

AN EMPIRICAL INVESTIGATION OF THE EFFECT OF MOBILE CHANNEL

INTRODUCTION ON PARKING REVENUES

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ABSTRACT

This research examines the relationship between online and offline sales in an omnichannel sales environment centered around the selling of parking spaces. This dissertation consists of a pilot study followed by an expanded study. The studies delved into the effects of e-commerce additions upon traditional brick and mortar revenue channels. The parking industry was selected as the backdrop, given the high degree of current relevant concerns in this space around internet sales-related cannibalization concerns against physical stores, and given the author's substantial access to relevant research data. Data was collected for an intervention group and a control group from a leading parking management firm with thousands of parking garages located across North America.

In the pilot study, and using panel data gathered from the firm, we sought to examine the effects of an online intervention to existing aggregate revenues through the implementation of a new 3rd party e-commerce sales channel (Parkwhiz.com). Under the intervention group, data was collected on 1.7 million revenue transactions over an approximately two-year period, from 2016 through 2018 across 15 parking properties in New York City. The control group consisted of 493,950 revenue transaction entries, also spanning a roughly two-year period from 2016 through 2018, and across 28 different parking properties throughout the City of New York. A fixed-effect model was used for analyzing the data, which came with unforeseen challenges of balance, outlier concerns, and sample size. Ultimately, insignificant results were observed, but these were attributed mainly to difficulties in data structure and sample size ($N = 386$) of daily revenue observations. Despite those challenges, individual summary statistics showed potential strength in the primary hypothesis, and this motivated further examination.

In the expanded study, an adapted approach from the pilot was used to correct for a majority of its shortcomings in the data structure, sample size, balance, and modeling. Further, several moderating components were incorporated to test practice relevant relationships between

revenue, the competitive landscape, and online search sessions. Using the same primary hypothesis from the pilot study, the expanded work provided for 15 intervention group properties and 15 control group properties in New York City, with a balanced dataset of 90 days pre-intervention and 90 days post-intervention for each property examined in the year 2018 or 2019. The original hypothesis (H1A) evaluates whether or not an online intervention increases total revenue at a given location. Additional hypotheses (H1B) evaluating whether offline revenue sources are affected by the online intervention, (H2) moderation of revenue by the volume of competition using the same online channel, (H3) moderation of revenue by the volume of parking locations in the marketplace (zip code area) regardless of selling online or offline, and (H4) revenue predicted by the volume of online searches for parking occurring in the marketplace. Sample sizes ranged from $N = 3,491$ to 5,098 across our various regression models.

Our overall H1 outcomes (across four different regression models) showed strong statistical significance with p-values less than 0.001, and moderate R^2 scores between 37%-47% for the online ParkWhiz intervention. Online intervention increases revenue per parking space in the range of \$1.171 to \$1.196 in the experiment. The results provide support for the proposition that adding an online sales channel to an existing body of physical parking facilities is additive, non-cannibalistic and overall productive for the business. Our H2 and H3 study outcomes were inconclusive, as the moderators were not significant. The tests of the moderating effects in H2 and H3 provided no practical results, other than perhaps anecdotal perception to supplement the other findings. The testing of H4 did show significance in the importance of the assessment of online search demand in a given zip code as an amplifier of the effect of online intervention on parking revenue. Search volume is positively related to a change in the net new revenues. Overall, the analysis generated learnings valuable for future researchers to expand upon through better data gathering, statistical models, and analysis.

In totality, the desired contribution of this body of research is to provide today's brick and mortar business manager with strategic insights into the conditions needed to make healthy e-

commerce decisions, based on observable market conditions, in an omnichannel environment that combines online and offline models for maximum aggregate revenue growth. Avoidance or minimization of cannibalization between existing channels and new channels can ensure success. Our work demonstrates several critical aspects of the phenomena of successful online and offline channel cohabitation with practical conclusions for the strategic decision-maker to use in reaching that equilibrium, and leaves a discernible path for future researchers to supplement our efforts with additional moderating variables.

Keywords: Omnichannel, cannibalization; externality; brick and mortar; platform; two-sided marketplace; e-commerce; parking; retail; online/offline; distribution; multi-channel; cross-channel; offline-to-online service platform, channel addition, mobile apps.

DEDICATION

Dedicated to my wife, Kellan, who inspires me to expand my knowledge of the world around me by keeping me curious.

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I would like to express my deepest gratitude to my wife, Kellan Tucker, for her shared sacrifice of time and effort to support me during the last three years of the academic process. Any scholarly work of any level comes with an unprecedented level of time commitment, and spouses share in this as much as the student. Similarly, thanks to my mother and father for their support, Nona Tucker and Richard Tucker, and the support of my in-laws Dee and Candy Stanley.

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Lastly, I must thank my faith in Jesus Christ for allowing me the opportunity to reach this important milestone in my life and career. I hope that the education I have achieved and the knowledge produced herein, in some small way, bring help to someone in his glory.

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CHAPTER ONE

INTRODUCTION

Implementation of Internet-based sales channels or e-commerce channels (e-channels) have quickly risen in popularity for many of the top companies in existence today. Few companies today fail to offer some means of purchasing their products or services through a website, app, or related online medium. Despite many noted advantages of adding new sales channels in general, adverse outcomes have been observed in numerous settings as well, both anecdotally and academically, relative specifically to the new addition of an e-channel. Cannibalism of the existing brick and mortar business is one such noted potential disadvantage for the focal firm. Debates remain pervasive for the scholar and the practitioner on these issues (Bell et al., 2018). Although many industries have been studied in the e-channel arena, the parking industry provides a unique opportunity to explore the phenomena from the perspective of the focal firm, the supply side of the equation versus the consumer side, and their various existing revenue channels.

In the pilot study, and using panel data gathered from the firm, we sought to examine the effects of an online intervention to existing aggregate revenues through the implementation of a new 3rd party e-commerce sales channel (Parkwhiz.com). Under the intervention group, data was collected on 1.7 million revenue transactions over an approximately two-year period, from 2016 through 2018 across 15 parking properties in New York City. The control group consisted of 493,950 revenue transaction entries, also spanning a roughly two-year period from 2016 through 2018, and across 28 different parking properties throughout the City of New York. A fixed-effect model was used for analyzing the data, which came with unforeseen challenges of balance, outlier concerns, and sample size. Ultimately, insignificant results were observed, but these were attributed mainly to difficulties in data structure and sample size ($N = 386$) of daily revenue

observations. Despite those challenges, individual summary statistics showed potential strength in the primary hypothesis, and this motivated further examination.

In this present research, an analysis was conducted to discover the overall effect (additive? cannibalizing?) emanating from the choice to add a new e-channel to existing tangible or digital channels in a parking industry setting. This study examines the objective financial results from before and after the addition of a new e-channel to an otherwise static channel system. The expected contribution is to provide strategic insights into e-channel decision making for the brick and mortar retail practitioner. These generalizable results build upon extant lines of research on channel switching and channel cannibalization (See Table 1). Of primary importance is supporting strategic management decisions on whether to invest in new online sales channels and how to evaluate its value contribution to the overall enterprise.

The last several decades have seen an incredible expansion of e-commerce channels, two-sided marketplaces, and transactional platforms. Some of the largest and most valuable companies in history have come into existence relatively recently and gained market dominance via business methodologies that are just now being considered typical. Examples of these firms include Amazon, eBay, Uber, Lyft, Air BnB, Alibaba, Facebook, Kayak, Hotels.com, and countless others. For established, entrenched traditional firms in specific industries, these platforms, also sometimes referred to as two-sided marketplace e-commerce firms represent, at best, disruption of their market dominance (Louca et al., 2019). In many cases, these new firms can represent the outright end of the traditional firm. Netflix is a prime example, having wiped Blockbuster's brick and mortar business from existence. Uber and Lyft rideshare have significantly impacted the taxi industry's long-standing hold on ride-hailing. Amazon has taken a massive market share from many national retail and catalog chains, as well as brick-and-mortar stores of all shapes and sizes worldwide.

Despite these concerns about industry disruption, new e-channel options exist for traditional firms, both external and internal, and they can have real benefits. Research has noted that additional sales channels conclusively improve the overall financial position of the firm (Zhang et al, 2019; Lim et al., 2018; Hernant et al., 2017; Herhausen et al., 2015; Bialogorsky et al., 2003; & Deleersnyder et al., 2002). In contrast, others seem to indicate the opposite, or at least suggest the answer is not as clear cut as we would like (Duch-Brown et al., 2017; Avery et al., 2012; Van Nierop et al., 2011; Pauwels et al., 2011; & Li et al., 2017). In light of conflicting conclusions, many firms continue to labor under the perception that the addition of e-channels is detrimental, cannibalistic, and has an overall negative impact on aggregate sales. This research seeks to use the parking industry as a proxy to explore the net effect on established firm channels, specifically brick and mortar, by adding new sales channels, specifically here through the addition of a single, new third-party online sales channel. Differing from many other businesses that Pozzi defined as a hybrid model, the parking arena has special considerations, as a physical store presence is always required (Pozzi, 2013).

In our present study, we begin with the basic structure of collecting revenue and sales data both before and after an intervention period, the latter of which introduces ParkWhiz as a new e-commerce sales channel. Our intent at this stage is to observe any correlation between existing revenue channels and the newly-added channel, and thereby observing any potential cannibalization that may or may not be occurring. We then expand beyond the basic revenue categories by adding in specific parking facility and digital environment characteristics. These include the number of other parking facilities that exist within the parking facility's zip code, the number of additional parking facilities that exist within the parking facility's zip code and that are also selling via ParkWhiz e-commerce channels, and a variety of online search data for parking being conducted by consumers within each zip code. By adding in these unique new

characteristics into our data set, we create an opportunity to test several possible antecedents, consequences, and moderators in their effect on gross revenue changes both before and after the ParkWhiz intervention. One inspiration for this research approach is the Pozzi (2013) study of grocery store chains, which employed a similar research strategy.

The Pozzi (2013) study of grocery store chains examined cannibalization of revenue channels between e-commerce methods and brick-and-mortar grocery stores, taking into consideration the effects of competition and demand within each zip code in a given market. Similar to Pozzi, we measure any correlation between the number of competing facilities within a given geographic area. We also go beyond Pozzi's research, however, by adding in additional characteristics relevant to parking. These include noting whether the amount of online search occurring in a given zip code, correlated with the presence or lack-of-presence of competition online, is relevant to the cannibalization examination and hypotheses. The Zhang et al. (2019) study provides much inspiration for the application of study design to our present dataset and body of hypotheses. Following the Zhang et al. (2019) methodology, we perform fixed effects econometric analysis to quantify the performance change of adding an online channel to existing brick and mortar channels. Our panel regression model follows the 3-step methodology, which mimicked the Pauwels et al. (2011) study methodology, regarding panel regression model management. Zhang et al. (2019) and the present work are similar in setup, subject matter, and intent.

CHAPTER TWO

RESEARCH MOTIVATION

As e-commerce grows due to the massive expansion of the Internet and the rapid dissemination of information via the same, this is causing unprecedented structural changes in many industries (Duch-Brown et al., 2017). “Despite significant advances in appreciating the rationale behind retailers' decision to migrate to multichannel environments, there has been comparatively less progress made in understanding the arguments against omnichannel business” (Chen et al., 2018, p.2). Chun and Kim (2018) noted several significant effects that are attributed to channel conflict. Relative to this research is their discussion of inter-cannibalization effects, which occur when a newly added online channel takes revenue or traffic from the existing retail channel (Chen et al., 2018, p.2).

Chen et al. (2018) notes several distinct ideas in our context. Decisions by brick and mortar businesses to embrace online environments are not simple. Identified needs for additional research include the exploration of conditions in which omnichannel environments can be beneficial for brick and mortar firms. Recent omnichannel scholars have noted a desire to see future work establishing the antecedents and consequences of cross-channel integration from the retailer perspective. Our present work seeks to fill these requests. Noted as needed future research, “there is still much work to be done in terms of ascertaining the tradeoff conditions under which retailers' migration to omnichannel environments are construed as a favorable move” (Chen et al., 2018, p. 3).

Two-sided marketplaces and e-commerce have changed the landscape of businesses across the globe. Due to ever-accelerating cycles of technological advancement, they quickly appeared on the scene and have become ubiquitous in a relatively short period across a multitude

of varying industries (Hänninen et al., 2018). Despite the rapid proliferation in our society, business to consumer e-commerce remains only a small segment of total retail in most developed countries. Still, it is demonstrating a rapid growth rate, even in the face of economic challenges (Duch-Brown et al., 2017). Given the pronounced effects of e-commerce on business and a rapidly growing presence as a total share of the marketplace, our research seems timely. Currently, with the COVID-19 crisis, e-commerce alternatives may represent even higher significance for brick and mortar businesses in order to survive. Further, as time has progressed, more historical facts have become evident regarding platforms and their reasons for their success or failure. Failure to create trust on both sides of the two-sided equation of a platform is one keynote reason why a large proportion of platforms end up failing (Yoffie, Gawer, & Cusumano, 2019). From the retailer's position as a supply-side producer in the two-sided marketplace ecosystem, our research stands to provide a component of trust in the mechanics of interplay between brick and mortar stores and the online environment.

Consumers demand these transparent, user-centric choices in their daily lives now - from food delivery, entertainment, transportation, lodging, travel, financial services, parking, and more. Some well-established, long-standing firms in all industries are now finding their market share dwindling due to younger e-commerce company upstarts who are responding to their customer's needs and desires faster than they can. Conversely, others would argue that the addition of e-channels creates new value and profitability, captures new customers, expands the marketplace, and increases overall returns. The debate seems to rage on academically, managerially, and anecdotally. Most concerning for senior management, practitioners may be harming their firm's competitive and strategic position in their markets by refusing or resisting e-channel additions, or they may be improving their position without an adequate understanding of how it is occurring and why; missing out on critical opportunities to leverage them further or at scale. In either case,

research can smooth the debate and provide more certainty for practitioners as they navigate decisions on these crucial matters to guide their firms more efficiently.

More overarching is the broad observation of the continual cycle of entrenched firm resistance to all forms of disruption, firm after firm, industry after industry, generation after generation. Adding to the stream of research on the adoption of innovation is highly valuable and relevant in today's disrupted world, with many disruptions not foreseen even a few months ago. Helping today's practitioner find their way through the strategic decision-making process is a primary goal of this research effort. The natural strategic reactions in the face of this uncertainty and these changing market circumstances are to (1) resist and fight against the disruption or (2) participate in the e-channel marketplace through either proprietary or third-party e-channels. Adding an e-channel to an entrenched or traditional channel system is a double-edged strategy: Although it costs money in the short run, it is as yet unclear whether the optimistic foresight about the long-term profit and growth potential will ever materialize in all cases (Geyskens, 2002, p. 116). In this context, one of the main conclusions of the eBusiness workshop organized by Penn State's eBusiness Research Center is that academic contributions on the subject are needed because, without sound research, eBusiness managers are sailing rudderless (Donath 1999, p. 2). Similar calls for more scholarly research are raised by numerous researchers who deplore the lack of a solid base on which to make Internet-related investment decisions (Hoffman, 2006; Geyskens, 2002, p.102; Oskam et al., 2016). More recently, we see that the need for additional research continues to remain unfulfilled. Most research to date has focused on consumer benefits from e-commerce additions but has not balanced the inquiry by focusing on the corresponding benefits to producers (Duch-Brown et al., 2017, p. 32)

In sum, research is needed to help guide the producer or supply-side practitioner in determining what the actual net effect of an added e-channel will be, and under what

circumstances e-channels make sense and when they do not. No matter the backdrop, the business strategy must adapt and evolve as time passes. Well-established theories of strategy, competition, and market management are now being challenged or eroded due to the new platform-based markets. Not all disruptions can be anticipated, but if no disruptions are considered, entrenched firms will find themselves being disrupted in ways they are unprepared for. Although the players and environment are different, similar mistakes are made over and over by established firm leaders in resisting innovative and possibly complementary business models (Rosenbloom, 2000). Recent omnichannel scholars have noted a desire to see future work developing the antecedents and consequences of cross-channel integration from the retailer perspective (Chen et al., 2018, p. 3).

One less well-known, but adequately generalizable, example of a disrupted-by-platform marketplace is the parking industry. For nearly a century, the process of searching for a parking space, purchasing it for a defined time, and storing an automobile in it while not in use has remained relatively unchanged. However, in the last ten years, numerous technology platforms have emerged to create more transparency and choice for the parking consumer. Not unexpectedly, these platforms have created business strategy challenges for established, traditional parking firms. Concerns over these challenges present a distressing scenario in many firms' minds - participate with these disruptive firms to access the vibrant and growing customer bases which are present and transacting or resist these disruptive firms as long as possible in the hopes that the disruptors fail to gain traction. Further, a "prisoner's dilemma" ensues when some firms begin transacting on these platforms, and others do not (Brito, 2010). One stated reason for the parking practitioner's resistance to e-channel additions in the parking sector is fear of cannibalization of existing, established, and traditional revenue channels. Like other businesses, the parking industry is fraught with anecdotal perceptions about disruption occurring due to the

impact of new technology on their field (Deskant, 2018).

For the parking industry, a 30 billion dollar annual business domestically, industry trade groups such as the National Parking Association and the International Parking Institute research numerous sectors of their industry (www.parking.org; www.weareparking.org). Despite a growing adoption of proprietary e-channels and third-party e-channels in the industry, and supportive data across many other more digitally mature industries providing evidence that added channels provides incremental growth, many of the leaders of the top parking industry firms in the United States still cling to the idea that cannibalization is too great of a risk to embrace additional e-channel sales options fully. Some refuse to use them at all for these reasons, perhaps forgoing desperately needed incremental improvements to revenue streams that are experiencing diminishing returns due to other anti-parking factors (Uber, Lyft, public transportation, cycling, scooter trends, etc.).

For all of these reasons, we seek to provide the first parking supply-focused, e-channel cannibalization study. Our contribution will be to not only solve a problem for the parking industry but also to further existing lines of cannibalization and e-commerce research. This research seeks to fill a void, not only in the parking business but to supplement an existing debate for which a relatively small amount of research exists relative to the larger body of consumer-based e-commerce literature - does the addition of a new e-sales channel cannibalize the existing brick and mortar channels? Is there net new total revenue created? Does the choice of industry affect the outcome of a cannibalization study, or are the results provided from other industries highly generalizable as hoped? Under what circumstances might cannibalization phenomena occur or not occur? Is there an acceptable level of cannibalization or externality for parking businesses? Can firms identify, isolate, and manage these negative variables to ensure they retain their current channels' health? What is the right study design to adequately assess these research

questions? What is the right balance of brick and mortar to online sales for hybrid models of conducting business? These questions of externality effects drive our research motivation.

Further, a focused supply-side study supplements the noted glut of research in this particular portion of the two-sided marketplace (Duch-Brown et al., 2017). We desire to provide unique new dimensions, observations, and outcomes to contribute to the generalizability of previous conclusions from all sectors and industries that have been studied. Lastly, it is hoped that this work will create new lines of thought for future e-channel research, as this unique methodology for distribution of goods and services shows no sign of slowing down in the near-term future.

From a platform perspective, failure to create trust on both sides of the two-sided equation of a platform business model is one noted reason why a large proportion of platforms end up failing (Yoffie et al., 2019). From the retailer's position as a supply-side producer in the two-sided marketplace ecosystem, our research stands to contribute a dose of trust via insights into the revenue relationship mechanics between brick and mortar service locations and the online environment. Additional research is needed to help guide the supply-side practitioner in determining what the actual net effect of an added e-channel will be, and under what circumstances e-channels make sense and when they do not.

No matter the backdrop, the business strategy must adapt and evolve as time passes. Well-established theories of strategy, competition, and market management are now being challenged or eroded due to new platform-based online markets that exist alongside their brick and mortar counterparts. Brick and mortar service based-firms find themselves being disrupted in ways they are unprepared for. Although the players and environment are different, similar mistakes are made over and over by established firm leaders in resisting disruption (Rosenbloom, 2000). Even the most recent literature calls upon academics to perform more work in this sector

and directly on these points (Herhausen et al. 2015; Gil et al., 2017; Hernant et al., 2017; Li et al., 2017; Lim et al., 2018; Zhang et al., 2019).

Several questions drive our research motivation. Does the addition of a new e-sales channel cannibalize existing brick and mortar channels? Does the choice of industry affect the outcome of a cannibalization study, or are the results provided from other industries highly generalizable as hoped? Under what circumstances might cannibalization phenomena occur or not occur? Can firms identify, isolate, and manage these negative variables to ensure they retain their current channels' health? What is the right study design to adequately assess these research questions? What are the antecedents, consequences, and moderators of the cross-channel integration phenomena from the retailer/supplier perspective? These overall questions of externality effects drive our research motivation and elaborate on the research contributions possible to these disciplines through this study.

CHAPTER THREE

LITERATURE REVIEW

The wellsprings of today's digital technologies surfaced more than a half-century ago, stimulating successive waves of change that repeatedly threatened the survival of well-established firms in home entertainment, electronic components, communications services, data processing, and related fields (Rosenbloom, 2000, p. 1083). Even the most dominant firms in the information industries have found themselves challenged to develop new strategies and new capabilities to cope with the incursions of new rivals exploiting new technologies (Rosenbloom, 2000, p. 1083). Quite reasonably, established firms are often quite suspicious and resistant to disruptive business models, despite evidence that collaboration with them can be substantially complementary (Hsaio et al. 2012). As time has passed, technology has allowed for the cycle of disruption to accelerate. One author describes our current age as an age of hyper-competition wherein sustainable advantage is illusory (Parker et al., 2016, p. 209).

Intensifying market competition and the emergence of the World Wide Web are changing the channel system context (Ozuem et al., 2008; Huang et al., 2009; Hsieh et al., 2012). Using physical channels alone to access the market is less dominant, whereas merchants dealing in nearly all product and service categories are adding internet-based electronic channels of distribution to their existing channel systems as “brick-and-click” businesses (Hsiao et al., 2012). For numerous firms, e-channels added to existing channel systems are critical, and the use of an e-channel addition continues to increase dramatically (Frost et al., 2010; Liao et al., 2011; Yung-Hsin et al., 2014; Duch-Brown et al., 2017).

A large segment of the extant literature on the subject of e-channel management and cannibalization focuses on e-channel sales for numerous industries and retail products, and are focused on the consumer side of the e-commerce equation. Less research is concentrated in e-

channel sales in the services sector, under which parking falls, and producer/supply-side focused studies are the minority (Duch-Brown et al., 2017). Service sector research does exist for the hotel online travel agencies (OTA) which provides a somewhat applicable and generalizable body of work for comparable service industries, like parking, facing similar challenges. However, to date, no research exists looking at the parking industry e-channel management specifically, nor cannibalization concerns regarding the same. Given similarities to the hospitality industry in form, function, and substance, a parking based third party e-channel research study can provide the parking industry with valuable insights not yet in existence, but applicable to other industries.

The current body of omnichannel literature demonstrates an overarching framework composed mainly of four research streams labeled as perspective or research orientation (Chen, , Cheung, , & Tan, 2018). Under perspective, we see consumer vs. retailer groupings, and under research orientation, we see diagnostic vs. prescriptive groupings (Chen et al., 2018). “Diagnostic studies on retailer-centric issues related to omnichannel business have mostly been concerned with comprehending the causes behind why there is a growing trend for pure online and offline retailers to converge on multichannel arrangements” (Chen et al., 2018, p. 2). Traditional brick and mortar businesses are managing increased pressure to expand to online channels to capitalize on transactional capabilities available only in digital environments (Chen et al., 2018; Zettelmeyer, 2000).

The extant literature has also examined e-commerce’s use of new platforms for a competitive strategy (Celuch et al., 2007; Chang and Wang, 2011) with different advantages associated with adding the internet to the existing channel structure (Yung-Hsin et al., 2014, p. 47). Some examples of benefits identified through the addition of an e-channel include a better overall communication environment with customers, surfacing information more efficiently to exceed customer expectations, and support for the continuous development of a firm (Yung-Hsin et al., 2014). Consumers who have access to multi-channel options are expected to be

significantly more profitable than single-channel users because multichannel users are active shoppers, purchase larger quantities, and spend more money (Venkatesan et al., 2007; Hsiao et al., 2012). E-channels allow firms to provide customers with a range of value criteria, such as a convenient shopping environment, a broader and deeper product or service assortment, less waiting time, personalization, rewards programs, and interactivity (Yung-Hsin et al., 2014, p. 47). These values equip firms with IT-based efficiencies that may reduce transaction costs while increasing customer loyalty (Yung-Hsin et al., 2014, p.47).

