2018

The Relationship Among Demographics and Risk Attitude in Predicting Health Plan Enrollment

Stephen Gage
Walden University

Walden University

College of Social and Behavioral Sciences

This is to certify that the doctoral dissertation by

Stephen Gage

has been found to be complete and satisfactory in all respects,
and that any and all revisions required by
the review committee have been made.

Review Committee
Dr. Monny Sklov, Committee Chairperson, Psychology Faculty
Dr. Frederica Hendricks-Noble, Committee Member, Psychology Faculty
Dr. Grant Rich, University Reviewer, Psychology Faculty

Chief Academic Officer
Eric Riedel, Ph.D.

Walden University
2018

Abstract

The Relationship Among Demographics and Risk Attitude in Predicting Health Plan Enrollment

by

Stephen Gage

MA, San Francisco State University, 1991

BS, Lenoir Rhyne University, 1988

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

Industrial-Organizational Psychology

Walden University

August 2018

Abstract

Age, salary, family status, and health status are reported to be linked to high deductible health plan (HDHP) enrollment for pre-Affordable Care Act (ACA) health plans. There has been little research on HDHP enrollment post-ACA. This study quantitatively examined the demographic variables and attitude toward risk that contribute to enrollment in a HDHP that conforms to the ACA minimum essential coverage standards. Risk taking was measured by the Domain Specific Risk Taking Scale. Other independent variables were participant age, annual salary, employee status, enrollment tier, and gender. There were 144 participants recruited from the Amazon Mechanical Turk platform who participated in the research survey. The results of binary logistic regression analysis indicated that age and the presence of children on coverage predict HDHP enrollment. Older employees and employees with at least 1 child on coverage are less likely to enroll in a HDHP. As almost 40% of adults in the United States are covered under a HDHP and this number is expected to increase, it is important to determine the factors related to HDHP enrollment. By identifying the factors related to HDHP enrollment, better educational materials may be developed for employees related to the complex and often confusing insurance decision-making process thus supporting positive social change in the health insurance industry.

The Relationship Among Demographics and Risk Attitude in Predicting Health Plan Enrollment

by

Stephen Gage

MA, San Francisco State University, 1991

BS, Lenoir Rhyne University, 1988

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

Industrial-Organizational Psychology

Walden University

August 2018

Acknowledgments

I would like to thank my committee chair and methodologist, Dr. Monny Sklov, my committee member and content expert, Dr. Frederica Hendricks-Noble, and the university research reviewer, Dr. Grant Rich. I very much appreciate your guidance, instruction, and direction.

I would also like to acknowledge my family. My parents taught me to value education and to go at my own pace. A special thank you to my partner, Scott. I could not have taken this challenge without your love, support, and encouragement.

Table of Contents

List of Tables iv

Chapter 1: Introduction to the Study 1

Background of the Problem 2

Problem Statement 5

Purpose Statement 6

Research Questions 6

Theoretical Framework for the Study 11

Nature of the Study 12

Definitions of Terms Used 13

Assumptions 15

Scope and Delimitations 16

Limitations 16

Significance 17

Summary 18

Chapter 2: Literature Review 20

Introduction 20

Literature Search Strategy 20

Insurance Choice and HDHPs 21

Theoretical Foundation 23

Prospect Theory and Insurance Choice 27

Risk Taking 28

Cognitive and Neurological Factors and Risk Taking.. 29
Personality and Risk Taking 29
Demographic Factors and Risk Taking 30
Risk Taking in Organizations... 30
Risk Taking and Insurance Choice... 31
Risk Decisions and High Deductible Health Plans 32
Chapter 2 Summary... 33
Chapter 3: Research Method 35
Introduction.. 35
Purpose of the Study.. 35
Research Questions and Hypotheses.. 35
Research Design... 40
Setting and Sample.. 43
Instrumentation... 45
Analysis 47
Threats to Validity... 49
Ethical Considerations.. 49
Chapter 3 Summary... 50
Chapter 4: Results 51
Purpose of Study 51
Research Questions and Hypothesis 51
Sample Description 56

Data Collection and Analysis 56
Variable Analysis 58
Bivariate Analyses 63
Binary Logistic Regression 67
Assessing Assumptions for Logistic Regression 68
Model 1: Enter logistic regression 71
Model 2: Two-block enter method 73
Model 3: Interactions 78
Summary 79
Chapter 5: Discussion 82
Introduction 82
Interpretation of the Findings 84
Study Results Guided by Prospect Theory 85
Limitations of the Study 87
Recommendations 88
Implications for Social Change 89
Conclusion 90
References 92
Appendix B: Instrumentation 114

List of Tables

Table 1. Cases Removed to Fit Inclusion Parameters.....53

Table 2. Categorical Variable Frequencies.....56

Table 3. Continuous Variable Descriptive Statistics.....58

Table 4. Bivariate Analysis.....59

Table 5. Intercorrelations for the Financial/Gamble Subscale.....61

Table 6. Collinearity Statistics.....64

Table 7. Model 1: 4 Tier.....66

Table 8. Model 1: Dichotmous Tier.....67

Table 9. Model 2: Block 1, 4 Tier.....68

Table 10. Model 2: Block 2, 4 Tier.....69

Table 11. Model 2: Dichotomous Tier.....70

Table 12. Model 2: Dichotmous Tier.....71

Table 13. Model 3: Interactions.....72

Chapter 1: Introduction to the Study

Compensation and benefits are important components of talent management and any change in an employer's benefits strategy is significant (Giancola, 2012). As health insurance premium costs are expected to grow at a rate of 5.5% through 2024 (Custer, 2016), employers have a dilemma. Employers understand the benefits of offering health insurance to employees because it results in improved employee satisfaction, motivation, and commitment to the organization (Renaud, Morin & Bechard, 2017; Wealthington & Jones, 2006). However, at the same time, in spite of these positive employee factors, many are looking for ways to cut back on benefits in order to control their health insurance cost (Landman, 2016).

Currently, about 150 million people in the United States receive coverage through an employer-sponsored health plan (ESI) (Henry J. Kaiser Foundation, 2016), which is over half of the non-elderly population in the United States. Attempts to reduce employer healthcare costs in the past have centered on managed care such as health maintenance organizations (HMOs), preferred provider organizations, accountable health organizations, and consumer-driven health care utilizing high deductible health plans (HDHPs, Knickman, 2015). HDHPs have become popular as a strategy to lower insurance costs for employers (Gupta & Polsky, 2015). The number of employers offering a HDHP option has risen to 52% in 2016 from 15% in 2010 (Henry J. Kaiser Family Foundation, 2010). More employees are enrolling in this type of plan as well. In 2008, about 8% of employees offered a HDHP chose to enroll in that plan (Sedjo & Cox, 2009). In 2015, enrollment in HDHPs jumped to 25% (Henry J. Kaiser Family Foundation, 2015).

Although the use of HDHPs is cited as an effective tool in controlling health care costs for employers (Miller, 2016), HDHP plan parameters are often confusing for employees (Lave, Men, Day, Wang & Zhang, 2011). Employees who enroll in a HDHP that is inappropriate for them may end up delaying or discontinuing needed medical care (Galbraith, Soumerai, Ross-Degnan, Rosenthal, Gay & Lieu, 2012). It is therefore important to learn more about the factors related to HDHP plan choice in order to assist organizations with this benefit change.

Background of the Problem

HDHPs are a frequently used plan design under the category of consumer-driven health care (CDHP). In terms of insurance trends, CDHP is the most significant movement since HMOs became popular in the 1980s (Johnson & Wagner, 2007). The goal of CDHP is to encourage employee consumerism through linking catastrophic high-deductible health insurance with tax-advantaged spending accounts such as health reimbursement accounts (HRAs) and health spending accounts (HSAs). The HRA and HSA are considered the employee's money and the employee is challenged to spend that money wisely by making better health care decisions and engaging in preventive activities. By engaging in these consumer activities, employees may lower their health care spending which in turn results in a cost savings for the employer (Gupta & Polsky, 2015; Zhang, Haviland, Mehrotra, Huckfeld, Wagner & Sood, 2017). For example, because the employee is paying the full cost of services up to the deductible under a HDHP, employees in a HDHP engage in more shopping for lower-priced providers than other plans (Zhang, Haviland, Mehrotra, Huckfeld, Wagner & Sood, 2017) and show reduction in inappropriate use of expensive services such as the emergency room (Waters, Chang, Cecil, Kasteridis & Mirvis, 2011; Wharam, Langdon, Zhang, Soumerai & Ross-Degan, 2011). In addition to the potential cost savings at the service level, because these plans have a high deductible, they often have a lower premium cost for both the employer and employee, as well.

Lower-wage and less healthy individuals have typically avoided HDHPs because of the significant upfront out-of-pocket costs (Davis, 2005). Past research supports that when offered a choice between a HDHP and lower deductible health plan, employees with health conditions (Bindman, Hulett, Gilmer & Bertko, 2016; Jordan, 2014; Lave, Lave, Men, Day, Wang & Zhang, 2011), older employees (Barry, Cullen, Galusha, Slade & Busch, 2008; Lave, Men, Day, Wang & Zhang, 2011) and employees with lower salary (Barry, Cullen, Galusha, Slade & Busch, 2008; McDevitt, Haviland, Lore, Laudenberger, Eisenberg & Sood, 2014), are less likely to enroll in a HDHP. The literature supports that individuals that anticipate higher health care use will be less likely to elect a HDHP (Atanasov & Baker, 2014).

The Affordable Care Act (ACA) of 2010 had a significant impact on HDHP plan benefits. When HDHPs were first introduced, high deductible plans were not required to cover preventive care without meeting the deductible (Johnson & Wagner, 2007). This means that employees pay out-of-pocket for all health services prior to the deductible including yearly physical exams, immunizations, health screenings and well-child care. Prior to the ACA, an employer survey found that only 30% of employers who offered a HDHP covered preventive and wellness care before the deductible was met (Henry J. Kaiser Foundation, 2006). The ACA may make HDHPs more palatable to certain populations due to the elimination of cost-sharing for services including preventive services and some maintenance prescriptions (Cooper, Dong Kou, Dor & Koroukian, 2017). The ACA requires that employer-sponsored health coverage provides services such as screenings and counseling, immunizations, behavioral and developmental assessments, well-women's visits, yearly physical exams, contraceptives, and tobacco-cessation products at no cost to the employee. Research supports that after the ACA took effect, there was generally an increase in employee use of no-cost preventive services (Han, Yabroff, Guy, Zheng & Jemal, 2015) and a reduction in total out-of-pocket cost for certain racial/ethnic groups (Chen, Vargas Bustamante & Tom, 2015). As research indicates that a change in benefit plan parameters affects employee enrollment trends (Ye, 2015) and much of the past research on HDHP enrollment was conducted prior to the minimum essential coverage provision of the ACA (French, Homer, Gumus & Hickling, 2016), it is important to explore demographic variables and risk-taking perspective related to plan choice under the current ACA legislation.

Problem Statement

The cost to organizations of employer-sponsored health insurance (ESI) continues to outpace general inflation. There was a 6% increase in the cost of ESI in 2016 and this is expected to continue (Miller, 2016). Nonwage benefits such as health insurance are related to employee satisfaction, motivation, performance, commitment to the organization, and retention (Renaud, Morin & Bechard, 2017; Wealthington & Jones, 2006), and employers are exploring ways to control costs while at the same time keeping quality health coverage. An emerging trend to control costs among employers is to incorporate a less expensive high deductible health plan (HDHP) (Miller, 2016). Currently, about 52% of employers offer a HDHP (Henry J. Kaiser Foundation, 2016). Twenty-nine percent of employees covered under ESI are enrolled in a HDHP option (Henry J. Kaiser Foundation, 2016), up from 8% in 2008 (Sedjo & Cox, 2009).

Although the use of HDHPs is cited as an effective tool in controlling health care costs for employers (Miller, 2016), HDHP plan parameters are often confusing for employees (Lave, Men, Day, Wang & Zhang, 2011). Employees who enroll in a HDHP that is inappropriate for them may end up delaying or discontinuing needed medical care (Galbraith, Soumerai, Ross-Degnan, Rosenthal, Gay & Lieu, 2012). Industrial and organizational (I-O) psychologists may assist organizations by learning more about the factors related to HDHP plan choice.

A number of past studies have examined variables related to HDHP choice. A limitation of past research on plan choice is that much of the past research was conducted prior to the minimum essential coverage provision of the Affordable Care Act (ACA) of 2010 (French, Homer, Gumus & Hickling, 2016) and research indicates that a change in benefit plan parameters affects employee enrollment trends (Ye, 2015). The ACA set minimum standards for plans and therefore older research may not be generalized to today's ESI environment. In this study, I addressed a needed area of research by determining if certain demographic variables and risk attitude relate to plan choice within the current ESI climate.

Purpose Statement

The purpose of this study was to examine the demographic variables and attitudes toward risk that contribute to enrollment in an HSA-compatible HDHP that conforms to the ACA minimum essential coverage standards. To address this gap, I used a quantitative approach. My goal was to assist employers in developing educational materials for employees related to the insurance decision-making process.

Research Questions

Research Question 1 (RQ1): Does salary predict high deductible health plan choice for individuals given a choice between a HDHP and low deductible plan?

Null Hypothesis ($H_0$1): Salary does not predict enrollment in a high deductible health plan.

Alternative Hypothesis (H_a1): Employees with a higher salary are more likely to enroll in a high deductible health plan.

Research Question 2 (RQ2): Does age predict high deductible health plan choice for individuals given a choice between a HDHP and low deductible plan?

Null Hypothesis ($H_0$2): Age does not predict enrollment in a high deductible health plan.

Alternative Hypothesis (H_a2): Employees who are older are less likely to enroll in a high deductible health plan.

Research Question 3 (RQ3): Does employee status predict high deductible health plan choice for individuals given a choice between a HDHP and low deductible plan?

Null Hypothesis ($H_0$3): Exempt status not predict enrollment in a high deductible health plan.

Alternative Hypothesis (H_a3): Employees who are categorized as exempt are more likely to enroll in a high deductible health plan.

Research Question 4 (RQ4): Does dependent coverage predict high deductible health plan choice for individuals given a choice between a HDHP and low deductible plan?

Null Hypothesis ($H_0$4): Covering dependents does not predict enrollment in a high deductible health plan.

Alternative Hypothesis (H_a4): Employees who cover dependents are less likely to enroll in a high deductible health plan.

Research Question 5 (RQ5): Does gender predict high deductible health plan choice for individuals given a choice between a HDHP and low deductible plan?

Null Hypothesis ($H_0 5$): Gender does not predict enrollment in a high deductible health plan.

Alternative Hypothesis ($H_a 5$): Males are more likely to enroll in a high deductible health plan.

Research Question 6 (RQ6): Does total risk taking score as measured by the Domain Specific Risk Taking Scale (DOSPERT) predict HDHP choice for individuals given a choice between a HDHP and low deductible plan net of the predictive effect of demographic factors?

Null Hypothesis ($H_0 6$): Total DOSPERT score does not predict enrollment in a high deductible health plan net the predictive effect of demographic variables.

Alternative Hypothesis ($H_a 6$): Employees with a higher DOSPERT score are more likely to enroll in a high deductible health plan.

Research Question 7 (RQ7): Does risk-taking score in the ethical domain as measured by the Domain Specific Risk Taking Scale (DOSPERT) predict HDHP choice for individuals given a choice between a HDHP and low deductible plan net of the predictive effect of demographic factors?

Null Hypothesis ($H_0 7$): Risk-taking score in the ethical domain on the DOSPERT does not predict enrollment in a high deductible health plan net the predictive effect of demographic variables.

Alternative Hypothesis (H_a7): Employees with a higher risk-taking score in the ethical domain as measured by the DOSPERT are more likely to enroll in a high deductible health plan.

Research Question 8 (RQ8): Does risk-taking score in the financial domain as measured by the Domain Specific Risk Taking Scale (DOSPERT) predict HDHP choice for individuals given a choice between a HDHP and low deductible plan net of the predictive effect of demographic factors?

Null Hypothesis ($H_0 8$): Risk-taking score in the financial domain on the DOSPERT does not predict enrollment in a high deductible health plan net the predictive effect of demographic variables.

Alternative Hypothesis (H_a8): Employees with a higher risk-taking score in the financial domain as measured by the DOSPERT are more likely to enroll in a high deductible health plan.

Research Question 9 (RQ9): Does risk-taking score in the social domain as measured by the Domain Specific Risk Taking Scale (DOSPERT) predict HDHP choice for individuals given a choice between a HDHP and low deductible plan net of the predictive effect of demographic factors?

Null Hypothesis ($H_0 9$): Risk-taking score in the social domain on the DOSPERT does not predict enrollment in a high deductible health plan net the predictive effect of demographic variables.

Alternative Hypothesis (H_a9): Employees with a higher risk-taking score in the social domain as measured by the DOSPERT are more likely to enroll in a high deductible health plan.

Research Question 10 (RQ10): Does risk-taking score in the health domain as measured by the Domain Specific Risk Taking Scale (DOSPERT) predict HDHP choice for individuals given a choice between a HDHP and low deductible plan net of the predictive effect of demographic factors?

Null Hypothesis ($H_0 10$): Risk-taking score in the health domain on the DOSPERT does not predict enrollment in a high deductible health plan net the predictive effect of demographic variables.

Alternative Hypothesis ($H_a 10$): Employees with a higher risk-taking score in the health domain as measured by the DOSPERT are more likely to enroll in a high deductible health plan.

Research Question 11 (RQ11): Does risk-taking score in the recreational domain as measured by the Domain Specific Risk Taking Scale (DOSPERT) predict HDHP choice for individuals given a choice between a HDHP and low deductible plan net of the predictive effect of demographic factors?

Null Hypothesis ($H_0 11$): Risk-taking score in the recreational domain on the DOSPERT does not predict enrollment in a high deductible health plan net the predictive effect of demographic variables.

Alternative Hypothesis (H_a11): Employees with a higher risk-taking score in the recreational domain as measured by the DOSPERT are more likely to enroll in a high deductible health plan.

Research Question 12 (RQ12): Is there a significant interaction effect of the DOSPERT and its 5 subscales with demographic variables in predicting high deductible health plan choice for individuals given a choice between a HDHP and low deductible plan??

Null Hypothesis ($H_0$12): There is no significant interaction between the DOSPERT and its 5 domains with demographic variables in predicting HDHP enrollment.

Alternative Hypothesis (H_a12): There is an interaction effect between demographic variables and the DOSPERT in predicting high deductible health plan enrollment.

Theoretical Framework for the Study

Prospect theory is an influential model of decision-making under conditions of risk (Pachur, Suter & Hertwig, 2017) and Sheaf (2016) indicated that the tenets and research from this framework may contribute to the field of I-O psychology. Prospect theory has been used in I-O psychology research studies related to resource allocation and performance of sales people (Bonney, Plouffe & Wolter, 2014) and in evaluating effective methods of communicating production outcomes to employees (Kluge, Badura & Rietz, 2013). According to prospect theory, individuals judge possible outcomes based on a reference point (Heiman, Just, McWilliams & Zilberman, 2015). Prospect theory states that financial risk is subject to contextual effects and individual perception and is not linear (Lin, Xia and Bei, 2015). As health insurance addresses financial risk (Browne, Knoller & Richter, 2015), I used prospect theory as a framework for understanding how employees make decisions about HDHPs. Specifically, I examined how employee variables, one's financial status, and one's risk attitude determines plan choice.

