University of Kentucky

UKnowledge

Theses and Dissertations--Marketing and Supply Chain

Marketing & Supply Chain

2022

When Should Sales Managers Get Involved in Their Salesteams' Transactions

Daniel E. Chavez
University of Kentucky, danieleduardo.chavez@gmail.com
Author ORCID Identifier:
https://orcid.org/0000-0003-4790-9150
Digital Object Identifier: https://doi.org/10.13023/etd.2022.048

Right click to open a feedback form in a new tab to let us know how this document benefits you.

Recommended Citation
Chavez, Daniel E., "When Should Sales Managers Get Involved in Their Salesteams' Transactions" (2022). *Theses and Dissertations--Marketing and Supply Chain*. 11.
https://uknowledge.uky.edu/marketing_etds/11

This Doctoral Dissertation is brought to you for free and open access by the Marketing & Supply Chain at UKnowledge. It has been accepted for inclusion in Theses and Dissertations--Marketing and Supply Chain by an authorized administrator of UKnowledge. For more information, please contact UKnowledge@lsv.uky.edu.

STUDENT AGREEMENT:

I represent that my thesis or dissertation and abstract are my original work. Proper attribution has been given to all outside sources. I understand that I am solely responsible for obtaining any needed copyright permissions. I have obtained needed written permission statement(s) from the owner(s) of each third-party copyrighted matter to be included in my work, allowing electronic distribution (if such use is not permitted by the fair use doctrine) which will be submitted to UKnowledge as Additional File.

I hereby grant to The University of Kentucky and its agents the irrevocable, non-exclusive, and royalty-free license to archive and make accessible my work in whole or in part in all forms of media, now or hereafter known. I agree that the document mentioned above may be made available immediately for worldwide access unless an embargo applies.

I retain all other ownership rights to the copyright of my work. I also retain the right to use in future works (such as articles or books) all or part of my work. I understand that I am free to register the copyright to my work.

REVIEW, APPROVAL AND ACCEPTANCE

The document mentioned above has been reviewed and accepted by the student's advisor, on behalf of the advisory committee, and by the Director of Graduate Studies (DGS), on behalf of the program; we verify that this is the final, approved version of the student's thesis including all changes required by the advisory committee. The undersigned agree to abide by the statements above.

Daniel E. Chavez, Student

Dr. Brian Murtha, Major Professor

Dr. Nancy Johnson, Director of Graduate Studies

WHEN SHOULD SALES MANAGERS GET

INVOLVED IN THEIR SALESTEAMS' TRANSACTIONS

DISSERTATION

A dissertation submitted in partial fulfillment of the
requirements for the degree of Doctor of Philosophy in the
College of Business and Economics
at the University of Kentucky

By

Daniel Eduardo Chavez

Lexington, Kentucky

Director: Dr. Brian Murtha, Professor of Marketing

Lexington, Kentucky

2022

Copyright © Daniel Eduardo Chavez 2022
https://orcid.org/0000-0003-4790-9150

ABSTRACT

The existing literature on sales teams explores various aspects of team members and their effects on sales performance. The literature on sales management has described how managers can promote better results from salespeople. The question at the intersection of these two streams of literature – if managers should be part of sales teams -- has not been addressed and is what we explore. Using data from a Fortune 1,000 firm that operates automotive service stores across the US we test these effects. The data presents a natural experiment as sales teams with different compositions are assigned randomly to the customers. We identify different configurations where either the team is comprised only of salespeople or managers and salespeople. Based on insights from game theory and agency theory, given there are more opportunities to free-ride in salespeople-only teams, more shirking is expected in these teams, yielding less effort by all team members, an outcome that would, in turn, result in lower sales. Our results show that the presence of managers would reduce the shirking and increase sales.

KEYWORDS: Sales, Sales Managers, Sales teams, Agency Theory.

Daniel Eduardo Chavez

4/12/2022

WHEN SHOULD SALES MANAGERS GET
INVOLVED IN THEIR SALESTEAMS' TRANSACTIONS

By
Daniel Eduardo Chavez

Dr. Brian Murtha

Director of Dissertation

Dr. Nancy Johnson

Director of Graduate Studies

4/12/2022

Date

DEDICATION

Mamá, wish you were here. I hope I am making you proud with all the non-academic stuff I have done and continue to do.

Luna, I hope that you know someday how you were in my heart and my mind at all times. Te amo hija.

JoJo, I choose you. I am glad you chose me. I look forward to us choosing each other again and again.

ACKNOWLEDGEMENTS

Not only would it be unrealistic, but also disrespectful to fail to acknowledge some of the people who have been essential for getting me here. A huge thank you to my friend and guide Brian Murtha who has had the patience of a saint to teach me his ways and has been willing to be uncomfortable with me. A debt of gratitude also goes to my mentor and supporter Haipeng Chen, for the opportunity and encouragement me to join this program where I found my true calling, my home. I would also like to thank my committee members: Adam Craig for being a neutral judge to my ideas and wanting to use my skills, and Kenneth Troske for bringing me into the project that changed my life.

I also owe this moment to all the faculty members at University of Kentucky who showed the way to newfound knowledge and more often than not made sure I knew I had a place amongst them. Thanks also go to my friends, my colleagues, and the staff for making my time at University of Kentucky and Lexington a great experience.

Special thanks go to my mother, Elizabeth Paz, for her love, acceptance, understanding, and encouragement, thank you Mamá for giving me all. To my father, Jose Roberto Chavez, for pushing me to pick myself up and try again and never give up.

And finally, I wish to thank my daughter, Luna Chavez, for motivating to become a better person every day, and my partner in life, Jo Mackby, for giving me a practical application of asymptotics for low probability events, showing me the Bayesian nature of the statistics of life, and challenging me like no one can.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION

In 2019, US firms spent approximately $7.2 billion to compensate over 65,000 managers in retail contexts (BLS 2020). Managers recruit, train, coach, and evaluate employees and thus play a vital *supervisory role* for firms (Schmitz and Ganesan 2014; Wieseke et al. 2009). Unlike many types of managers, however, sales managers also take on a *selling role* whereby they're tasked with selling products and services to customers (Deeter-Schmelz, Goebel, and Kennedy 2008; Hughes and Ogilvie 2019). In practice then, sales managers often take on dual roles of supervising *and* selling (Rapp et al. 2020). Although having managers sell products and services to customers may increase sales, doing so takes time away from their supervising responsibilities which are also very important. Questions arise, therefore, as to how to balance these roles and whether and when sales managers should engage in their selling role.

Unfortunately, practitioners provide conflicting advice on this issue. On the one hand, a long-standing viewpoint is that managers should be managing, not selling (Loen 1964). Perpetuating this view, recent advice suggests that, "as a manager, although you miss it, resist the urge to jump in on the sale" (HubSpot 2020) and, "managers are responsible for making operations run, not running them" (LinkedIn 2017b). On the other hand, some suggest that "managers' work is selling" (CareerBuilder 2020) and, "a managers' job is to sell products" (LinkedIn 2017a).

With a couple of notable exceptions (see Arnold et al. 2009; Rapp et al. 2020), academic research provides little guidance on how to balance sales managers' supervising and selling roles. Although prior research examines sales managers, this research typically focusses on the *supervisory role* of managers. For instance, prior work sheds important light on managers' influence on teams (Ahearne et al. 2013; Atefi et al. 2018), managers' leadership and management styles (Mero, Guidice, and Werner 2012; Schmitz and Ganesan 2014), and managers' planning and execution (Deeter-Schmelz, Goebel, and Kennedy 2008; Grant 2003) (see Table 1). The present research, therefore, complements prior research by incorporating sales managers' *selling role* and assessing whether and when sales managers should engage in this role. Accordingly, we seek to make the following contributions to the literature on sales managers.

First, to our knowledge, the present study is the first to explore the effects of sales managers' direct interactions with customers on transaction performance. As such, we complement and extend the work by Arnold et al. (2009), who shine a light on how sales managers influence sales by gauging how much time sales managers dedicate to selling. Our work goes a step further and evaluates what happens when sales managers sell *with their salespeople*. Thus, we take a more fine-grained view and how sales manager involvement impacts the performance of individual transactions.

Second, given that sales managers also have to perform their supervisory role, it is important to understand *when* sales managers should engage in their selling role (i.e., when to get involved with individual transactions with customers). Recent research has begun to address this issue. For instance, Rapp et al. (2020) find that allocating time to managing (supervising role) yields higher performance with experienced sales units, i.e. salespeople working for the same supervisor (Venkatesh, Challagalla, and Kohli 2001), while dedicating time to customer facing activities (selling role) is a better choice for units with lower levels of experience. We build on this important insight by examining sales teams, i.e. a group organized so that they operate together (Holmstrom 1982), and by looking outside the characteristics of the sales units/teams for guidance on how to allocate sales manager time. More specifically on the latter, we examine *customers' relationship stage with the firm* and *product usage intensity* and how these interact with sales manager involvement in sales transactions. These two conditions are external to the sales team, and unlike team composition, they can be more accessible for firms (Aakvik, Hansen, and Torsvik 2017) to guide when managers can be most effective at maximizing sales performance.

In this research, a customer's relationship stage reflects whether they are a *new or returning* customer (Dagger and Danaher 2014; Evans et al. 2000; Lemon and Verhoef 2016). Product usage intensity is the extent to which a *product has been used relative to how long the product has been in use*[1] (Bolton and Lemon 1999; Challagalla, Venkatesh, and Kohli 2009; Ram and Jung 1991). Our results indicate that sales teams with managers: (a) perform best with new rather than returning customers, and (b) performance increases with product usage intensity. To our knowledge, the present research is the first to blend insights from the literature on customers' relationship stage and product usage intensity and how they may impact the efficacy of sales manager involvement in transactions. Thus, we provide an important first step in understanding variables *external* to the team to inform sales managers on how to prioritize getting involved in their sales teams' transactions. Importantly, customer relationship stage and usage intensity are relatively easy to distinguish across firms and industries. Thus, a broad range firms may readily implement changes to their sales processes based on these variables.

---

[1] This concept contrasts with the age of the product in the sense that a product can have low usage intensity even if it was acquired a long time ago and vice versa (e.g., high usage intensity of a recent purchase). For example, a washing machine acquired a three months ago that is used daily has higher usage intensity than a two-year old washing machine that is used once a month.

Third, prior research has not considered how sales manager involvement in (lower-level) transactions with customers may affect higher, store-level outcomes in which managers' supervisory role is most likely to manifest. Such an examination is important to understand because if the benefit at the transaction-level comes at the expense of store-level performance, then the necessity of managers having a selling role becomes questionable. The results of the present study suggest that managers' involvement in their sales teams' customer transactions increases transaction performance (i.e., the size of customers' invoices); however, results also suggest that manager involvement in sales teams' transactions has an inverted u-shaped relationship with store performance. This result implies that too little or too much manager involvement in individual sales transactions can be detrimental to store performance. This suggests a "sweet spot" of manager involvement in transactions that, to our knowledge, has not been documented before. Taken together, our results provide evidence of novel and nuanced effects of involving managers in their sales teams at both the transaction and store levels.

The results of the present research are based on analyzing a blend of two secondary datasets, i.e., personnel and invoice datasets, from a longitudinal study with a Fortune 1000 firm that operates nationwide automotive services in the US. The invoice dataset contains over 7 million invoices for more than 400 corporate operated stores located across the US. The personnel dataset details characteristics of all the frontline staff of the company including rank, age, gender, tenure, and promotion track. The partner firm's selling setup consists of teams of two salespeople per customer (one at the car window and one under the vehicle hood) that are randomly paired by the store managers. Customers are randomly assigned to each sales team on a first come first serve basis. Store managers walk around the store and can volitionally choose to become part of any of the sales teams in the store. Given the random assignment of customers to sales teams, of salespeople to the assigned teams, and sales managers choice to join sales teams, the data from this firm provide a natural experiment setup. Using the blend of the datasets, we are able to identify in each transaction whether the sales team had a sales manager or not to test the effects of manager involvement on sales performance.

The current research uses longitudinal measures of both *store* (daily store revenue) and *transaction* data (individual invoice revenue) to evaluate our contentions. The personnel dataset also allows us to be able to include data about the team members such as age, tenure, and other potential differences as controls to rule out potential competing explanations. These datasets allowed us to apply big data management techniques and machine learning algorithms to take an agnostic approach to the data and remove bias in the model selection and estimations, providing more robustness to the findings. While the setup of the firm helps address some potential endogeneity concerns, we also use state-of-the-art methods to address others. Our results provide important managerial implications on if and when managers should get involved in the sales teams.

The paper is structured as follows. First, we draw on insights from agency theory and relevant streams of the management (e.g., teams and monitoring) and consumer behavior (e.g., information acquisition and processing) literatures to develop our hypotheses. We follow this with a description of the firm and data setup used in the analysis. We then describe the models and identification strategy before presenting our results. We conclude with managerial and theoretical implications and some limitations of the research.

