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Essays on Financial Decision Making

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ESSAYS ON FINANCIAL DECISION MAKING

A Dissertation

by

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ESSAYS ON FINANCIAL DECISION MAKING

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ABSTRACT

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Individuals make financial decisions daily, yet the literature on the mechanisms that drive financial decisions is limited. This dissertation looks to examine how physical characteristics, and personality subconsciously influence financial decision making by conducting an experiment. Furthermore, this dissertation examines biased decision making in the betting market by using data from covers.com. First, this dissertation finds that the cognitive impairments associated with having a higher body mass index is positively correlated to poor financial decision making and being more likely to commit the present bias, and distorting probabilities. Second, this dissertation finds that business students are more apt to fit the prototypical psychopath compared to non-business students. The higher scores of psychopathy in business students help explain why they are more likely to deceive others. Finally, this dissertation finds that bettors make biased decisions and are more likely to bet on the favorite team and the over. Furthermore, bettors are biased by betting against line movement and preferring teams with the hot hand. The results show that these biased decisions cause bettors to lose more money as the sportsbook takes advantage of the biased decisions.

DEDICATION

I dedicate this dissertation to my parents who sacrificed much so I could have the life I have.

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I will always be grateful to my dissertation committee members: Dr. James Boudreau, Dr. Andre Mollick, Dr. Marie Mora, and Dr. Brice Dupoyet for their help with this dissertation and all those who have helped me throughout my academic career.

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CHAPTER I

INTRODUCTION

Everyone makes financial decisions daily. However, most do not recognize the repercussions that his or her decisions may have if they make poor financial decisions. For example, the finance literature shows how investors lose money due to investment biases such as the disposition effect, overconfidence, confirmation bias, performance chasing, and many others. Subsequently, this doctoral dissertation examines the multi-faceted determinants of poor financial decision making.

Every financial decision conveyed by the brain has an underlying biological and psychological component. For example, physical characteristics are shown to play a role in an individual's self-esteem (Adams, 1980; Melamed, 1994; Mocan & Tekin, 2009) and cognitive abilities (Case & Paxson, 2008; Smith et al., 2011, Naderali et al., 2009; Farr et al., 2008; Kanoski & Davidson, 2011). Additionally, research shows that obesity hinders cognitive function (Smith et al., 2011, Naderali et al., 2009; Farr et al., 2008; Kanoski & Davidson, 2011), while a healthy diet may improve cognitive function (Molteni et al., 2002; Morris et al., 2006; Kang et al., 2005; Polidori et al., 2009; Anderson et al., 2005). Therefore, it is suspected that individual's physical characteristics such as height and weight and their diet can be related to poor financial decision making.

Cerebral activity that impacts financial decisions is mediated by physiological factors such as brain structure. For example, psychopathy is linked to deficits in brain regions of the amygdala and prefrontal cortex, which is the part of the brain that regulates emotion, instinctual behavior, cognitive behavior, and decision making (Kiehl et al., 2001; Blair 2007; Blair, 2008; Glenn et al. 2009; Yang et al., 2009). Therefore, it seems safe to assume that psychopaths may not make the same financial decisions as non-psychopaths, and as such differences in psychopathic personalities may likewise contribute to poor financial decision making.

Finally, the literature frequently demonstrates investment biases in the stock market that leads to poor investment performance. However, there is a lack of research that examines biased decisions in other markets, such as the sports betting market. As such, it is important to consider how biased decisions, and poor decision-making strategies, impact bettors' profits in the NFL market. As such, this dissertation contributes to the developing literature on factors that contribute to poor financial decision-making by examining the relation of stature, obesity, and diet to poor financial decision making (Chapter 2), psychopathy to deceptive behavior (Chapter 3), and poor decision making in the NFL betting market (Chapter 4).

This dissertation is critical due to its practical implications for all individuals. First, this dissertation shows that financial decisions and outcomes are related to human features that are outside of a person's typical conscious control. Second, this dissertation provides information that could be useful for investment traders, managers, shareholders, and others in the business industry by drawing attention and understanding to how their physical characteristics or personality is related to financial decision making at the subconscious level so individuals can actively monitor their behavior in order to make more rational decisions as well as understand the decision making of others. Third, this dissertation highlights the need for traditional finance

literature to be aware of the underlying factors that drive decision making as I believe that by incorporating human behavior into traditional models will drastically improve their performance. Finally, by making bettors aware of their poor decision making may help them to produce more profits by making more rational decisions.

CHAPTER II

OBESITY, DIET, STATURE, AND FINANCIAL DECISION MAKING

2.1 Introduction

Given that risk plays a role in nearly all important economic decisions, it is pertinent to examine how individuals' physical attributes, such as height and weight, impact their financial decision making with the goal of being able to understand and predict economic behavior. The National Institute of Health (NIH) finds that nearly 70 percent of the American population is overweight or obese (NIH, 2017) with the Organization for Economic Co-operation (OECD) finding that the United States is the most obese country in the world with more than 38% of the population being obese and project that figure to continue to rise (OECD, 2017). Additionally, the World Health Organization (2016) finds that the number of adults that are obese has more than doubled since 1980. Therefore, as the number of individuals who are overweight increases, it is necessary to examine how this could impact economic decision making. Additionally, occupational stress is particularly high among finance professionals (Kahn & Cooper, 1990; Kahn et al., 1994; Jones et al., 2003), which can result in obesity and other unhealthy habits (Ganster & Schaubroeck, 1991; Laitinen et al, 2002; Chandola et al., 2006; Kivimaki et al., 2006; Siegrist & Rodel, 2006; Brunner et al., 2007; Torres & Nowson, 2007). Therefore, those who work in finance such as financial advisors, hedge fund managers, traders and corporate executives are at more risk for obesity than the general public.

There is a growing literature that crosses disciplines such psychology, economics, and finance to examine the influence of the physical attributes of individuals on their behavior and socioeconomic outcomes. For example, research shows that taller people earn higher amounts (Case & Paxson, 2008; Persico et al., 2004). Conversely, when examining weight, Hamermesh and Biddle (1994) find that obese individuals earn less money compared to individuals of normal weight, while Pagan and Davila (1997) and Harper (2000) concludes that there is a weight penalty in the labor market for women. Research consistently finds that individuals who are overweight are ranked last or second to last in preference ratings (Richardson et al., 1961; Richardson, 1970; Maddox et al., 1968). Furthermore, research demonstrates that physical attributes play a role in an individual's self-esteem (Adams, 1980; Melamed, 1994; Mocan & Tekin, 2009) cognitive abilities (Case & Paxson, 2008; Smith et al., 2011, Naderali et al., 2009; Farr et al., 2008; Kanoski & Davidson, 2011) and marriage success (Harper, 2000). However, there is little research on how height and weight impact financial decision making.

Rosen and Wu (2004) and Bressan et al. (2014) find that households in poor health are less likely to invest in risky financial assets while keeping more money in safe assets. One explanation for this is that individuals who are in poor health need to keep more money in cash in case of medical issues that could arise. Given the relationship between obesity and health conditions, it is intuitive that obesity has an impact on financial decision making. In fact, Goldman and Maestas (2013) find those who hold better medical coverage, and are less likely to incur health-related expenditures, are more apt to hold risky assets.

Research shows that economic and social conditions during childhood are positively correlated with height (Peck & Lundberg, 1995) and negatively related to obesity (Conti & Heckman, 2010). Persico et al. (2004) find that height is related to better social experience

during high school, which leads to professional success during their adult years, which could impact financial decision making. Conversely, as it relates to obesity, Cairney et al. (2008) find that the social stigma of obesity is a factor in anxiety. In fact, Vartanian (2010) find that the social discrimination against obese individuals is comparable to that against drug addicts. Research finds that peer-to-peer lending markets discriminate against those who are obese as they are subject to lower funding rates and pay higher spreads (Pope & Syndor, 2011; Duarte et al., 2012). Furthermore, Guthrie and Sokolowsky (2017) find that debt delinquency is 20% higher among obese individuals compared to non-obese individuals. Courtemanche et al. (2014) find that obese individuals display greater impatience, which could impact their financial decision making. Furthermore, literature demonstrates that those who are obese are less optimistic and are at higher risks of depression (Stunkard et al., 2003; Dong et al., 2004; Gariepy et al., 2010) which suggests they might take less financial risk (Puri & Robinson, 2007; Yuen & Lee, 2003; Nofsinger, 2005).

As it relates to economic decision making, Addoum et al. (2016) find that taller individuals and those of healthy weight have a higher tendency to participate in the equity market and hold riskier assets. Similarly, Dohmen et al. (2010) find that taller individuals are more risk tolerant in a Holt and Laury type task. Additionally, Koritzky et al., (2012) find that obese men are more likely to take risk in the Iowa Gambling Task compared to normal weight men, and that obese women are more impulsive compared to women of healthy weight. Additionally, Ratcliff et al. (2011) find differences in obese men and women compared to non-obese men and women in risky behavior such as alcohol/drug use, risky sexual activities, and smoking.

Research routinely shows the relationship between diet and obesity (Bonow & Eckel, 2003; Bray, 2004; Kopelman, 2000; Bazzano et al., 2002). Additionally, diet is shown to contribute to

brain regions which control decision making. For example, Molteni et al. (2002) find that saturated fat and refined sugar influence brain structure and function, and reduces hippocampus levels of brain-derived neurotrophic factor, which shows that a diet high in saturated fat and refined sugar inhibits learning and memory. Furthermore, Morris et al. (2006) and Kang et al. (2005) find that vegetable consumption has a positive impact on cognitive function, while fruit consumption has no bearing. Conversely, Anderson et al. (2005) and Polidori et al. (2009) find that both vegetable and fruit consumption has a positive effect on cognitive function. Jacka et al. (2010) conclude that improved diet quality can improve mood, which suggests they will be more risk taking (Puri & Robinson, 2007; Yuen & Lee, 2003; Nofsinger, 2005). However, Galizzi and Miraldo (2012) find that individuals who score higher on the healthy eating index have a greater degree of risk aversion in a Holt and Laury task. Therefore, given the relationship between diet and obesity, as well as diet and cognitive function and mood, it is intuitive that diet has an impact on economic decision making.

Rather than measure risk taking through a single risk factor such as the Iowa Gambling Task or Holt and Laury task, or proxy for it using stock market participation and the proportion of subject's allocation in equities, this study employs the Dynamic Experiments for Estimating Preferences (Toubia et al., 2013) to examine how individual's height, body mass index (BMI), and diet relate to financial decision making.[1] This questionnaire captures individual's probability distortion, the curvature of their utility function, and loss aversion based upon cumulative prospect theory to assess risk taking preferences and their present bias and daily discounting rate to evaluate time preferences.

[1] BMI is defined as (Weight / Height^2) x 10,000 where weight is measured in kilograms and height is measured in centimeters

The results can be summarized as follows. BMI is positively correlated with the present bias, loss aversion, and the discounting rate. Additionally, greater than average BMI is related to the distortion of the probability of gains and losses. Furthermore, when examining diet, participants' vegetables consumption is inversely correlated with the present bias, while fruit consumption is inversely related to loss aversion.

2.2. Methods

2.2.1. Participants

The sample consists of 123 participants that were recruited from upper-level undergraduate finance and economic courses to ensure that the participants understand the components of risk and reward. This sample of 123 subjects is in line with other behavioral finance experiments including Durand et al. (2013) who examine personality traits and investment performance in 115 finance students, Durand et al. (2017) who use 128 students to examine the impact of personality on loss aversion, and significantly higher than Durand et al. (2008) who examine the impact of personality on investment performance in 18 professional traders. Table 2.1 presents the participants' sample statistics, which shows that the sample consists of 56 (46%) males and 67 (54%) females. The sample consists of a diverse range of majors within the business department with 31 (25%) accounting 29 (24%) finance, 9 (7%) information systems, 36 (29%) management, 10 (8%) marketing and 8 (7%) other majors. The median age of the participants is 22.66 with a standard deviation of 5.49. The subjects' car value is used as a proxy for net worth as college students typically lack income. The median car value

of the participants is $5,839 with a standard deviation of $8,776. Age, gender, and car values are used as control variables.

Table 2.1
Subject Sample Statistics

Panel A: Gender & Major

Total	Male	Female
123	56	67

Accounting	Finance	Information Systems	Management	Marketing	Other
31	29	9	36	10	8

Panel B: Age & Car Value

	Mean	Median	Std Dev
Age	24.68	22.66	5.49
Car Value	$8,035	$5,839	$8,776

Notes: This table displays the subject sample statistics. Panel A shows the distribution breakdown of the subject's gender and major. Panel B presents the age and car value of the subjects.

Participants were given a survey that included the food frequency questionnaire (FFQ) from Hartmann et al. (2013) and questions about their height, weight, and demographic information. Additionally, participants engaged in the Dynamic Experiments for Estimating Preferences (DEEP; Toubia et al., 2013) to examine financial risk and time preferences. Luccasen and Thomas (2014) find no difference in outcomes or behavior when using class credit or monetary incentives during experiments. Therefore, rather than providing a $2 monetary reward for participating as done in Toubia et al. (2013), this experiment provides participants with class credit.

2.2.2. Stature, Obesity, & Food Frequency Questionnaire

I follow Addoum et al. (2016) to examine individual's stature and define relative height as the difference between the height of the participant and the mean gender group height. Since there are obvious height differences in males and females, this relative height measure captures the potential advantages or disadvantages of physical appearance more effectively than raw height variables. BMI is not examined in its relative form as there is no evidence that men and women have differences in their BMI.[2]

The food frequency questionnaire from Hartmann et al. (2013) was developed to assess food choice. This questionnaire is not a comprehensive FFQ, but instead only includes foods that can be regarded as contributors to a balanced or unbalanced diet (Hartmann et al., 2013). In the Hartmann et al. (2013) study, the foods included in the questionnaire were selected because either consuming them is encouraged by dietary guidelines (Keller et al., 2012) or because high consumption of them are frequently correlated with having adverse health effects (Faramawi et al., 2007; Hartmann et al., 2013; Hu & Malik, 2010).

As in the Hartmann et al. (2013) questionnaire, sugar-sweetened beverage, meat product, and sweet and savory consumption are assessed using a 6-point answer scale. Following Hartmann et al. (2013) and Keller and Siegrist (2015) results for "several times per day" is coded as 14 (14 times per week), "daily" is coded as 1 (7 times per week), "several times per week" is coded as 3 (3 times per week), "several times per month" is coded as .75 (3 times per month), "several times per year" and "less or never" are assumed to be negligible and coded as 0. Fruit

[2] Addoum et al. (2016) use relative BMI in their study as they have data from separate countries and years. Since this data is collected at the same time from the same region a relative BMI variable is not calculated.

and vegetable consumption is assessed on a 5 point scale where “daily” is coded as 7 (7 times per week), “4-6 times / week” is coded as 5 (5 times per week), “1-3 times/week” is coded as 2 (2 times per week), “1-3 times per month” is coded as .5 (2 times per month), and “less or never” is coded as 0. Additionally, participants were asked how many servings of fruits (one piece or handful) or vegetables (one serving = one handful) they consume when they do eat them. The 5 point answers are then transformed as the frequency per week multiplied by the number of portions consumed at the time eaten per week.

2.2.3. Dynamic Experiments for Estimating Preferences

The risk preferences and time preferences of the subjects in DEEP (Dynamic Experiments for Estimating Preferences) are captured dynamically by modifying the series of questions presented to each participant and finding the convergence of the simulation from cumulative prospect theory (CPT) and quasi-hyperbolic time discounting (QTD) models. The CPT simulations yield the following variables: utility function curvature (σ) examines individual’s sensitivity to deviations of wealth in place of total wealth; loss aversion (λ) reveals the subjects’s sensitivity to gains and losses of identical amounts; probability distortion (α) examines how participants weigh the probabilities of outcomes, most noticeably close to certainty. The variables are achieved by the series of gambles given to the subjects that are defined as $\{x, p; y\}$ where gamble x has the outcome of p probability, or result y yields the probability of 1-p.

A truncated normal distribution of $\alpha \in [0.05, 2]$ $\sigma \in [0.05, 2]$ and $\lambda \in [0,10]$ is implemented to assure that the parameters are in the acceptable range for cumulative prospect theory following Toubia et al. (2013). Thus, the model is written as U(x, p, y, α, σ, λ) where:

$$\begin{cases} \upsilon(y,\sigma)+\pi(p,\alpha)(\upsilon(x,\sigma)-\upsilon(y,\sigma) & \text{if } x > y > 0 \text{ or } x < y < 0 \\ \pi(\mathrm{p},\alpha)\upsilon(\mathrm{x},\sigma)+\pi(1\text{-p},\alpha)\upsilon(\mathrm{y},\sigma) & \text{if } x < 0 < y \end{cases}$$

Where

$$\upsilon(x,\sigma) = \begin{cases} x^{\sigma} & \text{for } x > 0 \\ -\lambda(-x)^{\sigma} & \text{for } x < 0 \end{cases}$$

And $\pi(p,\alpha) = \exp[-(-\ln p)^{\alpha}]$

Where $\upsilon(y,\sigma)$ denotes the reference point of total wealth, $\pi(p,\alpha)$ signifies the subjects probabilities weights, and $\upsilon(x,\sigma)$- $\upsilon(y,\sigma)$ represents the utility gained from the gamble. If $x < 0 < y$, $\pi(p,\alpha)\upsilon(x,\sigma) + \pi(1\text{-}p,\alpha)\upsilon(y,\sigma)$ signifies the magnitude of the gain and loss. x^{σ} indicates the subject's utility function curvature, whereas λ represents the scaling factor that signifies the steepness of the subject's utility function, and $\pi(p,\alpha)$ represents the probability weights.