Despite many noted and hypothesized advantages, adding an e-channel can also be harmful to a firm's operational performance (Yung-Hsin et al., 2014, p. 47). The e-channel's implementation costs, conflicts with brick and mortar stores, increased organizational complexity, and customer confusion are a few examples of the negative side of adding an e-channel (Yung-Hsin et al., 2014, p. 47; Geyskens et al., 2002; Li et al., 2004). Therefore, clarifying the usefulness of adding an e-channel to the current channel structure and predicting how the e-channel addition might affect a firm's overall financial performance are essential (Yung-Hsin et al., 2014, p. 47).

Thus, we perceive multiple gaps in the literature. Studies abound on both sides of the argument. Some research says that e-commerce channel additions are beneficial and complimentary, some have concluded that they are detrimental and cannibalistic to existing sales channels, and some seem to say both. All of them differ in defining the circumstances under which e-commerce channel additions provide net improvements to a firm's existing business structure or, conversely, create cannibalization. As a practitioner, little generalizable guidance can be found that offers great confidence to make a choice either way with high confidence. However, few could argue competently in today's modern age that almost every business in existence needs some sort of online transactional presence and channel. Our study seeks to address some of these perceived gaps, add yet another unique industry's operational structure to

previous studies from other sectors to find individual conclusions, and aim towards adding some more generalizability to the body of research. We explore two critical areas of the literature - one focused on Internet Channel Additions and one focused on the resulting Channel Cannibalization Concerns.

Internet Channel Additions

It should be noted from the inception that, for our research purposes, we identify two distinct business models. The Offline Business Model (Off BM) refers to how a company creates, delivers, and captures value over physical channels, such as brick and mortar retail stores and tangible physical real estate assets (Wiener, Holsbach, & Saunders, 2018). On the other hand, we find the Online Business Model (On BM), which refers to how a company creates, delivers and captures value through Internet channels, which are non-tangible and do not require a consumer to enter a physical space to complete a transaction (Wiener, Holsbach, & Saunders, 2018). The deployment of new sales and marketing channels within this framework are potent weapons in an increasingly competitive battle for consumers. An essential way in which companies use these weapons is by adding new channels to existing ones; for example, by adding a direct to an indirect channel (Geyskens et al., 2002, p. 102).

The emergence of the Internet has forced many firms to add e-channels to their existing channel system, and, as expected, studies have used various methods for analyzing the efficacy of a particular channel or the additions of new ones. Nevertheless, many empirical studies failed to provide direct evidence on whether e-channel addition could enhance the financial performance of the firm. In Cheng et al.'s (2007) research, an attempt was made to fill in this literature gap. Empirical data were collected from Taiwan's financial service sector, and the finding revealed that an e-channel addition announcement could increase a firm's cumulative abnormal returns and therefore concluded that e-channel addition could help improve the financial performance of the

firm (Cheng et al., 2007, p.50). This study joins others focused on stock return results and “announcements” of third-party channel additions (Yung-Hsin et al., 2014). Despite the uncertainty surrounding performance implications of adding an Internet channel to their channel portfolio, many firms, attracted by the potential access to millions of customers and the relatively low costs of setting up the channel, have rushed to establish an Internet channel or e-channel (Geyskens et al., 2002, pg. 102). Others, driven by fears of a continuing price squeeze and alienation of their entrenched channels, wait for more evidence to accumulate before taking action. (Geyskens et al., 2002, pg. 102).

Channel research has long emphasized the importance of recognizing the performance implications of channel decisions. This has fueled significant, multifaceted literature streams. An important stream of literature, starting with Jeuland and Shugan (1983) and McGuire and Staelin (1983) and including contributions of Gerstner and Hess (1995) and Lal, Little, and Villas-Boas (1996), has extensively analyzed the performance implications of a wide variety of channel decisions (e.g., coordination of channel efforts, use of exclusive resellers) and game theory (Geyskens et al., 2002, pg. 103). These studies focus on the performance implications of a supplier's channel decisions in terms of their effect on a single channel only, abstracting from their potential impact on other channels (Geyskens et al., 2002, pg. 103). Several game-theoretical studies have examined the performance implications of a firm's channel decisions, taking into account their effect on the firm's entire channel system (e.g., Purohit 1997; Purohit and Staelin 1994). Zettelmeyer's (2000) work used the profit implications of the decision to add an Internet channel to a conventional channel (Geyskens et al., 2002, p.103). Gentzkow (2007) noted that the introduction of a digital version of the *Washington Post* reduced the number of readers of the print edition. Other authors have pointed out that the act of releasing an online distribution channel involves similar trade-off as those seen traditionally with the release of new product lines for multiproduct firms (Shaked and Sutton, 1990) or by adding a new brick and

mortar store to an existing chain of the same (Holmes, 2011; Nishida, 2012; Pozzi, 2013, p. 570). Channel Migration is a dynamic process whereby a current customer repeatedly makes choices to frequent one of a merchant's varied channel options (Sullivan et al., 2004).

More recently, studies on channel cannibalization and migration have enjoyed the benefit of time on their research, to extract valuable additional evolutionary observations on the channel management issue in a digital context. New vernacular has emerged to describe channel elasticity, explaining the more generally understood migration of sales from one channel to the other in the short term and the long term (Avery, Steenburgh, Deighton, & Caravella, 2012). Understanding that the order of entry has meaning and impact on observed cannibalization between channels, new research has demonstrated that adding an Internet channel to an existing brick-and-mortar store is different from adding a brick-and-mortar store to an established Internet channel. This research was conducted in the context of retail stores versus online sales channel and catalog sales (Avery et al., 2012).

Compared with earlier studies focusing on only adding Internet channels to brick-and-mortar channels (Ansari, Mela, and Neslin 2008; Biyalogorsky and Naik 2003; Deleersnyder et al. 2002; Geyskens, Gielens, and Dekimpe 2002; Ward 2001), now the passage of time has allowed observations going both ways. An example would be the recent trend with Amazon opening physical stores in major metro areas to supplement their thriving e-commerce business. Research results show that adding a retail store has a different impact across channels, across time, and between first-time and repeat customers (Avery et al., 2012, p. 96). Over the long term, cross channel synergy is found to be positive and robust between brick-and-mortar, catalog, and Internet - with the latter being substantially affected. More specifically, research has demonstrated that adding a brick-and-mortar store does not cannibalize an existing Internet channel, but it does cannibalize catalog sales. There is a complex interplay between channels

that are affected by the passage of time, order of entry, type of channel, type of customer (repeat or new), and other factors (Avery et al., 2012, p. 106).

Other recent research has explored themes highly similar in nature to those presented in our present study and geared towards providing similar academic and practical contributions towards market share expansion. The impact of adding an online sales channel to a brick and mortar grocery store chain was explored with results suggesting that channel additions indeed provide incremental growth opportunities (Pozzi, 2013). Although this study delved into the realm of consumer travel costs as a moderator, we find more relevance and interest to our research in their methods and conclusions centered around the number of competitors in the same zip code. Specifically, Pozzi's study concluded that revenues increase more in markets where the grocery store chain faced competition, which suggests that the online channels can help to divert business from rival grocers (Pozzi, 2013, p. 569). With seemingly high relevance to the practitioner, the author noted many key substantive quantitative takeaways - (1) that the revenues of the average store experience a 13 percent increase after the introduction of the Internet service, (2) that for every dollar spent online, 67 cents represented new business for the chain and only the residual 33 cents were deemed displaced from the physical stores, and (3) that the online channel brought in an additional \$1,362 per customer over a two-year period which represented an 18% increase in sales per household (Pozzi, 2013, pp. 571). Finally, Pozzi added several relevant competitive notes regarding the impact of the Internet channel when engaged in business with rival grocers in the zip code. Valuable takeaways included noting revenue benefits are more abundant when online sales are rolled out in a zip code with two competitors versus when there are four or more, and if any of those grocers are also engaged in competing e-commerce, then the revenue growth seen via online channels is cut in half (Pozzi, 2013, pp.579-580). Similar to Pozzi, Lim et al. (2018) examined the impact of mobile channel

additions to an existing group of offline and online channels, also in a grocery store setting. Lim determined that the introduction of the mobile channel does cannibalize from the existing channels, with the offline channel cannibalization being minor (Lim et al., 2018).

More recently, we still see an absence of research regarding the benefits or detriments of adding Internet channels. Authors are still exploring both consumer and supply-side questions on e-commerce impacts, as well as desiring holistic viewpoints on the full effect on the health of the business (Duch-Brown et al., 2017). In yet another grocery store study, Hernant et al. (2017) examined the effects of introducing an online channel to an existing body of brick and mortar/offline Swedish grocery stores. The study concluded that the addition of a new online channel was associated with new customer acquisition and larger transaction sizes, but cannibalization was observed from the existing offline business (Hernant et al., 2017). The diverse outcomes of these various grocery store studies demonstrate well the variability seen in possible conclusions for a decision-maker (Pozzi, 2013). Even more recent research examines the effect of physical store presence on the online purchase behavior of its existing customers (Kumar et al., 2019). Results are highly dependent on the specific nuances of the industry, the study structure, the market environment, and a multitude of other factors. A practitioner trying to distill the outcomes of these various studies into a usable decision-making format may find challenges in arriving at recurring conclusions that allow for meaningful business strategy decisions.

Channel Cannibalization Concerns

Cannibalization in the context of our present study can be defined as an adverse effect from an online channel on the existing channel business due to inter-organizational sales diversion (Novelli, 2015). Adding an Internet channel to a current channel ecosystem may involve channel "shift" (customers moving from one channel to another) without channel "lift" or

actual new sales (Alba et al., 1997). Adding an Internet channel may even lead to a decrease in total sales when consumers buy less through the new channel than through their old channel. For example, when there are fewer impulse purchases through the Internet or when disenchanted distributors offer less support to the firm's products, resulting in more brand switching toward the firm's competitors (Geyskens et al., 2002, p. 103). Existing channels may view the new Internet channel as unwelcome competition. They may fear their sales will be reduced if firms reach out directly to their consumers (Geyskens et al., 2002, p. 103). Also, the low physical distribution costs and easily obtainable economies of scale of Internet channels may lead firms to reduce their prices and may put pressure on the existing channels' profit margins (Alba et al., 1997). When this happens, interchannel friction becomes likely. The firm's entrenched channels may lose motivation and reduce their support for the firm's products (a passive response), retaliate, or even discontinue their distribution (active responses) (Coughlan et al. 2001, p. 252).

To prevent entrenched channels from shirking, firms need to monitor them more extensively to check whether they live up to their agreements and, if necessary, enforce these agreements (Geyskens et al., 2002, p. 103). This is likely to increase ex-post transaction costs (Stump and Heide, 1996). In a recent survey of 50 consumer goods manufacturers by Forrester Research, 66% indicated that channel conflict, with its potentially costly result, was the most significant issue they faced in their online strategies (Gilbert and Bacheldor, 2000).

Cannibalization of one channel's efficacy by another is indeed a form of channel conflict. In 2002, Deleersnyder examined cannibalization between channels in the context of the newspaper publishing industry. Introducing an online channel to an offline channel and measuring sales revenue changes, Deleersnyder determined that online channel introduction, in most cases, does not cannibalize the circulation and advertising revenue of traditional newspaper channels in the long run (Deleersnyder et al., 2002). Biyalogorsky (2003) performed cannibalization research in

the music and records industry, again introducing an online channel option to existing offline channels. Using a time series model of analysis, Biyalogorsky concluded that the sales of online channels do not significantly cannibalize the sales of offline channels (Biyalogorsky et al., 2003).

Much of the research in the literature focuses on the consumer behavior side of the equation, and the related choices they make in the presence of various channel choices and within a specific firm's proprietary channels. This would be in contrast to studies that focus on the business, or supply side of the equation, as our present study directs. The consumer-facing studies have shown promise in the generalizability sense of multi-channel sales, providing increased profitability (Venkatesan et al., 2007). Overall, providing a multichannel experience to customers has the potential to improve two critical aspects of customer relationship management (CRM): customer retention and customer growth (Venkatesan et al., 2007, p.128). Further enticing is the observation that those with higher purchase frequency and spending levels have a greater preference for shopping in multiple channels (Venkatesan et al. 2007, p. 129). However, the Venkatesan study focused only on inter-firm multi-channel implementation, and not the use of any external third-party channel such as the ParkWhiz 3rd party channel test we employ here in the present work. It is unclear whether the inter-firm multichannel effects would hold in the externalized, 3rd party setting, identifying a research gap needing further review that our present work can fill.

A continued review of the literature indicates that channel cannibalization concerns remain consistently prominent (Brynjolfsson et al., 2000; Biyalogorsky et al., 2003; Neslin et al., 2009; Nierop et al., 2011; Herhausen et al., 2015; Hernant et al., 2017; Li et al., 2017; and Zhang et al., 2019). Research has indicated that the introduction of new e-channels to existing brick and mortar channels could be cannibalistic or, at the very least detrimental to consumer behavior (Nierop et al., 2011). Although focused on the impact of adding a single proprietary non-

transactional website to existing proprietary channels, Nierop's research saw declines to in-store purchases as a result of adding non-transactable web channels that merely provided information. Research findings like these could help explain practitioner resistance to the concept of adding new channels, such as that observed in the parking industry. These conclusions could be included under the concept of Channel Capability Theory, which refers to "an enabling characteristic of a channel that allows customers to accomplish their shopping goals" more efficiently (Avery et al. 2012, pp. 96–97). If the power of purchasing can be swayed simply by adding a wider berth of information to the consumer, then adding transactional capabilities to the equation could be catastrophic to some minds.

At the other end of the spectrum from cannibalization are Spillover Effects, which can be defined as the opposite of cannibalization; positive benefits from online channel addition to offline channels such as access to a broader customer base or enhanced brand equity (Zhang, 2019). Some studies indicate that multi-channel utilization can indeed be beneficial for firms. Research has attempted to determine whether and how online-offline channel integration (OI) leads to a competitive advantage for retailers, whether OI leads to synergies or cannibalization among channels, and whether OI has the same effects on all customers (Herhausen et al., 2015, p. 319). Online-Offline Channel Integration is defined as the successful, synergistic, parallel management of both offline and online channels in tandem (Wiener et al., 2018).

Managerial implications from this study included findings that brick-and-click retailers should feel confident in using OI as a route to achieving a competitive advantage in the marketplace, synergy rather than cannibalization exists with these activities, and the ability to drive higher sales prices via multi-channel methods exists (Herhausen et al., 2015). However, this research also only focused on the same owner physical stores and e-channels, versus e-channels managed and operated by third-party firms. We again perceive gaps in the literature when

reviewing third-party or exterior e-channel additions, and our present work is well-positioned to fill this literature.

Very recent research that is highly relevant to our parking study was published in June 2019 (Zhang et al., 2019). Examining the budding food service delivery business, Zhang's study analyzed the addition of an online channel to an existing brick and mortar network of fast food stores. Similar to our present research, sales revenue was one of the units of measure, and short- and long-term results varied. In the short run, some minor offline sales channel cannibalization was observed, but overall, in the long term, total sales, offline sales, and profits all increased (Zhang et al., 2019). Zhang et al (2019) defined Offline-to-Online Service Platforms (O2O) as platform-based mobile apps that allow customers to order local, daily services online and quickly receive them offline to fulfill their need for instant gratification - distinguished from O2O Product Platforms (Zhang et al., 2019). It was noted that superior capabilities in one channel could lead to the cannibalization of another (Zhang et al., 2019).

Again, similar to our present parking study, Gil (2017) examined B2B markets that introduced a mobile app to an existing offline focused business model. Sales revenues were also used as the unit of measurement but were adjusted for the cost of development. Even taking into account the development cost of building the mobile app, the app increased annual sales by 19-22%, noting a strong return on investment for the focal firm (Gil et al., 2017).

These recent studies demonstrate a continuing interest from both practitioners and academics to investigate phenomena falling within the bounds of our present parking research study and perfecting the art of Omni-Channel Management, defined as an environment wherein online and offline channels converge to deliver a seamless and efficient shopping experience - for both the consumer and the supplier (Choudhury et al., 2008). Further, our literature review establishes that the debate remains unsettled as to various e-commerce cannibalization, or lack

thereof, scenarios. Scholars and practitioners are desirous of more research in this area.

Practitioners and scholars alike are both seeking the holy grail of Omni-Channel Management. Along with achieving Spillover Effects, they also seek the Availability Effect, defined as adding channels as a form of increasing distribution, which lowers search costs and increases sales are also desired (Neslin, 2006; Pauwels et al., 2015; Hernant, 2017). Together, all of these concepts, properly managed, create new customers, establish consumer loyalty, expand markets, generate new revenue, and grow profitability.

Noted within Pozzi's (2013) study was that (1) the number of competitors within a zip code made an impact on the incremental revenue growth observed by the addition of a new internet channel and (2) whether those competitors also used internet channels provided a moderating factor on the revenue contribution observed. Given our ability to easily access similar data on both of these mediating or moderating factors in our research construct and context, these variables were added to our present study. Pozzi concluded that "the benefit from rolling out online shopping is estimated to be larger when the chain faces two competitors than when there are four or more of them" and that "the presence of a rival e-grocer halves the revenue growth induced by the Internet channel for the Retailer" (Pozzi, 2013, pp.579-580). Exploring these dimensions in the context of the present parking study add practitioner relevant support to Pozzi's research and perhaps extracts additional generalizable conclusions. Finally, Pozzi provided a myriad of highly specific quantitative outcomes measures that we hope to replicate in our present study, given the meaningful practitioner perspectives they provide (dollar amount and percentage increases in new revenue provided by Internet channels) (Pozzi, 2013).

Our present parking study design is comparable to methodologies that have been previously employed. Yet, ours adds new dimensions and approaches, fills the aforementioned research gaps, and overall seeks to create richer understandings of moderating factors that sway

cannibalization results one way or the other. Our study will also be the first of its kind within its context, compared to more common verticals such as retail, grocery, banking, apparel, home furnishings, music, and newspaper/publishing industries. We believe that our findings will provide added needed diversity to the present research stream while expanding the bounds of generalizability for all of it. See below in Table 1 for a non-exhaustive summary of examples of the more prominent, relevant literature listed chronologically over the past two decades regarding channel shifting and cannibalization. Note the final entry, which denotes our present parking study and its contribution within the body of literature. Also, see below in Table 2 for a non-exhaustive list of some of the more prominent definitions derived from the literature which we use in our study or refer to often.

Table 1. Key Literature Review Summary

Year	Author	Context	Pre-Existing Channel	Introduced Channel	Performance Metric	Modeling Approach	Conclusions
2002	Deleersnyder et al.	Newspaper	Offline	Online	Sales Revenues	Time-series econometrics	Online channel introduction in most cases does not cannibalize the circulation and advertising revenue of established channels in the long run
2002	Geyskens et al.	Newspaper	Offline	Online	Overall Firm Performance	Event study	Online channel introduction has a positive effect on a firm's stock price
2003	Biyalogorsky et al.	Music/Records	Offline	Online	Offline Channel Performance	Time series model	Sales of online channels does not significantly cannibalize the sales of offline channels
2011	Pauwels et al.	Apparel	Online & Catalog	Offline	Sales Revenues	VAR baseline method	Offline revenue impact of an informational website varies greatly across product categories & customer segments
2011	Van Nierop et al.	Retail Stores	Offline	Online	Number of shopping trips, amount of money spent	Poisson model and type-two Tobit model	For most customers, introduction and use of online informational channels reduce the number of shopping trips and amount of money they spend
2012	Avery et al.	Apparel & Home Furnishings	Online & Catalog	Offline	Sales Revenues	Matching Method, DID	Short run - catalog sales drop, Internet sales non-significant changes. Long run - Catalog and Internet sales increase
2015	Herhausen et al.	Retail Stores	Offline & Online	Offline & Online	Search intention, purchase intention & willingness to pay	Regression, multinomial logistic regression	Offline-online channel integration leads to competitive advantage and channel synergy, rather than cannibalization
2017	Gil et al.	B2B Market	Offline	Online / Mobile App	Sales Revenues, adjusted for development costs	Heckman model, DID	Mobile app increased annual sales by 19-22% even when adjusted for development costs - i.e. positive return on investment.
2017	Hernant et al.	Swedish Grocery Retailer	Offline	Online	Purchasing data at individual customer level - average transaction, purchase frequency and purchase regularity	Panel data analysis	Going online is associated with new customer acquisition but also is associated with cannibalization, average transaction size increased after first online purchase.
2017	Li et al.	Home decoration	Offline	Online	Overall firm performance (firm choice and order size) of the focal firm and its competitors	Bivariate probit and tobit models & panel regression models	Previous purchase from competitor online channel increases likelihood of channel adoption with focal firm that introduces channel after competitor's. Customer adoption and use of new online reduce purchase frequency of competitors but increase purchase frequency of the focal firm.
2018	Lim et al.	Grocery	Offline & Online	Online / Mobile App	Household purchasing behavior - weekly expenditures, weekly number of shopping trips and weekly average basket size	PSM, DID	Introduction of mobile channel cannibalizes the online channel but offline channel cannibalization is small
2019	Zhang et al.	Food service delivery	Offline	Online	Sales revenue & profit	Panel regression models	Short run - offline sales changes non-significant cannibalization. Long run - total sales, offline channel, and profit all increase.
2020	Tucker	Parking, transportation and mobility	Offline & Online	Online	Sales revenue, number of online competitors, total all offline competition, and online search demand	Panel data analysis, Fixed Effects Model & Linear Mixed Model	Addition of an online sales channel provided increases to aggregate revenue overall at a rate of 14%-18% improvement per parking space. Cannibalization was not found or was minimal in that it did not limit attainment of statistical significance in the hypothesis. Effects of two of three moderating independent variables were inconclusive. The H4 hypothesis showed an improvement to H1's effects in the presence of search demand.

Table 2. *Core Literature Review Key Definitions*

O2O Service Platforms - platform-based mobile apps that allow customers to order local, daily services online and quickly receive them offline to fulfill their need for instant gratification - distinguished from O2O Product Platforms (Zhang, Pauwels, & Peng, 2019).

Channel Migration - dynamic process whereby a current customer repeatedly makes choices to frequent one of a merchant's channel options (Sullivan, Thomas, 2004).

Channel Capability Theory - Refers to "an enabling characteristic of a channel that allows customers to accomplish their shopping goals" (Avery et al. 2012, pp. 96–97), superior capabilities in one channel can lead to cannibalization of another (Zhang, 2019).

Online-Offline Channel Integration - the successful, synergistic, parallel management of offline and online channels (Wiener, Holsbach, & Saunders, 2018).

Cannibalization - negative effect from online channel additions, erosion of existing due to interorganizational sales diversion (Novelli, F. (2015)

Spillover effects - opposite of cannibalization, positive benefits from online channel addition to offline channels such as access to wider customer base or enhanced brand equity (Zhang, 2019).

Omni-Channel - environment wherein online and offline channels converge to deliver a seamless shopping experience (Choudhury, Karahanna, 2008).

Offline Business Model (BM) - how a company creates, delivers, and captures value over physical channels (Wiener, Holsbach, & Saunders, 2018).

Online Business Model (BM) - how a company creates, delivers and captures value through Internet channels (Wiener, Holsbach, & Saunders, 2018).

Availability Effect - adding channels as a form of increasing distribution, which lowers search costs and increases sales (Neslin, 2006; Pauwels & Neslin, 2015; Hernant, 2017).

CHAPTER FOUR

RESEARCH QUESTIONS

Prior to completion of the present study, we engaged in a preliminary pilot study in 2018-2019. In that pilot study, we analyzed a prior, similar dataset against only one hypothesis regarding the impact to aggregate total revenues through the addition of a new online channel (essentially our H1 in the present Hypotheses Section herein). Our pilot study outcome, while ultimately inconclusive, did show some strength in our overall theory but fell short of statistical significance. We more deeply considered the present needs of the existing body of research, the nature of our motivations for this research, and higher desired practical takeaways for a practitioner. We determined that the refinement and supplementation of our pilot study research question was warranted, and undertook this work in the present research before you.

