ADDICTION, CONSUMER CHOICE, AND BUSINESS STRATEGIES
IN INNOVATIVE MARKET NICHES RELATED TO LEISURE –
THE CASE OF GEOCACHING.COM

A THESIS

Presented to

The Faculty of the Department of Economics and Business

The Colorado College

In Partial Fulfillment of the Requirements for the Degree

Bachelor of Arts

By

Kristina Shoyleva

May 2011

ADDICTION, CONSUMER CHOICE, AND BUSINESS STRATEGIES
IN INNOVATIVE MARKET NICHES RELATED TO LEISURE –
THE CASE OF GEOCACHING.COM

Kristina Shoyleva

May 2011

Economics

Abstract

This paper analyses the behavior of users of the website Geocaching.com. The study provides an insight on how internet services can relate to hobbies, sports, and leisure. In particular, this research analyzes the consumers' inclination to become addicted to the type of services offered by the webpage. With the assumptions made in this study, no patterns of addiction to the services offered by Geocaching.com are identified. This research also examines the characteristics of the new market niche created by Groundspeak with the introduction of the website. This innovative business model is now followed by an array of other companies. This work ends with suggestions of successful business strategies for companies entering or already positioned in the market niche.

KEYWORDS: (Addiction, Innovation, Marketing, Behavioral economics, Business strategies, Geocaching)

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF EQUATIONS

AKNOWLEDGEMENTS

I am grateful for the support I received from my academic advisor, Daniel Johnson, in writing this thesis. I am also thankful to the faculty members and staff at Colorado College, who turned my research into an enjoyable, yet intensive, learning experience and who supported me throughout my undertakings as a student. I am grateful to all who supported me in any respect during the completion of this project.

CHAPTER I

INTRODUCTION

The introduction of social platforms and other innovative internet services raises interesting questions of how web services develop. The case of Geocaching provides an insight on how hobbies can become related to internet services. This research explores how addictive a certain class of internet services can be.

This paper analyses the behavior of users of the website Geocaching.com. In particular, the research analyzes their inclination to become addicted to the services offered by the webpage. This study also examines the characteristics of the new market niche, created by Groundspeak. This innovative business model is now followed by an array of other companies. Chapter V suggests successful business strategies for companies entering or already positioned in the market niche.

What is Geocaching.com?

Geocaching.com is a website started by a company named Groundspeak in September 2000.[1] The firm is currently located in Seattle, WA (USA). The website is the first and biggest provider of web services facilitating geocaching activities. It now supports approximately 4 million users internationally.

[1] Groundspeak, Geocaching.com. Factsheet, Copyright © 2000-2011. Available at: http://www.geocaching.com/articles/Brochures/footer/FactSheet_GeocachingCom.pdf

Geocaching itself stands for an innovative type of a hobby, which users become engaged in through the web platform, although the activity takes place in physical locations. To participate in it, users log into a website to obtain the geographical information of where other people have hidden objects called caches. Geocaching.com currently supports an online data list of approximately 1 million such objects[2] (figure 1.) Using a GPS device, the users find the caches and replace them with new objects or leave them at the same place. For this reason, the activity is often referred to as treasure hunting.

Some consumers view the activity as a family game played outside.[3] For others, it can be related to other hobbies, such as hiking. Some geo-caches, recorded on the website, have geographical locations on the coast or even in the ocean, which suggests geocaching may also be a complimentary activity for people who enjoy surfing or scuba-diving.

[2] Geocaching.com Factsheet, Copyright © 2000-2011. Retrieved from: http://www.geocaching.com/articles/Brochures/footer/FactSheet_GeocachingCom.pdf

[3] Dave Caldwell. “Modern Treasure Hunts for the Whole Family.” *New York Times,* 2010. Available at: http://www.nytimes.com/2010/12/10/technology/10geocache.html

FIGURE 1.1

WORLD MAP: GEOCACHING LOCATIONS RECORDED ON GEOCACHING.COM

SOURCE: Data provided by Groundspeak.

Identifying addicts. Differentiating marketing strategies.

Economists' interest in addiction is mostly related to price sensitivity. According to economic theory,[4] people are less sensitive to severe increases in prices of products they are addicted to. Therefore, identifying the groups of people or individuals addicted to a product brings insight into what development and marketing strategies a company may implement.

However, addiction models have applications that go beyond the pricing decisions a company must make. Governments often use evidence of addiction patterns to impose special higher taxes on alcohol, cigarettes, or other products.[5]

Another application of the differentiation between addicted consumers and users who engage in the activity randomly relates to the features of the products to be advertised. Addicted consumers could be more interested in GPS devices facilitating geocaching. If the addicts' desire to geocache is related to an addiction to other outdoor activities, those users may be interested in viewing advertisements on special equipment for hiking and other outdoor activities.

Addiction models

Addiction models may explain the behavioral patterns some internet users fall into. Becker, Grossman, and Murphy[6] introduced in 1991 the traditional model of addiction.

---

[4] Suresh Narayanan and Balasingam Vicknasingam. "Responses to the Illicit Drug Problem: Insights from Supply and Demand Analysis." *Australian Economic Review* 43, no. 1 (2010): 88–99.

[5] Frank J. Chaloupka and Rima Nai. "International Issues in the Supply of Tobacco: Recent Changes and Implications for Alcohol." *Addiction* 95, no.12s4 (2000): 477–489.

[6] Gary S. Becker, Michael Grossman, and Kevin M. Murphy. "Rational Addiction and the Effect of Price on Consumption." *The American Economic Review* 81, no. 2, (1991): 237-241.

An improvement of the model was constructed by Fenn, Antonovitz and Schroeter.[7] This later version of the model allows for an interpretation in which individuals are prone to addiction to different goods and to a different extent. For example, the probability that a person can develop an addiction to something can depend on a range of factors,[8] such as genes, environment, characteristics of the substance or practice, etc.

Although the two addiction models, published by Becker et al and Fenn et al, respectively, focus on cigarette consumption, the applications of the models reach far beyond the tobacco industry. There have been discoveries that people fall into patterns of addiction-prompted behaviors related to various products and activities.

Addiction to sports and hobbies

People can develop addiction not only to certain drug substances, but also to leisure activities, such as sports and hobbies, and an array of other products and habits. There have been multiple studies on athletes' inclination to get addicted to sports. Addiction patterns showing that some people use recreational sports as a stress-reliever have also been researched.

The term "exercise addiction" describes the addiction people may develop to a habitual exercise. The chance that an athlete develops sports addiction depends to a great extent on the athlete's character.[9] Also, certain groups of athletes have a higher

---

[7] Aju J. Fenn and John R. Schroeter. "Cigarettes and addiction information: new evidence in support of the rational addiction model." *Economic Letters* 72, no. 1 (2001): 39

[8] Chuan-Yun Li, Xizeng Mao, and Liping Wei. "Genes and (Common) Pathways Underlying Drug Addiction." *PLoS Comput Biol* 4, no.1 (2008). Avalable at: http://www.ploscompbiol.org/article/info%3Adoi%2F10.1371%2Fjournal.pcbi.0040002

[9] Gary Kamen. "Foundations of Exercise Science." *Lippincott Williams & Wilkins*, (2001): 227-229.

chance to develop an addiction. Female dancers, for instance, are more likely to develop an addiction to dancing than other female athletes to the sport they practice.[10]

For these reasons, sports addiction can well be described through the model constructed by Fenn et al, in which differentiation is achieved between people who are addicted and people who simply use a product. Since the geographical data suggests that some users geocache as they engage in sports activities, this study raises the question of whether geocaching activities can be addictive in the same way sports are.

Studies on internet addiction and addiction to gambling have also been conducted.[11-12] The excessive usage of internet, especially when leading to a deterioration of one's quality of life, is referred to as Internet Addiction Disorder. This condition is also linked with and usually diagnosed after the appearance of socially problematic behavior, such as arguments, lying, poor performance, depression and fatigue. Although anecdotes and media prompt people to believe that many could be addicted to the internet, empirical studies define that condition as rare.[13]

An important aspect of a study of an innovative product is the definition of addiction to be implemented. While many people use the internet, it is the excessive amount or dosage that implies an addiction, in this case. Similarly, addiction to food and alcohol can be defined only through excessive and pathological use.

---

[10] Edgar F. Pierce, Myra L. Daleng, and Robert. W. McGowan "Scores on Exercise Dependence among Dancers." *Perceptual and Motor Skills* 76, no. 2 (1993): 531-535.

[11] Jerald J. Block "Internet Addiction." *American Journal of Psychiatry* 165 (2008): 306-307

[12] Lynn J. Dell, Mary F. Ruzicka, and Anthony T. Palisi. "Personality and Other Factors Associated with the Gambling Addiction." *Substance Use & Misuse* 16 no. 1 (1981): 149-156

[13] Mark Griffiths. "Does Internet and Computer "Addiction" Exist? Some Case Study Evidence." *CyberPsychology & Behavior* 3, no. 2 (2000): 211-218.

