

ESSAYS ON DECISION MAKING IN SERVICE OPERATIONS MANAGEMENT

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This dissertation investigates the impact of behavioral decisions on operational performance outcomes in service industries. We begin with an exploration of the research trends in Behavioral Operations Management (BOM) and Behavioral Economics and Decision Research (BEDR). BOM's primary contribution has been using human subjects in laboratory experiments to test economic and game theoretic models. Similarly, BEDR focuses on describing and modeling individual decision making patterns; primarily decisions that people make for themselves. An emerging subfield of the BEDR literature focuses on models of decision making for others. Professional services is a label many use to characterize an industry dedicated to decision making for others, while the actors in this industry are described as working for 'professional service firms.' Examples of professional service actors include doctors, lawyers, engineers, accountants, architects, and consultants.

In our first essay we take a deep dive into professional service firms (e.g. management consultants in the hospitality industry) in an attempt to better understand the unique characteristics and challenges that firms in this industry encounter. Using a survey instrument, choice experiment, and supported by qualitative data from leading consultants in the field, we challenge traditional professional service frameworks and call for a more contingent framework based on firm and individual characteristics such as size, seniority, and specialization.

In our second essay, we dig deeper into the professional service paradigm and test the influence customers (clients) have on their expert advisors (consultants) using a behavioral experiment. Using tools developed in behavioral economics and commonly used in BOM we design a

laboratory study which measures the influence that client and consultant decisions have on each other in a setting where consultants are tasked to make decisions (e.g. recommendations) for their clients. One perspective is that clients who hire consultants should trust their consultant's presumably expert recommendations. We explore circumstances in which experts may inadvertently give—or choose to give—advice that produces suboptimal outcomes for their clients.

In our final study we expand beyond the context of professional service firms to illustrate the impact of a specific decision faced by managers in the hospitality industry: the decision hoteliers face to pursue environmental certification. Using archival data from the hospitality industry we use a difference-in-differences approach, in the setting of a natural experiment, to measure the impact of an environmental certification (LEED) on hotel performance. We find that LEED certified hotels do outperform their non-certified competitors for at least a few years. We conclude this dissertation with a discussion of the managerial applications of this research and a plan for future research.

BIOGRAPHICAL SKETCH

Matt's research interests include behavioral and empirical research in the context of professional services and service operations management. More specifically, Matt studies how manager and customer behavior can influence service operations outcomes. Professional services for example is a context driven by manager/client interactions and one in which Matt has chosen to focus much of his research. This interest in professional service firms (PSFs) stems from Matt's own experience working for and observing professional service firms. Starting at a young age Matt observed his father—a Washington D.C area architect—operate his own business. In fact, one of Matt's first 'jobs' was to help his father build 3D models of his designs. Matt's interest in PSF continued as he later worked for other architectural firms as well as for engineering, consulting, construction, and real estate appraisal firms.

Matt took this background with him to Brigham Young University where he earned a BS degree from the Fulton School of Engineering in Construction Management. After four years working for multiple consulting firms in NYC, Matt returned to BYU's Marriott School of Management for an MBA. It was during his MBA that Matt decided to pursue a PhD in service operations management.

Professional services run in Matt's family as his five older brothers and one older sister all own or work for PSFs. Matt is lucky to be married to the most talented and beautiful woman he knows (Rebecca) and they have three amazing children. Matt enjoys gardening and has never found a sport he did not enjoy playing. One day he would like to hike all 2,168.1 miles of the Appalachian Trail and visit all 58 US National Parks.

DEDICATION

To: Rebecca, Natalie, Amelia, and Sam

Thank you for joining me in this journey. I look forward to many more adventures together.

Always remember:

Fear not, be of good cheer, the future is as bright as your faith!

AKNOWLEDGEMENTS

No dissertation is done in isolation and this one is certainly no exception to that rule. I have been the benefactor of so much wise guidance and goodwill that I can scarcely begin to thank all who have contributed to my journey. I would be remiss however if I did not thank a few specific people for their investment in me and their good natured direction.

First, my dissertation adviser Rohit Verma. Rohit has been the ideal adviser to me. He has trained me to be relentless in my pursuit of truth and rigorous in my research methods. Even more than that though he has been an inspiring example of a leader and motivator. Rohit always seems to know exactly what to say to get the best out of me. He has helped me craft my journey through graduate school with the greatest skill and always with my best interest at heart. Rohit has been all I could ask for in an adviser, and I also consider myself fortunate to call him friend. Rohit, thank you for always putting my goals first and for always giving good advice.

Second, my other committee members Chris Anderson and Andrew Davis. Chris has always had an open door for me and has been extremely capable in steering me towards the right questions and the right analysis. In four years I can rarely think of a time when I stopped by Chris's office (unannounced) that he did not have time for me. Thanks Buddy! Andrew provided much of the expertise needed to make chapter three in this dissertation possible. He taught me about experimental methods and trusted me to run lab sessions of his studies, which gave me the experience I needed to do it for myself. He was also understanding and forgiving when I made mistakes, virtues for which I respect him even more.

Next, my other colleagues in operations in both the Hotel School and the Johnson School. Nagesh Gavirneni is a master inquisitor who can get to the heart of a paper more quickly than

anyone else I know—a trait that often strikes fear into the heart of graduate students. To me though, Nagesh is an honest and genuine friend. He, like Nathanael of old, has no guile and only thinks of how he can make others better. Sheri Kimes, Gary Thompson, and Brett Massimino have all invited me into their offices numerous times and have listened to my ideas with great interest and offered meaningful guidance with great skill.

Many others outside of Cornell have also steered me along the way. Without Scott Sampson of Brigham Young University I would not be where I am. I first met Scott when I was an MBA student and at that time I had a distinct impression that he would greatly influence my life. He later mentored me and put me on a path towards academia and a PhD at Cornell. Mike Lewis and Alistair Brandon-Jones of the University of Bath and Suresh Muthulingam of Penn State have offered immeasurable advice and input as co-authors on chapters two and four respectively.

I am also grateful to my academic brothers and sisters who have taken great interest in me and offered great encouragement. Mike Dixon of Ivey Business School has given me a room to sleep at every conference we both attended and bought me countless meals. He has mentored me in quiet and unassuming ways often leading by example. Liana Victorino of the University of Victoria has always greeted me with a smile and a hug and wishes of success. I always look forward to meals with Liana at the Cheesecake Factory.

Outside the classroom and academia, David Just and Wayne Gustafson have provided much of the life advice I have needed to thrive in graduate school. David has been a spiritual leader both as the leader of my local congregation and as a close friend. Wayne has taught me new and helpful perspectives on how to live. He has labored extensively to teach me not to be too hard on myself and has built me up as a person. David and Wayne have both counseled me in difficult times when

few others knew of my inner struggles and helped me to design my life in a way that I can be successful.

I wish also to thank the Center for Hospitality Research (CHR), the Cornell Institute for Healthy Futures (CIHF), Smith Travel Research (STR), and Kevin Kniffin of the Lab for Experimental Economics and Decision Research (LEEDR) who provided or facilitated the data collection for this research.

Lastly, my family. My parents Tom and Janet Walsman have provided for my every need throughout my life and always encouraged me. They have always thought more of me than anyone else and believed in me. Thank you for helping me to develop curiosity by giving me opportunities to experiment with things and take things apart (which sometimes got back together).

My children: Natalie, Amelia, and Sam have sustained me all along the way. I have been in college for 7 out of Natalie's 10 ½ years and we have earned three degrees together (Amelia and Sam have been a part of two of those degrees). My children have lit up my life and brought me immense joy. I love coming home to you, playing together, talking together, and just being together. It is my greatest dream that we will be together always.

Finally, my greatest appreciation, admiration, and love goes to Rebecca my wife, my faithful companion through all of the ups and downs, and my truest friend. I have known many successful and smart people on this journey, but Rebecca is easily the most competent person I know. She has King Midas's touch—everything she touches turns to gold. She has touched my life perhaps more than any other and slowly I too am turning to gold. If I have experienced success, I owe much of it to her. Thank you Rebecca for being by my side. I am, and forever will be, committed to you.

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CHAPTER 1: ESSAYS ON DECISION MAKING IN SERVICE OPERATIONS MANAGEMENT

Abstract

This dissertation—in three essays—investigates the impact of operational decisions in service operations management. It brings together two growing sub-areas of operations management: behavioral operations management and service operations management. In this chapter we establish the motivation for this this research and summarize each subsequent chapter.

Introduction

This research is motivated in part by my personal experience working four years as a consultant prior to returning to school and many instances of hiring consultants and advisers. When I graduated with a Bachelors in Science in Construction Management (an applied management degree) from the Fulton School of Engineering at Brigham Young University I moved to New York City to work as a consultant in the construction industry. I worked for a boutique firm that primarily offered construction expertise to lawyers and project owners who needed help to resolve their construction related disputes. I spent many hours developing recommendations for my clients regarding which party was at fault, who was contractually obligated to pay for it, and how to proceed successfully.

One day when I was working on a project for a client I discovered some evidence that was harmful to our client's position in the case. I didn't know what to do. I went to my boss and asked him what our was obligation towards our client. His response highlights some of the important questions addressed in this paper. He said that we are not our clients' attorney. An attorney must always protect their client. We were hired as third party objective consultants with a primary duty

of discovering the facts of the case and making expert judgements based on those facts. We are not bound to defending our client, we are bound to being experts who speak to the truth of what happened. He then added, “If we can speak the truth in a way that is beneficial to our client however, we try to do that...it is better for business.”

This story highlights the competing incentives that often consultants must manage. In economics, this is called a principal-agent problem where the principal is the client and the agent is the consultant. The agent is bound to the client and should act in their client’s best interest, but it is difficult to do so when the agent, at times, has their own competing interests. In this story, how can a consultant be expected to give an unbiased recommendation when it is their client who is paying for their services? Even if the client tells the consultant they want the unbiased version of the story, there are behavioral biases that may influence the consultant’s ability to be truly objective.

A few years later a friend of mine had a similar experience, this time as the client, which cemented this idea in my mind. My friend had an irregular shape on their ankle that they wanted to get checked out. Prior to going to the doctor they did some online research and spoke with a friend who is a registered nurse. After this investigation, they felt like they had a pretty good idea that it may be ringworm. They then made an appointment with the doctor and informed the doctor of their research and self-diagnosis. The doctor looked at the ankle quickly, confirmed the self-diagnosis and prescribed medicine. My friend then returned from the doctor a bit annoyed that the doctor hadn’t taken the time to properly examine them, but got the medicine hoping that it would work. It did not and a follow-up appointment was made.

In this second story the client (my friend as the patient) interfered with the adviser’s (doctor) process by offering their own self-diagnosis. By doing so, they biased the doctor towards their

own novice opinion, which was wrong. The doctor may have truly believed in the diagnosis but it is hard to tell, since she was anchored by her patient. It is impossible to say if the doctor would have offered the same advice, had my friend not offered a self-diagnosis. In one sense, the customer offering an opinion was efficient because it quickly allowed the doctor to rule out alternatives, but it was also inefficient in that it produced a sub-optimal solution and more time was needed to resolve the issue. From the client side, the client (my friend) was not satisfied with their consultant's (doctor) advice because they felt like there was no value added. They felt frustrated to pay the doctor a fixed fee, only to be ushered away quickly after simply confirming their own self-diagnosis. They would have preferred that the doctor consider the self-diagnosis, develop alternative solutions, discuss those alternatives, and decide on a treatment together. This would have taken longer initially, but may have resulted in the correct solution the first time and saved time in the long run.

These two stories highlight some of the challenges that clients and consultants face when developing recommendations and solutions. Consultants have an obligation to present recommendations in their client's best interests, but also have competing self-interest. Clients may distrust consultant recommendations when ultimately they themselves bear the risk of implementing the recommendation.

In this dissertation I investigate these issues in three essays. First, I take a deep dive into professional service firms to understand more fully how they operate and inform the studies that follow. Next, I test experimentally the impact that client interference has on consultant decisions and subsequent client satisfaction (situation described above). Finally, I measure the impact of one specific operational decision in a service environment—the decision to pursue LEED certification in hospitality.

This dissertation is important because there is little existing work on the relationship between advisers (consultants and doctors) and advisees (clients and patients) in professional service environments. The work that has been done is primarily in accounting and management and focuses on how advisers (consultants) influence advisee's (client's) decisions. To our knowledge, this is the first work in an operations management setting that considers how clients influence their consultant's recommendations.

Throughout the rest of this dissertation I will write in the first person plural 'we'. This is intentional as I could not have accomplished this research without the help of many individual contributors and sponsor organizations. This work is stronger as a result of their support.

Chapter 2 – Characteristics and Challenges of Professional Service Firms

In our first essay we test empirically existing professional service frameworks in the context of management consulting in the travel, tourism, and hospitality (TTH) industry. Much of the previous work in professional services has been to attempt to classify or create taxonomies for what is and what isn't a professional service. Many scholars identified attributes that they describe as definitive to professional service firms. Some classic examples are that professional service firms are high in levels of customization and customer contact or customer interaction. Others describe professional services as very knowledge intensive, but having low levels of capital intensity (Table 1.1). While this work has been extremely useful in helping establish a research agenda around professional services, little has been done to test empirically whether these existing frameworks accurately describe practice. In our first essay we do exactly that, test empirically through a survey methodology, supplemented by a choice experiment and qualitative data, the characteristics and also managerial challenges of consultants in the travel, tourism, and hospitality industry.

Table 1.1. Key definitional characteristics of professional service offerings

Definitional characteristics	Reference
High extent of customization; high extent of customer contact	Maister and Lovelock, 1982
High degree of interaction and customization; High degree of labor intensity	Schmenner, 1986
High customer contact; High routinization	Wemmerlov, 1990
High contact time; High customization; High discretion; High front-office	Silvestro et al., 1992
Unique service package (full customization); Expert service (high degree of customer influence)	Kellog and Nie, 1995

We found that many of the existing frameworks are inadequate at describing consulting, and presumably other professional services as well. We discovered that consultants in TTH don't actually spend as much time interfacing with their clients as the models predict (roughly only 9% of their time). We also found that levels of many of the characteristics (i.e. customization and capital intensity) depend on firm level (scale and specialization) and individual level (seniority) attributes, proving that what was previously described as a homogenous group, is in fact vary nuanced. Finally, we found that many of the managerial challenges firms face also vary greatly by firm level attributes (in particular size).

This first essay acts as an initial stake in the ground for our professional service research agenda. This first project establishes the need for work in this area, and from there we expand into individual decisions made by professional service actors and their clients.

Chapter 3 – Client and Consultant Interactions and Decisions

In our second essay, we remain in the same context of professional service firms but expand to investigate how the individual decisions consultants and clients make influence each other. In a typical consulting engagement consultants provide recommendations, based on their expertise,

and clients (who bear the risk of the decision) decide whether to implement the recommendations. We explore, with the use of a behavioral experiment, how client interference and client training impact consultant recommendations, and then subsequently, how those recommendations are received by the client.

We find that when clients provide consultants with their estimate for the problem that consultants with little expertise ‘take the bait’ and make a recommendation in line with the client estimate. Clients who are expert on the problem however are more likely to disagree with the client estimate and give a significantly different recommendation. They do this even when the client estimate is correct, which often leads to expert consultants giving bad advice.

From the client perspective, clients are anchored heavily by their own estimates and don’t sufficiently adjust after considering their consultant’s recommendation. This happens even with novice clients who have no training on how to perform the task. Clients place more trust in their own ability (even when they are not trained) than in their consultants. This is also apparent in how clients with high levels of expertise express their satisfaction with their consultants. Expert clients don’t tend to blame their consultants when they lose money on a task and generally recognize their own role in the process. On the other side however, expert clients don’t give their consultants credit either when they make money. Clients with little expertise exhibit the opposite behavior: they blame consultants for bad outcomes but also give them credit for positive outcomes. These findings are highly relevant to consultants and other professional service actors and their clients who hire them.

Chapter 4 – Impact of LEED Certification in the Hospitality Industry

In our final essay we depart from the professional services context and measure the impact of one specific decision that managers make in a hospitality context: the decision to pursue

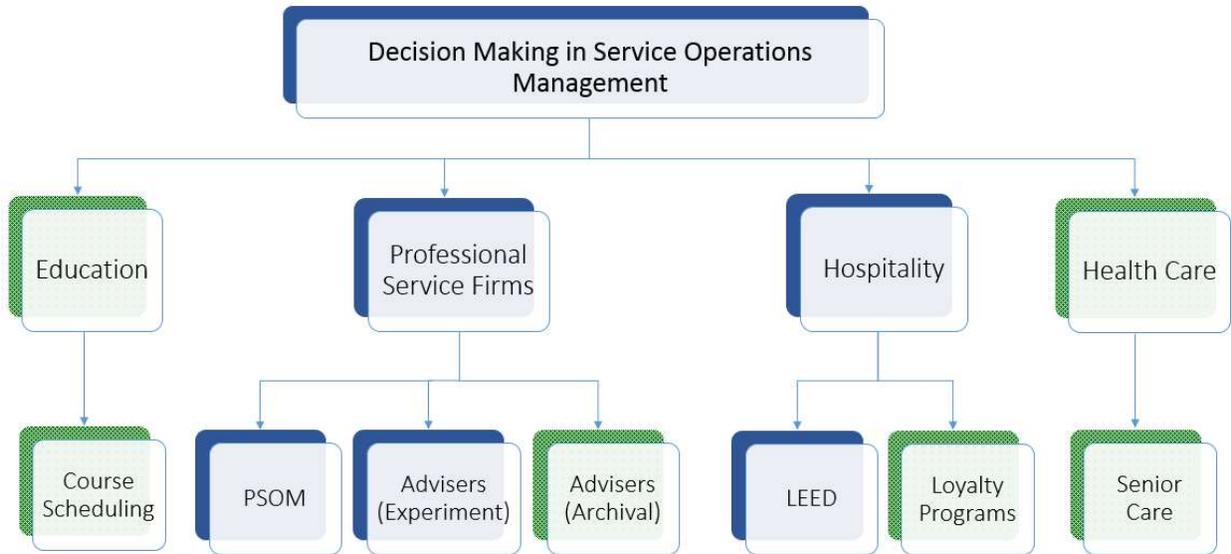
environmental certification. The Leadership in Energy and Environmental Design (LEED) certification is one type of environmental certification that has grown dramatically since it was introduced in 2000. LEED is almost universally promoted for its waste eliminating and cost cutting initiatives but there has been little research to examine the financial benefits of LEED from a revenue perspective. In this finally essay use an event study approach with a difference-in-differences methodology to measure the impact of LEED certification in a natural experimental setting: LEED Certification in Hotels. We supplement this methodology with a Hierarchical Linear Model (HLM) to gain a greater understanding of hotel performance over time.

We discovered that LEED Certified hotels do indeed outperform their uncertified counterparts for a period of time. The managerial implications of this study are far reaching because up to this time few managers have considered LEED from a revenue perspective. The hoteliers we spoke with said that those who do pursue LEED certification do it primarily to support the social goals of the firm. Few expect to make money from the decision. This study shows that LEED can be used not only to promote the social mission of a hotel company but also as a source of revenue

Chapter 5 – Managerial Implications and Future Research

We conclude this dissertation with a discussion of the managerial impacts of our research and our goals with future research. We believe that the relevance of our research in practice is a strength of this dissertation and of great importance to the business community. Business research in applied in nature and we are committed to the application of our research to the operations of real businesses and organizations. In this final section we review the potential impacts of our research on practice. We also identify future areas of research that are both extensions of existing topics and transitions into new ones.

Figure 1.1: Current and Future Research



CHAPTER 2: EXAMINING THE CHARACTERISTICS AND MANAGERIAL CHALLENGES OF PROFESSIONAL SERVICES: AN EMPIRICAL STUDY OF MANAGEMENT CONSULTANCY IN THE TRAVEL, TOURISM, AND HOSPITALITY SECTOR¹

Abstract

This paper finds that OM's 'one-size-fits-all' characterization of professional services, namely high levels of customer engagement, extensive customization, knowledge intensity, and low levels of capital intensity, does not hold when carrying out a 'deep dive' (to the best of our knowledge, a first in this area of OM) into consultancy in the US travel, tourism, and hospitality sector. We analyse mixed-method data (semi-structured interviews, focus groups, and a best-worst choice experimental survey) and observe that consultancy can actually be quite remote and passive and that any periods of face-to-face 'engagement' will typically be time limited and focused on specific project phases. Moreover, and further confirming the value of a study that allowed us to investigate professional service operations in a specific market context, our data suggest this may often be at the behest of the client. The significant variation observed in levels of customization we interpret as confirming Maister's (1993) notion of a portfolio of *brains*, *grey hair*, and *procedural* work. We also observed relatively high levels of capital intensity; reflecting perhaps the vintage of most OM characterizations and the dramatic ICT-related changes that have occurred in *all* business operations in the last 20 years. The work also demonstrates the necessity of a more contingent perspective on PSOM. We assess the impact of both firm (scale, specialization) and individual level (leverage) characteristics to demonstrate significant variation within what might be expected to be a relatively homogenous

¹ This chapter was recently published in the Journal of Operations Management: Brandon-Jones A., Lewis M., Verma R., Walsman MC. Examining the characteristics and managerial challenges of professional services: An empirical study of management consultancy in the travel, tourism, and hospitality sector. *Journal of Operations Management*. Vol 42, (9-24), 2016.

group of professional service operations. For example, investigating the effects of specialization (via a typology of consulting operations: super-specialists, generalists, deep knowledge traders, deep market knowledge traders) revealed that relative degree of interaction may be dependent upon degree of expertise, such that it was the *super-specialists* in our sample that spent less time with clients and the more *generalist* firms who were complementing their limited expert status with high levels of interaction (networking, etc.).

1. Introduction

Within the, albeit limited (Machuca et al., 2007; Hopp et al., 2009), professional service operations management (PSOM) literature generic conceptual perspectives predominate. All ‘professional’ operations – be they accountants, advertising agencies, architects, design engineers, doctors, executive recruiters, fashion designers, insurance brokers, investment bankers, lawyers, management consultants, media producers, R&D laboratories, software providers, social work agencies and universities – are presumed to exhibit certain characteristics. These include high levels of customer engagement, extensive customization, knowledge intensity, and low levels of capital intensity (Sampson and Froehle, 2006; Schmenner, 1986; Silvestro et al., 1992). Discussions of shared characteristics may be useful when contrasting professional services with, for example, mass services. However, any deeper reflection on the literature or review of the limited number of focused empirical studies highlight significant variance in the clients, professionals, bodies of knowledge, regulatory environments, and competitive landscapes, across different professional settings. Equally, although in some settings it may be accurate to challenge the effectiveness of “standard operating procedures” (Kellogg and Nie, 1995, p.329) and the managerial metaphor of ‘cat herding’ may indeed resonate (Løwendahl, 2000), there is limited empirical evidence regarding the specific managerial challenges that comprise PSOM (Heineke, 1995; Machuca et al., 2007) and, again, no real reflection on the key contingencies that may shape these challenges. Schmenner’s (1986) elaboration of the challenges associated with different service types provides some interesting points of departure but detailed questions remain unanswered. What, for example, have the effects of ubiquitous information and communications

technology (ICT), globalization and outsourcing, or the increased focus on standardization had on the nature of PSOM (Metter and Verma 2008).

Given this context, we identified three key research objectives. First, we wanted to explore the extent to which generic conceptual characterizations (i.e. high engagement, customization, and knowledge intensity, and low capital intensity) align with observed practice. To do so, we decided to narrow our focus to a particular professional service type, management consultancy². This focused approach is in line with previous studies. For example, McNeilly and Barr (2006) studied accounting services when exploring provider-client relationships, whilst Boone et al. (2008) collected data in an architectural engineering context to study learning and knowledge depreciation within the professional services. Moreover, given that a great deal of professional service competitive advantage relates to and is derived from client/sector insight and social capital (Nahapiet and Ghoshal, 1998), it was also appropriate to limit the study setting to a specific client/market space and correspondingly we selected the US travel, tourism, and hospitality (TTH) sector³. Such an approach inevitably limits the generalizability of any findings but given our first objective is, in essence, looking to disprove a null hypothesis (i.e. that there is no relationship between service type and operational characteristics), a single service type focus is suitable. Furthermore, given that ‘level of client interaction’ was a critical variable under investigation, this approach allowed us to engage with clients in interviews and focus groups. Our second objective was to investigate the relative importance of various managerial challenges in a specific professional setting and here again the ‘deep dive’ offered significant advantages; giving us control over a number of key professional service-related contingencies (i.e. regulations, competitive and market dynamics, etc.). Finally, our third objective was to begin to explore some of the other contingencies, including scale, leverage, and specialization, that, ex-ante, may influence both operational characteristics and managerial challenges.

² Management, human resource, IT, and technology consultancy together generate more than \$500 billion annually. Management consulting alone employs more than 780,000 people in the US.

³ The travel, tourism, and hospitality sector, is one of the largest in the US economy with a contribution of \$1,416 billion (8.4% GDP) and more than 14 million jobs (9.8% of all employment).

Given the exploratory nature of our research, we adopted a mixed methods approach, combining semi-structured interviews, a survey that included a best-worst choice experiment, and a focus group. The rest of the paper is structured as follows. First, we provide a synthesis of the literature as the basis for our research questions. Subsequently, we provide details of our research methodology, including study context, research design, data collection, and analytical approach. We then present the results of our analyses in relation to our research questions. Finally, we discuss our findings, highlight our contributions and limitations, and suggest avenues for future research.

2. Literature Review and Research Questions

This section reviews the literature relating to our research objectives and then uses these insights as the basis for research questions that structure our empirical investigation. First, we review the characteristics of professional service offerings; combining reflections on the generic/conceptual OM typologies with specific insights that relate to our chosen empirical focus, consulting services. Second, we explore the specific challenges that together comprise PSOM and, third, we reflect on the potential impact of scale, leverage, and specialization as contingent factors that might influence the nature of PSOM.

2.1 Characteristics of professional service offerings

Determining the characteristics of a professional service offering is a significant first step in building an understanding of PSOM. After all, it is the idiosyncrasies of any service type that correspondingly generate its specific managerial challenges. To date, a great deal of the reflection on professional service operations has been shaped by a series of theoretical/conceptual papers. For example, if there are high levels of client interaction and customization in a given professional service this could in turn create significant process variability. Similarly, if a professional service is reliant on high levels of knowledge intensive judgement this will in turn contribute to both variation and relatively extended process throughput times (Sasser et al., 1978; Schmenner, 2004). Finally, the extent to which professionals in a given service setting adhere to explicit external codes of ethics and implicit norms that guide appropriate behaviour (Fischer et al., 2014), reduces the need for, and associated costs of, internal service quality monitoring (Goodale et al., 2008), but

may also act to minimize the influence of operations managers (Harvey, 1990). Here, we examine characteristics in relation to customer engagement, customization, and knowledge/capital intensity.

2.1.1 Customer engagement in professional services

Many widely cited service classifications (Maister and Lovelock, 1982; Schmenner, 1986; Silvestro et al., 1992; Wemmerlov, 1990) differentiate professional services from other service types because of their high level of customer engagement. Although at its simplest, this characteristic refers to the extent to which a customer is present⁴ during the delivery of a service (i.e. front rather than back office operations), these typologies are also generally referring to the relative ‘activity’ of the interaction (Mersha, 1990; Goodale et al., 2008). In other words, a professional service is highly interactive because it is assumed that there is extensive dialogue between the client and the provider (Kellogg and Nie, 1995; Frey et al., 2013; Fischer et al., 2014), where both the service requirements and service package are discussed and designed. It is also asserted that these high engagement service operations allow the customer/client to actively intervene with their service processes (Verma, 2000), often to request modifications to what is being delivered. Given the implication that such high engagement causes a reduction in efficiency (Chase, 1981) there is, at least in part, an assumed increase in commercial pressure (Schilling et al., 2012) and a growing belief that high levels of customer participation in the creation of professional service offerings may be a ‘double-edged sword’ (Chan et al., 2010).

In our chosen service type – consultancy – assumptions relating to the nature of the business and operating model introduce significant scope for variation in actual levels of customer engagement. For example, if the ‘expert’ model involves providing clients with access to ‘exclusive’ knowledge (albeit in this case not regulated knowledge) in a particular practice area (including sector-knowledge: Fincham et al. 2008), then the engagement process can be interpreted as one of ‘diagnosing’ needs and suggesting

⁴ Of course, the growth in technology-mediated communication means that the physical presence of the client/provider may no longer be a critical component of any interactivity (Froehle and Roth, 2004; Ellram et al., 2008).

‘treatment’ options (Abbott 1988). In these circumstances, where there are strong knowledge/information asymmetries, the client role could be seen as relatively passive, primarily acting as ‘information supplier’ during problem diagnosis. Although the engagement process might involve quite intense periods of ‘interaction’ (i.e. the data collection phase of a consulting project), these will typically be time limited and therefore total interaction (on average) could be very low. Moreover, within the more ‘critical’ PSOM literature (e.g. Alvesson and Johansson, 2002; McKenna, 2006), the rarely explicit, but generally understood, *political* role of consultants is widely discussed. This notion of consultants being used for ‘alternative’, even symbolic, purposes would effectively render the question of interaction moot. The debate concerning engagement gives rise to our first research question:

RQ1a: To what extent does consultancy have high levels of customer engagement?

2.1.2 Customization in professional services

Closely related to the notions of engagement and interactivity is the generic idea that professional service offerings are highly customized or tailored for individual customers/clients (Chan et al., 2010; Stouthuysen et al., 2012). Here again however, such a classification rests largely on theoretical, rather than empirically, derived differences between services (Verma, 2000). For example, Schmenner (1986) uses a physician as an example of a highly customized service provider and yet many aspects of this and other professionals’ work (e.g. lawyers, accountants, engineers) are strongly controlled by regulatory standards and norms (Amonini et al., 2010). Other authors have pointed out that, “not all services rendered by ‘professionals’ necessarily involve a high degree of customer influence” (Kellogg and Nie, 1995: p.326). For example, in their case study of a legal professional service firm, Lewis and Brown (2012) find that the regulated and often routine nature of many areas of the legal ‘body of knowledge’ (Standard contracts, precedent ‘libraries’, planning procedures, and standard approaches to debt recovery, for example) limit the extent to which service offerings are customized. Similarly, Harvey (1990) argues that the relative power ‘gradient’ between professionals, managers and clients in a professional service firm (in this case, looking at social

workers) provides an important contingent variable for understanding how much adaptation to client requirements is feasible or desirable.

Although not widely incorporated in PSOM typologies, there is discussion of process customization as a contingency in Maister's (1993) classification of three types of operational practice in professional service firms like consultancies. The evocative labels "Brains", "Grey Hair" and "Procedure" are used to present distinct types of operational practice. Although not explicitly derived from classic volume-variety characteristics, these three types can be broadly interpreted using these dimensions: high variety but low volume work are key characteristics of the Brains mode; the Grey Hair mode is larger volumes, relying on accumulation and use of experience to manage towards low(er) variety, and; the Procedure mode is associated with still low(er) variety and higher volume. The debate concerning customization leads to our second research question:

RQ1b: To what extent does consultancy have high levels of service customization?

2.1.3 Knowledge and capital intensity in professional services

The third generic characteristic of professional services is that they are more knowledge intensive but less capital intensive than other types of service operations (von Nordenflycht, 2010; Frey et al., 2013). As such, they require substantial investment in knowledge assets (i.e. employees) but relatively little investment in infrastructure and equipment (Drucker, 1999; Hopp et al., 2007). Here again however, as in the discussion of customer engagement, significantly increased service technology spends, together with increasing levels of professional services outsourcing and offshoring (Ellram et al., 2008; Metters and Verma, 2008; Stouthuysen et al., 2012) may render such characterisation open to question. Interactive information technologies are ubiquitous in modern professional service settings (Froehle and Roth, 2004) and many consulting firms have been "enthusiastic adopters" of knowledge management systems (Brivot, 2011) that aim at identifying, codifying, and storing knowledge (Davies and Brady 2000, Kim and King, 2004). Similarly, the assumed operating model will likely have a significant impact on the extent and nature

of knowledge intensity. If a consultant is a sector specialist for example, knowledge intensity will reflect an accumulation of interactions/learning from the very people who are also the clients seeking their expertise (Fosstenløkken et al. 2003). As such, consulting expertise is also supported by individual status and contacts, supporting and building networks with influential actors. The debate concerning knowledge and capital intensity leads us to our third research question:

RQ1c: To what extent does consultancy have high levels of knowledge intensity and low levels of capital intensity?

2.2 Challenges in delivering professional service offerings

A number of conceptual papers have sought to articulate the generic challenges facing professional service operations. For example, highly customized tasks make standardization difficult, while knowledge intensity potentially limits the ability of an organisation to automate ‘judgement’ in operating systems and ‘routines’ (Davenport and Prusak, 2002; Ryu et al., 2005). Similarly, planning and control may tend to emphasize inputs (hours) and outputs (hours billed) rather than process measures (Hopp et al., 2009). Schmenner (1986) argued that professional operations must fight cost pressures; maintain quality; react to client intervention in service processes, and manage employee careers, in particular.

Here again however, detailed empirical examination of these challenges is far less evident. As part of a study of four different service types – service factory (fast food), service shop (automobile repair), mass service (retail sales), and professional service (legal services) – Verma (2000) examined positive and negative associations between Schmenner’s twenty-three managerial challenges. For the professional services in his study, the top five managerial challenges identified were maintaining quality, managing the customer experience, hiring employees, developing and controlling work methods, and training. Other empirical articles (e.g. Boone, et al., 2008; Cameran, et al., 2010; Karantinou and Hogg, 2001; Akerlund, 2005; Smedlund, 2008; Semadeni and Anderson, 2010; Ojasalo, 2001; Macintosh, 2009) explore specific aspects of professional services such as measuring learning and knowledge depreciation, managing

customer expectations, etc. but do not explore the full range of potential managerial challenges. Lewis and Brown (2012) observed that their law firm focused less on process standardization and automation and more on forms of leveraged work management where greater use is made of lower cost (e.g. junior lawyers or junior consultants) and/or differently qualified employees (e.g. paralegal or analysts).

Given that each of the defining professional service characteristics could contribute to a “distinct environment for managing operations” (Goodale et al., 2008, p. 670) a more focused study that still explored the full range of potential managerial challenges represents a significant gap in the literature and gives rise to the following research question.

RQ2: What is the relative importance of different managerial challenges for consultancy?

2.3 Preliminary reflections on contingencies in PSOM

Before exploring the detailed validity of the defining characteristics and key managerial challenges outlined above, it is also important to reflect on some of the other contingent factors that might, ex-ante, influence the nature of PSOM. Specifically, we chose to investigate the impact of *scale* and two dimensions of structure – the extent of *leverage* (i.e. senior employees carrying out different tasks to more junior colleagues), and the degree of *specialization*.