Specifically, we sought to add depth to our study by exploring the effect of several environmental factors within the zip code geography of our study design. These include the presence of competition using the same channel as our intervention channel within a given zip code, the presence of all competition selling within the zip code regardless of channel, and online search demand volume in each given zip code. These refined and additional research questions serve to enlighten our hypothesis development.

1. Does the introduction of a new online sales channel to existing brick & mortar businesses create net new revenue for an enterprise (total revenue)?
2. How does the introduction of new online sales channels into existing brick & mortar businesses affect existing revenue (offline revenue) and is there a cannibalizing impact?
3. What is the impact on the online channel in the presence of competing garages utilizing the same online channel?
4. What is the impact on the online channel due to the quantity/proximity of all available

facility choices in the same zip code?

5. How does the volume of parking searches conducted in a zip code affect the efficacy of the online channel relative to questions 1-4?

CHAPTER FIVE

HYPOTHESES FORMULATION

Our first hypothesis asks whether the addition of a new e-commerce sales channel erodes revenue from existing sales channels? The practical relevance here again is to identify the impact, to the potential extent of making the new channel addition worthless when seen on balance with existing aggregate revenue. As demonstrated by academic literature as recently as June 2019 (Zhang et al., 2019), this topic remains relevant and timely for most brick and mortar retail operators, parking or otherwise. We seek to contribute value to scholars and practitioners alike through the present work by identifying at least some of the precursors, moderators, and environmental characteristics that may allow a practitioner to predict more accurately the conditions under which adding a new e-commerce sales channel will be additive to their overall revenue mix.

Our first two hypothesis are motivated by the overall goal of determining is adding an online channel to an existing offline channel network is practically beneficial for a business and capable of producing net improvements to an existing revenue stream while simultaneously not reducing revenue already in play from existing alternative channels. Hypothesis 1 and its subsets are simply extensions of our hypothesis seen in our pilot study improved upon here with better data collection and time balancing.

H1A The addition of an online channel to existing offline channels will produce net new revenue gains for total revenue.

H1B The addition of an online channel to existing offline channels will not be cannibalizing.

Hypothesis Two and Three are similar in nature and intended to provide a competitive aspect to the study. By determining the impact of local zip code level competition between parking garages and lots, either competing online or not, can provide important insights for the

practitioner in determining the environmental aspects to consider when choosing to employ an online channel or not for a particular parking facility. Our motivations here borrow from similar zip code based competition level studies such as Pozzi's (2013) grocery store research.

H2 The effect of online channel introduction on revenue will be negatively moderated by the volume of competitors offering the same online sales channel within the same zip code.

H3 The positive effect of online channel introduction on revenue will be positively moderated by the volume of local competitors not offering the online channel within the same zip code.

Hypothesis Four adds novel new aspects to the extant lines of research by examining the impact of online search volume aspects on any effects seen in Hypothesis One – Three. Our expectation is that increased online consumer searching for parking services will be highly correlated with revenue improvements, if any.

H4 Net new revenue gains produced through the addition of an online sales channel will be positively moderated by the number of online consumer searches within the same zip code.

A variety of other possible demand-related or facility-related data points exist if future research dictates that our hypotheses presented above need enhancement, modification, or outright replacement, to meet larger practical goals. Those being to provide a practitioner with a meaningful understanding of the prerequisites for success in understanding what environments produce the best results when adding in e-commerce channels to existing revenue portfolios. Our Theoretical Construct for the above hypotheses can be viewed below in Figure 1.

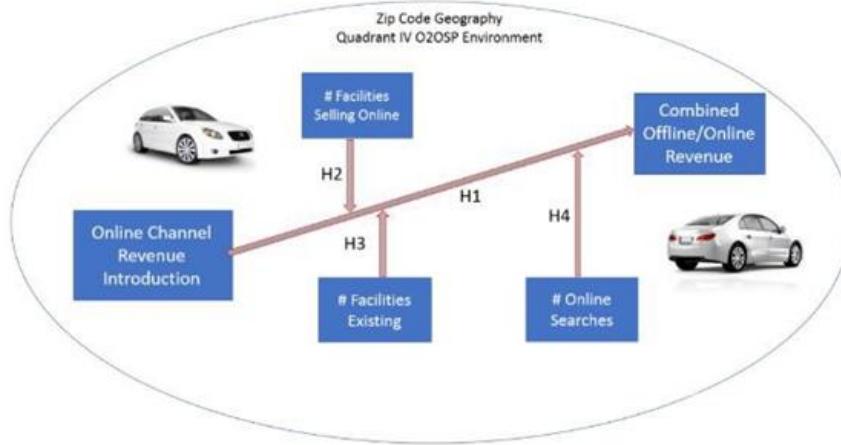


Figure 1. Theoretical construct.

CHAPTER SIX

RESEARCH METHODOLOGY

Study Context

As discussed earlier, we investigate the effect of the introduction of the ParkWhiz web and app-based sales channel to a traditional brick and mortar parking garage business' revenue streams. ParkWhiz has been in existence for approximately 13 years and has reached a North American presence in virtually all states and over 200 cities in the US. As of 2018, the company had expanded into Canada. The company has millions of proprietary consumers nationwide, and by extension, through other major platform partners, such as Ford Motor Company and Amazon, over forty million customers and multiplying. The company's founding mission was to make it easier for drivers to search for parking options, compare prices, and book online in advance for better convenience in the act of parking. In recent years, the firm has expanded into new market segments such as straightforward mobile payment technology, telematics, and creating a network of vast platform partnerships to power parking transactions in thousands of varying customer journeys in a myriad of digital environments, such as travel, car rental, automotive navigation systems, event ticketing and much more. Below in Figure 2 are examples of the ParkWhiz consumer app interface and demonstration of inventory coverage in a given market, using Detroit as an example.

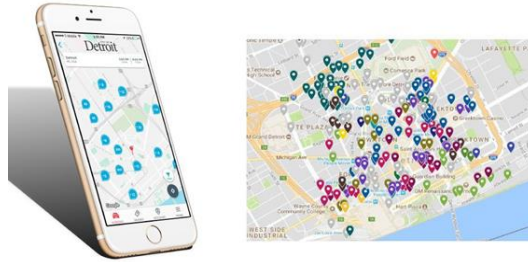


Figure 2. ParkWhiz Consumer App and Example Market Coverage.

To participate in the network, most consumers/drivers need only to download the ParkWhiz app, enter a single credit card to keep on file, and enter an email address. Other information may be required at later times, depending on the operational needs of the physical parking structure, such as license plate numbers or car make/model. Still, overall, the entry hurdles are small. Upon registration of their account, consumers/drivers are now free to search all parking options anywhere in North America, with corresponding searches providing available booking options and a multitude of details about each garage, merchandised to allow for features and benefits of each location to be ascertained by the consumer/driver. As can be seen, the app displays all parking coverage for a given geography allowing the consumer to choose from many different options. Note the price for each option on the graphic on the left, and the time/date picker that allows a driver to select parking for whatever window of time they desire.

The utility for the consumer is distinct compared to older ways of finding parking, namely driving around looking for a spot while behind the wheel and hoping to find the best prices. Once a consumer makes a selection, the credit card on file is charged, the app leads the consumer via integrations with embedded iPhone, Android or automotive telematics mapping programs to the site, and a unique QR code or barcode is generated which allows the driver to access the facility seamlessly and without pulling physical cash out of their pockets. The payment experience is a similar comparison of a traditional cab ride vs. a ride with Uber or Lyft today - no

cash or payment necessary at the end of the service. Given the extremely fragmented nature of the parking ecosystem, fulfillment may vary widely from property to property and city to city.

Potential benefits to consumers should be reasonably evident to those who have driven and parked their cars before. These include a high degree of choice and visibility in their selection of parking options, pre-payment in advance for a guaranteed spot, cashless transactions which are paid to a card on file, and nearly frictionless ingress and egress from the chosen facility. Possible benefits to the parking facility owner or operator are removing cash from the transaction streams (parking has a high cash shrinkage rate), payment in advance of the actual services rendered, knowledge in advance of pending demand for space and inventory in their garage, less wear and tear on traditional ticket dispensers and cash collection machines onsite, faster ingress/egress for patrons eliminating queuing at entry or exit points, ability to advertise their garage online to a presumed larger audience of drivers, presumed incremental additions to current revenue streams (this, of course, is the focus of our study), improved yield management through optimized pricing strategies, and access to better consumer data about the parking facility (who is accessing the facility, when, and under what price points).

A vital distinction for garage owners and operators is that they traditionally will provide some discounting to spaces listed online with channels like ParkWhiz. Much like a Hotels.com or Priceline approach, sales of distressed inventory are better to be sold at a discount than never sold at all. Space for sale in a parking garage or hotel is a perishable service - failure to sell one of the spaces or rooms today will never be recaptured and is lost forever. Better to discount some, provide a higher likelihood of a sale, and work towards a better overall yield rather than focusing on the maximum margin on each space or room sold. While this logic seems sound from an economic perspective, the thesis also has risks that are noted by many parking garage owners. A primary complaint is that of margin compression, or a negative contribution margin, which exceeds any incremental revenue benefit. This trade-off of higher revenues for lower overall

margins ultimately traces back to the genesis of the cannibalization fears. In a perfect world, the garage or lot owner will enjoy standard revenue capture through its existing revenue channels, and ParkWhiz provides a backfill channel to sell any excess capacity that otherwise was not going to be sold. However, as more and more consumers transition to mobile payment platforms and reservation engines, for everything in their daily lives, including parking, a belief exists that the fees associated with a firm like ParkWhiz coupled with discounting will cause a substantial overall drop in aggregate revenue over time. These are the paradoxical scenarios that drive our present research, and which we believe will contribute to generalizable results across e-commerce vs. brick and mortar scenarios in other industries and verticals. Lastly, and perhaps most importantly for our study, discounting may be a significant moderating or mediating factor for customer switching from offline to online sales channels, or this may create considerable bias in our results.

Methods and Data Pre-Processing

The dependent variables in this study are three measures of daily sales figures (total, offline, online) for all parking garage locations in the analysis for each day of the study. The study will be testing the introduction of the ParkWhiz sales channel as an independent variable (intervention) and measuring its impact relative to these three sources of revenue. The dependent variable was analyzed on a log-transformed basis of the per space revenue at each location (due to varying sizes of parking space capacity at each venue).

Examined as independent moderating variables in the construct in Figure 1, we see (1) the number of facilities selling online in the same zip code (2) the number of total facilities in existence in the same zip code (selling online or not) and (3) total online searches occurring for parking in the same zip code. See Table 5 for a detailed Variable Definition dictionary. To empirically estimate or test the effect of adding ParkWhiz to existing revenue channels, we worked collaboratively with one of the largest single parking management firms in existence

today in North America. Due to the competitive sensitivity of the data shared, the firm and its exact site addresses will remain anonymous. The parking industry is hugely competitive, and any revenue data derived from day-to-day operations is akin to protected trade secrets, considered highly proprietary and potentially irreparably damaging to the firm's market position should it become available to competitive third parties. Suffice it to say that the selected parking firm is well-established, maintains a substantial brick and mortar presence in North America, and employs an existing hybrid business model wherein offline sales channels are employed as the primary business tenet. However, in our present study population, any existing online sales channels are primarily limited to the firm's proprietary online sales channel of limited use vs. use of an external third-party firm such as ParkWhiz with a large user base. However, other third-party firms are in play, and there is undoubtedly a risk of confounding effects occurring in this experiment stemming from untested effects in that realm, although we focus on merely the single addition of ParkWhiz to the mix.

The New York City marketplace is considered highly diverse and mature in the digital parking, mobile payments, and reservations marketplace. Consumers are well versed in the usage of these types of systems, and they are well-established components of the parking marketplace throughout Manhattan. They have been widely in use for over a decade. Although New York is a single city within a single state, the exceptionally high population density coupled with its existence as likely the most mature parking market on the face of the Earth makes it an ideal lab for preliminary testing of our hypotheses. We employ a zip code based neighborhood differentiation system, similar to that seen in Pozzi's (2013) grocery store chain research, from which to sample and group our intervention and control group properties.

In collaboration with the parking firm, we gathered data from 30 locations divided into two groups, an intervention group, and a control group. There were no attempts to manipulate the

groups, and the only guidance given to the parking firm was to provide 180 days of data for thirty individual properties - one group of fifteen properties that had, at some point recently, begun using the ParkWhiz channel and another group of fifteen properties that had never used ParkWhiz at all. All locations were in the New York City metro area. The parking firm data analyst who assisted us with our project was aware of the study goals, design, and a rough outline of our hypotheses at the time. It is unclear, but possible that some selection bias may have existed in the parking firm data analyst's activities as they collected the information on our behalf and with knowledge of the study's goals. However, they have no vested interest in skewing results in any direction here, quite the opposite. This is unlikely, however, due to the general difficulty in finding sites to reasonably fit within each group. In effect, the site selection process was a retrospective case-control study, with site selection out of the author's control.

The intervention group analyzed \$2,675,930 in revenue over 180-day periods from 2018 through 2019 and across 15 distinct parking properties throughout the City of New York. The control group analyzed \$3,110,355 in revenue over 180-day periods from 2018 to 2019 and across an additional 15 different parking properties [SM1] throughout the city of New York. For each facility in the intervention group, daily revenue measurements were taken exactly 90 days before and 90 days after the introduction of the ParkWhiz intervention channel (see Table 3 below in the rows separated by blue or red highlights and delineated by the Y or N in the "Intervention Occurred?" Column).

The three categories of revenue observations were recorded as daily totals for each parking property location for all revenue, delineated as "Revenue (Non-ParkWhiz)", "Revenue (ParkWhiz)", and "Total Revenue (RevTotal)." Each garage is identifiable by a unique location ID number shown for each data entry point. The exact locale each parking facility observation spans a variety of distinct and well understood geographic, neighborhood sectors within Manhattan. These neighborhoods include Hell's Kitchen, Midtown, Midtown East, the Upper

East Side, Upper West Side, Tribeca, Koreatown, Murray Hill, Chelsea, and others. We obtained daily revenue measurements (versus weekly or monthly) for 6-month periods for each of the sites, which allowed us to obtain an initial 5,400 observations (N= 5,400) from which to begin our analysis.

In addition to total aggregate revenue and ParkWhiz channel revenue, for each garage in both the intervention and control groups, additional sample data was obtained. For each day of each 180 day period, and each parking facility, we collected the space count of the property, identification as a surface lot of parking garage, attended or unattended service structure, facility zip code, the number of total facilities competing in the same zip code using the ParkWhiz channel, the number of overall facilities in existence in the zip code, the number of online searches occurring for parking in the relevant zip code, and the number of events happening in the corresponding zip code. Table 3 below shows an example of one of the intervention group's sample data sets for demonstration.

Table 3. Panel Dataset Example by Single Parking Facility

Location ID	Space Count	Garage or Lot	Attended/Unattended	Market/City	Zip Code	Day	Month	Week	Revenue TOTAL	Revenue (ParkWhiz)	Revenue (Non-Park Whiz)	Intervention Occurred?	Number of Garages TRANSACTIONABLE w/ Zip Code	Number of TOTAL Off-Street Sites Existing w/ Zip Code	TOTAL Online Demand/Searches within Zip Code	TOTAL Events within Zip Code
6511	100	Garage	Attended	NYC	10023	3/26/2018	3	13	\$554.00		\$554.00	N	27	27	17	2
6511	100	Garage	Attended	NYC	10023	3/27/2018	3	13	\$768.00		\$768.00	N	27	27	19	4
6511	100	Garage	Attended	NYC	10023	3/28/2018	3	13	\$689.00		\$689.00	N	27	27	17	5
6511	100	Garage	Attended	NYC	10023	3/29/2018	3	13	\$509.00		\$509.00	N	27	27	18	3
6511	100	Garage	Attended	NYC	10023	3/30/2018	3	13	\$521.00		\$521.00	N	27	27	34	3
6511	100	Garage	Attended	NYC	10023	3/31/2018	3	13	\$485.00		\$485.00	N	27	27	15	7
6511	100	Garage	Attended	NYC	10023	4/1/2018	4	14	\$845.00		\$845.00	N	27	27	19	2
6511	100	Garage	Attended	NYC	10023	4/2/2018	4	14	\$521.00		\$521.00	N	27	27	17	1
6511	100	Garage	Attended	NYC	10023	4/3/2018	4	14	\$465.00		\$465.00	N	27	27	22	3
6511	100	Garage	Attended	NYC	10023	4/4/2018	4	14	\$469.00		\$469.00	N	27	27	43	7
6511	100	Garage	Attended	NYC	10023	4/5/2018	4	14	\$746.00		\$746.00	N	27	27	21	6
6511	100	Garage	Attended	NYC	10023	4/6/2018	4	14	\$571.00		\$571.00	N	27	27	35	7
6511	100	Garage	Attended	NYC	10023	5/24/2018	5	21	\$893.00		\$893.00	Y	28	28	63	5
6511	100	Garage	Attended	NYC	10023	5/25/2018	5	21	\$896.00	\$22.00	\$873.00	Y	28	28	52	4
6511	100	Garage	Attended	NYC	10023	5/26/2018	5	21	\$340.00		\$340.00	Y	28	28	37	7
6511	100	Garage	Attended	NYC	10023	5/27/2018	5	22	\$365.00		\$365.00	Y	28	28	46	2
6511	100	Garage	Attended	NYC	10023	5/28/2018	5	22	\$360.00	\$12.00	\$348.00	Y	28	28	45	0
6511	100	Garage	Attended	NYC	10023	5/29/2018	5	22	\$852.00	\$20.00	\$832.00	Y	28	28	73	3
6511	100	Garage	Attended	NYC	10023	5/30/2018	5	22	\$961.00		\$961.00	Y	28	28	60	5
6511	100	Garage	Attended	NYC	10023	5/31/2018	5	22	\$1,205.00		\$1,205.00	Y	28	28	48	5
6511	100	Garage	Attended	NYC	10023	6/1/2018	6	22	\$754.00		\$754.00	Y	28	28	77	4
6511	100	Garage	Attended	NYC	10023	6/2/2018	6	22	\$560.00		\$560.00	Y	28	28	62	8
6511	100	Garage	Attended	NYC	10023	6/3/2018	6	23	\$511.00	\$18.00	\$493.00	Y	28	28	70	3
6511	100	Garage	Attended	NYC	10023	6/4/2018	6	23	\$930.00		\$930.00	Y	28	28	91	1
6511	100	Garage	Attended	NYC	10023	6/5/2018	6	23	\$1,115.00	\$12.00	\$1,103.00	Y	28	28	107	3
6511	100	Garage	Attended	NYC	10023	6/6/2018	6	23	\$1,003.00		\$1,003.00	Y	28	28	100	5
6511	100	Garage	Attended	NYC	10023	6/7/2018	6	23	\$886.00		\$886.00	Y	28	28	100	4
6511	100	Garage	Attended	NYC	10023	6/8/2018	6	23	\$1,075.00		\$1,075.00	Y	28	28	105	3
6511	100	Garage	Attended	NYC	10023	6/9/2018	6	23	\$576.00	\$18.00	\$558.00	Y	28	28	145	6
6511	100	Garage	Attended	NYC	10023	6/10/2018	6	24	\$615.00		\$615.00	Y	28	28	140	2
6511	100	Garage	Attended	NYC	10023	6/11/2018	6	24	\$814.00		\$814.00	Y	28	28	86	1
6511	100	Garage	Attended	NYC	10023	6/12/2018	6	24	\$1,139.00	\$20.00	\$1,119.00	Y	28	28	88	1

A complete summary of the zip codes, Intervention Group dates of observation, and Control Group dates of observation are included below in Table 4.

Table 4. Intervention Groups, Control Groups, Zip Codes and Pre/Post Intervention Period Summary

Test Location	Test Location Zip	Control Location	Control Location Zip	Pre-Intervention	Post Intervention
6511	10023	1	11355	1/7/18-4/6/18	5/24/18-8/21/18
6569	11215	2	10029	4/20/18-7/18/18	9/25/18-12/23/18
51431	10014	3	10014	4/14/18-7/12/18	10/2/18-12/30/18
61459	10021	4	10011	11/23/18-2/20/19	3/12/19-6/9/19
61462	10128	5	11102	6/3/18-8/31/18	10/26/18-1/23/19
61468	10007	6	10012	6/29/18-9/26/18	9/27/18-12/25/18
61491	10024	7	10033	7/3/18-9/30/18	10/31/18-1/28/19
61603	10032	8	11216	6/29/18-9/26/18	9/27/18-12/25/18
61619	10028	9	10021	7/2/18-9/29/18	9/30/18-12/28/18
61625	10022	10	10032	5/27/18-8/24/18	2/14/19-5/14/19
61626	10022	11	10017	12/13/18-3/12/19	3/13/19-6/10/19
61644	10024	12	11101	6/29/18-9/26/18	9/27/18-12/25/18
61700	11415	13	11375	9/4/18-12/2/18	12/3/18-3/2/19
61704	10021	14	10029	6/10/18-9/7/18	9/8/18-12/6/18
91413	10007	15	7030	4/8/18-7/6/18	7/7/18-10/4/18

Overall Observation Drop Methodology				
Hypothesis		DataFrame ID	Z10	Z11
H1A	Beginning observation count (daily total revenue per location: 180 days * 30 locations)		5400	5400
	Drop observations without corresponding lags (Total Revenue)		7	7
	Drop observations with \$0 Total Revenue (presumed closed that day)		227	227
	Drop observations with Parkwhiz (online) revenue in control locations		68	68
	Drop observations that do not have last year's revenue available as a regressor			1607
	N Observations		5098	3491
H1B	Beginning observation count (daily offline revenue per location: 180 days * 30 locations)		5400	5400
	Drop observations without corresponding lags (Offline Revenue)		7	7
	Drop observations with \$0 Total Offline Revenue (presumed closed that day)		233	233
	Drop observations with Parkwhiz (online) revenue in control locations		64	64
	Drop observations that do not have last year's revenue available as a regressor			1605
	N Observations		5096	3491
H2	See H1A		5098	3491
H3	See H1A		5098	3491
H4	See H1A		5098	3491
<u>Conditions of additional analysis:</u>				
H2-H4	Beginning observation count (daily online revenue per test site, post-intervention: 90 days * 15 locations)		1350	
	Drop observations without corresponding lags (Online Revenue)		7	
	Observations		1343	
	N Downsampled to weekly data		191	

Note: last year's online revenue does not exist for an intervention that just occurred. Only ZF10 is relevant.

Figure 3. Observation drop methodology.

In the process of gathering data from our third party parking company for use in this study, it became evident that we were going to have two distinct groups to analyze based on limited data in some cases. Figure 3 above demonstrates the two datasets, identified as Z10 and Z11, or alternatively as ZF10 and ZF11 in some tables. Because only a portion of both our intervention and control groups had last year's revenue data available, our sample size was $N = 5,098$ for the Z10 model and lower $N = 3,491$ for the Z11 model. Throughout this study and for each hypothesis analyzed, a reference to, and work performed on, the Z10 (larger, all observations included) and Z11 (smaller, reduced to only observations with last year's revenue comparison) dataset will be observed.

The data collection and organization process began with 5,400 observations (180 days * 30 locations). The dataset was individually analyzed for dropping observations for each hypothesis evaluated in the study. For each hypothesis test, seven observations were typically dropped for the purpose of generating lagged values. For H1A (total revenue) and H1B (offline revenue), any observations from sites with \$0 revenue were dropped and presumed to be from locations closed that day (typically Saturday or Sunday for a subset of locations only). These observations totaled between 227 to 233.

