival? (ensuring data could be shared efficiently across providers)
3. Were encounters closed the same day they were completed? (ensuring other hospital processes could commence, such as insurance reimbursement)
4. Were approvals quickly completed for orders and medications (indicating effective coordination)
5. Were notes finalized in under 12 hours? (indicating capturing of time sensitive information)
6. Was documentation completed outside of physician shift hours? (indicating overwork)

For this analysis, I assume that patient-encounters that achieved each of these goals reflect an instantiation of the routine “as designed.” Thus – the “gap” for each of these encounters is 0. Adherence to these goals is tracked for each individual healthcare provider, at the level of the patient-encounter. So for each patient-encounter, compliance will be assessed for each individual. This formulation allows for flexibility in minor differences in activity sequences (such as the inclusion of a step deemed to be necessary in one case but not another – for example, a social work consult may be necessary for certain patients but not others). This formulation also allows for interdependencies in tracking compliance – hand-offs within the system that get delayed

at one stage may propagate to other steps in the process. Figure 1 shows how this is captured graphically.

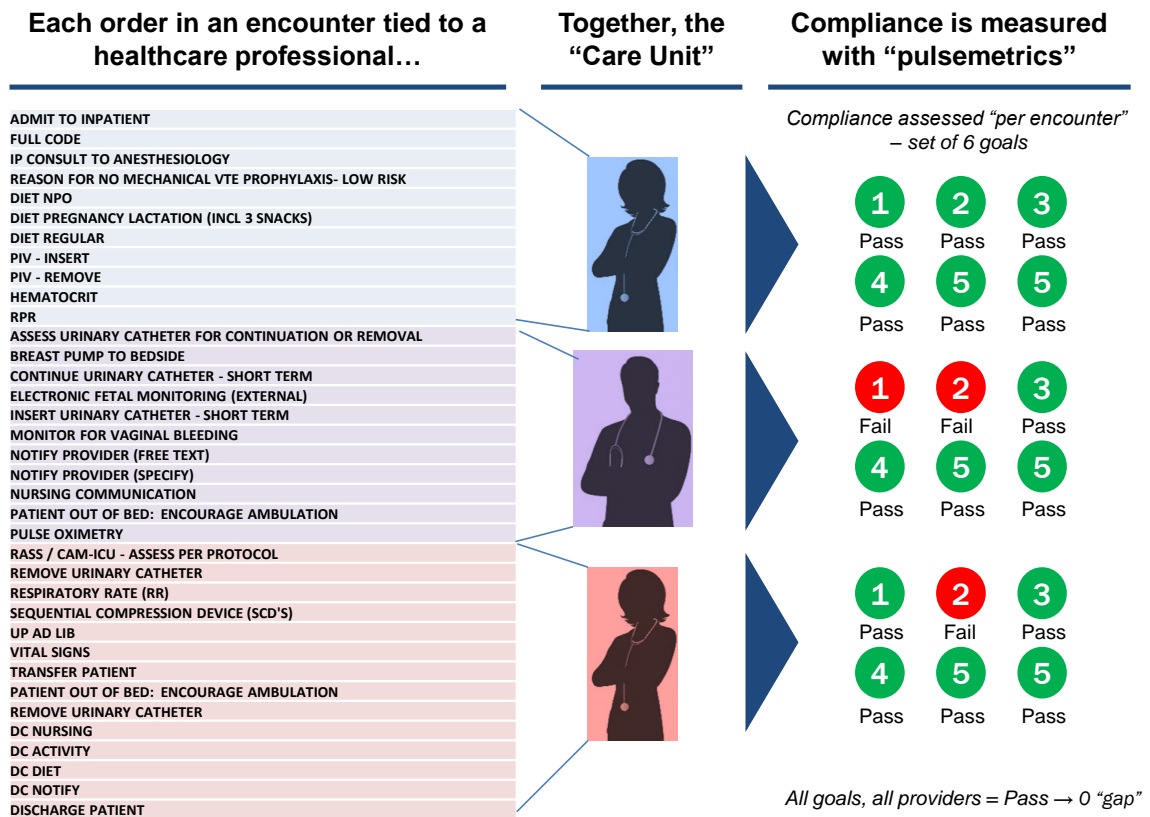


Figure 1: Relationship between Care unit, particular orders associated with the patient-encounter, and compliance as measured by the internal tracking ("pulsemetric") system

The next step in the analysis is to characterize the degree of difference between these patient encounters that reflect the routine "as designed" and all other realizations of the routine. This is accomplished using a technique called sequence analysis.

1.3.4 Quantitative Analysis of Organizational Routines

Much of the recent empirical research on change in organizational routines in practice is qualitative case study (Bechky, 2003; D'Adderio, 2003; Howard-Grenville, 2005; Lazaric & Denis, 2005). This is impractical in cases where multiple performances of a routine must be examined simultaneously, such as in this analysis, which examines over 32,000 realizations of organizational routines. As a result, scholars of organizational routines have begun to recognize the value of pushing beyond qualitative case study in the analysis of organizational routine. Winter (2014) states that “We should thus be very wary of letting any particular example drive us toward a general conclusion that “this is what routines are really like. Instead, he argues, “we should try to understand where the particular example examined at the moment fits in the diverse family of possibilities, and what its closest cousins are.” Hales and Tidd (2009), in their examination of the design and development of capital goods, find that representations captured as a byproduct of performing the routines (rather than formal representations of the routine) are most influential to organizational performance.

The predominant technique for the quantitative study of organizational routines is sequence analysis (Abbott, 1995; Pentland, Hærem, & Hillison, 2010; Pentland et al., 2011; Salvato, 2009). Sequence analysis takes as inputs the activities that comprise particular realizations of an organizational routine. These inputs closely mirror the factors that constitute organizational routines, including activity timing (Cohen &

Bacdayan, 1994; Grant, 1991), frequency of repetition (Ginsberg & Baum, 1994), and order (Cohen, 1991). The benefit of applying sequence analysis is that it allows for the measurement of these characteristics (order, timing, frequency, composition), and it also permits the numerical representation of similarity or dissimilarity between any two sequences of actions – thus making it possible to quantify how similar or different particular performances of an organizational routine are.

Dependent Variable - Gap between Routine as Designed and Realized

To measure the gap between organizational routines “as designed” and as “realized,” I build upon recent advances in the study of organizational routines that use sequence analysis and optimal matching techniques (Abbott 1995, Salvato 2009, Pentland et al 2011) to construct measures of the distance between routines “as designed” vs. “as realized” at the level of particular procedures (e.g. knee replacement, cesarean sections). I observe 32,640 sequences of activities over a year period following implementation. Each sequence, or *patient-encounter*, consists of all orders (e.g. administration of medicine, tests, consultations, patient movements within the hospital), which represent the activities that comprise the delivery of health care, performed by doctors and nurses from admission to discharge². I examine 166 organizational routines, which are distinguished by DRG (diagnosis related group) code. DRG classification

² For example, a three-day hospital stay would be logged as a single encounter. Two one-day stays by the same patient would be separate encounters.

provides an adequate basis by which to group routines, as procedures within the same DRG code are reimbursed similarly (Fetter and Brand 1991). These 166 routines represent the most standard and commonplace procedures in the hospital, such as caesarian section without complications, total knee replacement without complications, rather than activities such as heart failure, which is likely to have a number of complicating factors. To avoid measurement error associated with comorbidity, I focus on these more commonplace activities – the presentation of a particularly complex patient may warrant less routine care.

As described above, I use internal tracking data to identify particular *patient-encounters*, or realizations of the routine, that reflect performance of the routine as designed. I am then interested in the degree to which other patient-encounters of the same procedure, or realizations of the same routine, differ. To calculate the degree to which they differ, or my gap size measure, I adapt the methodology utilized by Salvato (2009) and Pentland *et al* (2011). First, I construct the event sequences associated with a particular patient encounter. Because all order data is standardized, I am able to assign each order a particular code. All data is derived from DEDUCE, which is a system developed by Duke University hospital that directly accesses the same information that is used in patient billing and governmental compliance. For this reason, the data is highly reliable. The data that are being sequenced consist of all clinical orders, tests, and medications administered to a patient. All data has been de-identified to remove all

personally identifiable health information and ensure confidentiality of medical records. Consequently, there is substantial reason to believe that this sequence not only accurately reflects the activities performed on a patient, but that it is also a complete transcript of the medical care associated with a particular patient encounter.³

The next step in the data analysis process is to compare the focal *patient-encounter*, which reflects a single realization of the routine, to the particular patient-encounters that reflect the routine “as designed.” Though this is often performed visually in the case of relatively few sequences (Mintzberg, Raisinghani, & Theoret, 1976), the large amount of sequences performed in this context necessitates the use of automatic procedures to assess similarity. Optimal matching methods (Abbott, 1990, 1995) are a type of sequence analysis technique (Bakeman, 1997) that use dynamic programming to compute distance measures among any set of sequences represented by a string of well-defined elements. I use the STATA implementation of optimal matching to perform the standard algorithm for distance calculation, the Needleman-Wunsch algorithm, which works in the following fashion (Brzinsky-Fay, Kohler, & Luniak, 2006). Conceptually, this distance value is constructed by the addition of items and the

³ While my data enable me to track the performance and sequence of particular activities, I am unable to distinguish between the component parts of any particular routine. Take, for example, an order that a patient is to receive pain medication. While my data capture that pain medication was administered to a patient at a certain point in time, I cannot distinguish between details in *how* the medication might have been administered. Thus, my measure of gap is driven by 1- what is done and 2- the order in which it is done. I cannot directly observe changes to particular components.

substitution of items, and represents the minimal number of additions and substitutions required to make one sequence resemble another. Details of the algorithm follow:

Consider two vectors, R and C , which are sequences of arbitrary length. Let m denote the length of R and n denote the length of C . A matrix L , which has dimension $(m+1) \times (n+1)$ is created, and each cell is initialized with a 0. The cells of the first row and the first column of this matrix are filled as follows:

$$L_{1,i} = L_{1,i-1} + d; \quad i = 2, \dots, m$$

$$L_{j,1} = L_{j-1,1} + d; \quad j = 2, \dots, n$$

Where d is the “indel” cost, which is the distance generated by inserting a step into the sequence.

The value of each cell $L_{(i,j)}$ ($i = 2, \dots, m, j = 2, \dots, n$) is computed using the following recursive formula: $L_{i,j} = \min(L_{i-1,j-1} + s_{i,j}; L_{i-1,j} + d, L_{i,j-1} + d)$, where $s_{i,j}$ is the cost of substituting one element for another. The unstandardized minimal distance between sequences R and C is in the cell $L_{m,n}$. Further details on this algorithm are available in Needleman and Wunsch (1970).

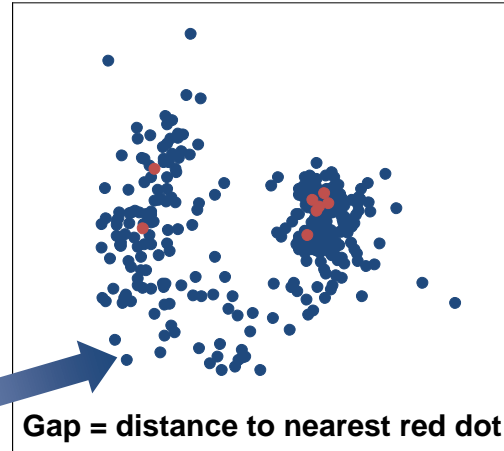
I use standard values for substitution costs (2) and indel costs (1), though the findings are not sensitive to adjustments to these parameters. Since sequences will differ in length, the distance measure will be heavily influenced by the disparity in sequence length, because the potential distance between a short and a long sequence is higher than for those of equal length. I use the standard correction to adjust for this

(Brzinsky-Fay, Kohler, & Luniak, 2006) which is to standardize distance measures by dividing the calculated value by the length of the longest sequence. I compare the sequences for all patient-encounters to each other using this algorithm, constructing a matrix consisting of the distance between the sequences for any two particular patient encounters.

Figure 2 displays an example of the data for one sequence in my data, as well as the results of the sequence analysis as applied to Cesarean section without complications. A multidimensional scaling algorithm (Borg & Groenen, 2005) is used to generate the scatterplot. In the scatterplot every point represents a single realization (i.e. patient encounter) of the routine (i.e. procedure), and the arrow reflects the distance between a realization and an intended sequence of activities.

ADMIT TO INPATIENT
FULL CODE
IP CONSULT TO ANESTHESIOLOGY
REASON FOR NO MECHANICAL VTE PROPHYLAXIS- LOW RISK
DIET NPO
DIET PREGNANCY LACTATION (INCL 3 SNACKS)
DIET REGULAR
PIV - INSERT
PIV - REMOVE
HEMATOCRIT
RPR
ASSESS URINARY CATHETER FOR CONTINUATION OR REMOVAL
BREAST PUMP TO BEDSIDE
CONTINUE URINARY CATHETER - SHORT TERM
ELECTRONIC FETAL MONITORING (EXTERNAL)
INSERT URINARY CATHETER - SHORT TERM
MONITOR FOR VAGINAL BLEEDING
NOTIFY PROVIDER (FREE TEXT)
NOTIFY PROVIDER (SPECIFY)
NURSING COMMUNICATION
PATIENT OUT OF BED: ENCOURAGE AMBULATION
PULSE OXIMETRY
R/S / CAM-ICU - ASSIGNED PER PROTOCOL
REMOVE URINARY CATHETER
RESPIRATORY RATE (RR)
SEQUENTIAL COMPRESSION DEVICE (SCD'S)
UP/D LIB
VITAL SIGNS
TRANSFER PATIENT
PATIENT OUT OF BED: ENCOURAGE AMBULATION
RESPIRATORY RATE (RR)
SEQUENTIAL COMPRESSION DEVICE (SCD'S)

Cesarean sections – no complications



Gap = distance to nearest red dot

*Sequence Analysis – Optimal Matching
Salvato (2009); Pentland et al (2011)*

Graph: Multidimensional Scaling Algorithm

Figure 2: Example of Sequence Analysis as Applied to all Cesarean Sections Without Complications at Duke University

1.3.5 Calculation of Shared Beliefs about the Expected Impact of the Change

To measure actors’ beliefs about the expected impact of the change, I use results from a pre-implementation survey administered two months prior to the change that asked 1,248 doctors and nurses across a variety of specialties a series of questions about their beliefs regarding the new system. This survey was developed in collaboration with healthcare analytics employees working for Duke University Hospital, and the questionnaire design followed largely that of the Primary Care Information Project (PCIP), a program of the New York City Department of Health and Hygiene. The questionnaire consisted of a number of sections that were relevant to these analytics

personnel, such as satisfaction with particular aspects of the existing electronic health record system. The survey consisted of five sections, comprising users' previous IT experience and level of expertise, the allocation of their time across various tasks (such as teaching, providing care, administration, and research), their level of satisfaction with existing EHR tools, communication patterns, and beliefs about the expected impacts of the new EHR system. The survey was administered staff-wide to physicians and nurses at Duke University Hospital. The overall response rate for this survey was 46%, with 42% of physicians and 48% of nurses replying to the survey, a figure which is in line with broad overall trends in survey response rates (Baruch & Holtom, 2008).⁴

The particular survey measures that were used to measure beliefs about the expected impact of the system came from two items in which doctors and nurses were asked to rate on a scale from 0 (worsen) to 100 (improve) what effect the system would have on "Quality of Care" and "Hospital Revenue." The survey also included questions that related to other outcomes that closely aligned with professional norms, such as "patient safety" and "continuity of care." The results are consistent with the measure of quality of care, and in the robustness section, I use a composite measure of beliefs to test

⁴ Armstrong and Overton (1977) suggests that differences between early and late responses to a survey may indicate the degree of non-response bias. A two-tailed t-test comparing early and late responders to the survey on the "Quality of Care" item returns a p-value of .52, indicating that there is no statistical difference between early and late responders. Additionally, no significant differences between responders and non-responders were observed on measurable characteristics, such as gender and years of experience. Together, these suggest non-response bias is likely to be minimal.

the hypotheses. As argued in the section on professional norms, belief that the change is likely to improve quality of care is consistent with medical professional norms, while improving in hospital revenue is inconsistent with medical professional norms. Because these data are tied to individual providers, I am able to link the performance of organizational routines with survey responses from individuals associated with particular realizations of an organizational routine. My quality of care and hospital revenue measures are calculated as the average of all responses of individuals associated with a particular routine.

Though hospital revenue and quality of care beliefs need not inherently be at odds, for the sample of doctors and nurses we examined, this was largely the case. 82% of survey responses indicated that the change would be beneficial to either “quality of care” or “hospital revenue” and harmful to the other. Only 18% indicated that the change would be beneficial or harmful to both outcomes. Figure 3 shows how particular care units responded to these questions.

		<i>Quality of care will improve</i>	
		<i>Yes</i>	<i>No</i>
<i>Hospital Revenue will improve</i>	<i>Yes</i>	10%	44%
	<i>No</i>	38%	8%

% of teams

Figure 3: 2x2 Showing Proportion of Respondents for Beliefs about Quality of Care and Hospital Revenue, Respectively

The survey findings about beliefs raise several questions about the origins of these beliefs within the hospital system, particularly considering that different individuals on the same team may have different beliefs about the expected impact of the system. Doctors and nurses differed slightly in the degree to which they expected the system to improve quality of care (50.68 vs. 56.32, respectively). Figure 4 shows how the quality of care belief varies with other observable characteristics of the respondents to the survey.