Subjects are asked to select between a sequence of gamble pairs to extract the parameters where their chosen gambles are indexed by I (I = 1,…, I) where w_i denotes the vector of selections for subject i: $w_i = [\alpha_i; \sigma_i, \lambda_i]$. The selected gamble is recorded by j (j = 1, …, J), where subject I must make a selection for question j where they must decide between gamble $X_{ij}^{A} = \{x_{ij}^{A}, p_{ij}^{A}, y_{ij}^{A}\}$ and gamble $X_{ij}^{B} = \{x_{ij}^{B}, p_{ij}^{B}, y_{ij}^{B}\}$. A lower probability transformation is denoted by a larger value of α. A utility function that has more curvature is characterized by a lower value of σ, with a value of 1 indicating a linear utility function. A higher value of λ demonstrates more loss aversion.

The simulations from QTD yield the discount function (β) which examines how individuals discount future cash flows and discounting rate (r), which analyzes the subject's daily discounting rate of the selected reward. During the QTD, the subjects must pick between two possible outcomes where one option results in a reward of less money that is collected at an earlier date, or a sum of higher value received at a later date. The selected outcome is denoted by {x, t} where reward x is earned in t periods (i.e. days). The model is denoted by U(x, t) = υ(x)d(t), where υ signifies the gained utility from outcome x, while d represents the discount function.

Following Toubia et al. (2013), a truncated normal distribution is employed to keep parameters within the acceptable range for QTD model, similar to CPT, where $\beta \in [0, 2]$ and $r \in [0, 0.05]$. The quasi-hyperbolic time discount model follows (Phelps and Pollak 1968; Laibson 1997; Benhabib et al. 2010; Toubia et al. 2013):

$$U(x, t, \beta, r) = xd(t, \beta, r)$$

where

$$d(t, \beta, r) = \begin{cases} 1 & \text{for } t = 0 \\ \beta \exp(-rt) & \text{for } t > 0 \end{cases}$$

Where β represents the subject's preferences for the two outcomes that have different discounting rates, which controls for the heterogeneity of how much importance the subject places on time. A discontinuous drop at t= 1 when $\beta < 1$ of the discount function shows how individuals' overweight present outcomes at time t = 0 compared to the future t > 0, also commonly known as the present bias (O'Donoghue & Rabin, 1999). The parameters from the QTD model can be written as $w_i = [\beta_i, r_i]$ where subject i must select amongst two payments that

have differing outcomes and payment dates for a sequence of selections. Subject I must select for question j that involves choosing between option $X_{ij}^{A} = \{x_{ij}^{A}, t_{ij}^{A}\}$ and $X_{ij}^{B} = \{x_{ij}^{B}, t_{ij}^{B}\}$. A lower value of β denotes a more substantial present bias. A larger r denotes a larger daily discounting rate.

Before the subjects starting the DEEP risk and time questionnaires, they were given the welcome page that offers the instructions for the survey. Before starting the questionnaires, they must correctly answer a pair of questions about time value of money and probabilities to certify that the subjects have a basic understanding in order to complete the surveys.[3]

After the subjects completed the survey, their preference selections are analyzed using Hierarchical Bayes analysis based upon the truncated normal distribution stated above. The code for the analysis is publicly available through the Columbia Business School Center for Decision Sciences website.[4]

2.3. Results

Table 2.2 presents the summary statistics for the sample. Panel A shows that the average height for the males in the sample is 70 inches with their average BMI being over 26. Females average height is almost 63 inches and their average BMI of nearly 25. According to the National Heart, Lung, and Blood Institute, a healthy BMI is between 18.5 and 24.9. Therefore, the average male in the sample is overweight, while the average female is just within the

[3] A demo of DEEP is provided for the risk survey: https://vlab.decisionsciences.columbia.edu/deeprisk/demo and time survey: https://vlab.decisionsciences.columbia.edu/deeptime/demo

[4] https://sites.google.com/a/decisionsciences.columbia.edu/cds-wiki/deep-software

guidelines for a healthy weight. Furthermore, the minimum and maximum for height and BMI for both genders shows a diverse sample.

Table 2.2
Summary Statistics

Variables	Mean	St. Dev.	Min	Max
Panel A: BMI and Height by Gender				
Male:				
BMI	26.57	5.45	15.00	46.84
Height (inches)	70.02	3.16	62.00	81.00
Female:				
BMI	24.75	5.34	17.85	43.42
Height (inches)	62.73	2.59	56.00	69.00

Variables	Mean	St. Dev.	Min	Max
Panel B: Food Frequency Questionnaire				
Sugar Beverage	6.34	5.38	0.00	14.00
Meat	7.95	2.43	0.00	14.00
Fruit	6.50	6.62	0.00	35.00
Vegetables	11.23	10.83	0.00	56.00
Sweet & Savory	4.22	2.97	0.00	14.00

Variables	Mean	St. Dev.	Min	Max
Panel C: Risk Preference Variables				
Lack of Distortion of Probability (α)	0.639	0.215	0.122	1.083
Diminishing Curvature (σ)	0.555	0.197	0.196	1.165
Loss Aversion (λ)	0.915	0.420	0.109	1.771

Variables	Mean	St. Dev.	Min	Max
Panel D: Time Preference Variables				
Discount Function (β)	0.869	0.328	0.0226	1.568
Discounting Rate (r)	0.011	0.007	0.001	0.024

Notes: This table displays the mean, standard deviation (St. Dev.) minimum (Min) and maximum (Max) for the BMI and Height by gender in Panel A, Food Frequency Questionnaire in Panel B and DEEP (Toubia et al., 2013) risk preferences in Panel C and time preferences in Panel D for the full sample (N=123). Section 2.2 describes the Food Frequency Questionnaire and Section 2.3. provides details about the DEEP variables.

Panel B provides the summary statistics for the FFQ. The average individual consumes about six sugar-sweetened beverages, eight portions of meat, and four sweet and savory snacks per week. Additionally, the average subject consumes 6.5 portions of fruit and over 11 servings of vegetables per week, which is well below the United States Department of Agriculture (USDA) recommendation of 14 servings of fruits and 17 servings of vegetables per week. These figures could explain why the average participant in the sample is overweight. In fact, only 26 (21%) of the sample eats the recommended number of servings of fruit, and 28 (23%) eat the recommended number of servings of vegetables with only 18 (15%) consuming the recommended amount of both.

Panel C provides the summary statistics for the risk preferences. Overall, the minimum and maximum show a diverse sample, with some participants preferring little risk and some exhibiting risk seeking behavior. For example, the average value for loss aversion is 0.915, but the minimum value is 0.109, and the maximum figure is 1.771 showing wide ranges of loss aversion for the sample. Similarly, Panel D indicates that some participants have a high present bias with a low value of β with the minimum value of 0.0226, while others exhibit little present bias with the maximum value being 1.568.

Table 2.3 presents the results for how relative height and BMI relate to financial risk taking and time preferences.[5] The selection of control variables of age, car value, and gender are selected for their well-known determinants of financial risk taking (e.g., see Campbell, 2006; Addoum et al., 2016). Elias et al. (2003) and Elias et al. (2005) find that obesity has an adverse effect on cognitive function in men but finds to significance with women. Therefore, the model

[5] The results in this chapter demonstrate the correlation between independent variables and the financial decision variable not causality.

includes a male dummy variable as well as an interaction between the male dummy variable and relative height and BMI to examine if there are gender-specific differences. The first column shows how BMI relates to the financial decision-making variable, while column two examines how participants' relative height correlates to their financial decision making. The third column illustrates the relationship of BMI and relative height together. The fourth column adds the control variables to the model. Finally, column 5 adds a male interaction variable with BMI and relative height to examine if there are any gender differences in the relationship of BMI and height on financial decision making.[6]

Table 2.3
Relation Between Obesity, Stature and Financial Decision Making

Indep. Var.	**Lack of Probability Distortion (α)**	**Lack of Probability Distortion (α)**	**Lack of Probability Distortion (α)**	**Lack of Probability Distortion (α)**	**Lack of Probability Distortion (α)**
BMI	-4.9202		-5.0908	-5.6872	-2.3350
	(3.557)		(3.644)	(3.793)	(5.220)
Relative Height		21.2040	-108.0508	-115.8566	301.3586
		(454.582)	(462.163)	(469.399)	(676.713)
Age				3.3147	3.2957
				(3.673)	(3.749)
Car Value				-0.0005	-0.0003
				(0.002)	(0.002)
Male				0.0422	175.1891
				(39.796)	(201.039)
Relative Height*Male					-808.5221
					(948.386)
BMI*Male					-6.8210
					(7.664)
R-squared	0.016	0	0.016	0.023	0.034

[6] Addoum et al. (2016) include a squared BMI and relative height variable in their analysis, however the squared analysis is not conducted in this analysis because test reveal multicollinearity within the model when the squared variables are included.

Table 2.3 Continued

Indep. Var.	Diminishing Curvature (σ)	Diminishing Curvature (σ)	Diminishing Curvature (σ)	Diminishing Curvature (σ)	Diminishing Curvature (σ)
BMI	-4.2341		-4.0506	-4.3470	-5.8994
	(3.271)		(3.352)	(3.498)	(4.835)
Relative Height		219.0573	116.2124	102.3660	-59.5171
		(417.266)	(425.081)	(432.918)	(626.874)
Age				0.6700	0.6402
				(3.388)	(3.473)
Car Value				0.0002	0.0002
				(0.002)	(0.002)
Male				12.4010	-69.6450
				(36.703)	(186.233)
Relative Height*Male					313.1880
					(878.540)
BMI*Male					3.1944
					(7.099)
R-squared	0.014	0.002	0.014	0.016	0.018

Table 2.3 Continued

Indep. Var.	Loss Aversion (λ)	Loss Aversion (λ)	Loss Aversion (λ)	Loss Aversion (λ)	Loss Aversion (λ)
BMI	19.4242***		18.9821***	19.1085***	22.6871**
	(6.796)		(6.963)	(7.255)	(10.018)
Relative Height		-761.9767	-280.0187	-307.0231	269.2718
		(887.812)	(882.992)	(897.884)	(1,298.778)
Age				3.1003	2.9185
				(7.026)	(7.196)
Car Value				0.0011	0.0012
				(0.004)	(0.004)
Male				-36.2441	146.8234
				(76.123)	(385.843)
Relative Height*Male					-1,118.9985
					(1,820.186)
BMI*Male					-7.1330
					(14.709)
R-squared	0.063	0.006	0.064	0.068	0.073

Indep. Var.	Discount Function (β)	Discount Function (β)	Discount Function (β)	Discount Function (β)	Discount Function (β)
BMI	-6.9956		-7.4869	-7.3879	-6.7995
	(5.437)		(5.568)	(5.805)	(8.027)
Relative Height		-121.1036	-311.1962	-335.8172	22.2887
		(694.141)	(706.132)	(718.492)	(1,040.639)
Age				-2.2252	-2.5799
				(5.622)	(5.766)
Car Value				0.0013	0.0011
				(0.003)	(0.004)
Male				22.7738	45.0014
				(60.914)	(309.155)
Relative Height*Male					-698.7528
					(1,458.416)
BMI*Male					-0.8732
					(11.785)
R-squared	0.013	0	0.015	0.018	0.02

Table 2.3 Continued

Indep. Var.	Discounting Rate (r)	Discounting Rate (r)	Discounting Rate (r)	Discounting Rate (r)	Discounting Rate (r)
BMI	0.2646**		0.2921**	0.2567**	0.2013
	(0.113)		(0.115)	(0.119)	(0.163)
Relative Height		9.9739	17.3903	18.7172	3.6542
		(14.598)	(14.575)	(14.686)	(21.196)
Age				0.0790	0.0894
				(0.115)	(0.117)
Car Value				-0.0001	-0.0001
				(0.000)	(0.000)
Male				0.9654	-1.6850
				(1.245)	(6.297)
Relateive Height*Male					29.3278
					(29.705)
BMI*Male					0.1034
					(0.240)
R-squared	0.044	0.004	0.055	0.076	0.084

Notes: This table presents the regression results where the dependent variable is one of the financial preference measures (see Section 2.3) and relative height and BMI with a list of control variables for the full sample (N=123). Standard errors are listed below the coefficients in parenthesis with significance shown at the 10% (*), 5% (**), and 1% (***) levels. Standard errors and coefficients are multiplied by 1,000 to make easier to read.

The first variable of interest in Table 2.3 is the lack of probability distortion. Column 1 shows that higher BMI is related to the distortion of the probability of gains and losses. However, the variable is just outside the normal level of significance as the coefficient of negative 0.49 has a standard error of 0.356, which corresponds to a p-value of 0.16. Additionally, Table 3 reveals that neither BMI nor relative height has any correlation to the curvature of the utility function, thus providing the result that neither variables are related to linear risk taking.

Conversely, the results show that BMI is positively related to loss aversion at the 1% level in column 1. Additionally, after including control variables, the results continue to show

that BMI is significantly correlated to loss aversion. This result shows that while BMI is not associated to linear risk taking, higher BMI is related to being sensitive to gains and losses of the same value.

In the examination of β and the present bias the results indicate that BMI is positively related to the present bias, as a lower discount function denotes a higher present bias, however, the results are insignificant. Finally, Table 2.3 shows that there is a positive relationship between BMI and the discounting rate. This result indicates that higher BMI is correlated to impatience and the inability to delay gratification. Overall, none of the variables show any gender-specific differences in BMI or height.

Addoum et al. (2016) find that height is positively related and BMI is inversely related to stock market participation and choosing equity investments while participating in the stock market, while these results show that neither is related to risk taking when examining the curvature of the subject's utility function. However, the results indicate that BMI is related to loss aversion. One possible explanation for the discrepancy between these results and the results in Addoumn et al. (2016) is because Addoumn et al. (2016) claim that taller individuals of average weight typically have more education, better self-esteem, and better life experience. Therefore, such persons may have higher financial literacy which could explain why they are more likely to invest in the stock market and equities, while they may actually have no greater risk preferences compared to shorter and more overweight individuals.

In the spirit of Addoum et al. (2016), BMI and relative height are split into terciles (3 quantiles) to examine how below and above average BMI and height relate to financial risk and time preferences. This type of analysis provides robustness to the previous results as well as accounting for individuals at the end of the spectrum of relative height and BMI which could be

driving the nonlinear effects. Table 2.4 shows higher than average BMI is related to the distortion of the probability of gains and losses. The results indicate that lower than average BMI is related to being less loss averse with a coefficient of -12.66 while higher than average BMI is positively correlated loss aversion with a coefficient of 8.60, however both figures fall slightly outside the range of normal significance level as the increased number of variables likely drives down the power of the model, suggesting that the results from Table 2.3 are more credible as they can detect smaller differences between individuals BMI differences and loss aversion estimates as compared to using 3 large groups. Further, the results suggest that those that fall into the lowest BMI may have a stronger linear relationship to help explain the results from Table 2.3. Additionally, the results show that lower than average BMI is related to a higher value of β which shows less present bias. Finally, lower than average BMI is related to a lower discounting rate. It is important to note that 90% of the individuals in BMI Q1 are of normal BMI levels.

The second part of this chapter examines the correlation between diet and financial decision making while controlling for many factors. Table 2.5 presents the results for diet and financial risk and time preferences. The results show that fruit consumption is inversely related to loss aversion, suggesting those who take higher risk with their diet and chose to ignore the health beneifts of fruit consumption are less likely to take financial risk. Additionally, vegetable consumption is correlated with a higher discount function, which is significant at the 1% level, showing that consuming vegetables may help people avoid committing the present bias. Additionally, vegetable consumption is negatively related to the discounting rate. Furthermore, BMI is still significant in loss aversion and the discounting rate when adding the diet variables. Table 2.6 presents the results for the food variables separated into terciles similar to Table 2.4. The results show that less sugar-sweetened beverages consumption than average is related to a

higher distortion of probability. Additionally, less fruit consumption than the average is correlated with loss aversion. Furthermore more vegetables consumption compared to the sample average is inversely related to the present bias, while less than average consumption of vegetables is positively correlated with the present bias.