Thus, models of addiction can be applied to many fields, such as sports, internet usage, leisure activities, etc. This paper examines addiction which is not clearly categorized as addiction to substances, physical activities or internet usage, but rather a combination of those. Specifically, this research examines addiction related to an internet service facilitating hobbies.

Consumer behavior and business implications

In the business world, addiction-oriented research has multiple applications. Finding a group of addicted people is similar to, although not equivalent to, identifying loyal customers. As mentioned above, addicts' demand curve for a product they need is steeper than the demand curve illustrating the behavior of the rest of the users. Also, while some customers may be loyal to a brand and have a preference for it, they may not be addicted to any product offered under the brand name.

People tend to prefer to purchase from the first mover on a market.[14] In other words, the first mover on the market usually gains a greater share of the market niche than the rest of the companies. However, the first-mover advantages are unrelated to processes of addiction. If consumers do not experience addiction to a given product, the company offering the good should follow a different business strategy than a company working with addicted consumers.

There are extensive differences in the decision-making processes addicts and loyal customers face. While an addict may experience intensive negative withdrawal

[14] Marvin B. Lieberman and David B. Montgomery. "First-Mover Advantages." *Strategic Management Journal* 9, Special Issue: Strategy Content Research.(1988): 41-58.

symptoms[15] if he or she tries to discontinue the consumption of the product, a loyal customer could simply switch to a substitute if dissatisfied with the product. For these reasons, appropriate analyses of addiction is valuable in modeling consumer choices.

Online marketing

Online records often contain information on consumers' interests and preferences, which allows for a division into target groups. This in turns provides an opportunity of a better match between consumers' interests and the commercials appearing on the webpage. The practice of matching consumer interests and internet advertisements is already being implemented into practice.[16]

Studies show that advertising online is often cheaper and more effective that traditional marketing.[17] A major reason for this is the fact that online marketing can use cross-consumer communication and internet records to identify target groups and stream advertisements accordingly. Also, consumers often recommend products they are fond of to other users on social platforms on the internet. A new word has been coined to describe how people actively engage in online communities: nethnography (the word is derived from ethnography).

---

[15] Steven E. Hyman and Robert C. Malenka "Addiction and the Brain: The Neurobiology of Compulsion and its Persistence." *Nature Reviews Neuroscience* 2 (2001): 695-703

[16] Paul M. Schwartz, Ronald D. Lee, and Ira Rubinstein."Data Mining and Internet Profiling: Emerging Regulatory and Technological Approaches." *Law and Technology Scholarship*, Berkeley Center for Law and Technology, UC Berkeley (2008) Retrieved from: http://escholarship.org/uc/item/2zn4z6q4

[17] Robert V. Kozinets. "The Field behind the Screen: Using Netnography for Marketing Research in Online Communities." *Journal of Marketing Research* 39 no.1 (2002): 61-72.

Internet forums and panels are an ever increasing public space for one of the cheapest and most effective marketing approaches – word of mouth. Consumer advocacy is an important factor influencing the reputation of a brand. Thus, consumer involvement can affect the demand for a product greatly. Websites give companies a vast array of opportunities to trigger and analyze such advocacy.[18]

Companies have recognized the increasing influence of online marketing . As Kozinets states in his article "The field behind the screen: using netnography for marketing research in online communities,"[19] companies have a two-fold interest in online communities and marketing: direct investment into advertisements and opportunity to research consumer tastes and preferences.

The internet business and marketing opportunities hold one more hidden advantage – the possibility to connect businesses and products easily. Through their paper "Deriving Value from Social Commerce Networks," Andrew Stephen and Olivier Toubia reveal that "(1) allowing sellers to connect generates considerable economic value (2) the network's value lies primarily in making shops more accessible to customers browsing the marketplace (the network creates a "virtual shopping mall"), and (3) the sellers who benefit the most from the network are not necessarily those who are central to the network but rather those whose accessibility is most enhanced by the

[18] Shawndra Hill, Foster Provost, and Chris Volinsky. "Network-Based Marketing: Identifying Likely Adopters via Consumer Networks." *Statistical Science* 21, no. 2 (2006): 256-276.

[19] Robert V. Kozinets. "The Field behind the Screen: Using Netnography for Marketing Research in Online Communities." *Journal of Marketing Research* 39 no.1 (2002): 61-72.

network."[20] In other words, the interconnectivity and the opportunity to target advertisements give companies a large comparative advantage.

The purpose of this paper is to discuss the behavioral patterns of the users of Geocaching.com. More specifically, this research examines the possibility that some of the consumers are addicted to the activity. Regular usage of the website is also analyzed. The results suggest appropriate business strategies, based on the characteristics inferred on the users. Chapter II begins with a review of the theoretical models used to study the processes of addiction. Chapter III describes the data on which this research is based. Chapter IV reveals the results of the study. Chapter V summarizes the conclusions reached in this research.

[20] Andrew T. Stephen and Olivier Toubia. "*Deriving Value from Social Commerce Networks*." *Journal of Marketing Research* 47, no. 2 (2010): 215-228

CHAPTER II

LITERATURE REVIEW AND MODELS

An overview of the traditional models incorporated into the study

The purpose of this chapter is to review the literature used to analyze the behavior of the users of Geocaching.com. This literature comes mainly from the research field known as the economics of addiction.

One now considered traditional addiction model in the field of economics was developed by Becker, Grossman, and Murphy in 1991.[1] This model depicts the level of desired current consumption of a good as a function of previous and/or future consumption, price, income, and other factors that can influence the demand.

An elaboration of the model adjusting for the fact that certain goods can be addictive for some people but not necessarily for all people was introduced by Fenn, Antonovitz and Schroeter in 2001.[2] It has been proven biologically that people's propensity to become addicted depends on genes and the environment, as is the case with many diseases.[3]

[1] Gary S. Becker, Michael Grossman, and Kevin M. Murphy. **"**Rational Addiction and the Effect of Price on Consumption." *The American Economic Review* 81, no. 2, (1991): 237-241.

[2] Aju J. Fenn and John R. Schroeter. "Cigarettes and Addiction Information: New Evidence in Support of the Rational Addiction Model." *Economic Letters* 72, no. 1 (2001): 39.

[3] David Goldman, Gabor Oroszi and Francesca Ducci, 2006. "The Genetics of Addictions: Uncovering the Genes," *American Psychiatric Association* 4 (2006): 401-415.

Models of addiction

Economic addiction models can be classified into two groups: rational and myopic. Both models express the current consumption of the addict as a function of the price of the product and the consumption from the previous periods. Additional control variables may be inserted to introduce more precision into the model. The rational model (equation 2.1) takes one more factor into account - the desired future consumption:

EQUATION 2.1

RATIONAL ADDICTION MODEL.

$$\boxed{\text{Current consumption} = \text{function (price, past consumption, future consumption)}}$$

The additional control variables can be taxes, income, etc. The traditional regression notation of the rational addiction model (equation 2.2) is expressed through relative time periods. Thus, in a sample, each time period can be regarded as a basic (current) period. Then, the leads and lags of the consumption over this basic period can be regarded as independent variables:

EQUATION 2.2

RATIONAL ADDICTION REGRESSION.

$$\boxed{C_t = \alpha_1 P_t + \alpha_2 C_{t+1} + \alpha_3 C_{t-1} + \alpha_4 C_{t-2} \ldots + \varepsilon}$$

In equation 2.2, C_t represents the consumption over the current (basic) period. P_t is the price of the product over the current period. C_{t+1} presents the lead consumption variable, reflecting consumption levels from the period following the basic period. C_{t-1} and C_{t-2} represent lagged consumption variables. The error in the equation is denoted by ε. The coefficients of the independent variables are $\alpha_{1,}$ $\alpha_{2,}$ … $\alpha_{n.}$

It is thus assumed that the myopic addiction model (equation 2.3) is applicable in cases in which the consumer is unaware he or she is addicted and/or does not plan his or her future consumption.

EQUATION 2.3

MYOPIC ADDICTION MODEL

Current consumption = function (price, past consumption)

Nevertheless, it is considered that the rational addiction model approximates the behavior of the addicts more precisely, because even if they are only aware of their addiction subconsciously, they would also subconsciously realize that they would demand the same good in a later period. To recognize both the rational and myopic processes as possible, a myopic regression (equation 2.4) is also tested in this research.