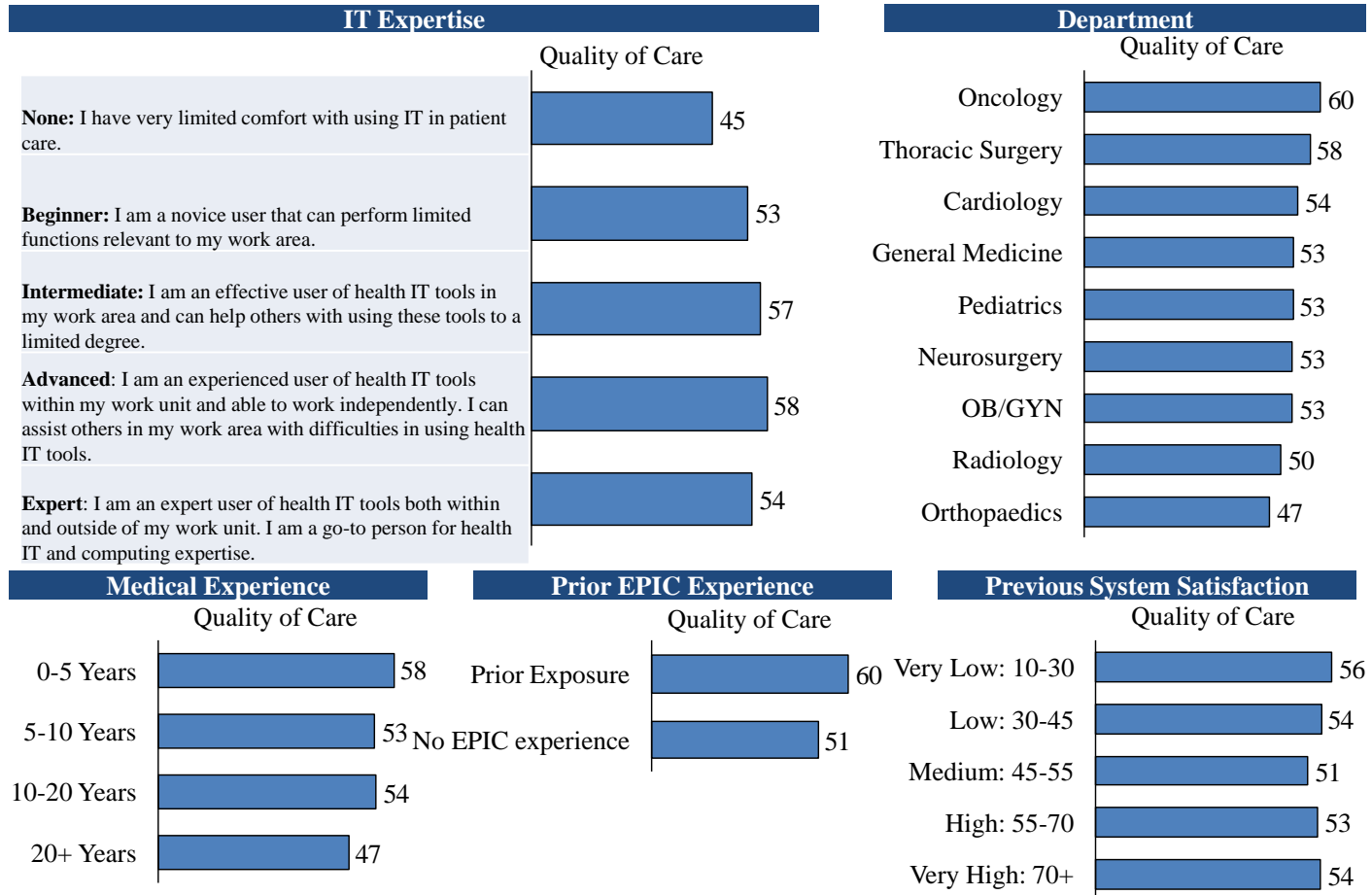


Figure 4: Quality of Care Beliefs by Key Demographics in Hospital (Experience, Satisfaction, Department)

First, quality of care belief was lowest among those participants with no IT expertise and was generally increasing as the professionals recognized they were more expert users of IT. Interestingly, expert users' beliefs were only moderately higher than those that described themselves as having limited comfort with IT in patient care. Satisfaction differed by department as well. Figure 4 shows the satisfaction results for 9 of the departments with the highest response rate to the survey. This is likely tied to the design of the new system, which consisted of a set of modules aligned to various clinical departments. Interviews with physicians in various specialties indicated general dissatisfaction when they felt that the module associated with their practice was not developed to the degree of previous tools.

Expectations about quality of care were generally decreasing with physician experience, with professionals with over 20 years of experience being most circumspect about the new system. Literature on technological adoption has found that older individuals have a difficult time adopting new technologies, which could also explain the anticipated lower results (Orlikowski & Gash, 1994). Prior experience with the EPIC system – the brand of EHR that was installed at Duke - was found to be associated with an increase in expected beliefs about the degree to which the system would improve quality of care. For these individuals, past prior experience may be informing the beliefs they apply to this situation. Finally, beliefs about the degree to which the system is

perceived as likely to improve quality of care seem to be somewhat independent of overall satisfaction with the previous system. The survey results indicate that individuals with low and very high satisfaction with the previous system demonstrated approximately the same intensity of belief that the system would likely improve quality of care.

Altogether, these survey findings suggest that belief about the impact of the change appear to be informed by experience (both with the EHR system in question as well as degree of professional experience), IT expertise, and the departmental affiliation of the professional. Satisfaction with the prior system seems to be independent of beliefs about the future system.

1.3.6 Professional Experience

Professional experience is calculated as the *average number of years practicing medicine* that the doctors on a care unit have. These data were scraped from publicly available physician information Duke Hospital website. Specifically, this variable is operationalized as years since the physician completed their residency. This data was checked against a survey item in which providers listed their years of medical experience. For nursing staff, the survey measure of experience was used.

1.3.7 Departmental Leadership Position

I include a dummy variable to indicate the presence of an individual with a *departmental leadership role* on the care unit. People are highly aware of the behavior of those in positions of authority or power (Lind & Tyler, 1992), which may affect their willingness to perform a routine in a particular way. Data on departmental titles was scraped from the Duke Hospital website using the BeautifulSoup package in Python.

1.3.8 Other Controls

Several other additional controls are included to test for alternative mechanisms that could affect the gap between performance as desired and performance as realized. Selection of these control variables was motivated by an examination of the literature on organizational and routine change as well as interviews with individuals involved in the change process at the hospital.

1.3.8.1 Care Unit Controls

To account for *experiential learning* (Epple, Argote, & Devadas, 1991; Pisano et al., 2001), I control for time since the new system went live. Thus, all results linking beliefs about the expected impact of the change and gap between routine “as designed” and routine “as realized” are above and beyond those associated with simple experiential learning effects. To account for structural differences in care units, I construct a measure of *unit composition* by calculating the ratio of doctors to nurses for any particular patient-

encounter. This also provides a crude control for cost, due to the higher personnel costs associated with physicians.

To account for varying degrees of skill with IT, I also include a control for *average IT comfort*, which was self-reported in the pre-implementation survey – respondents were asked to rate themselves from no experience to expert on a scale of one to five – each level was described as follows: 1- None: I have very limited comfort with using IT in patient care. 2- Beginner: I am a novice user that can perform limited functions relevant to my work area. 3 - Intermediate: I am an effective user of health IT tools in my work area and can help others with using these tools to a limited degree. 4 - Advanced: I am an experienced user of health IT tools within my work unit and able to work independently. I can assist others in my work area with difficulties in using health IT tools. 5 - Expert: I am an expert user of health IT tools both within and outside of my work unit. I am a go-to person for health IT and computing expertise. To control for variation in medical skill between care units, I control for the *presence of specialists* on a care unit – i.e. those physicians that have completed fellowship training. In the absence of more fine-grained quality measures, this provides a coarse control for heterogeneity in the skillset for the physicians performing a particular procedure. In specifications that interaction presence of departmental leadership with beliefs, I include the *departmental leadership beliefs* to account for the possibility that these senior leaders'

beliefs may take precedence or override those of the rank-and-file members of the care team.

1.3.8.2 Patient Controls

I include controls for basic demographic characteristics of the patients receiving the care associated with a particular realization of an organization routine. In particular, I control for *patient age* and *patient gender* ($1 = \text{male}$), as these factors may complicate or adjust the provision of care in a systematic fashion.

1.3.9 Empirical Specification

In order to examine the gap between routine as designed and routine as realized, I apply an OLS regression model, which has been used in other studies of organizational routine change (Pentland et al, 2011). To account for differences across routine types, fixed-effects for diagnosis-related groups (DRGs) are included to control for heterogeneity across procedures.¹ All comparisons are consequently made “within” particular procedures. For example: DRG 775 captures all newborn deliveries without complicating diagnoses. DRG 247 governs stenting without major complications, and DRG 470 encompasses major joint replacement without major complications. To account for heterogeneity in the specialized modules in the EHR system that different

¹ DRGs classify procedures in terms of their output, and are commonly used for reimbursement in medical billing in an inpatient setting.

departments had to use on a day-to-day basis, I also include departmental fixed effects. Robust standard errors are included to account for potential non-independence of observations.

1.4 Results

Table 2 shows the fixed-effect OLS models predicting the size of the gap between routine as designed and routine as realized. Above each column in the table is shown the correspondence to the particular hypothesis that is tested by that model. Model 1 includes only the control variables. Model 2 introduces the effect of average care unit beliefs that the change will improve quality of care, a belief which is perceived as consistent with professional norms. Model 3 shows the of average care unit beliefs that the change will improve hospital revenue, a belief perceived as in conflict with professional norms. Model 4 interacts average unit beliefs that the change will improve quality of care with professional experience. Model 5 interacts the presence of a departmental leader on the care team with unit beliefs that the change will improve quality of care. Model 6 shows all effects and interactions simultaneously.

Table 2: OLS Regression Models Predicting Gap Size

Model	(1)	(2)	(3)	(4)	(5)	(6)
DV	Gap Size	Gap Size	Gap Size	Gap Size	Gap Size	Gap Size
Hypothesis	<i>Control</i>	<i>H1a</i>	<i>H1b</i>	<i>H2</i>	<i>H3</i>	
Belief: Quality of Care (QoC)		-0.004*** (0.000)		0.007*** (0.000)	-0.006** (0.000)	-0.001** (0.000)
Belief: Hospital Revenue (HR)			0.004*** (0.000)			
Professional Experience				0.019*** (0.001)		0.010*** (0.000)
QoC * Professional Experience				-0.000*** (0.000)		-0.000*** (0.000)
QoC * Care unit has departmental leader					0.002** (0.000)	0.001** (0.000)
<i>Care Unit Controls</i>						
Experiential Learning: Time Since Go Live	-0.001*** (0.000)	-0.001*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.004*** (0.000)	-0.004*** (0.000)
Doctor: Nurse Ratio on care unit	-0.027*** (0.002)	-0.033*** (0.002)	-0.021*** (0.002)	-0.021*** (0.002)	-0.020*** (0.001)	-0.020*** (0.001)
Care unit has departmental leader	-0.006*** (0.001)	-0.006*** (0.001)	-0.007*** (0.001)	-0.004*** (0.001)	-0.003*** (0.000)	-0.002*** (0.000)
Average IT Comfort	-0.548*** (0.009)	-0.287*** (0.031)	-0.408*** (0.015)	-0.451*** (0.028)	-0.417*** (0.028)	-0.071** (0.023)
Care unit has fellowship physician	-0.004** (0.001)	-0.005*** (0.001)	-0.003** (0.001)	-0.002* (0.001)	-0.000 (0.001)	-0.002** (0.001)
Senior leadership beliefs					-0.023** (0.000)	-0.021** (0.000)
<i>Patient Controls</i>						
Patient Gender	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Patient Age	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Constant	2.089*** (0.032)	1.370*** (0.086)	1.351*** (0.067)	1.316*** (0.088)	-0.889*** (0.078)	-0.070 (0.069)
Departmental FE	Yes	Yes	Yes	Yes	Yes	Yes
DRG FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.487	0.537	0.516	0.574	0.574	0.597
N	32640	32640	32640	32640	32640	32640
Standard errors in parentheses	* p<.05	** p<.01	*** p<.001			

For all models, a negative coefficient associated with a variable means a smaller gap size between routine as designed and routine as realized, or a greater degree of adoption of the new practice. In model 1, I find that, consistent with literature on experiential learning (Argote 1999; Pisano et al. 2001), cumulative time since “going live” is associated with a decrease in gap size ($p < .001$). As doctors and nurses have greater exposure to the new practices, tools, and technology that accompany the change, they become more able to implement the practice as designed.

The Doctor:Nurse ratio was associated with a smaller gap size ($p < .001$). This effect may be offset by the relatively stronger beliefs on behalf of nursing staff that EHR was likely to improve quality of care relative to the group of doctors (average responses of 56.32 vs 50.68). The presence of a departmental leader (e.g. a department head / chair / etc.) on a care unit reduces the size of the gap ($p < .001$). This effect remains significant across all models. To the extent that these leaders had a larger say in shaping the new practices, then it would be expected that they would be more willing to accept them. I find that average IT comfort is associated with a smaller gap size – reflecting that these individuals had an easier time adjusting to the system. I find that the presence of a fellowship physician also reduces the size of the gap, but this effect is weaker depending on the specification. I find little effect on patient gender and patient age – suggesting

that patient characteristics do not drive the size of the gap between routine as realized and routine as designed.

Model 2 shows that an increase in the intensity of belief that the new practices will improve quality of care will reduce the size of the gap between routine as designed and routine as realized ($p < .001$), which is consistent with hypothesis 1a. This effect is substantively quite large, as a one standard deviation increase in quality of care belief reduces gap size approximately 12 times as much as a standard deviation increase in time since the change was launched. Normative assessments of the expected impact of change, which occur well in advance of the change itself, are associated with degree of routine change *following* the beginning of the change initiative. Model 3 shows that an increase in the intensity of the belief that the new practices will improve hospital revenue will increase the gap between routine as realized and designed ($p < .001$), in support of hypothesis 1b. Jointly, models 2 and 3 suggest that the beliefs of rank-and-file members of the organization will have a strong role in driving routine change.

Hypothesis 2 stated that professional experience would amplify the effect of belief about the expected impact of the change. To test this, model 4 shows the interaction between average unit belief that quality of care will be improved with average unit years of professional experience. Though I find that the main effect of the quality of care belief measure becomes positive, I note that the interpretation of this

result requires consideration of both the main and interaction terms for both coefficients (Jaccard & Turrisi, 2003). Consequently, to facilitate interpretation, I have graphed the main findings of model 4 in Figure 5.

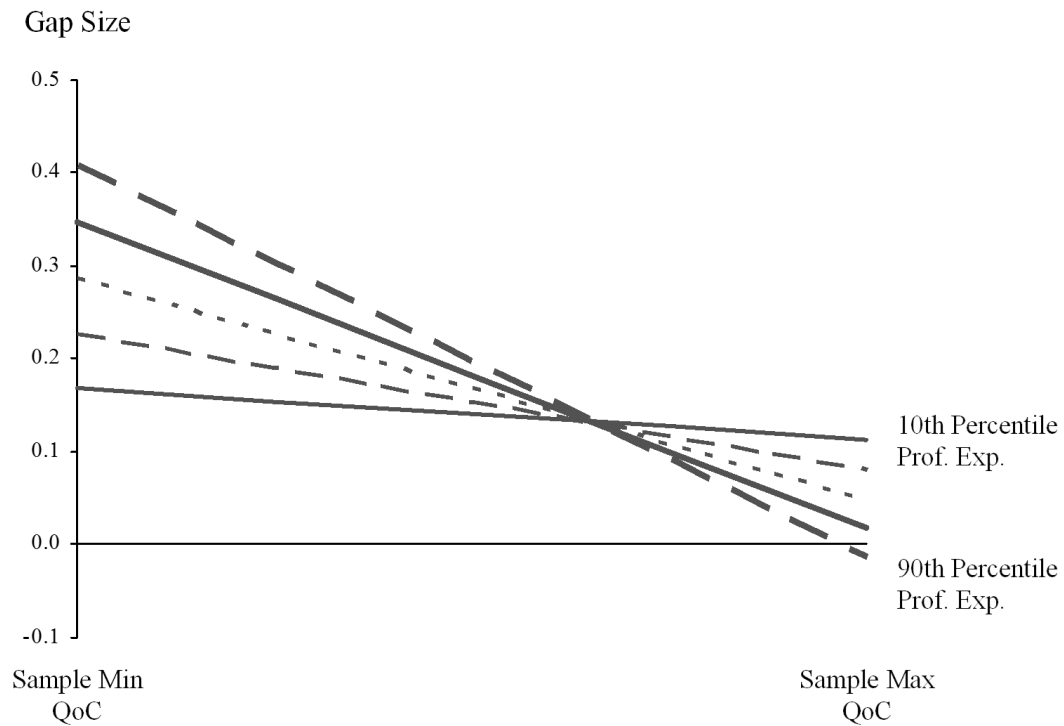


Figure 5: Interaction Between Belief that the Change will Improve Quality of Care and Professional Experience

Figure 5 shows the effect of the average unit belief that the intervention will improve quality of care (QoC) and average unit years of professional experience on the size of the gap between organizational routine as designed and realized. I graph the domains of both variables, showing five particular level curves of professional experience (from 10th percentile to 90th percentile). Hypothesis 2 discussed the slope of

the relationship between beliefs regarding the expected impact of the change and gap size at different levels of professional experience. Figure 5 shows that this slope is steepest when professional experience is high, and the coefficient on the interaction term is significant ($p < .001$). When shared beliefs about the expected impact of the change are aligned with professional norms, I find that highly experienced units demonstrate a smaller gap. Again, the magnitude of this effect is large – a standard deviation increase in quality of care belief at the 10th percentile of professional experience corresponds to an effect ~2.5x larger in magnitude than that of experiential learning, and the magnitude difference increases to ~20x at the 90th percentile of professional experience.

The coefficient associated with the main effect on professional experience (0.19) suggests that increased professional experience is associated with a larger gap between routine as designed and routine as realized, which is consistent with the notion of a “competency trap.” However, the interaction results and Figure 5 suggest that this trap exists only in the absence of quality of care beliefs.

Model 5 shows the impact of the presence of a departmental leader on routine adoption. Consistent with hypothesis 3, I find that the presence of a departmental leader reduces the impact of beliefs on gap size ($p < .001$). To facilitate interpretation, I have graphed the main findings of model 5 in Figure 6.

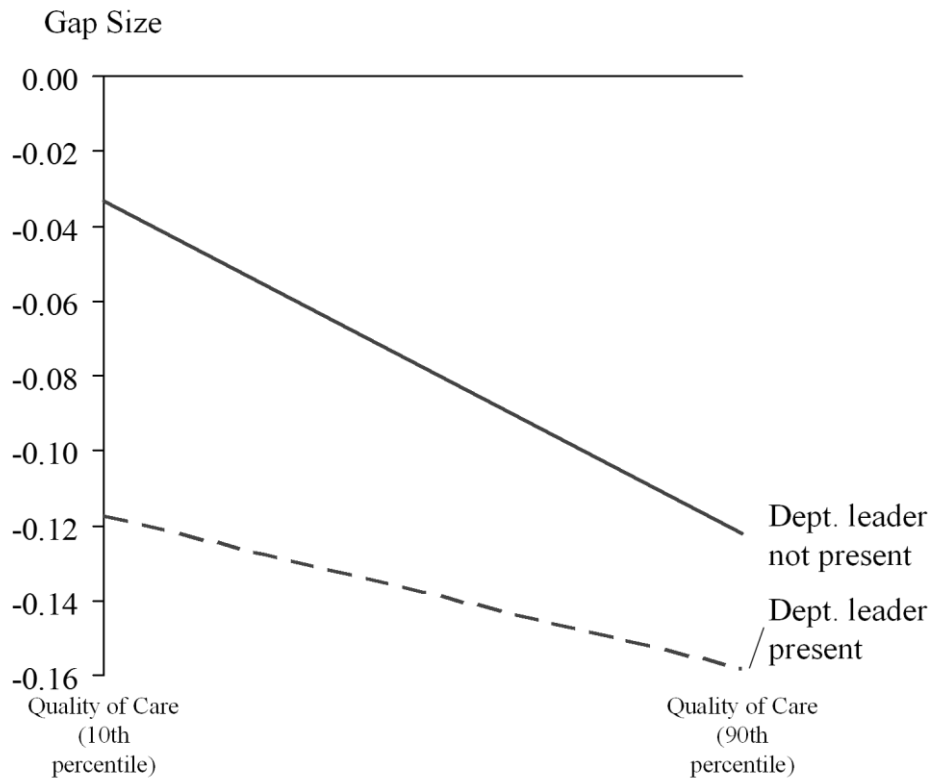


Figure 6: Interaction Between Belief that the Change Will Improve Quality of Care, Presence of Departmental Leader

Figure 6 shows the effect of the average unit belief that the intervention will improve quality of care (QoC) and the presence of a departmental leader on the size of the gap between organizational routine as designed and realized. I graph the domains of both variables, showing five particular level curves of professional experience (from 10th percentile to 90th percentile). Hypothesis 3 discussed the slope of the relationship between beliefs regarding the expected impact of the change and gap size when a departmental leader is present versus absent. Figure 6 shows that this slope is steepest

when a departmental leader is absent from the care team, and the coefficient on the interaction term is significant ($p < .01$)². Finally, Model 6 includes all effects simultaneously. These effects remain consistent with models 4, 5, and 6 individually.