Table 1: Overview of the literature on sales teams and manager involvement

Article	Manager selling	Manager supervising	Customer data	Level of analysis	Performance moderators (source)	Manager attributes	Team composition	Industry (context)	Data source	Duration
Ahearne et al. (2013)	No	Yes	No	Sales team	Control systems (internal)	Organizational & interpersonal identification	Non-managers	Non-descript (B2B)	Survey / records	One shot
Arnold et al. (2009)	No	Yes	No	Store	Supervisor & goal-setting activities (internal)	Effort, planning, leadership & selling orientation	Non-managers	Retail (B2C)	Survey / records	One shot
Atefi et al. (2018)	No	Yes	No	Store	Salesperson & manager tenure (internal)	Demographics Tenure	Non-managers	Apparel (B2C)	Field / records	One shot
Auh et al. (2014)	No	Yes	No	Sales team	Conflict handling style (internal)	-	Non-managers	CPG (B2B)	Survey	One shot
Bunderson et al. (2015)	No	Yes	No	Team	Task complexity (external)	-	Non-managers	Various (B2B/B2C)	Survey	One shot
Chen and Lim (2017)	No	No	No	Sales team	Team heterogeneity (internal)	-	Students	Lab (none)	Experimen t	One shot
Deeter-Schmelz, Goebel, and Kennedy (2008)	No	Yes	No	-	-	Values and attributes	Managers & non-managers	Non-descript (none)	Survey	One shot
Frick, Prinz, and Winkelmann (2003)	No	No	No	Team	-	-	Non-managers	Sports (none)	Records	Longitudinal
Garrett and Gopalakrishna (2019)	No	No	No	Sales team	Impression management (internal)	-	Non-managers	Insurance (B2C)	Field quasi experiment	One shot
Grant (2003)	No	Yes	No	Firm	-	-	Managers	Oil (B2B)	Survey	One shot
Greer and van Kleef (2010)	No	Yes	No	Team	Power level differences (internal)	Power	Managers & Non-managers	Finance (none)	Video recording	One shot

Table 1 (continued)

Hoogendoorn, Oosterbeek, and van Praag (2013)	No	No	No	Sales team	Gender (internal)	-	Students	Classroom (none)	Experiment	One shot
Huckman and Staats (2011)	No	No	No	Team	Task type Team familiarity (internal)	-	Non-managers	Software development (B2B)	Survey / records	One shot
Hughes and Ogilvie (2019)	No	Yes	No	-	-	Training focus	Non-managers	Non-descript (none)	Survey	One shot
Joshi, Liao, and Jackson (2006)	No	Yes	No	Salesperso n	Diversity proportions (internal)	Demographics	Non-managers	Equipment and Supplies (B2B)	Survey	One shot
Lount et al. (2019)	No	Yes	No	Team	Task visibility (internal)	-	Non-managers	Firefighters/ Lab (none)	Survey / lab	One shot
Mero, Guidice, and Werner (2012)	No	Yes	No	Team	-	Leadership style	Managers & Non-managers	Construction components (B2B)	Survey / records	One shot
Rapp et al. (2020)	Yes	Yes	No	Sales team	Team experience (internal)	Time allocations	Managers & Non-managers	Hospitality operators (B2B)	Survey / records	One shot
Schmitz (2013)	No	Yes	No	Sales team	Norm strength Reputation Ability (internal)	-	Non-managers	Industrial glass (B2B)	Survey	One shot
Schmitz and Ganesan (2014)	No	Yes	No	Sales team	Self-efficacy (internal)	Leadership style	Managers & Non-managers	Pharma (B2B)	Survey	One shot
Wellman et al. (2019)	No	Yes	No	Team	Hierarchical structure (internal)	-	Non-managers	Healthcare (none)	Survey / records	One shot
Wieseke et al. (2009)	No	Yes	No	Region or Unit	Tenure (internal)	Organizational identification	Non-managers	Pharma (B2B)	Survey / records	One shot
The present research	Yes	Yes	Yes	Invoice & Store	Customer type Product stage (external)	Involvement Demographics Tenure	Managers & Non-managers	Automotive (B2C)	Field / records	Longitudinal

CHAPTER II

THEORY AND HYPOTHESES

This study explores how a sales manager's involvement in individual transactions with his/her team members affects both transaction-level and store-level performance. In general, we propose that manager involvement in individual transactions increases team effort, i.e., "the amount of energy put into a behavior" (Mohr and Bitner 1995 p. 240). Customers appreciate and value what they perceive as increased effort (Buell, Kim, and Tsay 2016; Kirmani and Wright 1989), which manifests in greater customer satisfaction (Crosby and Stephens 1987; Homburg, Müller, and Klarmann 2011) and increases *transaction-level* performance (Christen, Iyer, and Soberman 2006; Fong and Tosi 2007). In the following sections, we draw on agency theory (Bergen, Dutta, and Walker 1992; Eisenhardt 1989) to provide the theoretical foundations upon which managers involvement in their sales teams impacts the effort of their teams.

Agency Theory

Enactment In almost every situation where two or more parties cooperate with each other, one of the parties has more information about the transaction than the other party (i.e., there is information asymmetry) (Akerlof 1970). Such information asymmetry in principal-agent relationships can lead to moral hazard (Jensen and Meckling 1976). Moral hazard ensues when the agent possesses information that would benefit the principal, but the former does not share or misrepresents the information to the latter (Pauly 1968). A common example of moral hazard in sales is when salespeople knowingly exert less effort than they are capable of, i.e., shirking. The principals (firms) want to get as much output (sales) while using the smallest quantity of resources (e.g., salaries, supervision, contracts, etc.). The agents (salespeople) want to get as much output (compensation) while using the least number of resources (e.g., effort, time, attention, etc.). If salespeople put more energy into the transaction, customers react positively to that, which results in higher sales (Román and Iacobucci 2010; Surprenant and Solomon 1987). This is the objective of the firm (principal), but the amount of effort salespeople are genuinely capable of is only known to them (agents), leaving room for moral hazard. Assuming that both parties in a principal-agent relationship are utility maximizers, the game theory prediction is that both parties will act selfishly. It follows that agents will shirk unless principals have forms to prevent them from doing so.

When Hölmstrom (1979) explored how moral hazard arose in principal-agent relationships as a consequence of information asymmetry, he showed that the presence of an intermediate agent on behalf of the principal – a supervisor – would reduce moral hazard. This formalized what Stiglitz (1975) had proposed and later became known in agency theory as monitoring. Formally, this type of monitoring – supervision – is the idea that an agent (sales manager) that has objectives more closely aligned to those of the principal (Ouchi 1979) can act on behalf of the principal (firm) with other agents (salespeople), and that the presence of the former agent (sales manager) makes the latter agents (salespeople) exert more effort. This is the *supervisory* role of managers, as agents acting on behalf of the principals, that has had attention in sales management research.

The literature has shown that without proper supervision, agent effort is not observable to the principals, thereby increasing the likelihood of shirking (Jones 1984; Stathakopoulos 1996). With supervision, the observability of effort is increased

(Eisenhardt 1985), which lowers the likelihood of shirking. In a store, for example, when sales managers are walking around the sales floor, without necessarily engaging with the customers and getting involved with selling, their mere presence is likely to increase the effort from salespeople (Deeter-Schmelz, Goebel, and Kennedy 2008; Rich 1997). This is the most basic form of supervising to improve sales performance: salespeople shirk less when managers are present, even if they are not involved in the sales process themselves.

Sales Teams

There is an additional layer of complexity when sales are being done by teams. When two or more agents with the same job (peers) are on a team, agents can free ride on the effort of each other, especially if all that can be observed is the output of the team (Holmstrom 1982). In a team with several utility-maximizing agents, each one is trying to maximize his/her benefits (compensation) while minimizing his/her costs (effort).

In teams with a collective output the game-theoretic prediction would be similar to a prisoners' dilemma (Rapoport, Chammah, and Orwant 1965), which means that all sales team members will try to maximize their utility by providing the least amount of effort and counting on the other agents to carry the weight (Nalbantian and Schotter 1997). The outcome is that all agents shirk as much as possible as long as the job gets done and they are not caught shirking by their supervisor (Baldwin and Clark 2006). This implies that performance will be suboptimal since the sales agents in the team will not exert their full effort. If managers can monitor (via their supervisory role) individual agent performance in a team (even with team output) shirking is reduced (Alchian and Demsetz 1972; Jones 1984). The expectation is that a team of salespeople with no supervision will shirk the most, while a sales team that is being supervised by a manager will exert a higher level of effort than that baseline.[2]

Unfortunately, the literature does not inform what to expect when managers engage their selling role and participate in sales transactions with their teams. Recent work on the conditions for equilibria in agent-principal contexts with multiple agents may provide some guidance. For instance, research suggests that heterogeneity among agents increases effort from all agents (Kaya and Vereshchagina 2015). One way team heterogeneity increases team effort is through perceptions of task visibility. Research on task visibility shows that when individuals perceive that others can evaluate their individual effort (increased task visibility), they become more concerned with exerting more effort (Harkins and Szymanski 1989). This generally results in all team members exerting more effort to a level higher than they do working alone (Lount and Wilk 2014). Differences in hierarchy among team members increase this effect, as those lower in the hierarchy are more concerned with how their effort will be perceived by those higher in hierarchy (Lount et al. 2019). In practice, this means that a team where members have different jobs has increased task visibility for members, which increases the effort of the whole team. This effect is even stronger when one of the team members is higher in the hierarchy. Therefore, in a sales team with managers there is increased task visibility for salespeople and differences in hierarchy, and both increase effort from sales agents. The resulting effort is higher than that of working alone, with other salespeople, and even higher than the effort driven by

[2] These predictions do not hold when individual incentives are present. The retail setting we evaluate, and many other sales contexts, however, do not offer individual incentives for salespeople.

mere supervision by the sales manager, leading to better sales performance. In summary, sales teams with managers are likely to have increased performance.

It could be argued, however, that in this setup sales managers are also agents, and as such, they are prone and susceptible to the same free-riding and shirking woes as salespeople. If sales managers in sales teams act like salespeople would, then sales managers could also hide their true effort and free ride on their salespeople's effort. This could result in the total effort of a sales team with a manager being equal or lower than a sales team without a manager. Although this scenario is plausible, extant research suggests it is unlikely. Promotion is one of the ways that firms incentivize good performance (Fairburn and Malcomson 1994), which results in a large number of sales managers having been salespeople who were promoted from within their organizations (Armstrong, Pecotich, and Mills 1993). But these folks were not promoted to managers only because they were good performers, but also because they "display a high internal commitment to the firm's objectives" (Ouchi 1979, p. 837) and they are "people whose preferences coincide with those of management" (Eisenhardt 1985, p. 148). These characteristics of sales managers imply that as sales team members they would be more likely to exert effort closer to their true effort even without supervision (Anderson and Oliver 1987). These characteristics of sales managers and the intuition about salespeople in teams with managers would result in higher sales for teams with managers than teams without managers.

Given the expectation that sales teams with managers would exhibit increased performance, the intuition for firms would be to increase the amount of time sales managers spend selling. Exploring the tradeoffs needed to deal with the dual roles of sales management (Rapp et al. 2020) leads inevitably to consider under which conditions sales manager involvement with their sales teams is maximized. We identify two such conditions in the next section.

Contingencies: Customer and Product Stages

With a limited number of managers that can be part of sales teams, maximization of resources is crucial. How should stores prioritize which transactions their managers should engage in with their sales teams? Allocation of managers should be done so that managers get involved in teams where the increased effort the sales team will exert produces the greatest sales. We identify two variables external to the team that can help in this regard: *customers' relationship stage with the firm* and *product usage intensity*.

Customers' relationship stage with the firm. Customers' relationship stages are defined as "the major transitions on how parties [sellers and buyers] regard each other" (Dwyer, Schurr, and Oh 1987 , p. 15). It is widely known and acknowledged that customers' interactions with firms are different at different stages (Reinartz, Krafft, and Hoyer 2004; Srivastava, Shervani, and Fahey 1998). In particular, when it comes to the distinction between new and returning customers, Anderson and Simester (2004 p. 13) propose that, "we would expect the first-time customers, who had almost no other information with which to form expectations, to be more sensitive to any learning effects." Initial impressions, values, or perspectives shape the judgment of the shopping experience (Epley and Gilovich 2006). Without prior experiences, new customers are more likely to be influenced than returning customers (Kaustia, Alho, and Puttonen 2008). These ideas suggest that new customers are likely to react to sales efforts more so than returning customers.

Alternatively, as customers interact more and more with a firm, they become less likely to change their perceptions of the firm (List 2011). As people gain more information about a firm, their perceptions become more firmly ingrained over time which makes them less sensitive to new information (Boulding, Kalra, and Staelin 1999; Hogarth and Einhorn 1992). As Dagger and Danaher (2014, p. 65) note, "[p]rior knowledge heavily influences purchase decisions and can make new information less impactful. That is, the more experienced a customer is with a particular store, the less impactful changes will be on their purchase decisions over time." In sum, therefore, effort by the sales team is likely to be more impactful with new customers who are still acquiring information and more susceptible to new information. If teams where managers are embedded are more likely to exert more effort than teams without managers, these ideas can be formalized as:

Hypothesis 1*: A team with a sales manager in it will have higher sales with new customers than with returning customers relative to a team without a sales manager in it.*

Product usage intensity. Product usage intensity refers to how much a product has been used relative to how long the product has been in use (Bolton and Lemon 1999; Challagalla, Venkatesh, and Kohli 2009; Ram and Jung 1991). For example, a 2-year-old car with 50,000 miles has high usage intensity, while a 10-year-old car with the same mileage has low usage intensity. Research on product usage provides a framework on how reactions to sales effort would differ across product usage intensity.