EQUATION 2.4

MYOPIC ADDICTION REGRESSION.

$$C_t = \alpha_1 P_t + \alpha_2 C_{t-1} + \alpha_3 C_{t-2} \ldots + \varepsilon$$

In equation 4, C_t presents the consumption over the current (basic) period. P_t is the price of the product over the current period. C_{t+1} presents the lead consumption variable. C_{t-1} and C_{t-2} represent lagged consumption variables. The error in the equation is denoted by ε. The coefficients of the independent variables are $\alpha_{1,}$ $\alpha_{2,}$ … $\alpha_{n.}$

Consumers' inclination towards addiction

The once traditional assumption in modeling addiction, introduced by Becker et al., is that the current addiction to a certain good depends on the consumption level from the previous period and the addiction level from the previous period (equation 2.5):

EQUATION 2.5

ADDICTION ASSUMPTIONS INTRODUCED BY BECKER ET AL.

$$A_t = C_{t-1} + (1\text{-}\delta)\ A_{t-1,}$$

In this model, addiction is always positive for every consumer. A_t represents current addiction. A_{t-1} denotes the addiction experienced by the consumer in the previous time period. The parameter δ takes values between 0 and 1. C_{t-1} represents past consumption.

In this equation, $(1-\delta)$ reflects how much a person gets addicted after the fist consumption dose. In this model, the addiction in the current period is always positive, if the good has been consumed once, because the addiction can be equal to zero for a certain period of time, but the fact that the person has consumed the good once leads to a positive or increasing current addiction.

The flaw in the model described above, according to the modern perception of addiction, is that the model assumes that each consumer starts accumulating addiction immediately. However, it has been biologically proven that some people have a greater genetic inclination to become addicted to certain goods, such as alcohol, than others[4]. The fact that a relatively addictive good can be addictive for some consumers but not for all has been successfully captured by the model constructed by Fenn et al. (equation 2.6):

[4] David Goldman, Gabor Oroszi and Francesca Ducci, 2006. "The Genetics of Addictions: Uncovering the Genes," *American Psychiatric Association* 4 (2006): 401-415.

EQUATION 2.6

ADDICTION ASSUMPIONS INTRODUCED BY FENN ET AL.

$$A_t = (1-\delta)\, C_{t-1} + (1-\lambda)\, A_{t-1}$$

In the equation above, addiction is not always positive. A_t represents current addiction. A_{t-1} denotes the addiction experienced by the consumer in the previous time period. C_{t-1} represents past consumption. A_{t-1} denotes the addiction experienced by the consumer in the previous time period. The parameters δ and λ take values between 0 and 1.

According to this model, after consuming the good, the person may not get addicted, depending on λ. If $\lambda = 1$, the person will not get addicted.

Differentiating between addiction and regular usage

Recently, addiction has been recognized as a disease. The reason for this is the definition currently used in the treatment of an addiction. According to the simplified version of the biological definition, addiction to substances is a condition in which the brain reacts to the absence of the addictive substance as to the lack of something that is necessary for the individual's ability to survive.[5]

For the analysis of addiction to certain products, however, this basic definition is not fully appropriate. In this day, even though food products, such as sugar and salt, are

---

[5] Jeanne Nagle. "Everything You Need to Know about Drug Addiction." *The Rosen Publishing Group*, (1999): 22.

seen as vital, the routine and excessive consumption of such products is regarded as addiction.[6]

Excessive consumption is also a key phrase in the study of sports addiction. A study on people's addiction-simulating or addiction-based behavior towards recreational activities, such as sports and hobbies, can also use a slightly different definition of addiction. In this case, addiction is defined as a person's consistent desire to devote a lot of time to a sports activity or hobby and to practice it frequently.[7] Thus, a rational addiction model can be used to approximate the process of developing an addiction towards sports or hobbies.

Time periods

The length of the time interval chosen to represent one period of consumption can reflect the final analysis of addiction. Shorter periods could, potentially, reveal greater fluctuations in consumers' decision-making patterns.

In a paper presented in 1979 to the Society for the Study of Social Problems, Boston 1979, ("What is an addict? Theoretical perspectives and empirical patterns of opiate use,") B.D. Johnson, P.J. Goldstein and N.S. Dudraine support the above-mentioned statement.[8] The researchers describe heroin consumption as an activity most addicts do not engage in every day. In addition, the researchers find considerable variations in daily dosages.

---

[6] Nick Heather. "Choice, behavioral economics, and addiction." *Elsevier*, (2003): 150-153.

[7] Kamen, Gary, 2001. "Foundations of Exercise Science" *Lippincott Williams & Wilkins*, (2001): 227- 229

[8] B.D. Johnson, P..J. Goldstein and N.S. Dudraine. "What is an Addict? Theoretical Perspectives and Emprirical Patterns of Opiate Use." *Paper presented at the meeting of the Society for the Study of Social Problems*, Boston. 1979.

The conclusion of this study is that although expectations for the addiction patterns usually include stability and a steady escalation of the consumption, such features are not present in the history of the researched individuals. One possible reason for the tremendous difference between this conclusion and the conclusions drawn through studies of cigarette addiction is the combination of different time frames and individualized versus generalized results.

In contrast with the research implemented by Johnson et al. in 1979, studies on cigarette consumption often analyze yearly periods[9] (instead of daily intervals). Also, sometimes the data used provides information on the consumption within a state, not of an individual.[10] The contrast in the results obtained from those two types of studies implies that breaking the data into smaller intervals or cross-sectional variables may make more of the fluctuations visible.

Thus, the length of the time interval which a researcher chooses to utilize in an analysis of addiction can affect the final results. For this reason, an effort to extend the data may include, for example, an effort to extend the time intervals utilized or otherwise choosing a more appropriate interval.

For instance, analyzing an athlete's addiction to club sports could be adequately analyzed through the athlete's commitment of participating every week when the team gathers. The above-mentioned fluctuations in addiction patterns can occur for various reasons. Some studies challenge the definition of addiction as a combination of neurological processes which involve survival instincts.

---

[9] Aju J. Fenn and John R. Schroeter. "Cigarettes and addiction information: New Evidence in Support of the Rational Addiction Model." *Economic Letters* 72, no. 1 (2001): 39.

[10] Aju J. Fenn and John R. Schroeter. "Cigarettes and Addiction Information: New Evidence in Support of the Rational Addiction Model." *Economic Letters* 72, no. 1 (2001): 39.

Stages of consumption

Examples of such challenges to the currently traditional perception of addiction as a psychological trap are introduced separately by Winick et al.[11] and Waldorf et al.[12] They conclude that individuals may simply become tired of or grow out of their desire to take drugs; even years spend as an addict may not be a factor in such a decision.

The fluctuations in the rational addiction model may also depend on the stage of usage. If a consumer has recently been introduced to a product, he or she may use the product regularly without experiencing psychological symptoms of addiction. It has been proven that in some cases neurological symptoms of addiction may take a year to develop.[13]

The question of how important the stage of the individual is, in terms of usage and time spent consuming the product, brings researchers to another perspective in the field of addiction modeling – the epidemiology perspective.

Epidemiology

The possibility that an adolescent consumer would transition into the group of addicts who are strongly dependant on a substance psychologically, can successfully be predicted through factors such as whether or not this individual's parents, siblings, or

---

[11]Chareles Winick. “Maturing Out of Narcotic Addiction,” *Bulletin on Narcotics* 14, no.1 (1962): 1-7

[12] Dan Waldorf. “Life without Heroin: Some Social Adjustments during Long-Term Periods of Voluntary Abstention.” *Social Problems Journal* 18, no. 2 (1970) 228-243.

[13] R. Gardner and P.H. Connell. “Opioid Users Attending a Special Drug Dependence Clinic 1968-1969.” *Bulletin on Narcotics* 23, (1971): 9-15.

friends consume same or similar products.[14-15] Most studies in the field analyze the behavior of adolescents and the factors that prompt them to consume addictive substances.[16]

Such individual factors can also be taken into account through a fixed-effects model for the cross-sectional variables in an addiction regression. The fixed effects account for the fact that each individual has a different inclination to become addicted to a product, which also coincides with the assumptions of the addiction model constructed by Fenn et al.[17]

Thus, individual factors of importance to the addiction model, such as family history, can be well captured through cross-sectional dummies or fixed effects models, when precise information on individual differences is not available.

Model

The purpose of the model used in this study is to analyze the behavior of the consumers of the services of the website Geocaching.com, focusing on the possibility of an addiction trend. Thus, the model used in this research draws on the rational model of addiction, which is, for psychological reasons, considered more precise than the myopic model. However, the appropriateness of a myopic addiction model is also analyzed.

---

[14] Ptrick West, Helen Sweeting and Russell Ecob. “Family and friends' Influences on the Uptake of Regular Smoking From Mid-adolescence to Early Adulthood,” *Addiction* 94, no. 9 (1999): 1397–1411.

[15] Jacqueline M. Vink, Gonneke Willemsen, and Dorret I. Boomsma. “The Association of Current Smoking Behavior With the Smoking Behavior of Parents, Siblings, Friends and Spouses,” *Addiction* 98, no. 7, (2003) 923–931.

[16] David Fergusson, Michael T. Lynskey, and L John Horwood, 2006. “The Role of Peer Affiliations, Social, Family and Individual Factors in Continuities in Cigarette Smoking between Childhood and Adolescence,” *Addiction* 90, no. 5, (2006): 647–659.