Table 2.4

Tercile Regressions for the Relation Between Obesity, Stature and Financial Decision Making

Indep. Var.	Lack of Probability Distortion (α)	Diminishing Curvature (σ)	Loss Aversion (λ)	Discount Function (β)	Discounting Rate (r)
BMI Q1	-45.6735	33.7006	-126.5765	126.3671*	-4.6754***
	(50.183)	(46.672)	(97.168)	(76.040)	(1.543)
BMI Q3	-81.8777*	9.8881	85.9845	-26.0333	-0.5377
	(49.240)	(45.795)	(95.343)	(74.613)	(1.514)
Relative Height Q1	-2.7731	-17.9801	16.6362	53.5747	0.7716
	(52.024)	(48.385)	(100.734)	(78.831)	(1.600)
Relative Height Q3	-45.9770	23.6878	-74.4047	9.5166	1.8014
	(52.153)	(48.504)	(100.982)	(79.026)	(1.604)
Age	2.7232	0.0849	4.0565	-1.6461	0.0972
	(3.684)	(3.426)	(7.133)	(5.582)	(0.113)
Car Value	0.0005	0.0001	0.0004	0.0016	-0.0001
	(0.002)	(0.002)	(0.004)	(0.004)	(0.000)
Male	-10.6135	17.2274	-54.4088	29.9772	0.3554
	(42.631)	(39.648)	(82.545)	(64.597)	(1.311)
R-squared	0.037	0.013	0.059	0.052	0.12

Notes: This table presents the regression results where the dependent variable is one of the financial preference measures (see Section 2.3), and the independent variables are terciles of relative height and BMI for the full sample (N=123). To avoid collinearity, the dummy variables corresponding to the second height and BMI are omitted. Standard errors are listed below the coefficients in parenthesis with significance shown at the 10% (*), 5% (**), and 1% (***) levels. Standard errors and coefficients are multiplied by 1,000 to make easier to read.

Table 2.5
Relation Between Diet, Obesity, Stature and Financial Decision Making

Indep. Var.	Lack of Probability Distortion (α)	Diminishing Curvature (σ)	Loss Aversion (λ)	Discount Function (β)	Discounting Rate (r)
Sugar Beverage	13.62995	58.80839	-83.71625	-27.17412	-0.13011
	(44.754)	(40.985)	(84.416)	(66.614)	(1.381)
Meat	36.86994	20.75255	-47.31960	117.97149	-1.93722
	(84.612)	(77.486)	(159.596)	(125.941)	(2.610)
Fruit	-13.87967	55.45231	-157.45286*	-74.90038	1.58928
	(43.902)	(40.205)	(82.809)	(65.347)	(1.354)
Vegetables	-20.82181	-9.68045	21.79460	106.86433***	-1.46827*
	(26.590)	(24.351)	(50.155)	(39.579)	(0.820)
Sweet & Savory	36.39458	-35.30573	28.09424	25.65992	-2.25994
	(81.670)	(74.792)	(154.047)	(121.563)	(2.520)
BMI	-54.46488	-48.99701	202.17904***	-61.28040	2.27930*
	(38.722)	(35.461)	(73.038)	(57.636)	(1.195)
Relative Height	369.26507	328.60957	517.71652	-5,670.70476	202.74629
	(4,932.715)	(4,517.297)	(9,304.141)	(7,342.136)	(152.176)
Age	36.24326	19.84874	1.47075	-28.15948	0.82594
	(38.099)	(34.890)	(71.862)	(56.708)	(1.175)
Car Value	-0.00079	-0.00006	0.02344	-0.00179	-0.00080
	(0.024)	(0.022)	(0.045)	(0.035)	(0.001)
Male	-12.80055	106.04466	-385.84224	344.15575	5.74354
	(418.814)	(383.543)	(789.972)	(623.387)	(12.921)
R-squared	0.046	0.053	0.116	0.094	0.123

Notes: This table presents the regression results where the dependent variable is one of the financial preference measures (see Section 2.3) and independent variables of food choice (see Section 2.2), relative height and BMI as well as a list of control variables for the full sample (N=123). Standard errors are listed below the coefficients in parenthesis with significance shown at the 10% (*), 5% (**), and 1% (***) levels. Standard errors and coefficients are multiplied by 1,000 to make easier to read.

Table 2.6
Tercile Regressions for the Relation Between Diet, Obesity, Stature and Financial Decision Making

Indep. Var.	Lack of Probability Distortion (α)	Diminishing Curvature (σ)	Loss Aversion (λ)	Discount Function (β)	Discounting Rate (r)
Sugar Beverage Q1	-120.6977**	24.9325	8.9769	86.3929	0.1161
	(54.173)	(50.516)	(106.141)	(78.513)	(1.666)
Sugar Beverage Q3	-64.3442	79.7198	-102.4119	91.6839	-1.8998
	(55.442)	(51.700)	(108.628)	(80.353)	(1.705)
Meat Q1	-26.7518	-65.7831	180.1201*	10.4739	-0.8401
	(53.575)	(49.958)	(104.969)	(77.646)	(1.647)
Meat Q3	-2.7333	-31.9743	71.8722	-109.8743	1.3401
	(59.437)	(55.425)	(116.454)	(86.142)	(1.828)
Fruit Q1	32.4181	31.8439	-32.5147	-130.1634*	1.4118
	(53.110)	(49.525)	(104.058)	(76.972)	(1.633)
Fruit Q3	-31.7946	71.5171	-64.2487	203.7491**	-2.2331
	(57.337)	(53.466)	(112.339)	(83.098)	(1.763)
Vegetables Q1	57.3688	-22.1597	-15.4345	53.4151	-2.2190
	(54.919)	(51.212)	(107.602)	(79.594)	(1.689)
Vegetables Q3	8.0484	-17.0378	-37.1607	10.5136	-1.4217
	(52.148)	(48.628)	(102.173)	(75.578)	(1.604)
Sweet & Savory Q1	-39.3744	-8.7267	-9.3985	-6.1915	-0.2079
	(46.930)	(43.762)	(91.950)	(68.016)	(1.443)
Sweet & Savory Q3	26.8299	-23.4280	-3.3366	64.9522	-1.3702
	(57.265)	(53.400)	(112.200)	(82.995)	(1.761)
BMI Q1	-60.5063	36.7979	-127.1568	123.7646*	-4.4309***
	(51.266)	(47.805)	(100.445)	(74.300)	(1.576)
BMI Q3	-97.7278*	4.5084	91.4151	9.7852	-0.8899
	(51.464)	(47.990)	(100.833)	(74.587)	(1.583)
Relative Height Q1	-18.8722	-5.4195	6.2419	76.2964	0.8829
	(54.019)	(50.372)	(105.838)	(78.289)	(1.661)
Relative Height Q3	-38.3675	28.2267	-75.0822	0.1426	1.6305
	(53.385)	(49.781)	(104.597)	(77.371)	(1.642)
Age	3.6796	1.4338	1.4162	-4.6220	0.1489

	(3.899)	(3.636)	(7.639)	(5.651)	(0.120)
Car Value	0.0007	-0.0004	0.0012	-0.0001	-0.00008
	(0.002)	(0.002)	(0.005)	(0.004)	-0.00007
Male	-13.4116	25.4346	-75.5389	42.9914	0.0233
	(45.375)	(42.312)	(88.903)	(65.762)	(1.395)
R-squared	0.107	0.081	0.107	0.196	0.185

Notes: This table presents the regression results where the dependent variable is one of the financial preference measures (see Section 2.3), and the independent variables are terciles of the variables from the FFQ (see Section 2.2), relative height, and BMI for the full sample (N=123). To avoid collinearity, the dummy variables corresponding to the second variable of the FFQ, height, and BMI are omitted. Standard errors are listed below the coefficients in parenthesis with significance shown at the 10% (*), 5% (**), and 1% (***) levels. Standard errors and coefficients are multiplied by 1,000 to make easier to read.

2.4. Conclusion

This chapter examines how observed physical attributes and diet are related to financial decision making. The psychology and economic literature show a positive relationship between height and negative relation for obesity to risk taking. Addoum et al. (2016) use stock market participation as the dependent variable for a large sample using the Survey of Health, Aging, and Retirement in Europe and find positive coefficients of relative height and negative effects of relative height squared. They also find negative effects of relative BMI on stock market participation. Additionally, the literature demonstrates that obesity hinders cognitive function (Smith et al., 2011, Naderali et al., 2009; Farr et al., 2008; Kanoski & Davidson, 2011), while a healthy diet may improve cognitive function (Molteni et al., 2002; Morris et al., 2006; Kang et al., 2005; Polidori et al., 2009; Anderson et al., 2005).

Consistent with the literature, my results show that obesity is related to the present bias, and giving stronger weights to payoffs that are closer to the present time, as well as the distortion of the probability of gains and losses and loss aversion. Thus, showing that the impaired

cognitive function on those who are overweight may spill over into biased financial decisions. In contrast to the literature, this chapter finds no relationship between height and financial decision making. Furthermore, when examining individuals' diet, the results show that vegetable consumption is inversely related to the present bias.

These results have important implications for the financial industry. For example, biased decision making of mutual fund managers, hedge fund managers, and corporate managers may be correlated with their body mass index or diet. Therefore, people who have less healthy diets should be aware that their lower regard for health might translate into other behaviors, such as poor financial decision making.

CHAPTER III

DECONSTRUCTING THE CORPORATE PSYCHOPATH: AN EXAMINATION OF DECEPTIVE BEHAVIOR

3.1. Introduction

The business industry is rampant with lying, deception, and unethical behavior. Recent examples include Enron, Volkswagen emissions scandal, Barclays Libor rigging, Wells Fargo fraud, the Ponzi schemes by Bernie Madoff and Allen Stanford and insider trading from Zvi Goffer and Raj Rajaratnam. Dyck et al. (2013) estimate that 15% of large publicly traded companies commit fraud during any year. Cohn et al. (2014) argue that business culture could explain the dishonesty in the financial industry. Additionally, Akerlof and Romer (1993) maintain that the most profitable strategy for executives of "too-big-to-fail" banks is to loot their company and pay themselves huge rewards because they know that the government will bail them out from bankruptcy, which provides incentives to behave unethically. A New York Time's article shows that only 20% of individuals trust banks after the fallout of subprime mortgages during the financial crisis (Porter, 2012). Additionally, the article shows that 62% of Americans believe that corruption is widespread across corporate America with nearly 75% of them believing that corporate corruption has increased in the previous three years.

The references above demonstrate the extensive amount of corporate corruption; however, little research is devoted to uncovering the origins of deceptive and unethical behavior

that preludes the corruption. In 2015, more than half of Fortune 100 CEOs hold undergraduate degrees in business, and 40% hold a Master's in Business Administration degree, which shows a strong relationship between business majors working in high levels of management (Stadler, 2015). This presents the question: are students majoring in business more likely to commit deceptive and unethical behavior compared to non-business majors? Additionally, the term "corporate psychopath" has been coined by professionals to describe individuals who work in the business industry that have no conscience, and are willing to lie, manipulate others, and be ruthless to gain a financial advantage (Boddy et al., 2010). If business students are more likely to deceive others, could it be because they are more psychopathic? Distinguishing between if business majors are more deceitful than non-business majors, and the influence of psychopathy has significant implications for the business industry and the design of public policy.

This study follows the cheap talk experiment from Gneezy (2005) to examine the difference in deceptive acts between business and non-business students where information asymmetry exists, giving individuals the choice whether to deceive others for personal gain. Additionally, following Gneezy (2005), participants are given a questionnaire on ethics following the cheap talk experiment to examine how individuals recognize the unethical behavior. The Psychopathic Personality Inventory- Revised (PPI-R) developed by Lilienfeld et al. (2005) is employed to create a psychopathic trait profile of how business students are fundamentally different from non-business students.[7] Finally, this chapter examines how these psychopathic traits relate to deceptive behavior and ethical viewpoints.

[7] Unlike fluctuating shocks to mood and behavior by outside factors, personality traits are habitual (i.e., fundamental) patterns of thought, emotion, and behavior

The results are summarized as follows. First, business students are more likely to use private information to deceive others when the personal rewards are the highest. However, when provided an example of others committing deceptive acts, business students view the behavior as unethical. Second, business students are more likely to fit the prototypical profile of a psychopath, including being more likely to be rebellious, manipulate others, and have a propensity towards guiltlessness. Third, these fundamental differences in psychopathic personality can help explain why business students deceive others more often compared to non-business students.

3.2. Related Literature

3.2.1. A portrait of business students

Individuals majoring in business are exposed to the self-interest model of economics through their coursework. Therefore, it is expected that they behave differently given they have attained a distinctive way of understanding and interpreting financial information. The self-interest model argues that in a market economy, the best economic benefit is accomplished when individuals act in their own self-interest. In the book “An Inquiry into the Nature and Causes of the Wealth of Nations,” Smith (1817) says "It is not from the benevolence of the butcher, the brewer, or the baker that we expect our dinner, but from their regard to their own interest." Smith explains that the baker bakes because of his own self-interest to earn enough money to feed his family. However, the baker must bake a bread of high quality that is cheap enough that others are

willing to pay for it. Thus, the baker serves his self-interest by producing a good that others find valuable.[8]

However, if there is not enough competition, or individuals hold private information, one can argue that the self-interest model could lead to price gouging, corruption, and cheating. For example, research shows that individuals exposed to the self-interest model are more likely to free ride (Marwell & Ames, 1981), cooperate less (Frank et al. 1993), exhibit a greater acceptance of greed (Long et al., 2011), cheat to gain an advantage (McCabe et al. 2006), bribe others for personal gain (Frank & Schulze, 2000), behave unethically for "the love of money" (Tang & Chen, 2008), and have less of a concern for fairness (Carter & Irons, 1991) compared to individuals not exposed to the self-interest model. Gandal et al. (2005) explain this behavior by finding that individuals exposed to the self-interest model place more value on achievement and less value on the welfare of others compared to individuals who have not been exposed to the self-interest model.

Research finds a gap in ethical behavior among business students and non-business students such as finding that as the number of business ethics' courses increases, there is no impact on the students moral reasoning (Ritter, 2006; Traiser & Eighmy, 2011). In fact, top business schools weaken the morals of their students as they shift their thoughts of what a company's priority should be from satisfying customers when they start the program to maximizing shareholder value at the end of their program (Schneider & Prasso, 2002). It has even been suggested that the business curriculum has contributed to the unethical behavior (Richards et al. 2002). Others argue that the social environment may shape individuals values

[8] For further explanation of the self-interest model see Federal Reserve Bank of St. Louis (2012).

and behavior differently for students with different majors (Sims & Keon, 1999, 2000). In fact, Cohn et al. (2014) find that the culture in the financial industry could cause deceptive behavior. Regardless of the reason behind the deception, the first hypothesis is developed as follows:

H1: Business students will deceive others more compared to non-business students.

3.2.2. A portrait of the corporate psychopath

The general incidence of psychopaths is less than one percent. However, Babiak and Hare (2006) find that the percent of psychopaths working in senior positions of business is roughly four percent. Psychopaths are thought to be attracted to business organizations and politics because it provides them with power, prestige, and money. Additionally, Cleckley (1988) argues that psychopaths rise quickly in organizations due to their manipulative charisma, deceitfulness, callousness, and determination. In fact, Boddy (2015) argues that the Enron organization and its CEO exhibit the traits of the prototypical psychopath which could explain the company's deceptive behavior. As such, the second hypothesis is developed as follows:

H2: Business students will display higher scores on psychopathy, and psychopathic traits, than non-business students

Research is limited on the behavior of corporate psychopaths. Recent studies show that psychopathy is related to the theft of employees (O'Boyle et al. 2011), corporate bullying (Boddy, 2011), poor management skills (Babiak et al. 2010), and treating employees, the environment, and society poorly (Boddy et al. 2010). Boddy (2011) theorizes that the manipulative, deceitful, and unethical behavior of psychopaths is responsible for the financial crisis in 2007-2008 because they influence the moral and ethical climate of the entire

organization. Ragatz et al. (2012) find that perpetrators of white collar crime, such as Ponzi schemes, embezzlement, insider trading, and fraud are more likely to be psychopaths than non-white collar criminals.

Research explains that psychopathic behavior may be due to an abnormality with connections within the brain, specifically in the areas of the amygdala and prefrontal cortex (Blair 2007; Blair, 2008; Glenn et al. 2009; Yang et al., 2009). Due to brain abnormalities, these individuals lack emotions and the ability to sympathize and empathize with others, which could contribute to deceptive behavior, and a lack remorse for their ruthless decisions.

Battigalli et al. (2013) postulate a theory that individuals are averse to deceiving others because of guilt. However, psychopaths do not empathize with others and do not feel guilty for their actions. Similarly, Tang and Sutarso (2013) develop a model where characteristics of psychopathy such as impulsive behavior and poor social moral values play a major role in deceptive and unethical conduct, as well as the monetary incentive and financial intelligence. The third hypothesis is developed as follows:

H3: Psychopathy, and its traits, will be related to the act of deception and views of ethical behavior.

3.3. Methods

3.3.1. Participants

This study selects participants from upper level (i.e. junior and senior) business students from finance, marketing, management, and accounting courses to collect a well-diversified group

of business students that have been exposed to the self-interest model and the social environment of the business school. The sample of 120 business students includes 39 (33%) management, 37 (31%) accounting, 23 (19%) finance, and 21 (17%) marketing majors. Within the sample of business students, there are 53 (44%) males and 67 females (54%) with a median age of 22.6.