Employee demographic variables and risk attitude may impact enrollment in a HDHP. Kusev, van Schaik, Ayton, Dent and Chater (2009) examined insurance choice within the framework of Prospect theory. The authors suggested that when making decisions related to insurance, precautionary decision-making plays a role. That is, in response to uncertainly (possibility of expensive health claims due to poor health status or high health risk), employees may choose the plan that they believe will avoid financial loss. Jordan (2014) reported that enrollment in a HDHP is associated with a higher salary consistent with prospect theory. Chapter 2 includes a review of prospect theory and insurance choice in more detail.

Nature of the Study

The nature of the study was quantitative. Socioeconomic and risk attitude may influence plan choice (Bundorf, Mata, Schoenbaum & Bhattacharya, 2013; Lave, Men, Day, Wang & Zhang, 2011). For this reason, a multivariate analysis was appropriate to examine the association between the independent variables and plan choice. The independent variables were employee demographics including salary, employee age (continuous), employee gender (M/F), family status (nominal – employee only coverage, employee plus spouse, employee plus child(ren), and employee plus family), score on the Domain-Specific Risk Taking Scale, and employee status (nominal – exempt, non-exempt). The dependent variable was enrollment in a HDHP or not (dichotomous). I used this quantitative analysis to identify the individual variables that predict HDHP choice.

Definitions of Terms Used

Employee Status: Employees are categorized as hourly or salaried by self-report. Employees who are categorized as salaried are typically employed in executive, administrative and professional positions, do not receive variable pay based on quality or quantity of work, and are paid a fully salary each pay period (Foley & Stokes, 1997). Hourly employees, on the other hand, are paid by the hour and are eligible for overtime pay ("Determining employee status," 2003). Research has identified a number of differences between hourly and salaried employees pertinent to high deductible health plan decisions. Hourly employees may think about their income on a more regular basis and may make certain decisions based on economic evaluation ("Study finds hourly employees happier than salaried," 2010). Related to health status and health risk, research points to a number of differences between hourly and salaried employees (Clougherty, Eisen, Slade, Kawachi & Cullen, 2009).

High Deductible Health Plan: A HDHP is a plan design that utilizes a specific minimum deductible set by the IRS and mandates n employer cost sharing for most services up to the deductible (Hardie, Kyanko, Busch, LoSasso & Levin, 2011). Medical expenses are paid by the employee up to the deductible, but the plan may be combined with a medical spending account for out-of-pocket costs. Since employees are responsible for initial medical expenses, the goal is for employees to become more involved in the health care decision-making process and appropriately manage their healthcare dollars (Gupta & Polsky, 2015). Because of the higher deductible, an advantage of these plans is that they typically have a lower premium cost and therefore the employee may have more take-home pay on their paycheck than if they had enrolled in a lower deductible health plan.

Medical spending accounts are a central component of HDHPs. McDevitt, Haviland, Lore, Laudenberger, Eisenberg & Sood (2014) indicate that HRAs were the most popular employee savings account when HDHPs were first introduced. HRAs require that employers contribute to a medical savings account that employees use for out-of-pocket expenses. A drawback to this type of savings account is the employee forfeits this account when they leave employment. On the other hand, HSAs, included in the Medicare Prescription Drug, Improvement, and Modernization Act of 2003 (MMA), are tax-exempt accounts owned by the employee. HSAs are gaining popularity for a number of reasons including contributions being excluded from taxable income, the employee owns the account and may take it from job to job, and capital earnings from the account such as investment income and interest build up tax free (Fronstin, 2015).

Risk Attitude: Risk attitude is described as individual differences in how people handle decisions involving risk and uncertainty (Blais & Weber, 2006). Risk attitude will be measured by the Domain-Specific Risk-Taking (DOSPERT) Scale. The scale measures risk attitude in five areas: ethical, financial, health/safety, social and recreational (Blais & Weber, 2006). Research using the DOSPERT indicates that insurance choice is linked to risk attitude with risk averse individuals preferring benefit plans that have low cost variance and predictable expenses (Bundorf, Mata, Schoenbaum & Bhattacharya, 2013). In addition, risk averse individuals have been shown to invest in more insurance (Dionne & Eckhoudt, 1985).

Assumptions

My first assumption was related to the provider networks of the available plans. I assumed that all plans that individuals have access to have the same percentage of "in-network" providers. If an employer is offering two group health plans, it would be highly unusual if one plan had many providers in the area and the other plan had few to no providers. It was outside the scope of this study to assess network provider availability under each plan to support this assumption. My second assumption was that although all HDHP plans, regardless of employer, have comparable employee responsibility parameters. Under ACA legislation, all services are subject to the deductible with the exception of preventive services and it is assumed that the employer is not significantly funding the HSA so as to remove the employee responsibility portion of the HDHP. My third assumption was that employees make rational plan decisions based on available data and resources.

Scope and Delimitations

This quantitative study used a nonexperimental design with survey data from a non-probability sample. The population of interest is all U.S. employees eligible for employer-sponsored group health insurance with access to at least one high deductible health plan and one lower deductible health plan. I recruited participants from Amazon Mechanical Turk (MTurk) who met specific criteria, such as, were employed and enrolled in health insurance at the time. No individuals under age 18 and no individuals who are eligible for Medicare were included, as these groups may receive additional assistance that may impact plan choice. I collected all variables from online survey data and the DOSPERT Scale.

Limitations

As this study was nonexperimental, cause and effect may not be concluded. Without randomization, the sample did not truly represent the population of interest, which is all benefit eligible employees covered under employer-sponsored coverage in the U.S. Sources of bias include selection bias due to using an online survey.

In order to address limitations related to sampling, methods should consider sample prototypicality and sample relevance (Burkholder, Cox & Crawford, 2016) to support reliability and validity. I used purposive sampling (Burkholder, Cox &

Crawford, 2016) to support prototypicality by surveying individuals that meet participation criteria including age limits, working status, and health insurance enrollment.

Significance

The employee benefits package is an important factor in employee performance and work attitude (Wealthington & Jones, 2006). Therefore, any change to the employer benefits strategy may affect more than just employer finances and has direct implications for the field of I-O psychology. Employees that are presented with plans that have very different deductibles should be educated on risk perception and decision making (Graves, Kozhimannil, Kleinman & Wharam, 2016; Gupta & Polsky, 2015; Lave, Men, Day, Wang and Zhang, 2011).

The findings of this study added to the current literature on employee benefit decision-making by identifying the factors related to HDHP choice using plans that conform to current Affordable Care Act (ACA) regulation. All past research on variables related to HDHP choice occurred prior to the ACA. In addition, this study focused on HDHP plans that use the more popular HSA medical spending account rather than the older HRA model. By focusing on HSAs, this research supports more timely and pertinent findings for practitioners in the field. Finally, this study incorporated an assessment of risk taking as a potential variable related to HDHP choice.

The proposed dissertation topic supports positive social change by adding to the knowledgebase about enrollment in HDHP plans. As more employees want health plan choice, but feel ill equipped to make health plan decisions (Fronstin, 2015), it is important to learn more about the factors related to HDHP enrollment. This information may help HR professionals design benefit communication programs to assist employees with this important financial and healthcare choice. For example, since all initial costs are 100% paid by the employee (up to the deductible) under a HDHP plan, employees must be prepared to manage those costs. When the employee is not educated about and prepared for enrollment in a HDHP, negative health outcomes may result (Waters, Chang, Cecil, Kasteridis & Mirvis, 2011). Therefore, this dissertation research contributes to the literature and help support employees through this important health and financial decision. A summary of this research is submitted to industry professionals through avenues such as *The Industrial Psychologist* (TIP) and the newsletter of the Society for Human Resource Management (SHRM) in order to support positive social change.

Summary

Human resources professionals view the company benefits package as a key component in attracting and retaining employees (Giblett, 2017). The employee benefits package also has a stronger relationship with employee turnover intention and organizational commitment than other company perks (Renaud, Morin & Béchard, 2017). As employers are managing the rising costs of health insurance by significantly changing the benefits strategy, employers should also engage strategies to mitigate any negative impacts of this change.

The increase in use of HDHP plans among employers has an especially significant impact on employees because these plans call for an actual behavior change in order to effectively manage the plans. Employees must become savvy consumers and evaluate their particular health care needs, financial stability and plan design when deciding on and using a HDHP (Gupta & Polsky, 2015). The purpose of this study was to identify the factors related to HDHP choice in order to assist employers with tools and strategy when making a significant benefit design change.

Chapter 2 includes a literature review of prospect theory, risk attitude and HDHP plan choice. Chapter 3 contains a discussion of the methodologies of this study as well as a review of the independent variables including salary, age, employee gender, family status, risk attitude and employee status. In addition, Chapter 3 includes participant selection and data collection methods. Chapter 4 provides baseline descriptives of the sample as well as the results of the data analysis. Chapter 5 contains an interpretation of findings and implications for this benefits and compensation study.

Chapter 2: Literature Review

Introduction

The purpose of this quantitative study was to examine specific employee variables that contribute to enrollment in a HDHP that conforms to the ACA minimum essential coverage standards. The independent variables were employee demographics including salary, employee age (continuous), employee gender (M/F), family status (nominal – employee only coverage, employee plus spouse, employee plus child(ren), and employee plus family), score on the Domain-Specific Risk-Taking Scale, and employee status (nominal – exempt, non-exempt). The dependent variable was enrollment in a HDHP or not (dichotomous). HDHPs are cited as an effective tool in controlling health care costs for employers (Miller, 2016), but HDHP plans may be considered a high-risk financial choice for certain groups (Lave, Men, Day, Wang & Zhang, 2011).

This literature review includes information regarding insurance choice, risk, and HDHP choice. This section also includes a gap in the research literature related to how ACA legislation may impact plan choice and the lack of current research on risk attitude and HDHP choice. Finally, this chapter includes a review of prospect theory as an appropriate theoretical model for framing how employees may consider risk when making health insurance choices.

Literature Search Strategy

The literature search included the databases PsychINFO, PsychARTICLES, Business Source Complete and MEDLINE. For the literature search, I used terms including *high deductible health plan, risk, prospect theory, consumer-driven health care, employee benefits,* and *employer-sponsored health plan.* I limited articles on variables related to HDHP choice to the past 10 years. Articles related to insurance trends were limited to the past 5 years in order to focus on meaningful results and conclusions. All articles were obtained in electronic format.

Insurance Choice and HDHPs

Insurance trends are moving toward giving individuals more choice (Bundorf, Mata, Schoenbaum & Bhattachara, 2013). For example, in the individual health insurance market, the ACA of 2010 established health insurance exchanges where consumers could choose among hundreds of plans based on their needs and preferences (Nadash & Day, 2014). For retirees, The Medicare Part D Prescription Drug Plan offers choice of subsidized private insurance drug plan options (Bundorf, Mata, Schoenbaum & Bhattachara, 2013). And for employees, 70% of mid-sized to large companies offer the choice of multiple medical plans (Kaiser Family Foundation 2017 Employer Benefits Survey, 2017).

When making a choice between multiple insurance plans, risk protection is a key consideration. For health insurance, premium cost and total out-of-pocket expenditure are key variables (Bundorf, Mata, Schoenbaum & Bhattachara, 2013). Simply put, plans that have the lowest premiums often carry higher out-of-pocket spending for the individual in the form of higher deductibles and coinsurance. When considering two or more health plans with very different out-of-pocket cost potential, employees must engage in risk-based decision making (Lluis & Abraham, 2013). On the one hand, employees that choose a plan with more benefits than they need may risk losing money on the high premium cost and on the other hand, employees that elect a plan with less benefits than they need may risk paying high out-of-pocket costs in the form of deductibles and coinsurance due to an unforeseen illness or accident.

HDHPs traditionally carry the most financial risk of employer group health plans (Wharam, Ross-Degan & Rosenthal, 2013). Prior to the ACA, all medical expenses for HDHP plans up to the deductible were paid for by the employee. The ACA reduced financial barriers and financial risk for certain services by removing the out-of-pocket cost for those services. Research prior to the ACA indicates that HDHPs were unpopular among certain groups because of the significant upfront out-of-pocket costs (Davis, 2005). Past research supports that when offered a choice between a HDHP and lower deductible health plan, less healthy employees (Jordan, 2014), older employees (Barry, Cullen, Galusha, Slade & Busch, 2008; Lave, Men, Day, Wang & Zhang, 2011) employees with lower salary (Barry, Cullen, Galusha, Slade & Busch, 2008; McDevitt, Haviland, Lore, Laudenberger, Eisenberg & Sood, 2014), and pregnant women (Graves, Kozhimannil, Kleinman and Wharam, 2016) are less likely to enroll in a pre-ACA HDHP.

Although in the past, pre-ACA plans were an unlikely choice for certain populations due to financial risk, it remains to be seen if enrollment trends for post ACA plans are the same. For example, if employees take advantage of no-cost preventive services and medications, this may reduce out-of-pocket risk and enrollment trends for HDHP plans may change. Research by Han, Yabroff, Guy, Aheng, and Jemal (2015) may shed light on this question. The researchers reported that for individuals under 65 and enrolled in private health insurance, the use of no-cost preventive services significantly increased after implementation of the ACA. Cooper, Dong Kou, Dor and Koroukian (2017) examined pre-ACA and post-ACA claims data of different socioeconomic groups. The authors found that individuals who reported a lower socioeconomic status were more likely to participate in free preventive care after for post-ACA plans. Han, Yabroff, Aheng and Jamal (2014) report that individuals with children also evidence an increase in the use of preventive services in post-ACA plans. In addition to HDHPs offering more generous preventive benefits under the ACA, the ACA standardized plan structure. There is evidence that when employees understand that HDHPs provide the same access to quality doctors as the more expensive plans, enrollment increases in those plans (Atanasov & Baker, 2014). The question remains whether groups such as those with lower salary, older individuals and females show increased enrollment in post-ACA HDHP plans.

Theoretical Foundation

Prospect theory is a popular framework for examining decisions under conditions of uncertain risk (Kothiyal, Spinu & Wakker, 2014). Prospect theory was created by psychologists Kahneman and Tversky (1979) and indicates that individuals make decisions based on potential gains and losses. Prospect theory outlines that individuals will be risk averse related to gains and risk seeking related to potential losses. Prospect theory has been used in I-O psychology research studies related to resource allocation and performance of sales people (Bonney, Plouffe & Wolter, 2014) and in evaluating effective methods of communicating production outcomes to employees (Kluge, Badura & Rietz, 2013). Sheaf (2016) indicated that the tenets and research from this framework may contribute to the field of I-O psychology.

Prospect theory outlines four essential elements of decision making: (a) reference dependence, (b) loss aversion, (c) diminishing sensitivity, and (d) probability weighting (Barberis, 2013). Kahneman and Tversky (1984) described reference dependence as the evaluation of options based on how the options compare to a reference point. According to the authors, the reference point is determined by the status quo and is affected by expectations and social comparisons. For example, an employee who expects to be paid $50,000 will view a $40,000 salary as a loss. Similarly, receiving an actual 20,000 tax bill when a $30,000 one was expected will be viewed as a gain (Kőszegi & Rabin, 2007). Reference dependence is one of the most studied variables related to choice (Bhatia, 2017). Research on reference dependence indicates that one's point of reference may be influenced by recent information (Huber, Viscusi & Bell, 2008; Yoon, Polpanumas, & Park, 2017), gender (Beckman, DeAngelo, Smith & Wang, 2016) and recent decisions (Huber, Viscusi & Bell, 2008). Interestingly, research shows that altering a subject's reference point can reverse choices (Bhatia, 2017).

Loss aversion is also a key element of prospect theory (Kahneman and Tversky, 1984) and differentiates prospect theory from expected utility theory (Rabin, 2000). Within prospect theory, loss aversion is the concept that individuals are more averse to losses than they are attracted by gains (Rabin, 2000). In fact, most studies report a loss coefficient of around two, indicating that losses weight twice as much as gains (Abdellaoui, Bleichrodt, Haridon & van Dolder, 2016). Kahneman and Tversky (1984) explain this outcome from an emotional perspective with the aggravation over loss being greater than the pleasure of a gain. Although a number of studies support this emotional perspective (Tang, Liang, Rao, Li, Zhou & Huang, 2016), loss aversion has been linked to other non-emotion variables as well. Individuals who are more loss averse may show more affect intensity and mood swings (Tang, Liang, Rao, Li, Zhou & Huang, 2016). A reduction in loss aversion is related to having more siblings, being of the male gender, and having greater prenatal testosterone exposure (Hermann, 2017).

Kahneman and Tversky (1992) described diminishing sensitivity as another component of prospect theory and propose that in the evaluation of outcomes, diminishing sensitivity relates to the impact of the change. The impact of a decision will lessen with distance from the reference point. A classic example is a positive change from $10 to $20 will have more impact than $110 to $120. In the same way, losing $10 with a change from -$10 to -$20 will have more of an impact than -$110 to -$120 (Wakker, Kobberling & Schwieren, 2007). The concept of diminishing sensitivity has been supported in a number of decision-making studies such as the disposition effect related to investing (Kohsaka, Mardyla, Takenaka & Tsutsui, 2017) and making choices involving trade-off considerations (Palmeira, 2013). However, there are other variables not described by Kahneman and Tversky (1992) that may relate to individual diminishing sensitivity differences. For example, Krekels and Pandelaere (2017) indicated that certain personality traits (such as "dispositional greed") impact the level of diminished sensitivity.

Probability weighting is a final key element of prospect theory and differentiates it from expected utility theory (Cavagnaro, Pitt, Gonzalez & Myung, 2013). Whereas expected utility theory weights outcomes based on their probabilities, prospect theory proposes an inverse-S shaped weighting function (Kahneman and Tversky, 1992). This weighting function indicates that small probabilities are overweighted and large probabilities are underweighted. Probability weighting is generally supported in risky choice research (Krčál, Kvasnička, & Staněk, 2016) and in the larger field of probabilistic inference (Boos, Seer, Lange & Kopp, 2016). Recent research points to individual and emotional factors that influence probability weighting, as well. For example, decisions that elicited negative affect (Petrova, van der Plight & Garcia-Retamero, 2014) and a person's negative mood (Fehr-Duda, Epper, Bruhin & Schubert, 2011), produced more biased probability weighting (i.e., S-shape). However, the impact of negative affect may only significantly increase the probability weighting function of individuals with less competence in mathematical options supporting the role of cognitive factors in the decision-making process.

Prospect Theory and Insurance Choice

Kairies-Schwarz, Kokot, Vomhof and Weßling (2017) examined whether the health insurance choices of individuals are consistent with prospect theory or other decision-making theories such as expected utility theory. As mentioned, the central features of prospect theory include diminishing sensitivity, probability weighting, and loss aversion. The authors reported that within their sample, behavior in the domain of gains and losses is consistent with prospect theory. In the area of gains, almost 63% of participants evidence risk averse behavior. In the area of losses, almost 57% were classified as risk seeking. In terms of probability weighting, individuals overweight small and medium probabilities and underweight high probabilities consistent with prospect theory. Finally, individuals demonstrated loss aversion where losses had a larger impact than gains of the same amount. Kusev, van Schaik, Ayton, and Dent (2009) reported that constant with prospect theory, there is increase in probability weighting for low hazardous events.