[17] Aju J. Fenn and John R. Schroeter. “Cigarettes and addiction information: New Evidence in Support of the Rational Addiction Model.” *Economic Letters* 72, no. 1 (2001): 39.

The price term is excluded in this case, because the service is offered by an open-source website. In this model, a user is considered an addict if the consumption level can be modeled as a rational choice.

CHAPTER III.

DATA AND METHODOLOGY

The purpose of this chapter is to describe the construction of an addiction model that can be applied to analyze the behavior of the users of the website Geocaching.com. This research provides an insight into the characteristics of innovative market niches, such as the one created by Groundspeak, the company which owns Geocaching.com.

Groundspeak has created a new business which draws on, but does not clearly belong to, more established categories, such as sports, family games, social networking, and internet services. The results of the analysis reveal efficient marketing policies and development strategies for Geocaching.com and comparable innovative internet-related service providers.

The model used in this research is based on the classical rational addiction model constructed by Becker et. al.[1] The addiction model introduced by Fenn et. al.[2] also provides a sound basis for analyzing the case of Geocaching.com. As mentioned in the previous chapters, the latter model allows for a differentiation between addicted consumers and other users.

---

[1] Gary S. Becker, Michael Grossman, and Kevin M. Murphy. "Rational Addiction and the Effect of Price on Consumption." *The American Economic Review* 81, no. 2, (1991): 237-241.

[2] Aju J. Fenn and John R. Schroeter. "Cigarettes and Addiction Information: New Evidence in Support of the Rational Addiction Model." *Economic Letters* 72, no. 1 (2001): 39.

Variables description;

data provided by Groundspeak

User data

For the purpose of this study, Groundspeak has provided data on geocaches – small packages, computer data, and other products – which the users look for in physical space. Geocaching.com keeps records of the places where those caches are, in the form of GPS location (table 3.1).

Anonymous user data is also available. Since most users have opened the website a few times during the summer, the first field, “accountid,” provides information which allows the website to distinguish each user. The second field, “logid,” allows each visit of the website, regardless of who the user opening his or her account was, to be recorded separately. In particular, the column “accountid” provides one unique account-ID code assigned to each registered user. In addition, each opening of the website (in jargon: website hit) receives an ID number itself, in the second field mentioned above: “logid.”

The data covers information on geocaching activities which take place on all five continents. The website is currently the biggest provider of information on caches and their GPS locations. The data provided by Groundspeak contains records spanning from January 2010 to October 2010.

Time frame

Table 3.1. from the appendix shows an excerpt of the data recorded by Geocaching.com. The field “datevisit” gives the exact date and time at which a user opened the website.

This research examines all geocaching activities in the USA and in the proximity of the US border. Only summer activities, recorded between June 6 and August 28, are analyzed. Thus, the sample characteristics neutralize weather differences across states, which are more severe during the other three seasons.

Cache data

Each object receives a unique number in the columns “cacheid” and “objectid.” The field “logtypeid” assigns a categorical numerical code to each opening of the webpage. Therefore, this code groups similar types of website attendances.

A qualitative (text) description of each cache is given in the field “cachetype.” There, the caches are divided into several groups. The first class is traditional caches, normally a box of small non-perishable goods. The second is virtual caches, such as flash drives, CDs, and other products that store information electronically. An example of another group is the category muticaches, which are combinations of several hidden objects. The column “cachetypei” assigns a number to each cache category, based on the objects’ characteristics.

Geographical data

The geographic location of each cache can be defined using the two columns "cacheat" and "cacheon", presented in table 1 in the appendix. They provide geographical information in terms of longitude and latitude.

The geographical information in the last two columns is used to create a new column, called "state." Each cache is assigned to a state. Costal and ocean caches close to the border are assigned to the nearest state. The procedure is implemented through GIS software. No points are double counted.

Creating variables for the addiction model

In order to implement a behavioral model based on the actions of each user, the following fields are used: "datevisit," "accountid," "logid," and "state." The data is divided into 12 weekly periods. Demographic information on the median household income in each state is added through GIS.[3] This information is used to approximate the income level of any person geocaching in a particular zone. This data is subsequently recorded in field "mhi" (median household income). Hence, user income estimation is made through the highest possible value, considering all states in which the consumer has used the services of the website.

The first proposed model takes the maximum income from the list of possible income levels for each user. The second and third models take the minimum and median income values, respectively.

[3] US Census Bureau, 1999. Available at: www.census.gov.

Identifying consumers inclined to addiction

In all models, consumption is measured through the number of times the user has visited the website. Based on the level of consumption, two groups are identified. The first group includes users who have use the services of the website for at least two random two-week periods. A dummy variable, “addicted,” is created to describe whether a user belongs to this group or not.

The purpose of the dummy variable is to allow for addiction tests to be run for these users separately. This approach is to be followed in case the regression including all users indicates that a trend of addiction cannot be identified within the population as a whole. As described in Chapter II, addiction models can be adjusted to account for the fact that some people are more inclined to becoming addicted to a certain product than others, depending on the product characteristics and other factors.

Another dummy variable, named “addict,” provides similar information on the users. Users who have visited the webpage for at least three random two-week periods are clustered into this group. The purpose of this dummy is the same as of the dummy described in the previous paragraph. The new variable, however, sets a higher benchmark on which consumers should be tested for addiction.

Alternative high benchmarks for testing addiction only within a group of users are set through the levels of total consumption over the time frame of this study. The users who are ranked within the top 5% and 1% in terms of total consumption are also tested for addiction. No variables are introduced to differentiate them.

Transforming the data into a panel

To allow for more precise estimates, the data is transformed into a panel (table 3.2). Using a long format, it is possible to analyze the whole population of users in the USA who use the website over the three months. The panel format which is introduced in table 3.2 also allows for an analysis of the differences across time periods and individuals.

Therefore, a panel format provides a higher statistical capacity for research when the number of individuals or groups is high. The format is also appropriate when the individual or group factors, not accounted for explicitly through other new variables, are strong. Thus, additional precision is achieved in this research through reformatting the data into a panel.

A Hausman test is performed to compare the precision of a random-effects model to a fixed-effects model. Based on the result, a fixed-effects model is implemented in all regressions. The fixed-effects model accounts for the fact that there is a strong individual factor. Each individual behaves differently in a way that strongly affects the final analysis. Hence, the usage of fixed effects can considerably decrease the bias of the regressions' estimators. Naturally, the fact that each individual's behavior is examined through 12 periods is also taken into account.

Data summary

Over the three-month summer period, 136,727 users have logged into the website. The mean consumption for the period is approximately 17 visits per user during the time frame. The minimum number of visits per user recorded in the data is 1 and the maximum is 45903. The standard deviation of the consumption is approximately 131 (table 3.3).

TABLE 3.3

SUMMARY STATISTICS OF THE CONSUMPTION OF SERVICES OFFERED BY GEOCACHING.COM:

Mean	Standard deviation	Minimum consumption over the 3 months	Maximum consumption Over the three moths
17.71439	131.9165	1	45903

Regression models

Table 3.2 from the appendix presents an excerpt from the panel data used in the regression models. Since the data was used to estimate the possibility that addiction patterns occur, the consumption of the website's services was examined thoroughly. In the models, one weeks is taken as a basic period and the consumption over this period is measured. This information is recorded into a basic consumption variable, which is used as a dependent variable in the regressions. A lead variable and two lagged variables of the basic consumption variable are taken as independent variables.

Hence, in table 3.2, as well as in equation 3.1, C_t denotes consumption over a particular (basic) period, C_{t-1} – the consumption over the period preciding t, and C_{t-2} – the consumption two weeks before the basic period. C_{t+1} is the lead variable in the addiction models. Variable Y introduces estimated income. Equation 3.1 represents rational addiction regression for services offered by Geocaching.com:

EQUATION 3.1

RATIONAL ADDICTION MODEL FOR THE SERVICES OF GEOCACHING.COM

$$C_t = \alpha_1 C_{t-1} + \alpha_2 C_{t-2} + \alpha_{12} C_{t+1} + \beta * Y$$

A myopic version of the model can also be implemented. The lead variable from the rational addiction model, $C_{t+1,}$ can be adopted here as a dependent variable. Thus, in this model, all other consumption variables are lagged variables.

Equation 3.2 presents the myopic addiction regression for the services offered by Geocaching.com:

EQUATION 3.2

MYOPIC ADDICTION MODEL FOR THE SERVICES OF GEOCACHING.COM

$$C_{t+1} = \alpha_1 C_t + \alpha_2 C_{t-1} + \alpha_{12} C_{t-2} + \beta * Y$$

Expected outcomes

Based on the characteristics of the coefficients in an addiction regression, the following results are hypothesized.

If the users analyzed are addicted, the alpha coefficients are positive. In literature, the level of addiction is allowed to fluctuate from period to period, which is reflected by fluctuations in the coefficients. This is referred to as the dynamics of an addiction.[4]

[4] Nick Heather. “Choice, Behavioral Economics, and Addiction.” *Elsevier*, (2003): 150-153.