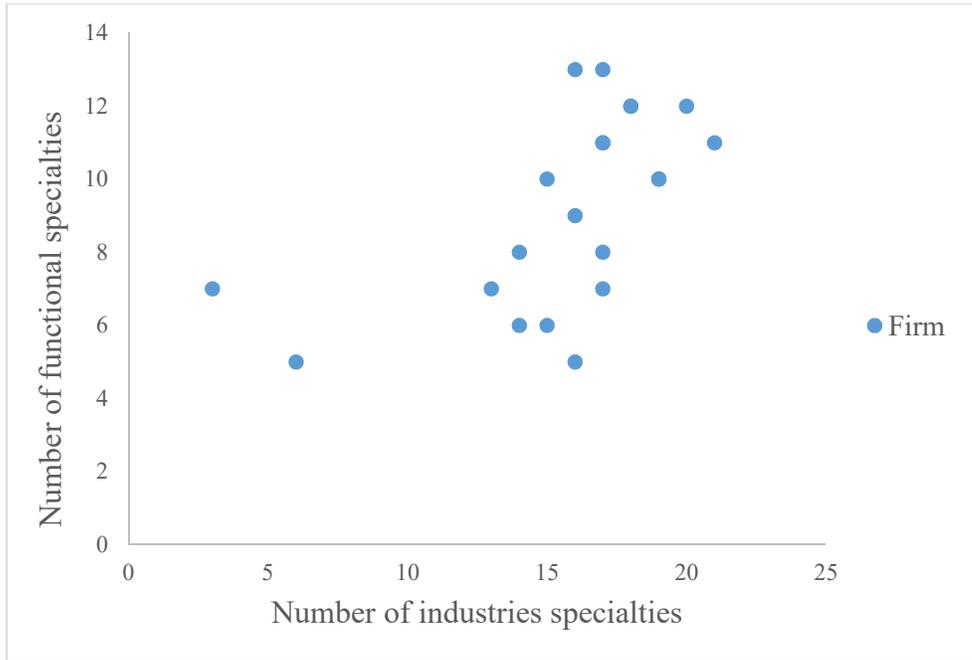
First, considering scale, there has been a great deal of merger and acquisition activity in the consulting market over recent years with many observers suggesting a process of consolidation is under way. As such, it seems sensible to consider the impact of the firm size on professional service characteristics and managerial challenges. The link between scale and decisions such as capital investment seems self-evident but there are also suggestions in the literature (See for example, Maister 1993) that larger firms may have a different process composition (i.e. more procedural work) when compared to smaller firms.

Second, considering leverage, the structure of a consultancy organization (i.e. the mix of junior, middle-level and senior staff) is often labelled as its degree of leverage. In the PSF literature (and practice) there is also reference to an idealized notion of “finders, minders and grinders.” Finders (usually the most senior

employees) are said to win work, engaging in the social capital building with clients; Minders do project and day-to-day people management and Grinders (usually the most junior employees) perform the analytical tasks. Implicit in this division of labour is its likely contingent effect on both process characteristics and managerial challenges.

Finally, we are interested in the extent to which the degree of firm specialization influences the nature of PSOM. For example the more asymmetric the client-provider knowledge the less the client can specify or intervene in the work. Management consulting firms in the US generally segment their businesses into functional and industry silos. We confirmed this by investigating the websites of 21 top US management consulting firms and noting the functional expertise and industry specialization promoted on their homepages (see Figure 1). Looking at the data by industry, each industry was serviced by an average of 14.9 firms (StDev 3.4) and the functional specialties were covered by an average of 11.4 firms (StDev 4.0). The focus of our study – travel, tourism, and hospitality – is serviced by 18 of the top 21 US consulting firms. These observations provided us with the preliminary dimensions for a model of specialization in the consulting field – the extent to which a firm is structured around (1) functional/knowledge expertise and (2) specific industries/markets – and correspondingly we categorized, ex-ante, four potential types of consultancy firm (Figure 2.1).

Figure 2.1: Mapping specialization for top US consulting firms



First we categorise the *Generalists*, who offer a range of skills and serve a broad range of markets (i.e. the classic branded global consulting firm). Second, and our largest group, we categorise the *Super Specialists*, who deal in specific functional capabilities such as HRM and trade in specific market segments. Third, we have the *Deep Knowledge Traders* whose functional specialisation is strong enough (and portable enough) to trade across multiple segments. Finally, we categorised a group labelled as *Market Knowledge Traders*, who operate more on the basis of market insights, experience and reputation rather than specializing on any specific functional capability (Figure 2.2).

Figure 2.2: Industry and functional specialization

		Functional specialization	
		Narrow	Broad
Industry specialization	Broad	Deep Knowledge Traders	Generalists
	Narrow	Super Specialists	Market Knowledge Traders

Our preliminary reflections on possible contingencies that may influence the nature of PSOM give rise to the following questions concerning the effect of scale, leverage, and specialization on characteristics and managerial challenges of consultancy.

RQ3a: What is the influence of organisational scale, leverage, and specialization on characteristics of consultancy?

RQ3b: What is the influence of organisational scale, leverage, and specialization on the relative importance of different managerial challenges for consultancy?

3. Research Methodology

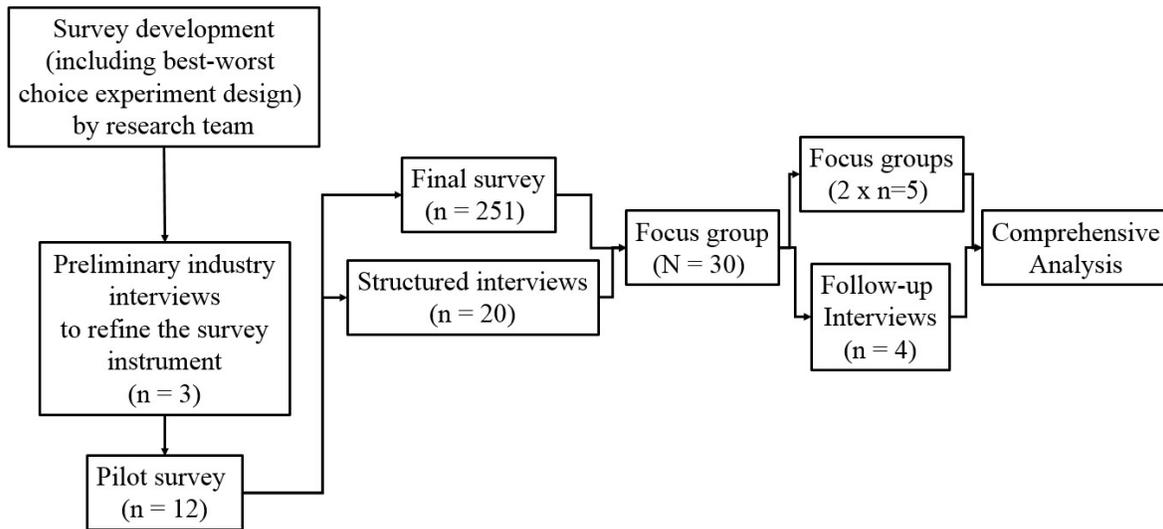
In this section, we describe the context for our study and present the overall research design. The logic of choosing an in-depth study of a single service type in a specific market setting was discussed in the introduction. In addition, all members of the research teams have experience working as consultants and two members of the team had extensive prior research experience of travel, tourism, and hospitality. The team were therefore able to bring to the data collection and analysis what Siggelkow (2007, p. 21) calls an ‘open but not empty mind’.

3.1 Research design

To explore our research questions, we adopted a multi-method, multi-stage research approach, combining semi-structured interviews, a survey that included a best-worst choice experiment (also known

as max-diff approach), and follow-up multi-stage focus groups and interviews. Figure 2.3 provides an overview of our approach.

Figure 2.3: Summary of Research Approach



3.1.1 Survey Instrument

At the heart of the data collection effort was a large-scale on-line survey. A template of the instrument was reviewed iteratively by members of the research team and by three senior consulting executives. After the collective feedback and revisions, the survey was pilot-tested by 12 additional respondents representing different types of consulting organizations. Again, based on the feedback, the survey was revised further, primarily to readability, ensure consistency of interpretation, and to reduce the length of the survey.

The survey was launched to a large group of potential respondents identified from the Cornell Center for Hospitality Research (CHR) database that includes over 150,000 industry professionals including approximately 10,000 self-identified consultancy professionals. Potential respondents were sent an invitation e-mail outlining the research, how data would be used, and a link to the online survey. Reminder e-mails were sent one week after our initial mailing offering respondents a summary report of key findings (Forza, 2002; Dillman et al., 2010). Of the e-mail invitations sent, the servers returned approximately 2,500

as undeliverable. The addressees opened approximately 3,000 e-mails, with approximately 1,000 potential respondents clicking on the survey link, and 318 completing the survey, representing an effective response rate of 10.6%. After removing the respondents not delivering consultancy services in our selected sector, a final sample size of 251 was obtained. Table 2.1 provides descriptive data on our final sample.

Table 2.1. Survey Sample Descriptive Statistics

Firm Level				Individual Level		
Variable	N	Percent	Variable	N	Percent	
<i>Area of Practice</i>			<i>Job Title</i>			
Information Technology	6	2.4%	Analyst	10	4.0%	
Financial/Accounting	14	5.6%	Consultant	43	17.1%	
Hospitality	77	29.9%	Sr. Consultant	50	19.9%	
Management	29	11.6%	Director	35	13.9%	
Law/Legal	5	2.0%	Vice President	14	5.6%	
Cross-Discipline	80	32.7%	President	22	8.8%	
Other	40	15.9%	Managing Director	32	12.7%	
			Other	45	17.9%	
<i>Firm Size</i>			<i>Income</i>			
0-10 employees	122	48.6%	Up to \$150,000	141	56.2%	
11-100 employees	50	19.9%	More than \$150,000	65	25.9%	
101-500 employees	36	14.3%	Missing	45	17.9%	
> 500 employees	41	16.3%	<i>Age</i>			
Missing	2	0.8%	< 40	70	31.9%	
			41-60	129	51.4%	
			> 61	40	15.9%	
<i>Industry Specialization #</i>			<i>Education</i>			
Travel, Tourism, Hos.	192	76.5%	Missing	2	0.8%	
Retail	60	23.9%	High school diploma	3	1.2%	
Healthcare	42	16.7%	Some college or associates degree	21	8.4%	
Manufacturing	52	20.7%	4-year college degree	56	22.3%	
Education	64	25.5%	Post-graduate or master's degree	139	55.4%	
Government	60	23.9%	PhD or doctorate	32	12.7%	
Other	59	23.5%	<i>Gender</i>			
			Female	68	27.1%	
			Male	178	70.9%	
			Missing	5	2.0%	

Total Sample Size = 251. # Subjects were allowed to select more than one industry specialization

The first section of this survey collected background information (firm size, client base, position, consultancy type, etc.) and then asked questions related to the characteristics of consulting work. Specifically, we asked respondents to indicate the average percentage of time they spend every week (summing up to 100 before proceeding to the next question) collaborating or working independently on different types of client and non-client related activities. Using the same technique, we asked the respondents to describe the relative customization of their work specific to the needs of their clients, and the level of knowledge and capital intensity in delivering these services.

The second section included a variant of experimental discrete choice analysis, which required respondents to identify alternatives that are respectively “best” and “worst” on some dimension. Whilst a series of studies have demonstrated the superiority of the best-worst technique to other approaches, such as constant sum scales, and ranking, when trying to measure the relative positioning of alternatives (cf. Louviere and Islam, 2008; Marley et al., 2012; Vermeulen et al., 2010; Adamsen et al., 2013), to our knowledge this is its first application in OM research to date. The best-worst choice approach is an appropriate technique for use within our research context because it effectively quantifies the relative importance of multiple managerial challenges (e.g. Garver, 2009; Anger et.al., 2007; Lancsar et.al, 2013). We adopted the widely used choice modeling software known as Sawtooth Software (<http://www.sawtoothsoftware.com/products/maxdiff-software>) to design and implement the best-worst choice experiment and to later estimate resulting utilities.

In our survey, each respondent was shown six best-worst choice sets of managerial challenges. Each best-worst choice set included lists of eight managerial challenges where the respondent was asked to identify the most and the least important. The best-worst experiment was designed in such a manner that each respondent saw a completely different sequence and mix of criteria on each screen automatically generated by the experimental design module within Sawtooth Software. Furthermore, we also conducted post-hoc analysis to ensure that on average each criterion appeared approximately an equal number of times on best-worst screens for each respondent. The final part of the survey included additional questions relating

to the respondents' organization (e.g. relative importance of firm objectives; management controls used) and respondent demographics (e.g. education, age, gender, income).

The preliminary results from the survey were presented during focus groups and follow-up interviews (See sections 3.1.2 and 3.1.3). Insights helped to direct additional statistical analysis of the survey data. Finally, to ensure that there were no systematic biases present within respondent sub-samples, we conducted a Monte-Carlo simulation study that randomly divided the entire survey sample into 30 different sets of two sub-samples. Then we conducted ANOVA tests and found that the differences between the two samples are non-significant (Thompson and Verma, 2003), indicating that there is no systematic bias present in the sample.

3.1.2 Semi-structured interviews

The aim of our qualitative interviews was to gain a detailed understanding of how consultancy firms provide professional services within the travel, tourism, and hospitality sector. The interviews were designed to help explore (1) the characteristics of professional service offerings, (2) the managerial challenges, and (3) contingent factors within the TTH study context. Details of our questions are provided in the interview guide in appendix 1.

We recruited well-qualified participants for the interviews. Thirty-one executives with diverse backgrounds representing both large and small firms and offering different types of consulting services to the travel, tourism and hospitality industry were contacted with a request to participate in interviews. Of these, seven individuals choose not to participate and a further four who initially agreed were unable to take part due to scheduling challenges during the data collection period. Of the twenty completed interviews, 15 were conducted in person and 5 via telephone. These respondents included Partners and Senior VPs at some of the largest multi-national consulting companies as well as CEOs and Presidents of smaller boutique firms. We also interviewed mid-level managers at both large and small firms. Most interviewees have extensive experience in both consulting and the TTH industry (10-25 years). Table 2.2 provides an overview

of the interviewees in our study. The interviews lasted approximately 30 minutes, and, with permission, extensive notes were taken throughout.

Table 2.2: Description of Semi-Structured Interview Participants *

Size	Specialization	Position (Seniority)	Type of Consulting
Small	Hospitality	Managing Partner	Hospitality Consulting
Small	Hospitality	VP Lodging Research	Marketing Research
Small	Hospitality	President	Strategy Consultants
Small	Multiple	Managing Director	HR Consulting
Small	Multiple	President/Principal	Analytics
Medium	Hospitality	CEO	Marketing Services for Hospitality
Medium	Hospitality	Vice President	Revenue Management Software
Medium	Hospitality	Senior VP	Hospitality Market Research
Medium	Hospitality	CEO	Customer Experience Measurement
Medium	Hospitality	Executive Vice President	Software
Medium	Multiple	Project Manager	Marketing Analytics Consulting
Medium	Multiple	CEO & Founder	Marketing Analytics Consulting
Medium	Multiple	Founder & President	HR Consulting
Medium	Multiple	Project Manager	HR Consulting
Large	Multiple	Principal	Management Consulting
Large	Multiple	Principal Industry Consultant	IT/Software
Large	Multiple	Managing Director	Management Consulting
Large	Multiple	Senior Strategist	Strategy Consultants
Large	Multiple	Client Partner	IT Consulting
Large	Multiple	Partner, Global Lead	Management Consulting

* Names of interviewee disguised to protect confidentiality

We subsequently interviewed 2 senior level consultants and 2 senior client side executives with extensive experience of hiring consultants. These follow up interviews were intended to both validate emergent qualitative and quantitative findings and help refine our interpretation of some specific questions that arose from the preliminary analysis.

3.1.3 Focus group

The final element of our mixed methods approach was to convene several focus groups where findings and preliminary conclusions from both interview and survey data were presented. In our first focus group we gathered 30 industry experts, including consultants, partners or clients (Senior executives from a number of large TTH industry organizations), to generate discussion and feedback. The focus group was organized

in conjunction with a major TTH industry conference / tradeshow within the United States. We used multiple research assistants as note takers to capture the rich and wide ranging content of the discussion. We then convened two additional focus groups of 5 mid-level managers (each) on the client side to respond to several questions regarding the preliminary analysis.

3.2. Data Analysis

Our analysis of the qualitative data (interviews and focus groups) relied on both open and axial coding of notes (based on the research questions and the associated literature). We read and re-read the data searching for common themes, contradictory, contingent, and more subtle findings. Miles and Huberman (1994) note that coding based on this approach can ensure that the “analyst is open-minded and context-sensitive” (p58), rather than simply force-fitting the data into pre-existing codes. We then sought to link these themes together into more coherent chunks of text, adding new and deleting marginal codes as we gained a clearer picture of what was important in our data set. Quantitative data were analyzed using both standard descriptive and multivariate statistical techniques. The specific approaches for each analysis are described in the relevant analysis sub-section. Analysis of the best-worst choice experiment (RQ2) was done by estimating multinomial logit (MNL⁵) models for each professional service respondent using a hierarchical Bayesian estimation technique (Hensher, et al., 2005).

4. Analysis

In this section we provide the analysis of data collected in our study and present our findings in relation to each research question in turn. In investigating the extent to which characteristics and managerial challenges may be contingent on three key variables the following characteristics of the sample were observed.

⁵ See Verma et al (1999) for a detailed description of how MNL models are developed for a standard discrete choice experiment.

- *Size of the firm (Scale)*. Consulting firms tend to be relatively small, in this dataset for example nearly half of the respondents worked for firms with 10 employees or less. For this reason, to investigate the effects of scale, we compare the responses of small firm respondents (i.e. firms with 10 employees or less, n=122) with those from firms with more than 10 employees (n=127). As a robustness check we created a regression model with firm size as a continuous predictor. This further analysis produced similar results, so we concluded that the simple small/large segmentation we selected above is appropriate.
- *Seniority of respondent (Leverage)*. We test the impact of seniority by examining those respondents reporting salaries in excess of \$150,000 (i.e. more senior respondents) as compared to those with lower salary levels (i.e. less senior respondents). We chose salary as a proxy for seniority because of the ambiguity surrounding the interpretation of job titles. We recognize the limitations of this choice but felt it was a better proxy for seniority than job title, years' experience, or age. We performed a robustness check with seniority by creating a regression model with salary as a continuous variable which produced similar results to those for the scale noted above.
- *Specialization of firm*. As noted earlier, we analyse specialization according to consultants declared industry and functional focus. For our dependent variable 'level of customization' we created a weighted average based on subject's responses to the question: For all client/project activities, please indicate the approximate proportion of activities that are: Fully, Significantly, Somewhat or Not at all customized.

Figure 2.4: Industry and Functional Specialization

INDUSTRY SPECIALTY (9 miss. values)	Broad (n=104)	Deep Knowledge Traders (n=57)	Generalist (n=47)
	Narrow (n=138)	Super Specialist (n=112)	Market Knowledge Traders (n=26)
		Narrow (169)	Broad (82) FUNCTIONAL SPECIALTY

4.1 Characteristics of consultancy in the travel, tourism, and hospitality sector

4.1.1 Customer engagement in consultancy

When asked in the interviews about engaging with their customers, the consultants all emphasized the centrality of the client relationship in their work, typified by strong statements such as “it’s all about the customer” and “it has to be a hurricane for me to say no to a client”. Some observed that their work had become “much more consultative” over time and that whereas “it used to be that you fly in, crank out a report with recommendations and fly home” management consultancy is increasingly “about relationships and not just transactions”. With interviewees identifying the critical nature of relationships in a consulting practice, we expected that customer engagement would be relatively high for these firms. Our survey data, however tells a rather different story. Surprisingly, given the evidence of the interviews and the high levels of interaction discussed in much of the literature, our analysis suggests that less than 10% of consultant time (independent of firm size, etc.) is spent working directly, collaboratively with clients (See table 2.3).

Table 2.3: Respondents’ Time Spent Working Collaboratively or Independently

<i>Please indicate the average percentage of time you spend every week on each type of activity below:</i>	Mean	Median	Std. Error
Working collaboratively...			
(own organization) on client project activities	14.62	10	0.98
(client organizations) on client project activities	9.36	5	0.74
on business development activities	6.52	5	0.54
(own organization) on non-client project activities	5.07	0	0.60
on other activities	1.29	0	0.29
Working independently...			
on client project activities	38.12	35	1.59
on business development activities	11.26	10	0.80
on non-client/project activities	10.39	10	0.79
on other activities not specified above	3.36	0	0.69

Key: Subjects were asked to divide 100 percentage points across the various options. Points were required to add up to 100.

When the focus group participants were presented with the survey findings it provoked an extended discussion regarding the conventional wisdom surrounding the consultant-client relationship. One senior interviewee argued that it was *only* collaborative working that differentiated what they did from other firms. Another, executive expressed shock, and challenged the group to answer “how can we say we are there for our clients if we never actually work with them.” Perhaps more surprisingly, others (i.e. the majority) felt the figure “looked about right.” Other interviewees suggested that time allocations are very much task dependent, “If we are running an implementation then I would expect to be collaborating much more.” Offering some support for this assertion, the data point to significant variation in the proportion of time assigned to different forms of collaborative and independent activities. Overall, the focus group participants provided support for the results from semi-structured interviews and survey.

The effect of scale, leverage, and specialization on customer engagement

First, considering the effect of scale on customer engagement, we utilized ANOVA with firm size as the independent variable and time working collaboratively with clients as the dependent variable (Table 4, column 1). We found no evidence of a statistically significant difference between small and larger firms in our sample in the amount of time they spend engaging with clients. Second, considering the effect of leverage (seniority) on customer engagement (Table 2.4, column 1), our analysis indicates that senior

consultants spend significantly more time with clients than junior colleagues. This confirms an assumed practice in the field of leveraging senior client relationships while more junior consultants spend larger proportions of their time working independently on analysis. Finally, considering the effect of specialization on customer engagement (Table 2.5, column 1), our data indicate that the super specialists spend significantly less time with clients than deep knowledge traders and generalists (almost half as much). There is not a significant difference between super specialists and market knowledge traders.

Table 2.4. Contingency Analysis of Customer Engagement, Level of Customization, Knowledge Intensity, and Capital Intensity by Firm Size (Scale) and Seniority (Leverage)

	Customer Engagement	Level of Customization	Knowledge Intensity	Capital Intensity
Firm Size				
10 employees or less (n=122)	9.47 [1.07]	70.97 [2.04]*	5.39 [0.11]	4.14 [0.10]*
More than 10 employees (n=127)	9.33 [1.04]	63.53 [2.22]*	5.27 [0.11]	4.41 [0.10]*
Seniority				
Salary of \$150,000 or less (n=141)	8.12 [0.90]*	63.76 [2.21]*	5.27 [0.10]	N/A
Salary of more than \$150,000 (n=65)	13.23 [1.70]*	72.42 [2.49]*	5.52 [0.12]	N/A

Note: * Denotes a significant difference in the mean value between the groups at the $p < .05$ level. Mean and Standard error (in brackets) are reported above.

P-values for all statistical tests reported in this paper were fixed to one value (0.05) as suggested by Verma and Goodale (1995) to ensure highest degree of statistical power.

Customer Engagement is a measure of the percentage of their time respondents reported to spend working collaboratively with clients on project related activities.

Level of Customization is a measure customization using a weighted average formula (See Table 6).

Knowledge Intensity is measured on a 7 point Likert Scale. It incorporates the 3 components of the knowledge intensity factor (See Table 8)

Capital Intensity is measured on a 7 point Likert Scale. It incorporates the 4 components of the capital intensity factor (See Table 8)

Table 2.5: Contingency Analysis of Customer Engagement, Level of Customization and Knowledge Intensity considering Interaction between Functional Area and Industry

	Customer Engagement	Level of Customization	Knowledge Intensity	Capital Intensity
Generalists (n=47)	12.47** [2.16]	74.71** [2.40]	5.50 [0.18]	4.40 [0.17]
Market Knowledge Traders (n=26)	11.54 [2.83]	64.14 [5.31]	5.28 [0.22]	4.36 [0.24]
Deep Knowledge Traders (n=57)	11.23** [1.59]	67.98 [2.75]	5.77** [0.12]	4.18 [0.16]
Super specialists (n=112)	6.69** [0.88]	65.26** [2.53]	5.09** [0.13]	4.27 [0.10]

Note: ** Denotes a significant difference in the mean value between the groups at the $p < .05$ level. Mean and Standard error (in brackets) are reported above.

4.1.2 Customization in consultancy

Our interview data suggests that the level of customization for consultancy services provided to TTH sector clients varies significantly. Specifically, many consultants talked about relying on ‘prescriptions’ when taking on a new project, several talking about “a tried and true methodology that has worked for thousands of clients” or suggesting that “the principle of what we are doing does not change...the way it is served up changes.” Conversely, others highlighted the need to provided highly customized offerings based on individual client requirements. Our survey data supports these findings, indicating that although respondents described a large majority (71%) of activities as fully or significantly customized, this left 29% that were somewhat or not all customized. Survey data also pointed to large variation in the extent of customization across different respondents (See Table 2.6 below).

Table 2.6. Respondents’ Reported Level of Customization

<i>For all client/project activities, please indicate the approximate proportion of activities that are:</i>	Mean	Median	Std. Error
Fully customized	43.52	40	2.14
Significantly customized	27.47	25	1.61
Somewhat customized	17.23	10	1.32
Not at all customized	11.78	0	1.29

We consolidated these four variables into one new measure (level of customization) using a weighted avg. formula where level of customization. = 1*(fully cust.) + .66*(sig. cust.) + .33*(somewhat cust.) + 0*(not cust.)

The effect of scale, leverage, and specialization on customization

First, considering the effect of scale on customization (Table 2.4, column 2), several interviewees put forward the notion that professional service operating models stratified according to firm size; where big(ger) firms follow process (i.e. “You don’t need to be smart to work at [Prestigious Global Consulting Firm], you just have to be able to follow the process...the process ensures success”) and small firms offer a more custom experience (“Boutique consultants have the attitude of, ‘I work for you and your needs,’ they see the big picture, not just the prescription”). In support of this perspective, our survey data suggests that small firms customize their service offerings to a significantly greater extent than larger firms in our sample. Second, considering the effect of leverage (seniority) on customization (Table 2.4, column 2), our analysis indicates that senior consultants (salaries in excess of \$150,000) report higher levels of customization of their service offerings when compared to those with more junior positions. When we divided the sample by firm size we also saw an interesting result (Table 2.7, column 2). While small firms tend to customize more (as noted above) there is no difference in the amount of customization by seniority at these firms. However, at larger firms whilst the *average* level of customization is lower, senior managers customize significantly more than their more junior colleagues. This suggests an interaction effect between firm size and seniority as they relate to customization. Larger firms customize less than small firms (main effect), with more junior employees within larger firms representing the group with the least customized work (interaction effect). Finally, considering the effect of specialization on customization (Table 2.5, column 2), we see that ‘generalists’ customize significantly more than ‘super specialists’. There is no difference in the amount of customization amongst the other groups.

Table 2.7: Contingency Analysis of Customer Engagement, Level of Customization and Knowledge Intensity considering Interaction between Firm Size and Seniority

	Customer Engagement	Level of Customization	Knowledge Intensity	Capital Intensity
10 Employees or less				
Salary of \$150,000 or less (n=63)	8.33 [1.26]*	69.29 [3.11]	5.35 [0.14]	N/A
Salary of more than \$150,000 (n=29)	14.14 [2.82]*	74.98 [3.54]	5.45 [0.23]	N/A
More than 10 employees				
Salary of \$150,000 or less (n=78)	7.95 [1.27]*	59.30 [3.02]*	5.20 [0.13]*	N/A
Salary of more than \$150,000 (n=35)	12.57 [2.14]*	70.18 3.57]*	5.68 [0.20]*	N/A

Note: * Denotes a significant difference in the mean value between the groups at the $p < .05$ level. Mean and Standard error (in brackets) are reported above.

4.1.3 Knowledge and capital intensity in consultancy

We now examine the extent to which characteristics of knowledge and capital intensity present themselves in TTH consulting. Unsurprisingly, interview data stressed the knowledge-intensive nature of consulting work, “our clients have data; we use analytics to answer their business questions”, suggesting a form of passive co-production, where clients provide inputs that the consultants transform with knowledge and training to create value. There were also some interesting insights into the (changing) nature of that knowledge, with one interviewee explaining how “we need people with a higher degree of analytical skills than before. We are number geeks that can communicate” or, similarly, “it used to be that consultants were generalists...we are smart, we can help you. Now there must be specific knowledge. Outcomes must be actionable.”

In our survey, we addressed this research question by asking participants to answer the following question: “Please rate the following characteristics for your organization’s work”. We then listed 15 items relating to different aspects of the organization’s work (Von Nordenflycht, 2010) using a 1-7 Likert scale from ‘extremely low’ to ‘extremely high’. We carried out an exploratory factor analysis on these characteristics using principal components analysis (Ahire et al., 1996). We removed five items that cross-loaded on multiple factors or did not load at all and settled on a parsimonious three-factor solution comprising ten items explaining 57% total variance. After running reliability tests, we removed one factor

because of a low reliability statistic (Alpha .547). The remaining two factors of ‘knowledge intensity’ and ‘capital intensity’ (Table 2.8) have alphas of .714 and .640 respectively, which although not high, exceed the recommended value for exploratory work (Nunnally, 1978).

In line with our interviews, survey data shows strong evidence of knowledge intensity with *reliance on knowledge assets/human capital, knowledge intensity of activities undertaken, and proportion of employees with a formal qualification* all scored highly within the work characteristics section of the survey⁶ (Table 2.8). Perhaps more surprisingly, our survey data also indicate that the level of capital intensity is much higher than might be expected for professional services. In particular, the *use of information technology to automate service delivery* and *level of investment in information technology* had high scores.

Table 2.8. Factor Analysis of Professional Service Organizational Characteristics

Organizational Work Characteristics	Mean		
Factor	1	2	
Eigenvalue	2.76	1.72	
Percent variance explained	27.7	17.2	
<i>Knowledge Intensity</i>			
Proportion of employees with formal professional (e.g. legal, technical etc.) qualifications	4.86	.789	.098
Organizational reliance on knowledge assets / human capital	5.58	.784	.197
Knowledge intensity of activities undertaken in your organization	5.45	.779	.001
<i>Capital Intensity</i>			
Level of investment in information technology (e.g. workflow management, time recording software, customer relationship management)	4.43	.292	.760
Capital intensity of activities undertaken in your organization	3.83	-.145	.703
Organizational reliance on physical equipment and infrastructure	4.18	-.028	.651
Use of information technology to automate service delivery	4.62	.370	.620

Extraction Method: Principal Component Analysis. Rotation Method: Promax with Kaiser Normalization.

The effect of scale, leverage, and specialization on knowledge and capital intensity

In line with the previous analysis, we use our three contingencies as independent variables. For our dependent variable ‘knowledge intensity’ we averaged the three components that made up the knowledge

⁶ The slightly lower level of employees with formal professional (e.g. legal, technical etc.) qualifications reflects the non-regulated nature (cf. Law, Accountancy, etc.) of consultancy services.

intensity factor. We found no evidence of firm size (scale) or seniority (leverage) influencing the level of knowledge intensity. We then examined the interaction of scale and leverage on knowledge intensity (NB. we did not examine the interaction effect of seniority, an individual level variable, on capital intensity, a firm level variable). Again, our analysis provides interesting results (Table 2.4, columns 3 and 4, above). As main effects, scale and leverage on knowledge intensity produced no results but by interacting them we see significantly greater levels of knowledge intensity of more senior managers in larger firms. This suggests a hierarchy or stratification of knowledge intensity among larger firms that is not present in small firms.

Regarding specialization (Table 2.5, columns 3 and 4 above), data indicate that ‘deep knowledge traders’ reported significantly higher levels of knowledge intensity than ‘super specialists’. There is no measurable difference among any of the other groups. This may suggest that there is a certain amount of additional training (perhaps certification) necessary to specialize in one functional area. With ‘capital intensity’, where we once again averaged the four components that made up the factor, we found no evidence of differing levels of capital intensity by specialization but there were the expected significantly lower levels of capital intensity for the smaller firms. The interviews added some richer insight regarding the implications of this, on the surface unsurprising, finding, “We as a large company have many more resources and are more capital intensive. We don’t have the domain knowledge that small companies have, but we have the products that they do not.” Another consultant for a large company described it this way, “Small firms have good people and good tech...but what we can do is provide the plumbing”.

4.2. Managerial challenges for consultancy in the travel, tourism, and hospitality sector

Our second research objective was to examine the managerial challenges associated with delivering consultancy services. Table 2.8 provides descriptive survey data for the 23 managerial challenges based on the best-worst choice experimental procedure outlined in our research methods section. Our survey data suggest that for consultancy firms serving the TTH sector, the most important managerial challenges are *maintaining the quality of service* (2.96), *enhancing service experience* (2.24) and *knowledge management*

(1.62). The significance of managing quality may reflect the nature of management consultancy where, one interviewee noted that, unlike an accredited profession, “there is no standardized reference point...there is no universally recognized independent mark of quality”. Other respondents connected the challenge to the knowledge asymmetry and specifically, the relative immaturity of the sector as a buyer of such services; “In hospitality, customers don’t quite know what they expect. How do you meet/exceed expectations when your customers don’t even know entirely what they want?”

The least important challenges reported by our survey respondents are *attention to physical surroundings* (-2.48), *managing rigid hierarchy* (-1.48), *managing flat hierarchy* (-1.32), and *employee hiring* (-1.27). These findings, especially with respect to employees, are more surprising and were contradicted by the qualitative data. Many interviewees specifically mentioned the challenges they face with finding (“We are constantly competing for talent and we have great competitors”) and managing employees (“By far our #1 issue is talent management.”). It was also interesting to note that, despite a widely held belief that “opaque quality” (von Nordenflycht, 2010, p. 161) requires professional services to signal quality through other implicit aspects of their service package, such as attractive offices and meeting rooms, etc., this issue was ascribed a very low importance (-2.48 utility score). This may reflect the specific work model of consultancy, where most face-to-face interaction (Note, and this is relatively limited) takes place on the client’s site.

Data analysis also suggest some divergence in our managerial challenge data relative to expectations of positioning based on extant literature. Whilst *managing growth*, *developing work and control methods*, *maintaining quality of service*, and *reacting to consumer intervention in service processes* are all relatively important challenges for the managers in our study (i.e. a utility score great than +0.5), other professional service challenges, including *controlling work across geographically dispersed locations*, *scheduling workforce*, *start-up of new operations at new locations*, *employee hiring*, *fighting cost increases*, *managing career advancements of employees*, and *managing flat hierarchy with loose subordinate-superior*

relationships all have much lower utility scores than would be expected based on existing conceptual frameworks (Table 2.9).