With low usage intensity, customers are more susceptible to outside information (Cameron and Englin 1997) and customers who purchase lightly used products are more likely to provide good care to them (Brough and Isaac 2012). This suggests that users of products with low usage intensity are more sensitive to the effort exerted by sales teams.

The expectation would be different for median usage intensity. At the median usage intensity, users choose options with lower costs than users with low usage intensity (Nunes 2000) and they believe it would not be “fair” to pay extra (Einhorn 1994; Yang and Peterson 2004). These notions imply users of products with median usage intensity are less susceptible to sales efforts.

On the other extreme, users of products with high usage intensity tend to be more knowledgeable about product features, benefits, and issues (Jewell and Unnava 2004; Johnson and Russo 1984). The products with high usage intensity also need more maintenance and their users stand to lose more if they break down (Challagalla, Venkatesh, and Kohli 2009). These conditions imply that customers with high usage intensity products will be more receptive to sales efforts of sales teams. Given these conditions around usage intensity and the expectation that teams with managers exert more effort, the relationship between product usage intensity and manager involvement in sales teams can be framed as:

Hypothesis 2*: A team with a manager in it will have higher sales relative to a team without managers for low and high usage intensity, but not at the median usage intensity, following a convex function, i.e. a U-shape.*

Even if the sales managers joining the sales teams affects performance, there is a tradeoff to be made about whether they get involved in sales transactions. Although manager involvement is likely to benefit transaction performance Rapp et al. (2020 p. 144) also suggest that another benefit of manager involvement in transactions is that it “provide[s] direction for managers to prioritize activities that maximize team potential.” In other words, when managers are not involved with their sales teams, they are missing out on opportunities to learn how to prioritize their time, chances to train and coach, and failing to promote effort in sales teams. On the other hand, sales managers' supervisory duties – e.g. leadership (Deeter-Schmelz, Goebel, and Kennedy 2008), monitoring performance (Boichuk et al. 2019), fostering well-being (Kemp, Leila Borders, and Ricks 2013), and hiring (Marshall, Goebel, and Moncrief 2003) – are crucial for store performance (Hughes and Ogilvie 2019), but when managers are involved in too many sales transactions, they spend less time performing these duties, which would likely not impact the individual transactions immediately, but rather be observed at the store level.

The adequate level of trade-off between selling and supervising would have all the benefits from managers' selling, without the negative consequences of neglecting supervisory duties. This relationship suggests there is a manager involvement "sweet spot". Focusing on store sales instead of the individual transactions would capture the higher-order consequences of managers involvement in sales and allow for identification of said sweet spot. Using the percentage of transactions that have sales managers as a measure of manager involvement in selling, the previous notions can be formally expressed as follows:

Hypothesis 3*: The relationship between manager involvement in sales and store performance follows a concave function, i.e. an inverted U-shape.*

CHAPTER III

METHODOLOGY

Data Collection

To test our proposed hypotheses, we use data from a firm in the automotive maintenance and repair industry. The partner firm is a Fortune 1000 company whose automotive service division operates over 400 stores nationwide and manages a similar number of stores as franchisees. We use the data only from the corporate-owned stores to reduce the variation and unobserved heterogeneity that could come from including the franchises.

Prior to data collection, we had several meetings with the firm's management team and visited several locations (both with and without company management). These meetings and visits solidified for us the sales process and the sales team and customer assignment procedures (which we subsequently refer to in our discussion of endogeneity). Once we had a good understanding of these issues, we collected sales data at the transaction level for all the company-owned stores across the country from 2016-2019. We decided to use the fiscal year 2017-2018 for the analysis,[3] which gave us over 7 million transactions for our sample. We cleaned the dataset using the data handling libraries in Python (Van Rossum and Drake 2011). With a median ticket size of $62.99 per sale, sales that were above the 99th percentile (tickets over $233) were excluded from the analyses as they are likely special orders and services that are not frequent, and as such not

[3] We ran the estimations with the other fiscal years and found analogous results, with similar magnitudes, directions, and significance.

representative of the normal sales process. Our selection process also left out transactions that did not include the standard vehicle maintenance service offered by the firm, as those transactions are also not representative of the normal sales process. The analyses presented in the results section use the rest of the data, which is a little over 6 million independent observations grouped across 462 stores.

Generalizability

The findings of our analyses are informative and likely to be transferable to a large number of sales settings. Contributing to this ecological validity are the general attributes of the automotive services industry. The services provided by an automotive maintenance and repair provider are specialized, but not unique, just like many other settings. Appropriate training is required to provide vehicle maintenance and repair successfully. This training generally does not require a high degree of expert knowledge. In other words, although it is not just anybody who can provide high quality maintenance and repair for a vehicle, acquiring the expertise is not so difficult that only a selected few would be able to provide the service. Similar training and specialization requirements are common to other industries.

The economics of the automotive services and repair market also contribute to the generalizability of the findings. The vehicle maintenance and repair market is not highly concentrated, and there is ample competition in the market. The absence of an oligopoly with distorted demand and supply functions, is shared across most industries. The vehicle maintenance and repair market is a high-frequency market. Most vehicles require regular maintenance around every 5,000 miles, which results in a car shop visit every three to four months, according to the average mileage data of the US Department of Transportation (USDOT 2018). High-frequency products and services sales settings are abundant.

The specific sales format at the partner firm is another aspect that contributes to the generalizability of the findings. In a vehicle maintenance and repair store from this firm (and most of their competitors), sales are based on a standard basic service that can be upsold with replacement of parts and/or additional services. Successful sales teams will be able to upsell to customers who come to the store with the basic service in mind. This upsell of a basic product or service setup not only produces an interesting variance in the size of the sales ticket, but it is also popular in other sales contexts. Sales in the automotive service industry rely heavily on repeat purchases for the cash flow from operating activities. As such, loyalty plays an important role in the revenue stream, a characteristic of sales in many other industries. The incentive structure of the partner firm does not have any bonuses or commissions for salespeople, which is also a common feature to other sales settings. Finally, the firm partner firm operates all across the US, which contributes to generalizability across geographic and demographic lines.

Sales Process Setup

To better understand how the variables used in the analyses were operationalized, a description of the sales process is highly informative. At any of the stores for this automotive service firm customers drive to the store and are greeted by a staff member who directs them to the next available service bay. The assignment of the customer to a service bay follows a first-come-first-serve queue. In this firm, the store managers decide how many people they will assign to each service bay based on the average load of the stores and the number of team members available.

Each service bay has three positions where staff perform different duties. Below the service bay one employee is servicing the parts that are accessible only through the bottom of the vehicle – we call this person the *bottom*. In front of the car a second employee is servicing the parts that can be accessed through the hood – we call this team member the *top*. A third employee is talking with the customer, who remains in the car as it is being serviced, we call this person the *customer service representative* - *csr*. The *bottom* working underneath the car has no contact with the customer. The *top* working under the hood and the *csr* at the window with the customer are the ones who do most of the customer interaction, describing what the service will entail and doing most of the upsell/cross-selling efforts. With this setup, although three people comprise the full service-bay team, the sales team boundaries are more accurately defined when including only the two customer-facing employees (*top* and *csr*) as the sales team, since they are the ones doing the sales efforts.

Endogeneity Concerns

Addressing potential sources of endogeneity is important for the internal validity of the analysis (Papies, Ebbes, and Van Heerde 2017). The most important source of endogeneity in the result would come from self-selection of teams to customers with either higher sales potential or with easier sales. The random assignment of customers to service bays on a first-come first-serve basis rules out this selection bias as a potential explanation of the results and the endogeneity of sales team on sales potential or sales effort. Sales teams cannot know *a priori* if the customer that is driving into their assigned bay will be an easy sell or has a high potential, nor can the team change bays or switch the customer to a different bay. Furthermore, the incentive structure that the firm uses would also help rule out self-selection of managers into sales teams to maximize sales. Salespeople at the firm have a 100% salary compensation, no commission on sales. Sales managers, meanwhile, have an incentive as part of their pay. This incentive, however, is based on the *total amount of customers* that they service in a month, not on the amount of sales or sales per customer. If anything, such an incentive structure would be more likely to motivate sales managers to increase the speed at which customers are serviced, which would be contrary to joining sales teams to increase the sales per ticket.

Another concern about endogeneity in the results could come from the assignment of store managers to bays by staff needs. Under company policy, managers are asked to avoid getting involved as part of the sales team as a result of a shortage of staff, ruling out the possibility of manager involvement in sales based on staffing needs. We test the effect of staffing on manager involvement by regressing the number of sales transactions with managers on monthly staffing and find no statistically significant effect of staffing on manager involvement.

Nevertheless, managers can volitionally decide to be a part of the sales teams in any of the three roles if they choose to, which they may do for a number of reasons. Managers may choose to become part of a team to give a team member a break, to train a new employee, or simply to stay busy (some of them admit they miss it).

From this volitional assignment of managers to bays, however, another source of endogeneity may arise. It could be argued that there is a self-selection of managers into bays with easier sales or at least higher potential sales (e.g., with luxury cars). The service bays are equipped with computers to track customer data and provide guidance to the staff at the bay. The staff assigned to each bay has to log in to these computers when they are assigned to the bay and log out when they are going on breaks or ending their shifts. With this setup, although it not likely, it cannot be ruled out that a manager would decide to step into a team and log in to the service bay computer if they feel like they could maximize the sale. The company policies would not help address this concern.

We address this concern with a statistical approach by comparing the proportions of each team configuration across car brands. Luxury brands that could potentially be identified as having more sales potential (van Heerde, Srinivasan, and Dekimpe 2010). If the likelihood of managers selling is not statistically different for luxury versus non-luxury brands, the effects on sales could not be attributed to sales manager self-selection into teams with greater potential. Using a Kruskal-Wallis H-test (Kruskal and Wallis 1952) – a multi-category generalization of the Mann-Whitney (Mann and Whitney 1947) stochastic dominance test – we compare the proportions of transactions with and without managers for 4 different[4] brands (two luxury and two non-luxury) can be seen in Table 2.

Table 2: Different manager involvement configurations by brand

	Car Brand			
Configuration	LuxA	LuxB	NoLuxA	NoLuxB
No manager	73.7%	75.0%	75.2%	75.5%
With manager	24.6%	23.4%	23.1%	22.9%

The proportions of with- and without-manager teams are not statistically different across car brands. Given this result, the concern about self-selection of managers into higher sales potential transactions is alleviated.

[4] The tests were done with other subsets of brands and the results were similar in magnitude and significance.

Model Specification and Identification

As described in the data section, the stores have two customer-facing positions, the *top* and the *csr*. Although it is feasible that the same person performs both functions (*csr* and *top*), this is a rather rare occurrence for transactions that require the basic service and the transactions that do meet this criterion are excluded of the analyses. As managers walk around the store, they can decide to become a part of a sales team in the store by taking on either of those two roles in a bay. The sales team can then have one of four different configurations: (1) *top* and *csr* are not managers (team with no managers), a mix where either (2) *top* is a manager but *csr* is not a manager or (3) *top* is not a manager but *csr* is a manager (team with a manager), and finally (4) a setup where both *top* and *csr* are managers (team with only managers). The last case is a rare occurrence (less than 2% of the data) and as such we do not include it in the analysis.

The first set of hypothesized effects occur at the individual transaction level. To gain insight about what manager selling does to the sales ticket sizes each transaction in the data is coded to reflect the three possible sales team configurations. Any customer-facing role being done by a manager is coded as 1 (0 otherwise) for each transaction. This coding is used to create a qualitative variable for managers involved as part of sales teams (*Invol*) that takes three values: one for teams with no managers (0,0), a second value for teams with a manager as *top* (1,0), and a third value for teams with a manager as *csr* (0,1). Almost three quarters of the transactions in the data (74.8%) fall in the manager team category. Less than a quarter (23.5%) of the sales in the data have one manager, with the remaining of the transactions (1.7%) being tended by teams of only managers (which were excluded from the analyses). The initial model measuring managers as part of sales teams at the transaction level regresses individual ticket value in USD of each transaction (*Sales)* on the different levels of manager involvement for the invoice (*Invol*), and is stated formally as:

$$Sales = \alpha_0 + \beta\ Invol + \lambda + \delta + \psi + \theta\ Csr + \Gamma\ Top + \epsilon \qquad \textit{Eq. 1}$$

If there is an effect of managers selling on sales outcomes, competing explanations of the results could either be that managers are more experienced and/or that asymmetry of genders and/or ages could bring biases in the results. Therefore, the specification of this model uses vectors of employee data to control for tenure, age, race, education level, and gender of the *csr* (θ) and the *top* (Γ). By controlling for these variables, the model aims to isolate the effects of sales managers being part of the sales teams on the individual transactions.