Therefore, no particular trend, such as fading-away addiction indicated by decreasing consumption coefficients, is expected. A weaker dependence between consumption variables which are further away from each other is, therefore, also not expected.

As mentioned above, positive coefficients in front of the consumption variables in an addiction regression indicate addiction. The expected results are that only the top five percent of the users, ranked by consumption, are addicted.

Therefore, a positive relationship between the levels of consumption is expected for the top 5% (and thus, for the top 1% as well). Negative coefficients are expected for the sample as a whole, as the low median value, four visits, suggests many of the users engage in the activity randomly.

The coefficient in front of the income variable is expected to be positive for a normal good and negative for an inferior good, according to the law of demand. Since the activity has features of a normal good, the beta coefficient is expected to be positive.

It is expected that a fixed-effects model, accounting for the strong differences among individuals, will provide more precise estimates for two reasons. First, individuals using the website can have strongly varying time constraints. It is logical to assume that users may need to prioritize differently in terms of the hobby, which can lead to different decision-making processes for the consumers. Second, the time periods are relatively short, which suggests that hidden individual differences, including time constraints and preferences, may become obvious in the research and affect the results.

CHAPTER IV

RESULTS

The purpose of this chapter is to present and interpret the results of the behavioral analysis. The implications of the results are not included in this chapter. Chapter V provides an overview of the conclusions and implications of the results.

This chapter begins with an outline of the assumptions and hypotheses related to the regression models. Next, the chapter provides details on the econometric problems encountered during the study and how those problems were handled. Then, the characteristics of the variables are described. The chapter ends with a description of the regression results.

To estimate the coefficients appropriately, a fixed-effects model is compared to a random-effects model. Next, the more precise approach is implemented in finding the effects of the factors included in the final model.

For this purpose, the behavior of a few groups of consumers, considered to be more likely to classify as addicts, is evaluated separately. Thus, the possibility that only certain users or particular groups of consumers become addicted to the website is carefully examined. Summary statistics facilitates parts of this approach.

Summary of the results

Starting with the assumption that the activity can be analyzed as a hobby or sports activity in which consumers strive to engage every week, the following observations are made: (1) The activity is not equally addictive for each consumer. Individual factors, such as time constraints varying among users, strongly affect the final analysis. (2) The coefficients in front of the lags and leads of the independent variable, which are positive when consumers are addicted to a product, are negative for all final regressions implemented for this study. (3) Importantly, these results are drawn from data which is distributed into weekly periods. It is possible that an analysis involving longer time periods would yield different results and would suggest that an addiction process exists, as literature in the field implies.[1]

Assumptions

Geographical data on the whole country suggests that potential addiction to geocaching can be strongly related to addiction to sports, such as hiking. In addition, urban data reveals many users may choose to engage in the activity while taking casual walks around city areas and parks. For these reasons, geocaching is hypothesized to lead to addiction when it appears as a complementary activity to hobbies and habitual physical exercises, which can also trigger addiction. This suggestion, however, does not exclude the possibility that other types of geocaching addiction are detected through this research.

[1] B.D. Johnson, P..J. Goldstein and N.S. Dudraine. “What is an Addict? Theoretical Perspectives and Emprirical Patterns of Opiate Use.” *Paper presented at the meeting of the Society for the Study of Social Problems*, Boston. 1979.

Athletes and sports addicts often commit to exercising several times a week. People who prefer to dedicate time to less intensive leisure activities are also typically capable of dedicating free time to casual walks in parks, urban, and less-populated areas on a weekly basis. For these reasons, weekly time intervals are assumed to reflect appropriately the habit formation of most geocaching addicts. Thus, the results described below are expected to provide a precise estimation of the coefficients if the hypothesis that geocaching is related to other complementary activities, which consumers to engage in on a weekly basis.

Some of the activities which geographical data suggests users engage in are sports such as scuba-diving and intensive hiking. These sports may require a much longer and more rigorous preparation than a habitual walk in a park or in a relatively urban region. For this reason, it may be impossible to detect addiction trends related to such activities through the model constructed in this paper. Time periods longer than those implemented in this study could better capture such an addiction trend.

The data provided by Groundspeak included approximately 10 months. Thus, the data set poses some restrictions on how long the time intervals used in the analysis can be.

Econometrics problems

Autocorrelation

First order autocorrelation is detected in the consumption levels through a Wooldridge test[2]. This autocorrelation is expected, since it defines the existence of a trend. According to economic theory, addiction is, in essence, the presence of a positive

---

[2] David M. Drukker. "Testing for Serial Correlation in Linear Panel-data Models." *The Stata Journal* 3 no. 2 (2003): 168–177

relationship between the consumption in a given period and the consumption in past and future periods. In other words, addiction is the tendency to wish to consume the product again.

As the literature reviewed in Chapter II suggests, having close friends or relatives consuming drug substances considerably increases the chance that a given individual will decide to engage in the same activities.[3-4] Therefore, it is expected that a (social) trend exists in the regression model and cannot be expressed through introducing new variables when using anonymous data.

In the case of autocorrelation, a fixed-effects regression model is recommended. As described in detail below, cross-sectional variables do provide additional precision for this analysis. Hence, the most appropriate approach to the basic model is a fixed-effects regression.

Unit root

This analysis includes an attempt to implement an Im-Pesaran-Shin unit root test for panel data sets. Nevertheless, restrictions of the panel data studied in this research, do not allow for the test to be implemented. This econometric problem is common in panel data sets.

As described in the next section, the R-squared values of the regressions report a relatively low dependence between addiction-related factors and current consumption. Thus, the regressions do suggest that a large portion of the motives in the consumers'

---

[3] Patrick West, Helen Sweeting and Russell Ecob. "Family and friends' Influences on the Uptake of Regular Smoking From Mid-adolescence to Early Adulthood," *Addiction* 94, no. 9 (1999): 1397–1411.

[4] Jacqueline M. Vink, Gonneke Willemsen, and Dorret I. Boomsma. "The Association of Current Smoking Behavior With the Smoking Behavior of Parents, Siblings, Friends and Spouses," *Addiction* 98, no. 7, (2003) 923–931.

decision-making processes is based on factors which are not available through the anonymous data or are dependant random events.

Collinearity

Collinearity between the cross-sectional fixed effects, implemented in the final analysis, and the income estimation variable, leads to the removal of the income estimation from the final regression models.

The initially proposed control variable in the model is income. As mentioned in Chapter III, this variable is estimated based on the 1999 Census data on the median household income[5] in each state and through the locations at which consumers have geocached.

Therefore, income estimations are generated in a way which makes them dependable on spatial data from the sample but not on time period data. In the case of a random-effects model, the individual factors are considered unimportant. Then, a control variable for income could contribute to the final analysis by examining a particular factor varying among users.

In the final analysis, however, a Hausman test is used to compare fixed-effects and random-effects models for the data. According to the tests, this study, fixed-effects regressions yields more precise estimations of the regression coefficients. Thus, cross-sectional effects are inserted into the model. These fixed effects are collinear with the income estimation variable. The collinearity appears because both factors vary among users, but remain constant for each user in time. Because the fixed effects account for a larger spectrum of individual factors than the estimated income, and because statistical

---

[5] US Census Bureau, 1999. Avalable at: www.census.gov.

analysis indicated a fixed-effects model introduces more precision into the study, the cross-sectional user factors are preferred over the income variable. Thus, the income estimation is eventually excluded from the regression.

Tools for correcting for the econometric problems

Although no control variables are presented in the tables of the final regression results, a few hidden factors compensate for the bias which could result from their absence. As mentioned above, the fixed effects for the individuals account for the differences among users. The individual factors do not only compensate for the removal of the initial control variable, they are the reason for the variable to become unnecessary. Also, fixed effects account for various motives in consumers' decision-making processes, such as flexibility, leisure, hobby preferences, etc.

Additional precision is inserted through analyzing the whole population. Samples of users who have symptoms of addiction are also analyzed. The final analysis compares the results obtained for the whole population with those observed for special groups. These groups cluster consumers who have symptoms of addiction, such as regular usage or excessive usage of the website's services.

As mentioned in the previous chapters, the focus of the study is also carefully chosen to neutralize some differences that may not be easily identified through variables, since the data provided is anonymous. This research encompasses geocaching activities within USA only, thus minimizing cultural and technological differences among users, which an international sample would inevitably contain. As mentioned in previous chapters, the time frame chosen as a basis for this analysis is a three-month summer period. This also minimizes the more sporadic weather conditions which vary across states in other seasons.

Characteristics of the variables

The following tables provide summary statistics of the data. Table 4.1 presents the number of users included in the major groups into which users are categorized. Table 4.1 also reveals the minimum consumption per user for each group.