1.5 Robustness

To provide additional support for these findings, I provide below two robustness tests. The first constructs an alternative dependent variable, using the raw internal tracking data as a measure of compliance rather than the sequence analysis exercise. Consistency between this DV and the gap size metric suggests the results are not driven by particular issues or sensitivities to the parameters of the sequence analysis algorithm. The second robustness test is the inclusion of a composite belief measure as opposed to the single item measures used in Models 1-6. The findings on this test indicate that the results were not driven by an idiosyncrasy of a particular survey item.

1.5.1 Alternative DV

Underlying the distance measures of compliance (which can be translated into differences in action sequences and consequently measure changes to organizational routines more directly) are the data used to measure compliance themselves – the six

² To assess whether the impact of the role of leader was conditional upon the beliefs of the leader, I ran supplemental models including the leader's belief in a triple-interaction with team belief and presence of the leader on the care team. This triple interaction was not significant, suggesting that the attenuation associated with the presence of the leader was not conditional upon their beliefs.

internally tracked goals that were used to identify routines “as designed.” To provide further support for the gap size metric created using sequence analysis techniques, I rerun the analysis using a composite compliance measure across these six dimensions (full compliance being given a score of 1, non-compliance 0). For each patient-encounter, all available scores for all healthcare providers were aggregated and used to create a compliance measure, the results of which are displayed in Table 3.

Table 3 reruns models 1-6 using this compliance measure rather than the sequence analysis derived distance measure. Unlike in table 2, a negative value here would correspond to a larger gap size. I note that the results remain highly robust to this alternative formulation – this is unsurprising given their high correlations.

Table 3: OLS Regression Models Predicting Compliance (Using Internal Tracking Data)

Model	(1)	(2)	(3)	(4)	(5)	(6)
DV	Compliance	Compliance	Compliance	Compliance	Compliance	Compliance
Hypothesis	<i>Control</i>	<i>H1a</i>	<i>H1b</i>	<i>H2</i>	<i>H3</i>	
Belief: Quality of Care (QoC)		0.000*** (0.000)		-0.001*** (0.000)	0.001** (0.000)	0.000** (0.000)
Belief: Hospital Revenue (HR)			-0.000*** (0.000)			
Professional Experience				-0.001*** (0.000)		-0.001*** (0.000)
QoC * Professional Experience				0.000*** (0.000)		0.000*** (0.000)
QoC* Care unit has departmental leader					-0.000** (0.000)	-0.000** (0.000)
<i>Care Unit Controls</i>						
Experiential Learning: Time Since Go Live	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Doctor: Nurse Ratio on care unit	0.002*** (0.000)	0.002*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Care unit has departmental leader	0.000*** (0.000)	0.000*** (0.000)	0.001*** (0.000)	0.000*** (0.000)	0.000** (0.000)	0.000* (0.000)
Average IT Comfort	0.042*** (0.001)	0.020*** (0.003)	0.032*** (0.001)	0.033*** (0.003)	0.033*** (0.003)	0.007* (0.003)
Care unit has fellowship physician	0.000** (0.000)	0.000** (0.000)	0.000* (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Senior leadership beliefs					0.000** (0.000)	0.000** (0.000)
<i>Patient Controls</i>						
Patient Gender	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Patient Age	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Constant	0.968*** (0.000)	0.937*** (0.001)	1.037*** (0.001)	0.983*** (0.002)	0.962*** (0.001)	0.989*** (0.002)
Departmental FE	Yes	Yes	Yes	Yes	Yes	Yes
DRG FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.318	0.378	0.330	0.443	0.403	0.457
N	32640	32640	32640	32640	32640	32640
Standard errors in parentheses	* p<.05	** p<.01	*** p<.001			

1.5.2 Composite Measure of Belief

To avoid potential issues with using a single item measure, I constructed a composite belief measure, which consisted of four items from the survey, in which participants were asked to rate from 0 (worsen) to 100 (improve) what impact the new system would have on patient safety, quality of care, continuity of care, and hospital revenue. I created a simple composite measure of these four outcomes (reverse coding hospital revenue because of its high negative correlation with the other measures) by averaging these four items. I then reran the analysis using this composite measure, which is shown in Table 4.

Table 4 reruns the models associated with H1a, H2, H3, and the full model. I find that the results of the composite measure mimic those of the single item scale that examined quality of care, in support of hypotheses 1-3.

Table 4: OLS Regression Models Predicting Gap Size (Composite Belief Measure)

Model	(1)	(2)	(3)	(4)	(5)
DV	Gap Size	Gap Size	Gap Size	Gap Size	Gap Size
Hypothesis	<i>Control</i>	<i>H1a</i>	<i>H2</i>	<i>H3</i>	
Belief: Composite Measure		-0.009*** (0.002)	0.003*** (0.001)	-0.004** (0.001)	0.000* (0.001)
Professional Experience			0.023*** (0.001)		0.014*** (0.000)
Composite * Professional Experience			-0.000*** (0.000)		-0.000*** (0.000)
Composite * Care unit has departmental leader				0.002* (0.000)	0.000* (0.000)
<i>Care Unit Controls</i>					
Experiential Learning: Time Since Go Live	-0.001*** (0.000)	-0.001*** (0.000)	-0.002*** (0.000)	-0.004*** (0.000)	-0.004*** (0.000)
Doctor: Nurse Ratio on care unit	-0.027*** (0.002)	-0.027*** (0.002)	-0.017*** (0.002)	-0.016*** (0.001)	-0.017*** (0.001)
Care unit has departmental leader	-0.006*** (0.001)	-0.006*** (0.001)	-0.004*** (0.001)	-0.003*** (0.000)	-0.002*** (0.000)
Average IT Comfort	-0.548*** (0.009)	-0.568*** (0.051)	-0.809*** (0.048)	-0.228*** (0.042)	-0.140*** (0.037)
Care unit has fellowship physician	-0.004*** (0.001)	-0.004*** (0.001)	-0.002* (0.001)	-0.001 (0.001)	-0.002** (0.001)
Senior leadership beliefs				-0.011** (0.000)	-0.007** (0.000)
<i>Patient Controls</i>					
Patient Gender	0.001 (0.001)	0.001 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Patient Age	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Constant	2.089*** (0.032)	2.140*** (0.132)	2.090*** (0.131)	-0.244* (0.111)	0.465*** (0.103)
Departmental FE	Yes	Yes	Yes	Yes	Yes
DRG FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.520	0.570	0.597	0.601	0.643
N	32640	32640	32640	32640	32640
Standard errors in parentheses	* p<.05	** p<.01	*** p<.001		

1.6 Discussion and Conclusions

This chapter examines the relationship between the beliefs held by decision makers and the “gap” between routine “as designed” versus routine “as realized.” I argued that new practices that are perceived to align with professional norms will be seen as legitimate, increasing motivation and capacity to change, which would in turn reduce the size of the gap between routine “as designed” and routine “as realized.” To bolster this argument, I then explored some factors that would moderate this relationship, particularly professional experience and presence of a departmental leader on a team. I reasoned that professional experience amplifies the effect of beliefs perceived to be aligned with professional norms due to increased socialization to professional norms and that the presence of a departmental leader lowers the effect of the rest of the team’s beliefs. My findings support these claims, and the consistency of the interaction effect with the hypothesized direction helps support the claim that professional norms are a basis by which these changes are evaluated as legitimate or not.

This study makes several contributions. While it is established that cognitive factors have a role in explaining how firms make the decision to engage in change (Kaplan, 2008) or develop capabilities (Gavetti, 2005), we still understand little about how particular beliefs, such as those regarding the expected impact of a change, shape the interpretation and realization of particular routines and the ultimate impacts of these

beliefs on the firm's ability to execute its vision and strategy (Salvato & Rerup, 2010).

This research offers new insights into the determinants of routine change in organizations. In particular, I highlight the importance of beliefs about the expected impact of the change. My findings - that when beliefs regarding the expected impact of the change align with professional norms, gap between routine as designed and routine as realized will decrease - suggest the beliefs held by rank-and-file members of an organization are critical in new routine adoption. This belief, however, is less impactful when a departmental leader, who may be attuned to the broader goals of the organization, is present. Furthermore, I identify a set of factors that affect the magnitude of the impact of shared beliefs about the impact of an initiative on routine change. The importance of expectations around the purpose and impact of a change as a driver of routine change depends on the level of professional experience and the involvement of senior leadership within the organization, which has implications for studies of change initiatives. It may be less critical to seek buy-in for routine change in a less experienced organization. On the other hand, broad buy-in in experienced organizations may assist in breaking out of "competency traps."

Consequently, this study's findings raise an interesting question about the role of beliefs about the purpose and impact of change in other organizations. In the healthcare organizations, the influence of medical professional norms is particularly strong - so

how might this research generalize to organizations not comprised of “professionals?” Not only may beliefs still play an important role, but the organization may have increased latitude to shape those beliefs. Rather than appealing strictly to professional norms, if the expected effect of a proposed change in practice conforms to whatever the workers believe to be consistent with what they view as the legitimate mission of the company or organization they work for, then capacity and motivation to change may still increase.

Also, this study focuses on “top-down” change, in which management has a particular desired practice in mind. While beliefs about whether the organization’s behaviors align with professional norms or the organizational mission cannot condition degree of gap between routine “as designed” and routine “as realized” when there is no explicit design for a practice, it is likely that these beliefs will still affect the trajectory by which routines evolve naturally overtime (Feldman and Pentland 2003). It is not difficult to imagine motivated employees seeking to improve the policies of their workplace even in the absence of top-down direction to do so. To the extent that lower-level employees possess a greater degree of tacit knowledge on the firm’s operations (Winter 1998), bottom-up change might even be more beneficial for firm performance than top-down change.

In all, an implication of this work is that there may be an opportunity for organizations in which professional norms are not widespread and well-defined. These companies might benefit by appealing to some “greater mission” to motivate employees. In particular, this study suggests that such companies may be better able to change routine practice, which will help them adapt as their environment and technological landscape changes. Further research is needed not only to examine other potential benefits, such as the recruitment and retention of employees, but to explore the mechanisms that lead to the development of organizational norms.

However, it is not sufficient that companies inculcate this strong sense of mission; they must also ensure that employees understand how their actions are aligned with this mission. Just as companies benefit when their actions are consistent with professional norms, they are similarly punished when they are perceived to be acting inappropriately. Thus, firms must be careful in both framing the goals and mission of the organization as well as in communicating the implications and rationale for change initiatives to employees.

This study also enhances our understanding of new practice adoption, reframing what is often assumed to be a discrete change as a question of degree. I introduce the notion of a gap between routine “as designed” versus routine “as realized,” a helpful construct to understand degree of routine adoption in the context of top-down change

initiatives. This construct, which is an extension of the work done using sequence analysis techniques (Salvato 2009; Pentland, *et al*, 2011), can be extended to future studies of top-down routine change. The replication of the findings using internal hospital compliance data reinforce the reliability of this approach, which may be beneficial in situations in which such data do not exist. Linking individual actions to performances of an organizational routine allow me to examine shared belief patterns among participants of a routine, providing insight into how rank-and-file members' beliefs can shape the organization.

This study is not without its limitations. While focusing on a single organization enabled me to control for many confounding factors, I am still confined to one organizational and environmental context. Extensive change or strong organizational norms may be undesirable for companies not facing strong environmental pressure to change, as was the case with Duke's change to a new EHR system. Furthermore, a larger "gap" between the practice "as designed" and "as realized" may or may not be desirable in all circumstances, and further research is necessary to evaluate performance implications of the gap.

In sum, this chapter finds that beliefs about the expected impact of a change play a critical role in facilitating or hampering attempts at top-down routine change. These beliefs are consequential because they resonate with a deeper

understanding of the “purpose” of the organization, in this case, the importance of patient care as held up by medical professional norms. Thus, beliefs about the expected impact of a change affect degree of new routine adoption – in particular, the gap between routine “as designed” and routine “as realized.” A topic of much interest in strategy is the development of organizational routines (Dosi, Nelson, and Winter, 2000; Winter 2003; Becker 2004, 2008; Salvato 2009). When organizational change processes are perceived to resonate with shared beliefs about the purpose of the organization, this can facilitate routine change, and thus spur the adoption of new routines. However, when the changes in question conflict with these beliefs, then change will be resisted. Processes that reinforce belief or strengthen an individual’s understanding of the organization’s purpose (such as socialization into organizational or professional norms) will magnify this relationship. Finally, this chapter suggests a critical role for the rank-and-file members of an organization – what they believe to be the purpose of the change in question will have a large role in shaping the extent to which the practice is adopted.

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

This chapter examines the effects of organizational structure and performance feedback on termination decisions—in particular, product phase out. Using quarterly product-level data on the major mobile handset manufacturers for the period 2004–2009, we analyze how product-level feedback affects product phase-out, 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 phase-out decreases. We find that as performance declines below aspirations, the rate of phase out 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 phase-out 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.

2.1 Introduction

This study examines the effects of organizational structure and performance feedback on product phase-out. Product phase-out is part of a broader category of termination decisions that also includes decisions to dissolve organizational units (Mitchell, 1994), halt investments (McGrath and Nerkar, 2004; Guler, 2007), abandon practices (Greve, 1995; Gaba and Dokko, 2015), sell off units (Villalonga and McGahan, 2005; Hayward and Shimizu, 2006; Karim, 2006; Desai, 2015; Vidal and Mitchell, 2015), end alliances (Heimeriks, Bingham, and Laamanen, 2014) and exit technologies (Eggers, 2014). Termination decisions are an important aspect of firm evolution; they bear on a firm's distinctive competencies and even on its ability to survive (Schoonhoven, Eisenhardt, and Lyman, 1990). Product termination figures prominently in high-tech industries, where firms must respond to rapidly changing market conditions by actively managing their product portfolio (Sorenson, 2000; Henderson and Stern, 2004; de Figueiredo and Kyle, 2006). Although the mechanisms driving new product introductions have been studied extensively (cf. Brown and Eisenhardt, 1995), relatively little is known about the drivers of product phase-out.

The problem with product phase-out, 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 (Puranam, Powell and

Singh, 2006; Benner and Tripsas, 2012; Posen and Levinthal, 2012). These decisions can thus be affected by perceptions of product success or failure (Baum and Dahlin, 2007), which suggests the Behavioral Theory of the Firm as a suitable lens through which to view such decisions (Cyert and March, 1963; March and Shapira, 1987; Greve, 2003; Bromiley, 2005). Behavioral theories of performance feedback demonstrate that organizations persist with successful activities (Audia, Locke, and Smith, 2000) but change their activities following perceived failure (Greve, 1998). Although there is considerable support for models of performance feedback (see Greve, 2003), 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 (Child, 1972).

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 on structure (Gulati, Puranam, Tushman, 2012), with particular attention given to the coordination (Nadler and Tushman, 1997; Burton and Obel, 2004; Puranam, Raveendran, Knudsen, 2012) and screening properties (Csaszar, 2012; Csaszar and Eggers, 2013; Garud, Nayyar and Shapira, 1997; Siggelkow and Rivkin, 2005; 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 Sorenson, 2001; Vissa, Greve, and Chen, 2010; Gaba and Joseph, 2013; Sengul and Obloj, 2014). For example, Audia and Sorenson (2001) examined the behavioral outcomes that follow from horizontally differentiated subunits' feedback. Similarly, Gaba and Joseph (2013) focused on the unique responses that follow from vertically differentiated corporate and business unit feedback. However, these studies focus on how the firm's subunits respond to their respective feedback (e.g., corporate- and business unit -level); thus they leave 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 coordinating activities, 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 (Barr, Stimpert, and Huff, 1992; Ocasio, 1997; Ocasio and Joseph, 2005). Organizational structure may thus condition problemistic search behavior and responses to feedback.

We test our predictions using a dataset of product sales in the German mobile device industry for 2004–2009, a period that was part of the “feature phone era” of the mobile device industry. That era was characterized by high turnover of discrete and observable product units, making it a suitable setting in which to test our hypotheses. Product phase-out decisions were country-specific decisions, and as Germany is the largest and most advanced European market for devices, we can trace phase-out decisions in this country with confidence. Our main effects models indicate that as

performance increases above aspirations, the rate of phase-out decreases. We find that as performance declines below aspirations, the rate of phase out 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 that 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 analysis seeks to reduce that gap and argues that structure exerts not only a direct effect on decision making but also an indirect cognitive effect on organizational actors. In particular, we link theories of attention (Ocasio, 1997, 2011) with theories of performance feedback (Lant, Milliken, and

Batra, 1992; Bromiley, 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 phase-out 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, Levinthal, and Ocasio, 2007). In what follows, we first examine the main effects of performance feedback and centralization on termination and then consider their interaction effects.

2.2 Performance Feedback and Termination Decisions

Performance feedback theory is based on the premise that decision makers have limited attention (Simon, 1947; Ocasio, 1997) and rely on feedback when identifying the problems and opportunities to which they should attend. In models of performance feedback (c.f., Shinkle, 2012), 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 (Miller and Chen, 1994; Greve, 1998; Audia, Locke, and Smith, 2000; Mezas, Chen, and Murphy, 2002).

The aspiration level serves as a 'reference point that is psychologically neutral' (Kameda and Davis, 1990: 56) and the dividing line between perceived success (gain) and failure (loss). Hence, decisions – such as termination - follow from comparisons that suggest performance is either above or below that aspiration level (March and Shapira, 1987; Greve, 1998). Although performance feedback at the product level has received little attention, the theory suggests that phase-out may be affected when product performance deviates from aspirations because the retention or removal of a product reflects managerial perceptions of success or failure at the product 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 (Lant, Milliken, and Batra., 1992; Miller and Chen, 1994; Audia, Locke, and Smith, 2000; Guler, 2007), because success creates confidence in existing knowledge and biases decisions against changes (Greve, 1998) or novel alternatives (March, 1996; Denrell and March, 2001; Posen and Levinthal, 2012) such as new products. 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 (Audia, Locke, and Smith, 2000; Grohsjean, Kretschmer and Stieglitz,

2012). As a result, managers are more likely to remain committed to old products and keep them on the market longer.

That product termination decreases as performance falls below the aspiration level reflects the idea that failure triggers problemistic search (Cyert and March, 1963): “search that is stimulated by a problem...and is directed toward finding a solution to that problem” (Cyert and March, 1963: 121). Solutions come in the form of response repertoires, which are designed to address performance problems and include all the strategic actions for improving performance that are available to managers (Miller and Chen, 1994, 1996). Research has shown that performance-correcting solutions may involve changes to the organization (Karim, 2006; Gulati and Puranam, 2009; Boumgarden, Nickerson, and Zenger, 2012), to product development activities (Eggers, 2012), or to human resource policies (Moliterno and Wiersema, 2007).

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 which posit that managers utilize multiple reference points in decision making (Gooding, Goel and Wiseman, 2006; Bromiley and Washburn, 2010; Blettner, He, Hu and Bettis, 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 aspiration performance 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 (March and Shapira, 1987). Under such conditions managerial attention shifts to a survival threshold and away from the aspiration level, and corresponding actions are re-directed to efforts to avoid the “threat” of complete failure (Staw et al., 1981). Studies have observed this at both the individual (e.g., Forlani, 2002; Boyle and Shapira, 2012), and the firm level (e.g., Mone et al., 1998; Miller and Chen, 2004; Audia and Greve, 2006; Shimizu, 2007), where threats to survival motivate more conservative and less risky responses. In the context of this study, the shifting attention 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 phase-out.