In terms of deductible level, prospect theory proposes that in order to avoid loss, individuals lean toward low deductible plans (Koszegi & Rabin, 2009). Even though low deductible plans have a higher premium payment because these are planned and regular, individuals do not experience the same psychological loss as they would with a chance loss (Sydnor, 2006). Eckles and Wise (2011) examined prospect theory preferences and deductible choice and reported that individuals do prefer more insurance (lower deductibles) in order to avoid the experience of loss, but that wealth may influence a person's reference point and impact the decision-making process. This present study adds to the literature on prospect theory by investigating the preference for a lower deductible over a high deductible and the impact of an individual's reference point on decisions under conditions of risk. In addition, by including risk-taking preference, this study may identify an additional significant variable related to plan choice not described by prospect theory.

Not all research on insurance choice supports prospect theory as a model. Bundoft, Mata, Schoenbaum, and Bhattacharya (2013) reported that prescription decisions in their study were consistent with expected utility theory. Most individuals in their sample (66%) were not biased by the weighting function and consistently chose a plan that provided greater protection against financial risk. In addition, Kusev, van Schaik, Ayton, Dent and Chater (2009) reported that risk decisions are not independent of problem content, not consistent with prospect theory. Also, there was an overweighting for moderate and high probability events, not consistent with prospect theory.

Risk Taking

Kahneman and Tversky (1992) proposed that the reference point is central to risk taking. Individuals tend to be risk taking in the area of loss and risk averse in the area of gain. Numerous studies support prospect theory demonstrating that that by changing reference points, for example, presenting a loss as a gain, the framing effect results in a change in choice (Bhatia, 2017). However, individual differences may also be important in the understanding of risk taking.

Cognitive and Neurological Factors and Risk Taking

Individual factors that are associated with risk-taking include neurological impairments (Bechara, Tranel & Damasio, 2000), impulsivity (Lejuez et al., 2002), information processing style (Tan, Wee Hun Lim & Manalo, 2017) and prenatal testosterone exposure (Chicaiza-Becerra & Garcia-Molina, 2017). Kandasamy et al. (2014) investigated chronic elevation of cortisol among traders. The authors reported that sustained elevation of cortisol is related to less risk taking. Traders who had higher sustained cortisol levels opted for bets with lower variance and expected returns. Oxytocin may also modulate risk behavior and increase risk aversion (Zak, Stanton & Ahmadi, 2007). Research therefore supports that there are a number of neurological and hormonal correlates and determinants of risk.

Personality and Risk Taking

Personality is a lens through which individuals perceive, evaluate and engage with the environment and therefore it is not surprising that one's attributes influences choices related to risk taking (Gardiner & Jackson, 2012). Nicholson, Soane, Fenton-O'Creevy and Willan (2005) indicated that risk choice is related to personality. Using the Neo PI-R, which provides scores on the Big Five personality factors, the authors reported that individuals who score high in extraversion and openness and low in neuroticism, agreeableness and conscientiousness have a higher risk propensity. Similarly, Gardiner and Jackson (2012) reported that extraversion, openness and low agreeableness predict risk behavior. In term of prospect theory-based research, there is a personality trait impact on relative thinking (Krekels & Pandelaere, 2017) and framing effects (Xiao-fei & Wang, 2003).

Demographic Factors and Risk Taking

Risk taking is related to a number of demographic variables. Older individuals are more risk averse than younger individuals (Bonsang & Dohmen, 2015; Lee & Blais, 2014). Women are more risk averse than men (Byrnes, Miller & Schafer, 1999; Lee & Blais, 2014). Both male and female prisoners are more likely to take risks than the nonprison population (Wichary, Pachur & Li, 2015). In a study of military personnel, Lee and Blais (2014) reported that officers show more risk taking in recreational activities, but lower risk taking in health and safety activities as compared to non-officers. In addition, the authors reported that education is related to risk taking with individuals having lower education showing higher health and safety risk propensity.

Risk Taking in Organizations

Risk taking within an organizational context has been an important consideration for safety (Burns & Conchie, 2014; Pek, Turner, Tucker, Kelloway & Morrish, 2017), risk management (Coschi, Costantini, Dickert & Sartori, 2017), leadership (Berg, Grimstad, Skerlavaj & Cerne, 2017), and performance (Kotlyar, Larakowsky, Ducharme & Boekorst, 2014). Of interest to the current research study is differences in risk attitude among employee groups. Buurman, Delfgaauw, Dur & Van den Bossche (2012) indicated that employment setting is related to risk with public sector employees being more risk averse than private sector employees. In addition, one's position within the company may impact risk attitude. Kotlyer, Karakowsky, Docharme and Boekhorst (2014) demonstrated that individuals who were singled out and put on a high potential track were more risk averse than others. Finally, employees in jobs with a fixed rather than variable income and those in jobs that are perceived as short-term are associated with higher risk aversion (Di Mauro & Musumeci, 2011).

Risk Taking and Insurance Choice

The purpose of health insurance is to reduce risk. Determining the right among of health insurance involves a trade-off between risk reduction and the purchase of too much health insurance (Manning & Marquis, 1996). As health insurance often involves decisions under conditions of risk and uncertainty (Ottaviani & Vandone, 2015), it is pertinent to examine risk taking and risk attitude related to insurance choice.

One area of study relates to whether or not individuals make insurance decisions that match their underlying preferences for risk. Bundorf, Mata, Schoenbaum and Bhattacharya (2013) examined prescription drug choice related to this area and reported that most participants choose plans in a consistent way that seems to indicate a stable risk preference. A smaller percent of participants (36%) appear to be impacted to how the information was framed when choosing a plan rather than relying on a stable risk preference. Ottaviani and Vandone (2015) provide support that insurance decisions are related to both demographic variables and attitudes toward risk. Consistent with other research (Barry, Cullen, Galusha, Slade & Busch, 2008; Lave, Men, Day, Wang & Zhang, 2011), age is related to insurance choice and older individuals tend to be more risk averse (Bonsang & Dohmen, 2015; Lee & Blais, 2014) and buy more insurance than younger individuals (Lave, Men, Day, Wang & Zhang, 2011). Ottaviani and Vandone (2015) also reported that insurance decisions are related to risk attitude showing that individuals with a higher risk propensity purchase more insurance. Kairies-Schwarz, Kokot, Vomhof & Webling (2017) add support that for insurance choice, a majority of individuals choose insurance consistent with individual risk preference.

Kusev, Schaik, Ayton and Dent (2009) cautioned that risk preference may not be consistent across decision content (e.g. insurance decisions versus monetary gambles). Certain decisions, such as insurance decisions, may involve and be influenced by emotional factors (Tennyson & Kyung Yang, 2014; Kusev, van Schaik, Ayton, Dent, & Chater, 2009). It is therefore important to research the decision-making process of insurance choice using insurance content.

Risk Decisions and High Deductible Health Plans

The choice of a high deductible health plan versus a traditional medical plan is a decision of financial risk. Employees with chronic conditions, unforeseen procedures or who do not manage their health care services who enroll in a HDHP may end up paying more for health insurance even though the HDHP has a lower premium (Galbraith, Soumerai, Ross-Degnan, Rosenthal, Gay & Lieu, 2012; Waters, Chang, Cecil, Kasteridis, & Mirvis, 2011; Wharam, Ross-Degnan & Rosenthal, 2013). Atanasov and Baker (2014) reported that health consideration is part of the HDHP decision-making process. Within a group of university employees, those that anticipated more healthcare use were less likely to enroll in the HDHP. However, risk attitude may play a role, as well. Atanasov and Baker (2014) reported that employees with a high-risk propensity were twice as likely to enroll in the HDHP than low risk propensity employees.

Chapter 2 Summary

Research on employee variables that relate to HDHP choice was conducted prior to the minimum essential coverage provision of the Affordable Care Act (ACA) of 2010 (French, Homer, Gumus & Hickling, 2016). The ACA set minimum standards for plans and therefore older research may not be generalized to today's ESI environment. There is indication that HDHP enrollment may increase now that all plans, regardless of deductible level, offer the same quality services (Atanasov & Baker, 2014) and more individuals are realizing and taking advantage of no cost services under HDHP plans (Cooper, Dong Kou, Dor & Koroukian, 2017). For these reasons, it is important to examine the employee variables related to HDHP enrollment using post-ACA plans.

Prospect theory has been shown to be a useful decision-making theory for insurance choice (Kairies-Schwarz, Kokot, Vomhof & Webling, 2017). Plan choice including plans with high deductibles is becoming the norm for employees with the expectation that consumers make rational decisions about healthcare expenditures. However, prospect theory contends that there are biases in the decision-making process. Instead of making purely rational financial decisions, individuals may be risk seeking in the domain of losses and risk averse in the domain of gains (Kahneman & Tversky, 1992). In health insurance, this may be exemplified by most individuals preferring a low insurance deductible in order to avoid loss (Eckles & Volkman, 2011). Researchers also support that individuals make insurance decisions based on individual risk tolerance (Bundoft, Mata, Schoenbaum, Bhattacharya, 2013) consistent with expected utility theory. In addition to these models, research on risk taking supports a number of other factors related to risk such as gender, job status and educational level.

This study adds to the current research by investigating employee variables related to HDHP enrollment using post-ACA plans. In addition, this study incorporates a measure of risk attitude to help address whether employees make HDHP decisions that match their risk attitude. This information helps HR professionals craft communication materials when offering multiple benefits with different deductible levels.

Chapter 3: Research Method

Introduction

In this study, I examined employee choice between PPO plans and HDHPs. This chapter includes the research design, data and data sources, and analytical procedures. The chapter concludes with ethical considerations.

Purpose of the Study

The purpose of this study was to examine the demographic variables and risk-taking propensity that contribute to enrollment in a HDHP that conforms to the ACA minimum essential coverage standards. To address this gap, I used a quantitative approach. My goal was to assist employers in developing educational materials for employees related to the insurance decision-making process.

Research Questions and Hypotheses

Research Question 1 (RQ1): Does salary predict high deductible health plan choice for individuals given a choice between a HDHP and low deductible plan?

Null Hypothesis ($H_0 1$): Salary does not predict enrollment in a high deductible health plan.

Alternative Hypothesis ($H_a 1$): Employees with a higher salary are more likely to enroll in a high deductible health plan.

Research Question 2 (RQ2): Does age predict high deductible health plan choice for individuals given a choice between a HDHP and low deductible plan?

Null Hypothesis ($H_0 2$): Age does not predict enrollment in a high deductible health plan.

Alternative Hypothesis ($H_a 2$): Employees who are older are less likely to enroll in a high deductible health plan.

Research Question 3 (RQ3): Does employee status predict high deductible health plan choice for individuals given a choice between a HDHP and low deductible plan?

Null Hypothesis ($H_0 3$): Exempt status not predict enrollment in a high deductible health plan.

Alternative Hypothesis ($H_a 3$): Employees who are categorized as exempt are more likely to enroll in a high deductible health plan.

Research Question 4 (RQ4): Does dependent coverage predict high deductible health plan choice for individuals given a choice between a HDHP and low deductible plan?

Null Hypothesis ($H_0 4$): Covering dependents does not predict enrollment in a high deductible health plan.

Alternative Hypothesis ($H_a 4$): Employees who cover dependents are less likely to enroll in a high deductible health plan.

Research Question 5 (RQ5): Does gender predict high deductible health plan choice for individuals given a choice between a HDHP and low deductible plan?

Null Hypothesis ($H_0 5$): Gender does not predict enrollment in a high deductible health plan.

Alternative Hypothesis (H_a5): Males are more likely to enroll in a high deductible health plan.

Research Question 6 (RQ6): Does total risk taking score as measured by the Domain Specific Risk Taking Scale (DOSPERT) predict HDHP choice for individuals given a choice between a HDHP and low deductible plan net of the predictive effect of demographic factors?

Null Hypothesis (H_06): Total DOSPERT score does not predict enrollment in a high deductible health plan net the predictive effect of demographic variables.

Alternative Hypothesis (H_a6): Employees with a higher DOSPERT score are more likely to enroll in a high deductible health plan.

Research Question 7 (RQ7): Does risk-taking score in the ethical domain as measured by the Domain Specific Risk Taking Scale (DOSPERT) predict HDHP choice for individuals given a choice between a HDHP and low deductible plan net of the predictive effect of demographic factors?

Null Hypothesis (H_07): Risk-taking score in the ethical domain on the DOSPERT does not predict enrollment in a high deductible health plan net the predictive effect of demographic variables.

Alternative Hypothesis (H_a7): Employees with a higher risk-taking score in the ethical domain as measured by the DOSPERT are more likely to enroll in a high deductible health plan.

Research Question 8 (RQ8): Does risk-taking score in the financial domain as measured by the Domain Specific Risk Taking Scale (DOSPERT) predict HDHP choice for individuals given a choice between a HDHP and low deductible plan net of the predictive effect of demographic factors?

Null Hypothesis ($H_0 8$): Risk-taking score in the financial domain on the DOSPERT does not predict enrollment in a high deductible health plan net the predictive effect of demographic variables.

Alternative Hypothesis ($H_a 8$): Employees with a higher risk-taking score in the financial domain as measured by the DOSPERT are more likely to enroll in a high deductible health plan.

Research Question 9 (RQ9): Does risk-taking score in the social domain as measured by the Domain Specific Risk Taking Scale (DOSPERT) predict HDHP choice for individuals given a choice between a HDHP and low deductible plan net of the predictive effect of demographic factors?

Null Hypothesis ($H_0 9$): Risk-taking score in the social domain on the DOSPERT does not predict enrollment in a high deductible health plan net the predictive effect of demographic variables.

Alternative Hypothesis ($H_a 9$): Employees with a higher risk-taking score in the social domain as measured by the DOSPERT are more likely to enroll in a high deductible health plan.

Research Question 10 (RQ10): Does risk-taking score in the health domain as measured by the Domain Specific Risk Taking Scale (DOSPERT) predict HDHP choice for individuals given a choice between a HDHP and low deductible plan net of the predictive effect of demographic factors?

Null Hypothesis ($H_0$10): Risk-taking score in the health domain on the DOSPERT does not predict enrollment in a high deductible health plan net the predictive effect of demographic variables.

Alternative Hypothesis (H_a10): Employees with a higher risk-taking score in the health domain as measured by the DOSPERT are more likely to enroll in a high deductible health plan.

Research Question 11 (RQ11): Does risk-taking score in the recreational domain as measured by the Domain Specific Risk Taking Scale (DOSPERT) predict HDHP choice for individuals given a choice between a HDHP and low deductible plan net of the predictive effect of demographic factors?

Null Hypothesis ($H_0$11): Risk-taking score in the recreational domain on the DOSPERT does not predict enrollment in a high deductible health plan net the predictive effect of demographic variables.

Alternative Hypothesis (H_a11): Employees with a higher risk-taking score in the recreational domain as measured by the DOSPERT are more likely to enroll in a high deductible health plan.

Research Question 12 (RQ12): Is there a significant interaction effect of the DOSPERT and its 5 subscales with demographic variables in predicting high deductible health plan choice for individuals given a choice between a HDHP and low deductible plan??

Null Hypothesis ($H_0$12): There is no significant interaction between the DOSPERT and its 5 domains with demographic variables in predicting HDHP enrollment.

Alternative Hypothesis (H_a12): There is an interaction effect between demographic variables and the DOSPERT in predicting high deductible health plan enrollment.

Research Design

I used a cross-sectional nonexperimental online survey that I analyzed using multiple logistic regression. The dependent variable is enrollment in a HDHP or not. An online survey including the Domain Specific Risk Taking Scale (Blais & Weber, 2006) was used for data collection. The purpose of the survey was to determine if enrollment in a HDHP is predictable by the following independent variables: salary, employee age (continuous), employee gender (M/F), family status (nominal – employee only coverage, employee plus spouse, employee plus child(ren), and employee plus family), score on the Domain-Specific Risk-Taking Scale, and employee status (nominal – exempt, non-exempt). The target population was all employees enrolled in employer-sponsored health insurance in the United States and includes about 150 million people.

The relationship between a binary dependent variable and predictor variables may be modeled with binary logistic regression (Field, 2013). When the predictor variable is binary, logistic regression is a preferred alternative to discriminant analysis (Hair, Anderson, Tatham, & Black, 1998; Field, 2013). In addition, logistic regression supports a combination of both continuous and categorical independent variables (de Sousa Mendes & Devós Ganga, 2013). Researchers examining insurance choice have used binary logistic regression and have underscored the benefits of this method. For example, Brody, Highfield, Wilson, Lindell, and Blessing (2017) used binary logistic regression to isolate the factors contributing to decisions of purchasing voluntary insurance. Erlyana et al. (2015) used binary logistic regression to identify the significant predictors of health insurance information-seeking behavior. Jordan and Cotter (2016) used binary logistic regression to investigate factors related to the choice between HDHP and non-HDHP plans. As I used a binary dependent variable (i.e., enrolled in HDHP or not), a combination of continuous and categorical independent variables, and my goal was to predict plan choice based on a set of independent variables, I chose logistic regression as the most appropriate choice.

Field (2013) described three main types of logistic regression: hierarchical (blockwise), forced entry and stepwise. Hierarchical regression involves selecting predictors based on *a priori* decision criteria. This allows the researchers to investigate changes in the model when other independent variables are introduced. Forced entry involves all variables being forced into the model simultaneously. This allows the researcher to investigate the individual contribution of predictors while controlling for other variables. Finally, stepwise regression relies on purely mathematical criterion when determining the order of predictors in the model. The stepwise approach is generally only supported in exploratory analysis (Field, 2013; Hosmer & Lemeshow, 1989), and underfitting and overfitting are two main risks with this method (Field, 2013).

I used a hierarchical model in the regression analysis in order to test the predictive ability of the independent variables. Because past research supports the role demographic variables in HDHP plan choice (Barry, Cullen, Galusha, Slade, & Busch, 2008; McDevitt, Haviland, Lore, Laudenberger, Eisenberg, & Sood, 2014; Lave, Men, Day, Wang, & Zhang, 2011), I tested the demographic variables separately from risk score. In order to test the predictive utility of risk preference, I used a hierarchical two-block enter method with block one being demographic variables and block two being risk preference. This assisted in evaluating if risk preference provides predictive utility beyond employee demographic characteristics.

I examined a number of variables in the logistic regression model. Exp(B) (odds ratio) is the change in odds based on a unit change in the predictor (Field, 2013). The Wald statistic is used to identify significant predictor variables (Tabachnick & Fidell, 2007). The -2 x Log likelihood statistics were used to compare the model against a baseline state to evaluate if the model has improved the fit (Field, 2013). The R-statistic (Cox and Snell in SPSS) is a partial correlation between the dependent and independent variables and may be used as the model effect size (Field, 2013).