Following previous research, the control group is selected from students with liberal arts majors to compare to the business student sample (Tang & Chen, 2008; Traiser & Eighmy, 2011; Chen and Tang, 2013). This comparison is used because while business students may select their degree due to their strong love of money orientation (McCabe et al. 2006), those interested in helping people may choose liberal art majors such as psychology or sociology. Additionally, students from health science degrees are included in the control sample to achieve a more diverse sample with a group of individuals also concerned with helping people with majors in nursing and pre-med. The control sample of 129 students includes 56 (43%) biology or pre-med [9], 24 (18%) psychology, 19 (15%) nursing, 6 (5%) social work, 6 (5%) criminal justice, 6 (5%) chemistry, and 12 (9%) other liberal arts or health science majors. Within the control, sample there are 42 (33%) males and 87 females (67%) with a median age of 21.5.

The subjects took part in an experiment. First, the subjects participated in the cheap talk experiment where they sat down at their computer and were given instructions for the cheap talk experiment (see Appendix A). In the cheap talk experiment, they are told that they are taking part in the experiment with another student paired at a separate computer, and neither of them will ever know who their partner is. However, there is no other student, and the computer always selects option B to create a sense of empathy for the receiver. After the conclusion of the cheap

[9] Many students reported a dual major in biology and pre-med

talk experiment, the participants were given a questionnaire asking them two questions about how they view deception.

For compensation, students received extra credit in their course. Luccasen and Thomas (2014) find no difference in outcomes in experiments using class credit and monetary incentives.[10] Participants were told that the extra credit given was linked to the payoffs of the cheap talk experiment. However, they were all given a flat rate.

3.3.2. Procedure

3.3.2.1 Cheap talk experiment

This experiment follows Gneezy (2005) in a cheap talk communication game in which one player, the sender, holds private information about the monetary outcomes of option A and option B that the receiver does not have. Here, the sender can send one of two possible messages to the receiver:

Message A: "Option A will earn you more money than Option B."

Message B: "Option B will earn you more money than Option A."

After receiving the message, the receiver must pick between the two options but holds no information other than the message the sender chooses. Table 3.1 presents the three treatments with the potential payoffs for option A and B for each treatment.[11] Each treatment differs regarding the possible gains for the sender and possible loss for the receiver if the option B is

[10] For this reason, I argue that students would rather receive 5-15 points extra credit rather than a small monetary gain for their participation.
[11] Payments are based upon Gneezy (2005)

executed instead of option A. It is important to note that Option B will always earn the sender more money than option A. In the first treatment, the sender can earn an additional $1 while the receiver would lose $1 if option B is implemented. In the second treatment, the sender can earn an additional $1, while the receiver would lose $10 if option B is implemented. In the third treatment, the sender can earn an additional $10, while the receiver would lose $1 if option B is executed.

Table 3.1:
Payoffs in the Different Tasks

Treatment	Option	Payoff to Sender	Payoff to Receiver
1			
	A	5	6
	B	6	5
2			
	A	5	15
	B	6	5
3			
	A	5	15
	B	15	5

Notes: This table provides the possible payouts for option A and B for Treatment 1, 2, and 3.

3.3.2.2 Ethics questionnaire

Following Gneezy (2005), the students were given a questionnaire following the cheap talk experiment and asked to judge the following scenario:

"Mr. Johnson is about to close a deal and sell his car for $1,200. The engine's oil pump does not work well, and Mr. Johnson knows that if the buyer learns about this, he will have to reduce the price by $250 (the cost of fixing the pump). If Mr. Johnson does not tell the buyer, the engine will overheat on the first hot day, resulting in damages of $250 for the buyer. Being winter, the

only way the buyer can learn about this now is if Mr. Johnson were to tell him. Otherwise, the buyer will learn about it only on the next hot day. Mr. Johnson chose not to tell the buyer about the problems with the oil pump."

"In your opinion, Mr. John's behavior is: completely fair, fair, unfair, very unfair."

After they had completed this scenario, they were asked to judge the following scenario with the same outcomes of completely fair, fair, unfair, very unfair:

"What would your answer be if the cost of fixing the damage for the buyer in case Mr. Johnson does not tell him is $1,000 instead of $250?"

3.3.3. Psychopathy measures

The Psychopathic Personality Inventory–Revised (PPI-R) is employed to measure eight primary psychopathy traits, two secondary traits, and one global trait.[12] Subjects completed the PPI-R online at their own time before participating in the experiment. Appendix B provides a detailed description of these traits and how the secondary and global traits are calculated. The PPI-R contains three validity scales that are designed to detect insincere, fake, or inconsistent responses: virtuous responding, deviant responding, and an inconsistent responding tool.

3.4. Results

3.4.1. Deceptive behavior in business students

[12] Multiple studies find that the PPI-R is a valid and reliable questionnaire to evaluating psychopathy (Lilienfeld et al. 2005; Lilienfeld et al. 2006; Edens & Mcdermott, 2010).

Figure 3.1 presents the results from the cheap talk experiment, regarding the percentage of business students and non-business students who lied. In treatment 1, 47 percent of business students lied, while 50 percent of non-business students lied. In treatment 2, where the sender gains $1 for deceiving the receiver, while the loss to the receiver is $10, 48 percent of business students and 55 percent of non-business students mislead the receiver (p-value 0.120).[13] Finally, in treatment 3, where the gain to the sender for deceiving the receiver is $10 and the loss of the receiver is $1, 61 percent of business students and 54 percent of non-business students send a deceiving message to the receiver (p-value 0.145). The results from treatment 1 and 2 provide conflicting results to the first hypothesis that business students will deceive others more often than non-business students. However, when there is the most to gain by deceiving the receiver in treatment 3, business students deceive their partner more than non-business students, providing support for hypothesis 3.

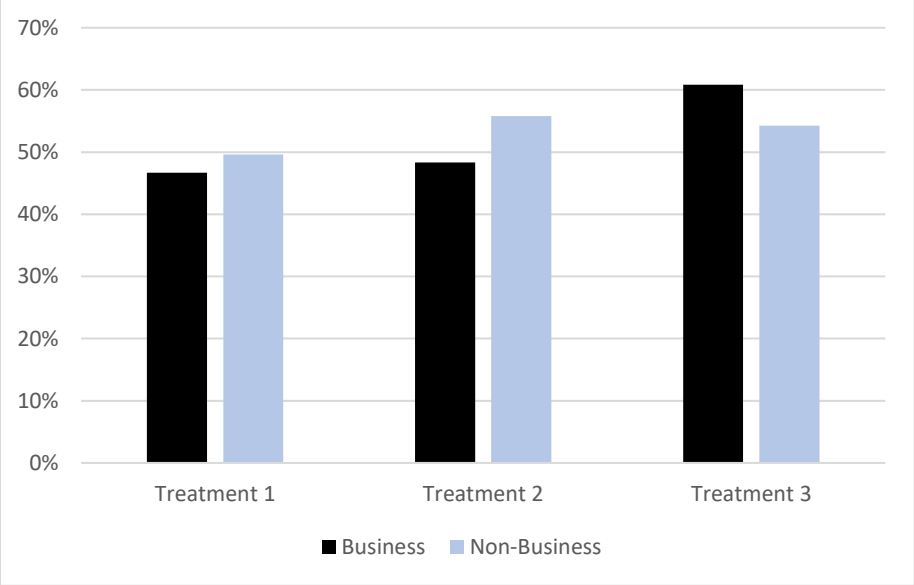

Figure 3.1. This chart shows the percentage of business students (n=120) and non-business student (n=129) who elect to send a deceptive message for each treatment.

[13] A one-tailed t-test is used to examine significance levels throughout the analysis similar to Gneezy (2005).

For non-business students, the number of individuals who send a deceptive message decreases from treatment 2 to treatment 3, which suggests that these individuals feel remorse for the receiver who has chosen option B in both treatments 1 and 2. However, the difference in the message that business students send in treatment 1 and treatment 2 compared to treatment 3 increases substantially to 61 percent which is statistically significant compared to the previous two treatments (p-value < 0.01). This result provides two important implications. First, when the stakes are the highest business students are more likely to lie to gain an advantage compared to when the possible gains are low. Second, even though the receiver has chosen option B in both treatments 1 and 2, business students do not show remorse to the receiver and continued to send a deceptive message.

Dreber and Johannesson (2008) and Erat and Gneezy (2012) find that men are significantly more likely to lie for monetary gain compared to women, while Childs (2012) and Gylfason et al. (2013) find no such gender differences using the cheap talk experiment. Given the ambiguity in previous research on gender differences in the cheap talk experiment, the sample is split by gender and major.

Figure 3.2 presents the results for the split sample by gender and major. The results show that 51 percent of male business students and 50 percent of male non-business students send a deceptive message in treatment 1. The percentage of business students lying decreases to 44 percent in treatment 2 while the proportion of non-business students increases to 52 percent for males. Finally, in treatment 3, 59 percent of male business students send a deceptive message to the receiver while only 50 percent of male non-business students send the same message (p-value 0.207). The results show that in task 1 and 3, where the amount gained by lying is the same or

greater for the sender, male business students are more likely to send a deceptive message for monetary gains, which provides evidence for hypothesis 1.

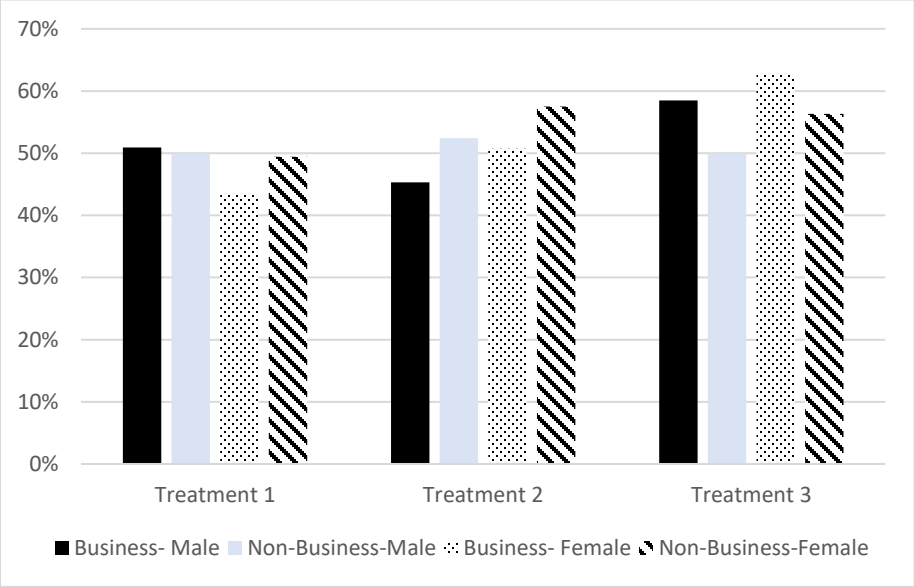

Figure 3.2. This chart shows the percentage of male business students (n=53), male non-business students (n=42), female business students (n=67), and female non-business students (n=87) who elect to send a deceptive message for each treatment.

Figure 3.2 shows that 43 percent of female business students send a deceptive message in treatment 1 compared to 49 percent of female non-business students. During treatment 2, 51 percent of female business students lie to the receiver while 58 percent of female non-business students send the same message. Finally, in treatment 3, 63 percent of female business students send a message hoping to deceive the receiver compared to 56 percent of female non-business students (p-value 0.215).

There are three main findings in these results. First, when comparing all genders and majors, female business students deceive the receiver less often in treatment 1 and most often in treatment 3 compared to the other groups. Finally, in treatments 2 and 3, female business students and non-business students send a deceptive message more often than their male

counterparts. This result is contradictory to previous research showing that males are more likely to deceive than females. However, none of the results (males vs. females, male business students vs. female business students, or male non-business students vs. female non-business students) are significant.

In the financial literature, it is typical to use a 90% confidence interval (p-value of 0.10) within the analysis. However, this chapter decreases the significance level when examining the difference between majors and genders for several reasons. First, the sample size is lower than most finance papers that are using thousands of observations; therefore, because of the decreased power of the tests due to the small sample size, this chapter uses lower standards of significance levels. Second, the results follow expectations based upon theoretical foundations. Therefore, it is unjust to omit results because they fall shy of the typical 90% threshold. Third, while it may be uncommon, there are finance papers that use broader confidence intervals such as 80% within their analysis (For example, see Galvao (2002), Killeen (2006), Bellotti et al. (2010) to name a few)

3.4.2. Ethical views in business students

The first experiment is designed to put the subjects in the position where they can lie, but it does not examine how ethical they view these lies. The ethics questionnaire described in section 3.2.2 is employed to examine how ethical the subjects believe deception is when it is committed by others using an empirically realistic scenario. Figure 3.3 shows two interesting results. First, business students are more likely to believe that the first scenario is fair compared to non-business students (p-value 0.20). This result shows that business students believe that it is

more ethical to deceive the car buyer, which is consistent with the results of the cheap talk experiment. Secondly, business students find that this deception is "very unfair" more often compared to non-business students (p-value 0.25). This shows that while business students find Mr. Johnson's deception as very unfair, they do not find their deception as unfair. However, in this situation, the car buyer will find out about the deception, which suggests they may fear getting caught lying.

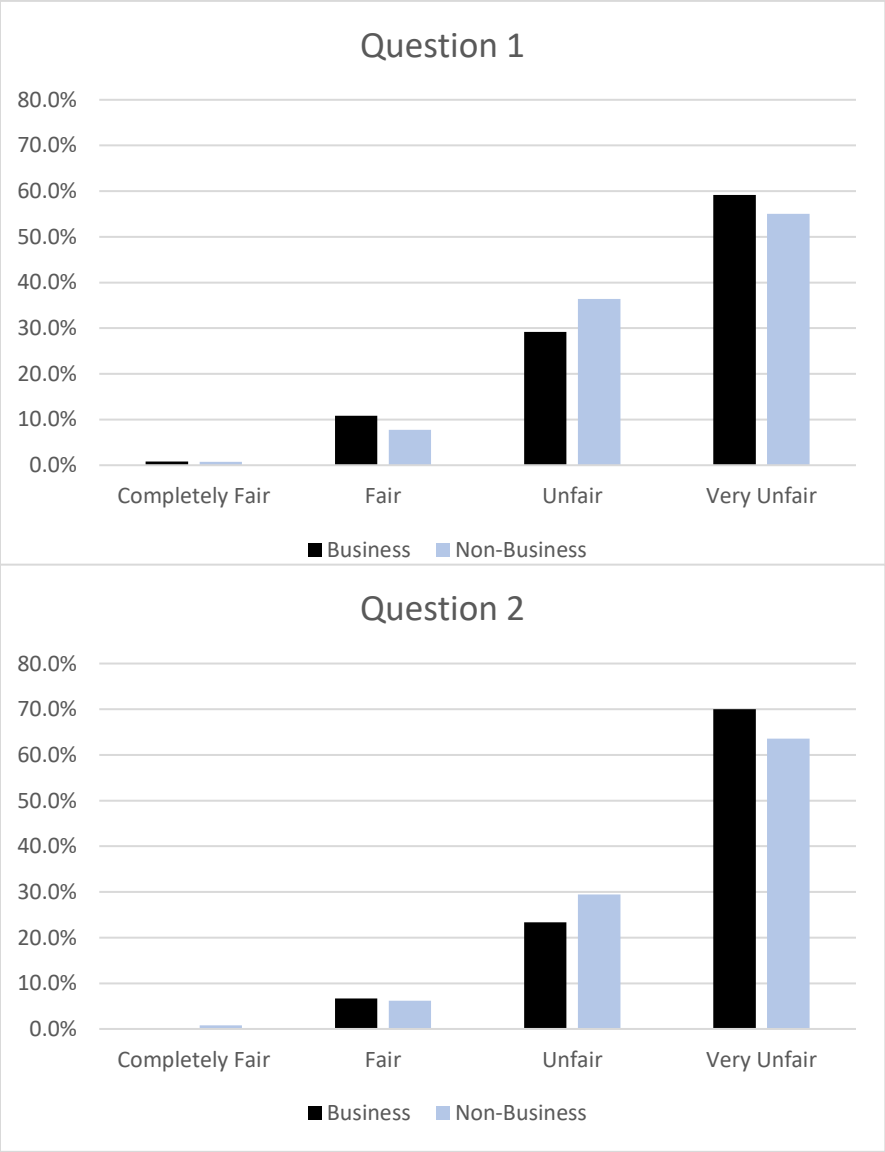

Figure 3.3. This chart shows the percentage of business students (n=120) and non-business student (n=129) who select each option for Mr. Johnson's action.

Question two in Figure 3.3 shows a similar percentage of business and non-business students who believe that Mr. Johnson's deception is completely fair or fair. However, 70% of business students believe the deception is "very unfair" compared to 64% of non-business students. The overall difference between business students and non-business students is significant (p-value 0.173). These results show that while business students are more likely to deceive others, they view the deception as unethical when others commit it.

Figure 3.4 reports the results for the ethics questionnaire after splitting the sample by gender and major. The results show that both male and female business students find Mr. Johnson's behavior in question one as more "fair" as well as more "very unfair" compared to their non-business counterpart consistent with Figure 3.3.