Given that each store is likely to have different clientele, geographic conditions, regional cultural differences, weather, etc., it is a safe assumption that there would be differences between stores and regions that could confound the effects of manager involvement on sales. We use the store identifiers for an estimation of panel models with fixed effects (δ) for each store. Another potential source of bias is self-selection of managers into the sales teams due to the staffing of the stores. To account for this, the monthly level of staffing per store is included (λ). Finally, to account for potential seasonality differences, indicators (ψ) for the different seasons (spring, summer, autumn, and winter) are also included.

It is also logical to assume that not all customers will react to sales efforts of sales teams the same way. These unobserved idiosyncratic differences between customers result in unobserved variation of sales being different across customers, which in statistical terms, implies that the error term in the model is unlikely to be homoscedastic. To account for heteroskedasticity, the model uses clustered robust standard errors (ϵ), using the stores as cluster units, as the customers of each store are more likely to have correlated unobserved variation.

As it was discussed in the theoretical context section, boundary conditions to how manager selling activities maximize returns are crucial to provide guidance for firms on how to allocate sales managers' time. We use some of the customer information in the data to evaluate the hypothesized moderators. The first moderator assessed in this research is customer stage. Following the firm's policies, a customer is considered *new* when they either do not have a history with the firm at all or when they have not had a visit to any store in two years or more. This setup allows us to create a qualitative variable (*New*) to indicate the customer type, where 1 identifies a new customer (0 otherwise). These identifiers are included as interactions in the initial sales model to measure the effects of sales managers being part of sales teams on sales performance conditional on being a new (returning) customer.

The other boundary condition evaluated is the product usage intensity. To obtain the product usage intensity for each transaction, the mileage and model-year of each vehicle serviced are used. For every model-year in the dataset the mileage is split into five quantiles. The quantile category for the vehicle in each transaction is used to classify them as low product usage (first quantile), high product usage (last quantile), or median product usage (median quantile). These identifiers of product usage are used to construct the three-level qualitative variable (*Usage*) included in interactions in the initial sales model. This model measures the effects of different sales team configurations on sales conditional on each product usage level. The model is specified as:

$$\begin{aligned} Sales = \alpha_0 + \beta\ Invol + \Lambda\ New * Invol + \Phi\ Usage * Invol + \lambda + \delta + \psi \\ + \theta\ Csr + \Gamma\ Top + \epsilon \end{aligned} \qquad \textit{Eq. 2}$$

To evaluate the stores' implications of managers selling, measures at the store level are necessary. To obtain a store sales variable (*Daily*), we simply sum all the sales in a store per day. For a store level measure of manager selling activity, the process is slightly more involved. We use the proportion of daily sales where managers are involved as customer facing team members. We first sum the count of managers involved across all the sales of a store per day. We then divide this sum by the total number of invoices per store per day to construct a daily store level measure of manager sales involvement (*StoreMI*). This store manager sales involvement measure represents the percentage of the daily sales in a store that has managers involved in sales, regardless of what customer-facing role they are performing, *top*, or *csr*.

The store level variables allow for a data driven exploration of the relationship between the sales of a store and manager involvement in sales. The choice of model provides the opportunity to find what the relationship is more likely to look like. For example, choosing a linear model would be assuming that the relationship between manager involvement and store sales is monotonically increasing, implying that more manager involvement would unequivocally result in higher sales. Choosing a log-linear model, on the other hand, would assume some form of exponential growth, which could imply that the as manager involvement increases, sales multiply exponentially.

Our theoretical discussion suggests that there might be a "sweet spot" of manager involvement in sales that produces optimal store sales results, where either too little or too much manager selling would be detrimental to sales. To find out if that is the case, a series of fractional polynomial models (Royston and Altman 1994) using the store level variables are estimated. Using different polynomial expressions of the manager involvement in sales in a model of daily store sales would guide a better understanding of the nature of the relationship between manager involvement in sales teams and sales. Furthermore, using fractional polynomials instead of a traditional linear or a simple polynomial approach, delivers more flexibility in the model fit. The models used in the analyses are therefore linear in parameters but polynomial on *StoreMI*, following the subsequent specification:

$$Daily = \alpha_0 + \alpha_1 StorMI^{p_1} + \alpha_2 StoreMI^{p_2} + \cdots + \alpha_k StoreMI^{p_k} + \lambda + \delta + \psi + \epsilon \qquad Eq.\ 3$$

This store sales model includes the store fixed effects, staffing, seasonality, and clustered robust standard errors that were included in the transaction level models. Following the instructions of Royston and Sauerbrei (2008) to use the same power multiple times in the model without collinearity, when the model uses a term *k* times, it multiplies each term with the same power by the natural logarithm of the independent variable to a power of *k-1*. For example, if a cubic term of the *StoreMI* is used three times, *k*=3, the first cubic term, $k-1=0$, of *StoreMI* is included without multiplying it by the natural logarithm, e.g. $StoreMI^{3.}$ The second cubic term, $k-1=1$, is constructed by multiplying *StoreMI* cubed times the natural log of *StoreMI*, e.g. $StoreMI^3 * \ln(StoreMI)$. The third term, $k-1=2$, is built with StoreMI cubed times the square of the natural log of *StoreMI*, e.g. $StoreMI^3 * \ln(StoreMI)^2$.

CHAPTER IV

RESULTS

Manager Involvement Effects on Sales Transactions

A linear model with indicator variables for the different team configurations and control variables (Equation 1) is used to explore the effects on sales of having managers involved in the sales process relative to teams without managers. The estimation used the team with no manager as the baseline category. The results of the estimation are in the first column of Table 3. Most of the employee characteristics that were included as control variables were not statistically significant. The ones that are statistically significant are the age of the *csr* and *top* and having a college education for *csr* and *top*. These results indicate, unsurprisingly, that regardless of rank and role, older customer facing employees and employees with a college education sell more. These results rule out potential alternative explanations of the results, such as the level of experience (reflected by the tenure of the employees). The seasonality indicator variables are negative, indicating that sales are lower in all seasons relative to spring. The level of staffing of the stores impacts sales negatively, but as mentioned earlier the number of invoices with managers is not impacted by how staffed the stores are, ruling out a self-selection of managers into transactions when stores are not fully staffed.

As for the effect of sales managers getting involved in sales transactions while controlling for other factors, this is captured by the estimated parameter in the first row of the first column of Table 3. This estimate indicates that a team with a manager has a positive and statistically significant effect on sales relative to the no-manager baseline. The interpretation of this result is easier when looking at the marginal effects of the different configurations, i.e., the forecasted sales for teams with and without managers. The estimated marginal effects are in Table 4 with the first three rows of the first column show the estimates for each sales team configuration. The sales teams without mangers have lower sales ($69.29) than teams where at least one of the customer-facing jobs is being done by a manager ($71.99 and $74.00), a statistically significant difference ($p < 0.01$), providing support for hypothesis 1.

Although teams with managers have better performance than teams without managers, the difference in sales between teams where the sales manager performs one role or the other needs to be addressed. In the empirical context where we test our hypotheses sales teams with managers can have managers in any of the customer facing positions (*csr* or *top*). One potential explanation would be that since sales managers in this setting are often salespeople that were promoted, they are better skilled at selling, suggesting that teams with managers having more customer facing time would perform better (manager as *csr*). This is not the result we find but rather the opposite.

Table 3: Fixed-effects panel regressions of sales with different manager involvement configurations, customer stage, and product relationship stages

Variable	Base model		With moderators	
Team w/manager	2.29*	(0.18)	2.31*	(0.18)
New customer			-1.99*	(0.09)
New w/manager			0.22*	(0.09)
Low usage			-0.91*	(0.11)
Low w/manager			-0.19	(0.13)
High usage			3.17*	(0.13)
High w/manager			0.22	(0.14)
Tenure *Csr*	-2.75e04	(7.17e04)	-4.01e04	(7.63e04)
Tenure *Top*	4.86e03	(6.16e03)	4.74e03	(6.07e03)
Age *Csr*	0.10*	(0.01)	0.10*	(0.01)
Age *Top*	0.02*	(0.00)	0.02*	(0.00)
Female *Csr*	0.08	(0.19)	0.07	(0.19)
Female *Top*	-0.13	(0.09)	-0.14	(0.09)
Race *Csr*				
Black	0.13	(0.25)	0.12	(0.25)
Latino	-0.21	(0.40)	-0.22	(0.40)
Other race	0.24	(0.67)	0.25	(0.67)
Race *Top*				
Black	-0.51	(0.79)	-0.52	(0.79)
Latino	0.01	(0.11)	0.01	(0.11)
Other race	0.46	(0.18)	0.45	(0.18)
Education *Csr*				
Trade/Tech	0.12	(0.49)	0.11	(0.49)
College	0.78*	(0.19)	0.78*	(0.19)
Education *Top*				
Trade/Tech	0.08	(0.18)	0.07	(0.18)
College	0.19*	(0.06)	0.19*	(0.06)
Store staffing	-0.88*	(0.32)	-0.95*	(0.32)
Season				
Summer	-0.19*	(0.09)	-0.28*	(0.10)
Fall	-0.72*	(0.10)	-0.66*	(0.10)
Winter	-1.05*	(0.10)	-0.97*	(0.10)
Intercept	66.07*	(0.41)	66.08*	(0.41)
Sample size		6,029,514		6,029,514
Log-likelihood		-29,359,060		-29,351,901
AIC		58,718,175		58,703,875
BIC		58,718,542		58,704,378

Cluster robust standard errors in parentheses. Significance at the 1% is denoted by *.

Furthermore, in teams where managers are doing most of the customer facing (*csr* position), it could also be argued that managers' status could be influencing customers in the transactions. If customers know that they are being serviced by a manager some status effects (Hu and Van den Bulte 2014) could increase the size of the sales ticket. This can be ruled out because the staff at the store cannot be identified by rank without prior knowledge. The staff wears are identical uniforms regardless of rank and while each team member has a name tag, this tag has no indication of the rank. These conditions suggest neither status effects nor manager sales expertise would be driving the increase in sales relative to the no-manager teams.

Table 4: Marginal effects sales with different manager involvement configurations, customer types, and product life cycle stages

Condition	Base model		By Customer Stage		By Product Stage	
Involvement						
No manager	69.29	(0.03)				
With manager						
1,0	71.99	(0.17)				
0,1	74.00	(0.13)				
New						
New no manager			67.50	(0.08)		
New w/manager			69.99	(0.17)		
Ret. no manager			70.99	(0.05)		
Ret. w/manager			72.34	(0.14)		
Usage intensity						
Low no manager					67.51	(0.12)
Low w/manager					70.15	(0.15)
Median no manager					68.49	(0.07)
Median w/manager					71.35	(0.10)
High no manager					71.69	(0.13)
High w/manager					74.88	(0.15)

Cluster robust standard errors in parentheses.

The difference between team configurations with managers can be explained with the specific setup of the firm. As mentioned in the methodology section, every service bay is equipped with a computer terminal where the transactions are registered, and sales teams log in to identify themselves as the team in charge of each transaction. The computer terminals also provide guidance to the *csr* on which services can be upsold/cross-sold based on the manufacturer's recommendations, usage, previous visits (for returning customers), etc. Given sales managers are incentivized to maximize the number of customers they service per month, sales managers in the *csr* position could be less likely to follow the recommendations if that would slow down the sale. Meanwhile, salespeople who are *csr* will exert effort to upsell and cross-sell the recommendations with their sales manager watching at the *top* position. More research would be needed to pinpoint precisely if this is the case.

Manager Involvement and Customer Stage

We proposed earlier that the effect of manager involvement on sales could be different for new and returning customers. The second columns of table 3 show the results of the estimation of a model where the effects of manager involvement on sales conditional on the moderators are calculated (Equation 2). The parameter estimate for the new customer indicator is negative, which implies that new customers have lower sales than returning customers. The parameter estimates for the interactions between manger involvement and customer stage is positive and statistically significant, which means that manager involvement increases the ticket size for both customers stages, but the effect is stronger for new customers.

Once again, the marginal effects can be of help for better understanding of this relationship. The middle columns of Table 4 show the predicted sales for each configuration. Just like in the unconditional estimation, manager involvement in sales transactions yields higher sales for both customer stages, but the effect is stronger for new customers than for returning customers. This relationship between manager involvement with customer stage is better illustrated graphically (Figure 1).

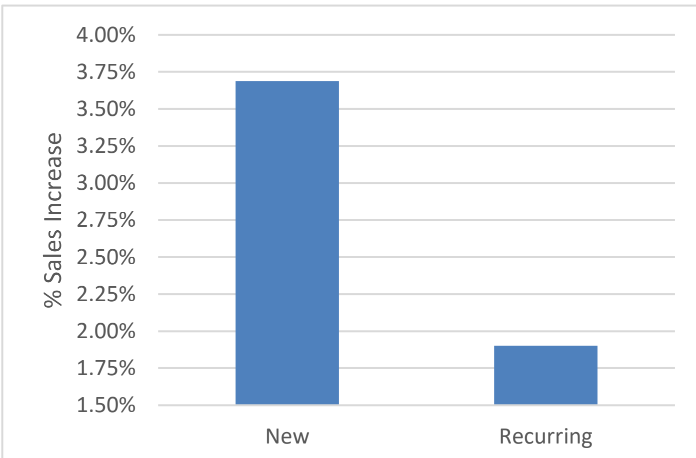

Figure 1: Increases in Sales by Team Configuration for New and Returning Customers

The graph in Figure 1 illustrates that although a sales team with a manager performs better than a team with no managers with a returning customer, the effect is stronger for new customers (3.7% vs. 1.9%, $p < 0.01$). The difference for these increases in sales is statistically significant, a result that supports hypothesis 2, indicating managers are more effective in increasing sales ticket size for new customers than for returning customers.