Table 2.9: Mean Centred Relative Utility Scores for Managerial Challenges (Estimated by Individual Level Multinomial Logit Model Derived from the Best-Worst Choice Experiment)

Managerial Challenge	Relative Utility Score	Std. Error
Maintaining quality of service	2.96*	0.07
Enhancing service experience.	2.24	0.08
Knowledge management	1.62	0.07
Managing growth	1.14	0.09
Marketing	1.04*	0.10
Developing work and control methods	0.95	0.08
Reacting to consumer intervention in service process	0.90	0.07
Gaining employee loyalty and retention	0.34*	0.08
Employee training	0.30*	0.07
Managing demand to avoid peaks and to promote off peaks	0.25*	0.08
Monitoring and implementing technological advances	0.16*	0.07
Scheduling service delivery	0.02	0.09
Employee welfare	-0.27	0.06
Controlling work across geographically dispersed locations	-0.54	0.11
Fighting cost increases	-0.66	0.08
Capital investment decisions	-0.78	0.11
Managing career advancements of employees	-0.80*	0.08
Scheduling workforce	-1.14	0.09
Start-up of new operations at new locations	-1.19	0.11
Employee hiring	-1.27*	0.09
Managing flat hierarchy with loose subordinate-superior relationships	-1.32	0.07
Managing fairly rigid hierarchy with need for standard operating procedures	-1.48*	0.10
Attention to physical surroundings	-2.48	0.06

Note: * indicates a significant difference at the $p < 0.05$ level across firm sizes (≤ 10 employees vs. < 10 employees). No significant differences at the $p < 0.05$ level across seniority ($\leq 150K$ vs. $> 150K$). No significant differences at the $p < 0.05$ level across industry specialization

The effect of scale, leverage, and specialization on managerial challenges

Although we found no differences based on seniority or specialization, firm size highlighted some significant differences emerged in relation to scale (firm size) (Table 2.10). Larger firms are significantly more concerned with *employee hiring, employee training, gaining employee loyalty, managing career advancement of employees, and managing rigid hierarchies*. This notion is supported by our qualitative data with executives at large firms making comments like, “By far our #1 issue is talent management,” and “We are constantly competing for talent”. Another interesting finding from this contingent analysis is that small firms are significantly more concerned with *maintaining quality of service, marketing, monitoring and implementing technological advances, and managing demand to avoid peaks and promote off-peaks*. For smaller consultancy firms, the particular emphasis on quality of service and marketing may not be particularly surprising given the higher level of criticality that arguably surrounds each individual piece of work as well as the more severe consequences of a dissatisfied or lost client. The emphasis on monitoring and implementing technological advances may at first appear somewhat counter-intuitive given the early discussion of large firm investment in technology. However, perhaps we are seeing a greater emphasis on monitoring and implementation precisely because the funds available to invest are more limited and thus selection of new technology and subsequent implementation take on greater importance in smaller consultancy firms. Finally, without the benefits of scale and resource re-allocation, smaller consultancy firms are arguably more likely to be concerned with looking to manage demand throughout the year in order to provide a steady flow of work for a small workforce.

Table 2.10: Mean Centred Relative Utility Scores for Managerial Challenges by Firm Size

	Mean Values	St. Error
Employee hiring		
10 employees or less	-1.55*	.13
More than 10 employees	-.99*	.12
Employee training		
10 employees or less	.02*	.10
More than 10 employees	.59*	.10
Gaining employee loyalty and retention		
10 employees or less	-.05*	.10
More than 10 employees	.71*	.11
Monitoring and implementing tech. advances		
10 employees or less	.38*	.11
More than 10 employees	-.06*	.10
Managing demand to avoid peaks and to promote off peaks		
10 employees or less	.60*	.118
More than 10 employees	-.08*	.108
Managing career advancement of employees		
10 employees or less	-1.15*	.108
More than 10 employees	-.47*	.109
Managing fairly rigid hierarchy with need for standard operating procedures		
10 employees or less	-1.73*	.139
More than 10 employees	-1.25*	.154
Maintaining quality of service		
10 employees or less	3.10*	.089
More than 10 employees	2.84*	.095
Marketing		
10 employees or less	1.40*	.134
More than 10 employees	.68*	.139

Note: Firm size: 10 employees or less (n=122), More than 10 employees (n=127). Mean values represent the relative utility score from the max-diff experiment. * Significant at the $p < .05$ level

5. Discussion

In this section, we reflect on the analysis of the data generated by our mixed method approach and review each of our research objectives in turn.

5.1 Do generic conceptualizations reflect the specifics of a particular type of PSO?

Our first research objective was to examine the extent to which levels of engagement, customization, knowledge intensity, and capital intensity present in our study reflect the predominant characterizations of professional service operations. Table 2.11 highlights that when observing the characteristics of a particular

PSO type, TTH management consultancy, a mixed picture emerges. Analysis confirmed the idea that consulting operations are knowledge intensive and reliant on knowledge assets/human capital. Interestingly, even though consulting is not a regulated profession⁷ we observed a high level of formal professional qualifications, with the qualitative data suggesting that the reputational benefits of such qualifications mean that they remain important (e.g. “In our business you can’t make Senior Consultant without an MBA...having an MBA is critical to *selling* our business.”). Set against this confirmatory data, practice diverged from theory informed expectations in three of the four dimensions. We now discuss each of these in turn.

Table 2.11: Summary of PSOM characteristics – findings versus expectations

RQ	Key measure	Overall sample
1a	Customer engagement	Substantially lower than expected
1b	Customization	High, but slightly lower than expected. High proportion of work un-customized
1c	Knowledge intensity	Similar to expectations
1c	Capital intensity	Higher than expected

5.1.1 Engagement: talking about the client more than talking to them

Our data suggests that, whilst consultants like to think of themselves as highly engaged, in practice much of their actual time is spent working independently or with colleagues rather than directly with clients. We interpret these findings (i.e. consultants say they work with clients all the time but, in practice, don’t) as offering support for a combined passive and active model of consultancy client engagement. There may be periods of face-to-face (sometimes remote) ‘engagement’ but these will typically be time limited (from our data this may, ironically, often be at the behest of the client, who doesn’t want too much interruption in their day-to-day activities) and perhaps focused on the initial service requirements or perhaps project close phases of any exchange (Chase and Dasu, 2001). There was also some anecdotal support for a more symbolic model of consultancy, with one senior consultant stressing that “clients often hire consultants for

⁷ Regulation was something advocated by at least one of interviewees: “consulting as a skill set is not currently recognized in any formal way (i.e. through certification)...there should be a governing organization that certifies quality in the consulting world.”

affirmation. They want a consultant to tell them they are doing well, they don't want a consultant to innovate".

5.1.2 Customization: a portfolio of bespoke and standard practice

The survey data suggests levels of customization that were, broadly, in line with expectations but, given the much lower than expected levels of customer engagement, this raises the intriguing prospect of customization without significant consultation or collaboration. Conversely, qualitative data analysis suggests a significant proportion of consulting offerings with low levels of customization. One executive in our interviews identified three operating models in TTH consulting firms. His observation was that firms sell "standard products with little customization, tested models 'a standard playbook but can run several plays', or hairballs 'you have to go in and figure it out'". We interpret the significant variation we see in levels of customization as indicating a mixed portfolio of bespoke and standard work, akin to Maister's (1993) brains, grey hair, and procedural work.

5.1.3 Knowledge intensity: gaining expertise through client network exploitation

Findings relating to levels of knowledge intensity and reliance on knowledge assets/human capital were in line with expectations ("We need people with a higher degree of analytical skills than before. We are number geeks that can communicate", etc.) but there were some interesting qualitative insights relating to the nature of client-customer knowledge flows. There was ample evidence of the traditional assumptions about knowledge transfer being a flow from expert to client ("[The] industry is immature ... consultants bring technical expertise that is in high demand and that doesn't already exist in the industry") but also evidence to support the notion, highlighted in the literature review, that consultants *become* sector experts by exploiting client networks ("[Given the] complexity of the industry, so many stakeholders involved with each property...often part of a consultant's job is to bring everyone together") and building upon repeat business. In this way some aspects of knowledge intensity are essentially context-bound ("Our knowledge is not scalable. What you know is only relevant to the context where you learned it"). As such, finding and

selling to clients is fundamental to both business development and operations management (“I don’t need operations people, I need people who can sell \$10 million in services next year”).

5.1.4 Capital intensity: High investment especially in communications technology (ICT)

More surprising was the finding that capital intensity is relatively high. In general terms we interpret this as reflecting, in part, the dramatic ICT-related changes in all business operations in the last 20 years and more specifically, the implementation of staff co-ordination and knowledge management systems in many consulting firms. We also revisit this issue in our subsequent discussion of contingencies (See section 5.3) as there were significantly lower levels of capital investment to support different activities in smaller consulting firms within our study.

5.2 Managerial challenges

Our second research objective was to examine the managerial challenges associated with delivering professional services. At a general level our data supports previous studies (Verma 2000) with respect to the most important managerial challenges - maintaining the quality of service, enhancing service experience, knowledge management, and managing growth. The least important challenges were more striking: attention to physical surroundings, managing rigid hierarchy, managing flat hierarchy, and employee hiring. It is interesting that consultants report very little concern with physical surroundings, given than the image of most consultants is that of fancy offices in expensive locations. It could be that physical surroundings is not an item that needs to be actively managed or once the office is leased there is very little that can be done about it. More interestingly, this may reflect the transition to a technology-mediated service model whereby the majority of client-related interaction occurs via e-mail, Skype, Google Hangout, and conference calls. The relatively limited amount of time spent in the physical presence of clients suggests that generic service models need to reflect the fact that this form of interactive medium is increasingly the norm (or at least widely adopted) in many professional services.

5.3 Towards a contingent perspective of PSOM

Our third research objective was to explore the effect of three potential contingencies on both PSOM characteristics and managerial challenges. Here, we reflect on three key observations based on analysis from this study.

5.3.1 Interaction of scale and leverage

Some of the contingent observations on characteristics were more confirmatory than novel. For example, larger firms placing greater emphasis on investment in information technology (e.g. workflow management, time recording software, and customer relationship management systems) or senior staff spending more time collaborating with clients. Building on this observation, after interacting all three variables with customization and knowledge intensity we found no difference in the level of customization between senior and junior consultants for small firms, perhaps suggesting an ‘all hands on deck’ approach to their work. Conversely, in the larger firms within our study we observe significant differences in customization. Taken together our findings suggest that, where scale allows, more senior consultants have a more creative and client relationship focused role than their junior colleagues who play a more procedural role requiring less engagement with clients and affording less opportunities for customization. There was also some evidence that more senior positions in large firms are only available to those with additional education.

The critical observation from these findings is that some insight regarding level of analysis (i.e. size and/or seniority) is absolutely fundamental to make sense of process structure in consulting. At the individual level of analysis, contingencies such as seniority of the consultants impact the business processes, while at the group level firm size and specialization impact operational characteristics. These levels of analysis must be taken separately and collectively to create a full picture of PSOM.

5.3.2 Contingent effect of firm type

The contingent effects of specialization generated some of the most interesting findings. We found that those who are functional and sector specialists (super-specialists) spend less time with clients. This offers

confirmation that expert services are not necessarily predicated on interaction or more provocatively, are actually predicated on *not* interacting to allow them to undertake their work, preserve status, etc.. The more generalist firms have to complement their more limited expert status with high levels of interaction (networking, etc.). Additionally, generalists customize their offering significantly more than specialists. This may be because of specialists' over reliance on prescriptions developed for the industry in which they market themselves as experts. Generalists may be expected to tailor their methods to some degree to access various industries while specialists may have a greater incentive to perfect methods and customize less. Table 2.12 summarises the significant findings relating to specialization.

Table 2.12: Summary of contingency effects in PSOM

Sub-samples, based on contingent factors examined		Key Measures			
		Customer Engagement	Customization	Knowledge Intensity	Capital Intensity
Specialization	Generalists	Engage more than super specialists	Customize the most, significantly more than super specialists		
	Market Knowledge Traders				
	Deep Knowledge Traders	Engage more than super specialists		Highest level of knowledge intensity, significantly higher than super specialists	
	Super Specialists	Engage the least with customers	Customize significantly less than generalists	Lowest level of knowledge intensity, significantly less than deep knowledge traders	

5.3.3 More detailed descriptions of managerial challenges?

Beyond the (perhaps unsurprising) observations regarding differences between small and large firms, the absence of any meaningful variation in the prioritization of challenges related to seniority or

specialization was unexpected; especially given how strongly these contingencies influenced work characteristics. If, as observed, senior managers customize work significantly more than their junior colleagues for instance, might we not have expected to see differential priorities emerging as well? One interpretation - with significant implications for PSOM - could be that the extant categorization of challenges are broadly 'correct' but too generic/insufficiently specified. This would explain the 'flattening' of expected differences in our study and suggest that, as currently detailed, they may offer limited conceptual and, more importantly, practitioner insight. This is rich ground for further work and we revisit this issue in the final section.

6. Conclusions

This paper reports on a mixed method examination of the characteristics and managerial challenges faced by consultancy firms serving the US travel, tourism, and hospitality sector, and the contingent factors affecting their operations. Such a focused study, looking at a specific type of professional service in a single sector is, to the best of our knowledge, a first in this area of OM⁸ and, in undertaking such a focused 'deep dive', we clearly demonstrate the limitations of generic SOM frameworks in their treatment of professional services. Before discussing key contributions, it is important to reflect on the limitations of our work. Although we adopt a mixed methods approach, the scope of the primary data collection method, the survey, was limited by the selection of ex-ante variables. The aim was to balance comprehensiveness and parsimony to maximize responses from professionals who were unlikely to complete a more time-consuming survey. Similarly, although the decision to examine one specific empirical context was central to our research design, it naturally limits the generalizability of our findings.

6.1 Key contributions

Whilst acknowledging its limitations, we suggest that the research generates contributions to the emerging PSOM body of knowledge in two specific ways. First, we have already noted that the predominant

⁸ The use of the Best-Worst (Max-Diff) technique to examine the relative importance of different managerial challenges also appears to be novel for the discipline.

characterizations of professional service operations do not appear, for TTH management consultancy at least, to hold. Consulting operations are indeed knowledge intensive but the most interesting aspect of this (self-evident) observation was actually the finding of high levels of formal professional qualification; suggesting perhaps that even in unregulated ‘professions’ both providers and clients value the reputational benefits of such barriers to entry. Our observation that consultants spent much of their time working independently or with colleagues rather than directly with clients provoked much debate (and some soul searching) in the focus group sessions but our data suggests that consultancy can be actually quite remote and passive and that any periods of face-to-face ‘engagement’ will typically be time limited and focused on specific project phases. Moreover, and further confirming the value of a study that allowed us to investigate PSOM in a particular market setting, our data suggests this may, ironically, often be at the behest of the client. The significant variation observed in levels of customization we interpret as confirming Maister’s (1993) notion of a portfolio of *brains*, *grey hair*, and *procedural* work (and echoed in some of the insights developed by Kellogg and Nie, 1995). Finally, we also observed relatively high levels of capital intensity; reflecting perhaps the vintage of most PSOM characterizations (i.e. Maister and Lovelock, 1982; Schmenner, 1986; Silvestro et al., 1992; Wemmerlov, 1990) and the dramatic ICT-related changes that have occurred in *all* business operations in the last 20 years. More specifically, there have been significant investments in the implementation of staff co-ordination and knowledge management systems in many consulting firms.

Second, through contingent analysis based on both firm characteristics (scale, specialization) and individual level characteristics (leverage) we further demonstrate significant variation within what might be expected to be a relatively homogenous group of professional service operations. For example, the *differences* in the levels of both engagement and customization are also a consequence of size, specialization and seniority. In a similar vein, we also saw the important (though, perhaps less surprising) effect of size on the levels of investment in technology and infrastructure. Additionally, we observed interaction effects between firm size and seniority for both customization and knowledge intensity,

highlighting the ways in which career progression is likely to have very different implications (in terms of operating characteristics and managerial challenges) for those operating in smaller as opposed to larger consultancy firms. Finally, investigating the effects of specialization generated a typology of consulting operations that also highlighted of the most interesting contingent findings. We found for example, that relative degree of interaction may be dependent on the degree of expertise, such that it was the *super-specialists* in our sample that spent less time with clients and the more *generalist* firms who were (complementing their limited expert status?) with high levels of interaction (networking, etc.).

6.2 Managerial implications

Our research also raises a number of implications for those working in (TTH) management consulting firms and for their prospective clients.

6.2.1 For Consulting Firms

The substantially lower than anticipated levels of client interaction confounded not only existing scholarly models but also the views of a number of respondents within our qualitative study. Although some of this disconnect is likely a function of dominant PSOM assumptions ignoring the key contingencies of seniority and specialization (ie. more senior staff and/or those working in more generalist consulting firms display higher levels of engagement than average), it may also reflect an industry logic, whereby practitioners spend so long *saying* their services involve extensive client-provider interaction that they believe this to be the case? One of our interviewees - a partner in a global consulting firm – answered the question “what research do you wish we were doing?” with the observation that “[w]e need research that will help us to gain an advantage over our competitors”. If our observations regarding client interaction are even partially valid, this suggests significant opportunities for consulting firms to differentiate through customer service.

Equally, our findings suggest that consulting firm customization strategies need to acknowledge key contingencies that reflect concerns common to all operations. For instance, large-scale generalist firms can

invest in a ‘standard set of models’ (cf. product modularity: Pankaj and Jayaram 2014) that can underpin a wide variety of client needs. Conversely, specialists (i.e. those with unique resource endowments) may decide to offer much lower levels of customization.

Finally, the (unexpected) levels of capital intensity in our data suggest the existence of managerial challenges regarding the effective application of technologies that support intra- and inter-firm collaboration in a context where traditional operational/process control is limited (i.e. how do you persuade individual professionals to use the knowledge management/CRM/time recording, etc. etc. system properly?).

6.2.2 For Consulting Clients

Although our data was more limited on the buyer/customer side, our research highlights the risk of assuming that a ‘general’ model of consulting exists. More specifically, if levels of engagement are generally much lower than assumed, client organizations should perhaps question if engagement is for their benefit or for the benefit of the consulting firm (i.e. developing new sector or functional knowledge). More generally, if such diversity exists in what might have been assumed to be a homogenous group (i.e. consulting firms serving a specific sector), we would anticipate significant diversity in other professional service settings. As such, clients looking to engage lawyers, accountants, software providers, R&D laboratories, architects, and universities (to name a selection) should similarly be careful to avoid generic assumptions regarding operating model and performance.

6.3 *Future research*

Our exploratory study (and its limitations) gives rise to a number of future research opportunities. First, as well as welcoming studies that seek to replicate our empirical approach (i.e. service and setting) to assess the extent to which our findings hold true (Kaynak and Hartley, 2006), we would strongly encourage research that examines alternative and more detailed market sectors and/or professional service settings (e.g. US cardiology services, European architects serving public bodies, etc.)

Second, whilst we have started the process of exploring the contingent factors at play with PSOM, further work is clearly needed. For example, refined (or alternative) measures of scale, leverage, and specialization, or different contingencies such as reward systems, organizational culture, and decision-making mechanisms (i.e. centralized versus decentralized) may all offer useful insights. In addition, the managerial challenge categories need to be refined to better reveal the (contingent) detail of PSOM. What might have been the impact of, say, refining the ‘enhancing service experience’ category to better capture what this means for a senior engagement manager (e.g. regular requirements capture and satisfaction tracking, etc.) versus a more junior consultant (e.g. ensuring delivery against work plan, compliance with method, etc.)?

Finally, whilst our analysis suggests support for an expert consultant-passive client model of service delivery, the notion of the singular client is problematic. Schein (1999) for example, discusses multiple types of client position (e.g. the first ‘contact’ client, who may differ from the problem ‘owner’, ‘intermediate’ clients who work directly with consultants, ‘unwitting’/‘indirect’ clients and ‘ultimate’ clients who might include client customers). In such a model, the direct interactions that ‘matter’ may not require lots of actual real time contact (cf. our discussion of the customer contact findings). Given the commercial and practical research challenge of accessing specific clients, behavioral experiments based on different types of clients-consultant interactions could thus provide invaluable insights.

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CHAPTER 3: THE IMPACT OF CLIENT INTERACTION AND CLIENT TRAINING ON CONSULTANT RECOMMENDATIONS AND CLIENT RESPONSIVENESS TO THOSE RECOMMENDATIONS: EXPERIMENTAL EVIDENCE IN CONSULTING

Abstract

It has become common practice in service based economies for individuals and corporations to outsource or delegate decision making power to consultants or advisers. While advisers provide recommendations—based on their expertise—clients usually bear the risk associated with the outcomes of the recommendations, which often leads to moral hazard. We investigate, through a behavioral experiment in a consulting context, the decisions that consultants and clients make and their influence on each other. Specifically, we test—from the client and adviser perspective—the impact of client seeded estimates on consultant’s subsequent recommendations and the resulting client decisions and satisfaction. We test for this effect with both trained and novice clients. We find that when clients interfere with the process by providing their consultants with an initial estimate, expert consultants don’t ‘take the bait’, but instead are more likely to give a different opinion, even when the client was right. We propose that the reason for this is that consultants are determined to add value to their client’s decisions, and if they simply go along with their clients, then they may not be seen as adding value. Consultants with little expertise however are more likely to ‘take the bait’ but often come up with better recommendations as a result. From the client perspective, expert clients are less likely to blame consultants for bad outcomes but also less likely to give them credit for good ones. Additionally, all clients (even untrained) were anchored by their initial estimate and were reluctant to move off that anchor, even when their consultants provided good recommendations.

“We are trying to get away from the stereotype that a consultant will steal your watch, then tell you what time it is.”

--Exec. VP of a management consulting firm

1. Introduction

Consulting is a well-established business model in today’s global economy. In the United States alone it is estimated that management, human resource, and information technology consulting firm revenues exceeded \$500 billion in 2013⁹. Consulting companies range from a sole proprietor, who only employ themselves, to massive multinational companies—some with more than 200,000 employees. Consultants work in every industry in the US and the world. The primary reason for this is that consulting is no longer a job description but a business model. Consulting as a business model generally defined means selling expertise for a fee. Large corporations and small businesses alike rely on consultants to provide advice and additional resources that are not kept in-house (e.g. flexing a workforce). Consultants are hired to perform a task and when it is finished they are dismissed with no promise of any future contract. While many consultants charge high hourly fees, many businesses rely on them because of the ‘on-demand’ nature of their service and consultants maintain that not having to keep these resources in house reduces total costs.

Despite the proliferation of consulting services in the economy, many businesses have become disenchanted with consulting in general. Some consultants have developed a reputation for greed and pursuing their own interest in lieu of their client’s. This tension highlights the consultant paradox. Consultants by definition are hired as ‘agents’ to their clients and therefore have a responsibility to pursue their clients’ interests, which could be at odds with their own self-interest.

⁹ IBISWorld industry reports (<http://clients1.ibisworld.com/reports/us/industry/home.aspx>)

Generally, clients' incentives align with the consultants' incentives and it works out well. Moral hazard arises in situations where incentives are not well aligned. In these difficult situations tension may arise and at times reputations are tarnished. In an effort to ebb the tide of negative perception many consultants have instituted cultural changes and made re-branding efforts. One partner at a big four accounting firm told us, "In my firm we do not use the word consultant. We are not consultants, we strive to be advisers to our clients; it is very different."

In a similar vein, consultants often are accused of charging high fees just to tell their clients what their clients already know (i.e. quote at the beginning of the paper). Do consultants really engage in this behavior that they are accused of? Or do they bring unique perspectives and recommendations? What about other types of professional service workers? Do doctors or lawyers, who are also tasked with making recommendations based on patient/client information, engage in similar behavior? In this study we created a behavioral experiment in which we observe and measure consultant and client interactions and test consultant's tendencies to go along with their client's opinions. We do this by asking clients to prepare an initial estimate for a common business problem. In half the treatments (client interference condition) we showed the consultants their client's estimate prior to asking them to provide a recommendation. In the other treatments consultants prepared recommendations without the benefit of seeing their client's estimate. After seeing the consultant's recommendations, the client made the final decision on the task. This design allows us to test the effect of one party's decision on the other party. We augment the design by testing the prevalence of this seeding effect with both novice and trained clients.

The rest of this paper will proceed in the following manor: first, we review literature (2) followed by a detailed explanation of our experimental design (3). In the section 4 we present our results, followed by a discussion (5) of the limitations, managerial application, and future research.

2. Literature Review

In this essay I will draw on literature from three areas: 1) Behavioral Operations Management, 2) Behavioral Economics and Decision Research, and 3) Service Operations Management. Each of these areas represents a vast body of literature and while we will not attempt to be comprehensive in this review, we will identify some relevant work from each of the areas as it relates to this study.

2.1 Behavioral Operations Management

Behavioral Operations Management (BOM) has grown as a field in concert with its related field of Behavioral Economics. At its core, BOM is concerned with using behavioral methods, introduced in economics and psychology (primarily laboratory experiments), to explain anomalies in human behavior observed in operational settings. In recent years there have been many review articles that describe the growth of the field and the interesting problems associated with BOM and we refer interested readers to those for more information (Bendoly, Donohue, and Schultz 2006, Gino and Pisano 2008, Bendoly et al. 2010, Katsikopoulos and Gigerenzer 2013, Hämäläinen, Luoma, and Saarinen 2013).

The major contribution of BOM has been the introduction of experimental techniques into the field of operations management to test the rigor of mathematical models using human subjects. Traditional problems in OM have used mathematical models to find closed form solutions to stylized problems. With the introduction of experiments in BOM, researches began testing these models with human subjects as the decision makers (Katok 2011). While the applications are endless, commonly studied problems in BOM include: Queuing (Kremer and Debo 2012, Batt and Terwiesch 2015), Auctions (Davis, Katok, and Kwasnica 2011), Supply Chain Contracts (Davis

2015), Forecasting (Kremer, Moritz, and Siemsen 2011; Moritz, Siemsen, and Kremer 2014), and Inventory Management (Tokar et al. 2014, Schweitzer and Cachon 2000, Diehl and Sterman 1995).

In this study we build on the BOM literature in a unique way by investigating (at a process level) the effects that decisions of a professional service actors (consultant) have on their clients and vice-versa. To our knowledge, this is the first study of its kind where we test experimentally in an operations setting the relationship between the decisions of clients and their consultants.

2.2 Behavioral Economics and Decision Research: Decision Making for Others

There is a vast literature on individual decision making in both psychology and behavioral economics. Behavioral Economics and Decision Research (BEDR) is where these two fields come together to study the economic impact of individual decisions. Much of this literature is dedicated to the identification and testing of various heuristics and biases that people have innately or develop and the influence that these heuristics and biases have on decision making. There have been many compilations that we recommend (Kahneman 2011; Gilovich, Griffin, and Kahneman 2002; Bazerman 2006).

2.2.1 Principal-Agent Models

The primary assumption of all consulting agreements is that the consultant will make recommendations that are in the best interest of their clients. This idea took root in the legal profession as agency law which states that an agent will “act on behalf of another (the principle).”¹⁰ This is the foundations of the attorney-client relationship and basically all other consulting agreements. In economic theory this has been formalized as the principal-agent problem (Grossman and Hart 1983, Ross 1973, Shavell 1979). Classic economic theory states that all

¹⁰ <http://www.law.cornell.edu/wex/agency>

players will act in their own best interests. This presents a problem for agents (i.e. consultants) who are tasked to act in the best interest of their clients. Classic theory predicts that problems will arise when the interests of the agent are not aligned with the interest of the principle. The study of this problem has motivated a vast literature in experimental economics (Anderhub, Gächter, and Königstein 2002; Fehr and Gächter 2000; Fehr and Schmidt 2004; Charness and Rabin 2005; Hamman, Loewenstein, and Weber 2010).

Much of the experimental economics literature on principle-agent theory to date relates to the way information asymmetry creates problems in the principal-agent relationship (Blomqvist 1991, Sappington 1983, Thomas and Worrall 1990). Often agents have more information than principals and they may be tempted to act in a way contrary to their agent's best interest. One prominent example is the dentist who recommends expensive unnecessary procedures to clients to improve his own financial situation. Many of these experiments highlight examples of when classic economic theory dominates the principle agent relationship. In other experimental settings agents defy classic economic theory by doing things that appear to be irrational. Examples include altruism and cases in the ultimatum game when agents continue the game longer than rational choice theories would expect.

Our study is a principal-agent at its heart where we have a principal that is responsible for making decisions and their agent that is responsible for giving advice. Our problem is different from previous versions of this model however because in our model the principal tells the agent what to do, and we observe whether the agent actually does it. We also introduce a unique incentive structure where the agent has an incentive to both make the client happy (client satisfied with recommendation) but also provide the right recommendation (part of their compensation is determined by the correctness of their answer).

2.2.2 Adviser/Advisee Decision Making

Adviser/advisee problems are a unique subset of principal-agent problems. Another unique aspect of our problem is that it is set up as an adviser/advisee problem where the agent is outside the organization. Principal-agent problems incorporate this type of problem but many also study internal principals (managers) and internal agents (employees).

Because of its close connection to psychology, much of the recent work in adviser/advisee relationships have come from psychologist and management scholars (Dana and Cain 2015). One particular, area of interest has been doctors as agents and patients as principals (Sah and Fugh-Berman 2013; Sah, Fagerlin, and Ubel 2016)). For example, a recent study (Sah and Loewenstein 2015) discovered that when advisers know that they are providing second opinions they provide very different recommendations than when they are providing primary recommendations. They provide more biased results and are keener on maximizing their own profits when they are aware of the availability of a second opinion. This study is very similar to our own except in our study the primary opinion comes from the client, not another adviser. We expect that when the primary opinion comes from the client, advisers will be even more biased by it, which is what we test.

2.3 *Service Operations Management*

The final literature that we draw on in this chapter is Service Operations Management (SOM). This is one of the primary distinctions of this study from previous studies on adviser/advisee relationships. Previous studies primarily study decisions from an individual perspective. We use the lens of service organizations where actors are not just interested in their own objectives but those of their client and firm. The service perspective is one where actors must consider their customer's needs and goals.

2.3.1 Professional Service Firms

Within the service literature there is a subset of literature interested in professional services; also known as white collar work (Hopp, Iravani, and Liu 2009) or knowledge intensive work (Narayanan, Swaminathan, and Talluri 2014; Gardner, Gino, and Staats 2012). There are many distinctions between professional services and ordinary services, which include: high levels of customization and customer contact (Maister and Lovelock 1982, Wemmerlov 1990), expert services (Kellog and Nie 1995), high knowledge intensity (Von Nordenflycht 2010). In this study we investigate operational decisions in the context of professional services (i.e. consulting environment).

2.3.2 Co-production in Service Operations Management

One final distinction of services is the high level of co-production between customers and producers (Sampson and Froehle 2006; Bettencourt et al. 2002; Maglio and Spohrer 2008). Because customers co-produce in service settings (perhaps especially in professional service settings) their decisions impact producers, or in our case advisers (consultants). Clients make consultant recommendations possible by providing the information necessary to accomplish the task. However they also provide additional information that may interfere with the process. For example, clients may provide their own estimates or solutions that can potentially bias their consultants. In this study we investigate the impact that client decisions have on consultant recommendations in this co-productive environment.

3. Experimental Design

In a client/consultant co-productive relationships information is dispersed and decisions are made on by both parties. Clients make decisions about who to hire, how much information to share, how much to pay, and ultimately whether they will implement their consultant's advice.

Consultants on the other hand make decisions about whether to accept work, how to staff it, the level of effort to commit to a project, and how to present their final recommendation. Our primary research question in this study is: How does client input in a business problem impact the co-productive process between clients and their consultant?

While it is obvious that client and consultant decisions impact each other, the challenge of studying this co-productive process lies in collecting data on how the decisions of each party impact their own—and their partners—subsequent decisions. For this reason, we determined that a controlled experiment in a laboratory setting would be the best method for observing decisions and measuring the impact they have on each other. We are interested in both client and consultant decisions, and for this reason, we recruited participants to play both roles. Half of our experimental subjects played the role of client, while the other half played the role of consultant.

3.1 Hypotheses

3.1.1 Consultant Perspective

Consultants (whether they be doctors, lawyers, accountants, or management consultants) are hired by their clients for their expertise with regard to a problem that the client/patient is experiencing. Generally, once consultants offer their recommendation, they are finished with the engagement. This relationship is complicated by the ‘one off’ nature of many consulting projects. One owner of an international consulting firm we spoke with described it this way, “as a consultant, I don’t have any hooks in my clients. When we finish an engagement that client is done with us and there is nothing that guarantees my next job.” This pressure to perform caused another consultant we spoke with to lament, “I’m only as good as their last job.”

Consultants who feel that they have no long term source of revenue from a client may feel pressure to satisfy a client's demands so that they will be awarded the next project, even when the client's demands are not in the best interest of the client. This begs the question, how are client's best served? Some clients may prefer a confirmation of an existing opinion, while others may favor a contrasting, innovative, or novel opinion. How is a consultant to know which type of recommendation a client would welcome most, and further, should they be trying to tailor their advice at all? Why not simply give their best recommendation, based on their expertise, regardless of the client eccentricities?

Theory development in psychology and behavioral economics gives us insight into how we may expect a consultant to behave given these complex and often competing incentives. One explanation from psychology is confirmation bias. Confirmation bias happens when people make snap judgements with imperfect or ambiguous information, then seek out additional information to justify their position. People do this because there is a discomfort caused by a gap between their snap judgements and logic called cognitive dissonance (Festinger 1962, Brehm and Cohen 1962). Confirmation bias and confirmatory information search (Frey 1986) is an effort to fill that gap by finding logical explanations for snap judgements. Consultants who are given a client's problem likely make snap judgements about how the problem should be solved. If the client interjects an opinion then it likely will either support or conflict with the snap judgements made by the consultants. If the client opinion supports the consultant's snap judgment then the consultant will likely be satisfied with the process and make a recommendation consistent with the client opinion. If the two opinions are in conflict then the consultant must make a decision which opinion they will recommend, their own, or their clients.

Another explanation how a recommendation is formed by a consultant is anchoring and insufficient adjustment. Operations scholars have used this behavioral bias to explain decision making in other newsvendor experiments (Schweitzer & Cachon 2000) and other operations contexts (inventory distribution: Diehl and Sterman 1995; supply chain design: Croson and Donohue 2006). Once a subject is exposed to an opinion or fact there is no taking it back. If a consultant discovers their client's opinion regarding a task it stands to reason that the discovery will influence or anchor their own opinion. In this situation consultants must decide if they are going to agree or disagree with their clients. The anchoring and insufficient adjustment heuristic says that decision makers become fixed on a focal value (in this case client opinion) and do not adjust adequately. In the context of this study, consultants who discover their clients opinions may be fixed on that opinion (even when it is wrong) and will not adequately adjust their own opinions to deliver a correct solution.

The application of confirmation bias and anchoring and insufficient adjustment to our client/consulting context lead us to three hypotheses relating to the way that consultants develop their recommendations:

H1: Consultants who are given client estimates will more closely conform their recommendations to client's estimates than consultants who do not receive their client's estimates.

H2: Consultants with little expertise are more likely to adopt client estimate, regardless of the quality of that estimate, than more expert consultants.

H3: Consultant expertise will moderate the relationship between client input and conformance to estimate.