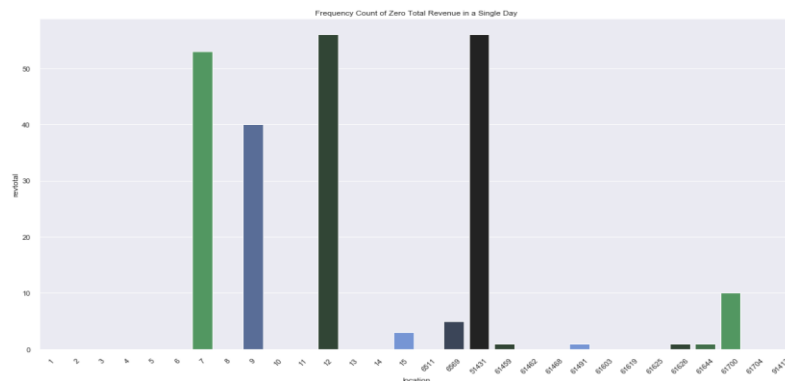


Figure 4. Frequency Zero Total Revenues at Various Locations for H1A.

Similarly, there are approximately 68 observations in the control group, which showed online revenue sales in the ParkWhiz channel, which were deemed outliers and dropped. This, too, can be explained by practical operational means. Given the low barrier to entry into the ParkWhiz system by a parking operator, it is quite easy for a local site manager to list their inventory on the site without initial detection by the parent company and without their approval.

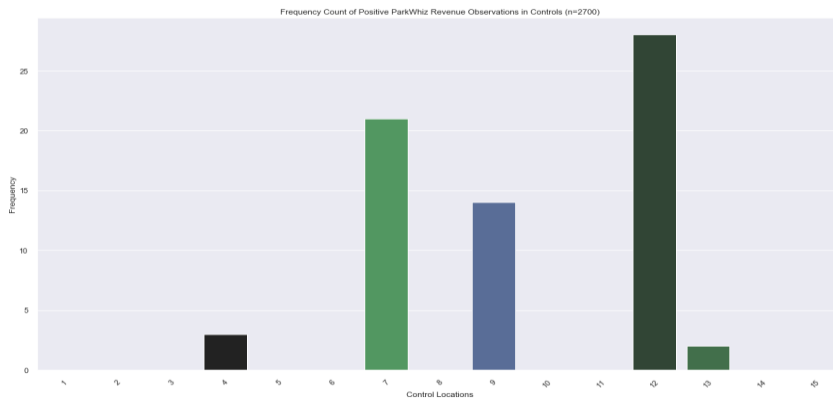


Figure 5. Frequency of Online Channel Revenues at Control Locations.

These outlier observations fall into the category of brief moments when a small fraction of sales emanated from the ParkWhiz channel but which were quickly halted by parent company audit oversight. Nonetheless, these also create confounding variables in our data analysis, which are best managed by being dropped from the study. A sample of these observations can be reviewed below in Figure 6. Finally, when the analysis was performed with last year’s revenue as an explanatory variable, approximately 1,600 observations were dropped due to specific locations not having this historical data available or due to the facility not being in operation at that time.

```
[232]: zf3[(zf3['location'].isin(cont_loc1)) & (zf3['rev_pw'] > 0)].head(10)
```

	location	year	spaces	garage	attended	city	zipcode	date	month	week	revtotal	rev_pw	rev_other	intervention	
3416		4	1	55	True	True	NYC	10011	2019-06-06	6	23	790.00	40.0	750.00	False
3418		4	1	55	True	True	NYC	10011	2019-06-08	6	23	678.99	107.0	571.99	False
3419		4	1	55	True	True	NYC	10011	2019-06-09	6	24	312.00	46.0	266.00	False
3865		7	1	165	True	True	NYC	10033	2018-09-26	9	39	1517.00	66.0	1451.00	False
3866		7	1	165	True	True	NYC	10033	2018-09-27	9	39	4053.00	1022.0	3031.00	False
3867		7	1	165	True	True	NYC	10033	2018-09-28	9	39	1236.00	75.0	1161.00	False
3871		7	1	165	True	True	NYC	10033	2018-11-01	11	44	1169.00	27.0	1142.00	False
3872		7	1	165	True	True	NYC	10033	2018-11-02	11	44	1342.00	20.0	1322.00	False
3877		7	1	165	True	True	NYC	10033	2018-11-07	11	45	1392.00	14.0	1378.00	False
3878		7	1	165	True	True	NYC	10033	2018-11-08	11	45	1425.00	24.0	1401.00	False

```
[234]: zf3[(zf3['location'].isin(cont_loc1)) & (zf3['rev_pw'] > 0)]['rev_pw'].count()
```

```
[234]: 68
```

Figure 6. Control Group Dropped Observations.

Dataset Variables and Pre-Processing Methodology

Building on the Zhang et al. (2019) methodology, we use various exogenous variables for control in a day-to-day basis: time (day=1 for first observation date), dummy variables for each day of the week (base case weekend=0), combined precipitation variable (snow and rain), temperature, quarterly dummy variables (Q1=0), the S&P 500 Index, and local events. See below in Table 5 for a detailed library of definitions for all variables.

Table 5. *Data Variable Definitions*

Variable	Abbreviation	Operationalization
Dependent Variable		
log_revtotal_ps		Daily total revenue (all sources) per parking space at a given location, log transformed.
log_revother_ps		Daily offline (Non-Parkwhiz) revenue per parking space at a given location, log transformed.
log_revpw_ps		Weekly online (Parkwhiz) revenue per parking space at a test location, log transformed.
Exogenous Variable		
log_revtotal_ps_lag		Log of total revenue per space, lagged 1 time period.
log_revtotal_ps_lag7		Log of total revenue per space, lagged 7 time periods (7 days).
log_revother_ps_lag		Log of other revenue sources per space, lagged by 1 time period.
log_revother_ps_lag7		Log of other revenue sources per space lagged by 1 week (7 days).
log_revpw_ps_lag		Log of Online channel revenue per space, lagged by 1 time period.
log_revpw_ps_lag7		Log of Online channel revenue per space, lagged by 1 week (7 days).
intervention		This variable simply denotes in a binary 1 or 0, whether the ParkWhiz intervention had occurred.
searchdemand		This variable denotes the volume of online searches for parking options that occurred in a specific zip code for a particular facility for a given day. Essentially this is the number of consumers actively seeking parking options on a day to day basis in a zip code geography in a digital environment.
location		Identifier of the location (1-15 controls, others are test sites)
group		Identifier for Group, Test = 1, Control = 0
transact_garage		This variable denotes the number of parking facilities in a particular zip code, for a single day, that were utilizing the ParkWhiz e-commerce sales channel. This variable occurs in both the intervention group or the control group.
offstreetsites		This variable denotes the number of parking facilities in a particular zip code, for a single day, that exist, no matter whether they sell online, offline or both. This variable occurs in both the intervention group or the control group.
site_diff		This variable is the difference in total competition (offstreetsites) and online competition (transact_garage) resulting in the difference of the sites equalling to the number of offline only competitors.
location		The unique proprietary identification number for each parking facility examined in this study. Identified with the coded number due to privacy and data security concerns on behalf of the participating 3rd party company.
garage		Identifies each property in both the intervention and control groups as a binary choice of either multi-level parking garage structure or a flat parking lot. This variable is used as a control variable. Garage = 1, Lot = 0
attended		Attended = 1, Unattended = 0, Identified each property in both the intervention and control groups as a binary choice of either attended, meaning operated by human labor, or unattended, meaning operated by modern automated technology without any human labor involved. Hybrid structures can exist but are not relevant in this context as a control variable.
zipcode		Identifies the zip code geography within which the particular parking facility exists and is the level of measurement in this study per site and the dependent or moderating effects within it.
precip		Combined daily value of both snow and rain in mm from the nearest weather station
temp		Average daily temperature (Celsius) based on 8 daily readings from the nearest weather station
googlesearch		Google Trends index for "parking" in NYC region
events		No. of events in the zip code that day
log_LY_ps		Log of last year's revenue per space (must be offline only, all pre-intervention period)
mon, tue, wed, thu, fri		Set of 5 dummy variables (excluding weekend = 0)
q2, q3, q4		Set of dummy variables for quarters (excluding Q1 = 0)
log_time		Log of time beginning at 1 for each location site and ending at 180 for the last observation date

“Attended or unattended” means whether or not human labor is used to operate the parking facility or automated machinery maintains the site. The online intervention (Parkwhiz) was also a binary variable. Offstreetsites represented the total number of competitive sites in a given zip code. Meanwhile, transact_garage represented the number of online competitors in the zip code using the Parkwhiz online channel. Consequently, the difference between total competitors (offstreetsites) and online competitors (transact_garage) is the number of presumed offline-only competitors (site_diff). searchdemand explained the level of search frequency in

the zip code specific to the Parkwhiz System. Googlesearch is Google Trends weekly data for the term “parking” in the greater NYC area. Dependent variables (revenue) were log-transformed. Predictor variables time, S&P500, and lagged revenue figures were also log-transformed. The dataset was split into two versions, those containing last year’s revenue (for year-over-year comparisons) and the data frame without year-over-year (full dataset).

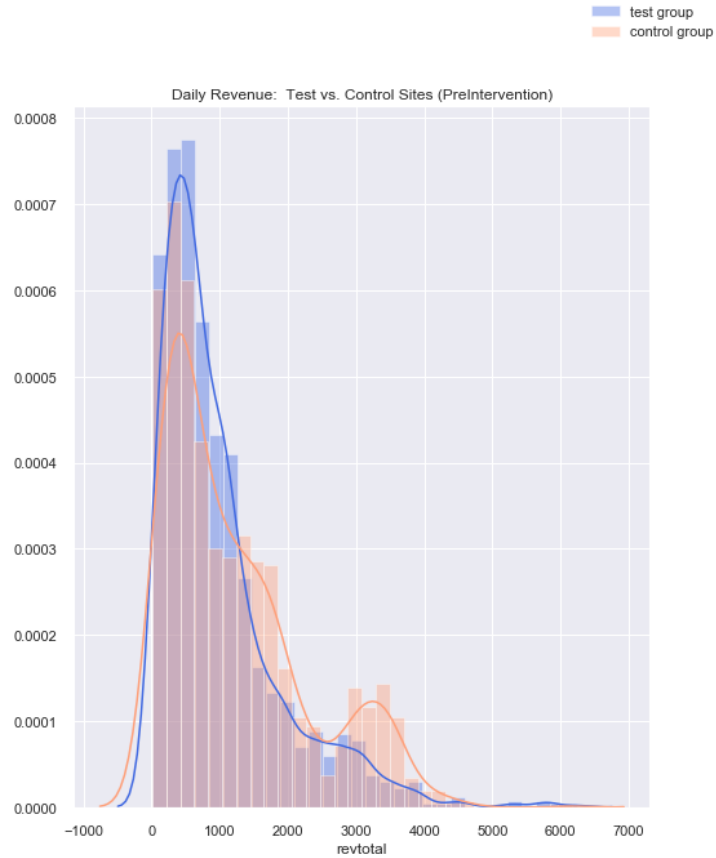


Figure 7. Frequency Distribution Plot of Daily Total Revenue for All Locations (Pre-Intervention).

It should be noted that certain revenue values were forward-filled when used as lagged predictors. For example, if a location was typically closed on the weekend, the Friday revenue figure would be forward filled to previously null Saturday and Sunday values, providing a 1-day lag for a Monday observation (i.e., Friday values constitute a 1-day lag for a Monday value in

certain locations that were closed on Saturdays and Sundays). We do not believe this skewed the dataset overall and a negligible impact on our overall analysis.

Pre-Regression Data Quality Checks

Unit Root. After log transformation of the dependent variables and other data series, we first conducted an Augmented Dickey-Fuller (ADF) test for each series and established that there was no unit root in any of the variables. Unit root tests are important checks upon serial correlation, multicollinearity, heteroskedasticity, can inflate R2 scores, and otherwise invalidate or weaken statistical inferences (Cochrane,1991). Because the distribution of these daily revenue figures was not normally distributed (pre-log transformation), we felt it more relevant to also check with the Phillips-Peron (PP) test for each series. ADF requires specification of a number of lags, whereas PP does not and is also more robust to serial correlation and heteroskedasticity in non-normal distributions. Our results determined there was no unit root in any of these variables, consistent with the already performed ADF checks.

Variance Inflation Factor. Variance Inflation Factor (VIF) tests are done to check for variable multicollinearity for each of our independent variables. These results should typically be below 2.5. For our analysis, on average, they are all within normal ranges (2.18) which gives a high level of confidence that multicollinearity is generally not an issue in most of our regressions. Resampled weekly data for H2 and H3 additional analysis resulted in a VIF of 1.73.

H1 is broken into two hypotheses. H1A - Does the Parkwhiz intervention add to total revenues? H1B - Does the ParkWhiz intervention have any negative effect on revenue from other revenue (non-ParkWhiz categories, presumed to be mostly offline)? The primary difference in separating H1A and H1B is to evaluate whether or not the online intervention was a contributor to total revenue (H1A) and whether or not the online intervention was a cannibalizing effect for non-Parkwhiz sources (H1B). H2 evaluated whether or not the number of competitors online in the Parkwhiz system (transact_garage) affected daily online revenue. H3 evaluated whether not

the number of total garages available (offstreetsites) for a zipcode affected the daily online revenue. H2 and H3 were analyzed explicitly on data in test sites only during the post-intervention period because they pertained to online revenue from Parkwhiz sources as the dependent variable. H4 examined whether or not searchdemand within the Parkwhiz system had predictive value for total and offline revenue.

Fixed Effects - Within Estimator:

$$(y_{ij} - \bar{y}_i) = \beta(X_{ij} - \bar{X}_i) + a_i - a_i + \epsilon_{ij} - \bar{\epsilon}_i$$

Where:

y_{it} = the j th occurrence of dependent variable for the i th location

\bar{y}_i = the mean dependent of location i 's dependent variable

β = vector of beta coefficients explaining

X_{ij} = array of X independent (exogenous) predictors

ϵ_{ij} = normally distributed error term

$\bar{\epsilon}_i$ = mean error of the i th location

\bar{X}_i = a vector of the mean of each exogenous predictor for the i th location

a_i = unobserved heterogeneity

Figure 8. Fixed Effects Econometric Model

Fixed effects panel data analysis was performed for all hypotheses. Unobserved heterogeneity was a serious concern upon evaluating the data, given the potential uniqueness for any individual location in this study. Every parking lot and garage is different from the others under many varieties of characteristics. Fixed effects analysis has the ability to analyze time-series cross-sectional data while attempting to control for unobserved heterogeneity (Wooldridge 2018). We believe fixed effects most accurately calculate relative changes in dependent variables as explained by relative changes in a regressor from its mean. This model was best suited to explain day to day variability in revenue at any given location.

Linear Mixed Effects (LMM) - Random Intercepts:

$$y_{ij} = \beta_0 + \beta_1 X_{ij} + \alpha_{0i} + \epsilon_{ij}$$

Where:

y_{ij} = the j th occurrence of dependent variable for the i th location

B_0 = global intercept for all location

B_1 = vector of coefficients for all independent variables (fixed effects)

α_{0i} = the intercept for the i th location (random effects)

ϵ_{ij} = normally distributed error term

Figure 9. Linear Mixed Effects Econometric Model.

A Linear Mixed Model (fixed slopes, random intercepts) was also performed for all hypotheses. This model is the functional equivalent of an ordinary least squares (OLS) regression with 30 intercepts for each distinct location in the study. Both models were employed for different reasons. The fixed effects panel data analysis is the analytical approach taken by Zhang et al. (2019), which most closely resembles this study and dataset. Secondly, panel data methods, specifically within fixed effects, might better parameterize variables at unit level (locations) while stripping away unobservable characteristics. The treatment of regressors and randomness (error term) is different in both models. In fixed-effects panel data methods, unobserved heterogeneity (α_i) is considered a random effect. In a hierarchical linear model, random effects slope for each location is actually considered a fixed effect (and the variance around that fixed effect is random). In linear regression, randomness occurs based on a mean (0) and variance of an error term framework, whereas panel data methods attempt to strip this away in unobserved heterogeneity terms that are ultimately subtracted out through differencing on the mean values.

Finally, the value of the Linear Mixed Model (LMM) is that it also provides validation for endogeneity against the panel data method. Difference in difference (DiD) models could be

used to evaluate endogeneity as a robustness check in econometric models. The LMM provides that confirmation check, as well as another approach to answer our hypotheses. In essence, both these models approach the hypotheses in question from slightly different ways and add value to our overall analysis. Fixed effects panel data models were performed with clustered covariance for robust standard errors to mitigate heteroskedasticity.

Further analysis on H2 and H3 were conducted to try to evaluate a relationship between independent variables (`transact_garage`, `site_diff`) and only online revenue (as a dependent variable) with weekly data (downsampled from daily) in the 15 test locations only, resulting in $N=191$. Downsampling to weekly data was decided because of the frequency of \$0 observations (no online revenue on a given day at a location), which is not conducive to a log transformation. This approach is elucidated further in the Results section.

Main Results

H1 - The addition of an Online Channel to existing Offline Channels will produce net new revenue gains.

Our hypothesis H1A is essentially examining two fixed effects models for both iterations of the dataset (ZF10 = full dataset, ZF11=dataset with last year's revenue available). Due to the fact that only a portion of both our intervention and control groups had last year's revenue data available, our sample size was $N = 5,098$ for the first fixed effects model and lower, $N = 3,491$ for the second fixed effects.

H1A: did the online channel intervention (Parkwhiz) have an overall positive effect as a revenue contributor?

Stated differently, did the addition of the online channel increase total revenue returns or reduce them? We find that the ParkWhiz intervention was a revenue contributor. For the fixed effects panel data, the larger dataset (ZF10) indicated the intervention added 43.75% ($43.75\% = \exp(0.1733) - 1$), the smaller dataset the intervention added 43.061%. The first fixed effects model had an R^2 of approximately 39.7% and improved in the second to 47.2%, with the inclusion of last year's revenue as a predictor. It is important to understand that these fixed effects R^2 constitute a marginal R^2 , or the explanation of the daily revenue per space at a specific location, due to the removal of the unobserved heterogeneity or random intercept for each location (Wooldridge 2018). The linear mixed-effects model indicated that the intervention added 18.070% in the larger dataset (ZF10) and 14.01% in the smaller dataset (ZF11). R^2 in the first LMM was 73.1%, and in the second it was 79.4%. All models are statistically significant coefficients for the intervention predictor when analyzed as seen in Figure 10-13.

PanelOLS Estimation Summary						
Dep. Variable:	log_revtotal_ps	R-squared:	0.3970			
Estimator:	PanelOLS	R-squared (Between):	-5.5013			
No. Observations:	5098	R-squared (Within):	0.3970			
Date:	Sun, Mar 22 2020	R-squared (Overall):	-3.4191			
Time:	08:09:09	Log-likelihood	-3441.3			
Cov. Estimator:	Clustered					
		F-statistic:	166.17			
Entities:	30	P-value	0.0000			
Avg Obs:	169.93	Distribution:	F(20,5048)			
Min Obs:	96.000					
Max Obs:	180.00	F-statistic (robust):	74.050			
		P-value	0.0000			
Time periods:	519	Distribution:	F(20,5048)			
Avg Obs:	9.8227					
Min Obs:	1.0000					
Max Obs:	24.000					
Parameter Estimates						
	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
const	-3.4336	4.2165	-0.8143	0.4155	-11.700	4.8326
intervention	0.1733	0.0435	3.9876	0.0001	0.0881	0.2585
log_revtotal_ps_lag	0.1610	0.0284	5.6596	0.0000	0.1052	0.2168
transact_garage	-0.0033	0.0076	-0.4382	0.6613	-0.0182	0.0115
log_time	-0.0083	0.0185	-0.4501	0.6527	-0.0445	0.0279
offstreetsites	-0.1025	0.0488	-2.1026	0.0355	-0.1982	-0.0069
log_sp500close	0.8942	0.5416	1.6512	0.0988	-0.1675	1.9559
log_revtotal_ps_lag7	0.2375	0.0408	5.8175	0.0000	0.1575	0.3175
q2	0.0761	0.0479	1.5894	0.1120	-0.0178	0.1700
q3	0.0055	0.0613	0.0898	0.9285	-0.1147	0.1257
q4	0.0456	0.0492	0.9262	0.3544	-0.0509	0.1420
mon	0.5763	0.0916	6.2900	0.0000	0.3967	0.7559
tue	0.4972	0.0829	6.0008	0.0000	0.3348	0.6596
wed	0.4461	0.0823	5.4198	0.0000	0.2847	0.6075
thu	0.5204	0.0807	6.4519	0.0000	0.3623	0.6786
fri	0.4965	0.0642	7.7320	0.0000	0.3706	0.6223
events	0.0311	0.0076	4.1181	0.0000	0.0163	0.0459
searchdemand	0.0019	0.0006	3.3298	0.0009	0.0008	0.0030
precip	-0.0039	0.0021	-1.8909	0.0587	-0.0080	0.0001
temp	0.0046	0.0027	1.7208	0.0854	-0.0006	0.0098
googlesearch	-0.0086	0.0023	-3.7161	0.0002	-0.0131	-0.0041
F-test for Poolability: 40.297						
P-value: 0.0000						
Distribution: F(29,5048)						
Included effects: Entity						

Figure 10. Fixed Effects, H1A, ZF10 Data Frame.

```

=====
PanelOLS Estimation Summary
=====
Dep. Variable:    log_revtotal_ps    R-squared:                0.4720
Estimator:       PanelOLS          R-squared (Between):     -5.2820
No. Observations: 3491          R-squared (Within):      0.4720
Date:            Sun, Mar 22 2020   R-squared (Overall):     -3.4950
Time:            08:42:02          Log-likelihood           -1881.9
Cov. Estimator:  Clustered

Entities:        21
Avg Obs:         166.24
Min Obs:         106.00
Max Obs:         180.00

Time periods:    423
Avg Obs:         8.2530
Min Obs:         1.0000
Max Obs:         17.000

F-statistic:     146.83
P-value:         0.0000
Distribution:     F(21,3449)

F-statistic (robust): 78.577
P-value:         0.0000
Distribution:     F(21,3449)

```

```

=====
Parameter Estimates
=====

```

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
const	-2.0495	2.3474	-0.8731	0.3827	-6.6520	2.5530
intervention	0.1575	0.0309	5.1037	0.0000	0.0970	0.2179
log_revtotal_ps_lag	0.1175	0.0184	6.3683	0.0000	0.0813	0.1536
log_LY_ps	0.3271	0.0217	15.082	0.0000	0.2845	0.3696
log_revtotal_ps_lag7	0.1387	0.0181	7.6812	0.0000	0.1033	0.1742
googlesearch	-0.0036	0.0012	-3.0465	0.0023	-0.0058	-0.0013
transact_garage	0.0037	0.0077	0.4790	0.6320	-0.0115	0.0189
offstreetsites	-0.1070	0.0236	-4.5362	0.0000	-0.1533	-0.0608
log_sp500close	0.7476	0.3011	2.4830	0.0131	0.1573	1.3379
q2	0.0299	0.0351	0.8515	0.3946	-0.0389	0.0987
q3	-0.0155	0.0428	-0.3626	0.7169	-0.0995	0.0684
q4	0.0305	0.0346	0.8826	0.3775	-0.0373	0.0984
log_time	-0.0073	0.0131	-0.5602	0.5754	-0.0331	0.0184
mon	0.3333	0.0306	10.902	0.0000	0.2733	0.3932
tue	0.2569	0.0272	9.4567	0.0000	0.2037	0.3102
wed	0.2453	0.0284	8.6309	0.0000	0.1895	0.3010
thu	0.2899	0.0263	11.017	0.0000	0.2383	0.3414
fri	0.2840	0.0258	11.006	0.0000	0.2334	0.3346
events	0.0247	0.0084	2.9311	0.0034	0.0082	0.0412
searchdemand	0.0015	0.0003	5.0981	0.0000	0.0009	0.0021
precip	-0.0048	0.0013	-3.6868	0.0002	-0.0073	-0.0022
temp	0.0028	0.0016	1.7302	0.0837	-0.0004	0.0059

```

=====

```

F-test for Poolability: 21.811

P-value: 0.0000

Distribution: F(20,3449)

Included effects: Entity

Figure 11. Fixed Effects, H1A, ZF11 Data Frame.