Manager Involvement and Product Usage

Another condition we proposed that would maximize the benefits of manager involvement in sales is the product stage. The last columns of table 3 have the results of the estimation of the effects of manager involvement conditional on product stage. The parameter estimate for low usage intensity is negative and statistically significant, which means that customers with low usage intensity vehicles have lower sales that vehicles with median product usage. The parameter estimate for vehicles with high usage intensity is positive and statistically significant, indicating that sales for customers with these vehicles are higher than sales for customers with vehicles at the median usage. The parameter estimates of the interactions are not statistically significant, meaning that the differences in sales by usage intensity is not coming from the involvement of managers in the sales transaction.

For a better grasp what happens with sales manager involvement across usage intensity, let us take look at the marginal effects shown in the last rows of Table 4. The results show that manager involvement yields a higher sales ticket for all product usages. The increase in sales generated by a team with managers relative to a no-manager team are higher for the high usage intensity ($72.01 vs. $75.57), than they are for the products at the median ($68.75 vs. $72.07) or low usage ($67.73 vs. $70.85). These differences across the usage intensity are all statistically different ($p < 0.01$).

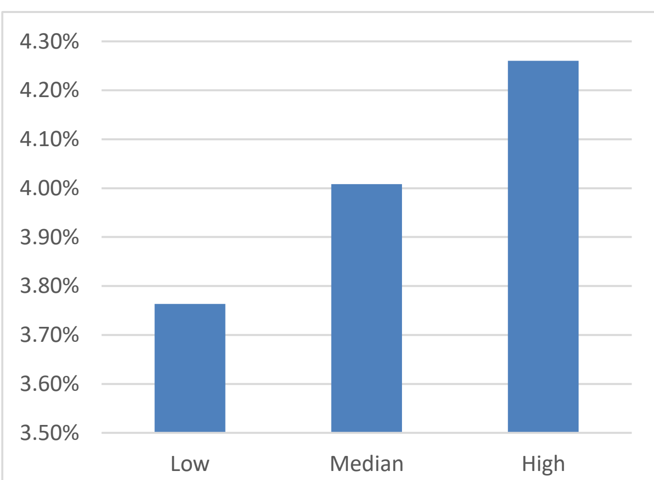

Figure 2: Increases in Ticket Size with Teams of Managers by Usage Intensity

Once again, a graphical representation of these results aids the interpretation of the findings. The increases in sales from teams with managers relative to no-manager teams are shown in Figure 2. The increase in sales for customers whose vehicles with low usage intensity are the lowest from all three (3.8%), followed by products with median usage (4.0%), and products with high usage intensity having the highest sales difference (4.3%). This result shows that manager involvement is more effective in increasing sales ticket size for customers as product usage intensity increases, which does not fully support hypothesis 3. One potential explanation for this result is that low usage intensity vehicles require less maintenance than the other levels of usage intensity, which would make the customers who own them less susceptible to sales efforts. More research is needed to understand this relationship.

Manager Involvement Effects on Store Sales

To test whether manager involvement has an effect at the store sales, we use the model described by Equation 3. The estimations use machine learning techniques to take advantage of the large size of the data, have a data driven exploration of the relationship between the variables of interest, and to reduce the possibility of introducing our own biases into the results.

A machine learning algorithm was designed to test a model with as many as ten terms (a tenth-degree polynomial) while potentiating each and any of the terms by the natural numbers up to the tenth power, trying all the permutations of these two criteria (dimension and powers) on the same independent variable (*StoreMI*). The algorithm was programmed to minimizing the log-likelihood (LL) to select the best model fit, avoiding bias in the selection of the polynomial degree and powers. The algorithm seeks for the best model by testing model improvement using a likelihood ratio test (Greene 2012) on the differences between the LL of the latest model and the LL of the previous one. The algorithm stops when the improvement in model fit ceases to be statistically significant at the 5% level. The model chosen by the algorithm is the last one that produced a statistically significant improvement.

The results of the algorithm indicated that the best fit for the store sales data is achieved with a polynomial of the fifth degree with three linear terms and a quintic term. This means that the model that fits the daily stores sales data the best includes the manager involvement variable (*StoreMI*) three times and the same variable to the fifth power. Although the algorithm chooses the model with the best possible fit, a different model can be chosen for other reasons such as parsimony using other fit measures such as the Akaike information criteria (AIC) or the Bayesian information criteria (BIC). The next best model fit was achieved by a model with a linear term and half a power. We chose to report the results from this model instead of the best model because it has a better BIC and it is easier to interpret[5].

[5] The results from the best model are available upon request. The interpretation of that model gives similar results.

Table 5: Polynomial regression of total daily sales

Variable	Total Daily Sales	
Manager Involvement		
Linear	259.13*	(26.30)
Half power	-663.57*	(22.02)
Store staffing	4.45	(22.65)
Season		
Winter	-98.66*	(7.18)
Spring	54.22*	(7.46)
Summer	209.55*	(8.18)
Intercept	2233.66*	(19.08)
Sample size	156,833	
Log-likelihood	-1,246,108	
AIC	2,492,228	
BIC	2,492,288	

Cluster robust standard errors in parentheses. Significance at the 1% is denoted by *. The model is fit using the daily store sales, thus the smaller sample size.

The output of the estimation of this model is shown in Table 5. The linear and non-linear terms of manager involvement are all statistically significant. What the parameter estimates mean is that manager involvement in transactions initially increases sales, then changes direction and decreases, but at a slower rate than the initial increase. These results are better demonstrated in graphical form (Figure 3). In the graph the initial growth in sales, the inflection, and subsequent decrease can be easily seen. In practice, these results imply that store sales increase as managers get involved in more transactions, up to a certain point at which store sales reach their maximum level, and then decline as a higher percentage of transactions have managers in them. These results support hypothesis 4, indicating that the relationship between manager involvement in sales transactions and the sales of the stores follows a concave function.

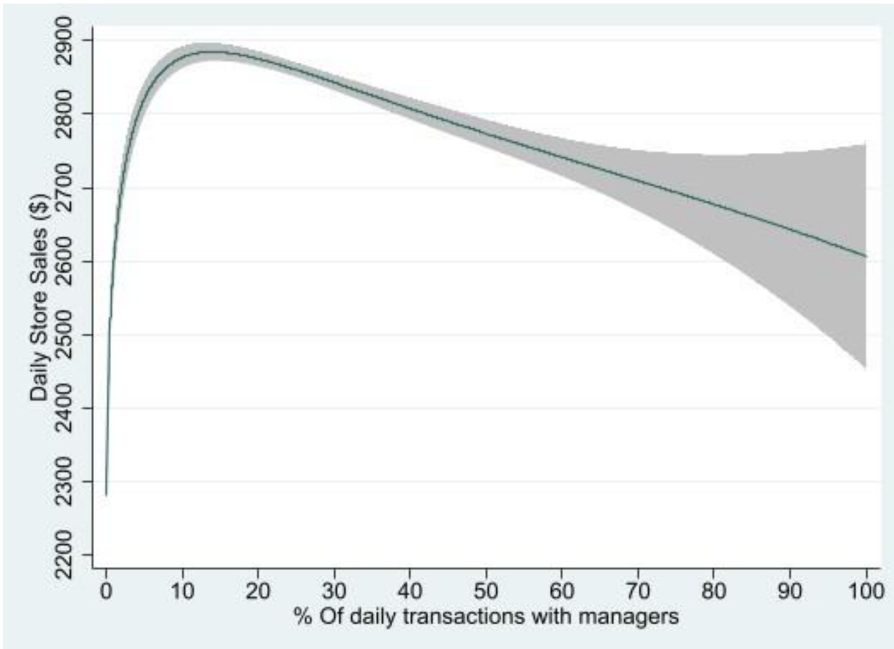

Figure 3: Daily Store Sales and Daily Transactions with Managers

CHAPTER V

IMPLICATIONS AND LIMITATIONS

Sales managers play an important role in sales organizations. The age-old question on whether sales managers should be selling with their teams has a nuanced answer. Managers supervisory role include recruiting, hiring, and monitoring performance. At the same time managers can provide coaching, motivation, and guidance to teams when they are selling with them. Without proper guidance from practitioners on when and how sales managers should get involved with their teams and with the scarce literature on the selling roles of managers, the present research seeks to provide some advice on this topic.

Managerial Implications

The practical implications of the findings are straightforward. Managers should be involved in the sales of their teams, no doubt. Our results show that relative to a team with no managers, the sales ticket is over 3% higher when a sales team has a manager. This relationship between manager involvement and ticket size would suggest managers get involved in as many transactions as they can, but it is not feasible or recommendable, to have managers always involved in the sales process.

Managers add value when engaging in other tasks and as the scarce resource that they should prioritize their time where it can produce the best outcome. To help firms decide on the sales managers' time allocation, firms can use *customer type* and *product usage intensity*, external factors to the teams, as possible tools to help decide which customers should get the manager treatment in order to maximize sales. By focusing on onboarding of new customers and tending to customers with high usage intensity products, managers are maximizing the effect of their presence on the sales team. Managers, however, should be cautious about not neglecting the supervisory duties as a result of involvement in the sales, as that would prove detrimental to the performance of the store. There is such a thing as “too much of a good thing” when it comes to sales managers selling.

Contributions to the Literature

The current study contributes to the sales literature by providing one of the few explorations of the selling role of managers. The existing literature mostly views managers as an organizational aspect of sales teams (Heaphy and Dutton 2008) [see Table 1], meaning that it focuses mostly on exploring the supervisory roles of managers. The gap in this literature can be bridged by exploring the impact on the performance of teams of having managers selling, not just supervising. Given the growing number of situations where sales managers are called upon and have the opportunity to become part of their teams, this research is timely.

Our research also contributes to the extant teams’ literature. In particular, the team composition literature has not included managers as part of teams. For example, team composition literature posits that heterogeneous teams exert more effort in contests than homogeneous teams, impacting performance (Chen and Lim 2017). A team that includes managers would be more heterogeneous than a team comprised of subordinates, so it is important to examine this form of heterogeneity in team composition. Research on team composition acknowledges that hierarchical structure and differences in hierarchy of team members impacts performance, finding that a structure where more members have high authority enhances team performance relative to a structure with the opposite distribution of authority (Wellman et al. 2019). This research stream does not explore managers as part of those teams, although these clearly impact the hierarchical structure and are different in their hierarchy to the rest of the team, presenting a potentially rich opportunity for research.

Limitations and Future Research Opportunities

As with most scientific endeavors, this research has several limitations that can be opportunities for future research. One limitation is that with the data used we are unable to identify the mechanism that makes manager involvement have a positive effect on average ticket size. In the setup of the firm where the data was gathered from, the customers cannot obviously know if the team member is a manager or not. Observant customers might be able infer the rank of their team, but there is not a way to be able to identify managers unequivocally. As such, we cannot suggest that suspect that the effect on sales coming from manager involvement is coming from customer perceptions of rank, but from the customer reactions to effort. It would be interesting, however, to find out in a context where managers are distinguishable from other team members, what are the effects of manager involvement, something that could be explored in future research.

Given the setup of the industry, another limitation of this research and avenue for future research is customer loyalty. The data does not allow for identification of the likelihood of becoming a recurrent customer based on the first experience. The literature suggests that a good first impression goes a long way in building customer loyalty. The results suggest that new customers that have had a manager team would have a better first impression based on their sales tickets. The question remains if that would make customers more likely to return. Future research could test this idea and measure the long-term value of manager involvement in the initial sale with new customers.

As it is often the case with research using secondary data, there are aspects of the interactions that cannot be identified from the data. The leadership styles of managers is one example of an aspect of the team interactions that cannot be identified from the data collected. Future research could look into how different leadership styles work with manager concentration to impact sales. The competitiveness of the work environment also cannot be observed from the data. The extant research on team composition has documented the effects of competitiveness of the work environment on team cohesion and performance. Future research could also test for these effects in the context of manager involvement.

In this exploration of the transaction and store performance effects of having sales managers be involved in their selling roles, we have been able to provide some guidance to firms, uncover interesting relationships with customer and product characteristics, and found that looking at a more holistic interpretation of the role of the sales manager is not only a worthwhile endeavor, but a necessary one. It is our hope that more work will be done to continue to help firms and scholars understand and assist the valuable resource that sales managers are.

REFERENCES

Ahearne, Michael, Till Haumann, Florian Kraus, and Jan Wieseke (2013), "It's a matter of congruence: How interpersonal identification between sales managers and salespersons shapes sales success," *Journal of the Academy of Marketing Science*, 41 (6), 625-48.