Small gaps between performance and aspirations increase decision makers’ tolerance for risk because they will perceive small gaps as a loss situation and take steps to improve it (Kahneman and Tversky, 1979; March and Shapira, 1992). 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 organizational resources to bolster sales of the product (Bromiley and Wiseman, 1989). By leaving products on the market at this point helps managers justify the products' development efforts (Ross and Staw, 1993), and by further delaying phase-out, the firm can still satisfy customers and potentially recover costs (House and Price, 1991). Larger drops in performance may further extend product life to the degree they reflect more complex problems and firm responses require assessment of a greater variety of factors. For example, a larger performance-aspiration gap might suggest problems involve more than one area (e.g., sales and marketing), and research shows that organizations are slower to solve problems that incorporate multiple disciplines (Henderson and Clark, 1990).

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). Since managers typically develop a stronger aversion to taking risks in such situations (Lopes, 1987; Sitkin and Pablo, 1992; March and Shapira, 1992), 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 phase-out 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 phase-out decreases.

Hypothesis 1b (H1b): As the performance–aspiration gap (below aspirations) increases, the rate of product phase-out first decreases and then increases (is U-shaped).

2.3 Organizational Structure and Termination Decisions

A long tradition of research recognizes that organizational structure plays a key part in orchestrating the overall decision-making process within firms and, as a consequence, the outcomes that follow (Burton and Obel, 2004; Gulati, Puranam, and Tushman, 2012). The design of an organization’s structure reflects “the pattern of communications and relations among a group of human beings, including the processes for making and implementing decisions” (Simon, 1947/1997: 18-19). Organizational 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 feedback (Tushman and Nadler, 1978: 614; see also Galbraith, 1974, 1977). This link is apparent in Bower (1972: 287): “when management chooses a particular organization form, it is providing not

only a framework for current operations but also the channels along which strategic information will flow.”

One of the critical design choices bearing on information processing (Simon, 1962) is that of centralization versus decentralization of decision making (Egelhoff, 1982; Miller and Dröge, 1986). Centralization of decision making reflects the extent to which the locus of authority to make final decisions affecting the organization is concentrated at higher levels of the hierarchy (Child, 1972). As a structural property of the firm, centralization reflects a variety of standard operating procedures, formal roles, communication channels, and informal interactions which emphasize vertical information flow (Galbraith, 1974).

2.3.1 Centralization and Information Processing

The information processing implications of centralized structures suggest that, *ceteris paribus*, products will be culled more quickly. Because centralized structures emphasize vertical information flow (Egelhoff, 1988: 131-132) and communication channels that elevate decisions within the corporate hierarchy (Galbraith, 1977), they may: 1) circumvent time-consuming political behavior (Wally and Baum, 1994; Baum and Wally, 2003); and 2) ease coordination problems that would otherwise delay phase out (Marschak and Radner 1972, Galbraith 1977, Tushman and Nadler, 1978).

In the mobile device industry, not all products may be culled simultaneously for a variety of operational (Cooper, 1972) and competitive reasons (Sorenson, 2000; de Figueiredo and Silverman 2007). Product phase-out involves adjusting a range of activities such as operator road maps, factory schedules, and supply chains, which creates interdependencies with respect to the phase out process (March and Simon, 1958). The presence of interdependencies creates the need for communication and agreement across functions and product managers. However, the requirement for agreement in the context of portfolio management may delay decision making owing to the diverse and often conflicting demands that must be served by any particular phase-out 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's command, Motorola was able to centralize product decisions and alleviate the internecine competition between product teams (Hansell, 2009).

Moreover, centralization's emphasis on vertical information flow may reduce delays owing to coordination problems (Khandwalla, 1974), following termination decisions. An emphasis on vertical communication may limit the potentially dense lateral communication flows that would be otherwise required to coordinate among phase-out activities (Arrow, 1974; 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, Nobel, and Ridderstrale 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 (Eisenhardt, 1989), we argue here as others (cf. Rivkin and Siggelkow, 2003) that, *ceteris paribus*, these factors are outweighed by political and coordination factors. We therefore offer the next hypothesis as follows:

Hypothesis 2 (H2): Greater centralization of decision making increases the rate of product phase-out.

2.3.2 Centralization and Performance Feedback

Information processing is only one mechanism through which organization structure (here, centralization) 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; Barnett, 2008; 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: 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). Thus, attention patterns within centralized and decentralized structures are different and so the respective responses to performance feedback may likewise differ.

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 (i.e., solutions) to performance problems

are chosen and enacted. This observation is consistent with strategy research showing that managerial perceptions are shaped by the environment in which they operate (Sutcliffe and Huber, 1998; Nadkarni and Barr, 2008) and also with feedback research showing that managerial perceptions, interpretation, and response to own feedback vary with the structural location of decision makers (Audia and Sorenson, 2001; Vissa et al., 2010; Gaba and Joseph, 2013).

Performance feedback in complex organizations reflects the distinctive content of aspiration levels, which together set the evaluative standard that activates the search for solutions when performance is unsatisfactory. Aspiration content (such as unit sales) is especially important to decision makers when it corresponds closely to the indicators used to assess their own performance.

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 (Walsh 1988). 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. Such management involves not only the timing of a phase-out but also related budgeting, planning, and operational issues relating to internal partners, carriers and the supply chain. It also includes the development and launch of replacement

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 phase-out 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 serve to justify retaining those products in the portfolio (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 successively 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, then, 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 alternatives (i.e., 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 (Siggelkow and Rivkin, 2005) and most consequentially for phase-out, 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 (Bushee, 1998) for products that do not perform well, effectively shortening their life. Costs are usually monitored and allocated at the corporate level by

the finance function (Vancil, 1978), so cost cutting is frequently invoked in centralized structures when responding to performance problems.

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 versus decentralized structures now suggest our next two hypotheses.

Hypothesis 3a (H3a): When performance increases above aspirations, centralization amplifies the effects of performance feedback on phase-out (decreases rate of phase-out).

Hypothesis 3b (H3b): When performance decreases below aspirations, centralization attenuates the effects of performance feedback on phase-out (increases rate of phase-out).

2.4 Methods

This study uses German mobile phone data from the GfK retail panel. GfK is regarded as the industry benchmark in data collection because it gathers retail sales figures at the point of sales and not from manufacturer surveys. The GfK data are also unique in providing phone-level price and sales information as well as certain other features. To ensure robustness, we followed Klingebiel and Joseph (2015),

supplementing and cross-checking the GfK data set with data from competing providers, such as the World Cellular Information Service, Informa World Cellular Handset Tracker, the Strategy Analytics online database, and consumer websites such as GSMarena.com, PDADB.net, PhoneArena.com, Handy-MC.de, and Inside-Handy.de. Market size (i.e., sales) estimates from GfK phone-level data were found to be in line with top-down estimates developed by Datamonitor.

Our data sample covers all mobile phones from the five largest firms that were introduced to the German market between January 2004 and December 2009. 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; they also were the industry leaders during this period at establishing the pace of product turnover and development as well as the major device strategies employed in this market.

There are three reasons why the German mobile phone industry is an ideal setting for our study. First, confining our analysis to a single 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, phase-out decisions are made on a country basis for large countries.

Germany was the largest and most advanced phone market within Europe, and this chapter's focus on that country minimizes the possibility that firm behavior is contingent on market experiences outside the scope of our observations (manufacturers pull from Germany first). Although handset manufacturers are global players, they develop distinct regional strategies because of different mobile network standards and varying consumer preferences (Walkley and Ramsay, 2011). Moreover, our primary supplier of data, GfK, is based in Germany and both its data quality and methodology are strongest in its home market.

Second, the mobile phone industry is characterized by a high rate of new product introductions and technological advances (Eisenhardt, 1989; Keil, McGrath, and Tukiainen, 2009). Our data suggests that a typical phone lifetime is only 4.3 quarters. This short lifecycle ensures that our data includes many product exits and captures multiple generations of handset manufacturers' product portfolios.

Third, the organizational charts of our sample firms are roughly similar. In each major firm, there is a business 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. The empirical model is specified so that the parameter estimates yield the full range of structure–phase-out relationships.

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. Firm financial data was acquired through Compustat and quarterly reports. Descriptive statistics and correlations for all predictor variables are given in Table 5.

Table 5: Summary Statistics and Cross-Correlations (N = 3,192 product-quarters)

	Mean	Std. dev.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
1 Phone level - perf. above aspirations (k)	33.94	68.63	1.00																
2 Phone level - perf. below aspirations (k)	2.40	4.25	-0.05	1.00															
3 Centralization	3.15	0.98	0.03	0.16	1.00														
4 Oversight	-0.27	1.07	-0.04	-0.06	0.46	1.00													
5 Indicator: In lowest 20% of sales	0.20	0.42	-0.16	0.02	-0.02	-0.02	1.00												
6 Indicator: Phone has a direct replacement	0.79	0.41	0.02	0.10	0.02	0.00	-0.01	1.00											
7 Firm size	666,411	1,904,379	0.01	0.15	0.49	0.18	0.14	0.01	1.00										
8 Absorbed slack	0.19	0.04	0.01	0.04	-0.03	-0.31	0.04	-0.07	0.11	1.00									
9 # of focal firm launches in period	4.37	3.73	0.03	0.09	0.42	-0.10	-0.02	0.02	-0.45	0.11	1.00								
10 # of 3G phones in portfolio	28.38	11.67	0.02	0.03	0.43	0.18	-0.10	0.00	0.02	-0.02	0.58	1.00							
11 # of smartphones in portfolio	27.89	10.25	0.02	0.04	0.49	-0.40	-0.07	0.00	0.07	0.06	0.59	0.97	1.00						
12 Average portfolio age	5.95	0.70	0.05	0.02	-0.08	-0.35	-0.08	0.08	-0.09	0.50	0.57	-0.18	-0.17	1.00					
13 Cumulative phone launches	303.64	61.97	0.03	0.06	0.14	0.06	0.00	0.07	0.18	0.21	0.03	-0.17	-0.02	0.46	1.00				
14 Experience: Degree of culling	0.96	0.47	-0.05	-0.07	-0.22	0.21	-0.04	-0.06	-0.11	0.04	-0.02	-0.02	0.06	0.50	0.21	1.00			
15 Vertical integration	2.08	1.08	-0.06	-0.04	0.37	0.28	0.11	0.05	0.60	0.24	0.07	0.35	0.42	-0.47	-0.46	-0.06	1.00		
16 # of competitors' phones on market	161.34	22.69	0.05	0.12	0.30	-0.11	0.01	-0.01	0.61	-0.06	0.29	-0.04	-0.01	-0.19	0.04	-0.01	-0.05	1.00	
17 # of competitors' launches	36.96	9.67	0.02	0.03	-0.02	0.00	0.05	0.06	0.08	0.02	0.16	-0.14	-0.13	0.03	0.03	0.06	-0.06	0.51	1.00

All bolded correlations significant ($p < .05$)

2.4.1 Dependent Variable

The key event for our analysis is phase-out 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 (Martin and Mitchell, 1998; Katila and Ahuja, 2002). The precise date of product phase-out is difficult to establish because such dates are seldom known outside the company (de Figueiredo and Kyle, 2006). Mobile phone phase-outs are also complicated by retail distribution channels, which purchase handsets 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 phase-out as the cessation of product shipments from the handset manufacturer to Germany (i.e. cessation of sales to German retailers), not as the cessation of retail sales (i.e. sales in the rest of the global market). The data give an indication of manufacturers' internal selection decisions in the form of a sudden and discontinuous fall in monthly sales, as the manufacturer does not itself give an exact discontinuation date.

All device phase-outs were coded manually by two individuals. Inter-rater agreement was high: for 94% of the devices, the coded phase-out dates were within three months of each other. For those few devices whose coded phase-out dates were not within three months, the coders jointly revisited the available information and

reached a consensus on the phase-out date. The coders did not identify phase-outs of any devices for which the observations were left-censored (i.e., devices that were already in the sample at $t = 0$; these were excluded from the analysis). For a small subsample of devices, we were able to locate data through firm-provided internal documentation and found these data to be consistent with our manual coding.

2.4.2 Aspiration Levels and 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 (Miller and Leiblein, 1996; Audia and Greve, 2006; Audia and Brion, 2007). Less 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. Our performance measure is based on quarterly unit sales at the device level because such sales represent a key performance indicator in the mobile phone 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; Baum and Dahlin, 2007; Chen and Miller, 2007; Harris and Bromiley, 2007).¹ We define a historical aspiration level for product performance as an exponentially weighted moving average of its past performance. Let HA_{it} denote the historical aspirations of phone i at time t , and let P_{it} denote the actual performance of phone i at time t . Then historical aspiration is given by $HA_{it} = \alpha P_{it-1} + (1 - \alpha)HA_{it-1}$. In the historical aspiration formula, α can be viewed as an adjustment parameter: a lower α corresponds to giving greater weight to performance farther in the past as compared with the weight given to more recent performance. The value of α was established by searching over all parameter values of α 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 rather slowly (cf. Greve, 2002). That result has previously been found experimentally (Lant, 1992) and in large multinational firms (Mezias, Chen, and Murphy, 2002).

¹ An alternative specification is to utilize a dummy variable which takes the 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.

The performance–aspiration gap was simply defined as the difference between performance and aspiration level for each of the phones, or the quantity $(P_{it} - HA_{it})$. We implemented a spline function to compare the effects of a performance–aspirations gap above zero ($P_{it} > HA_{it}$) and below zero ($P_{it} < HA_{it}$); in this we follow Greve (2003) and Chen and Miller (2007) among others. 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 1000). Thus,

$$(\text{Performance above historic aspirations})_{it} = \max[0, P_{it} - HA_{it}],$$

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:

$$(\text{Performance below historic aspirations})_{it} = |\min[P_{it} - HA_{it}, 0]|.$$

At any moment, only one of these two performance–aspirations variables can be nonzero. Also, because it does not change the magnitude of our estimate, we take the absolute value of our performance below historic aspirations measure (divided by 1000)

in order to facilitate interpreting the regression coefficients (i.e., so that the reader need not adjust for the otherwise strictly negative domain for this covariate when interpreting the sign of an effect).

All performance feedback variables are lagged by three quarters in the empirical specification. This is consistent with our review of internal product documentation and evidence from our semistructured interviews with individuals involved in product management. Three quarter temporal separation between feedback and phase-out recognizes that mean product life for mobile devices is relatively short and accommodates the ramp-down time required to coordinate all aspects of a product's phase-out. These activities include managing product returns, reallocating excess material from production runs, adjusting targets with demand planning teams, stopping or rerouting shipments within the supply chain, developing a budget for ramp-down activities, and managing carrier relationships. It also involves the ramp-up and roll-out of replacement products.

To model the survival level in this context, we adopt two approaches that have been used in the literature. The first approach is to square the performance below aspirations variable and include it in the specification, an approach used in Lehman et al (2011). The second approach is to use an indicator variable to model a discrete threshold for the survival level, an approach that is consistent with both theoretical (March and

Shapira 1987, 1992) and empirical (Miller and Chen 2004; Boyle and Shapira 2012) works that model the survival level as occurring at a discrete point. Based on evidence from firm-provided internal documentation, we set our survival-level indicator equal to 1 when a device is in the lowest 20% of sales for all devices in our sample.²

2.4.3 Centralization

To create the first (centralization) 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 during 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; this approach is similar to the one followed by Boumgarden, Nickerson, and Zenger (2012). The search covered newspapers and magazines, several business case publishers, and books spanning a decade of discussion about our five focal companies. It is fortunate for our purposes that all five companies are large, highly visible, and well documented. In total, we consulted more than 200 sources that addressed the product management process, organizational structure, or organizational change. This extensive

² Our findings are not sensitive to changes (e.g. 10%, 15%) in the chosen threshold.

review enabled us to build case narratives and facilitated our assessing the degree of centralization for each firm-year during our study period.

Using data from the case narratives over the study period, 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)?”

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 mobile device BU, he controlled everything, including design.” A second example is of high centralization (5) is Motorola. When Sanjay Jha took over (in August 2008) as both head of the mobile device unit and co-CEO, he centralized all product portfolio decisions in the corporate office (*Forbes*, 2012). Alternatively, Nokia exhibited a low degree of centralization (2) in the early years of the sample, but later became more centralized.

We then conducted semistructured interviews with individuals in each firm knowledgeable about the product management process. These interviews provided a

second source for the “triangulation” of our narrative describing the key structural characteristics of each firm across our observation period (cf. Jick, 1979). In all cases, we utilized professional or alumni contacts from the authors’ institutions to gain entry into the firms and, from that point, located the appropriate individuals. For each firm, we identified 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; they were held in person whenever possible and by telephone otherwise. 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 explicit 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. Most interviews were taped and transcribed, and care was given to motivate each informant’s full disclosure by filtering confidential information (Davis and Eisenhardt, 2011).

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 responders to evaluate structure (and several other factors not discussed in this chapter) on a scale from 1 to 5, as already described, for each

firm-year starting in 2004. Prior studies of centralization (e.g., McGrath, 2001; Tsai, 2002; Bunderson, 2003) document strong consistency across centralization measures constructed from multiple survey questions, which suggests that a single measure should be sufficient for an accurate assessment of the construct. 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 interpretation. The respondents' evaluations were then compared with those of the authors. The inter-rater 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. This approach is similar to the one undertaken by Henderson and Cockburn (1994).

In total, our data on structure exhibit 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 (Schoonhoven and Jelinek, 1990: 99; Siggelkow and Levinthal, 2005; Karim, 2009). Such patterns of reorganization have been observed in other contexts. In the context of managing innovation in multinational companies, for example, Bartlett and Ghoshal (1990:305) noted that Ericsson had created

a “constant ebb and flow in the centralization and decentralization of various responsibilities.”

2.4.4 Alternative Measure of Centralization

To ensure the reliability of our initial centralization measure of structure and also to avoid the problems associated with self-reports (see Podsakoff and Organ, 1986), we used archival data to construct a second measure that examines the degree of oversight that decisions are subject to within the business unit. For this measure, we borrowed from the financial economics literature (Lamont, 1997; Shin and Stulz, 1998; Stein, 2002) and considered the extent to which resources were disproportionately allocated by the corporate office to the mobile device business unit and, accordingly, the amount of attention paid by more senior managers to their decisions. Linkage between corporate resource allocation and organizational attention has been observed in different contexts (Tsang 2002; Gilbert 2005) and corporate allocations of resources have been found to predict managerial attention to particular business units (Dellestrand & Kappen, 2012).

Building upon this foundation, we reason that a disproportionate over- or underinvestment 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 managing the product portfolio. A number of studies have shown that, in a multidivisional firm, the corporate office pays more attention to business units that

have greater strategic significance (Bouquet and Birkinshaw, 2008; Gaba and Joseph, 2013) including units that receive a disproportionate amount of resources (Galunic and Eisenhardt, 2001). In cases of increased oversight, the corporate office involves itself with all types of decisions, including operational decisions and activities (McGrath, 2001); we expect the opposite to be true for reduced oversight. For our purposes, this measure is superior to patent based measures (e.g., Arora, Belenzon, and Rios 2013) which focus on R&D in subsidiaries rather than business unit product decisions or layer counts which fail to account for the locus of decision making.