TABLE 4.1

CONSUMPTION LEVELS FOR THE DIFFERENT GROUPS OF USERS:

Group	Number of users included	Min. Consumption
All users	136,727	1
“Addicted”	39,629	7
“Addict”	24,592	7
Top 10%	13672	45
Top 5 %	6836	79
Top 1%	1,368	178

The consumption of the upper half of the users (ranked by consumption), represented by the median consumption value for the whole population, is 4 or more visits. The top 10% of the users, ranked in terms of consumption, have visited the website 45 times or more. The top 5% have used the website at least 79 times over the summer. The top 1% have visited Geocaching.com more than 178 times for the 12 weeks.

Table 4.2 presents a consolidated description of the variables used in the regressions:

TABLE 4.2

CONSOLIDATED DESCRIPTION OF THE VARIABLES

Variable Notation	**Definition**	**Measure**
Con_t	Consumption at time t	Number of visits on the website by a user
Con_{t-1}	Consumption at time t-1	Number of visits on the website by a user
Con_{t-2}	Consumption at time t-2	Number of visits on the website by a user
Con_{t+1}	Consumption at time t+1	Number of visits on the website by a user

The variables described in the table above represent consumption levels in a structure which relates each calendar week to other adjacent time periods to analyze how the consumption in a chosen period is dependent on the consumption of three other periods. For example, in a a regression, when the independent variable takes the value of the consumption over the sixth period, the consumption over the seventh period is considered to be $Con_{t+1.}$ Then, the measures of past consumption, Con_{t-1} and Con_{t-2}, are taken from the fifth and fourth period.

Regressions

The following tables describe the results from the regression models utilized in this study. As mentioned above, the control variable providing an estimation of a user's income is removed from the regressions and a few econometric tools and approaches are used to correct for the bias which can occur. The remaining variables are past and/or future desired consumption.

Since the regression is run on a panel data set, with fixed effects, the within R-squared is reported in the tables. Standard errors are estimated through the robust clustered variance estimator.

The results of six regression models are reported in this chapter. The first regression tests all users of Geocaching.com for behavioral patterns of addiction (table 4.3.). The two groups named “addicted” and “addict,” described in detail in Chapter III, are researched separately (table 4.4 and table 4.5). Both groups consist of users who have been using Geocaching.com on a regular basis.

The users who rank in the top 5%, in terms of consumption of the services offered by Geocaching.com, and belong to the group named “Addict,” are analyzed separately. The results of this regression are described in table 4.6. The top 1 % users, who also belong to the group called “Addict” are also analyzed as an independent group (results in table 4.7)

All of the above-mentioned regressions are based on the economic rational addiction model. The regression results represented in table 4.8 describe the only myopic addiction model tested in this research. It studies exclusively consumers ranked in the top 1% in terms of consumption, who have also evinced symptoms of addiction and were thus included into the group “addict.”

TABLE 4.3

ALL USERS, RATIONAL ADDICTION MODEL

Regression	**Number of Users Included**	**Features**			
All users	136,727	Fixed effects, Robust clustered variance estimator			
	Dependent Variable	**R-squared**	**Constant**		
	Con_t	0.075	2.53		
	Independent Variables	**Coefficients**	**T-statistics**	**P-Values**	**Standard Errors**
	Con_{t-1}	-0.18	-16.93	0.00	0.01
	Con_{t-2}	-0.19	-22.35	0.00	0.008
	Con_{t+1}	-0.19	-28.65	0.00	0.006

TABLE 4.4

GROUP “ADDICTED,” RATIONAL ADDICTION MODEL

Regression	**Number of Users Included**	**Features**			
Group “Addicted”	39,629	Fixed effects, Robust clustered variance estimator			
	Dependent Variable	**R-squared**	**Constant**		
	Con_t	0.075	6.14		
	Independent Variables	**Coefficients**	**T-statistics**	**P-Values**	**Standard Errors**
	Con_{t-1}	-0.18	-17.35	0.00	0.01
	Con_{t-2}	-0.19	-22.28	0.00	0.008
	Con_{t+1}	-0.19	-30.49	0.00	0.006

TABLE 4.5

GROUP “ADDICT,” RATIONAL ADDICTION MODEL

Regression	**Number of Users Included**	**Features**			
Group “Addict”	24, 592	Fixed effects, Robust clustered variance estimator			
	Dependent Variable	**R-squared**	**Constant**		
	Con_t	0.076	6.72		
	Independent Variables	**Coefficients**	**T-statistics**	**P-Values**	**Standard Errors**
	Con_{t-1}	-0.18	-19.59	0.00	0.009
	Con_{t-2}	-0.19	-23.78	0.00	0.008
	Con_{t+1}	-0.19	-36.42	0.00	0.005

TABLE 4.6

TOP 5% AND INCLUDED IN GROUP “ADDICT,”
RATIONAL ADDICTION MODEL

Regression	**Number of Users Included**	**Features**			
Top 5%, “Addict”	4,377	Fixed effects, Robust clustered variance estimator			
	Dependent Variable	**R-squared**	**Constant**		
	Con_t	0.076	22.8		
	Independent Variables	**Coefficients**	**T-statistics**	**P-Values**	**Standard Errors**
	Con_{t-1}	-0.18	-20.46	0.00	0.009
	Con_{t-2}	-0.19	-24.83	0.00	0.007
	Con_{t+1}	-0.19	-38.99	0.00	0.005

TABLE 4.7

TOP 1% AND INCLUDED IN GROUP "ADDICT,"
RATIONAL ADDICTION MODEL

Regression	**Number of Users Included**	**Features**			
Top 1%, "Addict"	1,084	Fixed effects, Robust clustered variance estimator			
	Dependent Variable	**R-squared**	**Constant**		
	Con_t	0.077	46.17		
	Independent Variables	**Coefficients**	**T-statistics**	**P-Values**	**Standard Errors**
	Con_{t-1}	-0.18	-22.86	0.00	0.008
	Con_{t-2}	-0.19	-27.19	0.00	0.007
	Con_{t+1}	-0.19	-47.28	0.00	0.004

TABLE 4.8

TOP 1% AND INCLUDED IN GROUP "ADDICT,"
MYOPIC ADDICTION MODEL

Regression	**Number of Users Included**	**Features**			
Top 1%, "Addict" (myopic version)	1,084	Fixed effects, Robust clustered variance estimator			
	Dependent Variable	**R-squared**	**Constant**		
	Con_{t+1}	0.08	43.80		
	Independent Variables	**Coefficients**	**T-statistics**	**P-Values**	**Standard Errors**
	Con_t	-0.18	-43.73	0.00	0.004
	Con_{t-1}	-0.19	-25.64	0.00	0.007
	Con_{t-2}	-0.19	-28.88	0.00	0.006

In conclusion, the results show that the lag consumption variables and the lead consumption variable have a significant effect on current consumption. Chapter V presents the conclusions that can be drawn from the analysis and discusses the business implications and opportunities for future research in the field.

CHAPTER V

CONCLUSIONS

The purpose of this chapter is to discuss the implications of the results reported in chapter IV and to provide suggestions for further research related to the study described in Chapters II and IV. Chapter V begins with a summary of the conclusions. Then, the results are evaluated in detail and are juxtaposed against the findings of other studies in the area. Next, suggestions are made on what business strategies could be beneficial for Geocaching.com and for conducting further research in the area. Specific examples of business approaches and research possibilities are given.

The following observations represent economically important conclusions:

1) Information on the lags and leads of the independent consumption variable is important in predicting the demand for the product. This conclusion follows from the observation that all consumption variables are significant elements in the regression models.
2) The negative coefficients in front of the independent consumption variables suggest that the population of US users of the website Geocaching.com, is, as a whole, not addicted to the activities facilitated by the website.
3) With the assumptions made in this research, it is concluded that the group identified to bear the largest likelihood of experiencing addiction is also not addicted to the product. This group consists of consumers who are ranked

within the top 1%, in terms of consumption of the services of Geocaching.com and who visit the webpage on a regular basis.

4) Literature from the field suggests that, given a different choice of time frame and length of the time periods, the results and their conclusions can alter drastically.

5) The low R-squared reveals that there is an array of factors, such as free time available, schedule flexibility, and personal preferences, which are not available through the anonymous data but play an important and decisive role in the decision-making process of a consumer.

6) The individual effects are important in the analysis, which also leads to the conclusion that the product analyzed cannot be equally addictive for every consumer. Since the individual factors have a large effect on the consumption, different business approaches can exist towards specific groups of consumers or separate individuals.

Based on the conclusions listed above, the following future business and research approaches are suggested:

i. The anonymous data recorded on the website gives little information which can be used to create differentiated and narrowly targeted marketing policies. Thus, a development of the website in a direction which makes it resemble a social network platform and allows users to upload more information about themselves, their hobbies, and their preferences, would improve the marketing services available through Geocaching.com. In addition, such an expansion would allow Groundspeak to gather more information to conduct further behavioral and marketing research on the users.

ii. The anonymous data can be used to construct a model utilizing longer time periods and compare the results with the findings of this study.

iii. The anonymous data can be used to construct a model which includes a more detailed geographical analysis and/or provides conclusions on the factors which affect the performance of the website internationally.