Mixed Linear Model Regression Results						

Model:	MixedLM	Dependent Variable:		log_revtotal_ps		
No. Observations:	5098	Method:		ML		
No. Groups:	30	Scale:		0.2304		
Min. group size:	96	Log-Likelihood:		-3568.8739		
Max. group size:	180	Converged:		Yes		
Mean group size:	169.9					

	Coef.	Std.Err.	z	P> z	[0.025 0.975]	

Intercept	-7.245	1.800	-4.025	0.000	-10.773	-3.717
intervention[T.True]	0.166	0.026	6.511	0.000	0.116	0.216
garage[T.True]	0.124	0.247	0.502	0.616	-0.360	0.608
attended[T.True]	0.157	0.365	0.429	0.668	-0.558	0.872
log_revtotal_ps_lag	0.176	0.013	13.716	0.000	0.151	0.202
log_revtotal_ps_lag7	0.246	0.012	20.804	0.000	0.223	0.269
transact_garage	0.001	0.006	0.196	0.844	-0.010	0.013
offstreetsites	-0.007	0.006	-1.212	0.226	-0.019	0.005
log_sp500close	1.053	0.222	4.748	0.000	0.619	1.488
q2	0.036	0.033	1.085	0.278	-0.029	0.102
q3	0.010	0.040	0.261	0.794	-0.068	0.089
q4	0.040	0.028	1.440	0.150	-0.014	0.094
log_time	-0.007	0.009	-0.809	0.418	-0.025	0.010
mon	0.586	0.025	23.425	0.000	0.537	0.635
tue	0.507	0.023	21.721	0.000	0.461	0.552
wed	0.462	0.023	19.725	0.000	0.416	0.508
thu	0.545	0.024	22.985	0.000	0.498	0.591
fri	0.518	0.024	21.934	0.000	0.471	0.564
events	0.026	0.009	2.813	0.005	0.008	0.044
temp	0.005	0.001	3.241	0.001	0.002	0.008
precip	-0.004	0.001	-3.908	0.000	-0.006	-0.002
googlesearch	-0.009	0.001	-8.398	0.000	-0.011	-0.007
location Var	0.229	0.129				

Figure 12. Linear Mixed Model, H1A, ZF10 Data Frame.

Mixed Linear Model Regression Results

```

=====
Model:                MixedLM Dependent Variable: log_revtotal_ps
No. Observations:    3491   Method:                ML
No. Groups:          21     Scale:                0.1755
Min. group size:     106    Log-Likelihood:       -1962.3078
Max. group size:     180    Converged:            Yes
Mean group size:     166.2

-----
                Coef.  Std.Err.  z    P>|z|  [0.025 0.975]
-----
Intercept          -5.628    1.956  -2.877  0.004  -9.462  -1.795
intervention[T.True]  0.131    0.029   4.560  0.000   0.075   0.187
garage[T.True]       0.191    0.197   0.972  0.331  -0.194   0.577
log_revtotal_ps_lag  0.133    0.015   9.049  0.000   0.104   0.162
transact_garage      0.010    0.006   1.638  0.101  -0.002   0.022
offstreetsites      -0.016    0.005  -3.002  0.003  -0.027  -0.006
log_sp500close       0.824    0.248   3.319  0.001   0.338   1.311
q2                   -0.007    0.036  -0.198  0.843  -0.078   0.063
q3                   -0.029    0.044  -0.663  0.507  -0.114   0.057
log_time            -0.014    0.010  -1.354  0.176  -0.034   0.006
q4                   0.012    0.031   0.380  0.704  -0.049   0.072
mon                  0.339    0.027  12.530  0.000   0.286   0.392
tue                  0.263    0.025  10.392  0.000   0.213   0.312
wed                  0.255    0.026   9.876  0.000   0.205   0.306
thu                  0.308    0.026  11.811  0.000   0.257   0.359
fri                  0.298    0.026  11.499  0.000   0.247   0.349
events              0.020    0.009   2.151  0.031   0.002   0.039
temp                0.003    0.002   1.758  0.079  -0.000   0.006
precip              -0.005    0.001  -4.717  0.000  -0.007  -0.003
log_LY_ps           0.344    0.014  24.258  0.000   0.316   0.371
googlesearch        -0.004    0.001  -3.223  0.001  -0.006  -0.001
log_revtotal_ps_lag7  0.145    0.013  10.973  0.000   0.119   0.171
Group Var           0.083    0.066

=====

```

Figure 13. Linear Mixed Model, H1A, ZF11 Data Frame.

Table 6. H1A Key Independent and Interaction Variables (Green Indicates Significance p<0.05)

Model	Fixed Effects		Mixed Models	
	ZF10	ZF11	ZF10	ZF11
intervention	18.92%	17.06%	18.06%	14.00%
log_revtotal_ps_lag	17.47%	12.47%	19.24%	14.22%
log_revtotal_ps_lag7	26.81%	14.88%	27.89%	15.60%

H1B: Did the online channel intervention (ParkWhiz) have a negative effect on other revenue sources (i.e., is there cannibalization occurring)?

```

-----
PanelOLS Estimation Summary
-----
Dep. Variable:      log_revother_ps      R-squared:          0.3746
Estimator:          PanelOLS           R-squared (Between): -3.1376
No. Observations:   5096             R-squared (Within):  0.3746
Date:               Sun, Mar 22 2020    R-squared (Overall): -1.9110
Time:               08:09:14             Log-likelihood       -3497.5
Cov. Estimator:     Unadjusted

Entities:           30             F-statistic:        159.13
Avg Obs:            169.87          P-value             0.0000
Min Obs:            96.000           Distribution:        F(19,5047)
Max Obs:            180.00          F-statistic (robust): 159.13
Time periods:       519             P-value             0.0000
Avg Obs:            9.8189          Distribution:        F(19,5047)
Min Obs:            1.0000
Max Obs:            24.000

-----
Parameter Estimates
-----
Parameter  Std. Err.  T-stat  P-value  Lower CI  Upper CI
-----
const      -5.4151    1.8522  -2.9236  0.0035   -9.0462   -1.7841
intervention  0.1180    0.0271   4.3478  0.0000    0.0648    0.1712
log_revother_ps_lag  0.1704    0.0128  13.304   0.0000    0.1453    0.1955
log_revother_ps_lag7  0.2300    0.0119  19.359   0.0000    0.2067    0.2533
transact_garage -0.0076    0.0062  -1.2163  0.2239   -0.0198    0.0046
log_time     -0.0109    0.0093  -1.1732  0.2408   -0.0290    0.0073
offstreetsites -0.0780    0.0254  -3.0709  0.0021   -0.1278   -0.0282
log_sp500close  1.0016    0.2236   4.4787  0.0000    0.5632    1.4400
q2           0.0839    0.0342   2.4501  0.0143    0.0168    0.1510
q3          -0.0590    0.0401  -1.4718  0.1411   -0.1375    0.0196
q4           0.0327    0.0279   1.1709  0.2417   -0.0220    0.0874
mon          0.5902    0.0251  23.471   0.0000    0.5409    0.6395
tue          0.5056    0.0236  21.456   0.0000    0.4594    0.5518
wed          0.4524    0.0237  19.048   0.0000    0.4058    0.4989
thu          0.5280    0.0242  21.811   0.0000    0.4806    0.5755
fri          0.5030    0.0241  20.903   0.0000    0.4558    0.5502
events       0.0328    0.0092   3.5640  0.0004    0.0148    0.0509
searchdemand  0.0019    0.0003   7.5477  0.0000    0.0014    0.0024
precip      -0.0036    0.0010  -3.4169  0.0006   -0.0056   -0.0015
temp         0.0009    0.0014   0.6455  0.5186   -0.0019    0.0037
-----

F-test for Poolability: 39.244
P-value: 0.0000
Distribution: F(29,5047)

Included effects: Entity

```

Figure 14. Fixed Effect, H1B, ZF10 Data Frame.

```

=====
PanelOLS Estimation Summary
=====
Dep. Variable:      log_revtotal_ps      R-squared:              0.4704
Estimator:         PanelOLS           R-squared (Between):    -5.7770
No. Observations:  3491                R-squared (Within):     0.4704
Date:              Sun, Mar 22 2020      R-squared (Overall):    -3.8365
Time:              08:09:21           Log-likelihood          -1887.2
Cov. Estimator:    Unadjusted

Entities:          21                F-statistic:            145.89
Avg Obs:           166.24            P-value                 0.0000
Min Obs:           106.00            Distribution:            F(21,3449)
Max Obs:           180.00            F-statistic (robust):   145.89
Time periods:      423                P-value                 0.0000
Avg Obs:           8.2530            Distribution:            F(21,3449)
Min Obs:           1.0000
Max Obs:           17.000

=====
Parameter Estimates
=====
              Parameter  Std. Err.   T-stat   P-value   Lower CI   Upper CI
-----
const          -2.0845    2.0610    -1.0114  0.3119   -6.1254    1.9564
intervention    0.1791    0.0307     5.8290  0.0000    0.1189    0.2393
log_revother_ps_lag  0.1140    0.0145     7.8599  0.0000    0.0856    0.1424
log_revother_ps_lag7 0.1359    0.0132    10.330  0.0000    0.1101    0.1617
log_LY_ps      0.3277    0.0142    23.108  0.0000    0.2999    0.3555
googlesearch  -0.0036    0.0011    -3.2821  0.0010   -0.0057   -0.0014
transact_garage 0.0068    0.0071     0.9559  0.3392   -0.0071    0.0207
offstreetsites -0.1130    0.0262    -4.3161  0.0000   -0.1643   -0.0617
log_sp500close 0.7687    0.2499     3.0759  0.0021    0.2787    1.2587
q2              0.0297    0.0367     0.8105  0.4177   -0.0422    0.1017
q3             -0.0141    0.0439    -0.3211  0.7482   -0.1001    0.0719
q4              0.0333    0.0310     1.0732  0.2833   -0.0275    0.0940
log_time       -0.0092    0.0106    -0.8676  0.3857   -0.0300    0.0116
mon            0.3310    0.0270    12.239  0.0000    0.2780    0.3840
tue            0.2553    0.0253    10.083  0.0000    0.2057    0.3049
wed            0.2431    0.0260     9.3480  0.0000    0.1921    0.2941
thu            0.2876    0.0265    10.847  0.0000    0.2356    0.3395
fri            0.2828    0.0262    10.784  0.0000    0.2314    0.3343
events         0.0243    0.0094     2.5737  0.0101    0.0058    0.0427
searchdemand   0.0015    0.0003     6.0118  0.0000    0.0010    0.0021
precip        -0.0047    0.0010    -4.6036  0.0000   -0.0068   -0.0027
temp           0.0026    0.0016     1.6593  0.0971   -0.0005    0.0058
=====

F-test for Poolability: 23.363
P-value: 0.0000
Distribution: F(20,3449)

Included effects: Entity

```

Figure 15. Fixed Effect, H1B, ZF11 Data Frame.

Mixed Linear Model Regression Results						
=====						
Model:	MixedLM	Dependent Variable:		log_revother_ps		
No. Observations:	5096	Method:		ML		
No. Groups:	30	Scale:		0.2320		
Min. group size:	96	Log-Likelihood:		-3586.1051		
Max. group size:	180	Converged:		Yes		
Mean group size:	169.9					

	Coef.	Std.Err.	z	P> z	[0.025	0.975]

Intercept	-6.830	1.808	-3.778	0.000	-10.373	-3.287
intervention[T.True]	0.108	0.025	4.254	0.000	0.058	0.158
garage[T.True]	0.115	0.253	0.455	0.649	-0.381	0.611
attended[T.True]	0.166	0.374	0.444	0.657	-0.567	0.898
log_revother_ps_lag	0.173	0.013	13.414	0.000	0.148	0.198
log_revother_ps_lag7	0.241	0.012	20.257	0.000	0.218	0.264
transact_garage	-0.003	0.006	-0.507	0.612	-0.015	0.009
offstreetsites	-0.004	0.006	-0.653	0.513	-0.016	0.008
log_sp500close	1.001	0.223	4.500	0.000	0.565	1.438
q2	0.046	0.034	1.366	0.172	-0.020	0.112
q3	0.012	0.040	0.307	0.759	-0.067	0.092
q4	0.047	0.028	1.682	0.093	-0.008	0.101
log_time	-0.007	0.009	-0.828	0.408	-0.025	0.010
mon	0.588	0.025	23.457	0.000	0.539	0.638
tue	0.514	0.023	21.937	0.000	0.468	0.560
wed	0.467	0.024	19.854	0.000	0.421	0.513
thu	0.552	0.024	23.162	0.000	0.505	0.598
fri	0.525	0.024	22.100	0.000	0.478	0.571
events	0.025	0.009	2.737	0.006	0.007	0.043
temp	0.005	0.001	3.474	0.001	0.002	0.008
precip	-0.004	0.001	-4.205	0.000	-0.006	-0.002
googlesearch	-0.009	0.001	-8.472	0.000	-0.011	-0.007
Group Var	0.240	0.134				
=====						

Figure 16. Linear Mixed Model, H1B, ZF10 Data Frame.

```

Mixed Linear Model Regression Results
=====
Model:                MixedLM Dependent Variable: log_revother_ps
No. Observations:    3491   Method:                ML
No. Groups:          21     Scale:                0.1775
Min. group size:     106    Log-Likelihood:      -1981.8086
Max. group size:     180    Converged:           Yes
Mean group size:     166.2

-----
                Coef.  Std.Err.  z    P>|z|  [0.025 0.975]
-----
Intercept          -5.548    1.967  -2.820  0.005  -9.403  -1.692
intervention[T.True]  0.061    0.029   2.106  0.035   0.004   0.117
garage[T.True]      0.170    0.202   0.844  0.399  -0.225   0.566
log_revother_ps_lag  0.127    0.015   8.608  0.000   0.098   0.155
log_revother_ps_lag7 0.142    0.013  10.683  0.000   0.116   0.168
log_LY_ps           0.346    0.014  24.305  0.000   0.319   0.374
transact_garage     0.003    0.006   0.521  0.602  -0.009   0.015
offstreetsites     -0.011    0.005  -2.088  0.037  -0.022  -0.001
log_sp500close      0.817    0.250   3.274  0.001   0.328   1.307
q2                  -0.000    0.036  -0.014  0.989  -0.071   0.070
q3                  -0.037    0.044  -0.838  0.402  -0.123   0.049
log_time            -0.013    0.010  -1.283  0.199  -0.034   0.007
q4                  0.016    0.031   0.512  0.609  -0.045   0.077
mon                 0.347    0.027  12.744  0.000   0.294   0.400
tue                 0.272    0.025  10.708  0.000   0.223   0.322
wed                 0.266    0.026  10.239  0.000   0.215   0.317
thu                 0.319    0.026  12.143  0.000   0.268   0.371
fri                 0.306    0.026  11.720  0.000   0.255   0.357
events              0.022    0.009   2.307  0.021   0.003   0.040
temp                0.003    0.002   1.967  0.049   0.000   0.006
precip              -0.005    0.001  -5.032  0.000  -0.007  -0.003
googlesearch        -0.004    0.001  -3.229  0.001  -0.006  -0.001
Group Var           0.087    0.069

=====

```

Figure 17. Linear Mixed Model, H1B, ZF11 Data Frame.

Table 7. H1B Key Independent and Interaction Variables (Green Indicates Significance $p < 0.05$)

Model	Fixed Effects		Mixed Models	
	ZF10	ZF11	ZF10	ZF11
intervention	12.52%	19.61%	11.40%	6.29%
log_revother_ps_lag	18.58%	12.08%	18.89%	13.54%
log_revother_ps_lag7	25.86%	14.56%	27.25%	15.26%

Results from the fixed effects panel data indicate that the predictor variable intervention had a positive effect on the dependent variable of other (offline) revenue. In the larger dataset (ZF10), the intervention added 11.42% to offline revenue. The smaller dataset indicates the intervention added 19.61% in offline revenue per space. The first fixed effects model had an R^2 of approximately 37.5% and improved in the second model to 47.0%. Results from the LMM also indicated the predictor variable (intervention) had a positive effect on the dependent variable of other (offline) revenue. The LMM for the larger dataset indicated an 11.42% increase in revenue due to the predictor, and the smaller dataset suggested a smaller 6.25% increase. Both models resulted in statistically significant coefficients for the intervention predictor when analyzed, indicating high relevance to the dependent variable (offline revenue). We find that the online channel is contributing to offline revenue success and is not cannibalizing.

H2: The effect of Online Channel introduction on revenue will be negatively moderated by the volume of competitors offering the same Online sales channel within the same zip code.

We tested Hypothesis #2 to examine the effect of other parking facilities existing within the zipcode who are using the ParkWhiz channel for sales and their effect on the examined parking facilities in our study, to tease out any correlations or causation in these competitive (online competition only) scenarios. We evaluated whether there is an interaction effect (moderating behavior) between the number of online garages (transact_garage) and the introduction of the online channel (intervention). See Figures 18-21 below.

```

PanelOLS Estimation Summary
=====
Dep. Variable:    log_revtotal_ps  R-squared:                0.3957
Estimator:       PanelOLS         R-squared (Between):      0.6661
No. Observations: 5098           R-squared (Within):       0.3957
Date:            Mon, Mar 23 2020  R-squared (Overall):      0.5709
Time:            19:53:56         Log-likelihood             -3446.7
Cov. Estimator:  Clustered

Entities:        30
Avg Obs:         169.93
Min Obs:         96.000
Max Obs:         180.00

Time periods:    519
Avg Obs:         9.8227
Min Obs:         1.0000
Max Obs:         24.000

F-statistic:     165.29
P-value          0.0000
Distribution:     F(20,5048)

F-statistic (robust): 107.21
P-value          0.0000
Distribution:     F(20,5048)

Parameter Estimates
=====
Parameter  Std. Err.  T-stat  P-value  Lower CI  Upper CI
-----
Intercept  -5.1421    1.9984  -2.5731  0.0101   -9.0600   -1.2243
intervention[T.True]  0.0797    0.0395   2.0191  0.0435    0.0023    0.1571
transact_garage  -0.0113    0.0058  -1.9508  0.0511   -0.0227   5.599e-05
intervention[T.True]:transact_garage  0.0029    0.0012   2.4428  0.0146    0.0006    0.0053
log_revtotal_ps_lag  0.1623    0.0175   9.2811  0.0000    0.1280    0.1966
log_time     -0.0124    0.0108  -1.1442  0.2526   -0.0336    0.0088
log_sp500close  0.8161    0.2550   3.2002  0.0014    0.3162    1.3161
log_revtotal_ps_lag7  0.2356    0.0173  13.623  0.0000    0.2017    0.2695
q2           0.0491    0.0316   1.5512  0.1209   -0.0130    0.1111
q3          -0.0128    0.0407  -0.3143  0.7533   -0.0925    0.0669
q4           0.0366    0.0286   1.2787  0.2010   -0.0195    0.0926
mon          0.5776    0.0296  19.525  0.0000    0.5196    0.6355
tue          0.4982    0.0252  19.769  0.0000    0.4488    0.5476
wed          0.4468    0.0261  17.087  0.0000    0.3955    0.4980
thu          0.5214    0.0252  20.691  0.0000    0.4720    0.5708
fri          0.4977    0.0240  20.756  0.0000    0.4507    0.5447
events       0.0286    0.0087   3.2990  0.0010    0.0116    0.0455
searchdemand  0.0019    0.0003   7.1318  0.0000    0.0013    0.0024
precip      -0.0040    0.0012  -3.3878  0.0007   -0.0062   -0.0017
temp         0.0045    0.0015   2.9591  0.0031    0.0015    0.0074
googlesearch -0.0084    0.0011  -7.7267  0.0000   -0.0106   -0.0063

F-test for Poolability: 39.751
P-value: 0.0000
Distribution: F(29,5048)

Included effects: Entity

```

Figure 18. Fixed Effect, H2, ZF10 Data Frame.

```

=====
PanelOLS Estimation Summary
=====
Dep. Variable:    log_revtotal_ps    R-squared:                0.4717
Estimator:       PanelOLS          R-squared (Between):     0.8412
No. Observations: 3491           R-squared (Within):      0.4717
Date:            Mon, Mar 23 2020   R-squared (Overall):     0.7238
Time:            19:54:04          Log-likelihood            -1883.0
Cov. Estimator:  Clustered

F-statistic:                146.65
P-value:                    0.0000
Distribution:                F(21,3449)

Entities:                 21
Avg Obs:                  166.24
Min Obs:                  106.00
Max Obs:                  180.00

F-statistic (robust):       78.801
P-value:                   0.0000
Distribution:               F(21,3449)

Time periods:             423
Avg Obs:                  8.2530
Min Obs:                  1.0000
Max Obs:                  17.000

=====
Parameter Estimates
=====
Parameter   Std. Err.   T-stat   P-value   Lower CI   Upper CI
-----
Intercept   -3.8415    2.3248   -1.6524   0.0985    -8.3997    0.7167
intervention[T.True]  0.0037    0.0409    0.0914   0.9272    -0.0765    0.0840
log_revtotal_ps_lag  0.1181    0.0184    6.4169   0.0000    0.0820    0.1542
log_time    -0.0122    0.0131   -0.9304   0.3522    -0.0378    0.0135
log_sp500close  0.5898    0.3005    1.9627   0.0498    0.0006    1.1790
log_revtotal_ps_lag7  0.1358    0.0182    7.4743   0.0000    0.1002    0.1714
q2          0.0032    0.0348    0.0931   0.9258    -0.0650    0.0714
q3          -0.0338    0.0427   -0.7908   0.4291    -0.1175    0.0499
q4          0.0350    0.0350    1.0003   0.3172    -0.0336    0.1036
mon         0.3314    0.0306   10.812   0.0000    0.2713    0.3914
tue         0.2556    0.0273    9.3709   0.0000    0.2021    0.3090
wed         0.2434    0.0285    8.5290   0.0000    0.1874    0.2993
thu         0.2886    0.0264   10.951   0.0000    0.2369    0.3403
fri         0.2834    0.0259   10.941   0.0000    0.2326    0.3342
events     0.0218    0.0084    2.5908   0.0096    0.0053    0.0383
log_LY_ps  0.3316    0.0217   15.254   0.0000    0.2890    0.3742
searchdemand  0.0015    0.0003    4.8906   0.0000    0.0009    0.0020
precip     -0.0049    0.0013   -3.8201   0.0001    -0.0074    -0.0024
temp       0.0030    0.0016    1.8962   0.0580    -0.0001    0.0062
googlesearch -0.0033    0.0012   -2.8606   0.0043    -0.0056    -0.0010
transact_garage -0.0053    0.0080   -0.6613   0.5085    -0.0209    0.0104
intervention[T.True]:transact_garage  0.0047    0.0012    3.8343   0.0001    0.0023    0.0071
=====

F-test for Poolability: 21.906
P-value: 0.0000
Distribution: F(20,3449)

Included effects: Entity

```

Figure 19. Fixed Effect, H2, ZF11 Data Frame.

Mixed Linear Model Regression Results						
=====						
Model:	MixedLM	Dependent Variable:	log_revtotal_ps			
No. Observations:	5098	Method:	ML			
No. Groups:	30	Scale:	0.2302			
Min. group size:	96	Log-Likelihood:	-3567.4620			
Max. group size:	180	Converged:	Yes			
Mean group size:	169.9					

	Coef.	Std.Err.	z	P> z	[0.025 0.975]	

Intercept	-6.618	1.782	-3.714	0.000	-10.111	-3.126
intervention[T.True]	0.113	0.038	2.992	0.003	0.039	0.187
garage[T.True]	0.071	0.242	0.292	0.770	-0.404	0.545
log_revtotal_ps_lag	0.176	0.013	13.637	0.000	0.150	0.201
transact_garage	-0.006	0.004	-1.288	0.198	-0.014	0.003
transact_garage:intervention[T.True]	0.002	0.001	2.095	0.036	0.000	0.005
log_sp500close	0.990	0.224	4.417	0.000	0.551	1.430
q2	0.029	0.034	0.867	0.386	-0.037	0.095
q3	0.008	0.040	0.187	0.851	-0.071	0.086
log_time	-0.006	0.009	-0.676	0.499	-0.023	0.011
q4	0.038	0.028	1.388	0.165	-0.016	0.093
mon	0.586	0.025	23.434	0.000	0.537	0.635
tue	0.508	0.023	21.763	0.000	0.462	0.553
wed	0.463	0.023	19.764	0.000	0.417	0.508
thu	0.546	0.024	23.030	0.000	0.499	0.592
fri	0.519	0.024	21.988	0.000	0.473	0.565
events	0.025	0.009	2.766	0.006	0.007	0.043
temp	0.005	0.001	3.251	0.001	0.002	0.008
precip	-0.004	0.001	-3.918	0.000	-0.006	-0.002
googlesearch	-0.008	0.001	-8.330	0.000	-0.010	-0.006
log_revtotal_ps_lag7	0.245	0.012	20.707	0.000	0.222	0.268
Group Var	0.234	0.130				
=====						

Figure 20. Linear Mixed Model, H2, ZF10 Data Frame.