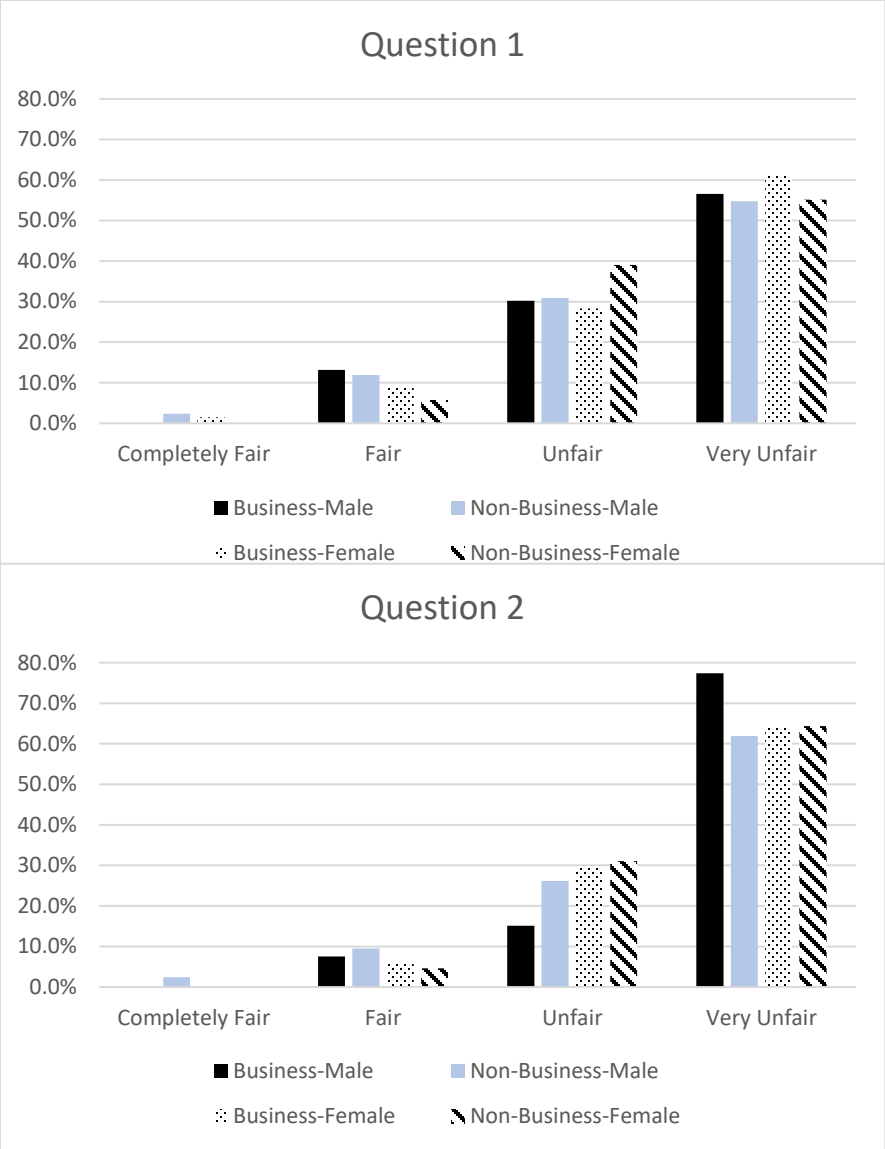

Figure 3.4. This chart shows the percentage of male business students (n=53), male non-business students (n=42), female business students (n=67), and female non-business students (n=87) who select each option for Mr. Johnson's action.

3.4.3. Psychopathic profile of business students

The second aspect of this chapter looks to explain why business students are more deceptive than non-business students. A probit regression is run with the dependent variable being 1, if the student is a business student or 0 otherwise to investigate hypothesis 2. In model

1, the dependent variable is regressed against the global psychopathy trait; in the second model the independent variables are the two secondary psychopathy traits, and the third model is run on all eight primary traits of psychopathy.

Table 3.2 reports the results from these probit regressions. Model 1 shows that business students are significantly more likely to have a greater probability of matching the features of the prototypical psychopath compared to non-business students. Model 2 reports that business students score significantly higher on fearless dominance which is a collection of the traits social influence, fearlessness, and stress immunity. Finally, Model 3 shows that business students have higher scores on rebellious nonconformity, social influence, and cold-heartedness while having lower scores on carefree nonplanfulness and fearlessness compared to non-business majors. These results suggest that business students are more rebellious, manipulate others more, are more callous, and plan their actions more carefully compared to non-business students. Primary traits of psychopathy can explain nearly 10% of the differences in business and non-business students. These results support hypothesis two and might explain why business students behave differently than non-business students. Additionally, as it is intuitive that business students will work in the business industry, these results support the notion of psychopaths having a higher presence in the business industry.[14]

[14] For example, Stadler (2015) show the high relationship to studying business in college and working for corporations.

Table 3.2:
Psychopathic Profile

	(1)	(2)	(3)
Psychopathy Traits	**Global Psychopathy**	**Secondary Traits**	**Primary Traits**
Psychopathy	0.617**		
	(2.330)		
Self-Centered Impulsivity		0.148	
		(0.379)	
Fearless Dominance		1.31***	
		(2.953)	
Machiavellian Egocentricity			-0.894
			(-0.707)
Rebellious Nonconformity			5.01***
			(3.374)
Blame Externalization			2.03
			(1.522)
Carefree Nonplanfulness			-3.56**
			(-2.293)
Social Influence			3.27***
			(2.823)
Fearlessness			-3.30**
			(-2.547)
Stress Immunity			1.16
			(0.791)
Cold-heartedness			2.51*
			(1.668)
R-Squared	1.6%	2.6%	9.8%

Notes: This table displays the results from a probit regression where the dependent variable is 0 if the student is a business major or 0 otherwise against psychopathy traits for the full sample (n=249). Model 1 is run against the global psychopathy trait; Model 2 uses the two secondary traits; Model 3 uses the eight primary traits. A description of these traits is in Appendix B. T-statistics are listed in parenthesis and significance is listed at the 10% (*) 5% (**) and 1% (***) levels. Coefficients are multiplied by 100.

3.4.3. Relation between psychopathy and deception

Table 3.3 presents the results for how psychopathy relates to the treatments from the cheap talk experiment. A probit regression on if the subject sent the deceptive message for each treatment is regressed against the global psychopathy measure in model 1, two secondary traits in model 2, and eight primary traits in model 3 for treatment 1, 2, and 3.[15] Model 1 shows that high scores of psychopathy are significantly related to sending a deceptive message in treatments 1 and 3. Model 2 indicates that the two secondary traits of self-centered impulsivity and fearless dominance are both positively related to sending a deceptive message, although both are insignificant for all treatments. Model 3 reports that carefree nonplanfulness is negatively related to sending a deceptive message in all three treatments, while Machiavellian egocentricity is positively related to sending a deceptive message in treatment 1 and rebellious nonconformity is positively related in treatment 3. These results support hypothesis 3.

Psychopathy research often examines the difference between psychopaths (clinically high) versus non-psychopaths (clinically normal) subjects (Babiak & Hare, 2006; Blair, 2008; Yang et al., 2009; Babiak et al., 2010). Therefore, the following analysis separates the sample of individuals who score clinically high (standardized score ≥ 65) on the various psychopathic traits from those who score in the normal range (standardized score < 65), and then compare their deceptive behavior.[16]

[15] The results are robust when including a dummy variable for both gender and major.
[16] Scores are standardized based on gender and age following the PPI-R protocol.

Table 3.3

Relationship Between Psychopathy Traits and Deception

VARIABLES	T 1 (1)	T1 (2)	T1 (3)	T2 (1)	T2 (2)	T2 (3)	T3 (1)	T3 (2)	T3 (3)
Psychopathy	0.461*			-0.152			0.546**		
	(1.749)			(-0.581)			(2.046)		
Self-Centered Impulsivity		0.601			-0.465			0.511	
		(1.530)			(-1.191)			(1.295)	
Fearless Dominance		0.420			0.233			0.642	
		(0.969)			(0.538)			(1.456)	
Machiavellian Egocentricity			2.55**			-0.554			0.822
			(2.045)			(-0.453)			(0.669)
Rebellious Nonconformity			-0.212			0.886			2.790**
			(-0.154)			(0.648)			(1.991)
Blame Externalization			-0.337			-0.774			-0.782
			(-0.263)			(-0.603)			(-0.602)
Carefree Nonplanfulness			-3.01**			-2.460*			-2.440
			(-1.972)			(-1.659)			(-1.603)
Social Influence			0.042			-0.832			-0.000
			(0.039)			(-0.761)			(-0.00)
Fearlessness			1.89			1.160			0.575
			(1.513)			(0.944)			(0.460)
Stress Immunity			-1.93			-0.383			-0.844
			(-1.346)			(-0.272)			(-0.592)
Cold-heartedness			0.835			-0.029			1.790
			-0.577			(-0.020)			(1.214)
R-Squared	0.8%	0.9%	4.2%	0.1%	0.5%	1.8%	1.2%	1.1%	3.5%

Notes: This table displays the probit regression results where the dependent variable is a 1 if the subject deceived the receiver for treatment (T) 1, 2, and 3 for the full sample (n=249). Model 1 is run against the global psychopathy trait; Model 2 uses the two secondary traits; Model 3 uses the eight primary traits. Appendix B provides a detailed description of these traits. T-statistics are listed in parenthesis and significance is shown at the 10% (*) 5% (**) and 1% (***) levels. All coefficients are multiplied by 100.

The results of the comparison between clinically high versus normal levels for all psychopathic traits are reported in Table 3.4. Panel A shows that clinical psychopaths send a deceptive message more often than normal individuals by sending a deceptive message 71% of the time for treatment 1, 59% for treatment 2 and over 82% for treatment 3 further supporting hypothesis 3. Panel B reports the results for the individuals with clinically high levels of the secondary traits. Interestingly, those in the clinical group of self-centered impulsivity send a deceptive message in treatment 1 significantly more often, while being significantly less likely to lie in treatment 2. Furthermore, individuals in the clinically high group of fearless dominance, a trait that business majors score higher on than non-business majors, is related to sending a deceptive message more than the normal group for all three treatments. Panel C shows that individuals in the clinically high group of Machiavellian egocentricity, social influence, and cold-heartedness send a deceptive message more than their normal counterparts in all three treatments.

One may posit that while the clinical levels of greater than or equal to 65 on the PPI are based on statistical difference compared to the general population, the difference between someone who scores 64 and 65 may be very small. Therefore, it makes sense to split the sample into terciles (3 quantiles) based upon their score in each of the traits and compare the high group and low group for each trait.[17] The sample of 249 is split into three groups which provide roughly 80 subjects per group for every trait.

[17] Analysis of the high group versus the middle group and middle group versus the low group is not examined as the scores in the middle group may be close to some of those in the other groups.

Table 3.4
Deception by Clinical Group

Panel A: Global trait	**Treatment**	**Clinically High**	**vs**	**Normal**
Psychopathy	1	70.6 (17)	>>	46.6 (232)
Psychopathy	2	58.8 (17)		51.7 (232)
Psychopathy	3	82.4 (17)	>>	55.6 (232)
Panel B: Secondary traits	**Treatment**	**Clinically High**	**vs**	**Normal**
Self-Centered Impulsivity	1	66.7 (12)	>	47.3 (237)
Self-Centered Impulsivity	2	33.3 (12)	<	53.2 (237)
Self-Centered Impulsivity	3	66.7 (12)		57.0 (237)
Fearless Dominance	1	50.0 (18)		48.1 (231)
Fearless Dominance	2	66.7 (18)		51.1 (231)
Fearless Dominance	3	77.8 (18)	>>	55.8 (231)
Panel C: Primary traits	**Treatment**	**Clinically High**	**vs**	**Normal**
Machiavellian Egocentricity	1	59.1 (22)		47.1 (227)
Machiavellian Egocentricity	2	50.0 (22)		52.4 (227)
Machiavellian Egocentricity	3	68.2 (22)		56.4 (227)
Rebellious Nonconformity	1	52.2 (23)		47.8 (226)
Rebellious Nonconformity	2	47.8 (23)		52.7 (226)
Rebellious Nonconformity	3	65.2 (23)		56.6 (226)
Blame Externalization	1	48.0 (25)		48.2 (224)
Blame Externalization	2	44.0 (25)		53.1 (224)
Blame Externalization	3	56.0 (25)		57.6 (224)
Carefree Nonplanfulness	1	33.3 (6)		48.6 (243)
Carefree Nonplanfulness	2	33.3 (6)		52.7 (243)
Carefree Nonplanfulness	3	33.3 (6)		58.0 (243)
Social Influence	1	54.5 (22)		47.6 (227)
Social Influence	2	59.1 (22)		51.5 (227)
Social Influence	3	59.1 (22)		57.3 (227)
Fearlessness	1	50.0 (22)		48.0 (227)
Fearlessness	2	50.0 (22)		52.4 (227)
Fearlessness	3	59.1 (22)		57.3 (227)
Stress Immunity	1	48.1 (27)		48.2 (222)
Stress Immunity	2	59.3 (27)		51.4 (222)
Stress Immunity	3	63.0 (27)		56.8 (222)
Cold-heartedness	1	61.8 (34)	>>	46.0 (215)
Cold-heartedness	2	55.9 (34)		51.6 (215)
Cold-heartedness	3	73.5 (34)	>>	54.9 (216)

Notes: This table shows the percentage of subjects who sent a deceptive message in each treatment for the sample (n=249) for subjects who score in the clinically high (standardized score ≥ 65) and subjects with normal psychopathy trait scores (standardized score <65). The sample size for each group is listed in parenthesis. The significance and direction of inequality

between the two groups is shown at the 10% (>) 5% (>>) and 1% (>>>) levels. Appendix B describes the psychopathy traits.

Table 3.5 presents the results for differences in message choice for individuals in the high and low group. The results show that those with higher scores of psychopathy send a deceptive message significantly more for treatment 1 and 3. Additionally, Table 3.5 indicates that individuals who score in the higher tercile for self-centered impulsivity and fearless dominance send a deceptive message more often than those who score in the low group on the respective trait. Finally, Panel C shows that individuals who score higher on Machiavellian egocentricity, rebellious nonconformity, fearlessness, and stress immunity send a deceptive message more often than their lower-scoring counterparts. These results provide robustness to the previous results by increasing the sample size in the groups and finding similar results.

Table 3.5
Deception by High and Low Groups Based Upon the Sample

Panel A: trait	**Treatment**	**High**	**vs**	**Low**
Psychopathy	1	51.8	>	41.6
Psychopathy	2	51.8		52.8
Psychopathy	3	61.4	>>	48.3
Panel B: Secondary traits	**Treatment**	**High**	**vs**	**Low**
Self-Centered Impulsivity	1	53.9	>	43.5
Self-Centered Impulsivity	2	52.6		54.3
Self-Centered Impulsivity	3	64.5	>	53.2
Fearless Dominance	1	53.2		44.9
Fearless Dominance	2	59.7	>>	46.1
Fearless Dominance	3	66.2	>>	49.4
Panel C: Primary traits	**Treatment**	**High**	**vs**	**Low**
Machiavellian Egocentricity	1	61.0	>>>	38.1
Machiavellian Egocentricity	2	48.1		58.3
Machiavellian Egocentricity	3	59.7		50.0
Rebellious Nonconformity	1	51.8		44.7
Rebellious Nonconformity	2	56.6		49.4
Rebellious Nonconformity	3	61.4	>>	44.7
Blame Externalization	1	52.0		47.6
Blame Externalization	2	46.7		51.2
Blame Externalization	3	58.7		57.1
Carefree Nonplanfulness	1	43.6		50.0
Carefree Nonplanfulness	2	49.7	<	60.5
Carefree Nonplanfulness	3	56.4		60.5
Social Influence	1	43.8		43.8
Social Influence	2	53.8		52.8
Social Influence	3	58.8		53.9
Fearlessness	1	55.3	>>	37.8
Fearlessness	2	55.3		46.7
Fearlessness	3	59.2		50.0
Stress Immunity	1	46.9		48.4
Stress Immunity	2	56.8	>	45.3
Stress Immunity	3	66.7	>	55.8
Cold-heartedness	1	46.8		45.3
Cold-heartedness	2	48.1		53.7
Cold-heartedness	3	60.8		52.6

Notes: This table shows the percentage of subjects who sent a deceptive message in each treatment for the sample (n=249) for subjects based on splitting the sample into terciles to examine the difference between high and low groups. The significance and direction of inequality between the two groups is shown at the 10% (>) 5% (>>) and 1% (>>>) levels. Appendix B describes the psychopathy traits.

3.4.4. Relation between psychopathy and ethics

Table 3.6 reports the results for how psychopathy relates to the ethics questionnaire. The results show that higher scores of psychopathy are related to believing that Mr. Johnson's actions are more ethical in both scenarios. Model 2 shows that individuals with higher scores of self-centered impulsivity are related to thinking that Mr. Johnson is making an ethical decision. Finally, individuals who are more narcissistic and fearless are more likely to think Mr. Johnson is behaving ethically.

Table 3.7 provides the comparison between clinically high versus normal levels for all psychopathic traits and the ethical view of Mr. Johnson's actions. The results show that those in the clinically high group of Machiavellian egocentricity, carefree nonplanfulness, and fearlessness view Mr. Johnson's actions as more ethical compared to their normal counterparts. To add robustness to the results and increase the sample size, the sample is split into terciles based on their psychopathic traits, and the high and low group are compared in the same fashion as Table 3.5.