Akerlof, George A. (1970), "The Market for "Lemons": Quality Uncertainty and the Market Mechanism," *The Quarterly Journal of Economics*, 84 (3), 488-500.

Alós-Ferrer, Carlos, Dura-Georg Granić, Fei Shi, and Alexander K. Wagner (2012), "Choices and Preferences: Evidence From Implicit Choices and Response Times," *Journal of Experimental Social Psychology*, 48 (6), 1336-42.

Anderson, Donald A. and James B. Wiley (1992), "Efficient Choice Set Designs for Estimating Availability Cross-Effects Models," *Marketing Letters*, 3 (4), 357-70.

Antonakis, John, Samuel Bendahan, Philippe Jacquart, and Rafael Lalive (2010), "On Making Causal Claims: A Review and Recommendations," *The Leadership Quarterly*, 21 (6), 1086-120.

Arnold, Todd J., Robert W. Palmatier, Dhruv Grewal, and Arun Sharma (2009), "Understanding Retail Managers' Role in the Sales of Products and Services," *Journal of Retailing*, 85 (2), 129-44.

Arrow, Kenneth J. (1978), "Uncertainty and the Welfare Economics of Medical Care," in *Uncertainty in Economics*, Peter Diamond and Michael Rothschild, eds. New York, NY: Academic Press.

Atefi, Yashar, Michael Ahearne, James G. Maxham, D. Todd Donavan, and Brad D. Carlson (2018), "Does Selective Sales Force Training Work?," *Journal of Marketing Research*, 55 (5), 722-37.

Azrieli, Yaron, Christopher P. Chambers, and Paul J. Healy (2018), "Incentives in Experiments: A Theoretical Analysis," *Journal of Political Economy*, 126 (4), 1472-503.

Balcombe, Kelvin, Michael Burton, and Dan Rigby (2011), "Skew and Attribute Non-Attendance Within the Bayesian Mixed Logit Model," *Journal of Environmental Economics and Management*, 62 (3), 446-61.

Baltussen, Guido, G. Thierry Post, Martijn J. van den Assem, and Peter P. Wakker (2012), "Random Incentive Systems in a Dynamic Choice Experiment," *Experimental Economics*, 15 (3), 418-43.

Banks, James, Cormac O' Dea, and Zoë Oldfield (2010), "Cognitive Function, Numeracy and Retirement Saving Trajectories," *The Economic Journal*, 120 (548), F381-F410.

Bardsley, Nicholas (2005), "Experimental Economics and the Artificiality of Alteration," *Journal of Economic Methodology*, 12 (2), 239-51.

Bates, John (1988), "Econometric Issues in Stated Preference Analysis," *Journal of Transport Economics and Policy*, 22 (1), 59-69.

Batsell, Richard R. and John C. Polking (1985), "A New Class of Market Share Models," *Marketing Science*, 4 (3), 177-98.

Baumeister, Roy F. and Kathleen D. Vohs (2007), "Self-Regulation, Ego Depletion, and Motivation," *Social and Personality Psychology Compass*, 1 (1), 115-28.

Beck, Matthew J., Simon Fifer, and John M. Rose (2016), "Can You Ever Be Certain? Reducing Hypothetical Bias in Stated Choice Experiments via Respondent Reported Choice Certainty," *Transportation Research Part B: Methodological*, 89, 149-67.

Becker, Gary S. (1985), "Human Capital, Effort, and the Sexual Division of Labor," *Journal of Labor Economics*, 3 (1, Part 2), S33-S58.

Bello, Muhammad and Awudu Abdulai (2016), "Impact of Ex-Ante Hypothetical Bias Mitigation Methods on Attribute Non-Attendance in Choice Experiments," *American Journal of Agricultural Economics*, 98 (5), 1486-506.

Berry, Christopher, Scot Burton, and Elizabeth Howlett (2017), "It's Only Natural: The Mediating Impact of Consumers' Attribute Inferences on the Relationships Between Product Claims, Perceived Product Healthfulness, and Purchase Intentions," *Journal of the Academy of Marketing Science*, 45 (5), 698-719.

Blomquist, Glenn C., Karen Blumenschein, and Magnus Johannesson (2009), "Eliciting Willingness to Pay Without Bias Using Follow-up Certainty Statements: Comparisons Between Probably/Definitely and a 10-point Certainty Scale," *Environmental and Resource Economics*, 43 (4), 473-502.

BLS, Bureau of Labor Statistics (2020), "National Occupational Employment and Wage Estimates," 2021), [available at https://data.bls.gov/oes/#/occInd/One%20occupation%20for%20multiple%20industries].

Bonsall, Peter (1985), Transfer Price Data-Its Definition, Collection and Use. Utrecht: VNU Science Press.

Börger, Tobias (2016), "Are Fast Responses More Random? Testing the Effect of Response Time on Scale in an Online Choice Experiment," *Environmental and Resource Economics*, 65 (2), 389-413.

Braga, Jacinto and Chris Starmer (2005), "Preference Anomalies, Preference Elicitation and the Discovered Preference Hypothesis," *Environmental and Resource Economics*, 32 (1), 55-89.

Brock, William A. and Steven N. Durlauf (2001), "Discrete Choice With Social Interactions," *The Review of Economic Studies*, 68 (2), 235-60.

Brown, Alexander L. and Paul J. Healy (2018), "Separated Decisions," *European Economic Review*, 101, 20-34.

Brown, Morton B. and Alan B. Forsythe (1974), "Robust Tests for the Equality of Variances," *Journal of the American Statistical Association*, 69 (346), 364-67.

Bryant, Peter G. and E. Woodrow Eckard (1991), "Price Fixing: The Probability of Getting Caught," *The Review of Economics and Statistics*, 73 (3), 531.

Bultez, Alain V. and Philippe A. Naert (1975), "Consistent Sum-Constrained Models," *Journal of the American Statistical Association*, 70 (351a), 529-35.

Camerer, Colin, George Loewenstein, and Drazen Prelec (2005), "Neuroeconomics: How Neuroscience Can Inform Economics," *Journal of Economic Literature*, 43 (1), 9-64.

Campitelli, Guillermo and Martín Labollita (2010), "Correlations of Cognitive Reflection With Judgments and Choices," *Judgment and Decision Making*, 5 (3), 182.

CareerBuilder (2020), "The career of a retail sales manager," 2020), [available at https://www.careerbuilder.com/advice/the-career-of-a-retail-sales-manager].

Carson, Richard T., Theodore Groves, and John A. List (2014), "Consequentiality: A Theoretical and Experimental Exploration of a Single Binary Choice," *Journal of the Association of Environmental and Resource Economists*, 1 (1/2), 171-207.

Cason, Timothy N. and Charles R. Plott (2014), "Misconceptions and Game Form Recognition: Challenges to Theories of Revealed Preference and Framing," *Journal of Political Economy*, 122 (6), 1235-70.

Cerroni, Simone, Verity Watson, Dimitrios Kalentakis, and Jennie I. Macdiarmid (2019), "Value-Elicitation and Value-Formation Properties of Discrete Choice Experiments and Experimental Auctions," *European Review of Agricultural Economics*, 46 (1), 3-27.

Chavez, Daniel, Marco Palma, and Alba Collart (2017), "Using Eye-Tracking to Model Attribute Non-Attendance in Choice Experiments," *Applied Economics Letters*, 25 (19), 1-5.

Chen, Haipeng, Howard Marmorstein, Michael Tsiros, and Akshay R. Rao (2012), "When More is Less: The Impact of Base Value Neglect on Consumer Preferences for Bonus Packs over Price Discounts," *Journal of Marketing*, 76 (4), 64-77.

Chiappori, Pierre‐Andre and Bernard Salanie (2000), "Testing for Asymmetric Information in Insurance Markets," *Journal of Political Economy*, 108 (1), 56-78.

ChoiceMetrics (2014), "NGENE User Manual & Reference Guide." 1.1.2 ed. Sydney, AU: Choice Metrics.

Chou, Eileen, Margaret McConnell, Rosemarie Nagel, and Charles R. Plott (2009), "The Control of Game Form Recognition in Experiments: Understanding Dominant Strategy Failures in a Simple Two Person "Guessing" Game," *Experimental Economics,* 12 (2), 159-79.

Collins, Jill P. and Christian A. Vossler (2009), "Incentive Compatibility Tests of Choice Experiment Value Elicitation Questions," *Journal of Environmental Economics and Management*, 58 (2), 226-35.

Colson, Gregory, Jay R. Corrigan, Carola Grebitus, Maria L. Loureiro, and Matthew C. Rousu (2016), "Which Deceptive Practices, If Any, Should Be Allowed in Experimental Economics Research? Results from Surveys of Applied Experimental Economists and Students," *American Journal of Agricultural Economics*, 98 (2), 610-21.

Corcoran, Kevin J. and Julian B. Rotter (1987), "Morality-Conscience Guilt Scale as a Predictor of Ethical Behavior in a Cheating Situation Among College Females," *The Journal of General Psychology*, 114 (2), 117-23.

Coursey, Don L., John L. Hovis, and William D. Schulze (1987), "The Disparity Between Willingness to Accept and Willingness to Pay Measures of Value," *The Quarterly Journal of Economics*, 102 (3), 679-90.

Darby, Michael R and Edi Karni (1973), "Free Competition and the Optimal Amount of Fraud," *The Journal of Law and Economics*, 16 (1), 67-88.

de-Magistris, Tiziana, Azucena Gracia, and Jr Rodolfo M. Nayga (2013), "On the Use of Honesty Priming Tasks to Mitigate Hypothetical Bias in Choice Experiments," *American Journal of Agricultural Economics*, 95 (5), 1136-54.

de Bekker-Grob, Esther W., Mandy Ryan, and Karen Gerard (2012), "Discrete Choice Experiments in Health Economics: A Review of the Literature," *Health Economics*, 21 (2), 145-72.

Deeter-Schmelz, Dawn R., Daniel J. Goebel, and Karen Norman Kennedy (2008), "What are the Characteristics of an Effective Sales Manager? an Exploratory Study Comparing Salesperson and Sales Manager Perspectives," *Journal of Personal Selling & Sales Management*, 28 (1), 7-20.

Diamond, Peter A. and Jerry A. Hausman (1994), "Contingent Valuation: Is Some Number Better than No Number?," *Journal of Economic Perspectives*, 8 (4), 45-64.

Ding, Min, Rajdeep Grewal, and John Liechty (2005), "Incentive-Aligned Conjoint Analysis," *Journal of Marketing Research*, 42 (1), 67-82.

Dong, Songting, Min Ding, and Joel Huber (2010), "A Simple Mechanism to Incentive-Align Conjoint Experiments," *International Journal of Research in Marketing*, 27 (1), 25-32.

Dunning, David, Chip Heath, and Jerry M. Suls (2004), "Flawed Self-Assessment: Implications for Health, Education, and the Workplace," *Psychological Science in the Public Interest*, 5 (3), 69-106.

Einhäuser, Wolfgang, James Stout, Christof Koch, and Olivia Carter (2008), "Pupil Dilation Reflects Perceptual Selection and Predicts Subsequent Stability in Perceptual Rivalry," *Proceedings of the National Academy of Sciences*, 105 (5), 1704-09.

Emons, Winand (1997), "Credence Goods and Fraudulent Experts," *The RAND Journal of Economics*, 28 (1), 107-19.

Feagan, Robert B and David Morris (2009), "Consumer Quest for Embeddedness: A Case Study of the Brantford Farmers' Market," *International Journal of Consumer Studies*, 33 (3), 235-43.

Fifer, Simon, John Rose, and Stephen Greaves (2014), "Hypothetical Bias in Stated Choice Experiments: Is It a Problem? And if so, How Do We Deal With It?," *Transportation Research Part A: Policy and Practice*, 61, 164-77.

Fischbacher, Urs and Franziska Föllmi-Heusi (2013), "Lies in Disguise - An Experimental Study on Cheating," *Journal of the European Economic Association*, 11 (3), 525-47.

Frederick, Shane (2005), "Cognitive Reflection and Decision Making," *Journal of Economic Perspectives*, 19 (4), 25-42.

Friedman, Daniel and Shyam Sunder (1994), Experimental Methods : A Primer for Economists. Cambridge, UK; New York, NY: Cambridge University Press.

Gächter, Simon and Elke Renner (2010), "The Effects of (Incentivized) Belief Elicitation in Public Goods Experiments," *Experimental Economics*, 13 (3), 364-77.

Giannakas, Konstantinos (2002), "Information Asymmetries and Consumption Decisions in Organic Food Product Markets," *Canadian Journal of Agricultural Economics*, 50 (1), 35-50.

Gilmore, William and S Altan Erdem (2008), "The Future of Online Internet Marketing: A Solution to Behavioral Marketing Using Biometrics," *Journal of Business and Economics Research*, 6 (2), 23-26.

Gino, Francesca and Cassie Mogilner (2013), "Time, Money, and Morality," *Psychological Science*, 25 (2), 414-21.

Gneezy, Uri (2005), "Deception: The Role of Consequences," *American Economic Review*, 95 (1), 384-94.