I used Amazon Mechanical Turk (MTurk), an online platform with a large participant pool, to present the study survey. MTurk has been shown to be more representative of the U.S. population than traditional study recruitment methods (Berinsky, Huber & Lenz, 2012), is one of the most researched crowdsourcing tools (Chan & Holosko, 2016), and considered a suitable recruitment tool for psychological research (Chandler, Mueller, & Paolacci, 2013). Landers and Behrend (2015) stated that MTurk is a useful tool for I-O psychology research and is not dissimilar from other convenience samples. The study survey includes questions about individual variables such as salary and employment status as well as the Domain Specific Risk Taking Scale. The Domain Specific Risk Taking Scale is a 30-item measure and is easily loaded to the online platform. Sufficient reliability (Chronbach's alpha range from .71 to .86) and discriminant validity is reported (Weber, Blais & Betz, 2002).

Setting and Sample

Participants. The participants of this study were a convenience sample of male and female MTurk participants who reside in the United States, are 18 years to 64 years of age, are enrolled in health insurance and had the choice between a HDHP and lower deductible PPO. Because I focused on health plan choice, using the age range of 18 to 64 removed individuals who were not eligible to enroll as an adult and individuals who had access to other healthcare such as Medicare. Participants were offered $1.50 to participate in the survey that took 10 minutes or less. This is an anonymous survey; no identifying information including MTurk identification was collected as part of the survey process. I was not directly involved in compensating MTurk participants. I set up an account from which MTurk paid participants directly for successfully completing the survey.

Procedures. I used effect size, significance level, and power to determine the sample size for this study. The level of significance (α) is the probability (*p*-value) of committing a type 1 error (Field, 2013). I set α =.05, which is the common level of significance in psychological research to differentiate between statistical significance and non-significance (Bradley & Brand, 2013). Effect size refers to the strength of the relationship among study variables (Creswell, 2015). Within this study, effect size measures the strength of the relationship between the independent variables (i.e., salary, employee status, gender, family status and risk attitude) and HDHP choice. Cohen's *d* is a common measure of effect size with *d* = .2, .5, and .8 indicating a small, medium and large effect, respectively (Chen, Cohen & Chen, 2010). Cohen (1988) extended this recommendation to odds ratio (*OR*) with equivalent levels being 1.49, 3.45 and 9. I used the minimum detectible *OR* of 1.5 (small effect size) as the effect size for the current study. Statistical power refers to the probability that an analysis will detect a real treatment effect (Anderson, Kelley & Maxwell, 2017). The generally accepted value for power is .80. This indicates that 80% of the time the null hypothesis is rejected when there is a true effect (Field, 2013).

I used G*Power, a power analysis program for statistical tests commonly used in psychological research (Faul & Erdfelder, Lang & Buchner, 2007), to calculate sample size for this study. Conducting an *a priori* power analysis, the researcher may determine the required sample size, given alpha level, power, and effect size (Faul & Erdfelder, Lang & Buchner, 2007). For my research problem, I used a binomial logistic regression with the dependent variable HDHP enrollment (dichotomous) and therefore the test family "z-tests" was used. Following the G*Power 3.1 manual (G*Power, 2014), the Hsieh et al. procedure was used with the statistical test of logistic regression, an odds ratio of 1.5, alpha of .05, and power of .8. The total sample size required is 208 with actual power of .801.

I posted the study survey on MTurk with criteria to participate and an informed consent statement. An email address was provided so that any additional questions regarding participation can be directed to the researcher. Participants agreed to participate by reviewing the informed consent and proceeding with the survey. The survey did not include any personally identifiable information to ensure anonymity. The MTurk platform automatically paid participants at the end of the survey.

Instrumentation

Demographics. Demographic questions included basic information regarding the participants' age, gender, and type of work position (i.e., hourly or salaried).

Enrollment. Enrollment questions included current plan election (HDHP or not) as well as dependents covered on the individual's plan.

Domain Specific Risk Taking Scale. The Domain Specific Risk Taking Scale (DOSPERT), developed by Weber, Blais and Betz (2002), is a self-report 30-item scale that analyzes risk preference in 5 domains: financial, health/safety, recreational, ethical, and social. Using a Likert-scale of 1 to 7, individuals were asked to rate the likelihood of engaging in activities under each domain. For example, under the social domain an item is, *disagreeing with an authority figure on a major issue* and under financial a sample item is, *betting a day's income at the horse races*. The score for each domain is the sum of each item within the domain and higher scores indicate greater risk behaviors (Blais & Weber, 2006; Bundorf, Mata, Schoenbaum & Bhattacharya, 2013). Although the DOSPERT offers an optional Part II assessment on the perceptions of the magnitude of risks as well as the expected benefits of risk activities, the current study uses the risk taking scale consistent with other research on insurance choice (e.g., Bundorf, Mata, Schoenbaum & Bhattacharya, 2013) and financial decisions (Gurdal, Kuzubas and Saltoglu, 2017; Markiewicz & Weber, 2013). The tool along with the scoring guide are available on the Columbia Business School website (www8.gsb.columbia.edu/decisionsciences/research/tools/dospert) with instructions to freely use the scales along with appropriate citations. No additional permission is needed to use the DOSPERT.

The DOSPERT scale has been validated in a number of settings and populations (Blais & Weber, 2006) and has become the risk measure of choice in the area of risk decision making (Appelt, Milch, Handgraaf & Weber, 2011; Mishra & Lalumiere, 2011). Adequate internal consistencies (α) are reported for the different test domains with ethical = .75, financial = .83, health/safety = .71, recreational = .86 and social= .79 (Blais

& Weber, 2006). Factor analysis supports the 5 domains with mean risk taking levels varying significantly between the test areas. The highest mean level was found in the health area ($M = 28.15$, $SD = 5.94$) and lowest mean found in the social domain ($M = 17.01$, $SD = 5.93$).

I chose the DOSPERT because of its broad use in decision making in health and financial areas. Bundorf, Mata, Schoenbaum & Bhattacharya (2013) examined insurance choice using the DOSPERT and indicate that risk taking in the insurance domain are correlated with insurance choices. Because the present study focuses on health insurance, this provides support that the DOSPERT may be used to assess risk taking in the area of insurance decisions. In addition, scores on the DOSPERT are related to real-life financial risk-taking decisions. For example, Gurdal, Kuzubas and Saltoglu (2017) reported that risky decisions related to investing are positively related to higher scores on the DOSPERT. Because this study is exploring real life financial decisions and not hypothetical decisions in a laboratory, it is important to use a measure that is associated with real-life decisions. A copy of the DOSPERT is available in the Appendix.

Analysis

I conducted separate logistical regressions to assess whether the two sets of variables, demographics and risk preference, significantly predict HDHP enrollment. RQ1 to RQ5 focus on demographic variables predicting high deductible health plan choice for individuals given a choice between a HDHP and low deductible plan. Logistic regression using forced entry was used to investigate the individual contribution of predictor variables. RQ6 to RQ11 address the predictive ability of risk taking in the ethical, financial, health and safety, recreational, and social domain as measured by the Domain Specific Risk Taking Scale (DOSPERT) net of the predictive effect of demographic factors. A hierarchical logistic regression was used to test for the incremental predictive ability of risk perception with block one being demographics and block two being risk preference. RQ12 asks, is there a significant interaction effect of the DOSPERT and its 5 subscales with demographic variables in predicting high deductible health plan choice for individuals given a choice between a HDHP and low deductible plan? A logistic regression focusing on a series of interaction effects, using risk paired with each demographic variable was conducted to evaluate the effect of risk taking across the demographic variables.

The instrument was hand scored and the Statistical Package for Social Sciences (SPSS) version 10.12 was used for data analysis. The following were assessed related to assumptions for the binary logistic regression. Data screening and cleaning were conducted including using the missing value analysis routine in SPSS to examine the data for completeness prior to analysis. Z-scores were reviewed to examine for outliers that may lead to type I and type II errors. Multicollinearity was assessed using collinearity diagnostics to ensure that the independent variables are not highly correlated. The assumption of independence of errors was assessed as this may lead to overdispersion, which means the variance is larger than expected from the logistic regression model. A descriptive analysis using standard descriptive statistics was conducted for all employee variables.

Threats to Validity

Although MTurk has a large participant pool, a threat to validity is the sample. The study sample may not be representative of the United States employee population covered under employer-sponsored health insurance. MTurk tends to attract younger individuals and individuals who are not working full time (Chan & Holosko, 2016). In order to support sample prototypicality and sample relevance, participants met participation criteria including being employed full time, are covered under employer-sponsored health insurance and had the choice of a HDHP and lower deductible plan. The scale used in this study was carefully chosen based on the research questions. The DOSPERT is the measure of choice related to decision making under conditions of risk (Appelt, Milch, Handgraaf & Weber, 2011; Mishra & Lalumiere, 2011) and has been validated in a number of populations and settings (Blais & Weber, 2006).

Ethical Considerations

Careful consideration was given to the nature of this study and its possible effects on participants. This study used an anonymous survey format to protect the privacy of participants. The informed consent form was presented to all potential participants discussing the procedures for participation in the study, confidentiality, the voluntary nature of the study, the risks and benefits of participating in the study, as well as a way to contact the researcher with individual questions regarding the study. Participants were also notified that they are free to withdraw from the study at any time. Participants were not exposed to any risk that is greater than they would encounter in everyday life. Data collection only began after Walden IRB approval.

MTurk offers the option of collecting MTurk IDs on each participant. However, these IDs can be linked back to individual workers using an internet search (Lease et al., 2013). To ensure anonymity, MTurk IDs were not collected during the data collection process. In addition, no identifying information was collected in the survey such as name, social security number, or email. Participant payment occurred between the MTurk platform and the participant and therefore there was no contact between participants and researcher. Only the researcher had access to the data.

Chapter 3 Summary

The purpose of this study was to examine if risk-taking attitude and demographic variables predict enrollment in a HDHP. A quantitative analysis using multiple logistic regression was used to address the study research questions. Participants were asked to complete an online survey and the DOSPERT. The convenience sample is intended to represent employees covered under employer-sponsored health insurance within the United States. G*Power was used to calculate the sample size given alpha level, power, and effect size. Ethical considerations included utilizing an anonymous survey to protect participant identity and incorporating a clear informed consent statement. Chapter 4 presents the results of this study.

Chapter 4: Results

This chapter includes the results of the statistical analysis, guided by the theoretical model described in Chapter 2 and methodology described in Chapter 3. I present three research questions that address the demographic variables, additive utility of risk attitude, and the interaction of demographic variables and risk attitude in predicting HDHP choice. This chapter concludes with a chapter summary.

Purpose of Study

The purpose of this study was to examine the demographic variables and attitudes toward risk that contribute to enrollment in a HDHP that conforms to the ACA minimum essential coverage standards. To address this gap, I used a quantitative approach. My goal is to assist employers in developing educational materials for employees related to the insurance decision-making process.

Research Questions and Hypothesis

Research Question 1 (RQ1): Does salary predict high deductible health plan choice for individuals given a choice between a HDHP and low deductible plan?

Null Hypothesis ($H_0$1): Salary does not predict enrollment in a high deductible health plan.

Alternative Hypothesis (H_a1): Employees with a higher salary are more likely to enroll in a high deductible health plan.

Research Question 2 (RQ2): Does age predict high deductible health plan choice for individuals given a choice between a HDHP and low deductible plan?

Null Hypothesis ($H_0$2): Age does not predict enrollment in a high deductible health plan.

Alternative Hypothesis (H_a2): Employees who are older are less likely to enroll in a high deductible health plan.

Research Question 3 (RQ3): Does employee status predict high deductible health plan choice for individuals given a choice between a HDHP and low deductible plan?

Null Hypothesis ($H_0$3): Exempt status not predict enrollment in a high deductible health plan.

Alternative Hypothesis (H_a3): Employees who are categorized as exempt are more likely to enroll in a high deductible health plan.

Research Question 4 (RQ4): Does dependent coverage predict high deductible health plan choice for individuals given a choice between a HDHP and low deductible plan?

Null Hypothesis ($H_0$4): Covering dependents does not predict enrollment in a high deductible health plan.

Alternative Hypothesis (H_a4): Employees who cover dependents are less likely to enroll in a high deductible health plan.

Research Question 5 (RQ5): Does gender predict high deductible health plan choice for individuals given a choice between a HDHP and low deductible plan?

Null Hypothesis ($H_0$5): Gender does not predict enrollment in a high deductible health plan.

Alternative Hypothesis (H_a5): Males are more likely to enroll in a high deductible health plan.

Research Question 6 (RQ6): Does total risk taking score as measured by the Domain Specific Risk Taking Scale (DOSPERT) predict HDHP choice for individuals given a choice between a HDHP and low deductible plan net of the predictive effect of demographic factors?

Null Hypothesis (H_06): Total DOSPERT score does not predict enrollment in a high deductible health plan net the predictive effect of demographic variables.

Alternative Hypothesis (H_a6): Employees with a higher DOSPERT score are more likely to enroll in a high deductible health plan.

Research Question 7 (RQ7): Does risk-taking score in the ethical domain as measured by the Domain Specific Risk Taking Scale (DOSPERT) predict HDHP choice for individuals given a choice between a HDHP and low deductible plan net of the predictive effect of demographic factors?

Null Hypothesis (H_07): Risk-taking score in the ethical domain on the DOSPERT does not predict enrollment in a high deductible health plan net the predictive effect of demographic variables.

Alternative Hypothesis (H_a7): Employees with a higher risk-taking score in the ethical domain as measured by the DOSPERT are more likely to enroll in a high deductible health plan.

Research Question 8 (RQ8): Does risk-taking score in the financial domain as measured by the Domain Specific Risk Taking Scale (DOSPERT) predict HDHP choice for individuals given a choice between a HDHP and low deductible plan net of the predictive effect of demographic factors?

Null Hypothesis ($H_0 8$): Risk-taking score in the financial domain on the DOSPERT does not predict enrollment in a high deductible health plan net the predictive effect of demographic variables.

Alternative Hypothesis ($H_a 8$): Employees with a higher risk-taking score in the financial domain as measured by the DOSPERT are more likely to enroll in a high deductible health plan.

Research Question 9 (RQ9): Does risk-taking score in the social domain as measured by the Domain Specific Risk Taking Scale (DOSPERT) predict HDHP choice for individuals given a choice between a HDHP and low deductible plan net of the predictive effect of demographic factors?

Null Hypothesis ($H_0 9$): Risk-taking score in the social domain on the DOSPERT does not predict enrollment in a high deductible health plan net the predictive effect of demographic variables.

Alternative Hypothesis ($H_a 9$): Employees with a higher risk-taking score in the social domain as measured by the DOSPERT are more likely to enroll in a high deductible health plan.

Research Question 10 (RQ10): Does risk-taking score in the health domain as measured by the Domain Specific Risk Taking Scale (DOSPERT) predict HDHP choice for individuals given a choice between a HDHP and low deductible plan net of the predictive effect of demographic factors?

Null Hypothesis ($H_0$10): Risk-taking score in the health domain on the DOSPERT does not predict enrollment in a high deductible health plan net the predictive effect of demographic variables.

Alternative Hypothesis (H_a10): Employees with a higher risk-taking score in the health domain as measured by the DOSPERT are more likely to enroll in a high deductible health plan.

Research Question 11 (RQ11): Does risk-taking score in the recreational domain as measured by the Domain Specific Risk Taking Scale (DOSPERT) predict HDHP choice for individuals given a choice between a HDHP and low deductible plan net of the predictive effect of demographic factors?

Null Hypothesis ($H_0$11): Risk-taking score in the recreational domain on the DOSPERT does not predict enrollment in a high deductible health plan net the predictive effect of demographic variables.

Alternative Hypothesis (H_a11): Employees with a higher risk-taking score in the recreational domain as measured by the DOSPERT are more likely to enroll in a high deductible health plan.

Research Question 12 (RQ12): Is there a significant interaction effect of the DOSPERT and its 5 subscales with demographic variables in predicting high deductible health plan choice for individuals given a choice between a HDHP and low deductible plan??

Null Hypothesis ($H_0$12): There is no significant interaction between the DOSPERT and its 5 domains with demographic variables in predicting HDHP enrollment.

Alternative Hypothesis (H_a12): There is an interaction effect between demographic variables and the DOSPERT in predicting high deductible health plan enrollment.

Sample Description

In this section, I detail how the data were collected, fitted to study inclusion parameters, and how missing data were managed. I present descriptive statistics related to plan enrollment. In addition, I present variable analysis to address the assumptions underlying each analysis.

Data Collection and Analysis

I enabled the research survey with consent statement on the MTurk platform with access filters for United States residents only, enrolled in health insurance, and employed full time. For employees that elected to take the survey, a link was provided to SurveyMonkey in order to ensure anonymity and confidentiality. Data were collected over a period of 2 days. The data were downloaded from the SurveyMonkey platform in

Microsoft Excel format and loaded to the Statistical Package for the Social Sciences (SPSS) from IBM (version 21). Inclusion parameters described in Chapter 3 were applied to the data. Table 1 lists the inclusion parameters and cases removed to fit inclusion parameters. A total of 320 individuals responded to the survey. Among those that participated, 49 were eliminated from analysis because they did not fit plan inclusion parameters. Of this group, 38 did not have a choice between a HDHP and non-HDHP and were removed. Individuals that are not full-time active employees are typically not eligible for the same employer-sponsored coverage as full-time salaried and hourly employees (Jordan & Cotter, 2016). Because this study is focused on employer-sponsored group coverage for full-time employees, 11 cases were removed because they listed their employment status as contractor/consultant, part-time, and other. Another 18 were eliminated because of missing data. The total analyzed sample was 248 participants.

Table 1

Cases Removed to Fit Inclusion Parameters

Number of Cases Removed	Reason
32	No choice of health plan
11	Employee status
6	Not currently enrolled
10	Gender/DOB missing
2	No employment status
1	Salary missing
10	DOSPERT items not answered

Next, I scored the DOSPERT following scoring instructions by Blais and Webber (2006) to obtain risk domain scores and total risk score. The DOSPERT directed participants to report their likelihood of participating in various activities on a scale of 1 to 7 in the domains of financial, recreational, ethical, social, and health. Item ratings were totaled under each domain to calculate the domain score and domain scores were added together for the total DOSPERT risk-taking score.

Variable Analysis

Ott and Longnecker (2016) indicate that outliers have a higher impact on the results of the statistical analysis and therefore I assessed the data for univariate outliers. First, the variables with only two categories were analyzed to ensure that the split was more than 90-10, following recommendations by Field (2013). The dichotomous independent variables are HDHP enrollment, employment status and gender. The sample includes 132 women and 127 men, 168 hourly and 76 salaried employees, and 152 HDHP enrollments versus 107 non-HDHP enrollments. Based on this, no issue is indicated with the variable split.