Table 3.6
Relationship Between Psychopathy Traits and Ethics

VARIABLES	Car 1 (1)	Car 1 (2)	Car 1 (3)	Car 2 (1)	Car 2 (2)	Car 2 (3)
Psychopathy	-0.568***			-0.357***		
	(-4.040)			(-2.762)		
Self-Centered Impulsivity		-0.838***			-0.587***	
		(-4.020)			(-3.065)	
Fearless Dominance		-0.334			-0.0944	
		(-1.436)			(-0.441)	
Machiavellian Egocentricity			-2.21***			-1.18**
			(-3.478)			(-1.978)
Rebellious Nonconformity			0.593			-0.0255
			(0.831)			(-0.0383)
Blame Externalization			0.858			0.332
			(1.285)			(0.532)
Carefree Nonplanfulness			-0.687			-0.903
			(-0.892)			(-1.252)
Social Influence			0.106			-0.501
			(0.186)			(-0.941)
Fearlessness			-1.56**			0.0841
			(-2.429)			(0.140)
Stress Immunity			0.634			0.481
			(0.858)			(0.695)
Cold-heartedness			-0.378			-0.647
			(-0.506)			(-0.926)
R-Squared	5.8%	6.1%	10.0%	2.6%	3.0%	3.5%

Notes: This table displays the OLS regression results where the dependent variable is how ethical Mr. Johnson's actions are on a 4 point Likert scale with 4 being very unfair for the full sample (n=249). Model 1 is run against the global psychopathy trait; Model 2 uses the two secondary traits; Model 3 uses the eight primary traits. Appendix B provides a detailed description of these traits. T-statistics are listed in parenthesis and significance is shown at the 10% (*) 5% (**) and 1% (***) levels. All coefficients are multiplied by 100

Table 3.7
Ethics by Clinical Group

Panel A: Global trait	**Scenario**	**Clinically High**	**vs**	**Normal**
Psychopathy	1	3.4 (17)		3.5 (232)
Psychopathy	2	3.5 (17)		3.6 (232)
Panel B: Secondary traits	**Scenario**	**Clinically High**	**vs**	**Normal**
Self-Centered Impulsivity	1	3.3 (12)		3.5 (237)
Self-Centered Impulsivity	2	3.4 (12)		3.6 (237)
Fearless Dominance	1	3.4 (18)		3.5 (231)
Fearless Dominance	2	3.5 (18)		3.6 (231)
Panel C: Primary traits	**Scenario**	**Clinically High**	**vs**	**Normal**
Machiavellian Egocentricity	1	3.1 (22)	<<<	3.5 (227)
Machiavellian Egocentricity	2	3.3 (22)	<<	3.6 (227)
Rebellious Nonconformity	1	3.5 (23)		3.5 (226)
Rebellious Nonconformity	2	3.6 (23)		3.6 (226)
Blame Externalization	1	3.4 (25)		3.5 (224)
Blame Externalization	2	3.6 (25)		3.6 (224)
Carefree Nonplanfulness	1	2.7 (6)	<<<	3.5 (243)
Carefree Nonplanfulness	2	2.7 (6)	<<<	3.6 (243)
Social Influence	1	3.5 (22)		3.5 (227)
Social Influence	2	3.6 (22)		3.6 (227)
Fearlessness	1	3.2 (22)	<<	3.5 (227)
Fearlessness	2	3.4 (22)	<	3.6 (227)
Stress Immunity	1	3.6 (27)		3.5 (222)
Stress Immunity	2	3.6 (27)		3.6 (222)
Cold-heartedness	1	3.3 (34)		3.5 (215)
Cold-heartedness	2	3.5 (34)		3.6 (215)

Notes: This table shows the average choice of how ethical Mr. Johnson's actions are on a 4 point Likert scale with 4 being very unfair for the full sample (n=249) for subjects who score in the clinically high (standardized score ≥ 65) and subjects with normal psychopathy trait scores (standardized score <65). The sample size for each group is listed in parenthesis. The significance and direction of inequality between the two groups is shown at the 10% (>) 5% (>>) and 1% (>>>) levels. Appendix B describes the psychopathy traits.

Table 3.8 presents the results for the difference between the high and low groups of psychopathy traits and view of ethical behavior. First, individuals who score higher on psychopathy see the deception of Mr. Johnson as more ethical. Panel B shows that subjects with higher scores of self-centered impulsivity believe that Mr. Johnson is behaving ethically compared to those with lower scores. Finally, Panel C reveals that individuals with higher scores

of Machiavellian egocentricity, rebellious nonconformity, carefree nonplanfulness, fearlessness, and cold-heartedness are more likely to find the actions of Mr. Johnson as more ethical compared to those who score lower for the respective traits.

Table 3.8
Ethics by High and Low Groups Based Upon the Sample

Panel A: Global trait	**Scenario**	**High**	**vs**	**Normal**
Psychopathy	Car 1	3.27	<<<	3.64
Psychopathy	Car 2	3.43	<<<	3.67
Panel B: Secondary traits	**Scenario**	**High**	**vs**	**Normal**
Self-Centered Impulsivity	Car 1	3.30	<<<	3.62
Self-Centered Impulsivity	Car 2	3.47	<<<	3.71
Fearless Dominance	Car 1	3.48		3.53
Fearless Dominance	Car 2	3.61		3.56
Panel C: Primary traits	**Scenario**	**High**	**vs**	**Normal**
Machiavellian Egocentricity	Car 1	3.09	<<<	3.62
Machiavellian Egocentricity	Car 2	3.38	<<<	3.69
Rebellious Nonconformity	Car 1	3.35	<<<	3.60
Rebellious Nonconformity	Car 2	3.55	<	3.68
Blame Externalization	Car 1	3.40		3.50
Blame Externalization	Car 2	3.55		3.65
Carefree Nonplanfulness	Car 1	3.38	<	3.55
Carefree Nonplanfulness	Car 2	3.50	<	3.66
Social Influence	Car 1	3.48		3.51
Social Influence	Car 2	3.58		3.58
Fearlessness	Car 1	3.42	<<	3.61
Fearlessness	Car 2	3.62		3.60
Stress Immunity	Car 1	3.49		3.45
Stress Immunity	Car 2	3.64		3.58
Cold-heartedness	Car 1	3.41	<	3.55
Cold-heartedness	Car 2	3.51	<	3.65

Notes: This table shows the average choice of how ethical Mr. Johnson's actions are on a 4 point Likert scale with 4 being very unfair for the full sample (n=249) for subjects based on splitting the sample into terciles to examine the difference between high and low groups. The significance and direction of inequality between the two groups is shown at the 10% (>) 5% (>>) and 1% (>>>) levels. Appendix B describes the psychopathy traits.

3.5. Conclusion

The results from this chapter show that business students deceive others more often than non-business students when they have the most to gain, with female business students having the highest rate of deception of 63% in treatment 3 of the cheap talk experiment. However, when examining the ethics questionnaire, business students find deception as unethical when others commit it. The results explain that one reason that business students deceive others more often than non-business students is that they are more likely to fit the prototypical profile of a psychopath, including scoring significantly higher on psychopathic traits of rebellious nonconformity, social influence, and cold-heartedness. In fact, psychopathy and cold-heartedness are linked to the act of deception in the cheap talk experiment and are inversely related to the view of how ethical deception is.

These results have implications for the design of policies in the business industry. Individuals in high levels of organizations are more likely to be psychopaths than the general population (Babiak & Hare, 2006; Babiak et al. 2010) and hold private information not available to others, which is a major problem between company managers and shareholders. Thus, the evidence in this chapter suggests that policies should be designed accounting for the fundamental differences in individuals likely to work in the business, such as psychopaths. Boddy (2011) hypothesizes that psychopaths may have caused the financial crisis, and these results provide evidence that supports this notion as this chapter shows that psychopathy is highly related to deceiving others for private gain and viewing deception as ethical. Similarly, Stulz (2010) argues the financial crisis was due to financial institutions functioning at exceptionally high levels of leverage, due to holding risk off the balance sheet and lying about their true capital

requirement holdings. Therefore, showing that psychopathy is related to lying and deceiving, may explain the behavior of executives controlling company decisions.

In the Enron scandal in 2001, executives lied and deceived to hide large amounts of debt from their balance sheet and then shredded any evidence of their deception from the SEC. From this deception, investors lost billions and employees lost their jobs, but several of those involved never faced jail time and faced very little punishment. After this scandal, legislation changed, such as the Sarbanes-Oxley Act of 2002, to attempt to deter this behavior, but how did Bernie Madoff and Allen Stanford get away with their Ponzi schemes for so many years? Madoff was investigated numerous times in the 2000's for hiding his customer's orders, yet there was no detection of his Ponzi scheme, and many believe if it was not for the financial crisis in 2007-2008, the SEC might have never uncovered the Ponzi scheme. With psychopaths working at such high levels of organizations, there is no telling how much they are deceiving the public and taking millions for themselves.

CHAPTER IV

NFL BETTING BIASES, PROFITABLE STRATEGIES, AND THE WISDOM OF THE CROWD

4.1. Introduction

The wisdom of the crowd hypothesis suggests that the decision of a group of individuals will outperform decisions from a single expert (Hastie & Kameda, 2005; Larrick & Soll, 20006; Soll & Larrick, 2009; Sunstein, 2006). This hypothesis is derived from mathematical principles that argue that the more individuals in the crowd will cancel out the noise and extract a more precise signal (Hogarth, 1978; Makridakis & Winkler, 1983). Individuals who receive identical information will perceive it differently depending on personal preferences, expectations, and experiences (Vasile et al., 2012). Therefore, by combining all individual estimates, individual errors will disappear.

For example, Lorge et al. (1958) find that when asking students the temperature of the classroom, the student's average guess was only 0.4 degrees from the actual temperature, which was more accurate than 80% of the individual's estimate. Additionally, Treynor (1987) asked students to determine how many jellybeans were in a jar. The average estimate was 871, which was close to the actual number of 850, and better than 98% of the student's personal guess. Similarly, Galton (1907) asked people at a regional fair competition to guess the weight of an ox. The average estimate was 1,197 which was only one pound away from the actual weight of 1,198

of the ox. Additionally, Yaniv and Milyavsky (2007) find that individuals can make better estimates after consulting a group of advisors. As it relates to finance, Pelster and Breitmayer (2017) find that crowds' analyses of stocks from a social trading platform can provide explanatory power for stock returns, demonstrating the importance of the crowd in financial decision making. Following the wisdom of the crowd hypothesis, as the number of informed bettors increases, there should be less biased decisions, which should result in a better ability to predict outcomes in the NFL betting market.

In 2016, the American Gaming Association estimates that wagers on football games exceeded more than $90 billion for the second straight season, with approximately $4.7 billion wagered on the Super Bowl alone.[18] Given the large amounts of money involved, the efficiency of the wagering markets is of keen interest. In the wagering market, the bookmaker has a role similar to a stock exchange specialist as both match buyers and sellers for a fee, with the normal fee, also called the vigorish, being 10%. Due to the vigorish, a bettor must wager $110 to receive a profit of $100 if they win the bet. As such, a betting strategy that provides a profit of more than 50% of the time presents evidence that the wagering market is statistically inefficient. However, a betting strategy must be able to produce a profit of greater than 52.38% to provide evidence that the wagering market is economically inefficient due to the vigorish.[19]

In the National Football League (NFL) wagering market, the two most common bets are the point spread and the totals. The point spread is the forecasted amount of points by which the favorite team is expected to defeat the underdog. Therefore, a wager placed on the favorite team only wins if the favorite team has a winning margin greater than the point spread. If the favorite

[18] The America Gaming Association notes that about 97% to 98% of wagers are done illegally outside of Nevada.
[19] $110 divided by $210 provides the 52.38%

team loses or wins by less than the point spread, a bet on the underdog is a winning ticket. In the totals market, the bookmaker predicts the total points that are expected for the two teams combined. After the totals figure is set, bettors can place wagers on if the total points scored by the two teams combined will be over or under the posted total. If the outcome in the points spread or totals wager is a tie, all money is refunded.

Most individuals believe that the point spread and totals wagers are calculated to create equal amounts of bets on both sides of the bet (i.e. equal amount wagered on the favorite and underdog and the over and under) (Avery & Chevalier, 1999; Dana & Knetter, 1994; Gandar et al., 1988; Gray & Gray, 1997; Lee & Smith, 2002; Snowberg et al., 2005). If the bookmaker can collect equal wagers on both sides of the bet, they guarantee themselves a risk-free profit. However, Levitt (2004) finds that the bookmaker rarely has equal wager amounts on both sides of the bet. The bookmakers use their expertise to set the lines, as they are better at predicting game outcomes compared to the typical bettor, which apparently provides greater profits to the casinos, which is also confirmed by Paul and Weinbach (2007) and Paul and Weinbach (2011).

Previous research provides evidence of both statistical and economic inefficiencies in the sports betting market such as Zuber et al. (1985) who provides proof that the NFL betting market is inefficient. Furthermore, research finds that betting on the home team when they are the underdog can provide economically significant profits (Amoako-Adu et al., 1985; Golec & Tomarkin, 1991; Gray & Gray, 1997). Additionally, Vergin and Sosik (1999) find that in games that have national focus (i.e., Monday Night Football and playoff games) the home team produces a win rate of nearly 60%, with the win rate increasing when the home team is the underdog. Research finds that in the NFL the weather advantage for the home team can provide economically significant profits for the points spread (Borghesi, 2007) and totals wagers

(Borghesi, 2008). Wever and Aadland (2012) provide a strategy of betting on underdogs with large closing spreads can provide a profit rate of near 60%, while Nichols (2012) finds that teams that travel east and change time zones statistically increase the chance of the home team winning, although it is not economically significant. However, this home field advantage seems to only occur in the NFL as Gandar et al. (2001) find that the home field advantage is not evident in the National Basketball League or Major League Baseball. Conversely, Sauer et al. (1988) Dare and MacDonald (1996) and Dare and Holland (2004) find that betting on home underdogs does not provide statistically significant returns. Finally, research concludes that betting the under in the first week of the NBA (Girdner et al., 2013) and the NFL (DiFilippo et al., 2014) is a profitable strategy. Paul and Weinbach (2002) find a profitable strategy on betting the under on games with high totals.

It is intuitive, given the previous inefficiencies, that using the wisdom of the crowd could create economic profits from the betting market. However, Griffith (1949) and McGlothlin (1956) originally introduced the term favorite-longshot bias, which describes horse racing bettors' preference to bet the longshot rather than the favorite. Snowberg and Wolfers (2010) explain the favorite-longshot bias as bettors are irrational and have a distortion of probability following prospect theory. However, in other sports' betting market the favorite-longshot bias appears to be opposite as bettors have a biased preference to bet on the favorite in the NFL (Humphreys et al., 2013; Paul & Weinbach, 2011), NBA (Paul & Weinbach, 2005a), and MLB (Woodland & Woodland, 1994). Additionally, when examining the totals market, research demonstrates that bettors have a biased preference to bet the over in the NFL (Paul & Weinbach, 2011; Humphreys et al., 2013), college and arena football (Paul & Weinbach, 2005b), and European soccer (Paul & Weinbach, 2009). Furthermore, Paul and Weinbach (2011) find a

profitable strategy using a contrarian approach by betting on the underdog when over 70% of bettors are betting on the favorite, but do not find a profitable strategy in the totals market. Simmons et al. (2009) use a sample of NFL fans who may or may not have any betting experience and find that if you change the spread of the game, and increase the number of points the favorite team must win by to cover the spread, NFL fans will still select the favorite. Similarly, research finds that bettors are likely to follow the "hot hand" bias which is a strategy derived from betting on teams that have performed well relative to the spread in previous weeks in the NBA (Camerer, 1989; Brown & Sauer, 1993; Paul & Weinbach, 2005a; Paul et al., 2011). Finally, Paul et al. (2014) find that as money wagered increases, so does the percentage bet on the favorite in the NFL and NCAA football.

This study examines the betting decisions of individuals on both the points-spread and totals betting market in the context of the wisdom of the crowd. The results confirm previous literature that shows that NFL bettors prefer to bet the favorite and the over. Furthermore, this study adds to the literature by demonstrating that the biased decision to place wagers on the favorite and the over increase as more bettors place wagers. Additionally, bettors prefer to bet against the line movement to gain better odds. Both of these results conflict with the wisdom of the crowd hypothesis. The results show that bettors are more likely to bet on the favorite when the favorite has the hot hand and the underdog does not. Similarly, the results indicate that bettors are more likely to bet the over if both teams have the hot hand in the totals market. Furthermore, a nonlinear betting preference based upon the spread of the game is found, where bettors are less likely to wager on the favorite when the spread is small or large. Finally, profitable strategies are considered based upon betting with the crowd when a significant portion

the crowd is betting on the same side of the bet, as well as a contrarian approach betting against the crowd when the crowd is less sure.