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 the following:

$$\frac{I_{mobile,j,t}}{V_{j,t-1}} = a + b \frac{S_{mobile,j,t-1} - S_{mobile,j,t-2}}{S_{mobile,j,t-2}} + c \frac{C_{mobile,j,t}}{V_{j,t-1}} + d \frac{C_{other,j,t}}{V_{j,t-1}} + eq_{mobile,j,t-1} + \varepsilon_{mobile,j,t}.$$

Where $I_{mobile,j,t}$ 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 affairs of the mobile device segment (holding constant the expectations for mobile and other segment performance), 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. Residual signs are important for our study because there is a substantive conceptual difference between over- and under- involvement in decision-making (Zajac, Kraatz, and Bresser, 2000; Fong, Misangyi, and Tosi, 2010). 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 phase-out. A larger negative residual suggests that the corporate office has disproportionately under invested in capital for the mobile device segment and that decisions regarding the segment are less likely to require approval by senior management. Thus, a larger negative value of this residual measure is consistent with less oversight (i.e., decentralization), and consequently *less involvement* of senior managers in decisions such as product phase-out.

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. To distinguish these two constructs we refer to the latter as *oversight*.

2.4.5 Phone Replacement

Product replacement is an important part of product portfolio management. Rapid replacement is often desirable because of the limited space allocation by retail

outlets, the tendency for declines in price as products age, the rapid pace of technological innovation in the mobile device industry, and thus the potential for cannibalization (sales loss due to a newer products). All else equal, replacement may affect how the phase-out decision is made beyond the effects of structure and feedback processes. Because replacement can affect the decision to terminate a product, it was crucial to identify products for which a replacement was available. Toward that end, we examined PowerPoint presentations from several product teams from one of the sample firms. Close review of these presentations about portfolio lineups suggests we can approximate replacement products using launch date and price. In most cases, replacement devices were launched within a relatively short window around a predecessor device's exit.

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 mobile devices are quickly discounted after launch and marketers tend to "tier" phone offerings into price bands. According to this definition, 79% of our sample devices had a replacement. To assess the validity of our replacement variable, we compared the results of our algorithm to the subset of devices for which internal company documentation was available; we found that our measure of

replacement accurately reflected the preponderance of devices that were directly replaced. 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%.

2.4.6 Other Controls

Several additional controls were included to test for alternative mechanisms that could affect phase-out. The selection of these firm- and industry-level controls was motivated by interviews with product managers at the firms, internal documentation related to culling decisions, and the relevant theoretical literature on organizational decision making.

We used total firm sales from Compustat as a proxy for *firm size*, which may have an indirect influence on the firm's decision to cull a device (Hannan and Freeman, 1984; Henderson and Stern, 2004) and whose effect on product exit decisions we wish to assess. To account for the information processing benefits associated with the size of the corporate office (Wiseman and Bromiley, 1996), we control for *absorbed slack*; this is defined as the ratio of corporate selling, general, and administrative expenses (SG&A) 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. This also

helps account for resource constraints which 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 (Henderson and Stern, 2004).

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* that are similar to those used by Sorenson (2000). Following his specification, we defined this measure 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; hence the measure reflects learning processes as well as the diminishing returns to experience.

For each firm, we also developed a composite measure that captures its extent of *vertical integration*. Doing so entailed our recording whether the focal firm contains a semiconductor unit, a network division, a media/software division, and/or a LCD

division. For each period, we constructed a vertical integration score by summing indicators for each of these aspects of vertical integration; thus, the maximum score on this measure is 4. Vertical integration is a critical factor because upstream capabilities may well affect downstream behavior (de Figueiredo and Teece, 1996).

We controlled for two industry-level factors: *market density* (the total number of competitors' devices on the market) and the number of *same-period competitors' phone launches* (a count of the number of device launches competitors perform in each period) (Sorenson, 2000; Henderson and Stern, 2004) 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 for our theoretical variables.

2.4.7 Empirical Specification

In order to examine the factors that affect product phase-out, we applied a piecewise exponential hazard rate model which has been used in other studies of product culling (e.g. Sørensen and Stuart, 2000; de Figueiredo and Kyle, 2001, 2006). 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 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 7) indicates that the hazard rate differs for each of these time periods, so the intervals we used led to significant improvements in model fit.

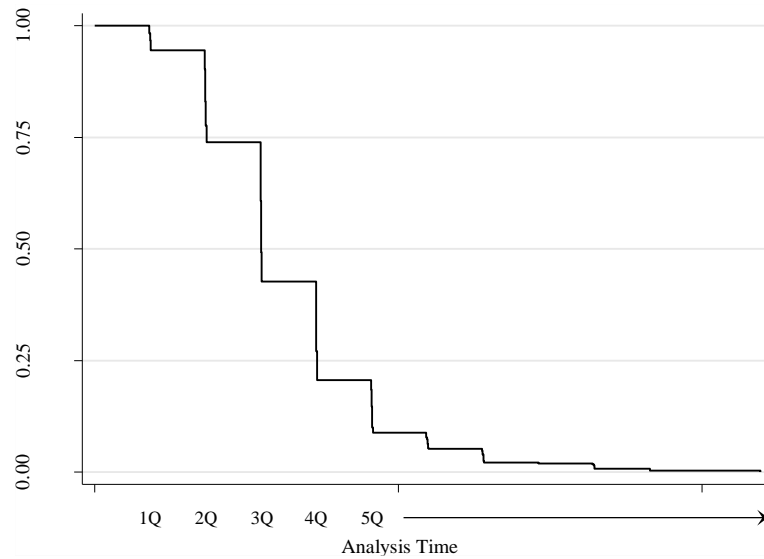


Figure 7: Kaplan-Meier Survival Graph (each discontinuity is one quarter)

Our specification follows that given in Blossfeld, Golsch, and Rohwer (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 non-independence of the multiple devices observed for each firm (cf. Bertrand, Duflo, and Mullainathan, 2004).

2.5 Results

Table 6 shows the piecewise exponential hazard rate results for quarterly device phase-out. Above each column in this table is shown the correspondence to the hypothesis that is tested by that particular model. Model 1 includes only the control variables. Model 2 introduces the effects of performance feedback above aspirations. Model 3 examines the effects performance below aspirations using a squared term and model 4 uses the survival-level indicator variable. Model 5 demonstrates the effect of centralization on phase-out. Model 6 shows the interaction between centralization and performance above aspirations. Model 7 shows the interaction between centralization and performance below aspirations, including the squared term and model 8 shows the survival-level indicator variable interaction effects. Models 9 and 10 show the full model with the squared term and survival-level indicator variable treatments of survival level, respectively.

The baseline model exhibits a highly significant fit to the data ($p < .001$ for a chi-square test). A log-likelihood test reveals that the inclusion of performance feedback above aspirations yields significant improvement in model fit for model 2 at the $p < .001$ level: the improvement in log-likelihood over the baseline model is 37.797. Interestingly, while the squared term model (model 3) does not improve overall model fit over the baseline model at the $p < .05$ level (the increase in log-likelihood is 1.391), the model that

uses a survival-level indicator variable (model 4) represents a significant improvement in fit over the baseline (log-likelihood improves by 26.675, significant at $p < .001$). In model 5, the improvement of fit of 3.856 is significant at the $p < .01$ level. When the interaction term between centralization and performance above aspirations is added in model 6, fit improves significantly over model 2 (by 6.061, $p < .01$). When the appropriate interaction terms are included in models 7 and 8, the log-likelihood increases by 6.678 and 8.267, respectively, when compared to the feedback only models (models 3 and 4). Both of these increases are significant at the $p < .01$ level. Model 8, which uses the survival-level indicator variable, exhibits improved model fit over model 7, the squared-term model (the difference in log-likelihood is 26.873; $p < .001$). Model 9 includes all variables from models 6 and 7, and is an improvement to model fit over each. Model 9 increases log-likelihood by 7.093 compared to the performance above interaction model (model 6), $p < .05$, and it increases log-likelihood by 42.882 over the performance below squared term model (model 7), $p < .001$. Model 10 consists of all variables from models 6 and 8, and is also an improvement to model fit over each. Model 10 increases log-likelihood by 13.588 compared to the performance above interaction model (model 6), $p < .01$, and it increases log-likelihood by 22.504 over the performance below survival level indicator interaction model (model 8), $p < .001$. Again

we find that the survival-level indicator full model (model 10) provides a better fit to our data than does the squared term model (increasing log-likelihood by 6.495; $p < .05$).

Table 6: Piecewise Exponential Hazard Rate Models for Phase-Out

Model Hypothesis	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		H1a	H1b	H1b	H2	H3a	H3b	H3b	Full	Full
			(squared-term)	(survival-level ind.)			(squared-term)	(survival-level ind.)	(squared-term)	(survival-level ind.)
Phone level - perf. above aspirations		-0.012** (0.004)				0.002 (0.003)			0.002 (0.003)	0.001 (0.002)
Phone level - perf. below aspirations			-0.134*** (0.031)	-0.034*** (0.005)			-3.747 (3.893)	-0.150*** (0.038)	-4.222 (5.079)	-0.175*** (0.038)
(P<A) ²			0.003*** (0.001)				0.092 (0.085)		0.090 (0.113)	
Indicator: In lowest 20% of sales				0.813*** (0.144)				0.359** (0.138)		0.304* (0.149)
Centralization					0.297* (0.137)	0.335* (0.148)	0.287* (0.133)	0.203 (0.161)	0.325* (0.157)	0.265 (0.173)
Centralization * P>A						-0.005* (0.002)			-0.005* (0.002)	-0.004* (0.002)
Centralization * P<A							0.958 (0.971)	0.035** (0.011)	1.032 (1.275)	0.038*** (0.009)
Centralization * (P<A) ²							-0.024 (0.021)		-0.022 (0.029)	
Centralization * Indicator: In lowest 20% of sales								0.171*** (0.022)		0.089* (0.043)
<i>Device Controls</i>										
Indicator: Replacement	0.354 (0.470)	0.615* (0.293)	0.356 (0.470)	0.166 (0.399)	0.517 (0.467)	0.662* (0.317)	0.512 (0.464)	0.280 (0.404)	0.666* (0.310)	0.472 (0.313)
<i>Firm Controls</i>										
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* (1.231)	2.547+ (1.499)	3.259** (1.187)	2.310* (1.007)	2.846+ (1.455)	2.623 (1.830)	3.249* (1.311)	1.931 (1.292)	3.252* (1.503)	2.107 (1.746)
# of focal firm launches in period	0.059*** (0.011)	0.056** (0.021)	0.062*** (0.010)	0.053*** (0.013)	0.058*** (0.012)	0.057* (0.023)	0.064*** (0.010)	0.047** (0.015)	0.066** (0.020)	0.050* (0.023)
# of 3G phones in portfolio	0.039 (0.219)	0.043 (0.340)	-0.035 (0.189)	0.226 (0.209)	-0.103 (0.212)	-0.021 (0.338)	-0.284 (0.195)	0.217 (0.213)	-0.293 (0.323)	0.153 (0.312)
# of smartphones in portfolio	-0.312 (0.267)	-0.325 (0.406)	-0.219 (0.229)	-0.523* (0.246)	-0.195 (0.273)	-0.301 (0.418)	0.050 (0.243)	-0.577* (0.256)	0.071 (0.388)	-0.501 (0.377)
Average portfolio age	-0.096 (0.182)	-0.049 (0.219)	-0.069 (0.174)	-0.113 (0.145)	0.058 (0.159)	0.067 (0.202)	0.094 (0.167)	0.045 (0.129)	0.109 (0.210)	0.064 (0.172)
Cumulative phone launches	-0.018+ (0.010)	-0.019 (0.017)	-0.021* (0.009)	-0.009 (0.011)	-0.028** (0.009)	-0.026 (0.016)	-0.034*** (0.009)	-0.015 (0.010)	-0.035* (0.016)	-0.018 (0.015)
Experience: Degree of culling	0.226 (0.222)	0.205 (0.244)	0.231 (0.223)	0.266 (0.222)	0.025 (0.195)	0.046 (0.199)	0.017 (0.211)	0.095 (0.197)	0.054 (0.229)	0.102 (0.221)
Vertical integration	2.081*** (0.458)	2.172** (0.687)	1.882*** (0.379)	2.325*** (0.397)	2.138*** (0.552)	2.390** (0.803)	1.540*** (0.433)	2.776*** (0.469)	1.464* (0.668)	2.667*** (0.700)
<i>Industry Controls</i>										
# of competitors' phones on market	-0.008*** (0.002)	-0.008*** (0.002)	-0.007*** (0.002)	-0.008*** (0.002)	-0.008*** (0.002)	-0.008** (0.003)	-0.008*** (0.002)	-0.009*** (0.003)	-0.008** (0.003)	-0.009** (0.003)
# of competitors' launches	0.014*** (0.004)	0.016** (0.006)	0.014*** (0.004)	0.012** (0.005)	0.016*** (0.005)	0.017** (0.006)	0.015** (0.005)	0.014** (0.005)	0.016** (0.006)	0.016** (0.005)
N	3192	3192	3192	3192	3192	3192	3192	3192	3192	3192
Log-likelihood	-169.958	-132.161	-168.567	-143.283	-166.102	-126.100	-161.889	-135.016	-119.007	-112.512
All time variant covariates lagged by 3 quarters; Standard errors displayed in parentheses; + p<0.10 * p<0.05 ** p<0.01 ***p<.001										22.504

In model 1 we find that the presence of a 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 ($p < .001$). Large firms may have additional resources and so are better able to leave products on the market longer (Bromiley, 1991). We find that absorbed slack has a positive effect on termination decisions, which suggests there are some information processing advantages of large corporate office. We note that our results in all models going forward remain robust to the inclusion or omission of absorbed slack³.

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

³ Prior 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 phase-out, we find no significant effects of corporate and business-unit level feedback on product phase-out.

product phase-out processes. This is consistent with our understanding of the industry, as no dominant designs emerged for such devices until after the sample period concluded. 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).

We find no relationship between average portfolio age and culling. We find a marginally significant negative effect ($p < .10$) relating cumulative phone launches to phase-out. 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 also that the average product life (4.3 mean quarters of product time on market) was much shorter in our study than in that of 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*). 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. 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 phase-out timing to coincide with competitor moves.

Model 2 shows how phone-level feedback affects phase-out when performance is above aspirations. Consistent with H1a, we find that performance above aspirations is associated with a decreasing hazard of product phase-out at the $p < .01$ level. This finding accords with our argument that product managers maintain the status quo when performance is above aspirations.

For both 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 $p < .001$ 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 ($p < .001$) just as the survival-level indicator variable is positive and significant in model 4 ($p < .001$). These findings indicate that when

performance falls sufficiently below aspirations, attention shifts to survival, the exhaustion of solutions and phase-out. We note the better fit of the survival-level indicator variable approach, suggesting that when it comes to termination, there may be a particular sales threshold below which options to improve performance are exhausted and products are simply not supported. This is consistent with prior studies (Miller and Chen 2004; Boyle and Shapira 2012) which use a discrete cutoff for survival.

Model 5 tests Hypothesis 2 and examines the effect of centralization measure on phase-out. Consistent with H2, we find a statistically significant coefficient for centralization in model 5 ($p < .05$); the main effect coefficient is positive across all specifications, suggesting that the coordination properties of centralized structures facilitate phase-out behavior.

Models 6-8 show how centralization conditions the effects of performance feedback on phase-out. 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). As stated by Jaccard and Turrisi, 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. In model 6, for example, performance feedback above aspirations slows phase-out at all values of centralization (with an implied coefficient of $-.008 [.002 + 2 * -.005]$ at centralization of 2 and $-.023 [.002 + 5 * -.005]$ at centralization of 5). Consequently, the effect 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 model 2, which showed the main effect of performance feedback above aspirations only.

Accordingly, the formal test for Hypotheses 3a is whether the centralization-performance feedback interaction variable in model 6 is significant and negative. We find support for H3a ($p < .05$); 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 $p < .01$ and $p < .001$ levels, respectively. Again, we find the survival-level indicator approach is a better representation of our data. When it comes to

termination, more centralized decision makers are quicker to cull a device when it reaches a level below which further support of the product in the country no longer makes sense.

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 as 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 8, building on an approach used by Davis and Greve (1997). The x -axis of Figure 8 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 (Cen. = 2 and 4), which illustrate how centralization affects the likelihood of phase-out after four quarters at different levels of performance relative to aspirations. All displayed values are within the data range.

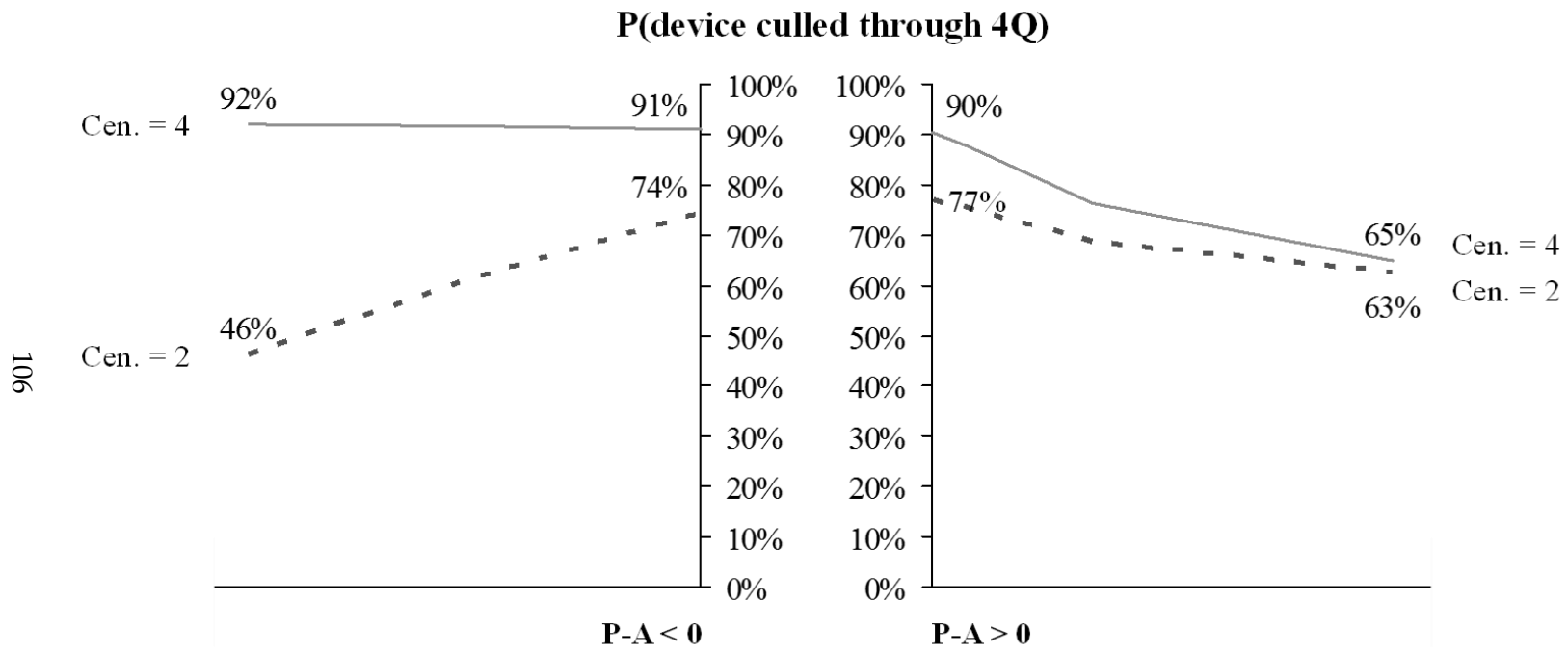


Figure 8: The Effect on Product Phase-out of Centralization and of Performance Relative to Aspirations; Dashed and Solid Plots Indicate where Centralization Equals 2 and 4, Respectively (These Results Correspond to Table 6, Model 10)

Figure 8 makes an important point by demonstrating that product phase-out depends on the firm's degree of centralization. The net effect of centralization can either increase or decrease the hazard of phase-out, 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 ($p < .05$), and the rate of change of phase-out 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 Hypothesis 3b, 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 (Cen. = 4) are 1.99 times more likely to cull products performing below aspirations than more decentralized firms (Cen. = 2) through four quarters.