3.1.2 Client Perspective

The client perspective in a client/consultant relationship is the opposite side of the same coin. Clients are willing to compensate consultants/advisers in exchange for their expertise in solving a particular problem of interest. Consultants of course give advice, but in the end it is the client that must live with the consequences of that advice. Clients therefore bear almost all of the risk associated with a consultant recommendation. Additionally, often clients have developed their own expertise relative to the particular problem. Patients are experts of their own bodies and business owners are experts of their own businesses. For this reason clients often develop their own opinions about a course of action prior to hiring consultants. Their purpose for hiring a consultant therefore may be varied: 1) confirm an opinion that they already suspect, 2) seek new insight into a problem that they know something about, 3) outsource the problem to another more expert than themselves, 4) obtain a third party non-partial opinion relative to a course of action (i.e. a gut check). The challenge that consultants face is that clients rarely reveal their purpose and many consultants are left guessing.

The diversity in client's purpose for hiring consultants lead to equally diverse goals for the relationship. One client may be thrilled with a client who confirms their opinion and think, "Wow, I'm so smart, even my consultant agrees with me." Another client after receiving the same recommendation may respond, "Why am I paying a consultant to tell me what I already know." This potential for diverse client perspectives have lead us to the following hypotheses:

H4: When clients are trained, they will make better decisions.

H5: When a client shares their estimate (interference condition), client satisfaction will increase as consultant recommendations conform to client estimates, regardless of whether the estimate was good or bad.

H6: Clients will be more satisfied with consultants who confirm to their own opinion in positive outcomes, but less satisfied with conforming consultants in negative outcomes.

3.3 Laboratory Experiment

We conducted this study in a university lab using a program written with the experimental economics software *zTree* (Fischbacher 2007). Originally used by behavioral economists, this software has been used widely by operations management scholars to study behavioral decision making in many operations management settings (Davis 2015; Davis, Katok, and Santamaria 2014; Katok 2011). Our goal in this experiment is to measure and test the impact of decisions from clients and consultants in a co-productive professional service setting. To do this we designed a laboratory simulation of a common supply chain management problem (single period stochastic demand inventory problem, i.e. newsvendor problem). Specifically, we measure the impact of client decisions on consultant recommendations and conversely, the impact of consultant recommendations on client decisions.

3.2.1 Participants

We recruited a total of 252 students from various colleges across Cornell University using laboratory participant recruiting system. Students were both undergraduate and graduate students.

All participants were told that they would receive \$5 for participating and would have the opportunity to earn more money based on their decisions, the decisions of others, and chance. The study took an average of 78 minutes and students made an average \$28.58 for their time.

3.2.2 Treatments

We designed three manipulations which account for a 2x2x2 full factorial design: 1) *Client Training*, 2) *Client Interference*, and 3) *Sharing* evaluation scores with the participant’s partner (Table 3.1). In the *training* treatment all clients and consultants were trained on how to solve the problem that they would encounter in the simulation. In the *NO Training* treatment clients were not trained on how to solve this specific problem but consultants were. This manipulation simulates real world situations where clients bring varying levels of expertise to a client/consulting relationships. Sometimes clients are very capable of solving their own problems, while other times they have little or no expertise

Table 3.1: Number of Subjects by Treatment (n = 252)

Treatments	1	2	3	4	5	6	7	8
Client Training	N	N	N	N	Y	Y	Y	Y
Client Interference	N	N	Y	Y	N	N	Y	Y
Sharing Evaluations	N	Y	N	Y	N	Y	N	Y
Number of Subjects	38	20	38	NA	42	38	38	38

The second manipulation is client interference. In the *Interference* treatment consultants were given their client’s estimates. In order to avoid deception, clients were instructed in the lab documents that their estimates would be shared with their consulting partners. In the *NO Interference* treatment consultants were not given their client partners estimates. This treatments models the effect of a client seeded solution to a consultant. The consultant received the client

estimate prior to even seeing the problem itself. This was important because we wanted the client estimate to be an anchor for the consultant, and not their own opinion.

The final manipulation is sharing evaluation scores. Each client and consultant were evaluated after the training exercise to see how well they learned to perform the task. This evaluation score became a proxy for expertise throughout the rest of the experiment. Clients and consultants were told how well they performed on the evaluation and one of our manipulations was to reveal how well the partner performed. This manipulation is important to the managerial impact of this study. In real life situations client and consultant expertise is often ambiguous. Clients accept or reject consultant recommendations without really knowing their consultant's level of expertise. If they knew however, they may act differently. While this manipulation is very interesting in an effort to focus our analysis, we do not discuss it in this paper. However, this data is already collected and is an opportunity for future research. Removing the shared evaluation treatment from this analysis, we finished with a total of 156 participants (78 clients & 78 consultants).

3.2.3 Lab Protocol

Participants were recruited using the laboratory's subject management system. We ran a total of 13 sessions but subjects were only permitted to participate in one session (between subject design). Registered participants entered the lab and were seated at a computer. With a lab capacity of 24 computers, two sessions of each treatment was necessary (except in one case there was only one treatment). The computers in the lab were divided into two channels so that subjects would play the game with only half of the room. The reason for this is to speed up the simulation as it reduces the variation. Subjects are told that they would participate with others in the room but they did not know which channel they were on. Communication between subjects was expressly forbidden and none was observed by the experimenter.

After being seated subjects were given 10 minutes to read through the lab documents provided. The proctor then read the instructions aloud and fielded any questions. Subjects were given multiple opportunities to ask questions and were instructed that if they did have a question at any time they should raise their hand and the proctor would come to them. After going through the instructions the simulation began with two distinct phases: 1) Training and Evaluation, 2) Client and Consultant Collaboration.

Stage 1: Training and Evaluation. In the training and evaluation stage participants were given 15 minutes to learn the task, practice doing the task, and, demonstrate their knowledge of the task through an evaluation. The process consisted of two practice problems, and three evaluation problems. In the practice problems a step-by-step solution was provided. During the evaluation the formulas were provided as reminders but without the step-by-step instructions. Every participant received the same practice problems and evaluation. This training and evaluation tool was pretested on 26 students (none of those pre-tested later participated in the study). In the pretest students averaged 14 minutes to complete the training and scored an average of 1.6 out of 3, with an approximate uniform distribution of 0, 1, 2, and 3. This was desirable and indicated that the training was not too easy or too hard as we wanted to produce a spread in expertise.

In the treatment where clients were not trained, they were given a similar format of two practice problems and three evaluation problems but these problems were more generic business problems not related to the specific task in this study. The general business problems also tended to be easier and not take as much time. In the actual study consultants scored an average of 1.3 on the evaluations while clients scored an average of 1.15. The complete text from the training is included in Appendices E-F.

Stage 2: Client and Consultant Collaboration. After completing training, consultants and clients were ready to begin the actual game. The game consisted of 20 rounds. Each round began with a client's decision to order units to meet the demand for the round. Both clients and their consultants were given several important pieces of information to make the ordering decision:

1. Revenue per unit.
2. Cost per unit.
3. Penalty cost if you run out of units. If the client does not have sufficient units to meet demand then they must get extra units at the last minute to meet the demand. The client will always meet demand whether it is with the regular ordered units or the last minute units.
4. Holding costs. If you have too many units on hand you may incur an additional costs.
5. Salvage value. If you order too many units, you may be able to recover some of the value.
6. Your performance on the evaluation. [In some treatments subjects were also given their partners performance on the evaluation].

Using this information the clients made an initial estimate of how many units they believed they should order (Figure 3.1). To help them make a decision more easily, clients were given the opportunity to test various ordering decisions as decision support. This was done using a test button in the top center area their screen.

Figure 3.1: Screenshot for Client Estimate Decision

Round 1 You are the Client .		
Decision Parameters	Test Section	Test Results
Average Demand: 50 Revenue per item: 10 Cost per item: 5 Last minute cost per item: 12 Holding cost: 0 Salvage value: 0 Your score on the training (out of 3): 1	Test stocking quantity: <input type="text" value="1"/>  <input type="button" value="Test"/>	Actual demand: 0 Order quantity: 0 Last minute order quantity: 0 Total revenue: 0.00 Total order costs: 0.00 Total last minute order costs: 0.00 Total profit: 0.00
Please indicate your initial estimate of how many items to order. Estimate: <input type="text"/> <input type="button" value="Continue"/>		

Next the consultant made a recommendation to the client. They were given the same opportunity to test various ordering quantities using the test area in the same area of their screen. In addition, consultants in the interference condition were given client's initial estimates (Figure 3.2). In the no interference condition consultants were not given client estimates and consultants were given the opportunity to develop their recommendation simultaneously while the client developed their estimate.

Figure 3.2: Screenshot for Consultant Recommendation Decision (Interference)

Round 1 You are the Consultant .		
Decision Parameters	Test Section	Test Results
Average Demand: 50 Revenue per item: 10 Cost per item: 5 Last minute cost per item: 12 Holding cost: 0 Salvage value: 0 Your score on the training (out of 3): 2	Test stocking quantity: <input style="width: 50px;" type="text"/> <input style="width: 50px; margin-left: 100px;" type="button" value="Test"/>	Actual demand: 0 Order quantity: 0 Last minute order quantity: 0 Total revenue: 0.00 Total order costs: 0.00 Total last minute order costs: 0.00 Total profit: 0.00
<div style="border: 1px solid gray; padding: 10px; margin: 10px auto; width: 80%;"> <p style="font-size: small;">Your client's initial estimate is that they should order (units): 1</p> <p style="font-size: small;">Please recommend to your client how many items you believe they should order.</p> <p style="text-align: right;">Recommendation: <input style="width: 50px;" type="text"/></p> <p style="text-align: right;"><input style="width: 50px;" type="button" value="Continue"/></p> </div>		

After the consultant made a recommendation, the client made the final decision of how many units to order (Figure 3.3). They were given their initial estimate and the consultant's recommendation. In the condition of sharing evaluations they were also reminded of their consultants score on the evaluation. Finally, clients were asked to indicate whether they were satisfied with their consultant's recommendation. We required clients to indicate satisfaction prior to revealing demand because we did not want demand (random) to influence client satisfaction. A good recommendation is independent of randomly realized demand and we used this measurement to capture the client's satisfaction with the recommendation itself, independent of the outcome.

Figure 3.3: Screenshot for Client Final Decision

Your Estimate: 1
Consultant Recommendation: 100
Final Decision: 1
Are you satisfied with your consultant's recommendation?
No Yes

After the client made the final ordering decision, profit for the round was calculated. Profit depended on the number of units sold, or *Sales (S)*. Sales were always equal to demand regardless of the ordering decision. If a client did not order enough units then they would have to procure extra units at a higher cost to fill demand (similar to a hotel having to walk guests to another hotel if they overbook). If clients ordered too many units then they had extra units that they could not sell. After the actual sales were revealed (uniformly distributed between 0-100 units), profits were calculated with the following equation:

$$\text{Profit} = \text{Total Revenue} - \text{Total Ordering Cost} - \text{Total Last Minute Ordering Cost}$$

After the client made the ordering decision all participants were taken to a new screen where they learned actual demand for the round (sales) and profit (based on the formula above). Information from previous rounds was also reported at the bottom of each screen. Participant's final task was to indicate (after viewing the results) their desire (on a scale of 1-5) to work with their partner again (both clients and consultants did this). This second measure of satisfaction was collected after demand was realized and is therefore not independent of demand. In this measurement we expect that demand (random) and conformance toward estimate/recommendation to influence client and consultant willingness to work with their partner again. This concluded

one round. Subjects played the game for a total of 20 rounds. At the beginning of each round, participants were randomly re-matched with another participant of the opposite role.

Clients earned money in each round according to the outcomes of their decisions. Consultants earned money each round based on a combination of three things: (1) a fixed fee of \$50 for their service, (2) a penalty of \$100 if the client was unsatisfied with the consultant's recommendation, (3) the earnings the client would have received had they accepted the consultant's recommendation. This three part incentive scheme was designed to embody the incentive structure for consultants in the real world. Firstly, many consultants are paid a fixed fee for their service, independent of outcomes. In repeat games however, these outcomes matter and clients have an opportunity to fire consultants which may cost consultants goodwill or cause reputational damage. This cost is represented in the penalty that clients were allowed to assess. In our results clients recommended clients 64% of the time. We designed the study so that if a client flipped a coin to decide whether they were satisfied then the consultant fee and penalty would cancel each other out ($50 + (-100 * 0.5) = 0$). The final part incentivizes the consultant to give the correct answer, and not just what they think their client wants to hear. Consultants averaged \$104.60 per round while clients averaged \$91.17 per round. The primary reason for this is because clients recommended consultants more than 50% of the time. Additionally, consultants produced (on average) better recommendations than client's final decisions. At the end of the session earnings from each round of the game were converted to US dollars at the rate of \$125 laboratory dollars for \$1 US dollar. These earnings were added to participant's \$5 show-up fee and paid in cash as participants left the room.

3.2.4 Variables

Our primary dependent variables are those that relate to the consultant and client decisions. In our experiment clients are asked to provide an initial estimate, followed by a consultant's recommendation, and then the client's final decision. These three decision variables are the most important dependent variables in our study as they reflect a decision that was made by a participant. These variables are captured by the ordering decisions made by the parties (described above) and are continuous ratio variables. Another area of interest is client satisfaction and the client/consultant willingness to rehire their partner. Client satisfaction was captured with a binomial (yes/no) decision while willingness to rehire was captured on a 5 point Likert scale.

The primary independent variables in this study are the controlled experimental manipulations. We designed and tested three treatment manipulations which account for a 2x2x2 full factorial design: 1) *Client Training*, 2) *Client Interference*, 3) *Sharing* evaluations scores with the participant's partner (see Table 1 above). In addition to the treatments, certain dependent variables were used as independent variables in additional models. For example, the consultant's recommendation is a DV when considering the consultant's perspective, but it becomes an IV when considering the client's final decision. Similarly, the client's estimate and final decision can be IVs or DVs. Finally, the analysis requires a number of additional variables to control for variability in the model. These include demand for previous rounds, number of participants in the session, the round number (to model repeat data in the longitudinal model), and a nested variable which includes the grouping of the subjects, the experimental channel they played on, and the session.

4. Results

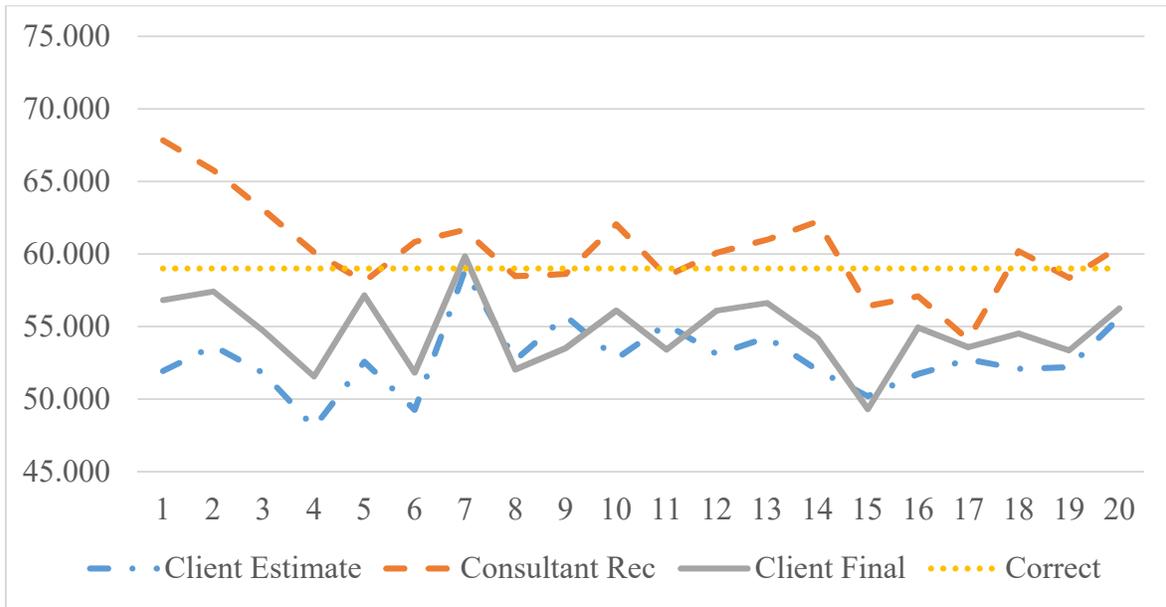
In this section we compare the decisions made by clients and consultants across treatments. This is done initially with Analysis of Variance (ANOVA) comparing the difference in mean decisions made by clients and consultants. Because this data was taken over 20 rounds it was necessary for us to average the decisions across the rounds to perform this analysis. By doing this, each subject had only one data point per variable associated with it (average decision across all rounds). This practice is common in these types of repeated experimental studies.

We followed up our initial analysis with a more thorough multi-level longitudinal model (also called Hierarchical Linear Modeling or HLM) where we are able to analyze all of the unique data points for each round across subjects and levels (groupings, rounds, and sessions)

4.1 General Trends and Descriptive Statistics

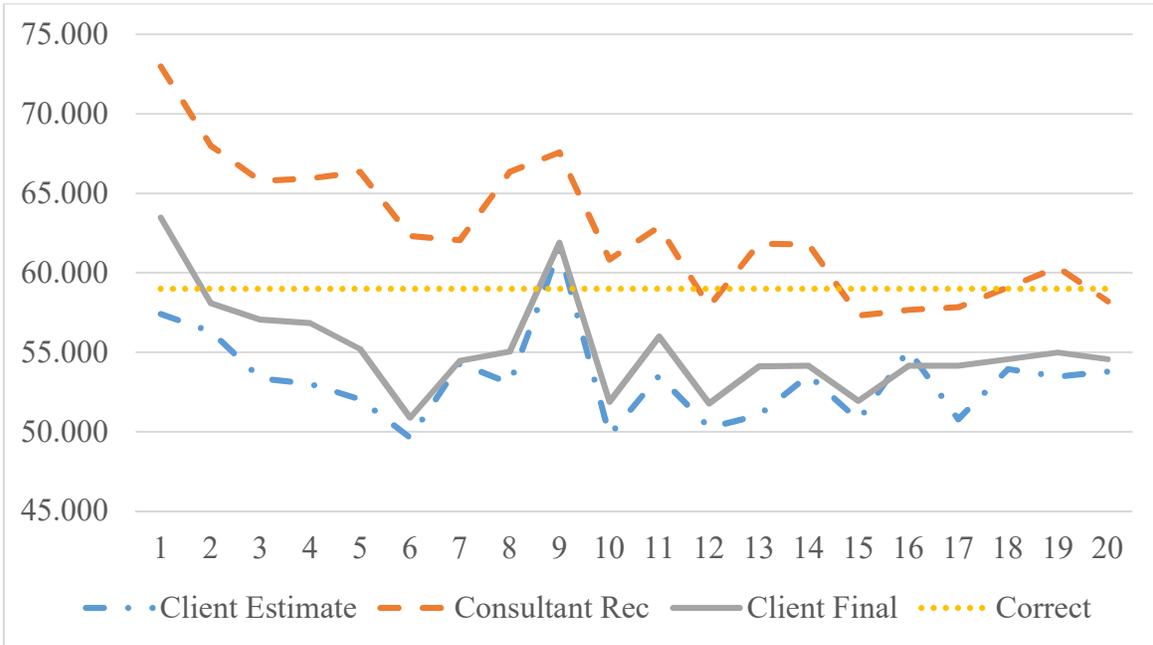
In the most basic analysis we are primarily interested in the effect of the treatments (Client Training and Client Interference) on the decisions made by the clients and consultants. We first plot these three primary DVs on the same graph and observe how they change over time. In the baseline condition with no training and no interference (n=38, 19 clients & 19 consultants), average consultant recommendations are always higher than client estimates and client final decisions (Figure 3.4). We also notice that the client final decisions appear to be much closer to their initial estimates than the consultant recommendation. This is interesting because in this case clients are not trained on the problem, but they appear to be anchored more strongly on their initial estimate than their consultant's recommendation (even though the consultant has been trained on the problem and is producing better answers).

Figure 3.4: Baseline Condition – No Training and No Interference (n = 38)



In Figure 3.5 we see the impact of interference when clients remain untrained but express their opinions to consultants. What is interesting here is that the gap between client and consultant actually widens. Consultants see client's estimates, and appear to not follow it, but decide in favor of providing their own unique recommendations. Another interesting note, is that the consultant recommendations are actually worse than in the no interference condition. Why would consultants provide worse recommendations in interference condition? One potential explanation is that a trained consultant who gets input from a client may believe that their only way they can add value is by giving a unique recommendation. For this reason, when clients do interfere it influences consultants to make more extreme (and often wrong) recommendations. In many cases the client would have received a better recommendation had they not interfered with their estimate.

Figure 3.5: Impact of Client Interference on Decisions (n = 38)



In Figures 3.6 and 3.7 we see the impact of training in the interference and no interference conditions. When clients are trained their decisions begin to look much more like consultants (as can be expected) because they now have the same tools to perform that the consultants do.

Figure 3.6: Trained Clients with No Interference (n = 42)

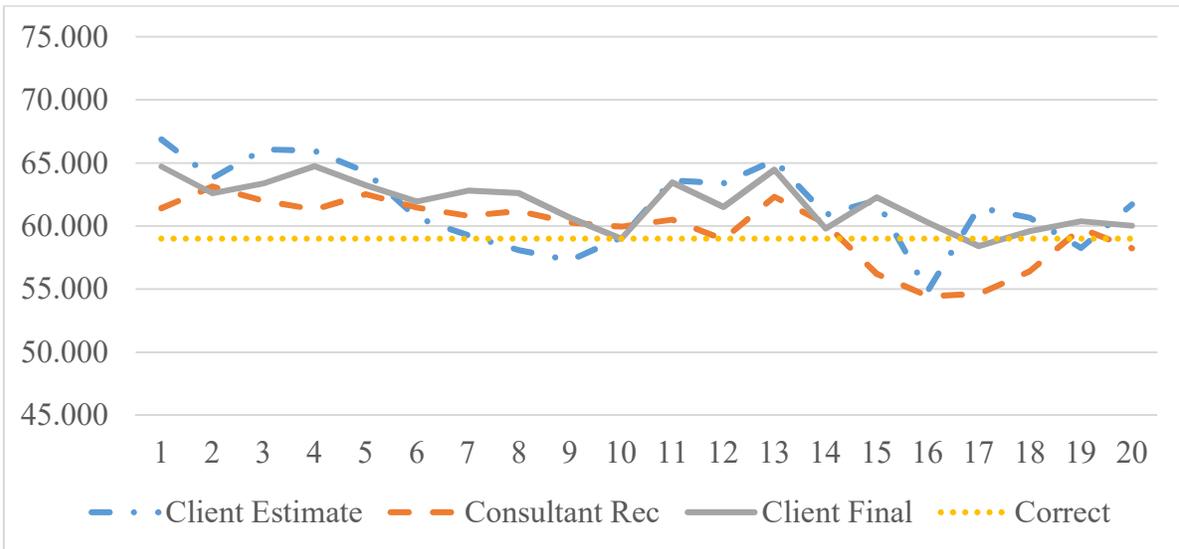
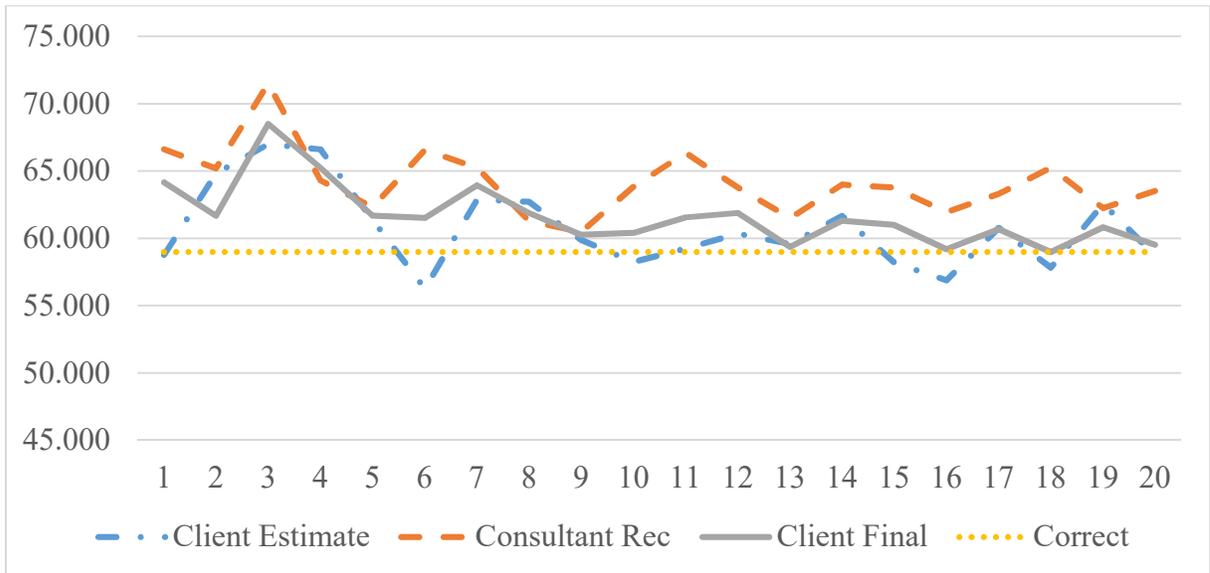


Figure 3.7: Trained Clients with Interference (n = 38)



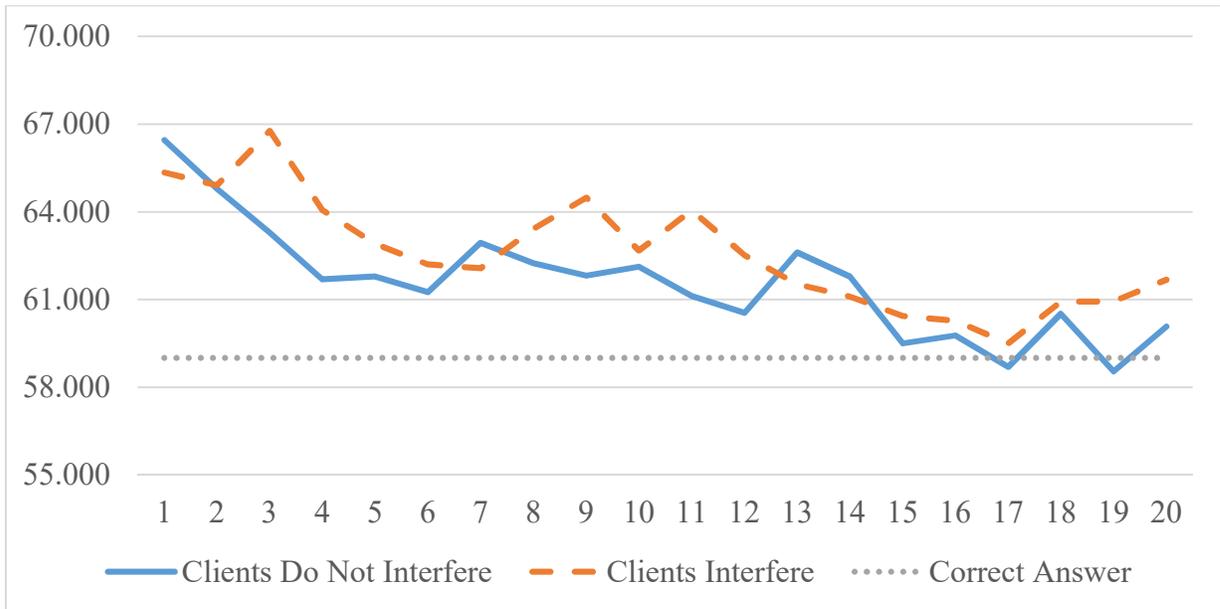
4.2 Consultant Decisions

In the second part of the analysis we focus on specific DVs of interest. In particular, we are interested in the consultant's recommendation and how it is influenced by the treatments (Client Training and Client Interference). Again, we begin this analysis with some simple charts and ANOVA, followed up with a longitudinal HLM model.

4.2.1 Training and Interference

Client training has no impact on consultant decisions. Intuitively this makes sense, why should a consultant change their recommendations based on whether or not the client is trained. In the interference condition (Figure 3.8) we notice that it appears that when clients interfere consultants actually make worse recommendations (higher) than when clients don't interfere (p-value 0.068).

Figure 3.8: Client Interference Impact on Consultant Recommendation (n = 78)



We hypothesized that when a consultant receives an estimate from a client, then their own recommendation will more closely resemble the estimate, than when they do not receive the estimate. In our data we see that the opposite is true. When consultants receive client estimates their recommendations are actually more different than client estimates, than when they did not receive client estimates. We believe this may be explained by a consultants desire to bring value to the relationship and they appear to be interpreting value as unique recommendations, not necessarily optimal recommendations.

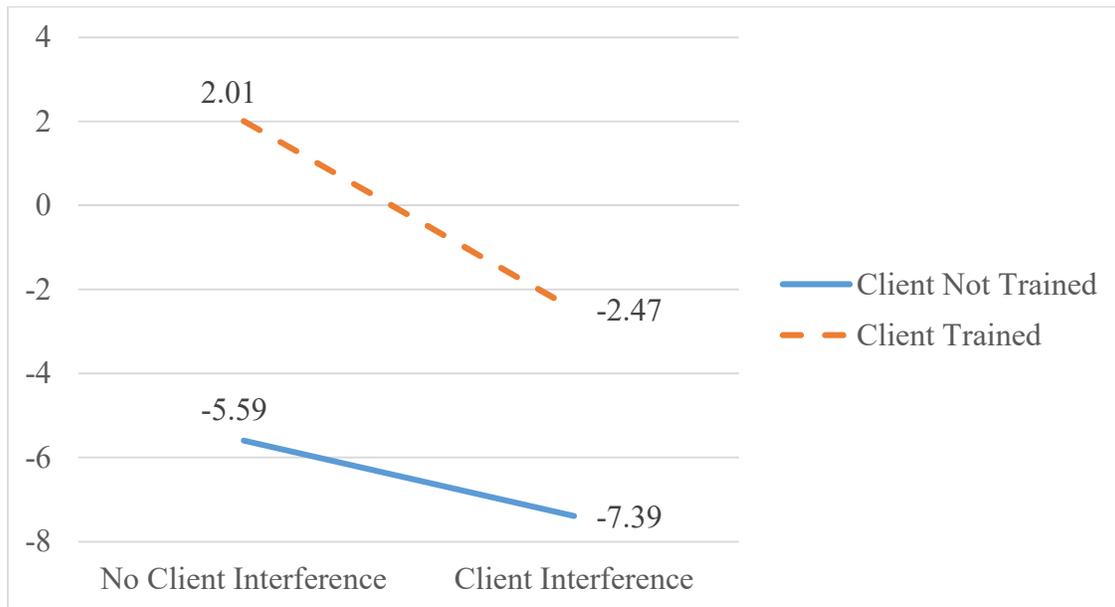
H1: Consultants who are given client estimates will more closely conform their recommendations to client's estimates than consultants who do not receive their client's estimates. (Rejected)

Decision making literature demonstrates that anchoring and inadequate adjustment takes place when subjects have difficulty moving away from an initial anchor point. We tested this by anchoring subjects playing the role of consultant with an initial estimate that was provided by the client. We hypothesized that in the condition where clients interfere with the process and provide an ordering estimate, the following consultant recommendation would more closely align with the client estimate, then in the condition where there was no interference. To measure this anchoring effect caused by the interference of clients we measured the average difference between the initial client estimate and the consultant recommendation over the twenty rounds (client estimate – consultant recommendation). Our results show a mean difference in the interference condition that is actually greater, than in the no interference condition ($n = 78$, p -value 0.067). The difference is driven by higher consultant estimates (60.01 no interaction vs. 63.41 interaction) as the client estimates are almost identical (57.47 no interaction vs. 57.03 interaction).

When considering the impact of training on the difference between client estimates and consultant recommendations we also see a significant main effect ($n = 78$, p -value < 0.01), but the cause is different. In this case consultant recommendations were almost identical (61.45 no training vs. 61.87 training) while client estimates were wildly different (53.08 no training vs. 61.23 training, table not shown). Finally, in Figure 3.9 below we demonstrate the interaction effect between client interference and client training on the difference between client estimates and consultant recommendations. When clients are trained there is a large difference between the interference and no interference conditions (4.46), but when the client is not trained, the difference in the interference and no interference condition shrink (1.8). This is quite interesting as a consultant appears to be unaffected by input from an untrained client, but is influenced by input from a trained client. They are not influence in the way that we expected however. Instead of

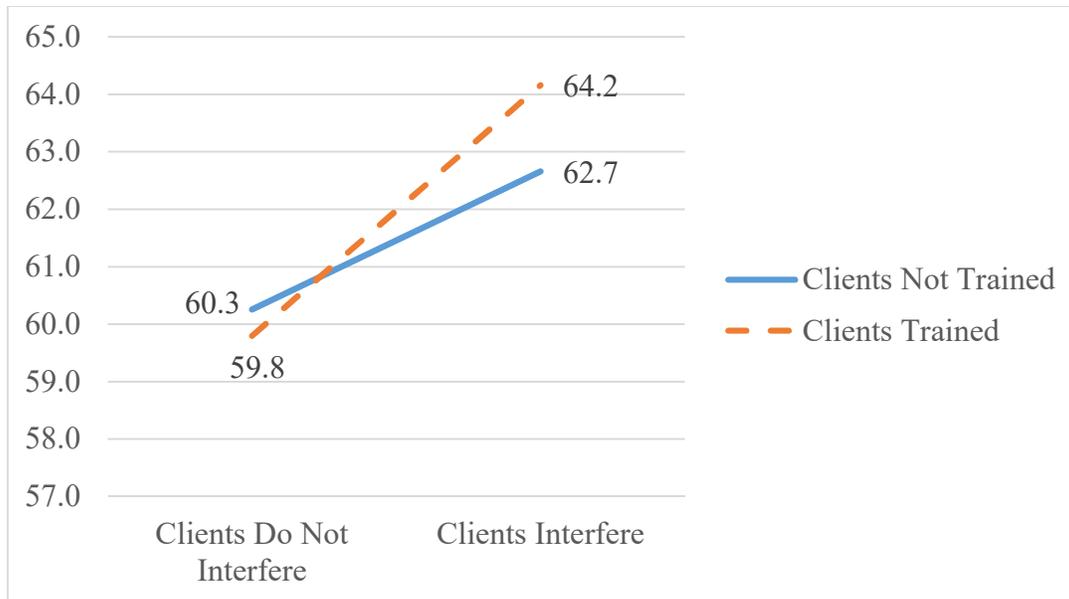
confirming to client estimates, consultants make more extreme recommendations when trained clients interfere and similar recommendations when untrained clients interfere.

Figure 3.9: Interaction of Client Interference and Client Training on Client Estimate - Consultant Recommendations (n = 78)



If we look specifically at consultant recommendation and not the difference in the client and consultant opinions we see the same trend. This one is not quite significant but with a relatively small sample it deserves a closer look (p-value = 0.136). When clients interfere it appears that consultants are more extreme with their recommendations, rather than simply going along with their clients estimates. This is potentially dangerous however if they solution they are recommending is worse than the one the client already had (which is what we saw in our data). In the no interference conditions consultants provide very good recommendations in both the trained and untrained client conditions. However, when clients interfere, consultants provide worse answers in the effort to be different from the client (Figure 3.10).