4.2. Data

Data on bettor information is collected from Covers.com for the 2015-2016 and 2016-2017 seasons with the odds for the spread and totals market purchased from oddswarehouse.com for the regular season and playoffs providing a sample of 527 games. Covers.com is a sportsbook simulation that has previously been referenced in publications such as *USA Today*, *New York Times*, and *ESPN The Magazine* where users can join leagues to make wagers and compete to win prizes, which provides a dataset rich with knowledgeable sports bettors. The average number of individuals placing bets for each game is 2720 against the spread and 1848 for the totals. Covers.com claims that "Covers Public Money data is a unique way to evaluate the money spent on individual teams throughout the season by the betting public. Although our numbers come from Covers free League Contests, with over 50,000 contest players participating this past year; these figures provide an accurate comparison of where the 'real' betting public is laying their cash." Simmons et al. (2009) argue that the wisdom of the crowd only works when the crowd's judges are knowledgeable, motivated to be accurate, independent, and diverse, which is provided by the sample from Covers.com. For each game, the number of bettors on both sides of the wager for the spread and totals market are collected to find the percentage of individuals on each side of the bet.

4.3. Results

4.3.1. Point Spread

Figure 4.1 shows both the percentage of bettors who placed wagers on the favorite and the percentage of games where the majority placed bets on the favorite for each septile (seven quantities) as research shows that bettors prefer betting the favorite. Figure 4.1 shows possible effects of nonlinear betting patterns. The percentage bet on the favorite and the percentage of times the majority bet on the favorite consistently rises from the first septile when the spread is -1 to when the spread is between -3.5 and -4 with the majority betting the favorite over 85% of the time. However, as the spread increases after 4, the percentage bet on the favorite and the times the majority bet on the favorite slowly decreases. Therefore, the following analysis will examine if there are possible non-linear betting preferences on the favorite.

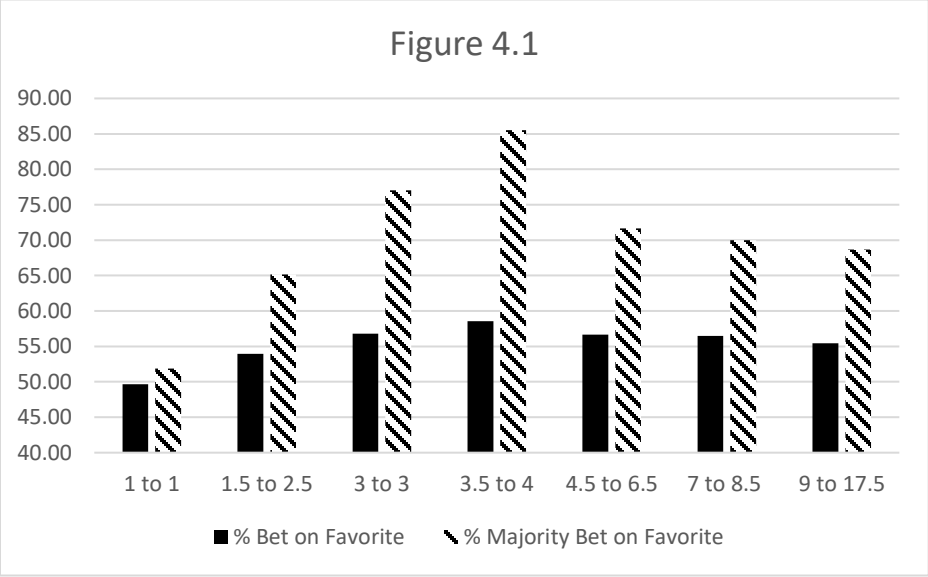

Figure 4.1. This table provides the percentage of bettors who bet on the favorite and the percentage of games the majority bet on the favorite based upon the point spread.

A simple regression model is employed to examine the impact of the spread on betting behavior similar to Paul and Weinbach (2011):

$$(\%\text{ bet on the favorite or majority betting or favorite dummy})_i = \alpha_0 + \beta_1(\text{Point Spread})_i + \beta_2(\text{Road favorite})_i + \beta_3(\#\text{ of bettors})_i + \beta_4(\text{Spread Movement})_i + \beta_5(\text{Favorite Hot Hand})_i + \beta_6(\text{Underdog Hot Hand})_i \ \beta_7(\text{point spread})^2_i + \varepsilon_i \quad (1)$$

Where the dependent variable is either the percentage of bettors who place a wager on the favorite or a dummy variable that equals 1 if the majority of bettors bet on the favorite or 0 otherwise. The independent variables are: The point spread for the game (presented as a negative number with greater favorites having a more negative figure); the road favorite which is a dummy variable that equals to 1 if the favorite is the road team; the number of bettors that placed a wager; the spread movement defined as the difference between the opening odds spread and the closing spread; the hot hand of the favorite team measured by the number of times the favorite has covered the spread in the last 5 games; the hot hand of the underdog measured by the number of occasions the underdog has covered the spread in the last 5 games; the point spread squared.

The dummy for a road favorite is used due to research that shows that road favorites are commonly over bet (Paul & Weinbach, 2011; Golec & Tamarkiin, 1991; Gray & Gray, 1997; Humphreys et al., 2013). The number of bettors' variable is included because the wisdom of the crowd hypothesis suggests that the more bettors that place a wager, the less biased the group's decision should be. Paul et al. (2014) find that when the volume wagered on football games increases so does the percentage bet on the favorite, however, instead of examining the amount wagered, this study examines the number of bettors which gives each bettor an equal share regardless of how much is bet.

In the betting market, there is an opening spread that is created days or weeks prior to the game, and there is the closing spread which all bets placed compete against regardless of when they are placed. The bookmaker often changes the odds because from the bookmaker's perspective too much money is placed on one side of the bet. Therefore they move the line in accordance. There are betting theories based on the line movement. Some believe that bettors should follow the line as they believe that the wisdom of the crowd provides additional information about the game (i.e., if the spread moves from -3 to -5 bettors should place a wager on the favorite as more people are betting on the favorite). This is similar to the ADR underpricing in that IPO's that receive a price upgrade exhibit greater returns (Hanley, 1993) Conversely, some believe that bettors should wager against the line movement, also known as contrarian betting, (i.e. if the spread moves from -3 to -5 bettors should place a wager on the underdog) to exploit sports bettors' tendencies to select the favorite and to gain better odds (i.e. betting on the underdog when the spread is -5 provides a better wager than when it was -3).

In finance, research finds that momentum strategies as buying stocks that have recently increased can be profitable (Jegadeesh & Titman, 1993; Carhart, 1997; Jegadeesh & Titman, 2001). In the betting market, this is called the "hot hand", which research shows that bettors are more likely to bet on teams with the hot hand in the NBA (Camerer, 1989; Brown & Sauer, 1993; Paul & Weinbach, 2005a), but has not been examined in the context of the NFL to the best of the available research. Therefore, the study includes variables to detect the hot hand of covering the spread in recent games for both teams.

If bettors prefer to bet on the favorites, β_1 will be negative and significant. If bettors prefer to place wagers on the road favorites, β_2 will be positive and significant. If more individuals who place a bet on the game create a less biased group decision, β_3 will be

insignificant. β_4 will be negative if bettors follow the spread and bet on the favorite after the line moves towards the favorite. Conversely, β_4 will be positive if bettors favor the contrarian strategy and bet on the underdog when the betting line moves toward the favorite as this improves the odds of the underdog. β_5 will be positive if bettors prefer to bet on teams that have hot hand of covering the spread in recent games. β_6 will be negative if bettors prefer to bet on the favorite when the underdog does not have the hot hand of covering the spread in recent games. β_7 will be negative if bettors prefer to bet less on the favorite when the spread is smaller or larger.

Table 4.1 presents the results for bettors' preferences in the point spread market. The first column supports previous research that investors prefer to bet on the favorite especially when the road team is the favorite. The second column shows that the number of bettors is positive and significant, which shows that when more bettors engage in making a wager, the higher the percentage of bets are made on the favorite which is consistent with Paul et al. (2014). This result directly contradicts the wisdom of the crowd hypothesis, but does provide evidence for the Levitt hypothesis (Levitt, 2004) which suggests that sportsbooks use experts to set betting lines in which they know the majority of bettors will place a wager on the wrong side of the bet to help the sportsbook increase their profits. Additionally, the spread movement is positive and significant which shows that bettors prefer the contrarian strategy and bet on the favorite when the line moves toward the underdog. This result also contradicts the wisdom of the crowd hypothesis, however, as Paul and Weinbach (2011) show a contrarian betting strategy is profitable, bettors may be wagering against the wisdom of the crowd to place a contrarian bet. This result also goes against Simmons et al. (2009) who find that bettors continue to wager on the favorite even after the line moves disadvantageously, however, in their study, their participants were unaware of the disadvantageous movement. Therefore, in Simmons et al.

(2009), their sample does not see the spread movement from the opening line prior to making their wager, which the results in this chapter show are an important contributor to wagering decisions. The third column examines the impact of teams' hot hand on bettors preferences. The results show that the point spread is no longer significant and bettors prefer to bet on the favorite when the favorite has the hot hand and the underdog does not, which is consistent with previous research (Camerer, 1989; Brown & Sauer, 1993; Paul & Weinbach, 2005a). Finally, when all variables are examined in column 4, the results show that bettors have a nonlinear betting preference and are less likely to bet on the favorite when the point spread is small or large. Column 4 indicates that the variables for the number of bettors and line movement are robust to the inclusion of these variables and that bettors place more emphasis on the hot hand of the underdog rather than the favorite.

Table 4.1
Point Spread Betting Percentages

Variables	**% Bet on Favorite**	**% Bet on Favorite**	**% Bet on Favorite**	**% Bet on Favorite**
Panel A:				
Point Spread	-0.0040***	-0.0067***	-0.0008	-0.0108***
	(-3.402)	(-5.245)	(-0.600)	(-2.671)
Road Favorite	0.0899***	0.0955***	0.0715***	0.0810***
	(10.604)	(11.405)	(8.037)	(8.889)
# of Bettors		0.00001**		0.00001**
		(2.179)		(2.046)
Spread Movement		0.0101***		0.0077***
		(4.632)		(3.493)
Favorite Cover Hot Hand			0.0073**	0.0035
			(2.217)	(1.048)
Underdog Cover Hot Hand			-0.0209***	-0.0180***
			(-6.621)	(-5.613)
Point Spread^2				-0.0005*
				(-1.917)
Observations	480	480	480	480
R-squared	0.193	0.236	0.262	0.292

Variables	Majority Bet on Favorite	Majority Bet on Favorite	Majority Bet on Favorite	Majority Bet on Favorite
Panel B:				
Point Spread	-0.0228	-0.0533**	0.0036	-0.1100
	(-1.186)	(-2.415)	(0.158)	(-1.545)
Road Favorite	0.9237***	1.0096***	0.7958***	0.9405***
	(5.850)	(6.153)	(4.666)	(5.121)
# of Bettors		0.0003***		0.0003***
		(2.915)		(2.775)
Spread Movement		0.1048***		0.0923**
		(2.770)		(2.268)
Favorite Cover Hot Hand			0.0302	-0.0154
			(0.529)	(-0.253)
Underdog Cover Hot Hand			-0.2022***	-0.1707***
			(-3.709)	(-2.993)
Point Spread^2				-0.0053
				(-1.187)
Observations	480	480	480	480
R-squared	0.0675	0.0969	0.0949	0.121

Notes: This table presents the regression results for bettor's preference using OLS regression in Panel A to examine the percent of bettors placing a wager on the favorite and a probit regression in Panel B to examine when the majority bet on the favorite. The independent variables are the point spread where a more negative number implies a larger favorite, a dummy variable which equals 1 if the road team is the favorite, the number of bettors who place a wager on the game, the spread movement between the opening spread and closing spread, the hot hand of the favorite and the underdog of the number of games in the past 5 games that the given team covered the spread, and the point spread squared. T-statistics are listed below the coefficients in parenthesis and significance is shown at the 10% (*) 5% (**) and 1% (***) levels.

Panel B presents a probit regression with the dependent variable being a dummy variable based upon if the majority bet on the favorite. The results provide a similar conclusion with bettors more likely to bet on the favorite if the favorite is the road team, there are more bettors, the spread movement moves towards the underdog, and when the underdog has not covered the

spread in recent games. These results are robust to using different lags of the hot hand such as the past three or seven games.

To further examine bettors' nonlinear betting preference, the point spread is split into septiles, and betting behavior is observed. Table 4.2 presents the regression based upon the same models in Table 4.1 while the independent variables are the different septiles of the point spread instead of a single variable for the point spread. The 4^{th} septile is excluded due to multicollinearity issues to examine how all other septiles related to the 4^{th} septile. The results show that the percentage of bettors placing wagers on the favorite is significantly different for septile 1, 5, 6, and 7 compared to septile 4. Additionally, when the dependent variable is a dummy variable based upon if the majority bet on the favorite, all septiles are significantly different from septile 4. These results demonstrate that bettors are less confident betting on the favorite when the spreads are very low or very high, suggesting a nonlinear preference in the betting market. Furthermore, the variables for the number of bettors, spread movement, and underdog hot hand are robust.

Table 4.2
Point Spread Betting Percentages by Spread Septiles

Variables	% Bet on Favorite	Majority Bet on Favorite
Point Spread Q1	-0.0268*	-0.5510*
	(-1.843)	(-1.936)
Point Spread Q2	-0.0085	-0.4716*
	(-0.654)	(-1.853)
Point Spread Q3	-0.0178	-0.5046*
	(-1.376)	(-1.938)
Point Spread Q5	-0.0240*	-0.4382*
	(-1.907)	(-1.706)
Point Spread Q6	-0.0478***	-0.8876***
	(-3.654)	(-3.496)
Point Spread Q7	-0.0934***	-1.3159***
	(-5.364)	(-4.069)
Road Favorite	0.0784***	0.9909***
	(8.896)	(5.283)
# of Bettors	0.00001*	0.0003***
	(1.865)	(2.693)
Spread Movement	0.0055**	0.0714*
	(2.543)	(1.730)
Favorite Cover Hot Hand	0.0045	-0.0050
	(1.363)	(-0.081)
Underdog Cover Hot Hand	-0.0196***	-0.1979***
	(-6.307)	(-3.409)
Observations	480	480
R-squared	0.315	0.155

Notes: This table presents the regression results for bettor's preference using OLS regression to examine the percent of bettors placing a wager on the favorite and a probit regression to examine when the majority bet on the favorite. The independent variables are the point spread split into 7 septiles where a more negative number implies a larger favorite, a dummy variable which equals 1 if the road team is the favorite, the number of bettors who place a wager on the game, the spread movement between the opening spread and closing spread, the hot hand of the favorite and the underdog of the number of games in the past 5 games that the given team covered the spread. T-statistics are listed below the coefficients in parenthesis and significance is shown at the 10% (*) 5% (**) and 1% (***) levels.

Table 4.3 presents the results to examine profitable strategies based upon the percent of bettors on each side of the spread market bet following Paul and Weignbach (2007). The chapter discusses how profitable the strategy of betting with the majority is in panel A, as well as splitting the sample into two groups for when the majority bets the favorite and two groups when the majority bets the underdog in Panel B as if the percentage is higher or lower it shows that the group is more confident and according to the wisdom of the crowd, should be more accurate. While the percentages selected are arbitrary, they are chosen due to being simple rules for bettors to follow. Column 1 presents the odds selected, column 2 presents the number of wins for the favorite/home team, column 3 presents the number of wins for the underdog/away team, column 4 presents the win percentage for the favorite/ home team, column 5 shows the earnings for bettors that bet with the public (that is if bettors bet the favorite/home team when the percentage is greater than 50% or bet on the underdog / away team when the percentage is less than 50%). Additionally, column 6 presents the earnings for a bettor who takes a contrarian's strategy and bets against the public. Both betting strategies provide the returns to a hypothetical bettor who wagers $110 based upon the strategy and wins $100 due to the 10% vigorish.

Table 4.3

Point Spread Simulation Based Upon Public Betting Percentage on Favorite

Panel A: Percent Bet on the Favorite	Favorite Wins	Underdog Wins	Favorite win %	Earnings betting with the public	Earnings for contrarian bettors
Panel A:					
50% +	156	181	0.463	-4310	940
50% -	69	60	0.535	-1590	300
Panel B:					
60% +	92	84	0.523	-40	-1720
50% - 60%	64	97	0.398	-4270	2660
45% - 50%	31	31	0.5	-310	-310
45% -	38	29	0.567	-1280	610

Panel B: Percent Bet Overall	Wins	Losses	Win %	Earnings betting with the public	Earnings for contrarian bettors
60% +	112	101	0.526	90	-2220
55% - 60%	59	82	0.418	-3120	1710
50% - 55%	72	87	0.453	-2370	780

Notes: This table presents the percentage of bettors who place bets on the favorite and their accuracy. Two betting strategies are used to examine if betting with or against the public can profit economic profits after accounting for the vigorish. When more than 50% bet the favorite, betting with the public implies betting the favorite, when less than 50% bet on the favorite, betting with the public implies betting the underdog

The results from Table 4.3 show that a contrarian's approach to betting is profitable, in which a bettor would wager against the favorite if the majority of bettors are betting the favorite and betting on the favorite if the majority are betting against the favorite can provide economical profits after accounting for the vigorish. However, the results show that this strategy is not profitable if 60% or more of the bettors are betting on the favorite or between 50% and 55% are betting on the underdog. The best strategy to earn profit appears to be to bet against the majority when between 50% and 60% are betting on the favorite. Given that bettors prefer to bet on the favorite, it seems odd that when they bet on the underdog, they are still unsuccessful. These results imply that as the percentage of bettors betting on the favorite or underdog increase, they are less accurate, which goes against the crowd of wisdom hypothesis. Additionally, finding that a contrarian strategy is more profitable than betting with the public is consistent with Paul and Weinbach (2007) and Paul and Weinbach (2011). However, the results show that the contrarian strategy is not profitable when more than 60% bet on the favorite.