Next, I assessed continuous variables for outliers using standardized z-scores. Standardized z-scores greater than 3.3 represent possible outlier cases following the recommendation by Field (2013). For salary, there were four cases where z-score > 3.3. Examining the data, two of the cases were listed as full-time hourly, but had annual salaries greater than 200,000 per year. As these are outside of the typical range of an hourly employee (Bureau of Labor Statistics, 2018) and there is no way to know if the very high salary or employee status was miskeyed, these cases were removed. One case had an annual salary listed as $3,500 but employment status listed as full-time. Because this is below minimum wage for a full-time employee, and it is not possible to know if the salary or employment status was miskeyed, this case was removed. The final case with a standardized z-score of 3.34 had an annual salary of $180,000, was listed as salaried, and there was no indication that data were miskeyed and therefore this case was retained for analysis. The DOSPERT had a number of cases with z-scores > 3.3. When examining these cases, there was only one that appeared to be clearly invalid as there was a pattern to the ratings (all 30 items were given the highest score of a 7) and this case was removed from analysis. All other cases were retained as there was no indication that they were invalid. There were no z-scores > 3.3 for age and age range for the final sample was 19 to 64 years of age. Removing the identified cases brought the sample size to 244.

Table 1 provides variable frequencies for tier, employee status, and gender. Field (2013) indicates that it is important to compare my sample with the United States workforce to support generalization. Women make up about 47% of the United States workforce. Within my sample, 51% of the participants are reported as female. According to the U.S. Labor Department (2018), most of the U.S workforce (59%) are hourly workers. This is also consistent with my sample where over 65% are reported to be hourly workers. In terms of plan enrollment, about 28% of employees were enrolled in a HDHP in 2017 (Kaiser, 2017). The current research sample has a higher percentage of HDHP enrollments (58%) than not (42%), which is inconsistent with the enrolled employee population in the United States. Coverage tier election for this sample is consistent with employer surveys (Kaiser, 2017), and indicates that most individuals are enrolled in employee only coverage with the second highest enrollment being employee plus family.

Table 2

Categorical Variable Frequencies

		HDHP		Non-HDHP		Total Sample	
Variable	Category	Number	Percent	Number	Percent	Number	Percent
Plan		142	58.2	102	41.8	244	100
Gender	Male	76	64.4	42	35.6	126	48.4
	Female	66	52.4	60	47.6	118	51.6
Tier	EE	73	64.6	40	35.4	113	46.3
	ES	21	63.6	12	36.4	33	13.5
	EC	12	44.4	15	55.6	27	11.1
	EF	36	50.7	35	49.3	71	29.1
Status	Hourly	103	61.3	65	38.7	168	68.9
	Salaried	39	51.3	37	48.7	76	31.1

Note: Enrollment tiers are employee only (EE), employee plus spouse (ES), employee plus child(ren) (EC), and employee plus family (EF).

Table 2 provides descriptive statistics for age, salary and the DOSPERT. Buckley and Bachman (2017) report that a majority of the U.S. workforce (64.6%) is between 25 and 54 years old. About 13.7% is between 16 to 24 and 21.7% is over age 54. The current research sample appears to be younger with the 25th percentile being 31 years of age and the 75th percentile being 44 years of age. About 68% of the current research sample is between and 28 and 47 years of age. In addition, the workforce in the United States is expected to become more weighted toward older workers as people continue to work longer and there are lower birth rates, indicating a difference between the current sample and possible enrollment trends in the United States in terms of age.

The median salary for workers in the United States is about 45,000 per year with salaried workers averaging \$64,220 per year and hourly workers averaging \$28,028 per year. The current sample reports a median salary of \$51,000 with M = \$57,960 and SD = \$29,244. For the current sample, salaried workers report a mean salary of \$67,521, 95% CI [60,040, 75,002] and hourly workers report a mean salary of \$54,497, 95% CI [50,634, 58,361]. Although the statistically significant difference between the salaried and hourly employees in the current sample is directionally consistent with the reported salaries of U.S. workers (i.e. salaried workers tend to get paid more than hourly workers), the hourly workers in the current sample appear to have a higher average salary than the U.S. hourly population of employees.

Blais and Weber (2006), the developers of the DOSPERT, report that the highest domain mean is within the Social domain (M=32.58, SD = 4.65) and the lowest mean level is in the Ethical domain (*M*=16.92, *SD* = 2.42). The authors report the other domain mean scores to be 22.42, 20.63 and 19.61 for Recreational, Health/Safety and Financial respectively. Similar to Blais and Weber, the highest domain score for the current sample is within the Social domain (*M* = 29.3, *SD* = 6.5). The current sample is also consistent with Blais and Weber in that the Ethical domain had the lowest mean level of all domain scores (*M* = 12.4, *SD* = 5.4). The remaining domain scores were also consistent with Blais and Weber with the current study scores being 17.6, 17.1, and 15.1 for Recreational, Health/Safety and Financial respectively.

Table 3

Continuous Variable Descriptive Statistics

	HDHP		Non-HDHP		Total Sample	
Variable	Mean	SD	Mean	SD	Mean	SD
Age	36.66	.74	39.87	.90	38.00	9.05
Income	57,791.56	2334.46	60,322.54	2930.21	58,849.60	28,541.26
Recreational	17.63	.72	17.60	.89	17.62	8.84
Social	29.01	.56	29.69	.62	29.30	6.54
Health	17.42	.59	16.75	.69	17.14	7.03
Financial	15.47	.56	14.56	.57	15.09	6.30
Ethical	12.66	.49	12.07	.48	12.41	5.42
Total DOSP.	92.20	1.85	90.69	2.21	91.57	22.12

Bivariate Analyses

I used bivariate correlations to identify productive variables for a later logistic regression. A variable is productive if the relationship with the dependent variable is statistically significant ($p < .25$) and if the strength of the relationship is at least small (Bursac, Gauss, Williams & Hosmer, 2008; Kutner, Nachtsheim & Neter, 2014). The independent variables age, dependents on coverage, employee status, salary, and gender were included in this study as they were previously identified as related to HDHP enrollment. In addition, risk taking has been investigated related to health insurance choice and has a theoretical relationship to insurance preference. I used a relaxed *p*-value to judge statistical significance at this phase consistent with Bursac, Gauss, Williams and Hosmer (2008). The reason for using a cut-off point of .25 rather than the traditional .05 is that more restrictive levels such as .05 can fail to identify variables important for later logistic regression (Bursac, Gauss, Williams & Hosmer, 2008). In addition, the size of the relationship must be at least small.

I used point biserial correlation to measure the association of HDHP enrollment with the continuous independent variables age and salary and the total DOSPERT score as well as the DOSPERT subscales Ethical, Financial, Health/Safety, Social and Recreational risk taking. Table 4 displays the results of the variable selection analysis. Among the continuous independent variables, age was significant at $p = \leq .25$ with at least weak negative relationship to HDHP enrollment. Results from an independent samples t test indicated that individuals enrolled in a high deductible health plan ($M =$

36.66, *SD* = 8.79, *N* = 142) are younger than those in a lower deductible plan (*M* = 39.87, *SD* = 9.13, *N* = 102), *t*(212.673) = -2.752, *p* =.006, two-tailed, 95% CI of the difference [.911, 5.510]. The DOSPERT subscale Financial Risk approached the relaxed level of significance with *p* = .26.

Table 4

Bivariate Analysis

Variable	Coefficient of Correlation	*p*
Salary	-.04	.50
Age	-.18	<.01
Total DOSPERT	.03	.60
Ethical	.06	.41
Social	-.05	.43
Financial	.07	.26
Gamble	.14	.03
Invest	.-01	.91
Health	.05	.47
Recreational	.02	.98
Enrollment Tier		
Four Tier	.16	.11
With/Without Child	.15	.02
Status	.09	.14
Gender	.12	.06

Note: Phi coefficient and Cramer's V was used to test the relationship for categorical variables and point biserial correlation was used for continuous variables.

Blais and Weber (2006) provide scoring instructions that the Financial subscale may be split into separate gambling items and investment items. The Financial subscale is the only subscale that may be split into two categories per DOSPERT scoring instructions. Therefore, in order to explore the relationship of gambling and investment to HDHP enrollment separately, I split financial risk into these subdomains. Financial/Gamble reached significance with r_{pb} = .14, *p* = .03. Results from an independent samples *t* test indicated that individuals enrolled in a HDHP (*M* = 5.46, *SD* = 3.93, *N* = 142) scored higher on the Financial/Gamble subscale than those not enrolled in a HDHP (*M* = 4.47, *SD* = 2.81, *N* = 102), *t*(242) = -2.167, *p* =.031, two-tailed, 95% CI of the difference [.09, 1.88]. An independent-samples *t* test was conducted to compare the Financial/Gamble subscale for males and females. The independent samples *t* test indicated that males (*M* = 5.64, *SD* = 4.01, *N* = 118) scored higher on the Financial/Gamble subscale than females (*M* = 4.48, *SD* = 2.94, *N* = 126), *t*(242) = 2.565, *p* =.011, two-tailed, 95% CI of the difference [.278, 2.42]. An independent-samples *t* test was conducted to compare the Financial/Gamble subscale in salaried and hourly employees. There was a not a significant difference in scores from salaried (*M* = 4.93, *SD* = 3.52, *N* = 76) and hourly employees (*M* = 5.09, *SD* = 3.55, *N* = 168), *t*(145.97) = .330, *p* =.742, two-tailed, 95% CI of the difference [-.804, 1.126]. Table 5 displays the intercorrelations for the dichotomous variable gender, the continuous variables age, salary, and the Financial/Gamble subscale. Older employees scored lower on the Financial/Gamble subscale. In addition, older employees reported higher annual salaries.

There is also a significant correlation between the Financial/Gamble subscale and gender. Finally, the test of the relationship between the Financial/Investment subscale and HDHP enrollment was not significant ($r_{pb} = .01, p = .91$).

Table 5

Intercorrelations for the Financial/Gamble Subscale, Age, Salary, and Gender

Variable	1	2	3	4
1. Financial/Gamble		-.132*	.164**	NS
2. Age			.192**	192**
3. Gender				.213**
4. Salary				

Note: *Correlation is significant at .05 (2-tailed). **Correlation is significant at .01 (2-tailed). NS= Not significant.

I used the Phi coefficient and Cramer's V as measures of the strength of association between HDHP enrollment and the categorical variables gender, dependents covered, and employee status, Cramer's V was used for the multi-category enrollment tier independent variable and the Phi coefficient for dichotomous independent variables (Field, 2014). Table 4 displays the results of the variable selection analysis for the categorical variables. All variables were statistically significant using the *a priori* decision criteria of $p \leq .25$ as a cut-off point.

Past research has examined dependent coverage and HDHP enrollment using a four tier categorical approach (Jordan & Cotter, 2016) and dichotomous variable approach (Graves, Kozhimannil, Kleinman and Wharam, 2016; Lave, Lave, Men, Day, Wang & Zhang, 2011). Galbraith, Soumerai, Ross-Degnan, Rosenthal, Gay, and Lieu (2012) identify different risks for adults versus children on HDHPs. Shinkin (2014) states that HDHPs may be a poor choice for child coverage because children typically use more medical services than adults. Graves, Kozhimannil, Kleinman and Wharam (2016) report that there is reduced birth rates for employees covered under HDHPs as compared to lower deductible plans. The authors indicate that the medical costs related to child birth and child health care make HDHPs a poor decision for this group. For this reason, in addition to analyzing the four tiers separately, an additional variable was created that allowed for the analysis of a bivariate relationship between enrollments with and without children on coverage and HDHP election. In order to create the new independent variable of coverage with and without children, the four tier categorical variable was transformed by combining all tiers with children and all tiers without children into a dichotomous variable. The transformed variable with/without minor children achieved significance at $\alpha = .05$ with $\Phi = -.15$, $p = .02$. Results from this analysis showed that 5 of the 13 variables are meaningfully related to HDHP enrollment.

Binary Logistic Regression

Yearly income did not show a statistically significant difference between HDHP and non-HDHP enrollment and therefore was not included in the logistic regression analysis. In addition, the DOSPERT total score and subscales Ethical, Financial/Investment, Health/Safety, Social, and Recreational were not included because there was no statistically significant difference between the scores of HDHP enrollees and non-HDHP enrollees. The Financial/Gamble subscale was included. The impact of dependents on coverage was analyzed using a 4-tier categorical variable and separately using the dichotomous independent variable of the presence or absence of a child on the plan.

Assessing Assumptions for Logistic Regression

I used a multiple binary logistic regression for hypothesis testing. Binary logistic regression may be biased by failing to meet certain assumptions (Field, 2013). For the current study, the outcome variable HDHP enrollment is dichotomous and the outcome categories are mutually exclusive (Field, 2013). That is, at the time of the study, every case fit into one of the two categories: enrolled in HDHP plan or not enrolled in HDHP plan. As previously reported, variables were included in the analysis if they were productive. Additional assumptions include there is a linear relationship between continuous variables and the logit of the outcome variable, expected frequencies are sufficient for the goodness-of-fit tests, independent variables are not highly correlated resulting in multicollinearity, and the residuals are not more variable than expected resulting in overdispersion (Field, 2013).

Multicollinearity. Field (2013) reports that multicollinearity may affect the parameters in a logistic regression model and that tolerance and variance inflation factor (VIF) may be used to assess issues with collinearity. VIF scores and tolerance were obtained using a regression analysis in SPSS. There may be an issue with multicollinearity for VIF scores above 10 and tolerance scores less than .10 (Field, 2013). For the IVs retained, all VIF scores were below 10 and all tolerance scores are well above .1. No issues with multicollinearity are indicated within these data. Table 6 displays the collinearity statistics.

Table 6

Collinearity Statistics

Variable	Tolerance	VIF
Age	.974	1.03
Financial/Gamble	.953	1.49
4 Tier*	.984	1.02
With/Without Child*	.997	1.00
Status	.990	1.01
Gender	.972	1.03

Note: * IVs tested separately.

Linearity. Because the outcome variable is categorical in logistic regression, the assumption of linearity is violated. Therefore, in logistic regression, the assumption of linearity must be met by examining the relationship between the continuous independent variables and the logit of the outcome variable (Field, 2013). This is done by creating a log of each of the original continuous IVs and completing a logistic regression with the additional IVs that are interactions between each predictor and its log. If the interaction terms are significant, this is an indication that the main effect has violated the assumption of linearity of the logit (Field, 2013). Linearity was tested for age and the Financial/Gamble subscale of the DOSPERT by creating interactions terms between each predictor and its log and conducting a binary logistic regression with these interaction terms and the original variables. The output of the test showed that both interactions have significance values greater than .05 (logFinancial/Gamble p = .8; logAge p = .31) indicating that the assumption of linearity of the logit has been met for the independent variables.

Independence of Errors. Overdispersion is produced when violating the assumption of independence of errors in logistic regression (Field, 2013). Overdispersion occurs when the assumption of independence is broken and there is variability in success probabilities. Overdispersion is indicated if the dispersion parameter ($\boldsymbol{\Phi}$) is greater than 1. The dispersion parameter was determined by calculating the ratio of the chi-square goodness-of-fit statistic to its degrees of freedom. The result of this calculation was $\boldsymbol{\Phi} = \frac{\mathbf{7.68}}{\mathbf{8}} = \mathbf{.96}$. Therefore, there is no evidence of overdispersion.

Sufficient Data and Expected Frequencies. To support the goodness-of-fit test, sufficient data should be collected so that all combinations of variables are represented and no more than 20% of expected frequencies for each combination of variable is less than 5 (Field, 2013). A Crosstabs evaluation in SPSS revealed that no more than 20% of expected frequencies for the categorical variables were less than 5.

Model 1: Enter logistic regression

A binary logistic regression was conducted to identify the participant characteristics of age, employee status, gender, and dependent enrollment status that predict enrollment in a HDHP plan. The first logistic regression was conducted with dependent enrollment status being a 4-tier categorical variable. This block was statistically significant, $\chi^2(4, N = 244) = 17.601, p = .007$ and showed a total percent correctly classified at 60.2%. The Hosmer and Lemeshow test of model fit showed a good fit, $\chi^2(8, N = 244) = 6.507, p = .591$. The Nagelkerke R Square indicated that this block accounted for 9.4% of the total variance. Table 7 shows the results of model 1. Age was the only variable that was statistically significant with an odds ratio of .962, β = -.038, p = .011. An odds ratio of .962 points to an inverse relationship between age and enrollment in a HDHP. For a one year increase in age, the odds of being in the HDHP decrease by 3.8%.

Table 7

Model 1: 4 Tier

Independent Variables	β	SE_B	p	OR	95% CI
Gender	-.455	.279	.104	.635	[.367, 1.097]
Status	.335	.291	.249	1.398	[.791, 2.471]
Employee Spouse	-.094	.429	.827	.910	[.393, 2.111]
Employee Child	-.742	.450	.099	.476	[.197, 1.150]
Employee Family	-.585	.318	.065	.557	[.299, 1.038]
Age	-.038	.015	.011	.962	[.935, .991]

Next, the logistic regression was conducted with the dichotomous IV with/without children and the 4 tier variable was removed. This block was statistically significant, $\chi^2(4, N = 244) = 17.441, p = .002$ and showed a slight increase in the total percent correctly classified at 60.7%. The Hosmer and Lemeshow test of model fit showed a good fit, $\chi^2(8, N = 244) = 4.262, p = .832$. The Nagelkerke R Square indicated that this block accounted for 9.3% of the total variance. Table 8 shows the results of model 1. Age continued to be statistically significant with an odds ratio of .963, β = -.038, *p* = .011. The transformed IV with/without child(ren) on coverage was also statistically significant with an odds ratio of 1.833, β = .606, *p* = .026. The results show that when controlling for age, gender and employee status, for employees who cover at least one child, the odds of being in the non-HDHP are 83% greater than then odds of being in the HDHP.

Table 8

Model 1: Dichotomous Tier

Independent Variables	β	SE_B	*p*	*OR*	95% CI
Gender	-.467	.270	.084	.627	[.369, 1.065]
Status	.344	.289	.235	1.41	[.800, 2.486]
With/Without Child	.606	.272	.026	1.833	[1.075,3.126]
Age	-.038	.015	.011	.963	[.935, .991]

RQ1, RQ2, RQ3, RQ4, and RQ5 examined the individual variables of salary, gender, employee status, dependents covered and age and how these relate to predicting HDHP enrollment. There is insufficient evidence to reject the null hypothesis that salary (RQ1), employee status (RQ3), and gender (RQ5) do not predict enrollment in a HDHP. Age is meaningfully related to HDHP enrollment (p = .011, β = -.038, *OR* = .963). For a one year increase in age, the odds of being in the HDHP decrease by 3.8%. There is sufficient evidence to reject the RQ2 null hypothesis and conclude that older employees are less likely to enroll in a high deductible health plan. Dependents covered is also meaningfully related to HDHP enrollment. The independent variable related to dependent enrollment status using a four tier approach was not significant for any tier in the regression analysis. However, when just examining the effect of covering children on the plan or not, the transformed variable with children/without children, is meaningfully related to HDHP enrollment (p = .026, β = .606, *OR* = 1.833). Employees with children are less likely to be covered under a HDHP. Therefore, there is sufficient evidence to reject the RQ4 null hypothesis and conclude that employees covering dependents are less likely to enroll in a high deductible health plan.