Mixed Linear Model Regression Results

```

=====
Model:                MixedLM      Dependent Variable:  log_revtotal_ps
No. Observations:    3491      Method:              ML
No. Groups:          21      Scale:               0.1750
Min. group size:     106      Log-Likelihood:     -1958.2715
Max. group size:     180      Converged:           Yes
Mean group size:     166.2
=====

```

	Coef.	Std.Err.	z	P> z	[0.025	0.975]
Intercept	-4.811	1.965	-2.448	0.014	-8.663	-0.958
intervention[T.True]	0.013	0.045	0.288	0.774	-0.075	0.100
garage[T.True]	0.065	0.207	0.314	0.754	-0.340	0.470
transact_garage	-0.008	0.004	-1.934	0.053	-0.015	0.000
transact_garage:intervention[T.True]	0.005	0.001	4.154	0.000	0.003	0.007
log_revtotal_ps_lag	0.130	0.015	8.835	0.000	0.101	0.159
log_LY_ps	0.345	0.014	24.435	0.000	0.318	0.373
log_sp500close	0.721	0.249	2.894	0.004	0.233	1.209
q2	-0.004	0.035	-0.123	0.902	-0.074	0.065
q3	-0.028	0.044	-0.638	0.524	-0.113	0.058
log_time	-0.009	0.010	-0.940	0.347	-0.029	0.010
q4	0.025	0.031	0.798	0.425	-0.036	0.086
mon	0.337	0.027	12.467	0.000	0.284	0.390
tue	0.263	0.025	10.420	0.000	0.213	0.312
wed	0.255	0.026	9.887	0.000	0.204	0.305
thu	0.309	0.026	11.848	0.000	0.258	0.360
fri	0.299	0.026	11.568	0.000	0.249	0.350
events	0.020	0.009	2.100	0.036	0.001	0.038
temp	0.003	0.002	1.898	0.058	-0.000	0.006
precip	-0.005	0.001	-4.754	0.000	-0.007	-0.003
googlesearch	-0.003	0.001	-3.207	0.001	-0.006	-0.001
log_revtotal_ps_lag7	0.143	0.013	10.838	0.000	0.117	0.169
Group Var	0.098	0.079				

Figure 21. Linear Mixed Model, H2, ZF11 Data Frame.

Table 8. H2 Key Independent and Interaction Variables (Green Indicates Significance $p < 0.05$).

Model	Fixed Effects		Mixed Model	
	ZF10	ZF11	ZF10	ZF11
intervention	8.30%	0.38%	11.94%	1.29%
transact_garage	-1.13%	-0.53%	-0.56%	-0.77%
intervention*transact_garage	0.30%	0.47%	0.25%	0.51%

The marginal R^2 for the fixed effects regressions were 39.57% and 47.17% for ZF10 (large dataset) and ZF11 (smaller dataset). The R^2 for the mixed-effects model, 73.1%, and 79.45% for ZF10 and ZF11 datasets, respectively. The interaction variable indicated a statistically significant, positive relationship between the number of online competitors in a given

zip code and the intervention. The panel data and mixed model regressions reject the hypothesis that a larger number of online competitors negatively moderates the online intervention.

H3: The positive effect of Online Channel introduction on revenue will be positively moderated by the number of local offline competitors within the same zip code.

We tested Hypothesis #3 to examine the effect of other parking facilities existing within the zipcode who are not using the ParkWhiz channel (site_diff). This hypothesis was an attempt to tease out whether or not if an increasing number of offline competitors, who do not use the Parkwhiz online channel, might suggest an increased moderation in the value of the online channel/intervention.

```

PanelOLS Estimation Summary
=====
Dep. Variable:      log_revtotal_ps  R-squared:          0.3955
Estimator:         PanelOLS         R-squared (Between): 0.6606
No. Observations:  5098             R-squared (Within):  0.3955
Date:              Mon, Mar 23 2020  R-squared (Overall): 0.5719
Time:              21:04:49         Log-likelihood       -3447.8
Cov. Estimator:    Clustered

Entities:          30                F-statistic:        165.11
Avg Obs:          169.93            P-value             0.0000
Min Obs:          96.000           Distribution:        F(20,5048)
Max Obs:          180.00           F-statistic (robust): 106.94
Time periods:     519              P-value             0.0000
Avg Obs:          9.8227           Distribution:        F(20,5048)
Min Obs:          1.0000
Max Obs:          24.000

Parameter Estimates
=====
Parameter      Std. Err.    T-stat    P-value    Lower CI    Upper CI
-----
Intercept      -5.6741     1.9874   -2.8551   0.0043     -9.5703    -1.7780
intervention[T.True]  0.1073     0.0286    3.7532   0.0002      0.0513     0.1634
site_diff      2.673e-05   0.0061    0.0044   0.9965     -0.0120     0.0120
intervention[T.True]:site_diff  0.0049     0.0020    2.4672   0.0137      0.0010     0.0088
log_revtotal_ps_lag  0.1626     0.0175    9.2928   0.0000      0.1283     0.1969
log_time      -0.0154     0.0108   -1.4352   0.1513     -0.0365     0.0057
log_sp500close  0.8588     0.2532    3.3914   0.0007      0.3624     1.3553
log_revtotal_ps_lag7  0.2358     0.0173   13.623   0.0000      0.2019     0.2697
q2             0.0539     0.0315    1.7141   0.0866     -0.0077     0.1156
q3            -0.0043     0.0409   -0.1040   0.9172     -0.0844     0.0759
q4             0.0389     0.0286    1.3594   0.1741     -0.0172     0.0951
mon            0.5773     0.0296   19.529   0.0000      0.5193     0.6352
tue            0.4974     0.0252   19.745   0.0000      0.4480     0.5468
wed            0.4459     0.0261   17.056   0.0000      0.3947     0.4972
thu            0.5203     0.0252   20.653   0.0000      0.4709     0.5697
fri            0.4964     0.0240   20.705   0.0000      0.4494     0.5434
events         0.0287     0.0087    3.3171   0.0009      0.0118     0.0457
searchdemand   0.0019     0.0003    7.2242   0.0000      0.0014     0.0024
precip        -0.0040     0.0012   -3.3923   0.0007     -0.0062     -0.0017
temp           0.0044     0.0015    2.9381   0.0033      0.0015     0.0074
googlesearch  -0.0085     0.0011   -7.7901   0.0000     -0.0106     -0.0064

F-test for Poolability: 40.065
P-value: 0.0000
Distribution: F(29,5048)

Included effects: Entity

```

Figure 22. Fixed Effects, H3, ZF10 Data Frame.

```

PanelOLS Estimation Summary
=====
Dep. Variable:    log_revtotal_ps    R-squared:                0.4700
Estimator:       PanelOLS          R-squared (Between):     0.8459
No. Observations: 3491             R-squared (Within):      0.4700
Date:            Mon, Mar 23 2020   R-squared (Overall):     0.7263
Time:            22:01:41          Log-likelihood            -1888.5
Cov. Estimator:  Clustered

F-statistic:     145.67
P-value:         0.0000
Distribution:     F(21,3449)

Entities:        21
Avg Obs:         166.24
Min Obs:         106.00
Max Obs:         180.00

F-statistic (robust): 78.388
P-value:         0.0000
Distribution:     F(21,3449)

Time periods:   423
Avg Obs:        8.2530
Min Obs:        1.0000
Max Obs:        17.000

Parameter Estimates
=====
Parameter      Std. Err.    T-stat    P-value    Lower CI    Upper CI
-----
Intercept      -4.5317     2.3351   -1.9407    0.0524     -9.1101    0.0467
intervention[T.True]  0.0925     0.0314    2.9494    0.0032     0.0310    0.1540
site_diff      -0.0099     0.0077   -1.2919    0.1965     -0.0249    0.0051
site_diff:intervention[T.True]  0.0032     0.0019    1.7250    0.0846     -0.0004    0.0069
log_revtotal_ps_lag  0.1206     0.0184    6.5474    0.0000     0.0845    0.1567
log_time       -0.0152     0.0130   -1.1699    0.2421     -0.0406    0.0102
log_sp500close 0.6728     0.2997    2.2449    0.0248     0.0852    1.2604
log_revtotal_ps_lag7 0.1372     0.0182    7.5422    0.0000     0.1016    0.1729
q2             0.0050     0.0346    0.1432    0.8862     -0.0629    0.0728
q3            -0.0301     0.0430   -0.7010    0.4833     -0.1144    0.0541
q4            0.0233     0.0346    0.6740    0.5003     -0.0445    0.0912
mon           0.3341     0.0306   10.902    0.0000     0.2741    0.3942
tue           0.2561     0.0273    9.3809    0.0000     0.2026    0.3096
wed           0.2443     0.0286    8.5478    0.0000     0.1883    0.3004
thu           0.2890     0.0264   10.935    0.0000     0.2372    0.3408
fri           0.2831     0.0259   10.915    0.0000     0.2322    0.3339
events        0.0229     0.0084    2.7328    0.0063     0.0065    0.0393
log_LY_ps     0.3287     0.0218   15.071    0.0000     0.2859    0.3715
searchdemand  0.0015     0.0003    4.9668    0.0000     0.0009    0.0021
precip       -0.0049     0.0013   -3.7746    0.0002     -0.0074   -0.0023
temp          0.0028     0.0016    1.7628    0.0780     -0.0003    0.0060
googlesearch  -0.0034     0.0012   -2.8870    0.0039     -0.0056   -0.0011
=====

F-test for Poolability: 22.340
P-value: 0.0000
Distribution: F(20,3449)

Included effects: Entity

```

Figure 23. Fixed Effects, H3, ZF11 Data Frame.

Mixed Linear Model Regression Results

```

=====
Model:                MixedLM      Dependent Variable:  log_revtotal_ps
No. Observations:    5098        Method:              ML
No. Groups:          30          Scale:               0.2303
Min. group size:     96          Log-Likelihood:     -3568.0699
Max. group size:     180        Converged:           Yes
Mean group size:     169.9
=====

```

	Coef.	Std.Err.	z	P> z	[0.025	0.975]
Intercept	-6.980	1.765	-3.955	0.000	-10.439	-3.521
intervention[T.True]	0.149	0.028	5.246	0.000	0.093	0.205
garage[T.True]	0.102	0.244	0.421	0.674	-0.375	0.580
site_diff	-0.008	0.006	-1.251	0.211	-0.019	0.004
site_diff:intervention[T.True]	0.003	0.002	1.339	0.181	-0.001	0.007
log_revtotal_ps_lag	0.176	0.013	13.665	0.000	0.151	0.201
transact_garage	-0.005	0.005	-1.169	0.242	-0.015	0.004
log_sp500close	1.039	0.222	4.679	0.000	0.604	1.474
q2	0.036	0.033	1.086	0.278	-0.029	0.102
q3	0.015	0.040	0.367	0.714	-0.064	0.094
log_time	-0.007	0.009	-0.810	0.418	-0.025	0.010
q4	0.041	0.028	1.463	0.144	-0.014	0.095
mon	0.586	0.025	23.424	0.000	0.537	0.635
tue	0.507	0.023	21.737	0.000	0.461	0.553
wed	0.462	0.023	19.743	0.000	0.416	0.508
thu	0.545	0.024	23.004	0.000	0.499	0.592
fri	0.518	0.024	21.955	0.000	0.472	0.564
events	0.026	0.009	2.800	0.005	0.008	0.043
temp	0.005	0.001	3.242	0.001	0.002	0.008
precip	-0.004	0.001	-3.908	0.000	-0.006	-0.002
googlesearch	-0.009	0.001	-8.402	0.000	-0.011	-0.007
log_revtotal_ps_lag7	0.246	0.012	20.753	0.000	0.222	0.269
Group Var	0.229	0.129				

=====

Figure 24. Linear Mixed Model, H3, ZF10 Data Frame.

Mixed Linear Model Regression Results

```

=====
Model:           MixedLM      Dependent Variable:  log_revtotal_ps
No. Observations: 3491      Method:              ML
No. Groups:       21        Scale:               0.1755
Min. group size:  106      Log-Likelihood:     -1962.7945
Max. group size:  180      Converged:          Yes
Mean group size:  166.2

-----

```

	Coef.	Std.Err.	z	P> z	[0.025	0.975]
Intercept	-5.549	1.956	-2.836	0.005	-9.383	-1.714
intervention[T.True]	0.096	0.032	2.982	0.003	0.033	0.158
garage[T.True]	0.092	0.192	0.477	0.633	-0.285	0.469
site_diff	-0.017	0.006	-3.051	0.002	-0.028	-0.006
site_diff:intervention[T.True]	0.003	0.002	1.364	0.173	-0.001	0.007
log_revtotal_ps_lag	0.133	0.015	9.018	0.000	0.104	0.161
log_LY_ps	0.343	0.014	24.192	0.000	0.315	0.371
log_sp500close	0.810	0.248	3.265	0.001	0.324	1.297
q2	-0.016	0.036	-0.447	0.655	-0.086	0.054
q3	-0.028	0.044	-0.632	0.527	-0.113	0.058
log_time	-0.017	0.010	-1.657	0.098	-0.037	0.003
q4	0.015	0.031	0.476	0.634	-0.046	0.075
mon	0.339	0.027	12.533	0.000	0.286	0.392
tue	0.263	0.025	10.402	0.000	0.213	0.312
wed	0.256	0.026	9.890	0.000	0.205	0.306
thu	0.309	0.026	11.823	0.000	0.258	0.360
fri	0.299	0.026	11.513	0.000	0.248	0.350
events	0.020	0.009	2.131	0.033	0.002	0.039
temp	0.003	0.002	1.678	0.093	-0.000	0.006
precip	-0.005	0.001	-4.748	0.000	-0.007	-0.003
googlesearch	-0.004	0.001	-3.226	0.001	-0.006	-0.001
log_revtotal_ps_lag7	0.145	0.013	10.953	0.000	0.119	0.171
Group Var	0.089	0.070				

```

=====

```

Figure 25. Linear Mixed Model, H3, ZF11 Data Frame.

```

=====
PanelOLS Estimation Summary
=====
Dep. Variable:      log_revpw_ps      R-squared:           0.7887
Estimator:         PanelOLS      R-squared (Between): -11.877
No. Observations:  191          R-squared (Within):  0.7887
Date:              Sun, Mar 22 2020 R-squared (Overall): -8.4236
Time:              07:29:55      Log-likelihood       -14.032
Cov. Estimator:    Clustered

Entities:          14          F-statistic:         69.656
Avg Obs:          13.643      P-value              0.0000
Min Obs:          12.000      Distribution:         F(9,168)
Max Obs:          14.000      F-statistic (robust): 46.148
Time periods:     50          P-value              0.0000
Avg Obs:          3.8200     Distribution:         F(9,168)
Min Obs:          1.0000
Max Obs:          10.0000

=====
Parameter Estimates
=====
Parameter  Std. Err.  T-stat  P-value  Lower CI  Upper CI
-----
const      -15.383    11.092  -1.3870  0.1673   -37.280   6.5133
log_sp500close  1.3343    1.1679   1.1425  0.2549   -0.9713   3.6400
log_time    0.3007    0.1961   1.5334  0.1270   -0.0864   0.6878
offstreetsites 0.1395    0.1010   1.3818  0.1689   -0.0598   0.3388
events      -0.0349    0.0495  -0.7054  0.4815   -0.1326   0.0628
searchdemand -0.0016    0.0021  -0.7857  0.4331   -0.0057   0.0025
log_revpw_ps_lag 0.6898    0.0792   8.7064  0.0000   0.5334   0.8463
temp        -0.0007    0.0049  -0.1515  0.8797   -0.0105   0.0090
precip      0.0025    0.0090   0.2766  0.7824   -0.0153   0.0203
googlesearch -0.0052    0.0034  -1.5326  0.1272   -0.0120   0.0015
=====

F-test for Poolability: 5.2139
P-value: 0.0000
Distribution: F(13,168)

Included effects: Entity

```

Figure 26. H3 Weekly (Downsampled) Data for Online Revenue at Test Sites in the Post-Intervention Period.

The analysis yielded the following summary statistics:

Table 9. H3 Key Independent and Interaction Variables (Green Indicates Significance $p < 0.05$).

Model	Fixed Effects		Mixed Model	
	ZF10	ZF11	ZF10	ZF11
intervention	11.33%	9.69%	16.48%	10.02%
site_diff	0.00%	-0.98%	-0.80%	-1.68%
intervention*site_diff	0.49%	0.32%	0.30%	0.28%

The marginal R^2 for the fixed effects regressions were 39.55% and 47.00% for ZF10 (large dataset) and ZF11 (smaller dataset). The R^2 for the mixed-effects model, 73.1%, and 79.41% for ZF10 and ZF11 datasets, respectively. The results of the panel data and mixed model regression indicate that the intervention has a statistically significant effect. The interaction between the number of offline competitors and the intervention was only statistically significant in the fixed effects model with the largest dataset (ZF10). It indicated a positive moderation in

that single analysis. Otherwise, there was no statistical significance in an otherwise positive contributing coefficient for the increasing number of offline competitors and interaction with the online intervention.

H2 and H3 were challenging hypotheses to address given the structure of the dataset. Most locations exhibited a lack of variability with the number of online competitors (transact_garage) and limited variability with the number of offline-only competitors (site_diff). The number of competitors (offline, online, and in total) simply does not vary much day to day, week to week at these locations. And with only 30 locations in the overall dataset, the dataset did not lend itself easily to a model structure that would capture a very strong relationship with a dependent variable (total revenue) and an independent variable related to numbers of competition.

In an attempt to address H2 and H3, further analysis was sought to evaluate only online revenue (dependent variable), rather than total revenue, subject to the independent effects of competition. The original H2 and H3 ask whether or not online competition (transact_garage) or offline-only (site_diff) has a moderating effect on the intervention variable to the dependent variable of total revenue per space at a location. A different way of approaching the issue is to ask whether or not online revenue, as a dependent variable, is affected by the numbers of online competitors or offline competitors. In order to accomplish this analysis, the dataset was reduced to the test group only in the post-intervention period with downsampled results to weekly data from daily. These results (not shown here) were also unable to identify any meaningful statistical relationship.

H4: Net new revenue gains produced through the addition of an online sales channel will be positively explained by the number of online consumer searches within the same zip code; the online intervention on total revenue is amplified by the number of online consumer searches in the same zip code.

Our H4 examined the potential positive moderating effect of online search demand on any net new revenue gains observed in our H1 hypothesis. Recall that H1 asked - Will the addition of an Online Channel to existing Offline Channels will produce net new revenue gains? Given that our entire study is centered around online sales channels, the presence of online demand, as demonstrated by the volume of searches for consumers, is highly relevant. In the present model, we examined two search-demand channels that focused on parking - (1) the ParkWhiz channel and its proprietary search engine volume and (2) general Google search demand volume publicly available. Search demand has consistently been a statistically significant, positively associated independent variable in all analyses seen thus far. But the question of whether or not there is an interaction effect between the intervention and search demand level is a different matter.

```

=====
PanelOLS Estimation Summary
=====
Dep. Variable:    log_revtotal_ps    R-squared:    0.3970
Estimator:       PanelOLS          R-squared (Between):    -5.1038
No. Observations: 5098            R-squared (Within):    0.3970
Date:            Tue, Mar 24 2020   R-squared (Overall):    -3.1632
Time:            05:25:15          Log-likelihood    -3441.4
Cov. Estimator:  Clustered

F-statistic:    166.16
Entities:       30                P-value          0.0000
Avg Obs:       169.93            Distribution:     F(20,5048)
Min Obs:       96.000
Max Obs:       180.00           F-statistic (robust): 107.58
P-value          0.0000
Time periods:  519              Distribution:     F(20,5048)
Avg Obs:       9.8227
Min Obs:       1.0000
Max Obs:       24.000

=====
Parameter Estimates
=====
Parameter      Std. Err.      T-stat      P-value      Lower CI      Upper CI
-----
Intercept      -3.5703        2.0501      -1.7415      0.0817        -7.5895        0.4489
intervention[T.True]  0.1782        0.0377        4.7301      0.0000         0.1043         0.2520
searchdemand   0.0019        0.0003        7.1509      0.0000         0.0014         0.0024
intervention[T.True]:searchdemand -8.845e-05    0.0002        -0.4583      0.6467        -0.0005         0.0003
offstreetsites -0.1017        0.0229        -4.4503      0.0000        -0.1465        -0.0569
log_revtotal_ps_lag  0.1608        0.0174        9.2224      0.0000         0.1266         0.1950
log_time       -0.0102        0.0104        -0.9837      0.3253        -0.0305         0.0101
log_sp500close 0.9022        0.2540        3.5514      0.0004         0.4042         1.4003
log_revtotal_ps_lag7 0.2373        0.0172       13.780      0.0000         0.2036         0.2711
q2             0.0719        0.0316        2.2760      0.0229         0.0100         0.1339
q3             0.0055        0.0408         0.1358      0.8920        -0.0744         0.0854
q4            0.0466        0.0285        1.6341      0.1023        -0.0093         0.1026
mon           0.5761        0.0295       19.543      0.0000         0.5183         0.6338
tue           0.4972        0.0251       19.795      0.0000         0.4480         0.5464
wed           0.4462        0.0260       17.132      0.0000         0.3952         0.4973
thu           0.5205        0.0251       20.733      0.0000         0.4713         0.5698
fri           0.4966        0.0239       20.773      0.0000         0.4497         0.5435
events        0.0312        0.0087        3.6048      0.0003         0.0142         0.0482
precip        -0.0039        0.0012       -3.3871      0.0007        -0.0062        -0.0017
temp          0.0046        0.0015        3.0147      0.0026         0.0016         0.0075
googlesearch  -0.0086        0.0011       -7.8886      0.0000        -0.0107        -0.0065
=====

F-test for Poolability: 40.301
P-value: 0.0000
Distribution: F(29,5048)

Included effects: Entity

```

Figure 27. Fixed Effects, H4, ZF10 Data Frame.

```

=====
PanelOLS Estimation Summary
=====
Dep. Variable:      log_revtotal_ps  R-squared:          0.4722
Estimator:         PanelOLS         R-squared (Between): -4.2303
No. Observations:  3491            R-squared (Within):  0.4722
Date:              Tue, Mar 24 2020  R-squared (Overall): -2.7740
Time:              05:26:37         Log-likelihood       -1881.4
Cov. Estimator:    Clustered

F-statistic:       146.92
P-value           0.0000
Distribution:      F(21,3449)

Entities:         21
Avg Obs:          166.24
Min Obs:          106.00
Max Obs:          180.00

F-statistic (robust): 78.483
P-value          0.0000
Distribution:      F(21,3449)

Time periods:     423
Avg Obs:          8.2530
Min Obs:          1.0000
Max Obs:          17.000

=====
Parameter Estimates
=====
Parameter  Std. Err.  T-stat  P-value  Lower CI  Upper CI
-----
Intercept  -2.4656    2.3593  -1.0451  0.2961    -7.0913   2.1601
intervention[T.True]  0.1985    0.0399   4.9704  0.0000    0.1202   0.2768
searchdemand  0.0016    0.0003   5.4436  0.0000    0.0010   0.0022
searchdemand:intervention[T.True] -0.0002    0.0002  -1.2604  0.2076   -0.0006   0.0001
offstreetsites -0.0960    0.0242  -3.9652  0.0001   -0.1434  -0.0485
log_revtotal_ps_lag  0.1168    0.0184   6.3383  0.0000    0.0807   0.1530
log_time -0.0065    0.0124  -0.5201  0.6030   -0.0308   0.0179
log_sp500close  0.7665    0.3011   2.5459  0.0109    0.1762   1.3568
log_revtotal_ps_lag7  0.1381    0.0181   7.6407  0.0000    0.1026   0.1735
q2  0.0356    0.0340   1.0485  0.2945   -0.0310   0.1023
q3  -0.0107    0.0429  -0.2488  0.8035   -0.0948   0.0735
q4  0.0278    0.0348   0.7995  0.4240   -0.0404   0.0959
mon  0.3332    0.0306  10.900  0.0000    0.2733   0.3932
tue  0.2571    0.0272   9.4660  0.0000    0.2039   0.3104
wed  0.2456    0.0284   8.6626  0.0000    0.1900   0.3012
thu  0.2901    0.0263  11.022  0.0000    0.2385   0.3416
fri  0.2845    0.0258  11.018  0.0000    0.2339   0.3351
events  0.0254    0.0084   3.0277  0.0025    0.0090   0.0418
log_LY_ps  0.3267    0.0216  15.094  0.0000    0.2843   0.3691
precip -0.0047    0.0013  -3.6710  0.0002   -0.0073  -0.0022
temp  0.0028    0.0016   1.7358  0.0827   -0.0004   0.0059
googlesearch -0.0036    0.0012  -3.0463  0.0023   -0.0058  -0.0013
=====

F-test for Poolability: 21.857
P-value: 0.0000
Distribution: F(20,3449)

Included effects: Entity

```

Figure 28. Fixed Effects, H4, ZF11 Data Frame.