One disadvantage on examining betting strategies based upon the percentage of individuals placing bets on the favorite is that many games do not have a favorite. Therefore, the previous analysis is examined again for all games in the sample based upon the percentage of bettors on each side of the bet regardless of who the favorite is in Panel B. The results show that when more than 60% of the bettors place a wager in the spread market it is economically profitable to bet with the crowd. Conversely, if the crowd has less than 60% on either of the teams, a contrarian strategy of betting against the crowd is a profitable strategy.

4.3.2. Totals Market

Figure 4.2 presents an illustration of how individuals bet as the posted total increases by separating the posted total into septiles. The percentage bet on the over increases from every septile starting at 49% for games with a total between 37.5 and 41 to over 63% for games with a posted total between 50 and 60. The percentage of games that the majority bet on the over increases from every septile with the lowest septile having the over bet 48% of the time to over 98% of the time for the highest septile. Unlike the point spread market, the totals market does not appear to have a nonlinear impact of the posted total on bettor preferences.

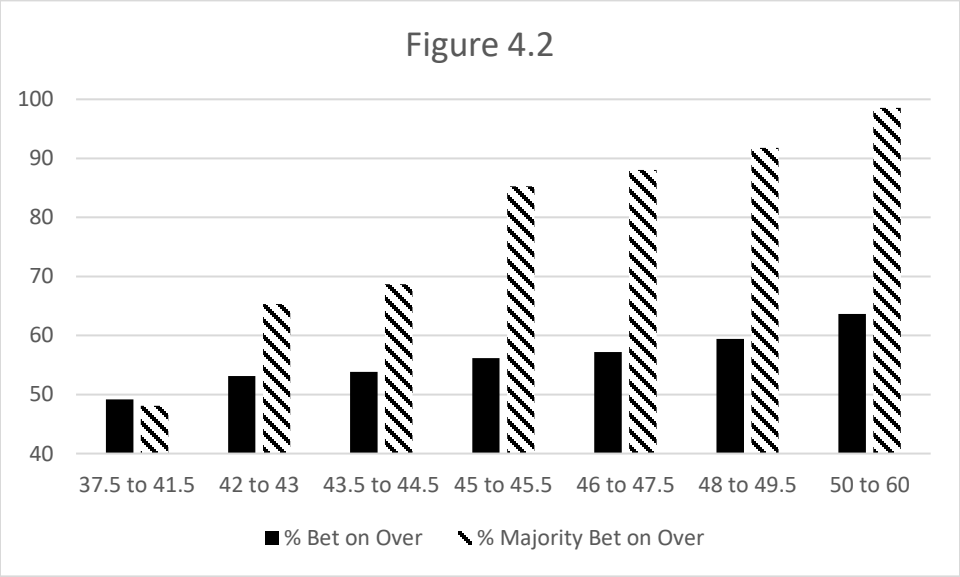

Figure 4.2. This table provides the percentage of bettors who bet on the over and the percentage of games the majority bet on the over based upon the posted total.

A simple regression model is employed similar to equation 1 to examine the impact of the totals on betting behavior:

$$(\%\text{ bet on the over or majority betting or over dummy})_i = \alpha_0 + \beta_1(\text{Posted Total})_i + \beta_2(\#\text{ of bettors})_i + \beta_3(\text{Spread Movement})_i + \beta_4(\text{Home Over Hot Hand})_i + \beta_5(\text{Away Over Hot Hand})_i + \varepsilon_i \quad (2)$$

Where the dependent variable is either the percentage of bettors who place a wager on the over or a dummy variable that equals 1 if the majority of bettors bet on the over or 0 otherwise. The independent variables are; the posted total defined as the closing total points for the game created by the bookmaker; the number of bettors; the home over hot hand defined as the number of times the home team covered the over in the recent 5 games; the away over hot hand defined as the number of times the away team covered the over in the recent 5 games.[20] β_4 and β_5 will be positive if bettors prefer to bet on teams that have covered the over in recent games.

Research examines the impact of wager volume (Paul et al., 2014) and hot hand (Paul et al. (2011) in the context of increased biased betting on the favorite. However, they do not examine the impact it has in the totals market.

Table 4.4 presents the results for betting behavior in the totals market. Consistent with previous literature, bettors prefer to bet on the over as the posted total increases. Additionally, the results show that the percent of bettors wagering on the over increases as the number of bettors increases and decreases as the difference between the line movement increases. Similar to the points spread preferences, both of these two results contradict the wisdom of the crowd hypothesis. Furthermore, bettors are more likely to bet the over if the home and away team have the hot hand in covering the over in recent games despite Paul et al. (2004) finding that the hot

[20] The hot hand of the home and away team are used instead of the favorite and underdog as every game has a home and away team, while in games where the point spread is 0 there are no favorites or underdog which would decrease the sample size

hand bias is not a profitable strategy in the NBA. This result is robust to using different lags for the hot hand such as 3 or 7 games. Panel B shows that it is more likely that the majority bet on the over when the line movement decreases and both the home and away team have the hot hand in covering the over.

Table 4.4
Over Betting Percentages

Variables	**% Bet on Over**	**% Bet on Over**	**% Bet on Over**	**% Bet on Over**
Posted Total	0.0011***	0.0009***	0.0009***	0.0008***
	(4.065)	(3.480)	(3.573)	(2.976)
# of Bettors		0.00002*		0.00002*
		(1.768)		(1.717)
Line Movement		-0.0063***		-0.0065***
		(-2.827)		(-2.984)
Home Over Hot Hand			0.0153***	0.0153***
			(4.648)	(4.677)
Away Over Hot Hand			0.0101***	0.0102***
			(3.220)	(3.288)
Observations	527	527	527	527
R-squared	0.0287	0.0451	0.0798	0.0967
Variables	**Majority Bet on Over**	**Majority Bet on Over**	**Majority Bet on Over**	**Majority Bet on Over**
Posted Total	0.0083*	0.0063	0.0071	0.0048
	(1.815)	(1.352)	(1.513)	(0.998)
# of Bettors		0.0001		0.0001
		(0.598)		(0.639)
Line Movement		-0.0971**		-0.1015***
		(-2.542)		(-2.627)
Home Over Hot Hand			0.1604***	0.1650***
			(2.712)	(2.759)
Away Over Hot Hand			0.1258**	0.1297**
			(2.240)	(2.293)
Observations	527	527	527	527
R-squared	0.00589	0.0179	0.0273	0.0401

Notes: This table presents the regression results for bettors preference using OLS regression in Panel A to examine the percent of bettors placing a wager on the favorite and a probit regression in Panel B to examine when the majority bet on the favorite. The independent variables are the posted total, the number of bettors who place a wager on the game, the spread movement between the opening posted total and closing posted total, the hot hand of the favorite and the underdog of the number of games in the past 5 games that the given team

covered the over. T-statistics are listed below the coefficients in parenthesis and significance is shown at the 10% (*) 5% (**) and 1% (***) levels.

Table 4.5 presents the results to examine profitable strategies based upon the percent of bettors on each side of the totals market bet following Paul and Weignbach (2007) and Table 3. The results in Panel A find no profitable strategy when the majority bet on the over, but a contrarian strategy is profitable when over 50% bet on the under. Once again this seems like an odd result given that the majority rarely bet the under, but when they do, they are economically inaccurate. Panel B shows that betting with the public when more than 65% bet the over can be economically profitable. However, a contrarian strategy is profitable when between 55% and 65% bet the over. The results that a contrarian strategy is profitable is consistent with Paul and Weinbach (2007) and Paul and Weinbach (2011). However finding that betting with the public can be profitable under certain circumstances is inconsistent with their work and shows an inefficiency in the NFL betting market, however due to the low sample size these results do not provide a strategy that produce a win rate statistically different than 52.38%.

Table 4.5
Totals Simulation Based Upon Public Betting Percentage

Percent Bet on the Favorite	Over Wins	Under Wins	Over win %	Earnings betting with the public	Earnings for contrarian bettors
Panel A:					
50% +	192	207	0.481	-3570	-420
50% -	67	51	0.568	-2270	1090
Panel B:					
65% +	35	29	0.547	310	-950
55% - 65%	102	124	0.451	-3440	1180
50% - 55%	55	54	0.505	-440	-650

Notes: This table presents the percentage of bettors who place bets on the over and their accuracy. Two betting strategies are used to examine if betting with or against the public can profit economic profits after accounting for the vigorish. When more than 50% bet the over, betting with the public implies betting the over, when less than 50% bet on the over, betting with the public implies betting the under.

4.4. Conclusion

This chapter examines betting preferences using the NFL point spread and totals markets using betting data from oddswarehouse.com and bettors' data from covers.com. The results show that betting preferences go beyond the previous literature that only shows preferences for betting on the favorite and on the over. The results indicate that biased decision to bet the favorite and the over increases as more participants place wagers, suggesting support for the Levitt hypothesis. Additionally, bettors prefer to bet against the line movement in both the point spread and totals market to increase the odds, as they may be attempting a contrarian betting strategy. However, both of these results conflict with the wisdom of the crowd hypothesis. Furthermore, the results show that bettors prefer betting on teams with the hot hand in both the point spread and totals markets. Finally, bettors in the point spread market display nonlinear preferences as they are less likely to bet the favorite when the spread is low or high.

The wisdom of the crowd hypothesis argues that as more individuals boast their opinion, a better group decision can be made. The results show that when over 60% of bettors bet on the same team in the point spread market, a profitable strategy is to follow the advice from the crowd. However, if the crowd is less sure of their bets and neither team has more than 60% bet on them, a profitable strategy is to bet against the crowd with a contrarian approach. Similarly, in the totals market, when 65% or more of the bettors bet on the over, it is profitable to bet the over. Conversely, when less than 65% of individuals wager on the over it is profitable to use a contrarian approach especially when less than 50% are betting the over. These results show that when there is the least amount of noise in the group decision, the wisdom of the crowd can provide economically profitable strategies.

The results from this chapter uncover previously unknown biased decision making in the NFL betting market that have important implications for both sports bettors and bookmakers. First, sports bettors need to be aware of their biased decisions in order to make more rational decisions in the attempt to maximize profits. Second, as point spread bettors prefer betting on the favorite, especially if it is the road team, against spread movement, and with the hot hand of the teams playing, the bookmaker can take advantage of this in setting the point spread to take advantage of bettors further biased decisions if bettors do not become self-aware of their biased decision making. Similarly, the bookmaker can increase the totals for games when both teams playing have the hot hand for covering the over to get more people betting the over while simultaneously increasing the odds that the final score will be under the posted total.

CHAPTER V

CONCLUSION

Financial decisions are made every day, yet many do not understand characteristics that may be causing their biased decisions. This dissertation adds to the literature by showing how physical characteristics, such as weight and diet, and personality have on financial decision making. Additionally, this dissertation provides evidence of biased decisions in the NFL betting market that had not been previously shown. If individuals understand how their subconscious influences their financial decisions and are aware of different biased decisions, they are more likely to be able to self-monitor and make better decisions.

This dissertation shows that the cognitive impairment associated with those who have a higher body mass index is positively correlated to committing the present bias, and giving stronger weights to payoffs that are closer to the present time, distorting the probability of gains and losses more, and being more loss averse. Additionally, the results show that vegetable consumption is correlated to being less likely to commit the present bias, while lower fruit consumption is positively correlated with loss aversion. These results add to the literature of how individual's health relate to their risk-taking preferences, and are the first to demonstrate the relationship between obesity and diet to poor decision making. These results have important implications as the population's obesity continues to rise. Moreover, future research can look to find a causal relationship to the results in this chapter to examine if losing weight and improving diet quality can cause more rational financial decision making

This dissertation uses a cheap talk experiment and an ethics questionnaire to examine the subject's behavior and how fundamental differences, such as psychopathic personality, influence deceptive and unethical behavior. The results show that business students deceive others for personal gain more often than non-business students when there is the most to gain which adds to the literature of how those with an education in business behave different from those with degrees in other fields. However, business students find deception committed by others as unethical, which shows they are not self-aware of their deception of others. Moreover, I add to the literature by showing that business students exhibit more psychopathic tendencies compared to non-business students, including being more likely to fit the prototypical psychopath profile. This fundamental difference in psychopathy can help explain why individuals deceive others and other unethical behavior frequently discussed throughout the business industry. These results have important implications for the business industry and the design of policies. Furthermore, more research is needed to examine other aspects of the influence that having psychopaths in positions of power have on the business industry.

Finally, this dissertation finds that betting biases in the NFL market go beyond the previously known biases of bettors preferring to bet on the favorite team and the over. The results show that as more bettors place wagers, the favorite team and over bias increases, and bettors have a preference to bet against the line movement to receive better betting odds in both the point spread and totals market. Both of the previous results go against the wisdom of the crowd hypothesis. Additionally, bettors prefer betting on teams with the hot hand in the point spread and totals market. Furthermore, bettors have a nonlinear preference in the point spread betting, as they are less likely to wager on the favorite when the spread is small or large. Finally, economically profitable strategies are put forth based upon the percentage of bettors betting on

the favorite or over. For example, betting with the crowd when over 60% of bettors are on the same side of the point spread and 65% in totals market or betting against the crowd when the crowd is less sure of their decisions can be profitable. Further research can look at other betting markets such as the MLB, NBA, and NHL to uncover betting biases in other markets that have more games scheduled per year to increase the sample size. Additionally, further research can be done on this topic to examine if differences in individuals, such as personality or physical characteristics, can influence bettors to make biased decisions.

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APPENDIX A

APPENDIX A

INSTRUCTION FOR SENDER

This is a short experiment in decision making. In this experiment, you will be matched with another student from a different class. Neither of you will ever know the identity of the other. You will know the payout options for both payments, option A and option B, and the other student will not. The choice of which option your counterpart chooses rest with the other student who can freely choose option A or B. The only information your counterpart will have is the information sent by you in a message.

The two possible monetary payments available to you and your counterpart are as followed:
Option A: you receive $5 and the other student receives $6
Option B: you receive $6 and the other student receives $5

We will show the other student your message, and ask them to choose either option A or B. As a reminder, your counterpart's choice will determine the payout of the experiment, however, they will never know the sums that were actually offered. (They will never know if your message was true or not).

Which message would you like to send to the other student?
Message 1: "Option A will earn you more money than option B"
Message 2: "Option B will earn you more money than option A"

APPENDIX B

APPENDIX B

DESCRIPTION OF PSYCHOPATHY MEASURES

Scale		Construct Descriptions
Panel A: Psychopathy (Global)		
P	Psychopathy (SCI + FD + C)	The greater the probability that the respondent matches the features of the prototypical psychopathic individual, such as guiltlessness, callousness, dishonesty, manipulativeness, superficial charm, egocentricity, risk taking, and poor impulsive control
Panel B: Secondary Traits		
SCI	Self-Centered Impulsivity (ME + RN + BE + CN)	Tendency toward self-centeredness, ruthless use of others, brazen flouting of traditional values, propensity to attribute blame to others for one's mistakes, and reckless impulsivity
FD	Fearless Dominance (SOI + F + STI)	Lack of anticipatory social and physical anxiety, low levels of tension and worry, low harm avoidance, and high levels of interpersonal dominance
Panel C: Primary Traits		
ME	Machiavellian Egocentricity	Narcissistic and ruthless attitudes in interpersonal functioning
RN	Rebellious Nonconformity	Reckless lack of concern regarding social norms
BE	Blame Externalization	Tendency to blame others for one's problems and to rationalize one's misbehavior
CN	Carefree Nonplanfulness	Attitude of indifference in planning one's actions
SOI	Social Influence	Perceived ability to influence and manipulate others
F	Fearlessness	Absence of anticipatory anxiety concerning harm and willingness to participate in risky activities
STI	Stress Immunity	Absence of marked reactions to anxiety-provoking events
C	Cold-Heartedness	propensity toward callousness, guiltlessness, and lack of sentimentality

Notes: This table displays the descriptions of the psychopathic dimensions described in the PPI-R (Lilienfeld, Widows, & Staff, 2005).

BIOGRAPHICAL SKETCH

Corey Allen Shank has received his undergraduate degree in finance from Virginia Tech in 2012, Master's in Business Administration from the University of Findlay in 2014, and Ph.D. in Finance from University of Texas Rio Grande Valley in 2017. Corey has worked as a research and teaching assistant in the Economics and Finance Department while pursuing his doctorate Degree. To date, Corey has published academic papers in *Research in International Business and Finance* and T*he Review of Behavioral Finance*. Corey's permanent mailing address is 3838 Sherman, Fort Wayne, IN 46808 and his personal email address is cashank01@gmail.com.