Model 2: Two-block enter method

A binary logistic regression was conducted to identify if Financial/Gamble DOSPERT subscale provided predictive utility beyond the participant characteristics of age, employee status, dependents enrolled, gender, and tier. As in model 1, block 1 was conducted with the 4 tier dependents covered IV first. The results of block 1 are listed in Table 9. This block was statistically significant, $\chi^2(5, N = 244) = 17.601, p = .007$ and showed a total percent correctly classified at 60.2%. The Hosmer and Lemeshow test of model fit showed a good fit, $\chi^2(8, N = 244) = 6.507, p = .591$. The Nagelkerke R Square indicated that this block accounted for 9.4% of the total variance. As in model 1, age was the only variable that was statistically significant with an odds ratio of .962, β = -.038, p = .011. An odds ratio of .962 points to an inverse relationship between age and enrollment in a HDHP. For a one year increase in age, the odds of being in the HDHP decrease by 3.8%.

Table 9

Model 2: Block 1, 4 Tier

Independent Variables	β	SE_B	p	OR	95% CI
Gender	-.455	.279	.104	.635	[.367, 1.097]
Status	.335	.291	.249	1.398	[.791, 2.471]
Employee Spouse	-.094	.429	.827	.910	[.393, 2.111]
Employee Child	-.742	.450	.099	.476	[.197, 1.150]
Employee Family	-.585	.318	.065	.557	[.299, 1.038]
Age	-.038	.015	.011	.962	[.935, .991]

The financial/gamble subscale was added in block 2. The results of this block are listed in Table 10. This block was statistically significant, $\chi^2(7, N = 244) = 20.517, p = .005$ and showed a total percent correctly classified at 62.7%, a slight increase over block 1. The Hosmer and Lemeshow test of model fit showed a good fit, $\chi^2(8, N = 244) = 7.420, p = .492$. The Nagelkerke R Square indicated that this block accounted for 10.9% of the total variance, a slight increase over block 1. Age was the only significant variable although the enrollment tier *employee plus family* approached significance with p = .051.

Table 10

Model 2: Block 2, 4 Tier

Independent Variables	β	SE_B	p	OR	95% CI
Gender	-.394	.283	.163	.674	[.387, 1.174]
Status	.322	.293	.271	1.381	[.777, 2.453]
Employee Spouse	-.146	.433	.737	.865	[.370, 2.020]
Employee Child	-.751	.453	.098	.472	[.194, 1.147]
Employee Family	-.626	.321	.051	.535	[.285, 1.002]
Age	-.035	.015	.019	.965	[.937, .994]
Financial/Gamble	.070	.042	.098	1.073	[.987,1.166]

The binary logistic regression was also conducted for model 2, block 1 with the dichotomous IV related to dependents covered. The results of this block are listed in Table 11. This block was statistically significant, $\chi^2(5, N = 244) = 20.331, p = .001$ and showed a total percent correctly classified at 60.7%. The Hosmer and Lemeshow test of model fit showed a good fit, $\chi^2(8, N = 244) = 4.269, p = .832$. The Nagelkerke R Square indicated that this block accounted for 9.3% of the total variance.

Table 11

Model 2: Dichotomous Tier

Independent Variables	β	SE_B	p	OR	95% CI
Gender	-.467	.270	.084	.627	[.369, 1.065]
Status	.344	.289	.235	1.410	[.800, 2.486]
With/Without Child	.606	.272	.026	1.833	[1.075,3.126]
Age	-.038	.015	.026	.963	[1.075, 3.126]

Block 2 is reported in Table 12. This block was statistically significant, $\chi^2(5, N = 244) = 20.331, p = .001$ and showed a total percent correctly classified at 63.9%. This increase in percent correctly classified is an improvement over block 1 and an improvement over block 2 of the 4 tier IV. The Hosmer and Lemeshow test of model fit showed a good fit, $\chi^2(8, N = 244) = 4.675, p = .792$. The Nagelkerke R Square indicated that this block accounted for 10.8% of the total variance, an increase over block 1. Although age and coverage with children continued to be significant, the financial/gamble subscore was not significant at alpha = .05.

Table 12

Model 2: Dichotomous Tier

Independent Variables	β	SE_B	p	OR	95% CI
Gender	-.398	.274	.147	.672	[.392, 1.149]
Status	.333	.292	.254	1.395	[.787, 2.473]
With/Without Child	.628	.275	.022	1.873	[1.093,3.209]
Age	-.035	.015	.020	.966	[.938, .994]
Financial/Gamble	.070	.042	.100	1.072	[.987, 1.165]

RQ6, RQ7, RQ8, RQ9, RQ10, and RQ11 examined the additive contribution of total risk taking score and risk taking in the ethical, financial, health and safety, recreational, and social domain as measured by the Domain Specific Risk Taking Scale (DOSPERT) in predicting HDHP choice for individuals given a choice between a HDHP and low deductible plan net of the predictive effect of demographic factors. Even though HDHP enrollees had a higher Financial/Gamble subscore, this subscore did not predict HDHP enrollment when controlling for other variables such as age. It is notable that past studies indicate that risk-taking behavior is sensitive to age differences (Mata, Josef, Sammanez-Larkin & Hertwig, 2011). The findings indicate that there is insufficient evidence to reject the null hypothesis and conclude that the total DOSPERT score (RQ6) or the ethical (RQ7), financial (RQ8), health/safety (RQ10), recreational (RQ11), and social (RQ9) domains as measured by the Domain Specific Risk Taking Scale (DOSPERT) predict HDHP choice for individuals given a choice between a HDHP and low deductible plan net of the predictive effect of demographic factors.

Model 3: Interactions

The final model was to test possible interactions between the Financial/Gamble subscale of the DOSPERT and participant characteristics of age, employee status, gender, and with/without child on coverage. Since the 4 tier variable of employee only, employee plus spouse, employee plus child and employee plus family has not been significant at $\alpha = .05$ in any previous model, this variable was dropped for model 3 and only the variable related to employee coverage with a child on coverage and without a child on coverage was analyzed. This block was statistically significant, $\chi^2(9, N = 244) = 20.292, p = .016$ and showed a total percent correctly classified at 63.5%. The Hosmer and Lemeshow test of model fit showed a good fit, $\chi^2(8, N = 244) = 11.584, p = .171$. The Nagelkerke R Square indicated that this block accounted for 11.9% of the total variance. Table 13 shows the results of model 3. Age was no longer significant in this model. The transformed IV with/without child(ren) on coverage was also statistically significant with an odds ratio of 3.480, β = 1.247, p = .014. The results show that when controlling for age, gender, employee status, and financial/gamble subscore and the interaction of financial/gamble with all other individual variables, for employees who cover at least one child, the odds of being in the non-high deductible plan are 248% greater than the odds of being in the HDHP.

Table 13

Model 3: Interactions

Independent Variables	β	SE_B	p	OR	95% CI
Gender	-.317	.505	.531	.729	[.271, 1.961]
Status	.269	.536	.616	1.308	[.458, 3.731]
With/Without Child	1.247	.507	.014	3.480	[1.287, 9.409]
Age	-.035	.030	.241	.966	[.911, 1.024]
Financial/Gamble	.149	.220	.497	1.161	[.755, 1.785]
Financial*Gender	-.017	.089	.848	.983	[.825, 1.171]
Financial*Status	.002	.095	.985	1.002	[.831, 1.207]
Financial*W/Child	-.128	.090	.155	.880	[.737, 1.050]
Financial*Age	.000	.006	.981	1.000	[.989, 1.011]

RQ12 addressed if there is a significant interaction effect of the DOSPERT and its 5 subscales with demographic variables in predicting high deductible health plan choice for individuals given a choice between a HDHP and low deductible plan. There is insufficient evidence to reject the null hypothesis and conclude that there is a significant interaction effect. No interactions were significant at alpha = .05.

Summary

Based on results across models, the top predictors for enrollment in a HDHP are age and the presence of a child on coverage. To arrive at this conclusion, two sets of analysis were conducted. First, bivariate analyses were run to describe the population and assess all variables for possible inclusion into the model. A relaxed alpha level of .25, supplemented by a Pearson's *r* value of at least a small effect size was used to identify variables for the logistic regression. Of the DOSPERT subscales, only Financial/Gamble met the *a priori* decision criteria. Salary was not significant and was not retained for the logistic regression. Enrollment tier was analyzed in two ways. First using a 4 tier approach and secondly as a dichotomous variable with/without child(ren) on coverage. VIF scores >10 and tolerance scores <.1 were used to identify multicollinearity and no variables showed signs of multicollinearity.

Next, multivariate analyses were conducted to determine a set of predictors for HDHP enrollment. Retained variables were analyzed using an enter method logistic regression that consisted of three models. Model 1 included all individual variables. Age and the dichotomous variable with/without children on coverage were the two independent variables that were significant at alpha = .05. The older the employee, the less likely the employee would be enrolled in a HDHP. In addition, the dichotomous variable with/without children resulted in an odds ratio of 1.833 indicating a small effect size (Cohen, 1988). Employees with children were less likely to be enrolled in a HDHP controlling for all other variables. The 4 tier enrollment variable was not significant. The purpose of model 2 was to investigate the additive predictive utility of the Financial/Gamble subscale. The Financial/Gamble subscale was not significant and did not add predictive utility. The purpose of model 3 was to analyze the possible interaction between the Financial/Gamble subscore and the participant characteristics of age, employee status, gender and enrollment tier. No interactions were significant in this model. The results point to the importance of two variables, age and the status of children on coverage, as being significant predictors of HDHP enrollment for employees.

Chapter 5: Discussion

Introduction

The purpose of this study was to examine the demographic variables and attitude toward risk that contribute to enrollment in an employer-sponsored HDHP. As healthcare costs continue to rise, employers are looking for ways to reduce health insurance premiums. A popular option is to offer a lower cost HDHP. Insurance professionals claim that HDHPs result in lower costs both for the employee and employer by encouraging consumerism (Gupta & Polsky, 2015). The theory is that if employees are spending their own money on first dollar health care services due to the high deductible, then they will be more likely to shop for lower cost services.

An unintended consequence of HDHPs is that there are associated adverse selection issues (Gupta & Polsky, 2015). Even though employers do not set out to offer a health insurance plan targeted for certain employee groups, research shows that HDHPs have attracted employees who are younger, healthier, and have a higher salary (Bindman, Hulett, Gilmer & Bertko, 2016; Jordan, 2014; Lave, Lave, Men, Day, Wang & Zhang, 2011). This is understandable because prior to the ACA, most HDHPs required that the employee pay for all medical services up to the deductible. Since HDHPs have deductibles at or above $1,350 per Federal guidelines, these plans were a financial risk for employees who had even the occasional medical visit or prescription. However, insurance plans have been enhanced due to ACA regulations. Now all insurance plans, even HDHPs, must cover certain procedures and medications at no cost to the employee.

These no-cost services include annual physicals, mammograms, colonoscopies, immunizations, cancer screenings and certain maintenance medications. I designed the current study to address a gap in the research related to enrollment in HDHPs post-ACA. Specifically, the purpose of this study was to investigate the demographic variables and attitudes toward risk that contribute to enrollment in plans that conform to the minimum essential coverage standards of the ACA. My goal for this study was to assist employers in developing educational materials for employees related to the insurance decision-making process within the current health insurance environment.

I employed variable analysis, bivariate analysis, and binary logistic regression in analyzing survey data. My goal was to determine if individual variables and attitude toward risk were statistically significant in predicting HDHP enrollment. It is important to understand how employees choose insurance when faced with two or more plans that have widely different coverage. By understanding plan choice process, employers can improve health insurance communication materials. In this study, I investigated age, employee status, the status of dependents covered, salary, gender, and risk attitude.

Results from bivariate correlation analysis revealed that employees enrolled in a HDHP were younger and had statistically significant higher Financial/Gamble subscale risk scores than those in the non-HDHP option. In addition, in terms of enrolment status, employees with a child or children on coverage were less likely to be enrolled in the HDHP plan than employees without a child or children on coverage. I used bivariate logistic regression to develop a regression model for significant variables. The logistic regression indicates that when controlling for gender, Financial/Gamble subscore, and employee status, age and the presence of a child or children on coverage predicts HDHP enrollment. Older employees and those covering children on the plan or less likely to enroll in a HDHP option. For a 1-year increase in age, the odds of being in the HDHP decrease by 3.8%. In addition, the presence of a child or children on coverage results in the increase in the odds of being in the non-HDHP option by 83.3%.

Interpretation of the Findings

Consistent with previous studies on pre-ACA plans (Barry, Cullen, Galusha, Slade, & Busch, 2008; Lave, Men, Day, Wang, & Zhang, 2011), older employees in the current study were less likely to enroll in the HDHP option. The odds ratio found in this study for age is similar to previous findings (Lave, Men, Day, Wang & Zhang, 2011). As aging is related to an increase in healthcare spending (Dielman et al., 2017), older individuals tend to be more risk averse (Bonsang & Dohmen, 2015; Lee & Blais, 2014) and buy more insurance than younger individuals (Lave, Men, Day, Wang & Zhang, 2011). Even through the ACA enhanced medical coverage by requiring that plans cover a wider range of benefits and services that may reduce the financial burden of medical services under HDHPs for older employees, an increase in age continues to be associated with reduced HDHP enrollment.

Having a dependent on coverage is associated with non-HDHP enrollment in past studies (Lave, Men, Day, Wang & Zhang, 2011). For children specifically, HDHPs have been viewed as a poor choice due to the medical services that children tend to use

(Shinkin, 2014), and research shows that there may be reduced birth rates for employees covered under HDHP plans (Kozhimannil, Kleinman & Wharam, 2016). The current study is consistent with previous pre-ACA results. Employees with a child on coverage are less likely to enroll in a HDHP option. Based on these results, it seems that even for post-ACA plans, covering a child on health insurance is significantly related to plan choice. Although the ACA includes a wider range of services at low or no cost to children such as immunizations, yearly exams, and developmental screenings that may reduce the financial risk of HDHP plans, the presence of children on coverage continues to be associated with being less likely to enroll in a HDHP.

The results of the bivariate analysis showed that the DOSPERT subscale Financial/Gamble was related to HDHP enrollment. The mean score on the DOSPERT Financial/Gamble subscale was higher for HDHP enrollees than non-HDHP enrollees. However, in the current study, bivariate analysis showed that the Financial/Gamble subscale was also significantly related to age and gender and past studies indicate that risk-taking behavior is sensitive to age differences (Mata, Josef, Sammanez-Larkin & Hertwig, 2011). In the full logistic regression model, the Financial/Gamble subscale did not add predictive utility beyond age and the presence of a child(ren) on coverage.

Study Results Guided by Prospect Theory

The majority of employees in the current sample were enrolled in a HDHP option. This is inconsistent with past research on HDHP enrollment, which reported that only about 25% of employees were enrolled in a HDHP (Henry J. Kaiser Family Foundation, 2016). Past research points to a higher percentage of employees in non-HDHP plans as consistent with the loss aversion aspects of Prospect Theory (Eckles & Wise, 2011; Koszegi & Rabin, 2009). For this reason, the high percentage of employees in HDHPs in the current study may be viewed as inconsistent with prospect theory.

In terms of risk preference, the findings of this study may be consistent with prospect theory. The main competitor of prospect theory, expected utility theory, outlines that individuals choose a plan that is consistent with underlying risk preferences (Cavagnaro, Pitt, Gonzalez & Myung, 2013). For example, individuals who indicate that they are high-risk takers may be more likely to enroll in a higher financial risk plan such as a HDHP. This type of risk choice is less consistent with prospect theory (Bundoft, Mata, Schoenbaum & Bhattacharya, 2013). According to prospect theory, individuals are biased during the decision making process and decisions may deviate from risk preferences. In the current study, risk preference did not predict HDHP enrollment, which may be viewed as consistent with Prospect Theory.

According to prospect theory, one's reference point is key to decisions related to risk and uncertainty (Heiman, Just, McWilliams, & Zilberman, 2015). Alan, Julie, and Gordon (2008) reported that personal factors such as age and previous illness may impact a decision-maker's reference point. In the current study, age and the presence of a child on coverage were personal factors that impacted people's reference points. Prospect theory proposes that in the domain of gains, individuals prefer a sure prospect. In the current study, the sure bet was the lower deductible plan with predictable copays and limited out of pocket cost. Older employees and parents who envision multiple trips to the pediatrician may trend toward to the lower deductible plan due to being risk averse in the domain of gains. Having insurance is a gain that protects against loss and the sure bet is the one that provides the most coverage. On the other hand, younger employees who do not expect to use health insurance may view the insurance premium of all plans as a loss (Eckles and Wise, 2011). This puts them in the domain of loss. According to prospect theory, in the domain of loss, individuals are risk seeking. The choice of a higher-risk HDHP by younger employees is consistent with risk-seeking behavior in the loss domain.

Because in the current study I did not directly measure the reference point of participants, it is not possible to substantiate the role of prospect theory in the results of this study. Reference points that define the domain of gain or loss are complex and more research is warranted on how many reference points individuals use and how they are combined (Alan, Julie & Gordon, 2008). Nonetheless, prospect theory is a useful theory for investigating the biases that may occur in decisions of risk and uncertainty related to health insurance choice.

Limitations of the Study

A significant limitation of this study was the generalizability of the results to all employees covered under employer-sponsored coverage with a choice between a HDHP and non-HDHP. Sample prototypicality and sample relevance supports reliability and validity (Burkholder, Cox & Crawford, 2016). The convenience sample in this study differed from the working population in that it trended younger and salary levels were higher. In addition, HDHP enrollments were higher in this sample than would be expected based on national surveys.

The ability to fully explain plan choice is limited by the design of the study. First, the nonexperimental design of this study was limited to inferential findings. Secondly, using data directly from a Human Resource Information System (HRIS) may be more accurate than relying on self-reported enrollment status (Jordan, 2014). Thirdly, research supports the inclusion of other variables important to plan choice such as health status (Bindman, Hulett, Gilmer & Bertko, 2016; Jordan, 2014; Lave, Lave, Men, Day, Wang & Zhang, 2011), the anticipation of upcoming health care use (Atanasov & Baker, 2014), and plan cost (Lave, Lave, Men, Day, Wang & Zhang, 2011) that were not included in the current methodology and beyond the scope of this study.

Recommendations

This study provides support that certain demographic variables such as age and the status of children on coverage continues to be significantly related to HDHP enrollment. As employers continue to modify plan designs in order to control health care spending, examining the factors related to plan enrollment is critical. I recommend that in future studies, the contribution of age and the presence of children on coverage to HDHP enrollment be verified by using actual enrollment data from multiple employers. This would support accurate data collection as well as the ability to control for plan differences such as cost, physician network availability, and number of plans offered to the employee.

The literature supports that health status (Bindman, Hulett, Gilmer & Bertko, 2016; Jordan, 2014; Lave, Lave, Men, Day, Wang & Zhang, 2011) and the anticipation of upcoming health care use (Atanasov & Baker, 2014) are important variables in plan choice. Therefore, I recommend that future research examine the contribution of past, current and anticipated health care use on plan choice. Finally, from the current study, it is unclear if a model such as prospect theory or others such as expected utility theory is accurate in framing insurance enrollment decisions. In the current study, there were findings that were both consistent and inconsistent with prospect theory. Further research is warranted in this area.