Grant, Robert M. (2003), "Strategic planning in a turbulent environment: evidence from the oil majors," *Strategic Management Journal*, 24 (6), 491-517.

Grebitus, Carola and George C. Davis (2019), "Does the New Nutrition Facts Panel Help Compensate for Low Numeracy Skills? An Eye-Tracking Analysis," *Agricultural Economics*, 50 (3), 249-58.

Greene, William H. (2012), Econometric Analysis (7th ed.). Boston, MA: Prentice Hall.

Greene, William H. and David A. Hensher (2010), "Does Scale Heterogeneity Across Individuals Matter? An Empirical Assessment of Alternative Logit Models," *Transportation*, 37 (3), 413-28.

---- (2013), "Revealing Additional Dimensions of Preference Heterogeneity in a Latent Class Mixed Multinomial Logit Model," *Applied Economics*, 45 (14), 1897-902.

Grover, Joel and Matt Goldberg (2010), "False Claims, Lies Caught on Tape at Farmers Markets," in NBC Southern California.

Haghani, Milad and Majid Sarvi (2018), "Hypothetical Bias and Decision-Rule Effect in Modelling Discrete Directional Choices," *Transportation Research Part A: Policy and Practice*, 116, 361-88.

Hallagan, William (1978), "Self-Selection by Contractual Choice and the Theory of Sharecropping," *The Bell Journal of Economics*, 9 (2), 344-54.

Hensher, David A (1994), "Stated Preference Analysis of Travel Choices: The State of Practice," *Transportation*, 21 (2), 107-33.

Hensher, David A., John Rose, and William H. Greene (2005), "The Implications on Willingness to Pay of Respondents Ignoring Specific Attributes," *Transportation*, 32 (3), 203-22.

Hensher, David A., John M. Rose, and William H. Greene (2012), "Inferring Attribute Non-Attendance From Stated Choice Data: Implications for Willingness to Pay Estimates and a Warning for Stated Choice Experiment Design," *Transportation*, 39 (2), 235-45.

Herriges, Joseph, Catherine Kling, Chih Chen Liu, and Justin Tobias (2010), "What are the Consequences of Consequentiality?," *Journal of Environmental Economics and Management*, 59 (1), 67-81.

Hertwig, Ralph and Andreas Ortmann (2001), "Experimental Practices in Economics: A Methodological Challenge for Psychologists?," *Behavioral and Brain Sciences*, 24 (3), 383-403.

Heslin, Richard and Blair T. Johnson (1992), "Prior Involvement and Incentives to Pay Attention to Information," *Psychology and Marketing*, 9 (3), 209-19.

Hess, Stephane, David A. Hensher, and Andrew Daly (2012), "Not Bored Yet – Revisiting Respondent Fatigue in Stated Choice Experiments," *Transportation Research Part A: Policy and Practice*, 46 (3), 626-44.

Hoeks, Bert and Willem J. M. Levelt (1993), "Pupillary Dilation as a Measure of Attention: A Quantitative System Analysis," *Behavior Research Methods, Instruments, & Computers*, 25 (1), 16-26.

Hoffman, Elizabeth and Matthew L. Spitzer (1985), "Entitlements, Rights, and Fairness: An Experimental Examination of Subjects' Concepts of Distributive Justice," *The Journal of Legal Studies*, 14 (2), 259-97.

Hole, Arne Risa, Julie Riise Kolstad, and Dorte Gyrd-Hansen (2013), "Inferred vs. Stated Attribute Non-Attendance in Choice Experiments: A Study of Doctors' Prescription Behaviour," *Journal of Economic Behavior and Organization*, 96, 21-31.

Hölmstrom, Bengt (1979), "Moral Hazard and Observability," *The Bell Journal of Economics*, 10 (1), 74-91.

Hoppe, Eva I. and David J. Kusterer (2011), "Behavioral Biases and Cognitive Reflection," *Economics Letters*, 110 (2), 97-100.

Houston, B. Kent and David S. Holmes (1975), "Role Playing Versus Deception: The Ability of Subjects to Simulate Self-Report and Physiological Responses," *The Journal of Social Psychology*, 96 (1), 91-98.

Hoyos, David (2010), "The State of the Art of Environmental Valuation With Discrete Choice Experiments," *Ecological Economics*, 69 (8), 1595-603.

HubSpot (2020), "The Ultimate Guide to Sales Management," 2020), [available at https://blog.hubspot.com/sales/sales-management].

Hughes, Douglas E. and Jessica L. Ogilvie (2019), "When Sales Becomes Service: The Evolution of the Professional Selling Role and an Organic Model of Frontline Ambidexterity," *Journal of Service Research*, 23 (1), 22-32.

Igawa, Kazuhiro and George Kanatas (1990), "Asymmetric Information, Collateral, and Moral Hazard," *Journal of Financial and Quantitative Analysis*, 25 (4), 469-90.

iMotions (2018), "iMotions Biometric Research Platform." 6.0 ed. Copenhagen, DA: iMotions A/S.

Janssen, Ellen M., Deborah A. Marshall, A. Brett Hauber, and John F. P. Bridges (2017), "Improving the Quality of Discrete Choice Experiments in Health: How Can We Assess

Validity and Reliability?," *Expert Review of Pharmacoeconomics & Outcomes Research*, 17 (6), 531-42.

Kaplinski, Oleg and Laura Tupenaite (2011), "Review of the Multiple-Criteria Decision-Making Methods, Intelligent and Biometric Systems Applied in Modern Construction Economics," *Transformations in Business & Economics*, 10 (1), 166-81.

Karp, David (2010), "Market Watch: Farmers Market Cheating Alleged," in Los Angeles Times: Los Angeles Times.

Khushaba, Rami N., Chelsea Wise, Sarath Kodagoda, Jordan Louviere, Barbara E. Kahn, and Claudia Townsend (2013), "Consumer Neuroscience: Assessing the Brain Response to Marketing Stimuli Using Electroencephalogram (EEG) and Eye Tracking," *Expert Systems with Applications*, 40 (9), 3803-12.

Kløjgaard, Mirja Elisabeth, Mickael Bech, and Rikke Søgaard (2012), "Designing a Stated Choice Experiment: The Value of a Qualitative Process," *Journal of Choice Modelling*, 5 (2), 1-18.

Knetsch, Jack L. (1989), "The Endowment Effect and Evidence of Nonreversible Indifference Curves," *American Economic Review*, 79 (5), 1277-84.

Kouchaki, Maryam and Isaac H. Smith (2013), "The Morning Morality Effect: The Influence of Time of Day on Unethical Behavior," *Psychological Science*, 25 (1), 95-102.

Kübler, Dorothea, Wieland Müller, and Hans-Theo Normann (2008), "Job-Market Signaling and Screening: An Experimental Comparison," *Games and Economic Behavior*, 64 (1), 219-36.

Lahey, Joanna N. and Douglas Oxley (2016), "The Power of Eye Tracking in Economics Experiments," *American Economic Review*, 106 (5), 309-13.

Landry, Craig E. and John A. List (2007), "Using *Ex Ante* Approaches to Obtain Credible Signals for Value in Contingent Markets: Evidence from the Field," *American Journal of Agricultural Economics*, 89 (2), 420-29.

Lazari, Andreas G. and Donald A. Anderson (1994), "Designs of Discrete Choice Set Experiments for Estimating Both Attribute and Availability Cross Effects," *Journal of Marketing Research*, 31 (3), 375-83.

Leland, Hayne E. and David H. Pyle (1977), "Informational Asymmetries, Financial Structure, and Financial Intermediation," *The Journal of Finance*, 32 (2), 371-87.

Levitt, Steven D. and John A. List (2007), "What Do Laboratory Experiments Measuring Social Preferences Reveal About the Real World?," *Journal of Economic Perspectives*, 21 (2), 153-74.

Liebe, Ulf, Klaus Glenk, Marie von Meyer-Höfer, and Achim Spiller (2018), "A Web Survey Application of Real Choice Experiments," *Journal of Choice Modelling*, 33, 100-50.

LinkedIn (2017a), "10 Reasons Why Your Industry's Next Hire Should be a Retail Manager," 2020), [available at https://www.linkedin.com/pulse/10-reasons-why-your-industrys-next-hire-should-retail-beth-swinney/].

---- (2017b), "Sales Management Central: A Success Hub for Sales Managers," 2020), [available at https://business.linkedin.com/sales-solutions/sales-strategies-tips/sales-management-success-sales-managers].

List, John A. (2001), "Do Explicit Warnings Eliminate the Hypothetical Bias in Elicitation Procedures? Evidence From Field Auctions for Sportscards," *American Economic Review*, 91 (5), 1498-507.

List, John A. and Craig A. Gallet (2001), "What Experimental Protocol Influence Disparities Between Actual and Hypothetical Stated Values?," *Environmental and Resource Economics*, 20 (3), 241-54.

Loen, Raymond O (1964), "Sales managers must manage," *Harvard Business Review*, 42 (3), 107-14.

Loomis, John B. (1996), "How Large is the Extent of the Market for Public Goods: Evidence From a Nationwide Contingent Valuation Survey," *Applied Economics*, 28 (7), 779-82.

Louviere, Jordan J. (2006), "What You Don't Know Might Hurt You: Some Unresolved Issues in the Design and Analysis of Discrete Choice Experiments," *Environmental and Resource Economics*, 34 (1), 173-88.

Lu, Hui, Tony Fowkes, and Mark Wardman (2008), "Amending the Incentive for Strategic Bias in Stated Preference Studies: Case Study in Users' Valuation of Rolling Stock," *Transportation Research Record*, 2049 (1), 128-35.

Luchini, S. and V. Watson (2014), "Are Choice Experiments Reliable? Evidence From the Lab," *Economics Letters*, 124 (1), 9-13.

Lusk, Jayson L. (2003), "Effects of Cheap Talk on Consumer Willingness-to-Pay for Golden Rice," *American Journal of Agricultural Economics*, 85 (4), 840-56.

Lusk, Jayson L. and Ted C. Schroeder (2004), "Are Choice Experiments Incentive Compatible? A Test with Quality Differentiated Beef Steaks," *American Journal of Agricultural Economics*, 86 (2), 467-82.

Mann, H. B. and D. R. Whitney (1947), "On a Test of Whether One of Two Random Variables is Stochastically Larger than the Other," *The Annals of Mathematical Statistics*, 18 (1), 50-60.

Maughan, Lizzie, Sergei Gutnikov, and Rob Stevens (2007), "Like More, Look More. Look More, Like More: The Evidence From Eye-tracking," *Journal of Brand Management*, 14 (4), 335-42.

Mead, Nicole L., Roy F. Baumeister, Francesca Gino, Maurice E. Schweitzer, and Dan Ariely (2009), "Too Tired to Tell the Truth: Self-control Resource Depletion and Dishonesty," *Journal of Experimental Social Psychology*, 45 (3), 594-97.

Mero, Neal P., Rebecca M. Guidice, and Steve Werner (2012), "A Field Study of the Antecedents and Performance Consequences of Perceived Accountability," *Journal of Management*, 40 (6), 1627-52.

Michaud, Celine, Daniel Llerena, and Iragael Joly (2013), "Willingness to Pay for Environmental Attributes of Non-food Agricultural Products: A Real Choice Experiment," *European Review of Agricultural Economics*, 40 (2), 313-29.

Mishra, Debi Prasad, Jan B. Heide, and Stanton G. Cort (1998), "Information Asymmetry and Levels of Agency Relationships," *Journal of Marketing Research*, 35 (3), 277-95.

Morrison, Mark (2000), "Aggregation Biases in Stated Preference Studies," *Australian Economic Papers*, 39 (2), 215-30.

Moser, Riccarda, Roberta Raffaelli, and Dawn Thilmany-McFadden (2011), "Consumer Preferences for Fruit and Vegetables with Credence-Based Attributes: A Review," *International Food and Agribusiness Management Review*, 14 (2), 121-42.

Muller, Laurent, Anne Lacroix, and Bernard Ruffieux (2019), "Environmental Labelling and Consumption Changes: A Food Choice Experiment," *Environmental and Resource Economics*, 73 (3), 871-97.

Muraven, Mark and Roy F. Baumeister (2000), "Self-regulation and Depletion of Limited Resources: Does Self-control Resemble a Muscle?," *Psychological Bulletin*, 126 (2), 247-59.

Murphy, James J., P. Geoffrey Allen, Thomas H. Stevens, and Darryl Weatherhead (2005), "A Meta-analysis of Hypothetical Bias in Stated Preference Valuation," *Environmental and Resource Economics*, 30 (3), 313-25.

Orquin, Jacob L. and Kenneth Holmqvist (2018), "Threats to the Validity of Eye-movement Research in Psychology," *Behavior Research Methods*, 50 (4), 1645-56.

Pang, Bo and Lillian Lee (2008), "Opinion Mining and Sentiment Analysis," *Foundations and Trends® in Information Retrieval*, 2 (1–2), 1-135.

Paul, J. H. Schoemaker (1982), "The Expected Utility Model: Its Variants, Purposes, Evidence and Limitations," *Journal of Economic Literature*, 20 (2), 529-63.