Evaluating the results

All dependent consumption variables are significant in this research. Empirically, studies conducted on substance and sports addiction prove that knowledge of previous (and future desired) consumption can provide valuable information in estimating how much an individual would choose to consume a product or engage in a hobby in a given period. The high significance of the consumption variable is thus expected.

Neither the population of US users, nor the sample of users evincing features of addiction, tested positive for addiction through the regressions. This result has two implications.

The possibility of rare addiction cases

First, it is possible that the condition of addiction exists only in extremely unusual cases, for example, in 50 people from the population of 136,727 registered users. In this case, information on addicted users would be practically useless for the company managing Geocaching.com.

Data on regular users does, however, have value in differentiating marketing policies. While addicted users have a stronger impetus to continue using the services of the website than a group of regular customers, the latter group can still be subject to a special marketing policy.

The possibility of an incorrect assumption regarding the time frame

It is possible that the initial assumption made in this study was incorrect and the length of time periods utilized in this research was too small. This study begins with the suggestion that since it is expected that potential addiction to geocaching is dependent on addiction to sports and outdoors leisure activities, which can be undertaken on a weekly basis, then the potential addiction to geocaching itself should be studied through weekly periods.

An example of why addiction to sports and outdoor activities can be appropriately studied through weekly periods is found in the organization of varsity and club sports in schools and club centers, offering sports activities such as martial arts, dancing, aerobics, etc. Individuals joining athletic teams and sports centers are usually expected to commit to participating in the activity on a weekly basis.

Nevertheless, it is possible that the users of geocaching.com experience addiction patterns which need to be studied through longer time spans. Activities related to geocaching, such as hiking and very long walks in urban or non-urban areas, may take up more of the free time of a consumer. Hence, geocaching activities may not always be an option of how consumers can spend their leisure time every week. Also, some activities, such a s hiking or scuba-diving may require longer preparation and a greater financial commitment, which is why it is possible that even when addicted to such sports, consumers can only practice them in rare occasions.

Literature on addiction and behavioral patterns suggests that a change in the length of the time periods, through which addiction is analyzed, can drastically change the results and reveal valuable information on the habit formation of such behavioral patterns. For example, many addicts abusing highly addictive drug substances may choose to receive a dosage of the drug a few times a week, but they may decide not to consume it on a daily basis.[47] Thus, it is possible that a study of the behavioral patterns of the users of the website Geocaching.com reveals different results when longer time periods are used. Therefore future research in the field utilizing alternate time periods may identify a group of addicted consumers.

The influence of a trend

Research on the factors which affect the formation of an addiction suggests that the social environment of an individual has a large effect on his or her decision to engage in or abstain from drug substances.[48-49] Therefore, the existence of a trend in the community to engage in or not engage in an activity, such as geocaching, is an important factor in the formation of a group of addicted users.

---

[47] B.D. Johnson, P..J. Goldstein and N.S. Dudraine. "What is an addict? Theoretical perspectives and emprirical patterns of opiate use." *Paper presented at the meeting of the Society for the Study of Social Problems,* Boston. 1979.

[48] Ptrick West, Helen Sweeting and Russell Ecob. "Family and friends' Influences on the Uptake of Regular Smoking From Mid-adolescence to Early Adulthood," *Addiction* 94, no. 9 (1999): 1397–1411.

[49] Jacqueline M. Vink, Gonneke Willemsen, and Dorret I. Boomsma. "The Association of Current Smoking Behavior With the Smoking Behavior of Parents, Siblings, Friends and Spouses," *Addiction* 98, no. 7, (2003) 923–931.

Through the anonymous data on the users of Geocaching.com, information on the details of the social interaction among users is not available and the direct influence of factors, such as how many other users who play the game are related to a given consumer registered on the website, is not available.

Consumer decision-making processes

The low R-squared reported in the regression tables implies that factors which vary among individuals, such as free time, flexibility, and social influence can have a large effect on the consumers' decision-making processes regarding the website. Also, since the individual features are important factors in the addiction model, in principle, geocaching is not an activity equally addictive for every user.

Business strategy implications

Expanding the website as a social platform

Since the anonymous user data set imposed restrictions on how much is known about the behavior of the users and how much information can be used in modeling their rational consumer choices, a successful strategy in differentiating the marketing policies would include an expansion of what information users can upload onto their profiles.

Expanding the user profiles: advantages

First, this strategy can make users more engaged in the website and show a greater commitment to the activity. Consumers will be able to connect with each other more and perceive the website not only as a service location but a virtual location for social interaction. Thus, the website will be able to benefit from social influence motivating users to express a higher commitment.

Second, users will be able to choose to provide more information about themselves, which would facilitate differentiating the marketing policies and conducting further research. Additional information, such as the field of work of the individual, or the hobby preferences the consumer has, is important for the marketing policies and further behavioral analysis. For example, a group of people who enjoy intensive hiking may strive to engage in geocaching and hiking regularly on a monthly, or even yearly, rather than on a weekly basis. Knowing what the individual’s time constraints may be, varying by occupation, can also provide a basis for choosing the length of the time period appropriately.

In addition, advertisements can be streamed differently on the website depending on the information available on the individual. Websites, such as Google and Facebook are able to utilize information on users’ preferences in order to choose what kind of advertisements appear on the website, depending on who the user is. Google utilizes information on what key words customers input in their searches and allows customers to choose whether or not demographic information is used for streaming special commercials or not.[50]

Facebook, on the other hand, can base the marketing differentiation on what users officially declare they are interested in, in the respective fields in their profile. Similarly, information on users likings, uploaded voluntary by the consumers themselves, and information on what geographical locations the users choose to geocache at, can be

[50]Google Inc. Google.com. Copyright © 2011
http://mail.google.com/support/bin/answer.py?hl=en&ctx=mail&answer=1217362

combined and used to differentiate marketing policies. For example, if a group of consumers define themselves as scuba-divers and choose to explore geocaching locations on the coast, it may be logical if they are more interesting in commercials providing information on specialized equipment related to swimming, diving, etc.

While users themselves can benefit from streamed marketing, companies will also prefer to advertise through Geocaching.com if they are guaranteed that a high percentage of the people who view the specialized commercials are interested in the advertised products. Also, given personalized information, Groundspeak can evaluate how specialized the activities complementing the geocaching activities are.

For example, it is possible that while many of the users of the webpage choose to often engage in geocaching as they hike, only few would geocache on the coast on a regular basis. In this case, a successful marketing policy will include advertisements of Geocaching.com in stores and on websites selling hiking equipment, but not in stores which offer equipment related to swimming, diving, or maintaining a boat. For example, posters and other marketing materials can be sent to stores which offer equipment in which users of Geocaching.com may be interested.

Consumers may choose to provide more personalized information on a social platform to expand their social interaction. If provided with the space to do so, users may choose to upload information on what movies they like, among other things. Thus, a differentiated marketing policy derived from an expansion of the website will not necessarily apply only to specialized products related to sports and hobbies.

Consumer advocacy and companies' involvement

Successful business strategies can include an expansion of the website in other directions, as well. One of the important values of online marketing is its enormous potential to provide an opportunity for consumer advocacy. The latter term refers to consumers' inclination to discuss brands, companies and various products on the internet and to recommend some of these to other users, thus giving way to one of the most powerful tools in marketing – the word of mouth.

In addition, online marketing policies can allow companies to actively participate in social platforms. Some firms choose to issue a poll or a game onto websites such as Facebook to increase the popularity of a product. Also, companies and public figures are usually allowed to create their own pages on such social platforms.

One business strategy which will allow companies to become active on the webpage Geocaching.com provides firms with an opportunity to create a forum, a group, or a page on the website.

Companies could, therefore, engage in the website through organizing company-sponsored geocaches. For example, firms could issue information on the website of geocaches where a few products being sold by the company are hidden and update the information when they are substituted with regular caches after they have been found. This will allow companies to motivate consumers to show how much they are fond of a brand. For example, if a company selling computer games hides geocaches of computer games in places which require intensive hiking or are simply hard to find, the firm will be able to persuade consumers that some users are willing to dedicate a lot of time or effort to finding the product because the product is worth this opportunity cost.

Cross-marketing

Given the directions of suggested expansions for the website, outlined above, Geocaching.com could undertake a cross-marketing approach together with other websites, which are already in the format of social platforms. For example, geocaching could be advertised through websites such as Youtube and Twitter, through videos and news.. Information on how these can be accessed can be then posted on Geocaching.com.

Further research

As mentioned in the sections above, approaches to further research on the topic may include a study utilizing longer time periods, combining geographical data with data on consumption patterns, and extending data through new personalized information on the users, if possible.

Therefore, new studies in the field can extend the time frame of the analysis, including, for example, a winter period, to capture the effect of weather differences. In addition, further research can be conducted to compare geocaching activities in various countries, measuring the effect of technology, climate, and others.