Implications for Social Change

I designed this study to provide evidence on some of the factors that are related to HDHP choice post ACA. Many factors go into employee health plan choice and it is important to investigate these factors especially as health plan requirements change. The current study is a beginning exploration of HDHP choice post ACA. Based on the results, there are a number of considerations. First, this study used the framework of Prospect Theory, which proposes that employees may be biased in decisions related to risk and uncertainty. However, this may not be immutable. Otuteye (2015) suggests that the cognitive biases of Prospect Theory may be overcome with education and training. Otuteye recommends that individuals be taught good decision-making process and receive adequate data to make rational decisions. By adhering to a decision-making approach and appropriately processing available data, individuals may avoid biased decisions and get rational outcomes. Therefore, I recommended that employers prepare employees in advance of plan choice by providing models on how to appropriately choose insurance plans and also provide sufficient information on each plan available. Next, employers offering HDHP plans should consider the impact of the employee's age on plan choice. Providing decision-support tools and educational information on the risks and benefits of each plan as related to age enables the employees to make an informed decision. Finally, providing specific education on health services and costs for children under available plans is important. If the employer is enhancing the HDHP plan to be more attractive for employees with children such as contributions to a medical spending account for each child covered or allowing children access to an onsite or near-site health clinic, these benefits should be clearly stated in educational materials.

Conclusion

Most of the non-elderly population receives health insurance coverage from their employer. Therefore, when an insurance strategy gains popularity and spreads rapidly among employers, it has an effect on millions of individuals. HDHPs have been one of those strategies. In 2017, HDHP enrollment reached 21 million members (Kaiser Family Foundation 2017 Employer Benefits Survey, 2017) and this upward trend is expected to continue (Miller, 2016). As employers institute strategies such as new plan designs to reduce their health care costs, it is important to understand the factors related to employee plan choice.

This study investigated the demographic variables and attitudes toward risk that contribute to enrollment in HDHPs that conform to the ACA minimum essential coverage standards. As employees age, they are less likely to enroll in a HDHP. In addition, employees that cover at least one child on their plan are less likely to enroll in a HDHP. Therefore, educational materials related to plan choice may address specific needs of older employees and employees with children in order to better prepare employees for the choice of a lower deductible plan or a HDHP.

References

Abdellaoui, M., Bleichrodt, H., L'Haridon, O., & van Dotder, D. (2016). Measuring loss aversion under ambiguity: A method to make prospect theory completely observable. *Journal of Risk and Uncertainty, 52*(1), 1-20. doi:10.1007/s11166-016-9234-y

Alan, S., Julie, G., & Gordon, H. (2008). Prospect theory, reference points, and health decisions. *Judgment and Decision Making, 3*(2), 174-180. Retrieved from http://journal.sjdm.org/

Anderson, S. F., Kelley, K., & Maxwell, S. E. (2017). Sample-size planning for more accurate statistical power: A method adjusting sample effect sizes for publication bias and uncertainty. *Psychological Science, 28*(11), 1547-1562. doi:10.1177/0956797617723724

Atanasov, P., & Baker, T. (2014). Putting health back into health insurance choice. *Medical Care Research and Review, 71*(4), 337-355. doi: 10.1177/1077558714533821

Barberis, N. C. (2013). Thirty years of prospect theory in economics: a review and assessment. *Journal of Economic Perspectives*, *1*, 173. Retrieved from https://www.aeaweb.org/journals/jep

Barry, C. L., Cullen, M. R., Galusha, D., Slade, M. D., & Busch, S. H. (2008). Who chooses a consumer-directed health plan? *Health Affairs*, *27*(6), 1671-1679. doi:10.1377/hlthaff.27.6.1671

Bechara, A., Tranel, D., & Damasio, H. (2000). Characterization of the decision-making deficit of patients with ventromedial prefrontal cortex lesions. *Brain: A Journal of Neurology, 123*(11), 2189-2202. Retrieved from https://academic.oup.com/brain

Beckman, S., DeAngelo, G., Smith, W., & Wang, N. (2016). Is social choice gender-neutral? Reference dependence and sexual selection in decisions toward risk and inequality. *Journal of Risk & Uncertainty, 52*(3), 191-211. doi:10.1007/s11166-016-9241-z

Berinsky, A. J., Huber, G. A., & Lenz, G. S. (2012). Evaluating online labor markets for experimental research: Amazon.com's Mechanical Turk. *Political Analysis, 20*(3), 351-368. doi:10.1093/pan/mpr057

Berg, S. S., Grimstad, A., Škerlavaj, M., & Černe, M. (2017). Social and economic leader–member exchange and employee creative behavior: The role of employee willingness to take risks and emotional carrying capacity. *European Management Journal, 35*(5), 676-687. doi:10.1016/j.emj.2017.08.002

Bhatia, S. (2017). Comparing theories of reference-dependent choice. *Journal of Experimental Psychology: Learning, Memory, And Cognition, 43*(9), 1490-1507. doi:10.1037/xlm0000384

Bindman, A. B., Hulett, D., Gilmer, T. P., & Bertko, J. (2016). Sorting out the health risk in California's state-based marketplace. *Health Services Research, 51*(1), 129-145. doi:10.1111/1475-6773.12320

Blais, A., & Weber, E. U. (2006). A Domain-Specific Risk-Taking (DOSPERT) scale for adult populations. *Judgment and Decision Making*, *1*(1), 33-47. Retrieved from https://doaj.org/article/08e1df744f2644f5a72770d1d4602f80

Bonney, L., Plouffe, C. R., & Wolter, J. (2014). 'I think I can…I think I can': The impact of perceived selling efficacy and deal disclosure on salesperson escalation of commitment. *Industrial Marketing Management*, *43*(5), 826-839. doi:10.1016/j.indmarman.2014.04.010

Bonsang, E., & Dohmen, T. (2015). Risk attitude and cognitive aging. *Journal of Economic Behavior & Organization*, *112*, 112-126. doi:10.1016/j.jebo.2015.01.004

Boos, M., Seer, C., Lange, F., & Kopp, B. (2016). Probabilistic inference: Task dependency and individual differences of probability weighting revealed by hierarchical Bayesian modeling. *Frontiers in Psychology, 7*, 755. http://doi.org/10.3389/fpsyg.2016.00755

Bradley, M. T., & Brand, A. (2013). Sweeping recommendations regarding effect size and sample size can miss important nuances: A comment on "A comprehensive review of reporting practices in psychological journals". *Theory & Psychology, 23*(6), 797-800. Retrieved from http://journals.sagepub.com/home/tap

Brody, S. D., Highfield, W. E., Wilson, M., Lindell, M. K., & Blessing, R. (2017). Understanding the motivations of coastal residents to voluntarily purchase federal flood insurance. *Journal of Risk Research, 20*(6), 760-775. Retrieved from https://www.tandfonline.com/loi/rjrr20

Brown, M., Knoller, C., & Richter, A. (2015). Behavioral bias and the demand for bicycle and flood insurance. *Journal of Risk and Uncertainty*, *50*(2), 141-160. doi: 10.1007/s11166-015-9212-9

Bundorf, M. K., Mata, R., Schoenbaum, M., & Bhattacharya, J. (2013). Are prescription drug insurance choices consistent with expected utility theory? *Health Psychology*, *32*(9), 986-994. doi:10.1037/a0033517

Burkholder, G. J., Cox, K. A., & Crawford, L. M. (2016). The scholar-practitioner's guide to research design. Baltimore, MD: Laureate Publishing.

Bursac, Z., Gauss, C., Williams, D., & Hosmer, D. (2008). Purposeful selection of variables in logistic regression. *Source Code for Biology and Medicine, 3*(17), 173-207. doi: 10.1186/1751-0473-3-17

Burnett, J. J., & Palmer, B. A. (1984). Examining life insurance ownership through demographic and psychographic characteristics. *Journal of Risk & Insurance, 51*(3), 453-467. Retrieved from https://onlinelibrary.wiley.com/journal/15396975

Burns, C., & Conchie, S. (2014). Risk information source preferences in construction workers. *Employee Relations, 36*(1), 70-81. doi:10.1108/ER-06-2013-0060

Buurman, M., Delfgaauw, J., Dur, R., & Van den Bossche, S. (2012). Public sector employees: Risk averse and altruistic? *Journal of Economic Behavior & Organization, 83*(3), 279-291. doi:10.1016/j.jebo.2012.06.003

Byrnes J. P., Miller, D. C., & Schafer, W. D. (1999). Gender differences in risk taking: A meta-analysis. *Psychological Bulletin*,125, 367–383. Retrieved from http://www.apa.org/pubs/journals/bul/

Cavagnaro, D. R., Pitt, M. A., Gonzalez, R., & Myung, J. I. (2013). Discriminating among probability weighting functions using adaptive design optimization. *Journal of Risk and Uncertainty, 47*(3), 255-289. doi:10.1007/s11166-013-9179-3

Ceschi, A., Costantini, A., Sartori, R., & Dickert, S. (2017). The impact of occupational rewards on risk taking among managers. *Journal of Personnel Psychology, 16*(2), 104-111. doi: 10.1027/1866-5888/a000184

Chan, C., & Holosko, M. J. (2016). An overview of the use of Mechanical Turk in behavioral sciences: Implications for social work. *Research on Social Work Practice*, *26*(4), 441-448. doi: 10.1177/1049731515594024

Chandler, J., Mueller, P., & Paolacci, G. (2017). Nonnaivete among Amazon Mechanical Turk workers: Consequences and solutions for behavioral researchers. *Behavior Research Methods, 46*(1), 112-130. doi: 10.3758/s13428-013-0365-7

Chen, J., Bustamante, A. V., & Tom, S. E. (2015). Health care spending and utilization by race/ethnicity under the Affordable Care Act's dependent coverage expansion. *American Journal of Public Health, 105*(3), S499-S507. Retrieved from https://ajph.aphapublications.org/

Chen, H., Cohen, P., & Chen, S. (2010). How big is a big odds ratio? Interpreting the magnitudes of odds ratios in epidemiological studies. *Communications in*

Statistics-Simulation and Computation, 39(4), 860-864. doi: 10.1080/03610911003650383

Chicaiza-Becerra, L. A., & Garcia-Molina, M. (2017). Prenatal testosterone predicts financial risk taking: Evidence from Latin America. *Personality and Individual Differences*, *116*, 32-37. doi:10.1016/j.paid.2017.04.021

Clougherty, J. E., Eisen, E. A., Slade, M. D., Kawachi, I., & Cullen, M. R. (2009). Workplace status and risk of hypertension among hourly and salaried aluminum manufacturing employees. *Social Science & Medicine, 68*(2), 304-313. doi:10.1016/j.socscimed.2008.10.014

Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Hillsdale, NJ: Lawrence Erlbaum Associates.

Cooper, G. S., Kou, T. D., Dor, A., Koroukian, S. M., & Schluchter, M. D. (2017). Cancer preventive services, socioeconomic status, and the Affordable Care Act. *Cancer, 123*(9), 1585-1589. doi:10.1002/cncr.30476

Creswell, J. W. (2015). Educational research: Planning, conducting, and evaluating quantitative and qualitative research (5th ed.). Boston, MA: Pearson.

Custer, W. S. (2016). Health care cost inflation in the next decade. *Journal of Financial Service Professionals, 70*(1), 37-39. Retrieved from https://national.societyoffsp.org/page/jfsp_subscribe

Dalal, R. S., Bonaccio, S., Highhouse, S., Ilgen, D. R., Mohammed, S., & Slaughter, J. E. (2010). What if industrial-organizational psychology decided to take workplace decisions seriously? *Industrial and Organizational Psychology: Perspectives on Science and Practice*, *3*(4), 386-405. doi:10.1111/j.1754-9434.2010.01258.x

Davis, K. (2005). High deductible health plans and health savings accounts: For better or worse? *Medical Benefits, 22*(4), 3-4. Retrieved from https://lrus.wolterskluwer.com/store/product/medical-benefits/

de Sousa Mendes, G. H., & Devós Ganga, G. M. (2013). Predicting success in product development: The application of principal component analysis to categorical data and binomial logistic regression. *Journal of Technology Management & Innovation, 8*(3), 83-97. Retrieved from http://www.jotmi.org/index.php/GT/article/view/art398/861

Determining employee status: There's more to it than 'exempt or non-exempt'. (2003). *Payroll Practitioner's Monthly, 11*(12), 11-14.

Di Mauro, C., & Musumeci, R. (2011). Linking risk aversion and type of employment. *The Journal of Socio-Economics, 40*(5), 490-495. doi:10.1016/j.socec.2010.12.001

Dionne, G., & Eeckhoudt, L. (1985). Self-insurance, self-protection and increased risk aversion. *Economic Letters,17,*39-42.

Dipboye (1990). Laboratory vs. field research in industrial and organizational psychology. *International Review of Industrial and Organizational Psychology*, *5*, 1-34

Eckles, D. L., & Volkman, J. W. (2011). Prospect theory and the demand for insurance. Retrieved from http://www.aria.org/rts/proceedings/2012/New2012Papers/Prospect%20Theory%20and%20the%20Demand%20for%20Insurance.pdf

Erlyana, E., Acosta-Deprez, V., O'Lawrence, H., Sinay, T., Ramirez, J., Jacot, E. C., & Shim, K. (2015). Health insurance information-seeking behaviors among internet users: An exploratory analysis to inform policies. *Journal of Health & Human Services Administration, 38*(1), 5-16.

Faul, F., Erdfelder, E., Lang, A., & Buchner, A. (2007). G*Power 3: a flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods, 39*(2), 175-191.

Fehr-Duda, H., Epper, T., Bruhin, A., & Schubert, R. (2011). Risk and rationality: The effects of mood and decision rules on probability weighting. *Journal of Economic Behavior and Organization*, *78*,14-24. doi:10.1016/j.jebo.2010.12.004

Field, A. (2013). Discovering statistics using IBM SPSS statistics (4th ed.). London, UK: Sage.

Foley, J. S., & Stokes, M. L. (1997). Common personnel practices can destroy the exempt status of salaried employees. *Labor Law Journal, 48*(4), 241.

Fowles, J. B., Kind, E. A., Braun, B. L., & Bertko, J. (2004). Early experience with employee choice of consumer-directed health plans and satisfaction with enrollment. *Health Services Research*, *39*(4 Pt 2), 1141-1158.

French, M. T., Homer, J., Gumus, G., & Hickling, L. (2016). Key provisions of the Patient Protection and Affordable Care Act (PPACA): A systematic review and presentation of early research findings. *Health Services Research*, *51*(5), 1735-1771. doi:10.1111/1475-6773.12511

Fronstin, P. (2015). Investment options and HSAs: Findings from the EBRI HSA database. *EBRI Notes, 36*(8), 2-9.

Fronstin, P. (2015). Views on employment-based health benefits. *EBRI Notes, 36*(2), 2.

G*Power 3.1 manual (2014). Retrieved from http://www.gpower.hhu.de/fileadmin/redaktion/Fakultaeten/Mathematisch Naturwissenschaftliche_Fakultaet/Psychologie/AAP/gpower/GPowerManual.pdf

Galbraith, A. A., Soumerai, S. B., Ross-Degnan, D., Rosenthal, M. B., Gay, C., & Lieu, T. A. (2012). Delayed and forgone care for families with chronic conditions in high-deductible health plans. *Journal of General Internal Medicine*, *27*(9), 1105-1111. doi:10.1007/s11606-011-1970-8

Gardiner, E., & Jackson, C. J. (2012). Workplace mavericks: How personality and risk-taking propensity predicts maverickism. *British Journal of Psychology, 103*(4), 497-519. doi:10.1111/j.2044-8295.2011.02090.x

Giancola, F. L. (2012). Are employee benefit programs being given enough credit for their effect on employee attitudes? *Compensation & Benefits Review, 44*(5), 291-297. doi:10.1177/0886368712464471

Giblett, S. (2017). Workplace protection plans: Complementing your attraction and retention strategy. *Human Resources Magazine, 21*(4), 36-37.

Gilman, J. M., Calderon, V., Curran, M. T., & Evins, A. E. (2015). Young adult cannabis users report greater propensity for risk-taking only in non-monetary domains. *Drug and Alcohol Dependence*, *14*, 726-731. doi:10.1016/j.drugalcdep.2014.12.020

Graves, A. J., Kozhimannil, K. B., Kleinman, K. P., & Wharam, J. F. (2016). The association between high-deductible health plan transition and contraception and birth rates. *Health Services Research*, *51*(1), 187-204. doi:10.1111/1475-6773.12326

Gupta, N., & Polsky, D. (2015). High deductible health plans: Does cost sharing stimulate increased consumer sophistication? *Health Expectations: An International Journal of Public Participation in Health Care & Health Policy, 18*(3), 335-343. doi:10.1111/hex.12031

Gurdal, M. Y., Kuzubas, T. U., & Saltoglu, B. (2017). Measures of individual risk attitudes and portfolio choice: Evidence from pension participants. *Journal of Economic Psychology*, *62*,186-203.

Hair, J.F. Jr., Anderson, R.E., Tatham, R.L., & Black, W.C. (1998). Multivariate data analysis, (5th Edition). Upper Saddle River, NJ: Prentice Hall.

Han, X., Robin Yabroff, K., Guy, G. P., Zheng, Z., & Jemal, A. (2015). Has recommended preventive service use increased after elimination of cost-sharing as part of the Affordable Care Act in the United States? *Preventive Medicine: An International Journal Devoted to Practice and Theory*, *78*, 85-91. doi:10.1016/j.ypmed.2015.07.012

Hardie, N. A., Kyanko, K., Busch, S., LoSasso, A. T., & Levin, R. A. (2011). Health literacy and health care spending and utilization in a consumer-driven health plan. *Journal of Health Communication, 16*(3), 308-321. doi:10.1080/10810730.2011.604703

Heiman, A., Just, D., McWilliams, B., & Zilberman, D. (2015). A prospect theory approach to assessing changes in parameters of insurance contracts with an application to money-back guarantees. *Journal of Behavioral and Experimental Economics*, *54*(1), 105-117. doi:10.1016/j.socec.2014.11.006

Henry J. Kaiser Family Foundation (2006). Employer health benefits 2006 annual survey. Retrieved from https://kaiserfamilyfoundation.files.wordpress.com/2013/04/7527.pdf

Henry J. Kaiser Family Foundation (2010). Employer health benefits 2010 annual survey. Retrieved from https://kaiserfamilyfoundation.files.wordpress.com/2013/04/8085.pdf

Henry J. Kaiser Family Foundation (2015). 2015 employer health benefits survey. Retrieved from https://www.kff.org/health-costs/report/2015-employer-health-benefits-survey/

Henry J. Kaiser Family Foundation (2016). Marketplace enrollment by metal level. Retrieved from http://kff.org/health-reform/state-indicator/marketplace-enrollment-by-metal-level/?currentTimeframe=0

Henry J. Kaiser Family Foundation (2017). Kaiser Family Foundation 2017 employer benefits survey. Retrieved from www.kff.org/health-costs/report/2017-employer-health-benefits-survey

Hermann, D. (2017). Determinants of financial loss aversion: The influence of prenatal androgen exposure (2D:4D). *Personality and Individual Differences*, *117*, 273-279. doi:10.1016/j.paid.2017.06.016

Hosmer, D. W., & Lemeshow, S. (1989) Applied logistic regression. New York, NY: Wiley.