2.6 Methods

2.6 Robustness

Models 11–14, which are included in Table 7, test the robustness of these findings to the exclusion of devices that appear on multiple markets internationally, firm and year fixed effects, and the usage of our oversight measure in lieu of and as a control for our centralization findings. These models build on the survival-level indicator approach used in model 10, which was the best fitting model.

Table 7: Robustness Tests of Piecewise Exponential Hazard Rate Models for Phase-out

Model	(11)	(12)	(13)	(14)
Robustness Test	German only	Fixed Effects	Oversight (as centralization)	Oversight (as control)
Phone level - perf. above aspirations	0.010 (0.007)	0.002 (0.002)	-0.012* (0.006)	-0.012* (0.006)
Phone level - perf. below aspirations	-1.820** (0.595)	-0.170*** (0.038)	-0.046*** (0.009)	-0.046*** (0.008)
Indicator: In lowest 20% of sales	1.432** (0.510)	0.290+ (0.160)	0.508 (0.311)	0.527+ (0.304)
Centralization	0.462*** (0.088)	0.287+ (0.157)		0.165 (0.123)
Centralization * P>A	-0.010*** (0.003)	-0.004* (0.002)		-0.000 (0.001)
Centralization * P<A	0.441** (0.151)	0.037*** (0.008)		0.142*** (0.010)
Centralization * Indicator: In lowest 20% of sales	0.319* (0.134)	0.091* (0.045)		0.105* (0.042)
Oversight			0.168** (0.053)	0.206* (0.096)
Oversight * P>A			-0.001+ (0.000)	
Oversight * P<A			0.139*** (0.013)	
Oversight * Indicator: In lowest 20% of sales			0.014 (0.061)	
<i>Device Controls</i>				
Indicator: Replacement	0.567 (0.702)	0.340 (0.363)	-0.331 (0.217)	-0.349 (0.218)
<i>Firm Controls</i>				
Firm size	-0.000** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
Absorbed slack	6.415*** (1.166)	3.003 (1.971)	4.886*** (1.116)	3.614** (1.329)
# of focal firm launches in period	0.110** (0.035)	0.031* (0.015)	0.067+ (0.039)	0.063 (0.039)
# of 3G phones in portfolio	-1.364** (0.425)	0.613*** (0.087)	-0.027 (0.421)	0.137 (0.328)
# of smartphones in portfolio	1.466** (0.492)	-1.006*** (0.141)	-0.247 (0.507)	-0.445 (0.392)
Average portfolio age	0.407 (0.308)	0.083 (0.205)	0.072 (0.204)	0.000 (0.176)
Cumulative phone launches	-0.086*** (0.025)	0.002 (0.004)	-0.024 (0.019)	-0.015 (0.015)
Experience: Degree of culling	-0.076 (0.235)	0.175 (0.306)	0.407 (0.274)	0.344 (0.287)
Vertical integration	-1.629+ (0.854)	3.303*** (0.423)	1.928* (0.893)	2.320*** (0.684)
<i>Industry Controls</i>				
# of competitors' phones on market	0.013 (0.012)	-0.012*** (0.003)	-0.003 (0.003)	-0.004+ (0.002)
# of competitors' launches	0.013*** (0.003)	0.015* (0.007)	0.016** (0.005)	0.015** (0.006)
Firm dummies		Yes		
Year dummies		Yes		
N	1053	3192	2123	2123
Log-likelihood	6.819	-110.595	-47.257	-47.014

All time variant covariates lagged by 3 quarters; Standard errors displayed in parentheses; + p<0.10 * p<0.05 ** p<0.01 ***p<.001

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. U.S., U.K., South Korea) and in the case of the US and Korea, the home markets for 3 of our 5 firms. For both measures of centralization, we identified less than a third of devices as being strictly German (which leaves us with 1053 product-quarters comprising 151 product exits across 191 devices), which is consistent with the global nature of this market. Even so, our findings remain quite strong in this subsample of devices. All of our hypotheses remain supported in this German-only sample. This result implies that the process we identify in our German sample is not significantly affected by the global nature of the mobile device industry.

To account for organizational and temporal idiosyncrasies—for instance, time-invariant firm characteristics and accelerating technological advancement—that may broadly affect phase-out patterns, we incorporate both firm and year dummy variables as an additional sensitivity analysis. Both year and firm dummies are commonly used in models of product management (de Figueiredo and Kyle, 2001). 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 10.¹ We note reduced significance on our survival-level indicator variable (though significance is retained at the $p < .10$ level). 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 vs model 12 is not significant at the $p < .05$ level). It is therefore reasonable to conclude that a model excluding these parameters yields a statistically similar and thus adequate fit to the data, which supports our decision to omit these effects from the model's original formulation.

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 $p < .05$ 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 our centralization measure, we generally find a similar pattern of sign and significance as

¹ Our results are also robust to the inclusion of either firm or year dummies separately.

model 10. The major differences are that the interaction between the performance above aspirations variable and centralization becomes significant at the $p < .10$ level (as opposed to the $p < .05$ level reported in model 13), and we lose significance on the survival-level indicator variable and its interaction with oversight, though both effects remain positive. 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 becomes loses significance at the $p < .05$ level. We mention these analyses as further confirmation of our centralization measure and to provide additional support for our hypotheses.

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 degree of centralization from 2004 through 2009 on 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 to drive our results.

2.7 Discussion

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 phase-out 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 phase-out. 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 phase-out and termination decisions more broadly. Much of the research on product exit has pointed to economic drivers (Greenstein and Wade, 1998) or prior experience (Henderson and Stern, 2004). Our findings—that performance below aspirations decreases the rate of phase-out—suggest that firms seek local solutions when doing poorly, which is consistent with behavioral explanations of organizational action. Such behavior reflects an implicit algorithm by which phase-out decisions depend not only on financial performance but also on local problem-solving efforts. In short, performance feedback explanations go beyond purely rational explanations for phase-out and add a new dimension that future studies may want to consider. We also include organizational structure as a key variable driving phase-out. This study highlights in particular that, when feedback is acquired and distributed within a centralized structure, it is aggregated. Centralized product assessments reflect a

broader range of factors in evaluations of product performance, and a more global set of solutions to address flagging products. The implication is that structure may be an important variable for studies of product exit and termination in general, and that it deserves greater consideration in future research.

Termination and its inverse (retention) have long been of interest to economists, psychologists and organizational scholars (Staw, 1997). The phenomena of termination, abandonment or exit have been linked to a variety of population (Hannan and Freeman, 1989), industry (Greve, 1995; Dobrev 2007), organizational (Burgelman, 1991; Mitchell, 1994; Guler, 2007; Shimizu, 2007; Gaba and Dokko, 2015) and individual-level (Staw and Hoang, 1995) drivers. We augment this body of work, by highlighting the joint contribution of structure and behavioral factors, and in particular, the nature of vertical information flow and feedback within corporate hierarchies. For example, we do find some evidence consistent with the escalation of commitment to a course of action (Staw, 1981; Staw and Ross, 1987; Guler, 2007). Escalating commitment following negative feedback has been interpreted as risk seeking in a situation framed as a loss (Bazerman, 1984; Northcraft and Neale, 1986). Studies show that people tend to commit more resources to the activity that caused the loss in order to justify the prior commitment. Moreover escalation of commitment and sunk cost effects can bias decision makers to

towards continuing current activities rather than replacing them with new ones (Staw and Huang, 1995; Guler, 2007).

Yet escalation does not account for the full range of behaviors observed in our data; our findings are consistent with studies which have placed boundary conditions on escalation of commitment behavior (e.g., Staw and Ross, 1978; Garland, et al., 1990; Whyte, 1991). In the first place, phase-out is a routine activity for these firms and is supported by a wide variety of structures and processes, so keeping products on the market should not be viewed as necessarily better than other alternatives. In fact, these managers are constantly comparing commitment to obsolete product lines to the challenge of replacing obsolete products with unproven alternatives. Importantly, our results also 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 upper echelons of management as unduly rigid, and suggests the aggregation and disaggregation of decisions plays a role in the commitment to a prior course of action.²

² Problem solving in the face of limited information and escalating commitment both differ also from structural inertia, a third possible explanation for the observed behavior. In terms of structural inertia theory, phase-out behavior is subject to structures and processes that inhibit

The second main contribution of this study is that it augments the growing scholarship on performance feedback by considering important conditional effects imposed by a centralized 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 phase-out 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 chapter 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 devoid of the other. This study

adaptation (see Hannan and Freeman, 1984). However, it is unlikely that inertia explains our findings. Phase-out 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.

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). In response, we offer here a structure–feedback theory of organizational decision making that integrates hierarchy and aspirations while placing in sharper relief the influence of decision-making procedures used by complex organizations.

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 echoes theories of ambiguity and choice (March and Olsen, 1976) and 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. Managers, rather than the external environment, are viewed as the primary evolutionary agents. Their 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., Karim, 2009; Christensen and Knudsen, 2010; Cardinal et al., 2011; Boumgarden, Nickerson, and Zenger, 2012; Karim and Kaul, 2014), yet it focuses specifically on the attentional implications of structure (cf. Rerup, 2006; Rhee, Ocasio, and Kim, 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, 2013). 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.

This study is also consistent with research suggesting that cognitive biases may be exacerbated or circumvented by the organizational context in which learning and decision making occur (Lave and Wenger, 1991; Guler, 2007). Previous research has argued 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 (1997) 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. Guler (2007) found the effects of institutional and political dynamics to be significant for sequential investment decisions. This means that models of decision making and cognition may be inaccurate in their predictions of real-life processes, including internal selection, if they fail to consider such important situational factors 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 efficiency concerns or environmental complexity, as documented in prior research, but also in its ability to shape the context in which alternatives are evaluated and enacted.

As Figure 8 illustrates, high levels of decentralization 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, Singh, and Zollo, 2006; Csaszar, 2012). Our model of centralized feedback may be the most suitable—at mean levels of performance—if rapid phase-out 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 phase-out 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 covers 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 futures 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 (Henderson and Clark, 1990). Future research could examine the effects of structure on product portfolio decisions across a greater variety of product categories.

2.8 Conclusion

Given the renewed interest in corporate-level effects on performance (Bowman and Helfat, 2001; Adner and Helfat, 2003; Martin and Eisenhardt, 2010) and the increased attention being devoted to organizational architecture (Gulati, Puranam, and Tushman, 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 chapter is an early step in that direction. Although we are beginning to see other work in this vein (e.g., Gavetti, 2005; Rerup, 2006; Csaszar and Eggers, 2013), more research is needed to illuminate the interconnectedness of cognition, structure, and performance both within and across complex organizations. Our study at least partially substantiates the claim that—because structure can affect (inter alia) attention, sense making, and decision making—it is fertile ground for future studies and provides a platform on which other researchers may build.

3. Organizational Attention and Technological Search in the Multibusiness Firm: Motorola from 1974-1997

This chapter examines the effects of organizational attention on technological search in the multibusiness firm. It is argued that attentional specialization and coupling, or (respectively) attention given to problems within and across units, affect a unit's ability to engage in distant and local search by shaping how problems are perceived and addressed. This theory is tested by applying a probabilistic topic model to all Motorola patents issued from 1974 to 1997, thus identifying and measuring attention to technical problems. The results suggest that (a) subunits with specialized attention are not myopic but instead explore broadly and (b) tight attentional coupling across units increases the breadth of search. This study contributes to attention-based views of the firm and to studies on organizational design and search.

3.1 Introduction

Organizational search has long been viewed as a critical aspect of the organizational learning process through which firms attempt to solve problems and adapt to a changing environment (Argote & Miron-Spektor, 2011; Cyert & March, 1963; Fleming & Sorenson, 2001; Huber, 1991). Research has identified two types of search: local and distant (March, 1991; Nerkar & Roberts, 2004). When firms engage in local search, they rely on knowledge that is closely related to their preexisting knowledge bases (Gavetti, Greve, Levinthal, & Ocasio, 2012; Helfat, 1994; Martin & Mitchell, 1998;

Stuart & Podolny, 1996). In contrast, distant search reflects an intentional effort to move away from current capabilities and to access knowledge that is novel and either outside or across organizational boundaries (Katila, 2002; March, 1991; Rosenkopf & Nerkar, 2001). Distant search is difficult because firms normally search in familiar and proximate areas, where they can rely on their own experience and routines for guidance (Nelson & Winter, 1982). Yet the search for new technologies is a critical process for the renewal and success of organizations, especially for firms in fast-paced or highly competitive industries (Brown & Eisenhardt, 1995).

Attention-based theories hold that firms' attentional structure plays a critical role in organizational search activities (March & Olsen, 1976; Ocasio, 1997). The central idea of this research is that organizational attention to particular problems and opportunities may drive decision makers to allocate relevant effort and resources to devising solutions where their attention resides (Ocasio & Joseph, 2005; Rerup, 2009; Sullivan, 2010). Within complex organizations, attentional processes that support search activities may be particularly important because of the structural allocation of attention into particular groups, functions, or divisions (March & Simon, 1958). So for multidivisional (M-form) firms, the challenge of shaping search behavior involves regulating the focus of attention within and across structurally differentiated subunits (Joseph & Ocasio, 2012; Rerup, 2009) that is, the processes of attentional specialization and attentional coupling.

There have been appeals for more research in this area (Gavetti et al., 2012; Gavetti, Levinthal, & Ocasio, 2007; Ocasio, 2011); even so, not much is known about how the structure of attention in an M-form firm affects the direction and balance of technological search. Extant research on the behavioral outcomes of attention allocation offers mixed results. One strand of research has lauded the benefits of attention specialization (Zollo & Winter, 2002), whereby firms focus on a limited number of problems and can therefore respond quickly to new feedback information (Baumann & Siggelkow, 2013). At the same time, specialization can increase the potential for myopic search at the expense of the overall firm (Levinthal & March, 1993; Zollo & Reuer, 2010). Research has also emphasized the benefits of tight coupling in other words, shared attention to similar issues (Bouquet & Birkinshaw, 2008; Gaba & Joseph, 2013; Joseph & Ocasio, 2012; Rerup, 2009). For example, it has been shown that shared attention within and across levels of a corporate hierarchy can increase the speed and accuracy of identifying new problems (Rerup, 2009) and also increase the rate of finding solutions (Gaba & Joseph, 2013). However, establishing tight coupling requires linkages and complex interactions between units. The result may be increased coordination costs (Grant, 1996) and reduced reliability of information, which would hamper search activities that are more distant (Martin & Mitchell, 1998).

In short, we have little clarity on the central question of this research: How does the structure of attention to problems within and between the business units of a multidivisional corporation affect their capacity to search? Our central proposition is that attentional specialization and coupling have important implications for search within large vertical hierarchies: the former because, when fewer problems are attended to, managers can engage with more unique problems and so become less likely to formalize or routinize behavior, thereby enabling search for more novel solutions; the latter because shared attention across units facilitates learning and provides a greater diversity of perspectives on a given set of problems.

This study relies on an analysis of patenting behavior and attention to technical problems within and across business units at Motorola over a 23-year period. Many studies have used patenting activity as a proxy for organizational search behavior (Carnabuci & Operti, 2013; Fleming, 2001; Katila, 2002; Katila & Ahuja, 2002; Sørensen & Stuart, 2000; Stuart & Podolny, 1996); the main reason is that a firm's patents reliably document its technological search trail (Jaffe, Trajtenberg, & Henderson, 1993). Thus, examining a firm's patenting activity allows one to assess the extent to which organizational search activity is driven by the distribution of attention within and across business units our central research question.

Our research makes three contributions to the literature. First, we offer insight into the cognitive determinants of organizational search. We provide a new perspective on the costs and benefits of attentional specialization and coupling in the multibusiness firm by highlighting how these aspects of attention affect search by organizational subunits. Second, we contribute to the literature on organizational design by developing two novel measurements for attentional structure, metrics that use information about the actual technological problems faced by business units to develop a representation of organizational attention. Finally, we offer insights on adaptation by the multibusiness firm; we consider in particular the evolution of attentional structure and its capacity to aid and constrain firm adaptation through distant search.

3.2 Attentional Structure in the Multibusiness Firm

The attention-based view (ABV) of the firm adopts, as its central focus, the problems to which organizations attend (Ocasio, 1997). Attention is defined as “the noticing, encoding, interpreting and focusing of time and effort by organizational decision makers on both (a) issues: the available repertoire of categories for making sense of the environment; and (b) answers: the available repertoire of action alternatives” (Ocasio, 1997, p. 189). Issues (e.g., problems, opportunities) and answers together form the firm’s agenda, which in turn shapes strategic behavior. These issues or instances when the

world's current state is perceived as being different from its expected or desired state attract the attention of organizational decision makers (Lyles & Mitroff, 1980).

In an organization, attentional structure plays the role of determining whether and how this attention is allocated (Bouquet & Birkinshaw, 2008; Joseph & Ocasio, 2012; March & Olsen, 1976; Rerup, 2009). The structure of attention to problems is especially important because the problems to which organizations attend lend impetus to strategic decision making (Mintzberg, Raisinghani, & Theoret, 1976; Nutt, 1984) and must be evident before managerial activity can be properly directed toward finding solutions (Kiesler & Sproull, 1982).

From an attentional perspective, structural divisionalization creates specialized decision-making contexts and focuses attention on different problems (Gaba & Joseph, 2013). In a multibusiness firm, then, the distribution of attention is not uniform and the relevance of particular problems in the external environment varies according to the structural position of decision makers within the hierarchy (Ocasio, 1997). Specifically, both the within-unit specialization in and the cross-unit attention to particular problems may have important implications for the technological search of organizations. Attentional specialization is based on the notion that attention is a limited organizational resource (Argote & Greve, 2007; Cyert & March, 1963; Simon, 1947) and reflects the division of attention, within an organizational unit, among a number of problems

(Joseph & Ocasio, 2012; Rerup, 2009). Attentional coupling refers to the degree to which business units focus on a common set of problems (Dutton & Ashford, 1993; Joseph & Ocasio, 2012; Rerup, 2009) and captures the extent of cognitive similarity between business units. In what follows, we explore the search implications of these two dimensions of attentional structure.

3.2.1 Attention Specialization and Technological Search

In our study, attention specialization refers to the allocation of attention to problems within a unit during some period of time. Business units may attend to many different problems or specialize in relatively few as a function of several factors in the internal and external environment. The major drivers of attention to technical problems in the mobile device industry are likely related to the development of particular technologies by competitors and/or to the demands of carriers such as AT&T and British Telecom. For example, problems faced by key customers (carriers) would become focal problems for the handset manufacturers attempting to solve technical problems on their behalf.

Greater specialization reflects the narrower focus of a unit on a fewer number of problems, which has implications for search behavior. First, when fewer problems are examined by a business unit, it is more likely that any single problem will be interpreted as unique. Greater novelty in problems may well add to the variety of problem-solving

approaches undertaken by the unit and might also increase exploratory behavior (Ahuja & Lampert, 2001). As the number of problems grows, similarities among them will likely arise. Decision makers can then regroup those problems into meaningful clusters (Salvato, 2009) and thereafter encode them in terms of familiar categories (Levinthal & Rerup, 2006). Hence decision makers will be more likely to rely on familiar technological solutions when addressing problems.