Mixed Linear Model Regression Results						
Model:			Dependent Variable: log_revtotal_ps			
No. Observations:	5098	Method:	ML			
No. Groups:	30	Scale:	0.2278			
Min. group size:	96	Log-Likelihood:	-3539.4386			
Max. group size:	180	Converged:	Yes			
Mean group size:	169.9					
	Coef.	Std.Err.	z	P> z	[0.025	0.975]
Intercept	-6.058	1.777	-3.409	0.001	-9.540	-2.575
intervention[T.True]	0.171	0.035	4.919	0.000	0.103	0.239
garage[T.True]	0.042	0.235	0.178	0.859	-0.419	0.503
searchdemand	0.002	0.000	7.673	0.000	0.001	0.002
searchdemand:intervention[T.True]	-0.000	0.000	-1.434	0.152	-0.001	0.000
log_revtotal_ps_lag	0.170	0.013	13.259	0.000	0.145	0.195
offstreetsites	-0.008	0.004	-1.839	0.066	-0.016	0.001
log_sp500close	0.925	0.224	4.134	0.000	0.486	1.363
q2	0.052	0.033	1.598	0.110	-0.012	0.116
q3	-0.009	0.040	-0.222	0.825	-0.088	0.070
log_time	-0.017	0.009	-1.928	0.054	-0.033	0.000
q4	0.037	0.028	1.355	0.175	-0.017	0.091
mon	0.578	0.025	23.227	0.000	0.529	0.627
tue	0.493	0.023	21.180	0.000	0.447	0.538
wed	0.441	0.023	18.829	0.000	0.395	0.487
thu	0.515	0.024	21.581	0.000	0.469	0.562
fri	0.491	0.024	20.688	0.000	0.444	0.537
events	0.029	0.009	3.202	0.001	0.011	0.047
temp	0.004	0.001	2.953	0.003	0.001	0.007
precip	-0.004	0.001	-3.782	0.000	-0.006	-0.002
googlesearch	-0.008	0.001	-8.362	0.000	-0.010	-0.006
log_revtotal_ps_lag7	0.242	0.012	20.547	0.000	0.219	0.265
Group Var	0.214	0.121				

Figure 29. Linear Mixed Model, H4, ZF10 Data Frame.

Mixed Linear Model Regression Results

```

=====
Model:                MixedLM      Dependent Variable:  log_revtotal_ps
No. Observations:    3491          Method:              ML
No. Groups:          21           Scale:               0.1736
Min. group size:     106          Log-Likelihood:     -1943.0918
Max. group size:     180          Converged:           Yes
Mean group size:     166.2
=====

```

	Coef.	Std.Err.	z	P> z	[0.025	0.975]
Intercept	-4.867	1.961	-2.482	0.013	-8.711	-1.024
intervention[T.True]	0.201	0.039	5.165	0.000	0.124	0.277
garage[T.True]	0.129	0.195	0.663	0.507	-0.252	0.510
searchdemand	0.002	0.000	6.405	0.000	0.001	0.002
searchdemand:intervention[T.True]	-0.000	0.000	-2.165	0.030	-0.001	-0.000
offstreetsites	-0.010	0.003	-3.250	0.001	-0.016	-0.004
log_revtotal_ps_lag	0.127	0.015	8.709	0.000	0.099	0.156
log_LY_ps	0.334	0.014	23.625	0.000	0.307	0.362
log_sp500close	0.723	0.249	2.905	0.004	0.235	1.211
q2	0.017	0.035	0.507	0.612	-0.050	0.085
q3	-0.027	0.043	-0.624	0.533	-0.112	0.058
log_time	-0.012	0.010	-1.265	0.206	-0.032	0.007
q4	0.011	0.031	0.372	0.710	-0.049	0.072
mon	0.332	0.027	12.331	0.000	0.280	0.385
tue	0.249	0.025	9.889	0.000	0.200	0.299
wed	0.237	0.026	9.169	0.000	0.186	0.288
thu	0.281	0.026	10.673	0.000	0.229	0.333
fri	0.275	0.026	10.552	0.000	0.224	0.326
events	0.023	0.009	2.480	0.013	0.005	0.042
temp	0.003	0.002	1.767	0.077	-0.000	0.006
precip	-0.005	0.001	-4.622	0.000	-0.007	-0.003
googlesearch	-0.003	0.001	-3.049	0.002	-0.005	-0.001
log_revtotal_ps_lag7	0.142	0.013	10.776	0.000	0.116	0.168
Group Var	0.081	0.064				

Figure 30. Linear Mixed Model, H4, ZF11 Data Frame.

Table 10. H4 Key Independent and Interaction Variables (Green Indicates Significance $p < 0.05$).

Model	Fixed Effects		Mixed Model	
	ZF10	ZF11	ZF10	ZF11
intervention	19.50%	21.95%	18.64%	22.21%
searchdemand	0.19%	0.16%	0.20%	0.16%
intervention*searchdemand	-0.01%	-0.03%	-0.03%	-0.04%

The fixed effects models demonstrated marginal R^2 of 39.70% and 47.22% for the large and smaller datasets, respectively. The mixed-effects models showed an R^2 of 73.08% and 79.68% for the large and smaller datasets, respectively. While searchdemand remained an excellent predictor of revenue per space effect at each location, it's interaction with the intervention was dubious with a negative trend. It may be that an incremental unit of searchdemand with the intervention is moderating to the negative, but this was only found to be statistically significant in one case.

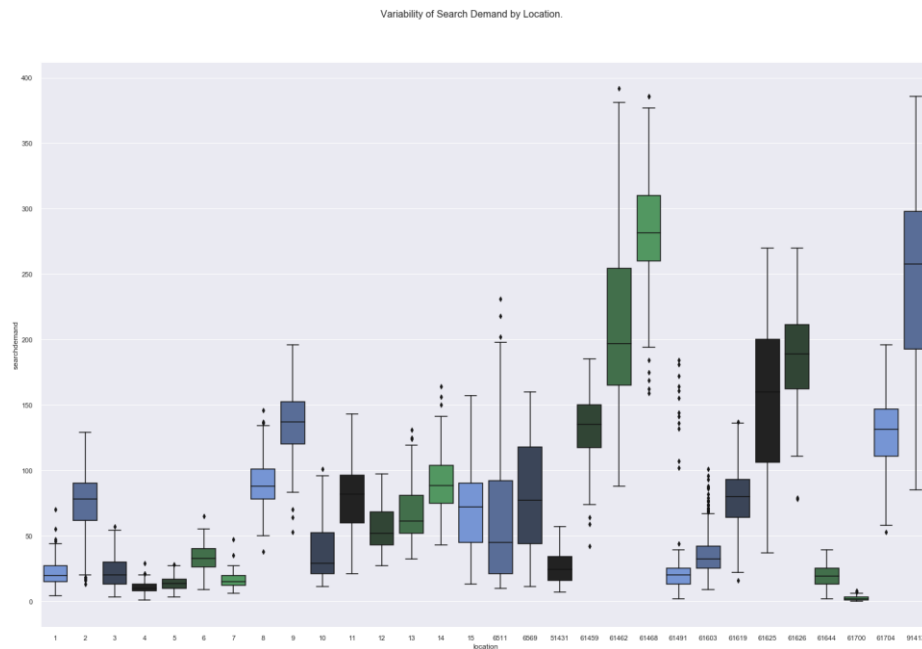


Figure 31. Distribution of Search Demand (searchdemand) by Location.

The variability of search demand was noteworthy for locations both on a within-location and between-location basis. Additional efforts were undertaken to characterize a direct relationship between search demand (an independent predictor) and online revenue (as a dependent predictor).

PanelOLS Estimation Summary

```

=====
Dep. Variable:      revpw_ps      R-squared:          0.1537
Estimator:         PanelOLS      R-squared (Between): -0.0696
No. Observations:  1343         R-squared (Within):  0.1537
Date:              Tue, Mar 24 2020 R-squared (Overall): -0.0009
Time:              06:40:38      Log-likelihood      -1562.2
Cov. Estimator:    Clustered

                               F-statistic:         15.895
                               P-value              0.0000
Entities:           15          Distribution:        F(15,1313)
Avg Obs:            89.533
Min Obs:            83.000
Max Obs:            90.000
                               F-statistic (robust):  8.4290
                               P-value              0.0000
Time periods:      376         Distribution:        F(15,1313)
Avg Obs:            3.5718
Min Obs:            1.0000
Max Obs:            10.0000
=====
Parameter Estimates
=====

```

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
transact_garage	0.0393	0.0284	1.3827	0.1670	-0.0165	0.0950
time	-0.0007	0.0011	-0.6242	0.5326	-0.0028	0.0015
sp500	0.0002	0.0003	0.7279	0.4668	-0.0003	0.0007
precip	-0.0015	0.0030	-0.4934	0.6218	-0.0073	0.0043
googlesearch	-0.0027	0.0032	-0.8443	0.3987	-0.0091	0.0036
events	-0.0180	0.0261	-0.6906	0.4899	-0.0693	0.0332
temp	-0.0058	0.0051	-1.1333	0.2573	-0.0158	0.0042
mon	0.2264	0.0727	3.1143	0.0019	0.0838	0.3691
tue	0.2408	0.0627	3.8421	0.0001	0.1179	0.3638
wed	0.2052	0.0682	3.0097	0.0027	0.0715	0.3390
thu	0.2258	0.0730	3.0945	0.0020	0.0827	0.3689
fri	0.2945	0.0748	3.9372	0.0001	0.1477	0.4412
revpw_ps_lag	0.1202	0.0412	2.9210	0.0035	0.0395	0.2010
revpw_ps_lag7	0.2637	0.0464	5.6865	0.0000	0.1727	0.3547
searchdemand	0.0024	0.0008	2.8291	0.0047	0.0007	0.0040

```

=====
F-test for Poolability: 15.989
P-value: 0.0000
Distribution: F(14,1313)

Included effects: Entity
=====

```

Figure 32. Fixed Effects, H4, Treatment Group, Post-Intervention Data Frame.

In an alternative analysis, we determined that online revenue (from Parkwhiz) appeared to be statistically predicted by searchdemand. In this case, each unit of search demand indicated \$0.002 of additional online revenue. However, this result is different from what H4 seeks to answer (total revenue affected by an intervention and moderated by searchdemand).

Robustness Checks

Multiple models were employed in an effort to check for robustness of results and evaluate the risk of endogeneity. Heteroskedasticity and autocorrelation invalidate standard

errors in fixed-effects panel data analysis. Our econometric fixed effects models were run with clustered covariance (by entity). This clustered covariance approach attempts to mitigate underlying serial correlation (within entity, by entity clustering), which adjusts standard errors higher for any such correlations (while maintaining the coefficient/parameter value for regressors) (Cameron 2011) and reducing t-statistics. Heteroskedasticity was not present in the linear mixed models (see Appendices). Normality of the linear mixed models were evaluated on the basis of skew and kurtosis. With such a large N , these models are confined to limits of testing and conform to Kim's (2013) guidance on using skewness and kurtosis to evaluate results.

Table 11. Linear Mixed Model Regression Characteristics

Linear Mixed Model - Residual Characteristics				
	ZF10		ZF11	
Hypothesis	Skew	Kurtosis	Skew	Kurtosis
H1A	-0.996	5.420	-0.808	5.303
H1B	-0.976	5.309	-0.787	5.210
H2	-0.998	5.423	-0.806	5.233
H3	-0.996	5.422	-0.807	5.305
H4	-0.966	5.327	-0.765	5.100

To be sure, there was some presence of serial correlation, which is an underlying risk to the results presented herein. Serial correlation is a persistent problem in difference in difference analysis and similar linear mixed-effects models (Bertrand 2002). Additional distributions of certain residuals for the mixed model are available in the Appendices. Finally, it should be noted that omitted variable bias is a significant issue that could contribute to faulty results presented herein.

CHAPTER SEVEN

CONCLUSIONS

Hypothesis One A

Observing all four summary statistics regression packages indicates reasonable strength for the overall H1A Hypothesis and indicating a rejection of the null hypothesis. Adding the YOY revenue provides an added dimension of strength to the proposition that the independent variables in our H1A hypotheses are truly impacting the dependent variables in a manner close to what we envisioned when we set out on our experiment. While the R squared scores could be stronger, and observations of Zhang's (2019) work showed extremely strong R squared scores for her hypotheses, we would note that the realm of the parking garage has many more unique and fragmented variables versus the food delivery model used by Zhang to perform similar tests. Also, the business characteristics of parking are substantially different in that a person is navigating to a fixed location (which can be known in advance) to receive a service potentially limiting the involvement of an online channel to mediate the customer interaction. Parking is substantially different than a customer sitting at home where the online channel moves a good or service to their fixed location. The fact that our results indicate strongly that the online channel is a significant revenue contributor is certainly beneficial to the operator of any such fixed location service.

Hypothesis One B

In evaluating whether or not there is a negative relationship, it is possible that our results may indicate a spurious correlation, but we do not think that to be the case. In practice, consumers often use online tools to identify services/goods providers that they navigate to for such offerings. Frequently, these consumers return (unaided) by any online tool after having identified the location of these providers. Our results more likely indicate that the market appears to have expanded and the parking facilities are enjoying spillover effects (Zhang, 2019), the

portfolio of garages has achieved online-offline channel integration (Wiener, Holsbach, & Saunders, 2018), and overall cannibalization (Novelli, 2015) seems to have been avoided.

An examination of our overall H1 summary statistics and outcomes (H1A and H1B together) suggests a beneficial relationship for the existing brick and mortar business based on the addition of the ParkWhiz online sales channel. Strong p-values for all H1 regressions result in two conclusions - (1) that the addition of the online ParkWhiz revenue channel provides net new revenue to existing revenue channels and (2) that these improvements are not coming at the expense of other revenue channels already present prior to the introduction of the online channel; i.e., there is no cannibalization, or it is very minimal and eclipsed by the overall upside of new revenue observed. Results were even more robust when analyzed against the previous year's revenues prior to the ParkWhiz intervention. In sum, H1's outcomes indicate that the sum of the whole becomes greater than its individual parts when online and offline business models are combined in the parking facility space.

Overall, for all of the H1 analyses, we enjoyed strong statistically significant outcomes that provide support for the inference of net new revenue creation and a lack of cannibalization via online channel additions to a physical store network. Drawing conclusions from earlier examined literature, it would appear that parking garages and lots in our analyses enjoyed the benefit of spillover effects (Zhang et al., 2019), avoided cannibalization (Novelli et al., 2015), achieved appropriate levels of online-offline integration (Wiener et al., 2018) and perhaps even succeeded in attaining aspects of the availability effect (Neslin et al., 2016; Hernant et al., 2017).

Hypothesis Two and Hypothesis Three

Conclusions of our H2 and our H3 summary statistics were mixed. H2 results suggest that an interaction effect is occurring between the number of online competitors (transact_garage) and the online intervention. This opposes our original hypothesis that increased competition might negatively moderate demand. But more likely, while the interaction variable suggests

increased total revenue per space at a given parking location, what we are likely seeing is not causative in nature. It may be that the interaction suggests that operators in certain areas that are advantaged by an online channel are merely keeping up with their numerous competitors, and these higher numbers of competitors online are predictive of highly demanded areas – correlative but not causative. The number of competitors in a given zip code (online, offline only, and total competitors) is almost exclusively a negative parameterized independent variable. The fact that the interaction variable is positive may suggest the aforementioned hypothesis. These locations may benefit from overcoming the independent regressor of competition by engaging in an online channel.

H3 results had limited value. We observed only one case in which the interaction variable was significant, though the remainder appeared to trend towards statistical significance. Again, we saw a similar pattern as in H2, but without significance. In a sense, the appearance of similar results of H3 vs. H2 for the coefficients makes some sense as they are both variables tied to the level of competition in a given market. Our dataset presented difficulties to fit our data to any statistical framework and reach any significant conclusions of use to scholars or practitioners regarding H3. An issue with fixed effects models (in particular) is that if a variable does not change over time, then any changes in the dependent variable (online revenue) must be due to influences other than these fixed characteristics. (Stock and Watson, 2003). Given the relatively fixed nature of the number of competitors over time, there was no variability to capture relative to daily revenues. And with only 30 locations, the true N of our analysis was more like 30, rather than the 3,000-5,000 daily readings we obtained from the operator. A different dataset with a higher number of locations and fewer daily readings could likely address H2 and H3 in a more direct way.

Overall, Both H2 and H3 demonstrated interesting results although surprising. For H2, intuitive logic would seem to dictate that a higher number of competing parking facilities in a

given zip code would create downward pressure on available revenue for consumption, and this is what our hypothesis theorized. However, as the results showed, the alternative positive correlation was observed. More competition seems to breed more market share for all. One possible theory for these phenomena is that there is a specific effect occurring at the user level whereby a higher number of parking garages making their inventory available online in a given zip code actually drives faster adoption of innovation such as use of the ParkWhiz all or other online channels. For H3, our results were inconclusive but the lack of variability from day to day in the number of all garages existing in a given zip code doesn't change much, causing analytical problems for the regression models we employed. Longer samples or time or alternative statistical analysis approaches may determine that stronger effects are actually occurring but were not represented here due to lurking variables or unobserved heterogeneity.

Hypothesis Four

Search demand appeared to have a negative moderating effect on the online intervention. Only one analysis came back with statistically significant results, and the size of the parameters in all analyses was minimal. After first glance, this outcome is counterintuitive to what we previously hypothesized. However, given that search demand (by zip code) is an excellent, statistically significant independent predictor of revenue in a given location, the interaction between online search and online revenue may be more tenuous. Search volume in proprietary channels (ParkWhiz) was more impactful than search volume in wider channels (Google Trends). Investment costs for adding an online channel may be recouped faster in high demand markets and provide more immediate benefit to the parking operator. The choice of the market is an important consideration for parking practitioners in the application of their online channel addition strategy, and locations with an online channel clearly perform better than locations without one.

It is unclear if searches are leading to actual converted sales by users and whether or not search demand is merely a superior index for overall demand, that may not act in confluence with the online channel, per se. Other differences in the outcome here would require further analysis to better understand the entire process by which users (demand) are accessing locations. Another issue to consider is that while search demand in a given zip code indicates a level of indirect demand for a given location, these search-demand figures we obtained are not the same as a consumer adding a 'favorite' to their list of online order restaurants in an app or specifically adding a 'Like' or a '5-star rating' to a given service or location. Search demand represents a broad interest in a zip code, not a specific location. As such, the lack of meaningful interaction may be something to investigate further. It may be that consumers search in a given location, but significant numbers fail to complete a transaction and ultimately park in a competitive, offline location (i.e., across the street) rather than completing a transaction online. Practitioners might find that the online channel additions in higher parking demand markets like NYC, Chicago, or San Francisco may enjoy more robust effects from the online channel addition in such high demand search markets.

Conversely, less demanding cities, or markets where consumer user bases are less likely to be online searching for parking services, will enjoy less dynamic impact when adding an online channel to their offline parking mix. Given that our dataset was exclusively in the NYC market, we could not ascertain whether or not that effect was occurring. But a broader multi-market approach might better address this concern. Analysis suggests search demand is predictive of online revenue, but interactive effects are elusive. An understanding of the unit level (location) demand from online channels and the actual underlying demand-driven user behavior should be an immediate first inquiry for the practitioner considering the addition of a new online channel. Again we theorize that lurking variables or unaccounted for predictors may exist that would provide more useful conclusions through better modeling.

		H1A				H1B			
		Fixed Effects		Mixed Models		Fixed Effects		Mixed Models	
		ZF10	ZF11	ZF10	ZF11	ZF10	ZF11	ZF10	ZF11
H1	Model								
	Dataset	ZF10	ZF11	ZF10	ZF11	ZF10	ZF11	ZF10	ZF11
	intervention	18.92%	17.06%	18.06%	14.00%	12.52%	19.61%	11.40%	6.29%
	log_revtotal_ps_lag	17.47%	12.47%	19.24%	14.22%	18.58%	12.08%	18.89%	13.54%
	log_revtotal_ps_lag7	26.81%	14.88%	27.89%	15.60%	25.86%	14.56%	27.25%	15.26%
H2	Model								
	Dataset	ZF10	ZF11	ZF10	ZF11	ZF10	ZF11	ZF10	ZF11
	intervention	8.30%	0.38%	11.94%	1.29%				
	transact_garage	-1.13%	-0.53%	-0.56%	-0.77%				
	intervention*transact_garage	0.30%	0.47%	0.25%	0.51%				
H3	Model								
	Dataset	ZF10	ZF11	ZF10	ZF11	ZF10	ZF11	ZF10	ZF11
	intervention	11.33%	9.69%	16.48%	10.02%				
	site_diff	0.00%	-0.98%	-0.80%	-1.68%				
	intervention*site_diff	0.49%	0.32%	0.30%	0.28%				
H4	Model								
	Dataset	ZF10	ZF11	ZF10	ZF11	ZF10	ZF11	ZF10	ZF11
	intervention	19.50%	21.95%	18.64%	22.21%				
	searchdemand	0.19%	0.16%	0.20%	0.16%				
	intervention*searchdemand	-0.01%	-0.03%	-0.03%	-0.04%				

H1 - Results indicate strongly that Online Channel is significant revenue contributor; beneficial operator of any brick and mortar facility

(1) Addition of online ParkWhiz channel provides net new revenue to existing revenue channels and;

(2) Improvements are not coming at expense of other channels already present - i.e. there is no cannibalization

H2 - results suggest interaction effect occurring between number of online competitors (transact_garage) and online intervention.

(1) Opposes H2 that increased competition negatively moderates demand.

H3 - results had limited value. Only one case with interaction variable significance, remainder appeared to trend towards statistical significance

H4 - Search demand appeared to have negative moderating effect to Online intervention

(1) Analysis suggests search demand is predictive of online revenue, but interactive effects are elusive

Figure 33. Summary of Exponentiated Coefficients, Significance Noted in Green, and Conclusions.

CHAPTER EIGHT

RESEARCH CONTRIBUTION & MANAGERIAL IMPLICATIONS

The research presented herein builds upon lines of research examined in Table 1 and throughout the Literature Review. Our contributions certainly are evident in the realm of context; that being the first parking and transportation app/online channel study that exists within the body of extant research. Our conclusions with H1 seem to provide arguments of generatability in our research, as they are similar in outcome to those results observed in comparable studies but in a very different context. Other differentiating factors of our study include nuances seen in the service industry vs. product sales as more commonly seen in other studies. Parking services are perishable goods that are gone forever that day if not sold, in contrast to other contexts such as retail stores, grocery or newspaper contexts seen in our Literature Review in Table 1. Other differentiating factors include the fact that parking services are almost always complimentary to some other good or service. Parking is rarely the destination, and is a means by which consumers access other parts of the economy which may be deemed essential (such as the grocery studies with Pozzi, 2013 or Hernant et al., 2017). Our H4 hypothesis appears to be truly novel, in that it attempts to combine user centric demand data with supplier centric sales data to seek correlations between them. Although our H4 hypothesis was ultimately rejected, it did demonstrate strong statistical significance opposite to what we theorized, setting the stage for excellent future research to explore these topics in more detail, and to add what appear to be more elusive predictor variables than initially hypothesized.