Figure 3.10: Interaction of Client Interference and Client Training on Consultant Recommendations (n = 78)



Our next area of interest is how consultant expertise impacts the client’s influence on consultants. In our experiment, we use the consultant’s evaluation score after training as a proxy for expertise. In our study it was important that the evaluation be designed carefully to create a spread in consultant expertise. Consultants who worked hard on the training to learn the task well should be rewarded with high evaluations scores. For this reason, we designed the training and evaluation so that it was neither too easy nor too hard. We achieved this as the final data for consultants produced a near uniform distribution of expertise scores: 27 scored 0, 17 scored 1, 18 scored 2, and 16 scored 3. This evaluation score then became a predictor of consultant decisions. We predict that consultants who score higher on the evaluation will be more confident in their own work and expertise and less susceptible to the client anchor.

H2: Consultants with little expertise are more likely to adopt client estimate, regardless of the quality of that estimate, than more expert consultants. (Supported)

Consultants with low expertise did make recommendations more closely aligned with client estimates than more expert consultants but the effect was not significant (p-value 0.207). While the difference in mean values is not significant, given the relatively small sample, and the visible trend, it warrants more investigation (Table 3.2).

Table 3.2: Difference in Client Estimate and Consultant Recommendation by Consultant Expertise (n = 78)

Consultant Expertise	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
.0	27	-1.3370	11.23954	2.16305	-5.7833	3.1092	-22.70	25.10
1.0	17	-7.6853	8.33638	2.02187	-11.9715	-3.3991	-22.80	4.60
2.0	18	-3.6306	13.20462	3.11236	-10.1971	2.9359	-22.50	28.55
3.0	16	-6.9906	9.77037	2.44259	-12.1969	-1.7844	-28.00	13.40
Total	78	-4.4096	11.01788	1.24753	-6.8938	-1.9255	-28.00	28.55

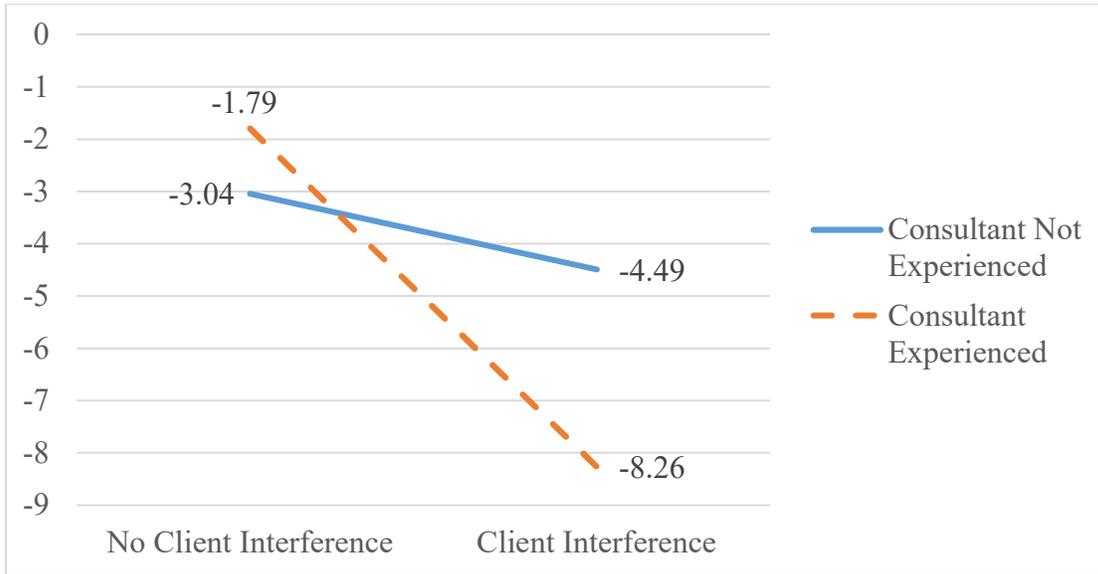
Client estimates were stable (56.91, 57.27, 57.73, 57.29) across the various levels of consultant expertise (as we may expect as they are independent), so the primary reason for the difference in their decisions is consultant behavior. Indeed, a closer look at a comparison between consultant recommendations and the optimal decision (Table 3.3) shows that consultants actually made worse decisions the more expert they were (p-value = 0.106).

Table 3.3: Difference in Consultant Recommendation and Optimal Solution by Consultant Expertise (n = 78)

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
.0	27	-.7481	10.17536	1.95825	-4.7734	3.2771	-20.70	18.30
1.0	17	5.9618	8.10441	1.96561	1.7949	10.1287	-4.35	19.00
2.0	18	2.3694	11.89523	2.80373	-3.5459	8.2848	-21.70	19.00
3.0	16	5.2813	8.05146	2.01286	.9909	9.5716	-5.80	19.00
Total	78	2.6705	10.02018	1.13456	.4113	4.9297	-21.70	19.00

Why would a more expert consultant give a worse recommendation to their client? We provide insight into this by investigating the interaction effect of consultant expertise and client interference on the DV: Client Estimate – Consultant Recommendation. In the Figure 3.11 below we see that when consultants have low levels of expertise (0-1 on the evaluation) they act pretty similarly regardless of client interference (slightly larger difference in client estimate and consultant recommendation in the interference condition). However, when consultants have high levels of expertise (2-3 on evaluation) they act very differently given the presence of client interference. When clients interfere with consultants with high expertise, the consultants respond with a recommendation that is very different (8.26) than the client estimate. Given that we have already established that clients make pretty good estimates, regardless of the consultant expertise, this difference of 8.26 represents a bad recommendation, which is surprising for consultants with high levels of expertise.

Figure 3.11: Interaction of Client Interference and Consultant Expertise on the Difference between Client Estimates and Consultant Recommendations (n = 78)



We believe that, similar to the situation before, the consultants with high expertise in an effort to add value are providing novel (but bad) recommendations. When they don't know their clients estimate, consultants with high expertise, on average, provide a very good recommendation (60.00). When expert consultants see their clients estimates however, they provide, on average, a very poor recommendation (65.18). This may be a result of an attempt to be seen as adding value by making recommendations that differ from their client's estimates, even when the client estimates are correct.

4.2.2 Results of Multi-Level Model

We follow up our initial ANOVA analysis with a more thorough examination using a HLM methodology. This methodology is similar to a regression model, but it allows for us to control for variance across different levels of the data (individual and group) as well as account for

repeated measures (decisions made over 20 rounds). Table 3.4 below reports the results from the HLM model across all treatments.

H3: Consultant expertise will moderate the relationship between client input and conformance to estimate.

Table 3.4: Growth Model Predicting Consultant Recommendation (n = 1560)

	Uncondition al Mean	Uncondition al Growth	Interfere & Training	Interact. Interfere & Training	Expertise	Demand & Client Estimate
	1	2	3	4	5	6
<i>Fixed Effects</i>						
Intercept	61.67 [1.13]***	65.4 [1.19]***	63.96 [2.03]***	63.73 [2.37]***	61.4 [2.75]***	50.5 [12.23]
Interference			3.88 [2.31]*	4.35 [3.32]	3.87 [2.36]*	3.66 [2.54]
Training			-0.88 [2.31]	-0.43 [3.24]	-0.37 [2.47]	-0.74 [2.50]
Interference* Training				-0.92 [4.64]		
Consultant Expertise					1.09 [1.01]	1.53 [1.02]
Client Expertise					0.51 [0.42]	0.41 [0.50]
Client Estimate						0.19 [0.02]***
Number of Participants						-0.38 [1.17]
Demand from Previous Round						0.03 [0.01]***
Demand from Two Rounds Previous						0 [0.01]
Demand from Test						0.02 [0.01]**
<i>Rate of Change</i>						

Round (1-20)		-0.36 [0.07]***	-0.36 [0.07]***	-0.36 [0.07]***	-0.36 [0.07]***	-0.23 [0.07]***
<i>Variance Components</i>						
Level 1						
Within-person	109.83 [4.03]***	95.76 [3.63]***	95.72 [3.63]***	95.7 [3.63]***	91.9 [3.56]***	81.37 [3.35]***
Level 2						
In initial status	94.91 [16.18]***	89.91 [16.95]***	88.61 [16.96]** *	89.99 [17.30]** *	88.73 [17.14]** *	87.29 [17.42]** *
In rate of change		0.25 [0.06]***	0.25 [0.06]***	0.25 [0.06]***	0.25 [0.06]***	0.2 [0.05]***
Group Nested in Session					4.75 [1.77]***	3.93 [1.64]**
<i>Model Fit</i>						
-2 Log-likelihood Deviance	11981.1	11861.75	11851.73	11846.78	11830.96	10510.42
AIC	11985.1	11867.75	11857.73	11852.78	11838.96	10520.42
BIC	11995.8	11883.80	11873.77	11868.83	11860.36	10546.62
DV: Consultant Recommendation. ***Significant at the $p < 0.01$ level, ** $p < 0.05$, * $p < 0.1$. Standard errors in brackets.						

Model 1 is the unconditional mean model and should always be the first model reported when modeling growth (Singer and Willett 2003). The unconditional mean model has no predictors, and reports the mean value of the data, before adding any controls or predictors. Similarly, Model 2 is the unconditional growth model where the only predictor is time. This shows the influence of time on the data. In our model time is modelled by round (1-20) and has a significant downward trend of time on consultant recommendations. Model 3 supports our findings from our ANOVA model where client interference is a significant predictor of consultant recommendations but client training is not. When clients interfere, this model predicts an increase in consultant recommendation of 3.88 units (which actually represents a bad recommendation). Model 4 shows an insignificant interaction effect of training and interference. Model 5 also supports our previous analysis and demonstrates that when client and consultant expertise are modelled, client interference is a significant predictor of consultant recommendations (interference causes the

recommendation to get worse). In the final model (Model 6) we add information on demand and the client estimates to the model. Here we see that client estimates and demand from the previous round are the overwhelming predictors of consultant recommendations. Consultants also relied on demand from their test trials to make their predictions. When we separate the models by treatment we are able to make more meaningful interpretations (Table 3.5).

Table 3.5: Growth Model Predicting Consultant Recommendation by Treatment (n = 1560)

	Client Interference Only (n = 760)	No Client Interference Only (n = 800)	Client Training Only (n = 800)	No Client Training Only (n = 760)
	7	8	9	10
<i>Fixed Effects</i>				
Intercept	57.14 [9.26]***	52.63 [9.49]***	42.7 [8.31]***	80.25 [16.02]***
Interference			5.14 [2.07]***	1.61 [1.91]
Training	0.17 [2.00]	-0.29 [2.25]		
Consultant Expertise	1.01 [0.56]*	1.18 [0.92]	1.15 [0.76]	1.41 [0.77]*
Client Expertise	1.05 [0.77]	0.04 [0.58]	0.83 [0.55]	-0.79 [1.00]
Client Estimate	0.34 [0.02]***	0.04 [0.02]*	0.19 [0.02]***	0.2 [0.02]***
Number of Participants	-1.51 [0.88]*	0.36 [0.90]	0.4 [0.73]	-2.97 [1.56]*
Demand from Previous Round	0.01 [0.01]	0.02 [0.01]*	0 [0.01]	0.03 [0.01]**
Demand from Two Rounds Previous	0 [0.01]	0 [0.01]	-0.01 [0.01]	0.01 [0.01]
Demand from Test	0.01 [0.01]	0.03 [0.01]**	0.02 [0.01]*	0.01 [0.01]
<i>Rate of Change</i>				
Round (1-20)	-0.28 [0.07]***	-0.19 [0.08]**	-0.18 [0.07]***	-0.32 [0.07]***
<i>Variance Components</i>				
Level 1				
Within-person	100.61	149.19	132.16	123.58

	[4.05]***	[6.04]***	[5.25]***	[4.98]***
Level 2				
In initial status	15.77	65.25	50.88	30.45
	[5.96]***	[13.69]***	[11.10]***	[8.60]***
In rate of change	0.08	0.09	0.07	0.08
	[0.03]**	[0.04]*	[0.04]*	[0.04]**
Group Nested in Session	3.84		0.57	6.3
	[2.93]		[2.05]	[3.62]*
<i>Model Fit</i>				
-2 Log-likelihood Deviance	10373.90	11493.17	11328.56	10667.76
AIC	10383.90	11503.17	11338.56	10677.76
BIC	10409.67	11529.49	11364.89	10703.83
DV: Consultant Recommendation. ***Significant at the $p < 0.01$ level, ** $p < 0.05$, * $p < 0.1$. Standard errors in brackets.				

Consultant expertise is a significant predictor of consultant recommendations only when there is client interference or when clients are not trained. In both cases consultants with more expertise produce higher recommendations (often a bad idea). Client estimates are very significant predictors of consultant's recommendations except when there is no interaction the significance is only mild. This is interesting because they are both trying to estimate the same thing so we would expect significance even when the estimates are not given to consultants. This tells us that consultants are using client estimates to make their recommendations. This is further supported by the evidence that when consultants did not have client estimates (no interference, model 8) they relied more heavily on the testing tool and demand from previous rounds. In contrast, when they did have client interference they did not rely on the test tool or demand from previous rounds.

Finally, by modeling our data with HLM we can confirm the interaction effects we suspected in the previous analysis (interference and consultant expertise, training and interference). When clients interfere, consultant expertise does influence their recommendations (more expert

consultants give higher recommendations). Also, when clients are trained, interference becomes a significant predictor of consultant recommendations.

The final thing we tested was the impact of consultant and client decisions on a consultant's desire to work with that client again. In this analysis the only reliable predictors were the consultant's profits and whether the client indicated they were satisfied with the consultant's recommendations (these two are strongly correlated with each other). As one could expect, when the consultants were recommended and they made money, they wanted to work with their clients again. Other things like their expertise, or the client settling on a decision consistent with their recommendation were not significant predictors of their desire to work with clients again.

4.3 Client Decisions

The other side of the coin in the client consultant engagement is the client. We were not only interested in how client decisions influenced consultants, but also, how early client decisions and consultant decisions, influenced subsequent client decisions. We used the same client interference and client training treatments in this analysis. Our primary dependent variable is the client's final decision. In later analysis we also investigate the client's decision to recommend consultants and rehire them.

H4: When clients are trained, they will make better decisions. (Not Supported)

4.3.1 Training and Interference

One perspective is that clients hire consultants to give them recommendations to problems they don't know how to solve. Another perspective is that they use consultants to confirm what they already know or suspect. We tested this by training half of our clients on the task and not training the other half. While client training did not affect consultant recommendations, it did influence

greatly client final decisions. When clients were not trained their final decisions on average were well below the optimal point, but when they were trained they were well above (p-value < 0.01). This indicates that even when clients are not trained they do not take the advice of their consultants because they are still well below the optimal level. Had they used their consultant recommendations more they would have made better decisions, but they were anchored on their initial estimates. The consultant recommendations helped them move in the right direction but it was an inadequate adjustment. After clients are trained their decisions reflect closely those of their clients. In our study client training however does not ensure better results, only different results (Figure 3.12). Trained clients were almost equally as far above the optimal solution as untrained clients were below it. Our other treatment of client interference does not impact client final decisions (p-value 0.48)

Figure 3.12: Impact of Client Training on Client Final Decisions (n = 78)



4.3.2 Results of Multi-Level Model

Similar to the consultant side, we constructed a longitudinal HLM model measure and control for client decisions over time. Table 3.6 presents these results in the same format as Table 3.4 above which reported the consultant perspective.

Table 3.6: Growth Model Predicting Client Final Decision (n = 1560)

	Uncond. Mean	Uncond. Growth	Interfere & Training	Interact. Interfere & Training	Expert.	Demand & Consult. Estimate
	11	12	13	14	15	16
<i>Fixed Effects</i>						
Intercept	58.45 [1.10]** *	60.63 [1.06]***	56.48 [1.67]***	56.12 [1.94]***	53.66 [3.63]** *	-3.63 [5.49]
Interference			0.85 [1.88]	1.57 [2.70]	1.24 [2.76]	0.21 [1.04]
Training			7.28 [1.88]***	7.97 [2.64]***	8.78 [2.94]** *	3.1 [1.28]**
Interference* Training				-1.4 [3.78]	-0.5 [3.97]	
Consultant Expertise					0.26 [0.84]	0.2 [0.42]
Client Expertise					0.92 [1.23]	0.61 [0.60]
Client Estimate						0.53 [0.01]***
Consultant Recommendation						0.29 [0.01]***
Number of Participants						1 [0.48]**
Demand from Previous Round						0.01 [0.01]*
Demand from Two Rounds Previous						0.01 [0.01]**
Demand from Test						0 [0.01]
<i>Rate of Change</i>						

Round (1-20)		-0.21 [0.07]***	-0.21 [0.07]***	-0.21 [0.07]***	-0.21 [0.07]** *	-0.02 [0.04]
<i>Variance Components</i>						
Level 1						
Within-person	109.25 [4.01]** *	99.94 [3.78]***	99.93 [3.78]***	99.92 [3.78]***	99.95 [3.79]** *	38.19 [1.52]***
Level 2						
In initial status	75.85 [13.11]* **	65.91 [12.98]** *	54.15 [11.23]***	54.96 [11.44]	29.89 [11.81]* **	7.11 [3.03]**
In rate of change		0.2 [0.05]***	0.2 [0.05]***	0.2 [0.05]***	0.2 [0.05]** *	0.02 [0.01]*
Group Nested in Session					++ ++	++ ++
<i>Model Fit</i>						
-2 Log-likelihood						
Deviance	11956.9	11893.1	11872.7	11868.1	11863.7	9306.2
AIC	11960.9	11899.1	11878.7	11874.1	11871.7	9316.2
BIC	11971.6	11915.2	11894.8	11890.2	11893.1	9342.4

DV: Client Final Decision. ***Significant at the $p < 0.01$ level, ** $p < 0.05$, * $p < 0.1$. Standard errors in brackets. ++ Nested variable (group within session) included in the model but coefficient values not shown here to conserve on space (significant).

In Table 3.6 above we see a significant effect of training on client final decisions across every model. Client interference is not significant however in any of the models and the interaction of training and interference is not significant. Some of our original thoughts were that when a client tells a consultant their estimate they will have increased expectation that the consultant will confirm that estimate, then the client will make their final decision based on that confirmation. We do not see this however. Client interference, has no significant role in the client's final decision.

When we included demand and consultant recommendation we see that clients were very aware of demand from previous rounds and it was a predictor of their decisions (even though they were told that demand was random). Client estimates and consultant recommendations were also

a significant predictors of client final decisions however it appears that clients relied more heavily on their own estimates than the consultant's recommendation as evidenced by a coefficient of 0.53 vs. 0.29. We also divided this model into four separate models each representing a treatment (similar to Table 3.5 above) and discovered that client estimates and consultant recommendations continue to be the strongest predictors of client final decisions. Furthermore, the client estimate is a stronger predictor in every case. One interesting point is that in the untrained client condition the client estimate was an even stronger predictor than any other condition (0.66 coefficient vs. 0.25 for consultant recommendation, both very significant). It is also the condition where client relied most heavily on demand information from previous rounds. This data seems to show that when clients are untrained and had an opportunity to learn from their trained consultants, they did not take the opportunity and relied instead on their own estimates and demand information, demonstrating the strength of the estimate anchor. When clients are untrained they seem distrustful the advice they are getting from their trained clients and prefer to trust themselves, even though they do not know how to solve the problem.

H5: When a client shares their estimate (interference condition), client satisfaction will increase as consultant recommendations conform to client estimates, regardless of whether the estimate was good or bad. (Not Supported)

When clients share their estimates with their clients it follows that they will likely develop some expectation that the estimate will be considered by the consultant, and if good, confirmed. Table 3.7 presents the results of the HLM model which predicts client satisfaction.

Table 3.7: Growth Model Predicting Client Satisfaction (n = 1560)

	All Treatments (n = 1560)	Client Interference Only (n = 760)	No Client Interference Only (n = 800)	Client Training Only (n = 800)	No Client Training Only (n = 760)
	17	18	19	20	21
<i>Fixed Effects</i>					
Intercept	0.567 [0.347]*	1.354 [0.491]***	0.514 [0.488]	0.897 [0.374]**	-0.09 [0.859]
Interference	0.125 [0.066]*			-0.005 [0.094]	0.27 [0.100]***
Training	0.59 [0.081]	-0.146 [0.116]	0.161 [0.117]		
Consultant Expertise	-0.022 [0.027]	-0.032 [0.030]	0.005 [0.044]	0.007 [0.033]	-0.076 [0.045]*
Client Expertise	0.016 [0.038]	-0.025 [0.050]	0.006 [0.059]	-0.181 [0.046]	-0.022 [0.077]
Client Estimate - Consultant Rec.	-0.005 [0.001]***	-0.004 [0.002]**	-0.004 [0.001]***	-0.003 [0.001]**	-0.004 [0.002]**
Client Final - Consultant Rec.	0.009 [0.002]***	0.011 [0.003]***	0.007 [0.002]***	0.005 [0.002]***	0.011 [0.003]***
Number of Participants	-0.001 [0.030]	-0.053 [0.045]	-0.01 [0.043]	-0.024 [0.031]	0.07 [0.081]
Demand from Previous Round	0.001 [0.000]**	0.001 [0.001]	0.001 [0.001]*	0 [0.001]	0.001 [0.001]**
Demand from Two Rounds Previous	0 [0.000]	0 [0.000]	0 [0.001]	0 [0.001]	0.001 [0.001]
Demand from Test	0 [0.000]	0 [0.000]	0.001 [0.001]	0 [0.001]	0 [0.001]
Correct Estimate	0.04 [0.039]	0.145 [0.055]***	-0.58 [0.052]	0.004 [0.050]	0.068 [0.060]
Correct Recommendation	0.082 [0.030]***	0.08 [0.045]*	0.068 [0.041]*	0.209 [0.045]***	-0.007 [0.041]
<i>Rate of Change</i>					
Round (1-20)	-0.001 [0.003]	-0.006 [0.004]	0.003 [0.003]	0 [0.004]	-0.003 [0.003]
<i>Variance Components</i>					
Level 1					
Within-person	0.154 [0.006]***	0.149 [0.008]***	0.156 [0.009]***	0.153 [0.009]***	0.151 [0.009]***

Level 2					
In initial status	0.009 [0.012]	0 [0.010]	0.005 [0.24]	0.001 [0.016]	0.018 [0.019]
In rate of change (Round)	0 [0.000]***	0 [0.000]***	0 [0.000]	0 [0.000]**	0 [0.000]
<i>Model Fit</i>					
-2 Log-likelihood Deviance	1644.66	816.94	888.64	878.05	826.40
AIC	1654.66	826.94	898.64	888.05	836.40
BIC	1680.84	849.48	921.45	910.86	858.94

DV: Client Satisfied with Recommendation. ***Significant at the $p < 0.01$ level, ** $p < 0.05$, * $p < 0.1$. Standard errors in brackets. Nested variable (group within session) included in the model but coefficient values not shown here to conserve on space (significant).

Considering all the treatments together (Model 17), interference is a mildly significant predictor of client satisfaction. When clients did interfere, there was a greater probability that the client would be satisfied. We also see in model 17 that the correctness of the consultant's recommendation and its distance to the client's estimate and final decision were significant predictors of satisfaction. By dividing the data into the treatments we notice that the consultant being correct in their recommendation is a significant predictor in every treatment except when clients are untrained. When clients are untrained (Model 21), the consultant's expertise is a more valid predictor (negative) of client satisfaction. As consultant expertise goes up, client satisfaction goes down. This is likely because of what we observed in the previous analysis where consultant recommendations deviate more from client estimates when consultants are more expert.

H6: Clients will be more likely to rehire consultants who confirm to their own opinion in positive outcomes, but less satisfied with conforming consultants in negative outcomes.

In our simulation, we asked clients and consultants to express (on a scale of 1-5) their desire to work with their partner again after showing them the results of their decisions. We suspected

that most of the decision would be based on the profit they realized. We hoped that clients would be able to look past the outcome and assess the entire engagement when deciding to work with their partner again. The results of this analysis are included below in Table 3.8.

Table 3.8: Growth Model Predicting Client Decision to Rehire Consultant (n = 1560)

	Clients Lose Money (n = 467)	Clients Make Money (n = 1093)
	22	23
<i>Fixed Effects</i>		
Intercept	-1.379 [1.339]	2.001 [1.041]*
Interference	0.464 [0.254]*	0.099 [0.196]
Training	0.898 [0.312]***	-0.442 [0.244]*
Consultant Expertise	0.038 [0.101]	-0.066 [0.079]
Client Expertise	0.467 [0.146]***	-0.217 [0.114]*
Client Estimate - Consultant Rec.	-0.005 [0.001]***	0.003 [0.004]
Client Final - Consultant Rec.	0.009 [0.002]***	-0.012 [0.006]*
Number of Participants	0.085 [0.115]	-0.035 [0.090]
Demand from Previous Round	0.001 [0.002]	0.001 [0.001]
Demand from Two Rounds Previous	-0.002 [0.002]	-0.001 [0.001]
Demand from Test	-0.004 [0.002]*	0.001 [0.001]
Correct Estimate	0.075 [0.204]	0.139 [0.142]
Correct Recommendation	0.468 [0.166]***	0.263 [0.113]***
Client Satisfied with Rec.	0.723 [0.1137]***	1.326 [0.100]***
Profit	0.002 [0.001]***	0.005 [0.000]***

<i>Rate of Change</i>		
Round (1-20)	0.006 [0.012]	0.004 [0.009]
<i>Variance Components</i>		
Level 1		
Within-person	1.174 [0.093]***	1.47 [0.072]***
Level 2		
In initial status	0.261 [0.207]	0.25 [0.110]**
In rate of change (Round)	0.002 [0.001]*	0.001 [0.001]**
<i>Model Fit</i>		
-2 Log-likelihood Deviance	1487.36	3371.15
AIC	1497.36	3381.15
BIC	1517.47	3405.48

DV: Client Rehire Consultant. ***Significant at the $p < 0.01$ level, ** $p < 0.05$, * $p < 0.1$. Standard errors in brackets. Nested variable (group within session) included in the model but coefficient values not shown here to conserve on space (significant).

When clients lose money interference is positive correlated with the client rehire decision. In other words in outcomes where the client loses money and the client interferes, and a consultant follows it (difference in estimate and recommendation also significant) the client does not hold that against the consultant when making the rehire decision. When clients make money however, interference is not significant. Additionally, the distance between the client estimate and consultant recommendation is not significant when making money, but it is significant when clients lose money. Another interesting trend is that when clients lose money client expertise is a strong positive predictor of rehire. Another way of saying this is that, as client expertise goes up, they are more likely to rehire consultants, even when they lose money. This seems to suggest that the client takes ownership of bad decisions when they are more expert and are less likely to blame the consultant. However, when clients make money, client expertise is a negative predictor of consultant rehire. Working with an expert client appears to be a two edge sword, when things go

poorly they don't blame their consultants, but when things go well, they don't credit their consultants either.

5. Discussion

In this study we conducted a behavioral experiment where we measured and tested the influence that consultant and client decisions have on each other. We were primarily interested in the impact of client interference and client training on the recommendations consultants make and the subsequent client decisions. We found that when consultants are expert, they are less likely to simply go along with client estimates when they are provided. In fact, they make recommendations that are even more different than when they don't see the client estimates. Expert consultants do this even when the initial client estimates are good and their subsequent recommendations are bad. This behavior leads to lower client satisfaction as consultant expertise goes up. We believe that the expert clients engage in this behavior in an effort to add value. They likely believe that simply confirming a client estimate does not add value, when in reality, if the client estimate is right, then confirming it would be appropriate. Non-expert consultants, however do confirm client opinions and do so with more frequency, which in this context lead to better outcomes.

From a client perspective, client training made a major impact on client decisions but not quite as we expected it. Trained clients made estimates and final decisions that were similar to the consultants (as we would expect). Untrained clients however made estimates that were significantly lower than optimal. Additionally, even though they knew they were untrained they were reluctant to adjust their baseline anchors adequately once seeing the consultant's recommendation. This supports other work on anchoring and insufficient adjustment bias because the clients were more influence by their own novice estimate than they were their consultants trained opinion. Knowing that their consultants where trained and they were not, they still erred

way towards their own estimates and relied more on previous demand and test demand (both irrelevant to the problem) than they did their consultants' recommendations. This both supports the power of a strong anchor and suggests there may have been an issue of trust between clients and consultants.

Finally, the more expert a client was the more likely they were to accept responsibility for negative outcomes, but also take credit for positive outcomes. This creates a catch-22 for a consultant. Should a consultant prefer to work with a novice client where they are more likely to get credit and also blame, or an expert client where they are unlikely to get either? Perhaps it would depend on the type of engagement and the risk involved. In situations where risk of a negative outcome is high, a consultant may want to be certain that their client has competence in the area. Alternatively, when positive outcomes are more likely a consultant may get more utility out of working for a novice client.

3.1 Limitations

This is an experimental study conducted in a laboratory setting with students from Cornell University and is therefore subject to a class of limitations that all experimental studies must endure. The primary limitation of this work is the generalizability of a study conducted in a lab with students. While this is valid, laboratory studies do allow for a certain amount of control that is not possible in any other design (internal validity). For this reason we decided to present this study with this method. Additionally, Bolton Ockenfels and Thonemann 2012 demonstrated that students trained to perform newsvendor problems came up with solutions that closely mirrored those that were given by experienced managers working in industry.

3.2 Managerial Applications

Professional service providers have the difficult task (as this research demonstrates) to work on behalf of their clients and in their own best interests. This is complicated by the fact that it is sometimes difficult to know what is in the client's best interest. Is it to maximize profits or leverage a relationship? People are influenced by confirmation bias (i.e. they make a snap judgement and seek to support that judgement). Advisers, similarly, are influenced by the introduction of alternatives that may not necessarily lead to a good solution (client opinion). It appears from our result that inexperienced consultants conform to the client anchor while expert consultants reject it and seek novel recommendations. This behavior is exhibited by consultants, even in situations where it leads to negative outcomes to them and their clients.

This begs the question why are consultants recommending alternatives that lead to inferior outcomes? We can think of at least two potential explanations. First, it could be that their goal is not to maximize profit. It could be that clients get a certain amount of utility from co-producing and having their opinions heard. Advisers may be facilitating this by allowing their clients to 'be right' or including their opinion when offering recommendations, even when the opinion is wrong. A second explanation could be that consultants (especially expert consultants) feel pressure to provide novel recommendations to their clients, even when their client's opinion is correct. If this is the case we need to design a process where consultants are freer to express their recommendations objectively to clients without fear of clients devaluing that recommendation. One potential way to do this would be to hire advisers with the express purpose of acting as 'devil's advocates'. This way they would be free to give their expert advice without concern for agreeing or disagreeing with their clients.

Professionals working as consultants in various industries can use this research to improve their client relationships and business outcomes. Generally, consultants that engender a collaborative culture and work in their clients' best interest will find greater success in both outcomes and client satisfaction. They can do this by branding their consultants as advisors or mentors. They must be cautioned however. At times consultants must be courageous enough to tell their clients that they are wrong. This is consistent with working in the best interest of your clients but consultants who are trained as 'advisors' may find it difficult. Consultants who are trained as non-partial 3rd party consultants or even devil's advocates may be more prepared to make these recommendations. A firm may benefit from both scenarios if they cross train their consultants or if they assign different consultants to different types of projects depending on the specific client need.

3.3 Future Research

After testing the decision process between consultants/clients experimentally I hope to collect field data that will increase the support for my claims in this project. This data may be available in a health care setting where doctors are the advisers (consultants) and patients are the clients. In this case I could take a previous diagnosis as a proxy for an initial opinion (similar to client's opinion in my study) and test the likelihood that that initial diagnosis is overturned vs. supported. What are the conditions in which it is overturned? When is it supported? Getting data from the field would be a strong support to any of my claims.

Another area of future research is to investigate the impact that sharing evaluation scores (level of expertise) has on client and consultant decisions. We have already collected this data but we have not analyzed it in this paper in an effort to simplify our message. This is a natural and easy extension.

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CHAPTER 4: HOW ENVIRONMENTAL CERTIFICATION CAN AFFECT PERFORMANCE IN A SERVICE INDUSTRY: EVIDENCE FROM THE ADOPTION OF LEED STANDARDS IN THE US HOTEL INDUSTRY

Abstract

The Leadership in Energy and Environmental Design (LEED) certification has gained increased acceptance in building design and construction ever since its introduction in 2000. LEED is increasingly recognized and promoted by designers, government agencies, special interest groups, and commercial developers. However, little research has examined how LEED certification can affect the financial performance of the adopting firm. We investigate how the adoption of LEED certification can affect financial performance in the hospitality industry. We start with an event study approach (Corbett, Montes-Sancho, & Kirsch, 2005; Swink & Jacobs, 2012), where we match LEED certified hotels with their uncertified peer hotels and then use a difference-in-differences analysis. Our results indicate that LEED certified hotels outperform their uncertified counterparts. Then we use a multi-level longitudinal model (Singer & Willett, 2003), which confirms that LEED certifications is a significant contributor even after accounting for the newness of the LEED certified hotels.

1. Introduction

Buildings have a significant impact on the environment. In the United States, buildings account for 37% of the primary energy use, 68% of all electricity use, 40% of non-industrial solid waste, 12% of potable water use, 35% of carbon dioxide emissions, and 49% of sulfur dioxide emissions (Howard 2003). “Green building” evolved as a means to reduce this negative environmental impact throughout the complete building life cycle. The United States Green Building Council (USGBC) was founded in 1993 as a nonprofit organization that seeks “to transform the way buildings and communities are designed, built and operated, enabling an environmentally and

socially responsible, healthy, and prosperous environment that improves the quality of life.” The USGBC constituted a broad based committee including architects, realtors, owners, lawyers, environmentalists, and industry representatives to develop the LEED (Leadership in Energy and Environmental Design) green building rating system, which was launched in 1998 and which facilitates design, construction, and operation of high performance green buildings. Ever since the launch of the LEED green building rating system, it has gained increased acceptance. As of 2015, over 76,000 projects have been registered and certified to the LEED rating system.

Along with the growing acceptance of the LEED green building rating system, several studies have sought to investigate the benefits provided by this rating system. Two broad approaches have been adopted to assess the potential benefits. In the first approach, several studies have compared the performance of buildings with LEED certification to some baseline performance such as the performance they would have obtained without certification or the performance of some industry average. The general consensus which emerges from this approach is that adoption of the LEED green building rating system is beneficial as it lowers operational costs and improves productivity (e.g., Fowler and Rauch 2008, Kats 2003). In the second approach, several studies have sought to contrast the performance of buildings with LEED certification with comparable buildings without LEED certification. Using this approach, scholars have found mixed evidence on the benefits obtained from green buildings. On the one hand, several studies have shown that certification to the LEED rating system leads to higher market assessment of the buildings (Dermisi 2009), to higher commercial rents (Eichholtz et al. 2009), and reduces costs associated with regular operations (Miller et al. 2008). On the other hand, several studies have also shown that the certification to LEED rating system does not provide higher market assessment (Fuerst and McAllister 2011), nor additional energy savings (Scofield 2009), nor higher rents (Eichholtz et al.