Huber, J., Viscusi, W. K., & Bell, J. (2008). Reference dependence in iterative choices. *Organizational Behavior & Human Decision Processes*, *2*, 143-153. doi: 10.1016/j.obhdp.2007.10.005

Johnson, A. D., & Wegner, S. E. (2007). High-deductible health plans and the new risks of consumer-driven health insurance products. *Pediatrics, 119*(3), 622-626.

Jordan, D. W., & Cotter, J. J. (2016). Association between employee earnings and consumer-directed health plan choices. *Journal of Healthcare Management*, *61*(6), 420-435.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*(2), 263-291.

Kahneman, D. 1., & Tversky, A. (1984). Choices, values, and frames. *American Psychologist*, *39*, 341-350. doi:10.1037/0003-066X.39.4.341

Kairies-Schwarz, N., Kokot, J., Vomhof, M., & Weßling, J. (2017). Health insurance choice and risk preferences under cumulative prospect theory-an experiment. *Journal of Economic Behavior & Organization*, *137*, 374-397. doi:10.1016/j.jebo.2017.03.012

Kandasamy, N., Hardy, B., Page, L., Schaffner, M., Graggaber, J., Powlson, A. S., & ... Coates, J. (2014). Cortisol shifts financial risk preferences. *Proceedings of The National Academy of Sciences of The United States*, *111*(9), 3608-3613. doi:10.1073/pnas.1317908111

Kirstin C., A., Kerry F., M., Michel J. J., H., & Elke U., W. (2011). The decision making individual differences inventory and guidelines for the study of individual differences in judgment and decision-making research. *Judgment and Decision Making, 6*(3), 252-261.

Kluge, A., Badura, B., & Rietz, C. (2013). Communicating production outcomes as gains or losses, operator skill and their effects on safety-related violations in a simulated production context. *Journal of Risk Research, 16*(10), 1241-1258. doi:10.1080/13669877.2013.788059

Knickman, J. R. (2015). Health care financing. In J. R. Knickman, A. R. Kovner, J. R. Knickman, A. R. Kovner (Eds.), Jonas and Kovner's health care delivery in the United States, 11th ed (pp. 231-251). New York, NY: Springer Publishing Co.

Kohsaka, Y., Mardyla, G., & Tsutsui, Y. (2017). Disposition effect and diminishing sensitivity: An analysis based on a simulated experimental stock market. *Journal of Behavioral Finance, 18*(2), 189-201.

Kőszegi, B., & Rabin, M. (2007). Reference dependent risk attitudes. *The American Economic Review, 97*(4),1047–1073.

Kothiyal, A., Spinu, V., & Wakker, P. P. (2014). An experimental test of prospect theory for predicting choice under ambiguity. *Journal of Risk and Uncertainty, 48*(1), 1-17. doi:10.1007/s11166-014-9185-0

Kotlyar, I., Karakowsky, L., Ducharme, M. J., & Boekhorst, J. A. (2014). Do 'rising stars' avoid risk?: Status-based labels and decision making. *Leadership & Organization Development Journal, 35*(2), 121-136. doi:10.1108/LODJ-04-2012-0046

Krekels, G., & Pandelaere, M. (2017). Part D: Consumer psychology and behavior: Helpless (bad feelings and consumption): $5 of $125 is still $5: The link between dispositional greed and thinking styles. *AMA Summer Educators' Conference Proceedings, 28*D-10-D-11.

Kusev, P., van Schaik, P., Ayton, P., Dent, J., & Chater, N. (2009). Exaggerated risk: Prospect theory and probability weighting in risky choice. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *35*(6), 1487-1505. doi:10.1037/a0017039

Landers, R. N., & Behrend, T. S. (2015). An inconvenient truth: Arbitrary distinctions between organizational, Mechanical Turk, and other convenience samples.

Industrial and Organizational Psychology: Perspectives on Science and Practice, *8*(2), 142-164. doi:10.1017/iop.2015.13

Landman, J. H. (2016). High deductibles, high value? *Healthcare Financial Management, 70*(3), 92-93.

Lave, J. R., Men, A., Day, B. T., Wang, W., & Zhang, Y. (2011). Employee choice of a high-deductible health plan across multiple employers. *Health Services Research*, *46*(1, pt1), 138-154. doi:10.1111/j.1475-6773.2010.01167.x

Lease, M., Hullman, J., Bigham, J. P., Bernstein, M. S., Kim, K., & Lasecki, W. (2013). Mechanical Turk is not anonymous. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2228728

Lee, J. C., & Blais, A. (2014). An exploratory analysis of the correlates of risk-taking propensity in Canadian military personnel. *Psychology, 5*(1), 53-61. doi:10.4236/psych.2014.51010

Lejuez, C. W., Read, J. P., Kahler, C. W., Richards, J. B., Ramsey, S. E., Stuart, G. L., & ... Brown, R. A. (2002). Evaluation of a behavioral measure of risk taking: The Balloon Analogue Risk Task (BART). *Journal of Experimental Psychology. Applied, 8*(2), 75-84.

Lin, Y., Xia, K., & Bei, L. (2015). Customer's perceived value of waiting time for service events. *Journal of Consumer Behaviour*, *14*(1), 28-40. doi:10.1002/cb.1498

Lluis, S., & Abraham, J. (2013). The wage–health insurance trade-off and worker selection: Evidence from the medical expenditure panel survey 1997 to 2006.

Industrial Relations: A Journal of Economy & Society, 52(2), 541-581. doi:10.1111/irel.12023

Manning, W. G., & Marquis, M. S. (1996). Health insurance: the tradeoff between risk pooling and moral hazard. *Journal of Health Economics*, *15*(5), 609-639.

Manor, O., Matthews, S., & Power, C. (2000). Dichotomous or categorical response? Analyzing self-rated health and lifetime social class. *International Journal of Epidemiology, 29*(1), 149.

Markiewicz, L., & Weber, E. U. (2013). DOSPERT's gambling risk-raking propensity scale predicts excessive stock trading. *Journal of Behavioral Finance, 14*(1), 65-78. doi:10.1080/15427560.2013.762000

McDevitt, R., Haviland, A., Lore, R., Laudenberger, L., Eisenberg, M., & Sood, N. (2014). Risk selection into consumer-directed health plans: An analysis of family choices within large employers. *Health Services Research*, *49*(2), 609-627.

Mielcarska, K., Żelaźniewicz, A., & Pawłowski, B. (2017). Risk taking propensity in pregnancy: Longitudinal study. *Personality & Individual Differences*, *11*, 07-11. doi:10.1016/j.paid.2017.01.012

Miller, S. (2016, August 16). Employers project health premium hike of 6% in 2017. *Society of Human Resource Management*. Retrieved from https://www.shrm.org/resourcesandtools/hr-topics/benefits/pages/health-premiums-2017.aspx.

Mishra, S., Gregson, M., & Lalumière, M. L. (2012). Framing effects and risk-sensitive decision making. *British Journal of Psychology, 103*(1), 83-97. doi:10.1111/j.2044-8295.2011.02047.x

Nadash, P., & Day, R. (2014). Consumer choice in health insurance exchanges: Can we make it work? *Journal of Health Politics, Policy and Law, 39*(1), 209-235. doi:10.1215/03616878-2395217

Nicholson, N., Soane, E., Fenton-O'Creevy, M., & Willman, P. (2005). Personality and domain-specific risk taking. *Journal of Risk Research, 8*(2), 157-176. doi:10.1080/1366987032000123856

Ottaviani, C., & Vandone, D. (2015). Decision-making under uncertainty and demand for health insurance: A multidisciplinary study. *Journal of Psychophysiology*, *29*(2), 80-85. doi:10.1027/0269-8803/a000137

Otuteye, E. (2017). Overcoming cognitive biases: A heuristic for making value investing decisions. *Journal of Behavioral Finance, 16*(2), 140-149. doi: 10.1080/15427560.2015.1034859

Pachur, T., Suter, R. S., & Hertwig, R. (2017). How the twain can meet: Prospect theory and models of heuristics in risky choice. *Cognitive Psychology*, *93*, 44-73. doi:10.1016/j.cogpsych.2017.01.001

Palmeira, M. (2013). Intuitions in conflict: Preference reversals due to switch between sensitization and diminishing sensitivity. *Journal of Behavioral Decision Making, 27*(2), 124-133. doi: 10.1002/bdm.1791

Parthasarathy, S., & Campbell, C. I. (2016). High deductible health plans: Implications for substance use treatment. *Health Services Research*, *51*(5), 1939-1959. doi: 10.1111/1475-6773.12456

Pek, S., Turner, N., Tucker, S., Kelloway, E. K., & Morrish, J. (2017). Injunctive safety norms, young worker risk-taking behaviors, and workplace injuries. *Accident Analysis and Prevention*, *106*, 202-210. doi: 10.1016/j.aap.2017.06.007

Peter P., W., Veronika, K., & Christiane, S. (2007). Prospect-theory's diminishing sensitivity versus economics' intrinsic utility of money: How the introduction of the Euro can be used to disentangle the two empirically. *Theory and Decision*, *3*, 205 -211. doi: 0.1007/s11238-007-9040-8

Petrova, D. G., van der Pligt, J., & Garcia-Retamero, R. (2016). Feeling the numbers: On the interplay between risk, affect, and numeracy. *Journal of Behavioral Decision Making, 27*(3), 191-199. doi: 10.1002/bdm.1803

Rabin, M. (2000). Risk aversion and expected-utility theory: A calibration theorem. *Econometrica, 68*(5), 1281-1292. Retrieved from https://onlinelibrary-wiley-com.ezp.waldenulibrary.org/

Renaud, S., Morin, L., & Béchard, A. (2017). Traditional benefits versus perquisites: A longitudinal test of their differential impact on employee turnover. *Journal of Personnel Psychology, 16*(2), 91-103. doi:10.1027/1866-5888/a000180

Scheaf, D. (2016). Prospect theory. In S. Rogelberg (Ed) *The Sage encyclopedia of industrial and organizational psychology* (1271-1274), Thousand Oaks, CA: SAGE.

Sedjo, R. L., & Cox, E. R. (2009). The influence of targeted education on medication persistence and generic substitution among consumer-directed health care enrollees. *Health Services Research*, *44*(6), 2079-2092. doi:10.1111/j.1475-6773.2009.01023.x

Study finds hourly employees happier than salaried. (2010). *Report on Salary Surveys, 10*(4), 8. doi: 10.1177/0146167209346304

Tabachnick, B. G., & Fidell, L. S. (2007). Using Multivariate Statistics (5th ed.). New York, NY: Allyn and Bacon.

Tan, E. & Wee Hun Lim, S. (2017). Global-local processing impacts academic risk taking. *The Quarterly Journal of Experimental Psychology, 70*(12), 2434-2444. doi:10.1080/17470218.2016.1240815

Tang, H., Liang, Z., Rao, L., Li, S., Zhou, K., & Huang, G. (2016). Positive and negative affect in loss aversion: Additive or subtractive logic? *Journal of Behavioral Decision Making, 29*(4), 381-391. doi: 10.1002/bdm.1884

Tennyson, S., & Kyung Yang, H. (2014). The role of life experience in long-term care insurance decisions. *Journal of Economic Psychol*ogy, 42, 175–188. doi: 10.1016/j.joep.2014.04.002

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk & Uncertainty, 5*(4), 297-323. Retrieved from https://link.springer.com/journal/11166

Tyagi V, Hanoch Y, Hall S, Runco M., & Denham S. (2017) The risky side of creativity: Domain specific risk taking in creative individuals. Front. Psychol. 8:145. doi: 10.3389/fpsyg.2017.00145U

United States Department of Labor. (2018). Current employment statistics. Retrieved from https://www.bls.gov/ces/

Venkatraman, S., Aloysius, J. A., & Davis, F. D. (2006). Multiple prospect framing and decision behavior: The mediational roles of perceived riskiness and perceived ambiguity. *Organizational Behavior and Human Decision Processes*, *101*(1), 59-73. doi:10.1016/j.obhdp.2006.04.006

Wakker, P., Kabberling, V. & Schwieren, C. (2007). Prospect theory's diminishing sensitivity versus economics' intrinsic utility of money: How the introduction of the Euro can be used to disentangle the two empirically. *Theory and Decision, 63*(3), 205-231. doi: 0.1007/s11238-007-9040

Waters, T. M., Chang, C. F., Cecil, W. T., Kasteridis, P., & Mirvis, D. (2011). Impact of high-deductible health plans on health care utilization and costs. *Health Services Research, 46*(1), 155-172. doi:10.1111/j.1475-6773.2010.01191.x

Weathington, B. L., & Jones, A. P. (2006). Measuring the value of nonwage employee benefits: Building a model of the relation between benefit satisfaction and value.

Genetic, Social, and General Psychology Monographs, *132*(4), 292-328. doi:10.3200/MONO.132.4.292-328

Weber, E. U., Blais, A., & Betz, N. E. (2002). A domain-specific risk-attitude Scale: Measuring risk perceptions and risk behaviors. *Journal of Behavioral Decision Making, 15*(4), 263-290. doi:10.1002/bdm.414

Wharam, F., Ross-Degnan, D., & Rosenthal, M. (2013). The ACA and high deductible insurance: Strategies for sharpening a blunt instrument. The New England Journal of Medicine, 369(16), 1481-1484. doi:10.1056/NEJMp1309490

Wichary, S., Li, M., & Pachur, T. (2015). Risk-taking tendencies in prisoners and nonprisoners: Does gender matter? *Journal of Behavioral Decision Making, 28*(5), 504-514. doi 10.1002/bdm.1866

Xiao-fei, X., & Wang, X. T. (2003). Risk perception and risky choice: Situational, informational and dispositional effects. *Asian Journal of Social Psychology, 6*(2), 117. doi:10.1111/1467-839X.t01-1-00015

Ye, J. (2015). The effect of Health Savings Accounts on group health insurance coverage. *Journal of Health Economics*, *44*, 238-254. doi:10.1016/j.jhealeco.2015.09.009

Yoon, Y., Polpanumas, C., & Park, Y. J. (2017). The impact of word of mouth via twitter on moviegoers' decisions and film revenues: Revisiting prospect theory: How WOM about movies drives loss-aversion and reference-dependence behaviors. *Journal of Advertising Research, 57*(2), 144-158. doi:10.2501/JAR-2017-022

Zak, P. J., Stanton, A. A., & Ahmadi, S. (2007). Oxytocin increases generosity in humans. *Plos One, 2*(11), e1128. Retrieved from http://journals.plos.org/plosone/

Zhang, X., Haviland, A., Mehrotra, A., Huckfeldt, P., Wagner, Z., & Sood, N. (2017). Does enrollment in high-deductible health plans encourage price shopping? *Health Services Research*, doi:10.1111/1475-6773.12784

Appendix B: Instrumentation

Directions: There are two parts to this survey. The first part is intended to collect demographic information about you and your current health plan enrollment. The second part is intended to collect information about your risk-taking attitude. This survey is anonymous. You will automatically be paid by the MTurk platform so please do not include any personally identifiable information on this survey such as your name and email address. Also, do not include your MTurk ID number. You will be paid by MTurk directly after completing the survey. Since this survey is anonymous and your name and contact information is not collected as part of the survey process, you will not be contacted by the researcher or receive any further information about this study from the researcher.

Eligibility for this survey: As specified in the consent statement, only individuals who live in the United States, work full time, are enrolled in health insurance, and had the choice between a high deductible health plan and regular health plan are eligible for this study. The following questions verify your eligibility.

Part 1 - Demographics and Plan Choice:

1) Are you currently enrolled in health insurance? (yes/no)
2) When making a choice about health insurance, did you have the option of choosing either a high deductible health plan(s) and lower deductible health plan(s)? (yes/no) *(help text: A high deductible health plan is a plan with a higher deductible than a traditional insurance plan. The monthly premium is usually lower, but you pay more health care costs yourself before the insurance company starts to pay its share (your deductible). A high deductible plan (HDHP) can be combined with a health savings account (HSA), allowing you to pay for certain medical expenses with money free from federal taxes. The IRS defines a high deductible health plan as any plan with a deductible of at least $1,350 for an individual or $2,700 for a family.*)

Please note - if you answered no above, you are not eligible to participate in this survey and your data will not be used as part of this project. Please skip to the final screen without answering any further questions and you will still be paid for your time.

4) Please indicate your coverage level (forced choice: individual only, individual + spouse, individual + child(ren), individual + family)
5) Are you currently enrolled in a high deductible health plan. (yes/no) *(help text: A high deductible health plan is a plan with a higher deductible than a traditional insurance plan. The monthly premium is usually lower, but you pay more health care costs yourself before the insurance company starts to pay its share (your deductible). A high deductible*

plan (HDHP) can be combined with a health savings account (HSA), allowing you to pay for certain medical expenses with money free from federal taxes.
The IRS defines a high deductible health plan as any plan with a deductible of at least $1,350 for an individual or $2,700 for a family.)
6) Please type in your annual salary. Please include base salary as well as other eligible earned income such as bonuses and part-time jobs. (text box)
7) Please indicate your employment status (forced choice 1) full-time hourly employee (help text for hourly: receives an hourly wage for each hour worked), 2) full-time salaried employee (help text salaried: paid a fixed amount of money per year), 3) part-time employee, 4) contractor/consultant, 5) other (please indicate (text box)).
8) Please indicate your date of birth (calendar date picker with validation)
9) Please indicate your gender (Radio button: male, female, prefer to self-describe, prefer not to say). Follow up question, if prefer to self-describe please indicate here (text box).

Part II - Risk Taking:

For each of the following statements, please indicate the likelihood that you would engage in the described activity or behavior if you were to find yourself in that situation. Provide a rating from *Extremely Unlikely* to *Extremely Likely*, using the following scale:

1	2	3	4	5	6	7
Extremely Unlikely	Moderately Unlikely	Somewhat Unlikely	Not Sure	Somewhat Likely	Moderately Likely	Extremely Likely

Admitting that your tastes are different from those of a friend.
Going camping in the wilderness.
Betting a day’s income at the horse races.
Investing 10% of your annual income in a moderate growth diversified fund.
Drinking heavily at a social function.
Taking some questionable deductions on your income tax return.
Disagreeing with an authority figure on a major issue.
Betting a day’s income at a high-stake poker game.
Having an affair with a married man/woman.
Passing off somebody else’s work as your own.
Going down a ski run that is beyond your ability.
Investing 5% of your annual income in a very speculative stock.
Going whitewater rafting at high water in the spring.
Betting a day’s income on the outcome of a sporting event

Engaging in unprotected sex.
Revealing a friend’s secret to someone else.
Driving a car without wearing a seat belt.
Investing 10% of your annual income in a new business venture.
Taking a skydiving class.
Riding a motorcycle without a helmet.
Choosing a career that you truly enjoy over a more secure one.
Speaking your mind about an unpopular issue in a meeting at work.
Sunbathing without sunscreen.
Bungee jumping off a tall bridge.
Piloting a small plane.
Walking home alone at night in an unsafe area of town.
Moving to a city far away from your extended family.
Starting a new career in your mid-thirties.
Leaving your young children alone at home while running an errand.
Not returning a wallet you found that contains $200.