Second, as the number of problems increases, so too does the unit's attention load (Castellaneta & Zollo, 2014; Cohen, March, & Olsen, 1972; Rerup, 2009). Under such conditions, it may be necessary for the firm to economize on decision makers' limited attention capacity (Ocasio, 1997; Simon, 1947) by implementing new structures and routines to increase its ability to process additional stimuli (Castellaneta & Zollo, 2014; Davis, Eisenhardt, & Bingham, 2009; Levitt & March, 1988; Shapira, 1994; Sullivan, 2010). For example, the firm may create new roles, rules, or subunits to deal more efficiently with a large number of problems (Burns & Stalker, 1961) and accordingly may formalize or routinize problem-solving behavior. Yet even though formalization and routinization help manage attention (Rerup & Feldman, 2011; Weick & Sutcliffe, 2006), they can also become a basis for path dependency (Feldman & Pentland, 2003; Nelson & Winter, 1982) and thus limit firm flexibility (Martin & Eisenhardt, 2010; Miller & Friesen, 1980; Siggelkow, 2001). Under these conditions, the firm relies more heavily on familiar

technology domains (Leonard-Barton, 1992) and so may inhibit the development of new approaches to solving problems (Fiol & Lyles, 1985). These considerations lead to our first two hypotheses.

Hypothesis 1. If attentional specialization within a business unit increases, then the unit will exploit existing knowledge less (i.e., decrease its search depth).

Hypothesis 2. If attentional specialization within a business unit increases, then the unit will explore new knowledge more (i.e., increase its search scope).

3.2.2 Attentional Coupling and Technological Search

In a multibusiness organization, especially one viewed as a “related diversifier” (Rumelt, 1974), there may be similar and overlapping foci of attention across business units. Hence attentional specialization is insufficient to characterize a firm’s attentional structure; we must also consider the search implications of shared attention to similar problems between units.

Attentional coupling reflects the pattern of attention that emerges from the interactions that occur within channels that span organizational units (Ocasio & Joseph, 2005). These interactions create a shared dialogue and information exchange while simultaneously improving coordination (Clark & Fujimoto, 1987). Coupling may also reflect similar attention patterns in the absence of explicit communication. For example, organizational goals or informal decision premises may provide a means to integrate

otherwise disparate organizational units and thereby ensure that the decisions made are mutually reinforcing (Gavetti, 2005; Gavetti & Levinthal, 2000; Gulati, Puranam, & Tushman, 2012) despite the lack of direct contact between units.

Shared attention to similar problems may shape the way in which those problems are interpreted and addressed. Responding to problems is a cognitive process that involves an actor's ability to construct meaning for or assign meaning to the problem (Kiesler & Sproull, 1982; Lyles & Mitroff, 1980; Mintzberg et al., 1976). Different divisions within the same organization may construct radically different interpretations of the same problems (Leonardelli, Pickett, Joseph, & Hess, 2011) owing to the variety of professional experiences, backgrounds, and affiliations of their respective managers (Cho & Hambrick, 2006; Hambrick & Mason, 1984). Through attentional coupling, exposure to new and more diverse interpretations of any particular problem may frame the problem in a new light for the focal unit and broaden its apprehension of possible solutions.

At the same time, tight coupling may also help business units respond with a broader range of technologies. Problems that span business units are likely to require not only more novel problem-solving approaches but also the incorporation of knowledge from the respective units. Accessing this knowledge is useful in that it leads

to more novel combinations of components that is, from the different units (Henderson & Clark, 1990).

For example, Motorola's Land Mobile, General Systems, and Semiconductor sectors had (on average) the highest levels of attentional coupling. These units shared attention to similar problems, such as signal amplification, antenna reception, and battery consumption. The close relationship between General Systems and Land Mobile was a result of Motorola's corporate history: the former business unit started as a small division within the latter, and the two were split apart in 1985. The Semiconductor unit's tight coupling with Land Mobile and with General Systems reflected their vertical supply chain relationship. The shared attention among these organizational units provided a foundation for the units to explore new domains of knowledge individually and together, such as technologies designed to improve key subsystems (e.g., power, display) on portable electronic devices.

Overall, this evidence suggests that tight coupling is likely to shift the balance of search from exploitative to explorative activities. We thus have our next two hypotheses.

Hypothesis 3. If attentional coupling between business units increases, then they will explore a greater amount of new knowledge (i.e., increase their search scope).

Hypothesis 4. If attentional coupling between business units increases, then they will exploit existing knowledge less (i.e., decrease their search depth).

3.3 Methods

3.3.1 Research Setting

This study is a longitudinal analysis of Motorola, the attentional patterns within and across its business units, and the nature of its search activities from 1974 to 1997. Because it has often been in the vanguard of new technologies, Motorola is an ideal setting in which to examine the allocation of managerial attention to search. For much of its life, Motorola featured a multidivisional structure and comprised multiple major business units that each developed telecommunications-related technologies: Land Mobile produced two-way radio equipment for enterprise and government customers, while General Services produced cellular telephones, infrastructure, and satellite-based communication technologies; Government produced communications technologies for government and military purposes, and Automotive produced communications technologies both for original equipment manufacturers and for aftermarket retail. The Semiconductor unit was a major manufacturer and created products such as microprocessors, microcontrollers, digital signal processors and controllers, sensors, and integrated chips; Information Systems produced radio-frequency identification and software technologies, and Paging produced portable paging products.

Each unit faced unique challenges and industry pressures. Yet it is advantageous for our purposes that, as a whole, the telecommunications sector is a high-velocity

industry characterized by first-mover advantages and rapid product innovation (Eisenhardt & Tabrizi, 1995); these characteristics explain the importance of innovation and search to Motorola's business. Moreover, this single-firm setting allows for variation in the conditions of interest (i.e., attentional specialization and coupling) while controlling for common firm factors and ensuring that the firm's broad technological domain (here, telecommunications) varies little over time.

Finally, during the period of study, Motorola utilized advanced technology lab groups (i.e., labs associated with the respective business units) rather than a centralized research and development (R&D) organization; this fact helps ensure that it is the characteristics of business units' attention, and not the corporate R&D structure, driving our hypothesized effects.

3.3.2 Sample

The sample covers all seven of Motorola's business units for the period 1974-1997, an era during which Motorola was instrumental in developing many key technologies in communications. We obtained our list of Motorola patents from National Bureau of Economic Research (NBER) patent data (Hall, Jaffe, & Trajtenberg, 2001); we then used the patent numbers so derived to scrape our corpus of patent backgrounds directly from the US Patent and Trademark Office (USPTO) website using the

“BeautifulSoup” package in Python.³ We used Compustat to collect selected Motorola financial data. The data are analyzed by business-unit (BU) year, resulting in 117 BU-year observations. Table 8 gives the summary statistics and correlations for all variables in our sample.

Table 8: Summary Statistics

	Mean	Std. Dev.	1	2	3	4	5	6	7	8	9
1 Search Depth	0.33	0.17	1.00								
2 Search Scope	0.84	0.13	-0.89	1.00							
3 Attentional Specialization	30.50	29.26	-0.10	0.06	1.00						
4 Attentional Coupling	0.00	0.00	-0.58	0.56	-0.04	1.00					
5 BU Sales (\$MM)	1.75	2.14	0.31	-0.40	0.05	-0.61	1.00				
6 Firm Sales (\$M)	8.55	7.86	0.21	-0.36	0.14	-0.54	0.76	1.00			
7 R&D Intensity	78.23	10.72	0.19	-0.26	0.01	-0.45	0.35	0.57	1.00		
8 Technological Interdependence	34.75	49.41	0.25	-0.31	0.07	-0.54	0.54	0.67	0.42	1.00	
9 Competitive Intensity	62.86	22.31	0.23	-0.36	0.02	-0.54	0.74	0.80	0.43	0.57	1.00

We remark that some of the business units were not in existence throughout the entire observation period; for instance, Paging does not exist as a separate entity until 1990.

3.3.3 Dependent Variables: Search Scope and Depth

Our dependent variable is technological search, which we measure using patent data. Embedded in patents are both a technical problem and a solution to that problem (Walker, 1995), by which we mean patent data provides a detailed and consistent

³ The usage and relevance of patent backgrounds in particular is explained in the section “Topic modeling,” to follow.

chronology of how firms solve problems that is, of how they search. A number of studies have used patent data as an indicator of search activity (Katila, 2002; Rosenkopf & Nerkar, 2001; Stuart & Podolny, 1996). In formulating our measures of technological search, we followed the methodology used in Katila and Ahuja (2002). They calculate search scope, which captures the “theoretical notion of exploration of new knowledge,” by examining the proportion of previously unused citations in a firm’s focal year’s list of citations. Katila and Ahuja also calculate a measure of search depth, a metric for exploitative search that describes “the accumulation of search experience with the same knowledge elements”; it is calculated as the ratio of repetitions in citations within a unit to the total number of citations in the unit. Prior research has indicated that knowledge depreciates rapidly in high-technology organizations (Argote, 1999), so in constructing these measures we consider only the previous five years’ lists of citations. Because we focus on search behavior within Motorola, the measures are constructed at the business-unit level. Our measures therefore capture both a BU’s exploration of new knowledge and its exploitation of existing knowledge.

Owing to the decentralized and geographically dispersed nature of Motorola’s R&D organization, we could assign patents to their primary business unit by using the location of the first inventor listed on the patent along with the subclass to which the

patent pertained. We used NBER patent data (Hall et al., 2001) to link 81,023 citations to Motorola's patents during our sample period.

3.3.4 Topic Modeling: Text as a Measure of Attention to Technological Problems

The key independent variables of interest for our analysis are the degree to which attention to technological problems is focused within business units (attentional specialization) and shared between business units (attentional coupling). To generate our measures of attention, we rely upon probabilistic topic modeling (Blei, 2012), an unsupervised text-analysis tool that infers a set of topics under which a group of documents' contents can be organized.

Our corpus consists of 12,787 patent backgrounds obtained from the USPTO website. These include all patent backgrounds available digitally from 1967 to 1999, so they constitute a superset of all patents used in the citation analysis. Because we rely on patents to develop our understanding of the attention paid to particular problems over time, we must limit our study to only those technological problems for which patenting is a viable response. We generate a topic model using the full set of patents during this time period; doing so illuminates the ongoing technological problems that Motorola faced prior to the window for our collecting of data on the other covariates.

A patent's background is the best representation of the technological problem that it addresses, so it is the patent's best component to examine if we are interested in

managerial problem solving and attention. The patent background, according to the USPTO, should state both the “field of art to which the invention pertains” as well as “a description of the related art known to the applicant and including, if applicable, references to specific related art and problems involved in the prior art which are solved by the applicant’s invention” (emphasis added). Fig. 9 reproduces part of the background for a typical semiconductor patent from our data set, and the technological problem addressed by the patent is clearly described. In addition, the terms (e.g., “battery charging”) most determinative of the patent’s classification are circled in the figure. We use the text mining (“tm”) package in R to perform standard manipulations on our corpus, such as removing stop words (e.g., “the”), truncating words to their respective roots (e.g., “encryption” and “encrypting” to “encrypt”), and generating the document term matrix, which gives the count of each term appearing in each document.

The algorithm identifies key words that occur together...

Patent #5422559 – SEMI, 1993, Topic #69

The present invention relates, in general, to battery charger circuits, and more particularly to output stage circuits. One type of battery charger is a pulsed battery charger [...]

Overcharging this type of battery by more than a few millivolts may cause battery damage. [...] Pulse charging provides an accurate way of sensing battery voltage. The voltage is sensed between pulses when the battery is not being charged thereby providing an accurate measurement of the battery voltage.

[...] Standard battery chargers do not provide the precise control needed to charge a rechargeable alkaline battery without damage or shortening the number of times it can be charged. It would be of great benefit, if a battery charger output stage circuit is provided that could charge a battery to a precise voltage.

... and when these words appear together across many documents, these will load onto a “topic”

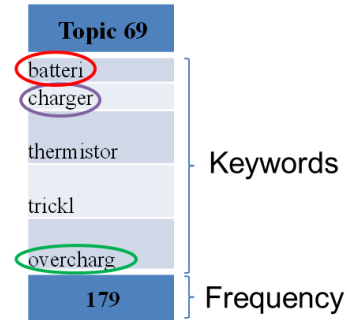


Figure 9: Sample Mapping from Patent Background to Topic

Our use of probabilistic topic models to characterize the content of patent data is a significant departure from the standard measures derived from citation counts or technological classes. After all, some researchers have expressed concern about the ability of patent classifications to reflect location in technological space (Benner & Waldfoegel, 2008), and work on patent citations has identified those classifications as but noisy reflections of actual knowledge flows (Alcacer & Gittelman, 2006; Roach & Cohen, 2013). Kaplan and Vakili (2013) describe these limitations extensively; they also discuss the differences between topics generated from patent data versus information, such as technological class, that is already encoded within the patent.

The topic modeling approach that we use is based in the Bayesian technique of latent Dirichlet allocation (LDA). In keeping with conventional notation for such

analyses, we use the language of text analysis. A word is the basic unit of discrete data and is part of a larger vocabulary in our case, all words used in our corpus of patent backgrounds. Each document is a sequence of N words, and a corpus is a collection of documents. Topic modeling assumes that documents in the corpus are generated by the following process (Blei, Ng, & Jordan, 2003):

1. Choose $N \sim \text{Poisson}(\xi)$
2. Choose $\theta \sim \text{Dir}(\alpha)$, where $\text{Dir}(\alpha)$ is a K -dimensional Dirichlet random variable
3. For each of the N words in a document:
 - a. Randomly choose a topic $z_n \sim \text{Multinomial}(\theta)$
 - b. Choose a word from the corresponding distribution over the vocabulary: a word w_n is chosen from $p(w_n | z_n, \beta)$, a multinomial probability distribution conditioned on topic z_n

The terms K , α , and β are parameters in our topic model, where K is the number of topics. The parameter α is a topic-smoothing parameter that affects the shape of the Dirichlet distribution; a smaller value of α corresponds to documents being more likely to consist of only a few topics. The parameter β is a term-smoothing parameter for which a smaller value corresponds to topics being more likely to consist of only a few words.

We must compute the posterior distribution of the remaining variables, z and θ , in the preceding expressions; it is expressed as $P(\theta, z | w, \alpha, \beta) = P(\theta, z, w | \alpha, \beta) / P(w | \alpha, \beta)$. This distribution is intractable for purposes of exact inference (Dickey, 1983), so we must employ an approximate inference algorithm. We use a variational expectation

maximization procedure to compute the per-word assignment distribution of topics (or themes) per document as well as a distribution of words per topic (for details, see Blei et al., 2003).

LDA works by resolving two competing goals: (1) allocate each document to as few topics as possible; and (2) allocate each topic to as few terms as possible. Classifying a document under only a single topic compromises the second goal (since all words would have equal probability of occurring under that topic), and including only a few words in each topic results in a document requiring many topics to generate. We used the topic models package for R developed by Grün and Hornik (2011) to implement LDA.

In line with recommendations of the Stanford Topic Modeling Toolbox (Ramage, Rosen, Chuang, Manning, & McFarland, 2009), we use parameter estimates of 0.1 for both the alpha (topic-smoothing) and beta (termsmoothing) parameters. We set the value of K to 100, the number of topics in our corpus; this approach is consistent with Kaplan and Vakili (2013) and with the recommendations of scholars who use topic modeling to generate interpretable topics (Blei & Lafferty, 2007).

All Motorola patents are assigned to the corporate office, so developing BU-level measures of structural attention required that we map each patent to a particular business unit. Unlike many organizations, in which R&D activities are organized at the

corporate level, each business unit within Motorola maintained separate R&D facilities what Motorola called advanced technology lab groups during our observation period. We were therefore able to use the geographic location of the primary inventor to greatly facilitate this assignment of patent to R&D facility. Of patents issued during 1974-1997, 94% were generated by R&D facilities in Arizona (whose research was mainly for the firm's Government and Semiconductor units) or Illinois (mainly Land Mobile, Automotive, and General Services sectors). Patents generated in Florida (resp., Massachusetts) likely pertain to the Paging (resp., Information) units. In addition to following these geographic rules of thumb, we downloaded patent abstracts for all sample patents from the USPTO website before employing two research assistants who manually coded the mapping of patents to business units at each geographic location. Because many of these patents could have applications to multiple business units, we asked the coders to indicate uncertain cases (since some patents were highly technical) as well as potential affiliation to multiple business units. Our interrater agreement was 73%. We then reconciled all remaining disputed patent-BU affiliations to generate our final coding. Altogether, we were able to code and find patent backgrounds for 7,629 patents during the period 1974-1997.

The results of applying the topic model to our set of patent backgrounds were compatible with our understanding of the ebb and flow of major technological issues

faced by Motorola during the time period. Major topics map to such problems as transmitting sound wirelessly, providing adequate power to mobile devices, sending messages over telephony systems, improving cellular technologies, developing satellite communication technologies, and overcoming various barriers to create better semiconductor chips. Furthermore, the analysis allows us to map the changing importance of these topics over time. Topics that lost substantial ground tended to involve adequately resolved technological issues (e.g., the wireless transmission of sound) or lines of business that never gained traction (e.g., a topic pertaining to technologies used in Iridium, a failed satellite phone service). Topics that gained substantial traction were associated with the rise of mobile telephony in the “feature” phone era of the 1990s. For our analysis, we are not concerned with the particular technological problem per se, simply that it represents another avenue of technological inquiry and (dis)similarity between business units.

3.3.5 Attentional Specialization

We construct our measure of attentional specialization by counting the number of problem topics examined by the business unit’s knowledge stock, which is assumed to cover five years (Argote, 1999). We then reverse-code this count variable by subtracting all observations from the sample maximum (100) to create a measure in which higher values indicate greater specialization. Resource constraints being equal,

we believe that our measure reflects the extent to which finite managerial attention must be allocated across a set of technological problems within a business unit (Argote & Greve, 2007; Greve, 2008). To simplify the measure, we assume that each problem can only be either present or absent. The measure's maximum value is 100, the selected parameter k in our topic model, which is standard in the literature on topic modeling.⁴ For units that are spun out of other units (e.g., General from Land Mobile in 1985), we consider topics examined in the parent unit when assessing whether a topic is present in the early stages of their lives.

3.3.6 Attentional Coupling

We use a measure of Euclidean distance to create a metric for attentional coupling. This approach captures the degree to which problems across business units are similar or different at any given time. We employ Euclidean distance because it has been used previously in the management literature to assess similarity across business units (Govindarajan, 1988).⁵ We calculate the position that each BU occupies in “wordspace” each year by using standard outputs from a probabilistic topic model.

⁴ Units might demonstrate similar levels of specialization yet rely on different knowledge bases. Nonetheless, the firms in our sample that were highly specialized tended to cite external patents more frequently than to cite knowledge developed in other parts of the firm. Relatively unspecialized units were more heterogeneous in terms of their patents' citation patterns (i.e., use of internal vs. external knowledge).