2010). One potential explanation for the mixed evidence could be that the comparisons in the literature have been mainly been restricted to snapshots of performance. For example, a LEED certified building may obtain higher rental price as compared to a comparable building immediately. However, over time because of various modifications and changes to the comparable buildings the difference in rental prices may erode. This is mainly because the literature has not been able to track the performance of LEED certified buildings and non-certified comparable buildings consistently over time. This study uses data from the hotel industry which overcomes these challenges. An additional advantage of using data from the hotel industry is that buildings play an important role in determining competitive outcomes in this industry.

To overcome the challenge of measuring financial performance of LEED certified buildings over time; in this study we implement a mixed methods approach. Our first goal is to establish that there is a difference in performance between LEED certified hotels and their competitors. We use a traditional event study methodology often referred in economics as the difference-in-difference approach (Swink & Jacobs, 2012) to answer this question. We demonstrate abnormal financial improvements of LEED certified hotels relative to a matched set of their non-certified peers. While effective at demonstrating abnormal performance, this form of event study analysis does not adequately answer the question of why these hotels outperform their peers. To examine effectively the question of why LEED Hotels outperform their non-certified peers over time we implement longitudinal multilevel modeling—also referred to as Hierarchical Linear Modeling (HLM) or Random Coefficient Modeling (RCM). Multilevel modeling has become a staple in research in management because of its usefulness in controlling for variance across both individuals and groups (Whitener, E. M., 2001; Seibert, S. E., Silver, S. R., & Randolph, W. A., 2004; Zohar, D., & Luria, G., 2005; Liu, et al., 2012). In operations this modeling capability is

rarely required (a few notable exceptions include: Chesteen, et.al., 2005; Naveh & Marcus, 2005; Azadegan, & Dooley, 2010; Lo, et.al., 2013; Liu, et.al., 2014). To our knowledge this is the first study to in the operations management literature to integrate these two methods to measure abnormal performance over time.

Our results suggest that, in general, hotels benefit from LEED certification. However, the advantage obtained from LEED certification is transient. LEED hotels tend to start in a disadvantaged position, quickly catch up and pass their competitors, then level off about two years after certification. There is no significant difference between LEED certified hotels and non-certified hotels two year after certification. Moreover, our analysis reveals that the superiority of LEED certified hotels can be attributed to two factors. First, LEED certified hotels obtain a significant improvement in average room occupancy rates subsequent to certification as compared to non-certified hotels. Second, LEED certified hotels realize higher average revenues per available rooms as compared to non-certified hotels. These results suggest that LEED certification not only increase the number of customers but also enables hotels to realize higher prices from customers for each room. However, we also observe that the higher occupancy rates and revenues for each available room get eroded after a period of two years. Additionally, while LEED certification is an important contributor to abnormal financial performance, the newness of a hotel is a much greater predictor. In this study we separate these two very important and highly correlated predictors.

This paper makes at least three important contributions to the literature. First, we establish the benefits of LEED certification in the hotel industry and show that the competitive benefits are transient in nature. Thus, our results provide one potential explanation for the mixed evidence on the benefits of LEED certification that has been observed in the prior literature. Second, we are

able to identify how the improvement in performance is driven by increases in the number of customers and average realization per customer. Thus, we are able to demonstrate how LEED certification can help in improving competitive positions. Finally, we make a methodological contribution to the operations management literature by integrating a classic event study with a longitudinal multilevel model, a new area of research in the OM literature.

The rest of the paper is organized as follows. In section 2, we discuss the relevant literature. In section 3, we present our hypotheses. In section 4, we describe the data and the measures used in our analysis. Section 5 discusses our methodology and in section 6 we present results. Finally, in section 7 we discuss the implications of our findings and the limitations of our analysis.

2. Literature

2.1 Impact of Certification on Performance in OM Literature

The investigation of certification programs on firm performance has become an important topic in the operations management literature. One area of particular importance to OM scholars is the impact of quality certifications like ISO 9000, ISO 14001, Six Sigma, and Lean. For example, ISO 9000 has been a particularly hot topic as a context for the investigation of certifications impact on performance. In a recent study, Gray, Anand, & Roth classify the work done in this area by the type of performance assessed and the research design (Gray, Anand, & Roth, 2015). They identify the type performances as either process compliance/quality (Singh et al., 2011; Naveh and Erez, 2004) or other (Martinez-Costa et al, 2009; Terziovski et al, 1997). Their classifications for research design are cross-sectional (Bernardo et al, 2012; Nair and Prajogo, 2009; Singh, 2008) and longitudinal (Iyer et al, 2013; Yeung et al, 2011; Levine and Toffel, 2010). For a more detailed

description of the impact of each of these findings on the field we recommend a closer examination of their work, which we will not attempt to replicate here (Gray, Anand, & Roth, 2015).

Other types of certification that have gotten attention in the OM literature are Six Sigma, Lean, and TQM. These studies similarly focus on adoptions impact on performance (Six Sigma: Swink and Jacobs, 2012; Zu et al, 2008; Gutierrez et al, 2009; Braunscheidel et al, 2011; Lean: Shah and Ward, 2003; Shah and Ward, 2007; Ward and Zhou, 2006; TQM: Martinez-Costa et al, 2009). A good summary of some of the early work done on quality management practices and firm performance is Anand Nair's the meta-analysis (Nair, 2006).

2.2 Environmental Sustainability and Certification

Environmental certification is an increasingly more important topic as environmental sustainability has become a social, political, and corporate agenda. As a result, we have seen many studies in the past several years that attempt to quantify the impact of environmental certifications on performance (Konar & Cohen, 2001; Repetto & Austin, 2000; Dwyer, et al. 2009). LEED is one such certification whose effects have been debated by scholars. Since its creation in 2000, the impact of LEED certification on financial performance has been a fertile area of research (Kok, McGraw, and Quigley, 2011; Eicholtz, Kok, & Quigley, 2009; Dermisi, 2009). Most of the work in this area has followed one of two broad approaches. The first approach is to compare the performance of a LEED certified building to a baseline such as an industry average or an estimate of a non-certified equivalent. These studies often include case studies, and many conclude that adoption lowers operational costs and improves productivity (Fowler and Rauch, 2008; Kats, 2003; Von Paumgarten, 2003). The second approach compares performance of a LEED building with a comparable non-certified building or set of comparable buildings. Using this approach,

scholars have found mixed evidence on the benefits obtained from green buildings. On the one hand, several studies have shown that certification to the LEED green building rating system leads to higher market assessment of the buildings (Dermisi 2009), to higher commercial rents (Eichholtz et al. 2009), and reduces costs associated with regular operations (Miller et al. 2008). On the other hand, several studies have also shown that the certification to LEED green building rating system does not provide higher market assessment (Fuerst and McAllister, 2011), nor additional energy savings (Scofield, 2009), nor higher rents (Eichholtz et al., 2010).

In either case, most of the work done in this area has posed the LEED certification question in terms of reducing operational costs (Newsham, G. R., Mancini, S., & Birt, B. J., 2009; Scofield, J. H., 2009; Kneifel, 2010) or analyzing investment trends (Fuerst, F., 2009; Jacobs, Singhal, & Subramanian, 2010). Very few studies have attempted to address this question from the perspective of how LEED impacts the revenue side of the financial equation (a few noteworthy exceptions include: Eichholtz et al., 2009; Fuerst & McAllister, 2009).

2.3 Hospitality Industry

The accessibility of performance data makes the hospitality industry an ideal setting for investigating the effects of certification on performance, but scholars have been slow to take up the call. The available scholarly work in hospitality has been primarily descriptive in nature (Buckley, 2002; Font, 2002; Font & Harris, 2004) rather than predictive. The predictive work has come through technical reports written to a practicing audience (Chong & Verma, 2013; Zhang, et.al., 2014; Peiro-Signes, Verma, and Mondejar-Jimenez, 2014; Walsman, Verma & Muthulingam, 2014; Bruns-Smith, et al., 2015). This signals an opportunity for academics to do rigorous predictive work in the hospitality industry.

Similar to academic researchers, the hospitality industry has been slow to adopt LEED. While the LEED certification program started in 2000, the first hotel was not certified until 2004. It was not until 2007 that certification began to trend in an increasingly positive direction. This trend continued as the number of certified hotels grew annually until 2010 when—in the wake of the global economic recession—the number of certified hotels took a step backward (Table 4.1). One simple explanation for this reversed trend is that the number of all new hotels in the economic pipeline was dramatically slashed almost overnight. Because LEED certification correlates highly with new hotels, it is natural that the number of certifying hotels would decrease dramatically. If LEED certified hotels do outperform their non-certified counterparts however, we should expect to see firms pursuing certification even during periods of economic trouble (Fuerst, F., 2009).

Table 4.1: LEED certification by year and level

Year	N	Certified	Gold	Silver	Platinum
2007	3	1	1	1	0
2008	7	0	2	4	1
2009	20	4	10	6	0
2010	29	6	13	10	0
2011	25	3	9	12	1
2012	18	4	6	8	0
Missing	6	1	2	2	1
	108	19	43	43	3

Despite the uncertainty surrounding payback some hoteliers have championed LEED. Marriott for example began a ‘LEED Volume Program’ which allows them to pre-certify prototypes. This facilitates the certification process for interested owners, but only for their more standardized mid-class and upper mid-class hotel brands. We spoke with an executive at Marriott about this program who said that the luxury brands—which tend to be more interested in LEED—are almost always custom designs and therefore cannot be certified under the volume program. Without the interest

of mid class and upper-mid class ownership, Marriott is re-evaluating the usefulness of the LEED Volume Program.

The USGBC has made attempts to adapt the certification process to various industries. In early versions of the LEED ratings systems all commercial properties were grouped together. According to one executive at a global hotel company we interviewed this created challenges in the certification process for hotel companies because, “we were compared to commercial office space...they only have 8-10 hours of occupancy, but we have 24 hour occupancy. Water and energy usage is completely different.” The USGBC responded by introducing LEED Version 4 in 2014 which separates hotels into their own category of commercial buildings, which could make certification more practical for many hoteliers. According to one hotelier we spoke to LEED has reached a critical juncture within their firm, “We have learned a lot from LEED, so it has been valuable, but now we have to decide whether we still want to continue paying for the certification process...we are implementing the savings opportunities but we may no longer pursue the plaque.” This suggests that hoteliers are benefiting from the operational efficiencies and reductions that LEED encourages, but there may not be a marketing benefit to certification. In this study we address this question by focusing on the impact of LEED certifications on the revenue side of the financial equation.

3. Hypotheses Generation

Our first area of exploration is the impact of LEED certification on existing buildings. While there are now many versions of the LEED ratings systems and many specializations (i.e. new construction, existing buildings, commercial interiors, hospitality, schools, homes, neighborhoods, etc.) at their basic level they can be broken into two groups: existing buildings and new buildings.

Most traditional event studies in the literature take a before and after approach to a certification event. This is consistent with existing hotels that undergo a certification event.

H1: Existing hotels which undergo LEED certification outperform their non-certified peers following adoption (measured by RevPAR).

The second type of LEED certified building does not lend itself to the traditional event study methodology as well. When a certified building is new, how do you collect pre-certification data? Fortunately, LEED certification lags behind hotel occupancy by 6 months to 2 years which allows for data collection after opening, but before certification, even in new buildings. In this case however it is difficult to separate the performance driven by a new hotel that was designed to be LEED and the actual certification event that follows a year later. It may not be reasonable to expect a change in performance a year after opening just because the hotel officially passed the audit and could now hang a plaque on the wall in the lobby. This problem is explored further in hypothesis 4-5.

H2: New LEED hotels outperform their non-certified peers (measured by RevPAR)

One major challenge in knowing whether new LEED hotels outperform their competitors is knowing the source of the competitive advantage. New LEED hotels by definition are also *NEW*. The next step is to investigate how new non-certified hotels compare to existing non-certified hotels?

H3: New non-certified hotels also outperform non-certified peer hotels (measured by RevPAR)

Difference-in-difference as a methodology is limited because it does not allow us to investigate the source of the abnormal performance; it only demonstrates that there is one. To understand the source of the abnormal performance we use multilevel modeling to measure the impact of LEED certification and separate the new variable of hotel from the certification variable. Performance. Both variables should improve performance; perhaps together the improvement is magnified.

H4: New LEED hotels achieve abnormal levels of performance beyond that of uncertified new hotels (measured by RevPAR)

Finally, once we establish that there is a difference in the performance of a LEED hotel (or a new hotel), what happens to that advantage over time? Is the change linear? Or Quadratic?

H5: The initial boost that LEED hotels get over their non-certified peers diminishes quickly (measured by RevPAR).

4. Data and Measures

4.1 Data Collection

In order to perform the longitudinal analysis necessary for this study we merged two databases: (1) the USGBC database of registered and certified properties and (2) hotel performance data from Smith Travel Research (STR), a private source. Our final merged database includes descriptive and annual performance data of 565 hotels—93 LEED certified hotels—over an eight year period (2005-2012). This data represents the entire population of LEED certified hotels as of 2012.

4.1.1 USGBC Certification Database

The United States Green Building Council (USGBC) is a non-profit organization that certifies the completion of LEED certification requirements for buildings across the globe. The USGBC maintains a public database of all building projects that have applied for certification, including: completed, ongoing, planned, or abandoned projects. By the end of 2012 when we accessed this data set it had grown to over 35,000 projects. Our first task was to cull out all properties overseas because there is not a critical mass of certified hotels in any one country (outside the US) that would stand up to rigorous analysis. We next queried the data set searching for the words ‘hotel’ or ‘inn’ within the name of the property or project description. Our initial query left us with 434 potential properties which included hotels (354), large development projects (43), and non-hotel projects (58). After removing large development projects because they typically involved the revitalization of a city block (of which a hotel was only a small part), and non-hotel projects; we were left with 354 hotels. Of these, 101 were certified and 253 were registered—meaning they showed interest in certification—but were not yet completed and certified. After collaborating with STR, who also tracks LEED certified hotels, we were able to augment our final sample to 108 completed and certified hotels. These 108 properties represent the population of LEED hotels in the US, not a sample of certified hotels.

4.1.2 Smith Travel Research Hotel Performance Database

Smith Travel Research (STR) is one of the largest research firms and data consultants in the hospitality industry. In hospitality it is common for data consultants to gather performance measures from hotels and sell the data back to the industry for benchmarking purposes. For example, a Hilton hotel in Washington DC will report their daily measures to STR along with the

names of similar competing hotels located close by (a ‘compset’ of typically 4-6 hotels). STR then approaches those 4-6 hotels for the same information and reports back to each hotel the performance of their hotel relative to their competition (with the names of the hotel masked to protect their anonymity). Using this model, STR currently collects daily transactional data from roughly 75% of all hotels in the US. We approached STR for access to their data set and secured annual performance data from only 93 of the 108 certified hotels in the US (86%). STR also supplied the financial data for all of the self-identified competitors (‘compset’) of our 93 LEED certified hotels. After removing 8 LEED certified hotels from ‘compsets’ of other certified hotels and 6 more LEED subject properties with missing certification dates, our final data set includes 87 LEED hotels (81% of the population of 108) and 472 non-certified competitor hotels (5.4 competitors per subject). This data spans 8 years (waves) from 2005 to 2012. STR also provided us with descriptive data regarding each of the properties (Table 4.2). By merging the USGBC and STR data we are able to track the performance of LEED certified hotels and non-certified comparable hotels consistently over time, something that has not been done in previous work on LEED certification. We also supplemented our analysis with a site visit to one of only three LEED Platinum hotels in the US and interviews of executives in hotel companies that have responsibility over environmental sustainability.

Table 4.2: Percentages of hotels within each category in population of LEED hotels and US hotels

Variable	LEED	US Avg	Variable	LEED	US Avg
<i>Class</i>			<i>Location</i>		
Economy	2.8%	46.1%	Airport	4.6%	4.3%
Midscale	1.9%	15.7%	Interstate	2.8%	14.1%
Upper Midscale	13.9%	10.4%	Resort	9.3%	7.3%
Upscale	34.3%	10.4%	Small Metro/Town	15.7%	31.3%
Upper Upscale	16.7%	5.3%	Suburban	35.2%	33.7%
Luxury	30.6%	2.1%	Urban	32.4%	9.3%
<i>Operation</i>			<i>Size</i>		
Chain Management	25.0%	8.2%	< 75	13.9%	55.2%
Franchise	36.1%	49.2%	75 -149	40.7%	32.4%
Independent	38.9%	42.6%	150 - 299	24.1%	8.4%
			300 - 500	11.1%	2.2%
			> 500	10.2%	1.0%

LEED hotels: N = 108. US hotels: n = 52,548 as of 2013 (obtained from STR). The data in the table represent the percentage within each category from the population data of LEED hotels and total US hotels

Within the population of LEED hotels we notice a number of trends. While LEED certified hotels are present in every class, there is a trend towards certification in higher classes with 31% of certified hotels being luxury and 84% upscale or above. This is despite the relatively low percentage of upscale and luxury hotels in the US. In fact, more than 2% of all luxury hotels in the US are LEED certified, compared to 0.01% of economy hotels that are certified. This is consistent with the problem Marriott is facing with their LEED Volume program mentioned earlier. The volume program pre-certifies lower class hotels, which tend to be less likely to certify. Regarding hotel ownership, chain managed hotels are also much more likely to certify as they represent a much larger percentage of LEED certified hotels (25%) than their national average (8.2%). Franchised hotels are the least likely to certify. It is also worth noting that the LEED certification rating system does not treat all hotel locations equally. The rating system favors buildings in suburban and urban markets so it is not surprising that we observe 68% of LEED hotels in these

two markets, compared to 43% nationally. Finally, LEED certification is more common in larger hotels as 45.4% of LEED hotels are 150 rooms or larger versus only 11.6% nationwide. Small hotels are very unlikely to certify as they make up over 55% of the hotels in the US but only 14% of LEED hotels.

4.2 Variables and Measures

4.2.1 Dependent Variables

In the hospitality industry there are three primary revenue measures: Occupancy (the % of rooms occupied on a given night), Average Daily Rate or ‘ADR’ (the average rate collected for each room), and Revenue per Available Room or ‘RevPAR’ (the product of occupancy and ADR). RevPAR is probably the single most important number hoteliers track because it captures information about occupancy and rate (Kimes, 1999). For this reason, RevPAR has become a common dependent variable in many studies in the hospitality literature (Kim, Gon Kim, & An, 2003; O’Neill, & Carlback, 2011; Xiao, O’Neill, & Mattila, 2012; Anderson, & Lawrence, 2014).

4.2.2 Independent Variables

The primary analysis in this study incorporates three critical independent variable: (1) LEED certification, (2) time, and (3) matched sets. First, the primary research question of this study regarding the impact of LEED certification on hotel performance indicates that LEED certification (binary variable measured as 1 = LEED certified, 0 = not certified) is the primary independent variable. Second, as with all longitudinal analysis, time is an important variable to capture, which we do using time before/since certification as an independent measure. In the initial difference-in-differences analysis ‘t’ denotes the certification event (Corbett, et.al., 2005) and we measure

performance changes in annual periods (-3 to -2, -1 to t, t to +1, etc.). In the supplemental multilevel model time is a scale between -7 and 8 that represents the time since certification. Finally, the matched set represents a critical IV because by creating a matched set we can measure change at the individual property level and at the group or compset level, which is one of the primary benefits of multilevel models. We can also test compset as a fixed effect by inserting a dummy code for each compset into the model (Eichholtz, et.al, 2010) or random effect and preserve the variance across the compsets (Singer & Willett, 2003). In this study we use both fixed and random effects models to test the robustness of the data and the measured effects.

4.2.3 Control Variables

One of the major benefits of the data in this study is that the difficult work of matching was already done by the hoteliers. Hoteliers choose as competitors properties similar in location, size, class, and price. By creating a group level variable for the entire compset we can control for most of the differences in characteristics across hotels within a particular compset. Our final dataset includes 87 groups (87 subjects and 472 comps). We performed a t-test to compare the characteristics of the subject properties with the mean and median of the competitors (Table 4.3). There is no significant difference between the class and size of the subject property and the mean or median class and size of the competitors. Hotel age is significantly different among our subject properties and competitors, the subject properties being much newer buildings. For this reason we include age of hotel as a control variable in our model. We also added a dummy variable “new hotel” for newly completed hotels because we believe there may be a connection between new hotels and performance. This also allows us to capture unique sources of variance among new

hotels as many LEED hotels are also new hotels. Our final control variables are time variant controls necessary for the multilevel model in the follow-up analysis

Table 4.3: Class, Size, and age of Matched Sample

Characteristic	N	Mean	t Stat	P value (two tail)	Median	t Stat	P value (two tail)
Class							
Subject	87	4.61	0.943	0.347	4.61	0.507	0.613
Competitor	87	4.46			4.53		
Size							
Subject	87	2.66	-1.105	0.271	2.66	-1.175	0.242
Competitor	87	2.82			2.84		
Opening Year							
Subject	87	1999.2	4.982	0.000***	1999.2	3.915***	0.000
Competitor	87	1983.5			1987.0		

Results of a t-test (two sample with equal variance). Comparison of values of subject properties to the mean/median of the 4-6 competitor properties in a grouping. ***Significant at the $p < 0.01$ level.

5. Methodology

5.1 Event Study Methodology

In this study we conducted an event study following a difference-in-differences methodology similar to other OM scholars (Corbett, et.al, 2005; Swink & Jacobs, 2012) as adapted from economics and finance (Barber & Lyon, 1996). The main purpose of an event analysis is to detect abnormal performance of a firm following an event, in this case LEED certification. In the first part of this paper we use the same definition for abnormal performance (AP) as Barber & Lyon where AP of firm i in year t (AP_{it}) is defined as actual performance (P_{it}) minus expected performance ($E(P_{it})$):

$$AP_{it} = P_{it} - E(P_{it}) \quad (1)$$

where performance is measured as one of three outcome variables: (1) Occupancy, (2) ADR, or (3) RevPAR; and expected performance is the mean/median performance of the non-certified hotels in the compset. Barber & Lyon suggest that measuring the change in performance relative to the change in the benchmark is a more accurate test than measuring the level performance relative to the benchmark (static annual performance). This helps to minimize the chance impact of boom or bust economies on the year of certification. One disadvantage of this method is that it masks relative position of the firms. For example a new hotel upon opening may begin in a disadvantaged position entering a new market relative to the incumbents. However, it likely will improve performance at a quicker rate, so this analysis would show that it is outperforming the competition year over year when in fact is merely catching up.

To control for difference amongst groups and location (assuming all hotels in a group are in the same location) it is common practice in the hospitality industry to create an index of hotel performance for each group where abnormal performance of firm i in year t (AP_{it}) is defined as actual performance (P_{it}) divided by expected performance ($E(P_{it})$):

$$AP_{it} = P_{it}/E(P_{it}) \quad (2)$$

where performance is measured as one of the three outcome variables of interest and expected performance is the mean/median performance of the non-certified hotels in the compset. In this analysis a performance index > 1 and a change in performance > 0 represent superior performance. This model appropriately captures the starting point of the entrant and incumbents and the change in the performance indexes. Additionally, Swink & Jacobs 2012 recommend measuring median competitor performance because of the influence outliers have on the mean. In our analysis we

test both median (Swink & Jacobs, 2012) and mean (convention in the hospitality industry) for abnormal performance.

With abnormal performance thus defined we followed the difference-in-difference approach outlined by Barber & Lyons 1996 which involves three discrete steps: (1) match properties with similar characteristics (already done by hoteliers as described above), (2) assess relative levels of annual performance and more importantly, change in annual performance, (3) test whether the annual performance and change in annual performance for the subject group (LEED) is significantly different from the competitive set using a non-parametric Wilcoxon Sign-Ranked Test (Barber & Lyons, 1996; Swink & Jacobs, 2012). If we observe a difference then we say that there is an abnormal performance in the subject hotel. If we do not observe a significant difference in annual performance of LEED hotels prior to certification, but post certification there is a significant difference in performance, then we can infer that LEED certification predicts a abnormal performance relative to non-certified hotels.

5.2 Multi-level Model

In this dataset there are two types of hotels that certify: (1) existing hotels that go through a renovation and subsequent certification process (26 total), and (2) new hotels that are designed to be LEED certified (61). In the first case, years of pre-certification data is available and the analysis is similar to that conducted by others studying ISO 9000 (Corbett, et.al, 2005) or Six Sigma (Swink & Jacobs, 2012). The second type is more complex however because the effects of the certification must be teased out of the effects of the newness of the hotel. Many new hotels are constructed with the intent to be LEED certified, but certification typically lags behind completion by a year or more. Additionally, there is a new hotel effect which can confound the LEED effect since the

variables ‘new’ and ‘LEED’ can be highly correlated. Difference-in-differences is useful for identifying differences in performance before and after a specific event (i.e. LEED Certification) when data is available on both sides of the event, but it is limited in its ability to provide evidence as to why the differences occur. It is also limited in its usefulness when data is only available on one side of the event. For example, in the case of the new LEED hotel a difference-in-differences approach cannot separate the boost in performance a hotel may get from being new, from the boost that it may get from being LEED. We therefore constructed a longitudinal multilevel model (Singer & Willett, 2003) to control for the unique variance of new hotels and LEED hotels and address the questions: (1) Does abnormal performance come from newness or LEED certification? (2) Why do LEED hotels outperform competitors?

6. Results

We first turn our attention to the raw data and notice a trend for superior performance amongst LEED hotels. Taken as a group, the 87 LEED certified hotels had a lower occupancy rate (62% vs 67% for non-certified hotels) and RevPAR (\$104 vs \$106), but a higher ADR (\$164 vs \$154). The lower RevPAR is driven by the low occupancy rate as RevPAR is the product of occupancy and ADR (Table 4.4).

Table 4.4: Occupancy, ADR, and RevPAR values for LEED and non-LEED matched sample

	Comp. Mean Performance			Comp. Median Performance		
	Occ	ADR	RevPAR	Occ	ADR	RevPAR
All LEED Hotels (N = 87)						
Mean	0.615	163.70	104.26			
Std. Dev.	0.163	88.00	66.63		all the same	
Max	0.913	709.25	590.98			
Min	0.056	43.03	2.95			
Competitor Hotels (n = 472)						
Mean	0.673	154.06	106.04	0.682	151.82	105.53
Std. Dev.	0.091	78.31	59.08	0.092	76.46	57.48
Max	0.893	567.71	483.40	0.914	559.73	460.28
Min	0.396	56.62	31.15	0.377	56.55	31.52

For LEED hotels data indicates aggregate of 87 subject hotel performance over 8 year collection period. The left panel aggregates mean performance of matched compset over the 8 year horizon. Right side aggregates median performance of matched compset over 8 year horizon.

6.1 Difference-in-Differences Analysis

While it is interesting to look at mean/median values, and a clear starting point, they don't tell the whole story. This aggregate data was matched by the mean of the competitive group and the median of the group, but did not take into account the certification event. Using the difference-in-difference approach described earlier we were able to not only match the properties but measure their performance before and after the event (LEED certification). The following six charts exhibit the results of this analysis. Tables 4.5-4.6 display the data on existing hotels (those not designed to be LEED certified, but renovated during their life cycle to become certified). Tables 4.7-4.8 show results from new certified hotels—those designed to be certified. Finally, in Tables 4.9-4.10 we removed all LEED certified hotels from our database and created a dataset of new non-certified hotels and compared them to existing non-certified hotels. In each table year t represents the certification year with the '-' representing the years before and the '+' representing the years following certification. We included the data from three years prior to certification up through

three years post-certification recognizing that the data is quite limited or even non-existent for some of these years.

Table 4.5: Abnormal performance in Occupancy, ADR, and RevPAR Indices for EXISTING LEED hotels for years -3 through +3

	Subject matched to competitor's mean					Subject matched to comp. median			
	N	Index	z-stat	% pos.	z-stat	Index	z-stat	% pos.	z-stat
Occupancy									
-3 to -2	24	0.958	-1.073	0.330	-1.696	0.966	-0.829	0.420	-0.811
-2 to -1	24	0.994	-0.160	0.380	-1.238	0.984	-0.399	0.380	-1.238
-1 to t	25	0.995	-0.200	0.440	-0.592	0.992	-0.262	0.480	-0.196
t to +1	21	0.997	-0.108	0.430	-0.645	1.001	0.034	0.480	-0.213
+1 to +2	16	0.930	-1.345	0.440	-0.488	0.916	-0.652	0.310	-1.567
+2 to +3	8	0.869	-2.004	0.380	-0.683	0.863	-2.153	0.380	-0.683
ADR									
-3 to -2	24	1.072	1.540	0.580	0.811	1.084	1.791	0.580	0.811
-2 to -1	24	1.076	1.686	0.630	1.238	1.092	1.958	0.630	1.238
-1 to t	25	1.053	1.190	0.600	1.000	1.064	1.401	0.600	1.000
t to +1	21	1.064	1.374	0.570	0.645	1.086	1.692	0.620	1.096
+1 to +2	16	1.078	1.484	0.560	0.488	1.102	1.484	0.630	1.000
+2 to +3	8	1.079	0.822	0.630	0.683	1.089	0.833	0.500	0.000
RevPAR									
-3 to -2	24	1.021	0.390	0.580	0.811	1.020	0.354	0.580	0.811
-2 to -1	24	1.082	1.293	0.710	2.198	1.076	1.215	0.670	1.696
-1 to t	25	1.058	1.019	0.680	1.890	1.058	1.047	0.640	1.429
t to +1	21	1.065	1.062	0.670	1.581	1.077	1.331	0.620	1.096
+1 to +2	16	0.998	-0.024	0.560	0.488	0.999	-0.017	0.500	0.000
+2 to +3	8	0.941	-0.577	0.500	0.000	0.937	-0.604	0.500	0.000

Dataset includes 26 existing hotels that became certified and 149 competitor hotels
Index = Actual Performance/Expected performance. Left panel (mean), right panel (median)
of competitive set.

Z-Statistic for Means and medians are obtained using a Wilcoxon Signed-Rank test

Z-Statistic for % positive are obtained using Binomial Sign test.

** Significant at the $p < .05$ level (two-tailed)

Table 4.6: Abnormal Annual changes in Occupancy, ADR, and RevPAR Indices for EXISTING LEED hotels for years -3 through +3

	Subject matched to competitor's mean					Subject matched to comp. median				
	N	Δ Index	z-stat	% pos.	z-stat	Δ Index	z-stat	% pos.	z-stat	
Occupancy										
-3 to -2	21	0.014	0.544	0.620	1.096	0.036	1.377	0.570	0.645	
-2 to -1	23	0.016	0.532	0.430	-0.617	0.002	0.062	0.350	-1.499	
-1 to t	24	0.004	0.186	0.420	-0.811	0.011	0.470	0.500	0.000	
t to +1	21	0.017	0.681	0.520	0.213	0.026	0.883	0.570	0.645	
+1 to +2	15	0.011	0.721	0.530	0.250	0.002	0.135	0.470	-0.250	
+2 to +3	8	0.006	0.130	0.500	0.000	0.004	0.080	0.380	-0.683	
ADR										
-3 to -2	21	0.027	1.206	0.620	1.096	0.022	0.986	0.570	0.645	
-2 to -1	23	0.000	0.024	0.570	0.617	0.006	0.402	0.610	1.045	
-1 to t	24	-0.009	-0.666	0.380	-1.238	-0.014	-1.142	0.420	-0.811	
t to +1	21	0.008	0.512	0.620	1.096	0.016	1.030	0.670	1.581	
+1 to +2	15	-0.009	-0.823	0.470	-0.250	-0.015	-1.361	0.330	-1.323	
+2 to +3	8	0.003	0.077	0.500	0.000	-0.017	-0.485	0.500	0.000	
RevPAR										
-3 to -2	21	0.026	1.129	0.520	0.213	0.019	0.855	0.480	-0.213	
-2 to -1	23	0.041	1.147	0.480	-0.204	0.034	1.016	0.480	-0.204	
-1 to t	24	-0.007	-0.387	0.420	-0.811	-0.001	-0.040	0.330	-1.696	
t to +1	21	0.020	0.857	0.520	0.213	0.040	1.531	0.570	0.645	
+1 to +2	15	0.002	0.130	0.530	0.250	-0.004	-0.256	0.530	0.250	
+2 to +3	8	0.043	1.213	0.630	0.683	0.029	0.811	0.630	0.683	

Dataset includes 26 existing hotels that became certified and 149 competitor hotels
Index = Actual Performance/Expected performance. Left panel (mean), right panel (median)
of competitive set.

Z-Statistic for Means and medians are obtained using a Wilcoxon Signed-Rank test

Z-Statistic for % positive are obtained using Binomial Sign test.

** Significant at the $p < .05$ level (two-tailed)

Tables 4.5-4.6 demonstrate that there is no significant difference in hotel performance before and after LEED certification in existing hotels that underwent a certification event. Certified hotels tended to outperform non-certified hotels prior to and post certification (although the difference is not significant). From this data it appears that the improved financial performance is not one of the major motivating factors for the renovation and subsequent LEED certification. This raises the obvious question: what is the driving force behind certification of existing hotels if not financial

performance? When we spoke to sustainability experts about this they said that hotel owners/managers that self-select into certification are often already the highest performing hotels. They said that these owners are able to choose LEED because their hotels are already well managed and they are not intimidated by adding ‘one more thing’ to their work load. Conversely, managers of poorly managed hotels (and poorly performing hotels) often feel overwhelmed with the day to day operations of their hotels that they don’t have time for ‘bigger picture’ things like LEED. This sentiment is supported by our data, with the LEED properties reporting higher ADR and RevPAR even before certification (not significant however).

H1: Existing hotels which undergo LEED certification outperform their non-certified peers following adoption (measured by RevPAR). (Not supported)

Table 4.7: Abnormal performance in Occupancy, ADR, and RevPAR Indices for NEW LEED hotels for years -3 through +3

	Subject matched to competitor’s mean					Subject matched to comp. median			
	N	Index	z-stat	% pos.	z-stat	Index	z-stat	% pos.	z-stat
Occupancy									
-3 to -2	9	0.837	-1.991	0.220	-1.890	0.848	-1.667	0.440	-0.316
-2 to -1	42	0.666	-7.395**	0.140	-6.535**	0.655	-7.575**	0.140	-6.535**
-1 to t	60	0.884	-4.692**	0.270	-4.053**	0.878	-4.853**	0.280	-3.693**
t to +1	50	0.975	-1.340	0.380	-1.731	0.957	-2.372**	0.360	-2.042
+1 tp +2	35	0.975	-1.529	0.400	-1.190	0.958	-2.638**	0.340	-1.930
+2 to +3	17	0.982	-0.868	0.590	0.717	0.974	-1.425	0.470	-0.236
ADR									
-3 to -2	9	1.091	1.230	0.780	1.890	1.125	1.474	0.780	1.890
-2 to -1	42	1.028	0.890	0.550	0.613	1.049	1.360	0.550	0.613
-1 to t	60	1.099	3.185**	0.680	3.027**	1.119	3.369**	0.650	2.416**
t to +1	50	1.117	3.382**	0.720	3.430**	1.145	3.522**	0.720	3.430*
+1 to +2	35	1.126	2.826**	0.690	2.333**	1.158	3.080**	0.690	2.333*
+2 to +3	17	1.139	2.268	0.710	1.807	1.194	2.245	0.590	0.717
RevPAR									
-3 to -2	9	0.910	-0.824	0.560	0.316	0.927	-0.646	0.560	0.316
-2 to -1	42	0.712	-4.836**	0.240	-3.937**	0.719	-4.540**	0.260	-3.467**
-1 to t	60	0.978	-0.532	0.430	-1.033	0.997	-0.069	0.450	-0.772

t to +1	50	1.089	2.252**	0.660	2.364**	1.099	2.340**	0.660	2.364**
+1 to +2	35	1.095	2.007	0.660	1.930	1.119	2.349**	0.660	1.930
+2 to +3	17	1.119	1.835	0.710	1.807	1.158	1.904	0.650	1.231

Dataset includes 61 new LEED hotels and 323 competitor hotels

Index = Actual Performance/Expected performance. Left panel (mean), right panel (median) of compset.