Pauly, Mark V. (1968), "The Economics of Moral Hazard: Comment," *American Economic Review*, 58 (3), 531-37.

Penn, Jerrod M. and Wuyang Hu (2018), "Understanding Hypothetical Bias: An Enhanced Meta-Analysis," *American Journal of Agricultural Economics*, 100 (4), 1186-206.

Pennycook, Gordon, Jonathan A. Fugelsang, and Derek J. Koehler (2015), "What Makes Us Think? A Three-Stage Dual-Process Model of Analytic Engagement," *Cognitive Psychology*, 80, 34-72.

Peters, Ellen, Daniel Västfjäll, Paul Slovic, C.K. Mertz, Ketti Mazzocco, and Stephan Dickert (2006), "Numeracy and Decision Making," *Psychological Science*, 17 (5), 407-13.

Poe, Gregory L and Christian A Vossler (2011), "Consequentiality and Contingent Values: An Emerging Paradigm," in *The International Handbook On Non-market Environmental Valuation*, Jeff Bennett, ed. Cheltenham, UK: Edward Elgar Publishing.

Proverbio, Alice Mado, Maria Elide Vanutelli, and Roberta Adorni (2013), "Can You Catch a Liar? How Negative Emotions Affect Brain Responses when Lying or Telling the Truth," *PLOS ONE*, 8 (3), e59383.

Quaife, Matthew, Fern Terris-Prestholt, Gian Luca Di Tanna, and Peter Vickerman (2018), "How Well Do Discrete Choice Experiments Predict Health Choices? A Systematic

Review and Meta-analysis of External Validity," *The European Journal of Health Economics*, 19 (8), 1053-66.

Raghavarao, D and JB Wiley (1986), "Testing Competing Effects Among Soft Drink Brands," in Statistical Design: Theory and Practice: Proceedings of a Conference in Honour of Walter T. Federer. Ithaca, NY: Cornell University.

Raghavarao, Damaraju and James B. Wiley (1994), "Experimental Designs for Availability Effects and Cross Effects with One Attribute," *Communications in Statistics - Theory and Methods*, 23 (6), 1835-46.

Rakotonarivo, O. Sarobidy, Marije Schaafsma, and Neal Hockley (2016), "A Systematic Review of the Reliability and Validity of Discrete Choice Experiments in Valuing Non-market Environmental Goods," *Journal of Environmental Management*, 183 (Part 1), 98-109.

Rapp, Adam A., J. Andrew Petersen, Douglas E. Hughes, and Jessica L. Ogilvie (2020), "When time is sales: the impact of sales manager time allocation decisions on sales team performance," *Journal of Personal Selling & Sales Management*, 40 (2), 132-48.

Rasch, Carsten, Jordan J Louviere, and Thorsten Teichert (2015), "Using Facial EMG and Eye Tracking to Study Integral Affect in Discrete Choice Experiments," *Journal of Choice Modelling*, 14, 32-47.

Rayo, Luis (2007), "Relational Incentives and Moral Hazard in Teams," *The Review of Economic Studies*, 74 (3), 937-63.

Reutskaja, Elena, Rosemarie Nagel, Colin F. Camerer, and Antonio Rangel (2011), "Search Dynamics in Consumer Choice under Time Pressure: An Eye Tracking Study," *American Economic Review*, 101 (2), 900-26.

Robinson, Peter (1998), "Literacy, Numeracy and Economic Performance," *New Political Economy*, 3 (1), 143-49.

Rose, John M. and David A. Hensher (2006), "Handling Individual Specific Availability of Alternatives in Stated Choice Experiments," in *Travel Survey Methods*, Peter Stopher and Cheryl Stecher, eds. Bingley, UK: Emerald Group Publishing Limited.

Rothschild, Michael and Joseph Stiglitz (1978), "Equilibrium in Competitive Insurance Markets: An Essay on the Economics of Imperfect Information," in *Uncertainty in Economics*, Peter Diamond and Michael Rothschild, eds. New York, NY: Academic Press.

Sælensminde, Kjartan (2002), "The Impact of Choice Inconsistencies in Stated Choice Studies," *Environmental and Resource Economics*, 23 (4), 403-20.

Saha, Atanu and Graham Poole (2000), "The Economics of Crime and Punishment: An Analysis of Optimal Penalty," *Economics Letters*, 68 (2), 191-96.

Samuelson, Paul A. (1952), "Probability, Utility, and the Independence Axiom," *Econometrica*, 20 (4), 670-78.

Scarpa, Riccardo, Raffaele Zanoli, Viola Bruschi, and Simona Naspetti (2013), "Inferred and Stated Attribute Non-attendance in Food Choice Experiments," *American Journal of Agricultural Economics*, 95 (1), 165-80.

Schmitz, Christian and Shankar Ganesan (2014), "Managing Customer and Organizational Complexity in Sales Organizations," *Journal of Marketing*, 78 (6), 59-77.

Schwartz, L. M., S. Woloshin, W. C. Black, and H. Welch (1997), "The Role of Numeracy in Understanding the Benefit of Screening Mammography," *Annals of Internal Medicine*, 127 (11), 966-72.

Segal, Uzi (1990), "Two-Stage Lotteries without the Reduction Axiom," *Econometrica*, 58 (2), 349-77.

Shi, Savannah Wei, Michel Wedel, and FGM Pieters (2013), "Information Acquisition During Online Decision Making: A Model-Based Exploration Using Eye-tracking Data," *Management Science*, 59 (5), 1009-26.

Shu, Lisa L., Francesca Gino, and Max H. Bazerman (2011), "Dishonest Deed, Clear Conscience: When Cheating Leads to Moral Disengagement and Motivated Forgetting," *Personality and Social Psychology Bulletin*, 37 (3), 330-49.

Silva, Andres, Rodolfo M. Nayga, Benjamin L. Campbell, and John L. Park (2011), "Revisiting Cheap Talk with New Evidence from a Field Experiment," *Journal of Agricultural and Resource Economics*, 36 (2), 280-91.

Small, Dana M., Darren Gitelman, Katharine Simmons, Suzanne M. Bloise, Todd Parrish, and M. Marsel Mesulam (2005), "Monetary Incentives Enhance Processing in Brain Regions Mediating Top-down Control of Attention," *Cerebral Cortex*, 15 (12), 1855-65.

Smith, Vernon L. (1976), "Experimental Economics: Induced Value Theory," *American Economic Review*, 66 (2), 274-79.

Smith, Vernon L. and James M. Walker (1993), "Monetary Rewards and Decision Cost in Experimental Economics," *Economic Inquiry*, 31 (2), 245-61.

Spence, Michael (1973), "Job Market Signaling," *The Quarterly Journal of Economics*, 87 (3), 355-74.

StataCorp (2015), "Stata." 14 ed. College Station, TX: StataCorp LP.

Svensson, Elisabeth (2000), "Comparison of the Quality of Assessments Using Continuous and Discrete Ordinal Rating Scales," *Biometrical Journal*, 42 (4), 417-34.

Taylor, Laura O., Michael McKee, Susan K. Laury, and Ronald G. Cummings (2001), "Induced-value Tests of the Referendum Voting Mechanism," *Economics Letters*, 71 (1), 61-65.

Thaler, Richard H and Cass R Sunstein (2008), Nudge: Improving Decisions About Health, Wealth, and Happiness. New Haven, CT: Yale University Press.

TobiiAB (2015), "Tobii Studio User Manual & Referene Guide." v3.4.3 ed. Stockholm, SW: TobiiPro.

Toplak, Maggie E., Richard F. West, and Keith E. Stanovich (2011), "The Cognitive Reflection Test as a Predictor of Performance on Heuristics-and-biases Tasks," *Memory & Cognition*, 39 (7), 1275.

Train, Kenneth (2009), Discrete Choice Methods with Simulation (2nd ed.). New York, NY: Cambridge University Press.

Train, Kenneth and Melvyn Weeks (2005), "Discrete Choice Models in Preference Space and Willingness-to-pay Space," in *Applications of Simulation Methods in Environmental and Resource Economics*, Riccardo Scarpa and Anna Alberini, eds. Dordrecht, NL: Springer.

U.S. Census (2019), "USA QuickFacts from the US Census Bureau," U.S. Department of Commerce.

USDA-ERS (2019), "After falling in the late 1990s and early 2000s, supermarkets' share of at-home food spending has stabilized," USDA-ERS (Ed.) Vol. 2019.

USDOT (2018), "Average Annual Miles per Driver by Age Group," (accessed May, 2020, 2020), [available at https://www.fhwa.dot.gov/ohim/onh00/bar8.htm].

Van Rossum, Guido and Fred L Drake (2011), The python language reference manual: Network Theory Ltd.

Vossler, Christian A., Maurice Doyon, and Daniel Rondeau (2012), "Truth in Consequentiality: Theory and Field Evidence on Discrete Choice Experiments," *American Economic Journal: Microeconomics*, 4 (4), 145-71.

Vossler, Christian A. and Mary F. Evans (2009), "Bridging the Gap Between the Field and the Lab: Environmental Goods, Policy Maker Input, and Consequentiality," *Journal of Environmental Economics and Management*, 58 (3), 338-45.

Vossler, Christian A. and Michael McKee (2006), "Induced-Value Tests of Contingent Valuation Elicitation Mechanisms," *Environmental and Resource Economics*, 35 (2), 137-68.

Vossler, Christian A. and Sharon B. Watson (2013), "Understanding the Consequences of Consequentiality: Testing the Validity of Stated Preferences in the Field," *Journal of Economic Behavior and Organization*, 86, 137-47.

Wang, Joseph Taoyi, Michael Spezio, and Colin F. Camerer (2010), "Pinocchio's Pupil: Using Eyetracking and Pupil Dilation to Understand Truth Telling and Deception in Sender-Receiver Games," *American Economic Review*, 100 (3), 984-1007.

Weller, Joshua A., Nathan F. Dieckmann, Martin Tusler, C. K. Mertz, William J. Burns, and Ellen Peters (2013), "Development and Testing of an Abbreviated Numeracy Scale: A Rasch Analysis Approach," *Journal of Behavioral Decision Making*, 26 (2), 198-212.

Wieseke, Jan, Michael Ahearne, Son K. Lam, and Rolf van Dick (2009), "The Role of Leaders in Internal Marketing," *Journal of Marketing*, 73 (2), 123-45.

Yang, Liu, Olivier Toubia, and Martijn G. de Jong (2018), "Attention, Information Processing and Choice in Incentive-Aligned Choice Experiments," *Journal of Marketing Research*, 55 (6), 783-800.

VITA

EDUCATION

2020 Ph.D. Managerial Economics, Texas A&M University. Graduated December 2020.

2015 M. Sc. Agricultural Economics, Texas A&M University. Graduated May 2015.

2009 Green Belt Six-Sigma Process Management, PMI Institute. Graduated August 2009.

2002 B.Sc. Agronomy & Food Science, Zamorano. Graduated December 2002.

PROFESSIONAL EXPERIENCE:

2013 Maersk Line (Mexico) – Trade Manager for Asia-Latin America

2010 Maersk Line (Nicaragua) – Senior Officer

2009 Maersk Line (Honduras) – Business development North Region

2007 USAID (Honduras) – Monitoring and evaluation specialist north region

2004 CADECA (Honduras) – Breeder farm manager

ACADEMIC AWARDS AND RECOGNITIONS

2021 Doctoral Student Research Award, Department of Marketing and Supply Chain, Gatton College of Business and Economics, University of Kentucky

2020 AMA-Sheth Foundation Doctoral Consortium Fellow

2018 Second place Three Minute Thesis, University of Kentucky

2018 First Place Lightning Research Annual Symposium for Agricultural and Applied Economics Research, Texas A&M University

2015 Best Master's Thesis Award, Southern Agricultural Economics Association

1998 Highest admission score from Honduras applicants to Zamorano

PUBLISHED PEER-REVIEWED WORK

Chavez, Daniel E.; Chen, Haipeng (Allan) (2021) "Product Innovation and First Mover Advantages: A Contingency Approach" *Journal of Business and Industrial Marketing.*

Wei, Jiuchang; Liu, Tingting; Chavez, Daniel E.; Chen, Haipeng (Allan) (2020) "Managing Corporate-Government Relationships in a Multi-Cultural Setting," *Industrial Marketing Management.*

Chavez, Daniel E.; Palma, Marco A.; Nayga, Rodolfo M.; Mjelde, James (2020) "Product availability in discrete choice experiments with private goods," *Journal of Choice Modelling.*

Chavez, Daniel E.; Palma, Marco A.; Byrne, David H.; Hall, Charles; Ribera, Luis (2018) "Willingness-to-pay for Rose attributes: developing a consumer-oriented breeding program," *Journal of Agricultural and Applied Economics.*

Chavez, Daniel E.; Palma, Marco A. (2018) "Pushing Subjects Beyond Rationality with More Product Offerings in Experimental Auctions," *Agricultural Economics.*

Chavez, Daniel E.; Palma, Marco A.; Collart, Alba J. (2017) "Using Eye-Tracking to Model Attribute Non-Attendance in Choice Experiments," *Applied Economic Letters.*

Daniel Eduardo Chavez