⁵ An extensive literature in computer science discusses the use of Euclidean and alternative distance measures in the context of assessing similarity. Qian, Sural, Gu, and Pramanik (2004) compare different distance-type calculations and find that, when dimensionality is high (i.e., more than 100 dimensions),

The particular standard outputs are two matrices of interest. The first is a matrix that maps the loading of each word onto each particular topic. The topic model algorithm is designed to load as few unique, predictive words on as few clusters as possible (in the resulting “topicword” matrix). Our corpus contained over 12,000 unique words, which were used to generate 100 topics (this value is a parameter of the topic model; recall that it is standard). The dimensions of this matrix are therefore $100 \times w$, where w is the number of unique words in our corpus.

The second output is a matrix that contains the loading of each topic onto each individual patent within the data set (a “patent-topic” matrix). The dimensions of this matrix are $p \times 100$, where p is the number of patents in our data set. The multiplication of the patent-topic and the topicword matrices generates a $(p \times w)$ -dimensional patent-word matrix; this matrix represents the loading of each word onto each patent, which is equivalent to the position of each patent in wordspace.

Because we have mapped patents not only to business units but also to patent application years, we can create a vector that characterizes the position (in wordspace) of each BU for each year in our sample by averaging all of the constituent patents for

cosine similarity and Euclidean distance are reasonable approximations of each other. The word-BU matrix has more than 10,000 dimensions, so this condition is easily met.

each BU year.⁶ Once we have created these vectors, we can calculate the Euclidean distance between any two BU-year vectors as follows:

$$d(\vec{bu1}, \vec{bu2}) = \sqrt{(bu1_1 - bu2_1)^2 + (bu1_2 - bu2_2)^2 + \dots + (bu1_n - bu2_n)^2}$$

where bu1 and bu2 are different BU years and n is the number of terms in the corpus.

This calculation enables us to determine how similar any BU year is to any other BU year, which in turn allows us to measure change in similarity over time as regards any two organizational units of interest. For this study, our aim was to use a simple measure of change when constructing an attentional coupling indicator.

Our attentional coupling measure assesses whether (and to what extent) a business unit's problems become, over time, more or less similar (on average) to the problems of other units. To capture this dynamic, we calculate the average distance between a focal BU and all other BUs in each year of our sample. We then construct a change measure each year by subtracting this average distance at time t from the average distance at time t - 1. For the ease of interpretation, we create a measure of similarity based on reversing this change measure by subtracting each observation from the sample maximum.⁷ Thus, a positive number on this scale indicates that a BU has an

⁶ One could construct a similar vector using each patent's loading of topics, but that vector would not reflect the degree to which particular topics are more or less distant.

⁷ Using the distance measure preserves our findings, except with opposite signs.

attention pattern more closely resembling (i.e., is more tightly coupled to) other BUs than it did the previous year.

Our measure enables us to assess how similar the managerial attention paid to a set of problems faced by some BU at any period is to the set of problems faced by other Motorola BUs at any time. This measure of the degree to which the focus of attention is shared is our measure of attentional coupling. The values that result from using this metric make intuitive sense, since business units that create technologies of a more general-purpose nature tend to be located more “centrally” than are units creating more specialized technologies. Fig. 10 is a two-dimensional representation of the distance matrix between different business units; the plots were created using multidimensional scaling in Stata (Borg & Groenen, 2005). More specifically, Fig. 10 shows the degree to which business units within Motorola are coupled to each other at three separate times: 1975, 1985, and 1995. The multidimensional scaling of the distance matrix in Fig. 10 nicely displays tight versus loose coupling; from an attentional perspective, Motorola clearly has both core and peripheral business units. These graphs illustrate our earlier report that the Land Mobile, General Systems, and Semiconductor business units had the highest levels of coupling whereas the Information, Government, and Automotive business units had the lowest.

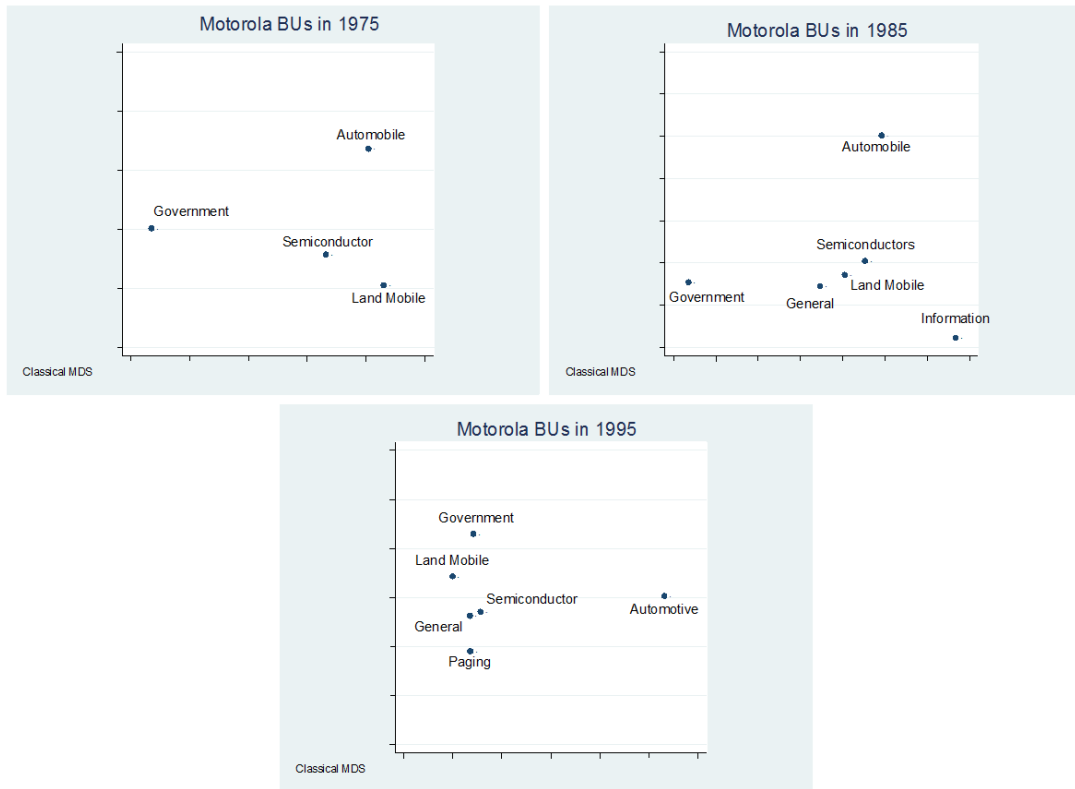


Figure 10: Multidimensional Scaling Applied to Measures of Attentional Coupling at Motorola in 1975, 1985, and 1995

3.3.7 Controls

Our controls yield some insight into alternative mechanisms that may be driving the emergence of new problems faced by Motorola’s business units. These controls were motivated by our discussions with managers at Motorola, internal documentation, and relevant theoretical literature on technological development and managerial problem solving. In the model’s specification we include business unit dummy variables to

account for industry differences between Motorola's business units. Note that all time-varying covariates are lagged one year in the model.

We use business unit sales in billions of dollars to proxy for the overall size of the business unit; hence we can distinguish the effects of attentional specialization and coupling from any effects due simply to changes in the business unit's size. We also control for firm sales in billions of dollars in order to control for the effects of overall firm size, such as organizational inertia (Hannan & Freeman, 1984).⁸ We control for firm-level R&D, which could affect the intertemporal likelihood of examining new problem patterns; this variable reflects differences in R&D-related expertise and has been associated with firm growth (Cohen & Klepper, 1992). This variable was calculated as an intensity measure, R&D spend divided by total sales (multiplied by 1,000 to aid interpretation). We also control for competitive intensity by including a weighted average of the number of competitors each business unit faces within its constituent groups' and divisions' four-digit SIC codes.

We count the number of cross-citations between business units' patents as a way of controlling for the degree of technological interdependence between business units at any moment in time. Consistently with prior literature that has examined patent

⁸ Regression results for key explanatory variables continue to hold when firm size is either omitted entirely or replaced with some other measure (e.g., revenue).

citations, we consider patents issued in a firm's previous five years to constitute its "knowledge base" (Katila & Ahuja, 2002) when calculating this count variable. The intuition here is that a business unit drawing more heavily on another BU's knowledge base is more technologically interdependent. As expected, BUs more distant from each other in Fig. 10 (e.g., Automobile and Information) as well as relatively more upstream units (e.g., semiconductors) engage in less cross-citation.

3.3.8 Empirical Specification

For the analysis, we shall employ a cross-sectional time-series (panel) data design. Because values of the dependent variables are bounded by 0 and 1, we conduct the analysis using a two-sided Tobit regression model (Long, 1997). Tobit regression is appropriate in this case because the independent variables could predict both the probability and the extent of distant and local search. In order to account for the nonindependence of observations, we use a "robust cluster" estimator (White, 1980) of the standard errors and cluster by business unit.

3.4 Results

Table 9 reports the Tobit estimates of search scope and search depth for each of Motorola's business units during our observation period. All models include business-unit fixed effects to control for idiosyncratic differences among units. Each pair of models examines search depth and search scope, respectively. Models 1 and 2 include

only the control variables' effects. Models 3 and 4 show the results for attention specialization and controls only, models 5 and 6 give the results for attentional coupling and controls only, and models 7 and 8 show the effects of all variables. Except in model 4, all explanatory variables contribute significantly ($p < 0.05$) to model fit.

Table 9: Tobit Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tobit regression predicting search scope and depth	Depth	Depth	Depth	Depth	Scope	Scope	Scope	Scope
1 Attentional Specialization		-0.003*		-0.003***		0.002		0.002*
2 Attentional Coupling			-22.453***	-22.798***			16.032*	16.047*
3 BU Sales (\$MM)	-0.034**	-0.034**	-0.024*	-0.023*	0.020**	0.021**	0.013	0.014
4 Firm Sales (\$M)	0.012**	0.012**	0.006	0.006	-0.010***	-0.010***	-0.006	-0.006
5 R&D Intensity	0.002	0.002	0.001	-0.000	-0.001	-0.001	-0.000	0.001
6 Technological Interdependence	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	0.000	0.000
7 Competitive Intensity	0.000	0.000	0.001	0.001	-0.000	-0.000	-0.000	-0.000
BU Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	117	117	117	117	117	117	117	117
Number of business units	7	7	7	7	7	7	7	7
Constant	0.115	0.172	0.311*	0.477**	0.960***	0.918***	0.830***	0.717***
Sigma	0.103***	0.101***	0.098***	0.097***	0.082***	0.080***	0.079***	0.077***
All covariates lagged by one year			* p<0.05 ** p<0.01 *** p<0.001					

Models 1 and 2 reveal that greater BU sales are significantly associated with a decrease in search depth yet with an increase in search scope. At the sample mean, a \$1 million increase in BU sales is associated with a nearly 9% decrease in search depth and a 3% increase in search scope. To the extent that BU sales indicate an increase in resources, one might expect both the depth and scope of search to be increasing in BU-level resources. Yet it turns out that, during the time horizon of this study, scope and depth exhibit a high negative correlation (-0.89); the implication is that Motorola did face a strong trade-off between exploration and exploitation during this period in its history. In line with an inertia-type hypothesis, we find that overall firm size is associated with greater degrees of search depth and with lesser degrees of scope; this finding suggests that, as Motorola grew in size, it engaged in more local search. At sample mean values, a standard-deviation increase in firm sales is associated with a nearly 17% increase in search depth and a 7.5% decrease in search scope. The other associations we examine are quite weak, and none are significant at the $p < 0.05$ level. We display these associations regardless as a further indication of our findings' robustness to BU-level competition, fluctuations in corporate R&D spending policies, and interdependence in technological portfolios across business units.

Model 3 and Model 4 show the effects of attentional specialization on (respectively) search depth and search scope. In line with Hypothesis 1, we find that an

increase in attentional specialization (focus on fewer problems) reduces search depth. In particular, each additional problem examined within a business unit could reduce search depth by 0.7% - which could be a substantial decline in light of this variable's large standard deviation (29.26). Although the sign of the relation between search scope and attention specialization is consistent with Hypothesis 2, we find no statistical support for the model that includes only specialization.

Models 5 and 6 show the effects of attentional coupling on search depth and scope, respectively. Consistent with Hypotheses 2 and 3, an increase in attentional coupling is found to be associated with a reduced depth of search but with a wider scope of search. A standard-deviation increase in attentional coupling is associated with (approximately) a 5% decrease in search depth and a 1.4% increase in search scope.

Models 7 and 8 replicate the intuition and signs of our results in models 3-6. Moreover, we find additional support for Hypothesis 2. Namely, the relationship between attention specialization and search scope is significant ($p = 0.011$) in the full model; this finding suggests that increased specialization increases search scope.

3.5 Discussion and Conclusions

This chapter examines the effects of attentional structure on the scope and depth of search in a large, innovation-centered, multibusiness firm. Making use of a novel topic modeling approach to identify the patterns of problem attention embedded in firm

patent backgrounds, we find a trade-off between both attentional specialization and coupling on search scope and depth. Specifically, specialized unit attention to a more narrow set of problems increases search scope but reduces search depth; increased attentional coupling also increases search scope at the cost of depth. As a whole our results suggest that, if the aim is to broaden search within a firm, then units (a) should focus on a limited number of problems and, at the same time, and (b) should focus on problems that are similar to those of other units in the organization.

Our study makes several contributions. First, it contributes to the literature on ABVs of strategy (Barnett, 2008; Bouquet & Birkinshaw, 2008; Ocasio & Joseph, 2005; Rerup, 2009). Although the performance outcomes of attentional structure have been explored elsewhere, we offer the first large-scale empirical study of attentional structure and thereby complement emerging qualitative work (e.g., Joseph & Ocasio, 2012; Rerup, 2009) and modeling work (e.g., Davis et al., 2009) on the subject. In particular, this chapter links the concepts of attention specialization and coupling to local / distant search, thus establishing a relationship between attention to technical problems and technological search behavior in the multibusiness firm.

Second, by linking the attentional structure of an organization to technological search, our study contributes to the literature on organizational design. Rather than boxes and arrows, the results reported here highlight the importance of distributed

cognition and attention patterns within an organization. This “cognitive structure” of the firm (Hutchins, 1995) may operate independently of the traditional levers (e.g., organizational structure) used by designers of organizations. We introduce a replicable methodology to measure attentional coupling and specialization via modern text-analytical tools, which constitutes the first empirical attempt to quantify shared attention across units. Research in cognition and strategy has increasingly examined how themes and relationships can be derived from text (see, e.g., Kaplan, 2011), and our study is another early foray into the rich promise of these tools for organizational theorists. More specifically, our work adds the importance of cognitive similarity between business units to the stream of research devoted to examining BU relatedness (Rumelt, 1974) and how knowledge is shared between business units (Tsai, 2001).

By extension, our study suggests that there may be an important relationship between attention and knowledge. We argue that attention to similar problems will enlighten the unit’s interpretation of a given problem and broaden the knowledge used to develop technological solutions. It could be that units focusing on similar problems draw upon much different sources of knowledge or use the same body of knowledge to resolve very different issues. The context studied in this chapter did not offer much variation across the entire range of coupling and technological interdependence, which limited our ability to assess how search is affected by the interaction between attention

and different patterns of drawing upon knowledge. That being said, further exploration of these conceptual relationships promises to be a fruitful avenue for future research.

Third, our study examines how allocation of attention within organizational subunits shapes adaptation in the form of search behaviors. Strategic adaptation is often constrained by cognition because the mental models of managers are, like routines, subject to inertial forces (Tripsas & Gavetti, 2000). Hence linking attention specialization to organizational search is an important insight, suggesting counterintuitively that organizational specialization in attention patterns may actually decrease myopia (cf. Levinthal & March, 1993). Thus our study offers a more nuanced understanding of the links between routinization and mindful choice (Winter, 1997) and of the ongoing theoretical debate over how best to link mindful and habitual perspectives on organizational learning (Gavetti & Levinthal, 2000; Levinthal & Rerup, 2006).

In finding that organizations can arrive at broader solutions through multiple paths, we suggest that the concept of “equifinality” (Gresov & Drazin, 1997; Katz & Kahn, 1978) may extend to the firm’s cognitive structure. This is a unique contribution to the ABV, which has typically focused on either the importance of attention specialization (singular top management focus, as in Kaplan, 2008) or the need to link attention of different units (e.g., Rerup, 2009). By integrating these two approaches, we show that both attentional mechanisms can operate simultaneously in an organization to

generate performance benefits. A logical extension of this line of thought would be to study in more depth the relationship between specialization and coupling and their joint effect on search.

Our results also point to the study's limitations. We limit our study to one firm in the telecommunications industry and thus to the particular actions of Motorola.

Although this setting facilitates a better understanding of the focal mechanisms by eliminating sources of cross-firm heterogeneity, a broader sample of firms would likely improve the generalizability of our findings. Note also that, during the period of study, Motorola underwent a dramatic period of growth; that growth could have affected the resources available for expanding attentional capacity and for investing in new technologies. Recall that Motorola during this period was typically at the leading edge of technologies in its industry; firms in other life-cycle stages or that pursue different strategies may exhibit different patterns. It is also important to recognize that, in large firms, attentional load may be handled by alternative means for instance, by establishing ways to balance exploration and exploitation. As other examples, research has shown that managers can change the organization's formal structure (Boumgarden, Nickerson, & Zenger, 2012), shift or increase executives' attention (Ocasio & Wohlgezogen, 2010) and working memory (Laureiro-Martinez, 2014; Laureiro-

Martínez, Brusoni, Canessa, & Zollo, 2014), and shift the focus of top management (Lakhani, Lifshitz-Assaf, & Tushman, 2013).

Finally, our study contributes to the research on innovation in complex systems. A wide range of work has recognized the trade-offs between modularity and integration within complex organizations. Fleming and Sorenson (2001) show that intermediate levels of modularity tend to produce the most useful inventions; similarly, Ethiraj and Levinthal (2004) demonstrate the benefits of avoiding excessive modularization or integration. Our attentional mechanisms find advantage in greater coupling. We move the conversation from direct interactions to a shared attention to problems, which is consistent with the notion that common ground is beneficial for coordinated action (Puranam, Singh, & Chaudhuri, 2009). We link this shared attention, which includes the organization's attentional structure, to its formal structure - thus answering the "neo-Carnegie" call for greater integration between theories of cognition and decision making (Gavetti et al., 2007). We develop a theory that links organizational attention to search. In examining the concepts of attention specialization and coupling, we put into sharper relief the roles played by innovation and attention in the multibusiness firm.

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Biography

Alex James Wilson was born to Guy and Justine Wilson on September 26th, 1986 and was raised in Poquoson, Virginia. After graduating as valedictorian from Poquoson High School, he moved to Philadelphia at age 17, where he attended the University of Pennsylvania. In 2008, he graduated magna cum laude from the Huntsman Program in International Studies and Business, earning his Bachelor of Science of Economics from the Wharton School (concentrating in Finance) and his Bachelor of Arts in International Studies and Hispanic Studies from the College of Arts and Sciences. He worked as an Associate in the Atlanta, Georgia office of the Boston Consulting Group before beginning his Ph.D.

During his Ph.D. in the Strategy department at the Fuqua School of Business, he was invited to present his work at several consortia and professional conferences, including the Trans-Atlantic Doctoral Consortium, the Consortium on Competitiveness and Cooperation, the Academy of Management, and the Strategic Management Society, where chapter #2 of this dissertation was nominated for best paper. In 2015, chapter #3 of this dissertation was published in the Cognition and Strategy issue of *Advances in Strategic Management*. His initial faculty placement was into the Strategic Management and Entrepreneurship Group in the Carlson School of Business at the University of Minnesota.