Z-Statistic for Means and medians are obtained using a Wilcoxon Signed-Rank test

Z-Statistic for % positive are obtained using Binomial Sign test.

** Significant at the $p < .05$ level (two-tailed)

Table 4.8: Abnormal Annual changes in Occupancy, ADR, and RevPAR Indices for NEW LEED hotels for years -3 through +3

	Subject matched to competitor's mean					Subject matched to comp. median			
	N	Δ Index	z-stat	% pos.	z-stat	Δ Index	z-stat	% pos.	z-stat
Occupancy									
-3 to -2	0	NA	NA	NA	NA	NA	NA	NA	NA
-2 to -1	9	0.118	3.230**	1.000	NA**	0.103	2.185	0.780	1.890
-1 to t	42	0.274	7.377**	0.930	10.655**	0.282	7.664**	0.900	8.829**
t to +1	49	0.109	6.075**	0.840	6.312**	0.100	5.393**	0.760	4.110**
+1 to +2	35	0.023	2.217**	0.630	1.552	0.025	2.578**	0.630	1.552
+2 to +3	17	0.007	0.366	0.650	1.231	0.012	0.867	0.590	0.717
ADR									
-3 to -2	0	NA	NA	NA	NA	NA	NA	NA	NA
-2 to -1	9	0.043	1.694	0.670	1.000	0.074	2.556**	0.780	1.890
-1 to t	42	0.074	3.871**	0.760	3.937**	0.082	3.953**	0.690	2.638**
t to +1	49	0.010	0.799	0.670	2.563**	0.015	0.997	0.630	1.906
+1 to +2	35	0.020	2.726**	0.690	2.333**	0.019	2.002**	0.660	1.930
+2 to +3	17	0.021	2.154	0.590	0.717	0.031	1.808	0.710	1.807
RevPAR									
-3 to -2	0	NA	NA	NA	NA	NA	NA	NA	NA
-2 to -1	9	0.177	3.189**	1.000	NA**	0.166	2.350**	0.780	1.890
-1 to t	42	0.329	7.773**	1.000	NA**	0.337	8.112**	1.000	NA**
t to +1	49	0.124	5.683**	0.900	9.108**	0.120	4.547**	0.920	10.586**
+1 to +2	35	0.044	4.175**	0.770	3.769**	0.054	4.515**	0.770	3.769**
+2 to +3	17	0.016	1.403	0.710	1.807	0.016	0.481	0.470	-0.236

Dataset includes 61 new LEED hotels and 323 competitor hotels

Index = Actual Performance/Expected performance. Left panel (mean), right panel (median) of compset.

Z-Statistic for Means and medians are obtained using a Wilcoxon Signed-Rank test

Z-Statistic for % positive are obtained using Binomial Sign test.

** Significant at the $p < .05$ level (two-tailed)

Tables 4.7-4.8 report the results from the difference-in-difference analysis on new hotels that were designed and constructed to be LEED certified buildings. These hotels begin in a disadvantaged position with respect to occupancy because they are new entrants to a market—a trend with all new hotels. New hotels however, tend to charge more than their existing competitors (Table 4.7).

Another interesting note is that LEED certification lags behind the opening of the hotel, sometimes by as many as three years. As noted before, occupancy lags in these start up years but catches up very quickly. By the time a hotel is certified 1-2 years after opening the gap has been closed and the higher ADR signals a RevPAR advantage. It is difficult to say however whether this advantage after certification is due to certification or the natural cycle of a new hotel.

Traditional difference-in-difference analysis which measures the change in performance (i.e. Table 8) clearly shows that LEED hotels are outperforming their non-certified competitors. That alone does not tell the whole story however. One of the major reasons the advantage in change annual performance is so dramatic is the disadvantaged starting point (Table 4.7). The new hotels are ‘closing the gap’ and as they do, the change in annual performance (or relative performance) diminishes from year to year until eventually it goes away and you are left with only absolute performance differences. For this reason, in this study we focus on both relative and absolute performance, while most event analysis studies focus on relative performance.

H2: New LEED hotels outperform their non-certified peers (measured by RevPAR).

(Supported)

Table 4.9: Abnormal performance in Occupancy, ADR, and RevPAR Indices for *NEW NON-CERTIFIED* hotels for years -3 through +3

	Subject matched to competitor's mean					Subject matched to comp. median			
	N	Index	z-stat	% pos.	z-stat	Index	z-stat	% pos.	z-stat
<i>Occupancy</i>									
-3 to -2	0	NA	NA	NA	NA	NA	NA	NA	NA
-2 to -1	0	NA	NA	NA	NA	NA	NA	NA	NA
-1 to t	33	0.640	-8.846**	0.030	-15.500**	0.640	-8.562**	0.060	-10.417**
t to +1	34	0.930	-2.218	0.470	-0.339	0.940	-2.173**	0.380	-1.391
+1 to +2	33	1.020	0.619	0.610	1.228	1.020	0.748	0.520	0.171
+2 to +3	31	1.050	1.721**	0.740	3.028**	1.040	1.319	0.610	1.270
<i>ADR</i>									
-3 to -2	0	NA	NA	NA	NA	NA	NA	NA	NA
-2 to -1	0	NA	NA	NA	NA	NA	NA	NA	NA
-1 to t	33	1.160	1.168	0.610	1.228	1.100	2.422**	0.640	1.604
t to +1	34	1.110	1.705	0.620	1.391	1.100	2.765**	0.590	1.030
+1 to +2	33	1.140	1.881	0.610	1.228	1.120	2.723**	0.580	0.867
+2 to +3	31	1.180	1.869	0.580	0.895	1.120	2.582**	0.580	0.895
<i>RevPAR</i>									
-3 to -2	0	NA	NA	NA	NA	NA	NA	NA	NA
-2 to -1	0	NA	NA	NA	NA	NA	NA	NA	NA
-1 to t	33	0.710	-4.029**	0.180	-4.667**	0.700	-5.755**	0.150	-5.498**
t to +1	34	1.020	0.357	0.470	-0.339	1.020	0.508	0.410	-1.030
+1 to +2	33	1.150	2.049	0.580	0.867	1.130	2.492**	0.610	1.228
+2 to +3	31	1.210	2.491**	0.610	1.270	1.160	2.721**	0.650	1.662

Dataset includes 34 new NON-certified hotels and 163 competitor hotels

Index = Actual Performance/Expected performance. Left panel (mean), right panel (median) of compset.

Z-Statistic for Means and medians are obtained using a Wilcoxon Signed-Rank test

Z-Statistic for % positive are obtained using Binomial Sign test.

** Significant at the $p < .05$ level (two-tailed)

Table 4.10: Abnormal Annual changes in Occupancy, ADR, and RevPAR Indices for NEW NON-CERTIFIED hotels for years -3 through +3

	Subject matched to competitor's mean					Subject matched to comp. median			
	N	Δ Index	z-stat	% pos.	z-stat	Δ Index	z-stat	% pos.	z-stat
Occupancy									
-3 to -2	0	NA	NA	NA	NA	NA	NA	NA	NA
-2 to -1	0	NA	NA	NA	NA	NA	NA	NA	NA
-1 to t	0	NA	NA	NA	NA	NA	NA	NA	NA
t to +1	33	0.305	8.175**	0.970	15.500**	0.302	8.863**	0.970	15.500**
+1 to +2	33	0.087	5.898**	0.850	5.498**	0.091	5.381**	0.910	8.050**
+2 to +3	31	0.029	1.835**	0.710	2.530**	0.010	0.702	0.550	0.533
ADR									
-3 to -2	0	NA	NA	NA	NA	NA	NA	NA	NA
-2 to -1	0	NA	NA	NA	NA	NA	NA	NA	NA
-1 to t	0	NA	NA	NA	NA	NA	NA	NA	NA
t to +1	33	-0.056	-0.633	0.550	0.516	0.004	-0.118	0.550	0.516
+1 to +2	33	0.030	2.057	0.670	2.000	0.018	1.430	0.640	1.604
+2 to +3	31	0.050	2.500**	0.770	3.592**	0.025	2.437**	0.580	0.895
RevPAR									
-3 to -2	0	NA	NA	NA	NA	NA	NA	NA	NA
-2 to -1	0	NA	NA	NA	NA	NA	NA	NA	NA
-1 to t	0	NA	NA	NA	NA	NA	NA	NA	NA
t to +1	33	0.320	6.734**	0.940	10.417**	0.327	8.128**	0.940	10.417**
+1 to +2	33	0.130	5.969**	0.910	8.050**	0.119	5.077**	0.910	6.565**
+2 to +3	31	0.065	3.013**	0.740	3.028**	0.040	1.932**	0.650	1.662

Dataset includes 34 new NON-certified hotels and 163 competitor hotels

Index = Actual Performance/Expected performance. Left panel (mean), right panel (median) of compset.

Z-Statistic for Means and medians are obtained using a Wilcoxon Signed-Rank test

Z-Statistic for % positive are obtained using Binomial Sign test.

** Significant at the $p < .05$ level (two-tailed)

In Tables 4.9-4.10 we removed all LEED hotels from the dataset and re-coded new non-certified hotels as the subjects within the same compsets. We then ran the analysis one more time. We see here a trend very similar to the new certified hotels. New hotels begin in a disadvantaged position with regard to occupancy but charge higher rates (ADR). RevPAR performance is impacted negatively by the relative low occupancy rates in the early years but recovers as occupancy improves. One difference between this and the previous analysis is that in this analysis

opening the hotel is the event (t) where in the previous analysis certification was the event. With opening as the event there should not be any data previous to the event. In Table 4.9 there are 33 hotels that report performance data prior to opening. This represents a partial year of data. The event t is the first full year of data reported.

H3: New non-certified hotels also outperform non-certified peer hotels (measured by RevPAR). (Supported)

6.2 Multilevel Modeling Analysis

It is clear from the initial difference-in-difference analysis that hotel age clearly has an impact on hotel performance. Difference-in-difference analysis does not allow for controlling for unique variance introduced by individual variables (i.e. hotel age or a hotel being new). The primary purpose of this multi-level model is to account for this weakness in the difference-in-differences approach and also add control at the group level—which cannot be done by typical OLS regression. Table 4.11 presents Pearson bivariate correlations for our variables of interest. We notice that LEED hotels are correlated with new hotels at a very high level (0.52). We expected this as most of the LEED hotels in our dataset are also new hotels. We also notice that LEED hotels are negatively correlated with chain operated and franchised hotels, validating what we already noticed in the descriptive analysis. New hotels however are positively correlated with franchise operations and negatively correlated with independent and chain operations.

Table 4.11: Pearson Bivariate Correlations Coefficients: Hotel Level Variables, Total Sample (n = 5,016)

	LEED Hotel	New Hotel	Year	Log Age	Op: Chain	Op: Fran.	Op: Ind.	LEED Adopt
New Hotel	0.52*							
Year	0.00	0.00						
Log Age	-0.44*	-0.79*	0.00					
Operation: Chain	-0.05*	-0.09*	0.00	0.07*				
Operation: Franchise	-0.07*	0.14*	0.00	-0.23*	-0.58*			
Operation: Independent	0.13*	-0.07*	0.00	0.18*	-0.39*	-0.52*		
LEED Adoption	0.59*	0.31*	0.25*	-0.23*	-0.05*	-0.05*	0.11*	
Yrs. Since Adoption	0.21*	0.13*	0.21*	-0.10*	-0.03	0.01	0.01	0.35*

*Significant at the $p < 0.01$

Another advantage of a multilevel approach is that we can measure the impact of time on the model. We model a discontinuous growth model with three linear change variables and two quadratic change variables (Table 4.12). The variable ‘Year’ models the annual change within individual hotels. ‘LEED Adoption’ captures the impact of the event occurrence. This is similar to our ‘LEED’ variable but there is an important difference. The ‘LEED’ variable is a categorical variable at the individual level that does not change over time. ‘LEED Adoption’ however changes based on the timing of the event occurrence so it allows us to measure pre-certification performance against post-certification performance (similar to diff-in-diff). Finally, ‘Years Since Adoption’ captures the post certification performance of the hotel. Modeling change thus detects a shift in magnitude and a change in slope of post-certification hotels.

Table 4.12: Coding and Interpretation of Change Variables in Discontinuous Growth Model Used in this Study

Variable	Measurement Occasion								Interpretation
	1	2	3	4	5	6	7	8	
Coding of Change Variable									
Year	0	1	2	3	4	5	6	7	Linear time intervals
LEED Adoption	0	0	0	1	1	1	1	1	Impact of event occurrence (certification)
Yrs Since Adopt	0	0	0	0	1	2	3	4	Linear time since event occurrence
Change Term Entered in Linear Model									
Year	0	1	2	3	4	5	6	7	Linear change in pre-certification period
LEED Adoption	0	0	0	1	1	1	1	1	Performance change as a result of certification
Yrs Since Adopt	0	0	0	0	1	2	3	4	Linear change in post-certification period relative to pre-certification period
Change Term Entered in Curvilinear Model									
Year	0	1	2	3	4	5	6	7	Linear change in pre-certification period
LEED Adopt	0	0	0	1	1	1	1	1	Performance change as a result of certification
Yrs Since Adopt	0	0	0	0	1	2	3	4	Linear change at the start of post-certification period relative to pre-certification period
Year ²	0	1	4	9	16	25	25	25	Quadratic change in pre-certification period
Yrs Since Adopt ²	0	0	0	0	1	4	9	16	Quadratic change in post-certification period

Adapted from Lang & Bliese (2009) and Singer & Willett (2003)

There is some debate in the literature over the definition and appropriate use of fixed and random effects in multilevel model. For our purposes fixed effects are those which do not change in the individuals in the population. For example, we specify a LEED certified hotel as a LEED hotel over every period, regardless of when it received certification. The value of this variable does not change. Random effects however do allow for variability (i.e. randomness). In our model specification, the treatment of fixed vs. random effects is particularly important in how we treat the group level variable. Our subject hotels were grouped with competitors in 87 groups (1 LEED, 4-8 non-LEED per group) and each group was given a number 1-87. We recognize that this group level variable could be treated as a fixed effect (group does not change over data collection period) or random (hotels come and go from the group). For this reason and to ensure the robustness of our analysis we modeled the group level variable (compset) as both a fixed (Table 4.13) and random effect (Table 4.14). In Table 4.13 where compset is modeled as a fixed effect we added 87 dummy variables to the model to control for variability among the different compsets. In Table

14 where compset is modeled as a random effect we inserted only one additional variable at the group level. Our data stands up to this rigor as the results are consistent across both models.

Table 4.13: Discontinuous Growth Model Predicting Hotel Performance (RevPAR) as a Function of LEED Adoption with ‘Compset’ Modeled as Fixed Effects

	1	2	3	4	5	6
<i>Fixed Effects</i>						
Intercept	107.88 [2.86]**	98.65 [2.81]**	87.78 [13.51]**	99.29 [14.80]**	108.95 [14.78]**	107.52 [14.97]**
Compset			++ **	++ **	++ **	++ **
LEED			4.01 [4.32]	7.27 [5.24]	17.21 [5.40]**	14.54 [5.15]**
New			24.61 [4.70]**	41.44 [10.51]**	43.7 [10.63]**	43.25 [10.69]**
LEED*New				-5.73 [9.53]	-14.69 [9.68]	-12.48 [9.62]
logAGE				-7.55 [2.65]**	-7.41 [2.63]**	-7.705 [2.67]**
Operation				+++ **	+++ **	+++ **
<i>Change Terms</i>						
Year		1.88 [0.28]**	1.66 [0.24]**	1.62 [0.24]**	0.9 [0.23]**	10.97 [0.46]**
Years Since Adoption					10.01 [1.31]**	8.24 [260]**
LEED Adoption					-13.12 [2.59]**	-13.91 [2.50]**
Year ²						-2.3 [0.09]**
Years Since Adoption ²						-0.74 [0.77]
<i>Variance Components</i>						
Level 1						
Within-hotel	424.47 [9.81]**	301.24 [8.04]**	321.89 [8.70]**	323.06 [8.71]**	311.25 [8.15]**	257.57 [6.78]**
Level 2						
In initial status	4611.95 [276.60]**	4238.92 [264.64]**	1160.65 [87.36]**	1101.6 [83.94]**	1093.14 [82.15]**	1138.65 [84.82]**
In rate of change		33.35 [3.51]**	21.12 [2.34]**	20.6 [2.27]**	16.97 [1.78]**	18.74 [1.82]**
<i>Model Fit</i>						
-2 Log-likelihood (Deviance)	40868.34	40402.81	39032.57	38989.31	38497.58	37911.90
AIC	40872.34	40408.81	39038.57	38995.31	38503.58	37917.90
BIC	40885.08	40427.92	39057.62	39014.35	38522.60	37936.92

DV: RevPAR. **Significant at the $p < 0.05$ level, * $p < 0.1$ level. Standard errors in brackets.

++ note: 87 dummy variables added as fixed effects, one for each compset

+++ Three operational dummy variables added as fixed effects (chain management, franchise, independent)

In Table 4.13 above, Model 1 represents the unconditional mean model, followed by the unconditional growth model (Model 2). According to Singer & Willett (2003) the first step in any discontinuous growth model should be to establish these as a baseline. The unconditional mean model models the sample mean before any predictors are added to the model, while the unconditional growth model only measures the effect of time on the response variable. In Model 3 we add the 87 dummy variables for the compsets, as well as the primary variables of interest (LEED and New) and notice that newness of a hotel emerges as a significant predictor but not LEED certification. We then add a few additional control variables (*log_age* and *operation*) as well as an interaction term *LEED*New* (Model 4). This interaction is important because it allows us to look at the LEED hotels that are also new as a separate group from the existing hotels that went through a certification process. Here we notice a negative coefficient for age meaning that an increase in the hotels age predicts a decrease in RevPAR. This is consistent with the positive significant coefficient for new hotels. Up to this point it would appear that LEED certification is *not* a significant predictor of financial performance and that the increased performance measured in the diff-in-diff approach is primarily due the fact that most LEED hotels are also new. In our final two models (5-6) we added change terms in addition to linear measurement for year. This strategy allows us to measure the impact of the certification event (*LEED Adoption*) and the post-event (*Years Since Adoption*) performance (Singer & Willet, 2003; Lang & Bliese, 2009). This method more accurately reflects the longitudinal nature of this data and returns more meaningful results. We notice first that the main effects of LEED and New are significant but not the interaction. This means that both the newness and LEED certification contribute to higher RevPar but the combination of the two does not give any additional benefit. Further, at the time of adoption RevPar among certifying hotels drops significantly (-13.12) but is quickly recovered (10.01 per

year after certification). In Model 6 we specify a curvilinear model by adding quadratic change terms for *Year* and *Year Since Adoption*. In this model *New* and *LEED* predictors continue to be significant along with *Log_age*, *Year*, and *Year Since Adoption*. The quadratic term $Year^2$ is a significant predictor of RevPAR indicating a curvilinear or quadratic growth model for time, but not for time since adoption.

The random component specified in all models in Table 13 is time (*Year*). By specifying the model in this manner we are able to observe changes at the individual hotel (Level 1) and the impact of time (Level 2). We use three tests for model fit, all of which demonstrate better fit as we added variables to improve the model.

H4: New LEED hotels achieve abnormal levels of performance beyond that of uncertified new hotels (measured by RevPAR). (Not Supported)

H5: The initial boost that LEED hotels get over their non-certified peers diminishes quickly (measured by RevPAR). (Supported)

Table 4.14: Discontinuous Growth Model Predicting Hotel Performance (RevPAR) as a Function of LEED Adoption with ‘Compset’ Modeled as a Random Effect

	7	8	9	10
<i>Fixed Effects</i>				
Intercept	89.82 [6.96]**	98.31 [8.28]**	103.16 [8.55]**	101.19 [8.60]**
LEED	2.51 [4.81]	7.37 [6.42]**	17.05 [6.70]**	13.52 [6.76]**
New	13.97 [4.40]**	30.65 [10.13]**	34.39 [10.43]**	34.47 [10.54]**
LEED*New		-5.89 [10.04]	-11.35 [10.34]	-9.03 [10.45]
logAGE		-7.56 [2.38]**	-7.13 [2.40]**	-7.30 [2.43]**
Operation		+++ **	+++ **	+++ **
<i>Change Terms</i>				
Year	1.27 [0.36]**	1.25 [0.36]**	0.71 [0.34]**	10.81 [0.53]**
Years Since Adoption			10.20 [1.26]**	9.77 [2.61]**
LEED Adoption			-13.39 [2.56]**	-14.20 [2.48]**
Year ²				-2.31 [0.09]**
Years Since Adoption ²				-1.00 [0.76]
<i>Variance Components</i>				
Level 1				
Within-hotel	339.62 [9.20]**	339.84 [9.16]**	321.75 [8.46]**	266.99 [7.09]**
Level 2				
In initial status (compset)	2997.67 [471.00]**	2825.66 [450.87]**	2896.90 [462.20]**	2853.32 [455.76]**
In rate of change (compset)	9.00 [1.89]**	9.01 [1.89]**	7.86 [1.68]**	7.85 [1.67]**
In initial status (individual)	1001.56 [70.84]**	957.74 [68.58]**	975.16 [69.70]**	1001.53 [71.46]**
In rate of change (individual)	8.40 [1.55]**	8.34 [1.51]**	7.81 [1.29]**	9.42 [1.32]**
<i>Model Fit</i>				
-2 Log-likelihood (Deviance)	40056.95	40008.84	39518.18	38944.03
AIC	40066.95	40018.84	39528.18	38954.03
BIC	40098.80	40050.68	39559.98	38985.83

DV: RevPAR. **Significant at the $p < 0.05$ level, * $p < 0.1$ level. Standard errors in brackets.
+++ Three dummy variables added to control for the operation type of the hotel (Chain Management, Franchise, and Independent). Several were significant

Table 4.14 reports the results of our discontinuous growth model with *compset* modeled as a random effect. Specifying the model in this way confirmed the results from the fixed effects model

and ensures more rigorous results. In this result we see that *LEED* and *New* continue to be significant predictors (Models 8-10) while their interaction is not significant. Additionally, the change variables are all significant predictors of financial performance, just as they were in the fixed effects model. In the random portion of the model we continue to measure individual change (Level 1) and the impact of time (Level 2), but we also add a second Level 2 component which accounts for variance at the group (or compset) level. The addition of this one variable at the group level removes the need for the 87 dummy variables used in the fixed effects model. We also report model fit with the same three measures as the fixed effects model and notice that the model improves as we add relevant predictors. In the final step of our analysis we attempt to explain why the differences in RevPar occur among certified and non-certified hotels. We do this by analyzing the individual components of RevPar, Occupancy and Average Daily Rate (ADR).

Table 4.15: Discontinuous Growth Model Predicting Hotel Performance (Occupancy & ADR) as a Function of LEED Adoption with ‘Compset’ Modeled as a Random Effect

Dependent Variable:	Compset Modeled as a Fixed Effect				Compset Modeled as a Random Effect			
	Occupancy		ADR		Occupancy		ADR	
	11	12	13	14	15	16	17	18
<i>Fixed Effects</i>								
Intercept	0.65 [0.049] **	0.64 [0.050] **	186.44 [20.32]* *	189.04 [20.94]* *	0.61 [0.025] **	0.58 [0.026]* *	174.12 [11.70]* *	174.28 [11.85]* *
Compset*	++ **	++ **	++ **	++ **				
LEED	-0.09 [0.026] **	-0.09 [0.026] **	3.16 [5.92] *	0.10 [5.50] *	-0.10 [0.026] **	-0.10 [0.026]* *	2.08 [8.98] *	-0.35 [9.15] *
New	-0.01 [0.036] **	-0.01 [0.036] **	9.48 [14.35] **	5.80 [14.69] **	-0.01 [0.035] **	-0.01 [0.035] **	3.01 [14.19] **	-0.69 [14.47] **
LEED*New	0.08 [0.035] **	0.08 [0.036] **	-8.95 [12.55] **	-5.61 [12.67] **	0.08 [0.022] **	0.08 [0.035]* *	-3.12 [14.05] **	-0.34 [14.33] **
logAGE	-0.02 [0.009] **	-0.02 [0.009] **	-5.81 [3.63]* **	-6.55 [3.75]* **	-0.01 [0.008] *	-0.01 [0.008]* **	-4.90 [3.28] **	-5.23 [3.34] **
Operation	+++ **	+++ **	+++ **	+++ **	+++ **	+++ **	+++ **	+++ **
<i>Change Terms</i>								
Year	0.00 [0.001] **	0.01 [0.004] **	0.92 [0.26]**	11.09 [0.46]**	0.00 [0.001] **	0.01 [0.004]* *	0.93 [0.38]**	11.08 [0.53]**

Years Since Adoption	0.02 [0.009] *	0.08 [0.023] **	4.71 [1.33]**	0.51 [2.48]	0.02 [0.009] *	0.08 [0.023]*	5.15 [1.30]**	1.18 [2.49]
LEED Adoption	0.09 [0.021] **	0.11 [0.022] **	2.47 [2.55]	1.71 [2.42]	0.10 [0.021] **	0.11 [0.023]*	1.67 [2.53]	1.01 [2.40]
Year ²		0.00 [0.001] **		-2.34 [0.09]**		0.00 [0.001]*		-2.34 [0.09]**
Years Since Adoption ²		-0.02 [0.006] **		-0.18 [0.74]		-0.02 [0.007]* **		-0.18 [0.74]
<i>Variance Components</i>								
Level 1								
Within-person	0.02 [0.001] **	0.02 [0.001] **	282.70 [7.33]**	224.68 [5.96]**	0.02 [0.001] **	0.02 [0.001]*	287.04 [7.43]**	229.49 [6.07]**
Level 2								
In initial status (individual)	0.01 [0.001] **	0.01 [0.001] **	2226.93 [161.80] **	2397.72 [175.30] **	0.01 [0.001] **	0.01 [0.001]*	1887.62 [131.57] **	1980.99 [138.71] **
In rate of change (individual)			25.57 [2.23]**	29.14 [2.46]**			16.55 [1.73]**	19.38 [1.89]**
In initial status (compset)					0.00 [0.001] **	0.00 [0.001]*	5648.44 [896.32] **	5638.87 [896.47] **
In rate of change (compset)					0.00 [0.001] **	0.00 [0.001]*	8.91 [2.11]**	8.77 [2.11]**
<i>Model Fit</i>								
-2 Log-likelihood (Deviance)	-2669.4	-2671.0	38641.4	37968.5	-2852.6	-2853.0	39725.0	39065.6
AIC	-2663.4	-2665.0	38647.4	37974.5	-2842.6	-2843.0	39735.0	39075.6
BIC	-2644.4	-2646.0	38666.4	37993.5	-2810.8	-2811.2	39766.8	39107.5

DV: RevPAR. **Significant at the $p < 0.05$ level, * $p < 0.1$ level. Standard errors in brackets.

++ note: 87 dummy variables added as fixed effects, one for each compset

+++ Three operational dummy variables added as fixed effects (chain management, franchise, independent)

In Table 4.15 above we report the results of specifying the *Compset* as a fixed effect (Models 11-14) and a random effect (Models 15-18). Models 11-12 and 15-16 report the results with Occupancy as the DV while Models 13-14 and 17-18 report ADR as the DV. Similar to our previous results on RevPAR, the model returned consistent results irrespective of whether we specified *Compset* as a fixed or random effect. For this reason, we will focus on the fixed effects

model for the remainder of this section. Regarding *Occupancy*, we see the main effect of *New* is not a significant predictor while *LEED* is a significant predictor. Their interaction is also significant. This means that the LEED certified hotels that are also new predict greater occupancy relative to their non-certified peers. Other significant predictors of occupancy include *Log_age* (greater age predicts lower occupancy), *Years Since Adoption* (as post adoption time increases so does occupancy), and *LEED Adoption* (adopting hotels get a boost in occupancy). The curvilinear model shows that the quadratic change variables are significant.

Considering ADR we notice that *LEED*, *New*, nor their interaction could significantly predict ADR. The only significant predictor of ADR in the linear model is *Log_age* (at the $p < 0.1$ level), *Years*, and *Years Since Adoption*, while in the curvilinear model the only significant predictors are *Log_age* (at the $p < 0.1$ level), *Years*, and *Years*².

7. Discussion, Limitations, and Future Research

7.1 Discussion

Other event studies have primarily dealt with certification adoption on existing companies (Corbett, et al., 2005; Swink & Jacobs, 2012). In this study on LEED Certification in the hospitality industry we study the impact of certification on both existing and new properties. When considering only existing properties that underwent a certification event with a diff-in-diff approach there is no significant difference in the pre/post event financial performance (RevPAR, Occupancy, and ADR) of certifying properties relative to their non-certified peers. This holds for both absolute levels over performance and year-over-year changes in performance. However, when this analysis is augmented by a multi-level model we see that existing LEED hotels do outperform their competitors (Tables 4.13-4.14). This analysis begins to answer the question: what

is the financial impact of certification? To answer this question more fully we spoke with sustainability officers in several multinational hotel companies. Their explanation was that hotel owners/managers are motivated by environmental and social issues when choosing to certify. Many luxury owners choose to certify to signal quality. Some branded hotels do it to add to the brand, or attract certain types of customers. From our discussion however, they do not do it for a financial gain because those gains are still not well understood. This is why one manager said that they have difficulty selling LEED to their economy and mid-scale owners, ownership simply does not want to pay for something without a clear return. This attitude of owners has made this particular branded hotel company reconsider whether they will continue to promote LEED to their individual owners.

One major difference with this study and previous studies is our attempt to analyze the impact of certification on new properties, which cannot be accomplished with traditional event studies. The result of our discontinuous growth model confirms that the abnormal performance of LEED certified hotels is attributable to LEED certification *and* the newness of the hotel. In fact, the newness of the hotel is the primary contributor to the abnormally high financial performance, but LEED certification is still a positive contributor to RevPAR. Being both LEED and new (interaction term) however, does not contribute significantly beyond the main effects. LEED hotels tend to take an immediate hit in RevPAR upon certification (mainly due to lower occupancy) they quickly recover and surpass their non-certified counterparts. Breaking down RevPAR into its component parts, the abnormal performance is primarily due to higher ADR generally among LEED hotels and increasing occupancy the further a LEED hotel gets from the certification event. In fact, LEED certification and newness are predictors of hotel occupancy but not ADR. This finding has

important implications to hotel managers and owners because it makes a case for the financial advantage of LEED certification over time.

To further our understanding of the impact of LEED certification on performance we did a site visit of a LEED Platinum hotel (one of three in the US) to speak with their management team. They explained that their decision to certify was not motivated by financial performance, but rather the mission of the company and the personal interests of the owner. We were a little surprised to find out that they did not even set out to become a LEED Platinum hotel but while reviewing the LEED ratings system (after initial design) they discovered they were so close that they ‘may as well go for it.’ We were also surprised that, while they did get some incidental press coverage upon certification, they did not actively market their LEED Platinum status to their guests. They recognize that some guests do know and come for that reason, but many do not, and they do not make attempts to inform them. They said, “We don’t want our customers to feel like they are sacrificing things, like they are losing out on luxury, so we don’t go overboard talking up our platinum status.” We followed up by asking how customers do find out about the platinum status. The responded that they leave that up to the customer, “People seek us out.”

To follow-up on the distribution of LEED status to the market we read 50 reviews on trip adviser for this particular hotel. Of the 50, only 2 mentioned that this is a LEED certified hotel, while 5 more mentioned that it was ‘green’ or environmentally conscious. The vast majority (43) either did not recognize the environmental status of the building or did not feel it was important enough to write about. Many reviews did highlight ‘cool’ aspects of the hotel that were integral in reaching LEED Platinum status (reclaimed floors, repurposed materials, etc.) but it appears that they did not connect those characteristics to environmental sustainability. Finally, while this

particular owner was satisfied with the outcome of their hotel and proud of the LEED Platinum status, they admitted that they would not pursue certification again on future properties, citing construction and program costs as the principal reason.

7.1 Limitations

One perceived limitation of our study is that the final dataset of US LEED certified hotels from 2007-2012 includes only 87 hotels. Some may contend that this is a small sample size, but we affirm that the strength of this data is in the fact that it is not a sample, but a population of all US LEED certified hotels (minus a few that were removed due to insufficient data). Because it is a population that we are studying and not a sample we are able to draw insightful conclusions even though our population ‘N’ may not be as large as the sample ‘n’ in other studies. Additionally, we have panel data with many measurement periods for all of our subject properties and competitor properties. While we have only 87 LEED certified hotels, we compare those against 472 non-certified hotels (most of which we have a full 8 years of data for). In all we have close to 5,000 measurement points, which is substantial compared to many similar studies.

Another possible limitation to this study is that we rely on the subject properties to identify competitors that are operationally similar. Many methods of statistical analysis rely on additional variables to control for demographic differences among subjects or the use of random assignment to negate the differences. In this study hotel owners were asked to identify their competitors. While hoteliers have an economic incentive to select similar hotels, we cannot control which competitors they choose.

7.2 Future Research

In this paper we analyzed only the revenue side of the profitability equation. The next step is to look at the cost side of the equation. While it is the express mission of LEED to reduce operating resources—and therefore costs—there can be a premium on initial investment (mentioned by several executives we spoke to). The payback period for LEED certification from a cost perspective is unclear and requires additional investigation. We may also be interested in segmenting the dataset further to see if there are differences in impact among hotel classes, locations, or sizes.

Another interesting question may be: what happens when a hotel begins the LEED certification process, but perhaps never follows it through to certification? Many projects register with the USGBC demonstrating their intention to certify but for various reasons do not finish the certification process. Does the act of registering itself have an effect on the project, even though final certification was never achieved? This is an interesting question because it's possible that the advantage is created in the learning that goes on through the certification process and not in holding the certificate itself. Could a hotel that goes through the process but never obtains the certificate enjoy the same profitability advantages as those that do hold the certificate? Or is there something about holding the certificate that is important to signal to customers that this is a LEED hotel? Anecdotal evidence from our site visit suggests that the signaling may not be very important, or that some hotels are not even actively marketing the certification to customers. If they choose not to market it, then why certify at all?