It should be noted that failure to create trust on both sides of the two-sided equation of a platform is one keynote reason why a large proportion of platforms end up failing (Yoffie et al., 2019). Most research to date has focused on consumer benefits from e-commerce additions but has not balanced the inquiry by focusing on the corresponding benefits or detriments to producers

(Duch-Brown et al., 2017, p.32). One stated reason for the parking practitioner's resistance to e-channel additions in the parking sector is fear of cannibalization of existing, established, and traditional revenue channels. Like other businesses, the parking industry is fraught with anecdotal perceptions about negative disruption to brick and mortar sales occurring due to the impact of new technology on their field (Deskant, 2018). The outcomes of this research fill some of that void, not only in the parking business, but these results generalize to other data in an ongoing debate in this matter across many industries and verticals for which a relatively small amount of research exists relative to the larger body of consumer-facing only based literature.

“Our results uncover the previously elusive synergy that comes from operating a multichannel system that includes retail stores...and Internet channels. Given a better understanding of both positive and negative cross-channel effects, retailers can better anticipate and respond to changes in sales in existing channels when a new channel is added, thus strategically managing its channels as a portfolio rather than as separate entities” (Avery et al., 2012, p. 109). We believe that Avery aptly notes the value of our conclusions in this study. The data analyzed in our current work would suggest truth in our H1 hypothesis, that the addition of the ParkWhiz channel provides a net positive revenue benefit over a relatively long-term period, and that cannibalization is negligible or non-existent.

For managers or practitioners who are examining the body of academic research regarding online channel additions, our work provides some support for their conclusions to promote a new online channel for their existing brick and mortar business. Our work also supports previous work in the field that reached similar conclusions, providing support to that existing stream of literature. To date, no one has added the unique parking industry to the field, which generally consists of more conventional retail store settings, such as brick and mortar grocery stores and the like.

Coming back around to the practical questions we posed in the Research Motivation section of this paper:

1. **Does the addition of a new e-sales channel cannibalize existing brick and mortar channels?**

Our H1 outcomes would demonstrate an answer in the negative to that question. Our H1 hypothesis demonstrated statistical significance in testing whether the addition of the online channel had a positive effect as an overall revenue contribution and no revenue cannibalization.

2. **Does the choice of industry affect the outcome of a cannibalization study, or are the results provided by other industries highly generalizable?**

Given the body of research in the extant literature at large, it would appear the majority of it would provide similar results; that being the addition of an online channel to a brick and mortar network has a net positive impact on the business revenues. As seen in the Literature Summary Table on page 25 herein, many other studies have reached similar conclusions in their industry vertical. Based on the aggregation of these studies, it would be fair to presumptively conclude that our results are in line with the generalizability of the majority of other studies.

3. **Under what circumstances might cannibalization phenomena occur or not occur?**

Examining our H2-H4 hypotheses, we then see the intent was to uncover a few potential guiding precursors and moderators of the relationships examined in our H1 hypothesis. H2 focused on the impact of other parking facilities utilizing the same channel within a given zip code, H3 focused on the impact of other parking facilities in the same zip code whether selling online or not, and H4 focused on the impact of online search demand (for parking) in the given zip codes and its moderating effect on potential cannibalization of H1. Our H2 and H3 analyses were ultimately inconclusive but provided some inferences to the relevance of their variables to changes in the dependent variables. Insights to improve future methods to reach significant conclusions in our H2 and H3 examinations were also derived. However, our H4 hypotheses

enjoyed a statistically significant outcome indicating a rejection of their null noting that these factors do indeed have an impact on moderating the revenue contributions observed in H1's results. This provides a modicum of guidance to the practitioner and the academic as to the environmental factors that can accelerate or decelerate results in any revenue growth attempts.

4. Is there an acceptable level of cannibalization or externality for parking businesses? Can firms identify, isolate, and manage these negative variables to ensure they retain their current channels' health?

Our study did not provide much useful guidance on acceptable levels of cannibalization externality for parking businesses, but we did succeed in identifying several variables that are key indicators of success or failure with the implementation of a new online channel. Although our H2 and H3 results were inconclusive, they did show some indicators in their summary stats that warrant more research, and identify a variable that a parking operator should consider before implementing a new online channel - i.e., how many of my competitors are using the same channel or other similar channels and how many are not? Additionally, a solid grasp on search demand, defined in several ways depending on access to information, and combined with insights from H2 and H3, provide guidance on considerations to ponder before any strategic decisions are made.

5. What is the right study design to adequately assess these research questions?

In our study, we employed a Fixed Effects Model approach combined with a Linear Mixed Effects Model approach. Results were significant in some cases and not in others. The non-significant cases could easily be traced to the need for better study design, either through improved data collection or statistical analysis. We examine this and other key takeaways in the Future Research section of this paper on page 90 herein.

6. What are the antecedents, consequences, and moderators of the cross-channel integration phenomena from the retailer/supplier perspective?

At least partially, we identify several antecedents and moderators of cross channel phenomena in our parking study, as previously mentioned. The number of competitors, the number of competitors engaged in online sales with the proposed channel, and the volume of online search demand all fall into these categories.

A summary of the generalizable expected research contributions emanating from our study, as it relates to the existing extant literature on the body of research, is provided below for further review and consideration:

- Improves the understanding of the relationship between Offline and Online Business Models.
- Improves the understanding of Omni-Channel sales management & the Availability Effect within it.
- Adds to the knowledge base of current, relevant sales and marketing lines of research.
- Provide practical guidance to business leaders in many types of business sectors regarding sales channel management and selection.
- Provide a deeper understanding of some of the environmental factors surrounding the presence or absence of channel migration, including geographical factors and online search demand.
- Help business leaders improve the chance for Spillover Effects; minimize Cannibalization. effects.

CHAPTER NINE

FUTURE RESEARCH

In the context of the present study, replicating the study design using a second geographical control market outside of Manhattan would be most desirable to further eliminate the potential for a number of biases, confounding variables, and uncontrollable environmental factors. Presently, we used a sampling of parking properties in New York City only; some received treatment while others did not, effectively creating a treatment population and a control population. However, more effective and robust study designs exist, such as a true difference in difference design, which theoretically neutralizes much of the bias, which would be expected when using only a single market for the sole geography of the study. Difference in difference estimates have the primary benefit of mimicking an experimental design using observational data more effectively because the treatments are applied in different locations at different times (geographically and temporally dispersed) (Wattal et al., 2012, p. 169). Future research for the ParkWhiz study could be more productive, rigorous, and valuable, both academically and practically, if alternative but close major metro geographies were employed, such as Philadelphia, coupled with the New York City data and observations contained in the present experiment. Our unobserved heterogeneity problems can be theoretically neutralized with this method of study design in the future.

“We recognize that other factors also play a role in determining customers' likelihood to switch channels in a multichannel system, such as company and product (Balasubramanian, Raghunathan, and Mahajan 2005), customer heterogeneity (Inman, Shankar, and Ferraro 2004; Thomas and Sullivan 2005), marketing (Ansari, Mela, and Neslin 2008), competitive, and contextual contingencies. These contingencies suggest moderating conditions that offer opportunities for further research” (Avery et al., 2012, p.107). Adding any of these or other

mediating or moderating factors to our present work would likely provide exciting dimensions with even higher practical relevance for managers. Our study provided mixed results in moderating variables for the online intervention. The framework of our study allows for innumerable additional moderating or mediating variables, perhaps with greater relevance, to be examined by future researchers.

The existing literature preceding our work provided additional meaningful ideas for future lines of research, some of which inspired our study. Pozzi's (2013) grocery store study and Zhang's foodservice mobile app delivery study (2019) both provided inspiration for our present work. Future additional work examples include the pricing differentiation between brick and mortar stores and online sales channels, which could provide a dimension to our present study that would have additional high relevance for the practitioner. Currently, many of ParkWhiz's listed prices online are lower than the brick and mortar stores. This loss leader aspect of the business almost certainly drives some business cannibalization in the hybrid model from the brick and mortar garages to the online channel. If prices were kept constant in both, would the conversions from one channel to another increase or decrease from the results presented in our summary statistics? Conventional wisdom and common sense say it would, but the numerous convenience factors that the ParkWhiz app provides to consumers may be a moderating factor that still moves customers from the physical stores into the online one. These theories provide interesting fodder for future research in parking or elsewhere.

Although our study utilized both fixed panel data methods and mixed-effect regression models, we acknowledge that the use of an Interrupted Time Series (ITS) model for the analysis might have been more desirable. For future versions of our research, employing this model would potentially increase the strength, accuracy, and validity of our conclusions, while mitigating any effects of serial correlation in a more concrete manner. ITS, sometimes known as quasi-

experimental time series analysis, is a method of statistical analysis involving tracking a long-term period before and after a point of intervention to assess the intervention's effects.

Zhang et al. (2019) specifically disclaimed the use of a difference in difference (DiD) model in her study for a robustness check of endogeneity due to the fact that her focal firm indicated no strategic plan to introduce O2OSP channels in specific stores (and not others) (Zhang et al., 2019, p.125). Alternative methods were used to address the risk of endogeneity (Linden 2015), which we reviewed but did not deploy. Zhang et al. (2019) essentially had no control variables in her model, compared to our substantial control locations. Our present work attempted to use a very similar method to DiD while not perfectly on point for it. Using a linear mixed effect model, controlling for random effect intercepts for each site, and a fixed-effects model essentially allowed us to come close to a DiD study methodology although our dataset structure was again not fully conducive to the true DiD model (note this was a challenge in our pilot study as well). The expectation of that future ITS work would be better fit-of-model metrics, higher R squared scores, and improved p values than observed using our present models.

Given our access to a robust library of extensive consumer and demand data through the ParkWhiz enterprise, we position ourselves well to expand this existing research into even more complex and exciting analyses in the future. For example, we can combine our study design of revenue and demand, with US Census data in future phases of this research to examine any correlation in our outcomes to age brackets of consumers, percentages of households with vehicles, income levels, education levels and much more. Because our study's value is in finding any moderators, antecedents, and consequences associated with brick and mortar cannibalization of sales through added sales channels, testing against any number of our enumerated variables can have high value for this study academically and practically. We use some of these as control variables in our present study, such as the S&P 500 index and weather,

as examples, drawing inspiration from the Zhang et al. (2019) study approach. The intent is to provide conclusions that elucidate daily fluctuations in total revenue, which might be due to online channels and for operators seeking such guidance when making e-commerce sales decisions.

Summary of Improvements for Future Work

Model Choice

Interrupted Time Series Model (ITS) analysis - would be more appropriate to address any underlying serial correlation in the data. Vector Autoregressive Moving Average with exogenous regressors (VARMAX) would seem an ideal fit. However, there are complexities in implementing this due to the fact each location's 180 recordings occurred at different time periods and were missing values (due to certain sites being closed on a weekend, holiday, etc.). They would need to be imputed to maintain the model structure.

Bayesian regression analysis (i.e., PyMC3, Stan-based package, etc.) - would allow for a non-distribution-based estimate of the parameters. Bayesian methods would also seem sensible because the model fit work here is based on evaluating parameters given the posterior of data experienced, rather than any forward forecast or out-of-sample data analysis.

Different Study Design

The addition of further locations would include additional (non-New York) sites from some similar major markets. We need far greater sites (with varying amounts of offstreetsites/transact garage values) and less required observations at each site. Further intervention work might include a greater washout period between pre and post-intervention times. Some sites had a substantial washout period (almost two months), and others had none at all. A clean 1-week washout period, uniformly implemented across all sites, might have been ideal. We do not believe the lack of consistency in a washout period before pre, and post-intervention data collection materially impacted the study.

More Exogenous (X) Variables

Examples include - the measurement of crime incidents, average income tax payments (by zip code) from IRS, other specific local data. Local data would better explain a study across greater geographies. Some of these other variables were considered but deemed not worthy of adding to the overall analysis in such a tight geographical region of New York City.

Summary

This research examines the relationship between online and offline sales in an omnichannel sales environment centered around the selling of parking spaces. The parking industry was selected as the backdrop, given the high degree of current relevant concerns in this space around internet sales-related cannibalization concerns against physical stores, and given the author's substantial access to relevant research data. Data was collected for an intervention group and a control group from a leading parking management firm with thousands of parking garages located across North America.

Our overall H1 outcomes (across four different regression models) showed strong statistical significance with p-values less than 0.001, and moderate R^2 scores between 37%-47% for the online ParkWhiz intervention. Online intervention increases revenue per parking space in the range of \$1.171 to \$1.196 in the experiment. The results provide support for the proposition that adding an online sales channel to an existing body of physical parking facilities is additive, non-cannibalistic and overall productive for the business. Our H2 and H3 study outcomes were inconclusive, as the moderators were not significant. The tests of the moderating effects in H2 and H3 provided no practical results, other than perhaps anecdotal perception to supplement the other findings. The testing of H4 did show significance in the importance of the assessment of online search demand in a given zip code as an amplifier of the effect of online intervention on parking revenue. Search volume is positively related to a change in the net new revenues. Overall, the analysis generated learnings valuable for future researchers to expand upon through better data gathering, statistical models, and analysis.

In totality, the desired contribution of this body of research is to provide today's brick and mortar business manager with strategic insights into the conditions needed to make healthy e-commerce decisions, based on observable market conditions, in an omnichannel environment that combines online and offline models for maximum aggregate revenue growth. Avoidance or

minimization of cannibalization between existing channels and new channels can ensure success. Our work demonstrates several critical aspects of the phenomena of successful online and offline channel cohabitation with practical conclusions for the strategic decision-maker to use in reaching that equilibrium, and leaves a discernible path for future researchers to supplement our efforts with additional moderating variables.

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APPENDIX A

H1A Residuals Scatterplot

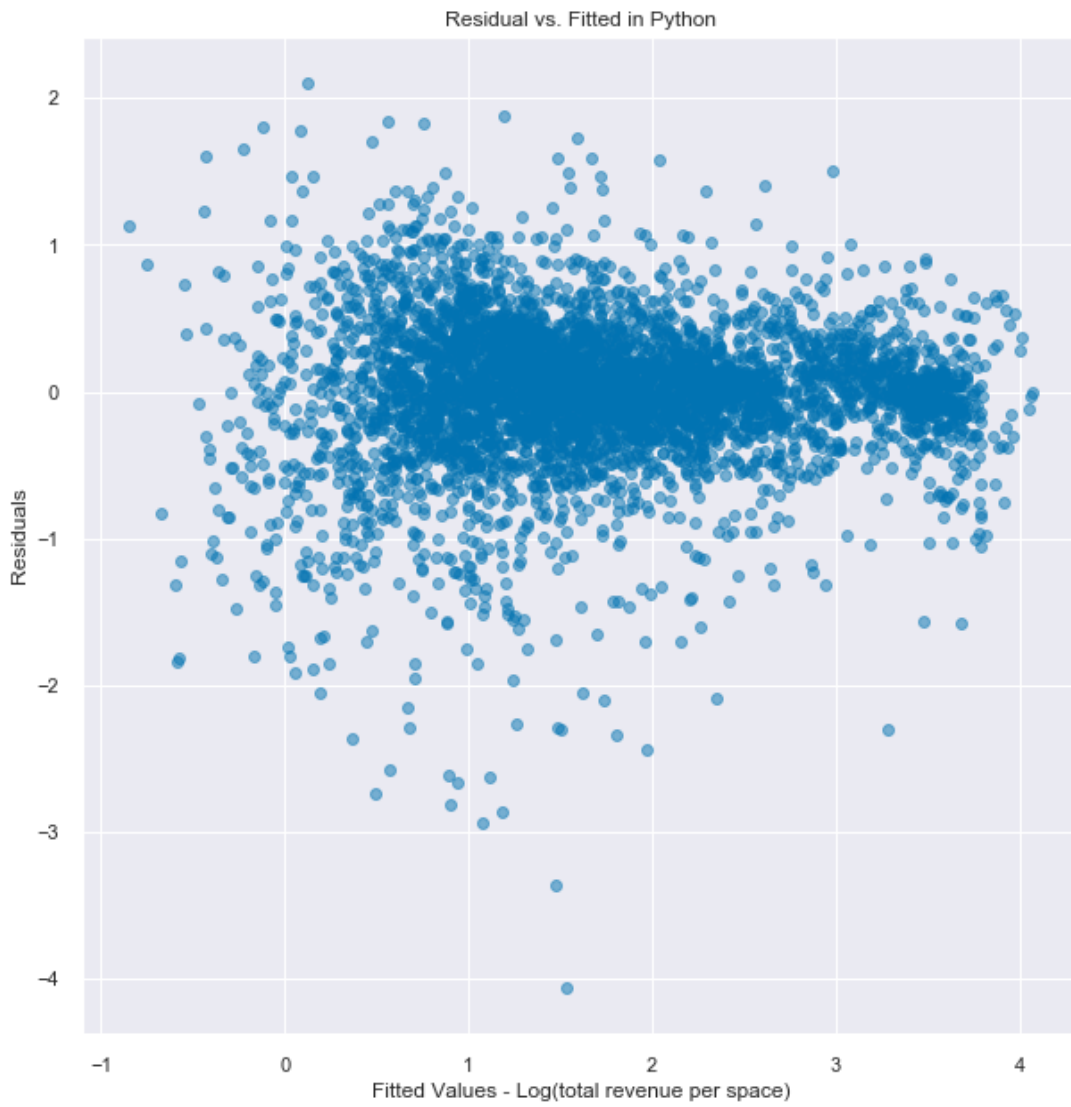


Figure 3. Residuals for H1A – Linear Mixed Effect Model – ZF10 Data Frame.

APPENDIX B

H1A Residuals Slope

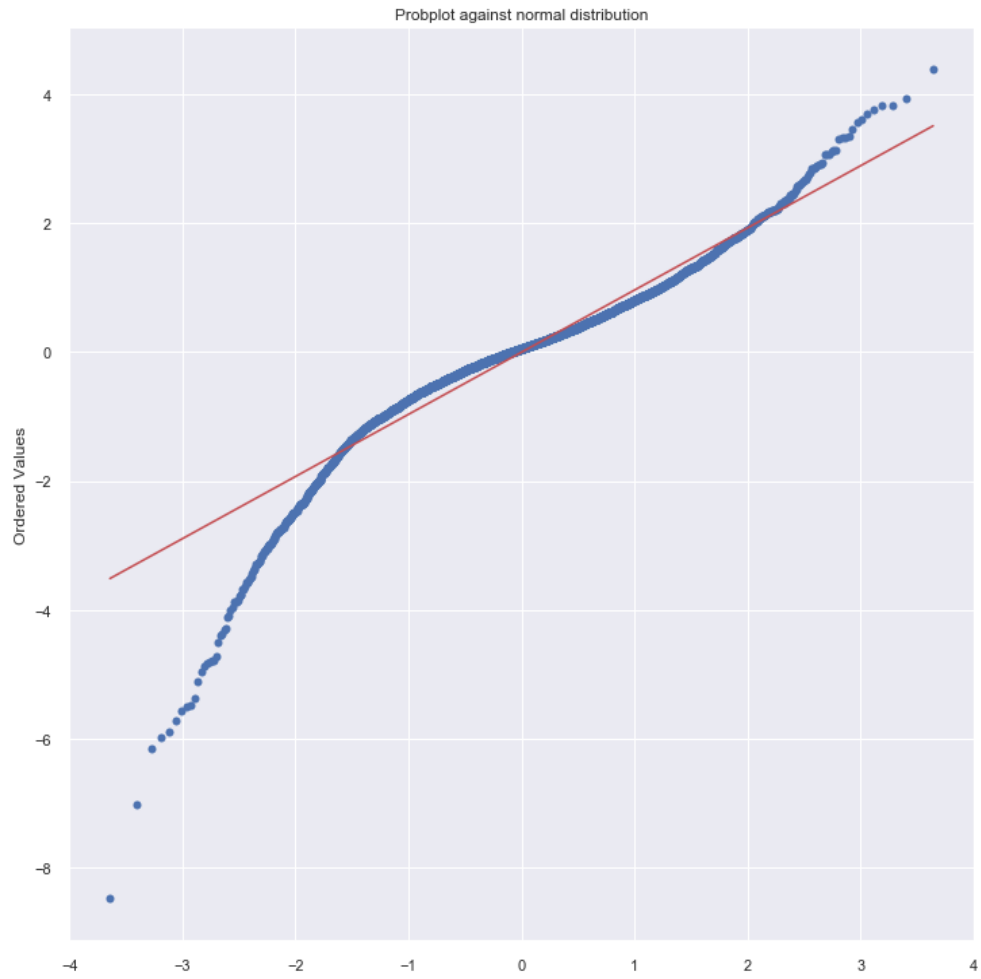


Figure 4. Residuals for H1A, Linear Mixed Model, Data Frame ZF10.

APPENDIX C

H1A Residuals Distribution

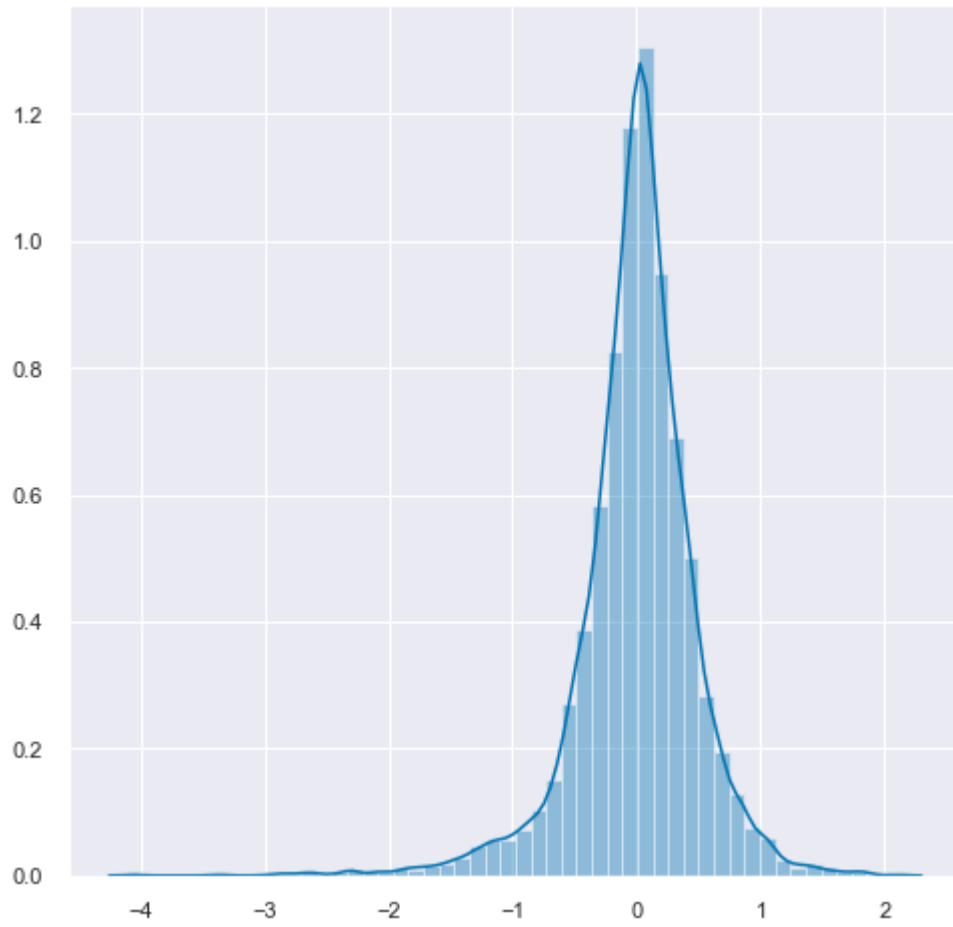


Figure 5. Residuals for H1A, Linear Mixed Model, ZF10 Data Frame.