8. Conclusions

Academics and practitioners have debated the merits of LEED certification in various industries since the establishment of the program in 2000, but there are very few empirical studies that measure its impact. In this study we tested the impact of LEED certification on hotel revenue in the US hotel industry. We analyzed the population of LEED certified hotels in the United States and discovered that LEED hotels do in fact outperform their non-certified competitors in common revenue benchmarking metrics like ADR and RevPAR. While this abnormal performance is driven primarily by the fact that most LEED hotels are also new hotels, and new hotels outperform their peers, the main effect of being LEED does contribute significantly to increase performance. This increased performance in RevPAR comes primarily from higher ADR and Occupancy (which initially lags behind but quickly catches up). We measured this increased performance for 2 years following certification. It is still too early to know the effects of LEED certification beyond the first two years, primarily due to the newness of the program.

Acknowledgements

This research would not have been possible without the support of the Center for Hospitality Research (CHR), School of Hotel Administration, at Cornell University. In addition, we would like to thank Smith Travel Research their support of CHR and for providing the performance data for the hotels in our dataset. We would also like to thank the management of the Hotel Skyler for allowing us to stop in for a site visit. Finally, we thank the sustainability officers from various hotels that gave generously of their time and knowledge by allowing us to interview them.

CHAPTER 5: MANAGERIAL IMPLICATIONS AND FUTURE RESEARCH

Introduction

Business by nature is an applied discipline and therefore good business research should make an impact on practice. Our research conducted in this dissertation is largely applied in nature as each essay operates in the context of a specific sector or industry segment. In this section we distill the learning from each study into applied actionable insights that firms can use to improve their operations and performance. We also discuss the future direction of our research and extensions into new areas and contexts.

Managerial Implications

Chapter 2: Characteristics and Challenges of PSOM

Many traditional professional services frameworks group all professional services in a similar category and make generalizations that we discovered are often misleading. Consultants in our study for example did not exhibit high levels of customer engagement, only spending roughly 9% of their time with their clients. We identified a need for more contingent analysis based on characteristics like firm size and specialization, or consultant experience. Managers of consulting firms can use this information in the daily operation of their firms. For example, large firms on average customize less and are more capital intensive than small firms. A large firm struggling to compete in a niche market or a particular service may decide they need to become more agile by developing specialized teams. Similarly, senior consultants tend to engage customers more and customize more than their junior colleagues. A senior manager who finds that he is repeating much of his routines and not spending enough time with clients may decide that he can pass some of the non-customized routine work to more junior consultants so that he can focus more on working directly with the client.

Consultants also differ based on specialization. A ‘super specialist’ who focuses on one service in one industry customizes much less than a generalist who performs multiple functions in multiple industries. Super specialists who are pulled in multiple directions may find that they need to make a strategic choice to limit their services and sell them more effectively or diversify and as a result customize their offerings much more. Similarly, a generalist trying to break into a niche market may decide they need to customize more than they are typically comfortable with in order to compete with the highly specialized incumbents.

Customers of consultants can also use this information to their benefit. Clients with highly technical or specific problems that need customized solutions may be best served by super specialists who have content and industry knowledge and not by a large generalist firm. On the other hand, a client who has a generic problem should be well served by more junior consultants who don’t customize as much in an effort to save money. In this situation, clients should not expect to spend a lot of time working directly with their clients. If they do have an expectation to spend time with their clients they should recognize that it will likely come in the form of a more senior consultant and cost more.

Chapter 3: Consultant/Client Interactions and Decisions

Our study of the process of developing a recommendation and solution between consultants and clients has several direct managerial implications. First from the consulting side, we discovered in a laboratory setting that consultants were influenced by clients interjecting their opinion, but not in the way we expected. Consultants with high levels of expertise did not ‘take the bait’ but instead were more likely to provide novel (but sometimes bad solutions). Why would an expert consultant deviate from their client’s opinion when their client told them what they believe to be the correct solution? The simplest explanation is that the consultants believe that the

clients are wrong in their estimates and they believe a different answer is better. In our study however, expert consultants deviated from clients even when the clients were correct in their estimates. When clients did not interfere with the process however, the consultants made recommendations more consistent with the client estimates. We believe that consultants deviate from clients because regardless of whether the client is correct or not they feel pressure to provide novel advice. They may feel that to justify their position as consultants they have an obligation to provide a unique perspective. This perspective is best suited when a client is novice, doesn't know the best solution, and needs help to solve a problem. In many consulting engagements however the client is expert at their own problems and only hires a consultant to confirm what they already know or to satisfy corporate requirements. In these situations a consultant that feels obligated to provide unique perspectives and by not confirming the client's opinion can jeopardize the client by providing bad advice. A clever consultant perhaps should make a greater attempt in the early stages of the engagement to discover what kind of client they are working for and how they can best reach their clients goals. If their client is only seeking confirmation of a good solution then the consultant should be willing to do that, but in other situations where the client genuinely doesn't know the best decision, the consultant can provide unique insight.

Another major finding from this study was that expert clients don't blame consultants for bad outcomes but they don't give them credit for good outcomes either. Clients with little expertise however tend to shift blame to consultants when outcomes are bad, but give credit to consultants when outcomes are good. If you were a consultant, which type of client would you want to work for? Savvy consultants may use discretion when bidding work and choose to work for expert clients when risk is high (recognizing that they will likely not receive blame if things don't work

out) and novice clients when risk is low (recognizing that they will likely receive credit for success).

From a client perspective we demonstrate that clients are reluctant to move off their initial estimate and even more so in the condition of client interference. They appear to not trust their consultants even when they are untrained, expecting recommendations that are in line with their own opinions. Clients could use these findings to appraise their own situations with a bit more judiciousness. When they are untrained, they should listen more to their consultants who are trained on the problems that they have hired them for. However clients must be a bit cautious because expert consultants in this study appear to prefer unique recommendations over good recommendations and it is only the consultants with low expertise that conform to client estimates. Clients therefore may be better served by not leaking their own opinions to consultants. This can be a challenge however as many consultants try to discover clients opinions in order to craft their recommendation.

Chapter 4: Impact of LEED Certification on Hotel Performance

One specific operational decision that managers of service firms must make is whether they will pursue environmental certification as part of their operational strategy. An example from the hospitality industry is a hotelier's decision to become LEED Certified. Our study on the financial implications of LEED Certification has direct managerial implications. In the hospitality industry many hoteliers are reluctant to pursue any investment that does exceeds a 12-18 month payback period. LEED Certified hotels are constructed at a cost premium and without a clear understanding of the financial returns, many hoteliers aren't interested. This study is the first that makes a financial case for LEED from a revenue perspective.

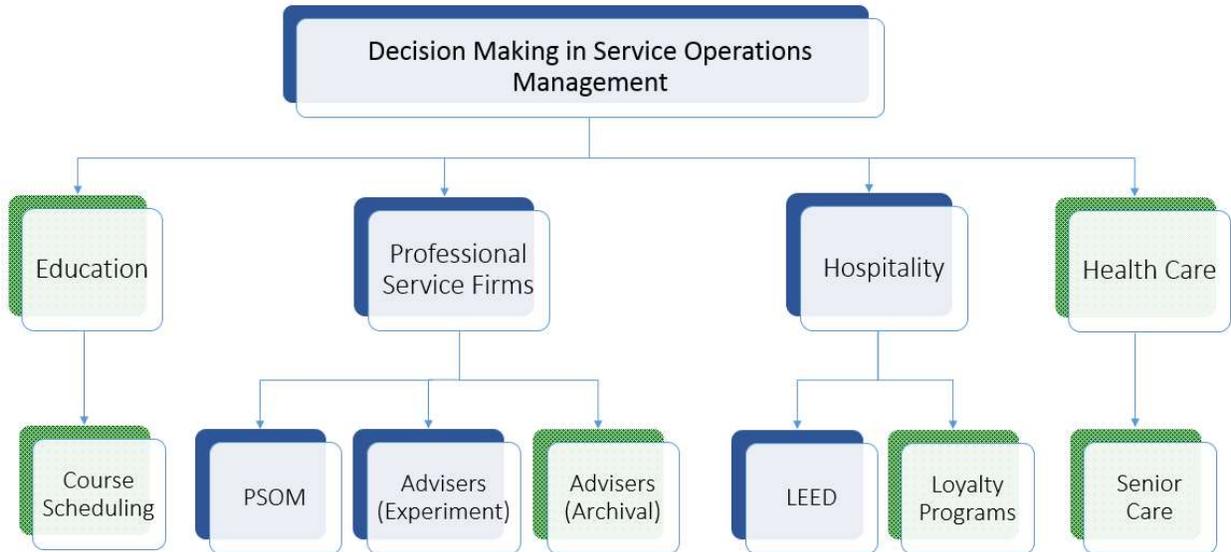
It has been well established that LEED buildings reduce costs through waste reduction, something hoteliers are keen on capturing. For this reason, many hoteliers have used the LEED Certification standards as a learning mechanism for how to implementing cost savings techniques. The cost conscious hotelier has not investigated certification with a serious consideration to certify. They are seeking savings without paying the premium that comes with a LEED Certification. Those that do pursue certification appear to be using LEED to achieve their company's social mission and not to improve their financial goals. We demonstrated that some companies are not even leveraging that certification through effective marketing to their customers. They may even worry that their customers will devalue their hotel as a result of the LEED Certification, thinking of it as 'skimping on quality'.

With this study hoteliers for the first time have evidence that LEED Certification has a positive effect on hotel revenue. Hoteliers should now be less reluctant to certify their hotels recognizing an opportunity to improve their financial performance. Recognizing this financial effect, they should be proud to promote LEED Certification to their customers and not dismiss it as merely a social goal of the company.

Future Research Opportunities

The opportunities for future research on operational decisions in service industries are virtually endless. In this dissertation we focused our research specifically on client/consultant decisions in professional service firms and the decision to pursue environmental certification in the hospitality industry. We have already identified many opportunities to expand this work, both within the professional services and hospitality industries, as well as new industries like healthcare and education (Figure 5.1). We look forward to the adventures ahead of us as we investigate various interesting questions in each of these areas

Figure 5.1: Current and Future Research



Education: Course Scheduling

In education, students make regular decisions about course registration while professors and administrators define capacity and schedules. One common problem experienced by virtually every university is matching students to their preferred courses in an efficient way. Many universities implement various techniques including first-come first-serve, auctions, matching mechanisms, and even open markets. Each of these methods has strengths and weaknesses but each has essentially the same goal: match students to their preferred courses in an equitable and efficient way.

In this paper we solve a course scheduling problem for a university by recommending a new system. We first design, then test the system in an experimental setting, prior to launching the system for students in a top 50 MBA program. We collected several semesters of data to test the efficacy of the new system. This research supports this dissertation because it investigates the behavioral games that customers (students) engage in when making decisions about constrained

capacity and a need to fill a basket of products (multiple courses), which impacts operational choices (i.e. capacity).

Expanding Professional Service Work

A natural extension of chapter three is to expand this work to collect empirical data in the field. We propose doing this by collecting data on referrals and second opinions in medicine. In our study we introduced customer interference with customer estimates that were given to the consultants. Another way to interfere with an expert's recommendation is to provide information regarding previous expert's recommendations. We can collect this data in the field from doctors who are asked to provide a second opinion on medical conditions. What is the effect of the first diagnosis on the doctor's likelihood to make a similar diagnosis? How is the doctor biased by this previous diagnosis?

Expanding Hospitality Work

Customers in today's marketplace are often inundated by offers to join rewards or loyalty programs (LPs). Where did this affinity for loyalty programs come from? We first sketch the evolution of LPs focusing on how firms have designed LPs over the past 200 years and why they use them. We distinguish between several types of programs (free rewards based programs and paid membership programs) as well as the types of benefits they offer (discounts, cash back, and premiums). We also investigate why customers engage with LPs and how they make program decisions. Finally, we analyze data from a paid membership based loyalty program to highlight some of the distinctions of these types of programs. This research extends this dissertation because, again, we measure the impact of customer decisions (participation in loyalty programs) on operations settings.

Healthcare: Senior Living and Care

Another extension of my work on advisers and clients could be done in the context of caring for seniors. We know from past work in behavioral economics and psychology that customers can be ‘nudged’, in their decisions, towards specific outcomes (Thaler and Sunstein 2009). In healthcare this type of influence can be used to improve health outcomes. For example, The Cleveland Clinic discovered that they could improve patient health and hospital profitability by improving the service experience (Merlino and Raman 2013). In the senior care industry there has been a similar trend to improve customer experience through increased services. However, in senior care, little research has been done to understand how an increase in service leads to improved healthcare outcomes and greater community health.

We hope to use the concepts of service design and behavioral economics to measure how specific service elements influence customer decisions in the setting of senior care. For example, we can improve community health by influencing seniors to adhere to their doctor’s advice (plan of care) so that they can avoid expensive hospital readmissions. However, does senior’s willingness to follow advice change depending on the environment in which they receive it (i.e. assisted living facility versus a hospital)? In what specific ways does the design of the environment (service experience) influence the patient’s decisions (willingness to follow a doctor’s advice)? If we can improve patient’s adherence to doctor’s recommendations by nudging them in the right direction, then we can also improve profitability of hospitals (through reduced penalties relating to readmission) and eliminate waste (i.e. costs) in the entire community.

APPENDIX A: PROFESSIONAL SERVICES SURVEY FROM CHAPTER 2

December 17, 2013

You are being invited to take part in a research study about professional services (e.g. accounting, financial, information technology, management, legal, and other types of consulting services).

This study is undertaken jointly by professors at Cornell University, University of Bath, and Manchester Business School. The purpose of this research is to develop a better understanding of the challenges and characteristics of professional services.

After collecting data from a diverse group of professional service providers, we will publish a managerial report (from the Cornell Center for Hospitality Research) that will provide a summary of results including practical guidelines for implementation. In addition, the results will be published in a top-tier academic journal.

As a token of our appreciation, we will be delighted to share the results and all publications resulting from this study with you.

Please note that there is no right or wrong answers to any questions in this survey and we are only interested in your perceptions and feedback. This survey should take approximately 10 minutes to complete.

We assure you that the responses provided by you will not be linked to any personal identifying information or to your organization. Your participation in this study is voluntary and you are free to withdraw at any time.

We thank again for your willingness to participate in this study. Please feel free to contact us if you need any additional information about this project.

Sincerely

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PLEASE CLICK ON THE “NEXT” BUTTON TO BEGIN THE SURVEY

SECTION 1

The first section of the survey includes questions about your professional background. Your responses to these questions will allow us to make comparisons across different groups of respondents.

1.1 Please state the type of professional services organization you currently work for? (please check all that apply)

- a) Information Technology Consulting
- b) Financial/Accounting Consulting
- c) Management Consulting
- d) Law / Legal Consulting
- e) Any other type of professional service organization (please specify)
- f) A non-consulting organization (please specify)

Do not ask Q2 if (f) is selected as answer for Q1

1.2 Please state the industries your firm/organization serves (please check all that apply)

- a) Travel, Tourism, and Hospitality
- b) Retail
- c) Healthcare
- d) Manufacturing
- e) Education
- f) Government
- g) Other (please specify)

1.3 Please state your current position

- a) Analyst
- b) Consultant
- c) Sr. Consultant

- d) Director
- e) Vice President
- f) President
- g) Managing Director
- h) Other (please specify)

1.4 How long have you been employed at your current organization

- Pull-down menu 1 – 40 years

1.5 How long have you been employed in the current profession

- Pull-down menu 1 – 40 years

SECTION 2

The second section of the survey includes questions about the nature and characteristics of your work. As we mentioned earlier, there are no right or wrong answers to any questions – we are only interested in your perceptions and opinions.

2 Please indicate approximate time you spend every week on each type of activity listed below.

- a) Working along on client/project related activities
- b) Working with colleagues in your own organization on **client**/project related activities
- c) Working with colleagues in client or partner organization on **client**/project related activities
- d) Working with colleagues in your own organization on **non-client**/project related activities
- e) Working on business development – related activities
- f) Working on other activities not specified above (please explain)

Sum of all responses above should add to 100

Section 3

Professional services providers have to face multiple managerial challenges in course of their work. However not all challenges are equally relevant/important to each professional. The next six screens display a subset of 8 managerial challenges. On each screen we would like you to indicate the most and least important challenges within the presented set.

Again, there are no right or wrong answers – we are only interested in knowing your opinion.

Sample Best|Worst Screen

Least Important	Management Challenges	Most Important
	#1	
	#2	
	#3	
	#4	
	#5	
	#6	
	#7	
	#8	

Q3.1 to Q3.6 Include six screens / respondents and 8 challenges/screen

Master List of Managerial Challenges for Best|Worst exercise (from Schmenner’s article)

- a) Attention to physical surroundings
- b) Controlling work for far-flung geographic locations
- c) Capital decisions
- d) Developing work & control methods
- e) Employee hiring
- f) Employee training
- g) Employee welfare
- h) Fighting cost increases
- i) Gaining employee loyalty
- j) Managing growth
- k) Monitoring and implementing technological advances
- l) Managing Demand to avoid peaks and to promote off peaks
- m) Managing career advancements of employees
- n) Managing flat hierarchy with loose subordinate-superior relationships
- o) Managing fairly rigid hierarchy with need for standard operating procedures
- p) Maintaining quality of service
- q) Making service "warm"
- r) Marketing
- s) Reacting to consumer intervention in service process

- t) Scheduling service delivery
- u) Scheduling workforce
- v) Startup of new operations at new locations

Section 4

The last section of the survey includes some demographics-related questions. Your responses to these questions will only be used to make sub-group level comparisons. As we mentioned earlier, individual responses will be not be analysed.

4.1 Your educational background

- a) High School Diploma
- b) Some College or an Associate College Degree
- c) A 4-Year College Degree
- d) A Post-Graduate / Master's Degree
- e) A PhD. Or Doctorate

4.2 Your Age

Pull-down menu (21 – 25, 25 – 30, 31 – 35, ... 60 - 65, more than 65 years)

Give option for “Rather Not Say”

4.3 Your Gender

- a) Male
- b) Female

Give option for “Rather Not Say”

4.4 Your current annual income

Pull-down menu (Less than \$25K, 25 – 50K, 51 – 75K 475 – 500K, more than 500K)

Give option for “Rather Not Say”

4.5 Please insert your email address below if you would like to receive a copy of the results.

Provide text-box for inserting email address

THANK YOU FOR YOUR ASSISTANCE IN THIS PROJECT

APPENDIX B: INTERVIEW GUIDE FOR CHAPTER 2

Q1: Describe your role as a consultant and how this role has changed (or business of consulting changed) in this industry during your career?

Q2: How is consulting in the travel, tourism, and hospitality sector distinct (from other sectors) (If not, why not)?

Q2a: Follow-up: Why are consultants so important to this industry? What makes consulting in this sector a viable/fertile business?

Q3: Within the sector, how are consulting firms different? (Size, functional area, boutique vs. full service firms)

Q4: Describe the key managerial challenges for consulting firms in this sector.

Q5: How do you expect the Travel, Tourism, and Hospitality (TTH) sector to evolve in the future?

APPENDIX C: LABORATORY INSTRUCTIONS FROM CHAPTER 3

You are about to participate in a decision making experiment. If you follow these instructions carefully and make good decisions you will earn money that will be paid to you in cash at the end of the session. Your earnings will depend on your decisions, the decisions of other participants, and chance. Please do not talk with one another, or use any sort of electronic devices (cellphones, etc.) for the duration of the experiment. If you have a question at any time, please raise your hand and I will answer it.

Game Overview

At the beginning of the session you will be randomly assigned one of two roles for the duration of the session: a consultant or a client. Each client has hired a consultant to advise them on a specific business problem. The business problem is that the client is a manager of a firm that needs to decide how many units of a particular item to order to meet customer demand. First, the client's will make an initial ordering estimate. Then, consultants will recommend to clients how many units to order. Finally, after seeing the consultant's recommendation, the client will decide how many items to actually order for the round. The client will also indicate if they are satisfied with their consultant's recommendation. After the ordering decision is final then demand for the round will be revealed and the client will collect a profit or loss.

The client's compensation for the game is based on earnings from their decisions. The consultant's compensation for the game is based on a combination of: (1) a fixed fee for their service (\$50 per round), (2) the earnings the client would have received had they followed the consultant's recommendation, and (3) a penalty if the client is unsatisfied with their recommendation (-\$100 per round).

You will play this game for 20 rounds, each representing one ordering decision. You will be randomly re-matched with a different person each round, but you will keep your role for the duration of the experiment.

Customer demand is randomly determined each round but will not be revealed until after the ordering decision is made. Demand is equally distributed between 0 and 100 units, with the same probability of each number being selected.

Stage 1 - Training

Prior to beginning the game, you will be trained how to solve the type of problem (ordering decision) that you will encounter in the actual game. Both consultants and clients will be trained. The training will take you through two practice problems followed by an evaluation where you will answer three similar problems. You will receive a score on the evaluation according to how many of the questions you answer correctly out of three. The training and evaluation stage will last approximately 15 minutes. You will have a calculator icon on your screen that you may use if you wish during the training and during the actual game itself. Please do not use cellphones to perform calculations.

Stage 2 – Playing the Game

After completing training, you will begin the actual game. Each round begins with a client's decision to order units to meet the demand for the round. Both clients and their consultants will be given several important pieces of information to make the ordering decision:

7. Revenue per unit.
8. Cost per unit.
9. Penalty cost if you run out of units. If the client does not have sufficient units to meet demand then they must get extra units at the last minute to meet the demand. The client will always meet demand whether it is with the regular ordered units or the last minute units.
10. Holding costs. If you have too many units on hand you may incur an additional costs.
11. Salvage value. If you order too many units, you may be able to recover some of the value.
12. Your performance on the evaluation.
13. Your counterpart's performance on the evaluation.

Using this information the client will first make an initial estimate of how many units they believe they should order. To help you make a decision more easily, clients will be given the opportunity to test various ordering decisions. You can do this using the test button in the top center area of your screen. Below is an example of a client's initial screen shot:

Round 1
You are the **Client**.

Decision Parameters	Test Section	Test Results
Average Demand: 50 Revenue per item: 10 Cost per item: 5 Last minute cost per item: 12 Holding cost: 0 Salvage value: 0 Your score on the training (out of 3): 1 Your consultants score on the training (out of 3): 2	Test stocking quantity: <input style="width: 50px;" type="text"/> <input type="button" value="Test"/>	Actual demand: 0 Order quantity: 0 Last minute order quantity: 0 Total revenue: 0.00 Total order costs: 0.00 Total last minute order costs: 0.00 Total profit: 0.00
<div style="border: 1px solid gray; padding: 10px; margin: 0 auto; width: 80%;"> <p>Please indicate your initial estimate of how many items to order.</p> <p>Estimate: <input style="width: 50px;" type="text"/></p> <p style="text-align: right;"><input type="button" value="Continue"/></p> </div>		

Next the consultant will make a recommendation to the client. They will be given the same opportunity to test various ordering quantities using the test area at the top center of your screen. Below is an example of a consultant's screenshot:

Round 1
You are the **Consultant**.

Decision Parameters	Test Section	Test Results
Average Demand: 50 Revenue per item: 10 Cost per item: 5 Last minute cost per item: 12 Holding cost: 0 Salvage value: 0 Your score on the training (out of 3): 3 Your clients score on the training (out of 3): 2	Test stocking quantity: <input style="width: 50px;" type="text"/> <input type="button" value="Test"/>	Actual demand: 0 Order quantity: 0 Last minute order quantity: 0 Total revenue: 0.00 Total order costs: 0.00 Total last minute order costs: 0.00 Total profit: 0.00
<div style="border: 1px solid gray; padding: 10px; margin: 0 auto; width: 80%;"> <p>Your client's score on the evaluation (out of 3): 2</p> <p>Your client's initial estimate is that they should order (units): 1</p> <p>Please recommend to your client how many items you believe they should order.</p> <p>Recommendation: <input style="width: 50px;" type="text"/></p> <p style="text-align: right;"><input type="button" value="Continue"/></p> </div>		

After the consultant makes a recommendation, the client will make the final decision of how many units to order. They will also signal whether they are satisfied with their consultant's recommendation. Below is an example of a client's screenshot:

The screenshot shows a client's interface with the following information:

Consultant score on the evaluation (out of 3):	2
Your Estimate:	1
Consultant Recommendation:	100
Final Decision:	<input type="text" value="1"/>

Are you satisfied with your consultant's recommendation?

After the client makes the final ordering decision, profit for the round is calculated. Profit depends on the number of units sold, or *Sales (S)*. Sales are always equal to demand regardless of the ordering decision. If you don't order enough then you will have to procure some units at a higher cost to fill demand. If you order too many units then you will have extra units that you cannot sell.

After the actual sales have been revealed, profits will be calculated with the following equation:

$$\text{Profit} = \text{Total Revenue} - \text{Total Ordering Cost} - \text{Total Last Minute Ordering Cost}$$

Results

After the client makes the ordering decision you will be taken to a new screen where you will learn the actual demand for the round (*Sales*) and profit (based on the formula above). Information from previous rounds will be reported at the bottom of each screen. You will also indicate your desire (on a scale of 1-5) to work with your partner again.

This concludes one round. You will play this game for a total of 20 rounds. At the beginning of each round, you will be randomly re-matched with another participant of the opposite role.

Payment

Clients earn money in each round according to the outcomes of their decisions. Consultants earn money each round based on a combination of three things: (1) a fixed fee of \$50 for their service,

(2) the earnings the client would have received had they accepted the consultant's recommendation, and (3) a penalty of \$100 if the client is unsatisfied with the consultant's recommendation. At the end of the session your earnings from each round of the game will be summed and converted to US dollars at the rate of \$125 laboratory dollars for \$1 US dollar. These earnings will be added to your \$5 show-up fee, displayed on your screen, and paid to you in cash at the end of the session.

LEEDR Participant Payment Sheet

PAYMENT AMOUNT _____ (round UP to the next nearest dollar)

Name _____

NetID _____

Cornell ID # _____

Signature _____

Date _____

Implied Informed Consent Form for Social Science Research
Cornell University

Principal Investigator: Matthew Walsman
455 Statler Hall
Cornell University, Ithaca NY 14853
(607) 255-1198 mcw237@cornell.edu

1. **Purpose of the Study:** The purpose of this research study is to examine how people make decisions.
2. **Procedures to be followed:** You will be asked to take part in an online game where you will be in the role of a decision maker. The computer will calculate your profit from each round based on a predetermined equation.
3. **Discomforts and Risks:** There are no risks in participating in this research beyond those experienced in everyday life.
4. **Benefits:** This research might provide a better understanding of how people make decisions. You may find participation interesting and enjoyable.
5. **Duration:** The study will last not more than 1.5 hours.
6. **Statement of Confidentiality & Access to Data:** Your participation in this research is confidential. The task does not ask for any information that would identify to whom the responses belong. In the event of any publication or presentation resulting from the research, no personally identifiable information will be shared because your name is in no way linked to your responses.
7. **Right to Ask Questions:** The researcher conducting this study is Matthew Walsman, PhD Candidate, Cornell University. Please ask any questions you have now. If you have questions later, you may contact Matthew Walsman at mcw237@cornell.edu or at 1-607-255-1198. If you have any questions or concerns regarding your rights as a subject in this study, you may contact the Institutional Review Board (IRB) at 607-255-5138 or access their website at <http://www.irb.cornell.edu>. You may also report your concerns or complaints anonymously through Ethicspoint (www.hotline.cornell.edu) or by calling toll free at 1-866-293-3077. Ethicspoint is an independent organization that serves as a liaison between the University and the person bringing the complaint so that anonymity can be ensured.
8. **Payment for Participation:** In return for your participation, you will receive \$5 plus any earnings from the games in which you participate. You will be paid in cash upon the conclusion of the experiment. All participants who show up on time will receive the \$5. To receive any additional earnings from the games, you must stay until the end of the session.
9. **Voluntary Participation:** Taking part in this study is completely voluntary. If you decide to take part, you are free to withdraw at any time.

You must be 18 years of age or older to take part in this research study. You will be given a copy of this form to keep for your records.

Please keep this form for your records or future reference.

APPENDIX D: TRAINING TOOL FOR CLIENTS AND CONSULTANTS

Practice Problem #1

Sam manages a rental car company at a major international airport. One decision that he constantly struggles with is how many cars to keep on his lot when customer demand at his airport location fluctuates constantly. Sam's company rents cars to customers for \$75 per car. It costs Sam's company \$25 per car to hold a car on the lot, regardless of whether a car gets rented. If Sam underestimates customer demand and runs out of cars then he must pay \$85 per car for last minute cars to keep his customers happy (even though he loses money on that car). If Sam overestimates customer demand then he cannot recover any value from an unrented car. If Sam knew the demand he could make better decisions but it appears to be random, somewhere between 50 and 100 cars.

There are three parts to solving this problem:

1. Defining the decision parameters.
2. Solving for the optimal service level.
3. Converting the optimal service level to an order quantity.

Step 1: Defining the decision parameters.

To solve this problem you need define a few decision parameters:

R = Revenue per unit (\$75).

C = Cost per unit (\$25).

P = Penalty you must pay for running out of units ($\$85 - \$75 = \$10$).

H = Holding costs or extra expenses incurred for having too many units on hand (\$0).

S = Salvage value or value that can be recovered from unsold units (\$0).

Step 2: Solving for the optimal service level (SL).

C_s = Cost of a shortage. This incorporates all of the cost associated with running out of an item (Lost Sales + Penalty associated with running out).

$$C_s = R - C + P$$

$$C_s = 75 - 25 + 10$$

$$C_s = \$60$$

C_e = Cost of excess units. This incorporates all of the costs associated with having excess items (Additional Holding Costs + Cost of Unit – Recoverable Costs).

$$C_e = H + C - S$$

$$C_e = 0 + 25 - 0$$

$$C_e = \$25$$

$$SL = \frac{C_s}{C_s + C_e}$$

$$SL = \frac{60}{60 + 25} = \frac{60}{85} = 0.7058$$

Step 3: Converting the optimal service level to an order quantity.

The problem states that customer demand is random between 50 and 100.

The range in the demand is 50 or $(100 - 50)$.

$$\text{Optimal Order Quantity} = (\text{Range} * SL) + \text{Min Demand} = (50 * 0.7058) + 50 = 85.29.$$

Sam should order 86 cars (always round up).

Practice Problem #2

A national department store has hired Amelia as a consultant to help them decide how many units of different types of clothing to stock. They are particularly interested in winter coats. Coats sell for \$150 and cost the store \$80. If the coats do not sell the shop must store them at a cost of \$5 per coat, but can then sell them to an outlet store for \$65. When the supply of coats are gone future customers are out of luck as this store does not try to get more. Demand fluctuates randomly between 0 and 500 units.

Step 1: Defining the decision parameters.

To solve this problem you need define a few decision parameters:

R = Revenue per unit (\$150).

C = Cost per unit (\$80).

P = Penalty you must pay for running out of units (\$0).

H = Holding costs or extra expenses incurred for having too many units on hand (\$5).

S = Salvage value or value that can be recovered from unsold units (\$65).

Step 2: Solving for the optimal service level (SL).

C_s = Cost of a shortage. This incorporates all of the cost associated with running out of an item (Lost Sales + Penalty associated with running out).

$$C_s = R - C + P$$

$$C_s = 150 - 80 + 0$$

$$C_s = \$70$$

C_e = Cost of excess units. This incorporates all of the costs associated with have excess items (Additional Holding Costs + Cost of Unit – Recoverable Costs).

$$C_e = H + C - S$$

$$C_e = 5 + 80 - 65$$

$$C_e = \$20$$

$$SL = \frac{C_s}{C_s + C_e}$$

$$SL = \frac{70}{70 + 20} = \frac{70}{90} = 0.7778$$

Step 3: Converting the optimal service level to demand.

The problem states that demand is random between 0 and 500. This means that the range in the demand is 500.

$$\text{Optimal Order Quantity} = (\text{Range} * SL) + \text{Min Demand} = (500 * 0.7778) + 0 = 388.8$$

Amelia should order 389 coats (always round up).

Evaluation:

Problem #3

Natalie has been hired by a professional sports team as a consultant to help them design their new stadium. Specifically, they would like to know how many seats to include in their design. The team charges \$120 per ticket per game and it costs the team \$40 per seat per game. There are no additional costs if they sell out a game because there is no other professional team in town and customers can't take their business elsewhere. If they design too many seats it will cost the team an extra \$15 per seat per game to maintain them. The team expects to attract between 30,000 – 35,000 fans per game.

How many seats should the new stadium hold?

Problem #4

Rebecca manages a radio network that needs to decide how much air time for commercial advertising next month. They charge their customers \$10,000 per minute of airtime which costs them \$2,000 per minute. They have between 100-120 customers that are each willing to pay for one minute of airtime. Unsold air time is used for public service announcements which they do for free for the community. If they don't allocate enough airtime for customers then Rebecca

figures that customers will go to a competitor which will cost them \$5,000 per minute in lost good will.

How many minutes should Rebecca allocate for advertising next month?

Problem #5

Matt sells newspapers in the downtown area of a major US city. He purchases his newspapers from a distributor for \$0.75 per paper and he sells them for \$1.50. Extra papers he sells for \$0.10 each to a pet store which shreds them for bedding for some of their animals. After years of experience Matt figures that demand fluctuates pretty randomly (150-200), depending on the headline. When Matt runs out of papers he just goes home for the day.

How many newspapers should Matt purchase from his distributor?

APPENDIX E: CLIENT EXERCISE IN THE NON-TRAINED CONDITION

Practice Problem #1

Sam runs a grocery store. His supplier of milk, “Please Drink Milk”, charges a 30% markup on their milk. Sam then charges another 20% markup to his customers. How much has Please Drink Milk’s original price increased by the time the final customer pays for milk?

Practice Problem #2

Amelia manages The Museum of Play in Rochester. The museum charges \$120 per family for an annual membership. Individual tickets are sold for \$15 per person. Amelia has forecasted 1.8 million dollars in total expenses for the coming year. Typically, the museum likes to cover 60% of expenses with annual memberships. How many annual memberships do they need to sell to reach their goal?

Evaluation:

Problem #3

Natalie manages a car dealership where she carries 30% Hondas and $\frac{3}{8}$ Toyotas. She has a total of 240 cars on the lot. How many of the cars are not Honda or Toyotas?

Problem #4

Rebecca manages a local music store specializing in string instrument repair. Rebecca’s store has \$375,000 in expenses each year. She expects to pay for 65% of her expenses through

instrument repair, the rest coming from instrument sales. She sells various instruments at an average of \$250 per instrument. How many instruments does she need to sell to break even?

Problem #5

Matt runs a minor league baseball team. He projects \$750,000 in revenue from tickets and food sales for this season. He has 25 players on his team that cost an average of \$35,000 per player. If he is short, he plans on making up the difference by selling merchandise. How much money does he need to earn in merchandise sales to break even?

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