The new marketing niche created by Groundspeak gives researchers and business analysts an interesting viewpoint on what business can do with the resources now available through internet and GPS technology. Geocaching.com is a pioneer in implementing GPS services into leisure activities and hobbies and its business model provides an insight into consumer choice and consumer behavior in this and similar market niches.

APPENDIX

Table 3.1. ANONYMOUS USER DATA. SOURCE: GROUNDPEAK.

logid	logtypeid	logtype	accountid	datevisit	cacheid	cachetypei	cachetype	cachelat	cachelon	objectid
4669****	2	Found it	156****	7-Aug-10	18128	4	Virtual Caches	39.777	-94.867	31
7189****	2	Found it	229****	15-Aug-10	55472	4	Virtual Caches	44.428	-86.247	129
7452****	2	Found it	242****	28-Jul-10	935108	2	Traditional Caches	39.152	-84.663	188
7036****	2	Found it	174****	19-Aug-10	1015889	8	Unknown (Mystery) Caches	44.349	-89.089	202
8459****	2	Found it	232****	3-Aug-10	276765	3	Multi-caches	38.995	-94.263	284
8094****	2	Found it	240****	1-Aug-10	1042438	2	Traditional Caches	42.213	-85.785	389
8946****	2	Found it	268****	25-Aug-10	1317430	5	Letterbox Hybrids	35.165	-101.864	463
8996****	2	Found it	248****	25-Jul-10	1407545	2	Traditional Caches	42.784	-96.175	496
8647****	2	Found it	248****	25-Jul-10	1407632	2	Traditional Caches	42.784	-96.166	498
8996****	2	Found it	248****	25-Jul-10	1407672	2	Traditional Caches	42.776	-96.18	499

TABLE 3.2.

PANEL FORMAT OF THE USER-CONSUMPTION DATA USED IN THE REGRESSION MODELS. SOURCE: GROUNDSPEAK

accountid	week-number	lump-sum	consumption	mhi	addicted	addict	con_t	con_tminus1	con_tminus2	con_tplus1
*500***	1	139	3	55146	1	1	3	-	-	16
*500***	2	139	16	55146	1	1	16	3	-	16
*500***	3	139	16	55146	1	1	16	16	-	12
*500***	4	139	12	55146	1	1	12	16	16	54
*500***	5	139	54	55146	1	1	54	12	16	5
*500***	6	139	5	55146	1	1	5	54	12	12
*500***	7	139	12	55146	1	1	12	5	54	8
*500***	8	139	8	55146	1	1	8	12	5	0
*500***	9	139	0	55146	1	1	0	8	12	0
*500***	10	139	0	55146	1	1	0	0	8	8
*500***	11	139	8	55146	1	1	8	0	0	5
*500***	12	139	5	55146	1	1	5	8	0	
*500***	1	15	0	55146	0	0	0	-	-	0

STATA CODE
(do file)

```
 set memory 1000000
* use "filename", clear
drop if datevisit ==.
sort datevisit
format %td datevisit
format datevisit %tg
* Creating weekly periods
gen week1 = 1 if datevisit < 18421
replace week1 = 0 if datevisit >= 18421
gen week2 = 1 if datevisit >=18421 & datevisit <= 18427
replace week2 = 0 if week2 == .
gen week3 = 1 if datevisit >= 18428 & datevisit <= 18434
replace week3 = 0 if week3 == .
gen week4 = 1 if datevisit >= 18435 & datevisit <= 18441
replace week4 = 0 if week4 == .
gen week5 = 1 if datevisit >= 18442 & datevisit <= 18448
replace week5 = 0 if week5 ==.
gen week6 = 1 if datevisit >= 18449 & datevisit <= 18455
replace week6 = 0 if week6 ==.
gen week7 = 1 if datevisit >= 18456 & datevisit <= 18462
replace week7 = 0 if week7 ==.
gen week8 = 1 if datevisit >= 18463 & datevisit <= 18469
replace week8 = 0 if week8 ==.
gen week9 = 1 if datevisit >= 18470 & datevisit <= 18476
replace week9 = 0 if week9 ==.
gen week10 = 1 if datevisit >= 18477 & datevisit <= 18483
replace week10 = 0 if week10 ==.
gen week11 = 1 if datevisit >= 18484 & datevisit <= 18490
replace week11 = 0 if week11 ==.
gen week12 = 1 if datevisit >= 18491 & datevisit <= 18497
replace week12 = 0 if week12 ==.
drop if datevisit >=18498
* Creating two-week periods
gen p1 = 1 if datevisit < 18428
replace p1 =0 if p1==.
gen p2 = 1 if datevisit >= 18428 & datevisit <= 18441
replace p2 =0 if p2==.
gen p3 = 1 if datevisit >= 18442 & datevisit <= 18455
replace p3 =0 if p3==.
gen p4 = 1 if datevisit >= 18456 & datevisit <= 18469
replace p4 =0 if p4==.
gen p5 = 1 if datevisit >= 18470 & datevisit <= 18483
replace p5 =0 if p5==.
```

```
gen p6 = 1 if datevisit >= 18484 & datevisit <= 18497
replace p6 =0 if p6==.
* Collapsing the observations
collapse (count) logid (sum) week1 (sum) week2 (sum) week3 (sum) week4 (sum) week5
(sum) week6 (sum) week7 (sum) week8 (sum) week9 (sum) week10 (sum) week11 (sum)
week12 (sum) p1 (sum) p2 (sum) p3 (sum) p4 (sum) p5 (sum) p6 (max) mhi, by
(accountid)
* Creating dummies for people who are more likely to be addicted. Thus, we can test
those groups separately.
gen addicted =0
replace addicted = 1 if (p1>0 & p2>0)|(p1>0 & p3>0)|(p1>0 & p4>0)|(p1>0 & p5>0)|(p1
>0 & p6>0)
replace addicted = 1 if (p2>0 & p3>0)|(p2>0 & p4>0)|(p2>0 & p5>0)|(p2>0 & p6>0)
replace addicted = 1 if (p3>0 & p4>0)|(p3>0 & p5>0)|(p3>0 & p6>0)
replace addicted = 1 if (p4>0 & p5>0)|(p4>0 & p6>0)
replace addicted = 1 if (p5>0 & p6>0)
replace addicted = 0 if logid < 7
gen addict = 0
replace addict = 1 if (p1>0 & p2>0 & p3>0)|(p1>0 & p2>0 & p4>0)|(p1>0 & p2>0 &
p5>0)|(p1>0 & p2>0 & p6>0)
replace addict = 1 if (p1>0 & p3>0 & p4>0)|(p1>0 & p3>0 & p5>0)|(p1>0 & p3>0 &
p6>0)
replace addict = 1 if (p1>0 & p4>0 & p5>0)|(p1>0 & p4>0 & p6>0)
replace addict = 1 if (p1>0 & p5>0 & p6>0)
replace addict = 1 if (p2>0 & p3>0 & p4>0)|(p2>0 & p3>0 & p5>0)|(p2>0 & p3>0 &
p6>0)
replace addict = 1 if (p2>0 & p4>0 & p5>0)|(p2>0 & p4>0 & p6>0)
replace addict = 1 if (p2>0 & p5>0 & p6>0)
replace addict = 1 if (p3>0 & p4>0 & p5>0)|(p3>0 & p4>0 & p6>0)
replace addict = 1 if (p3>0 & p5>0 & p6>0)
replace addict = 1 if (p4>0 & p5>0 & p6>0)
replace addict = 0 if logid < 7
* Panel format:
drop p1
drop p2
drop p3
drop p4
drop p5
drop p6
reshape long week, i(accountid) j(weeknumber)
rename week consumption
rename logid lumpsum
xtset accountid weeknumber
* Consumption variables:
gen con1 = consumption if weeknumber ==1
gen con2 = consumption if weeknumber ==2
```

```
gen con3 = consumption if weeknumber ==3
gen con4 = consumption if weeknumber ==4
gen con5 = consumption if weeknumber ==5
gen con6 = consumption if weeknumber ==6
gen con7 = consumption if weeknumber ==7
gen con8 = consumption if weeknumber ==8
gen con9 = consumption if weeknumber ==9
gen con10 = consumption if weeknumber ==10
gen con11 = consumption if weeknumber ==11
gen con12 = consumption if weeknumber ==12
by accountid, sort: egen conw1 = median (con1)
by accountid, sort: egen conw2 = median (con2)
by accountid, sort: egen conw3 = median (con3)
by accountid, sort: egen conw4 = median (con4)
by accountid, sort: egen conw5 = median (con5)
by accountid, sort: egen conw6 = median (con6)
by accountid, sort: egen conw7 = median (con7)
by accountid, sort: egen conw8 = median (con8)
by accountid, sort: egen conw9 = median (con9)
by accountid, sort: egen conw10 = median (con10)
by accountid, sort: egen conw11 = median (con11)
by accountid, sort: egen conw12 = median (con12)
* Coding consumpion in terms of t
gen con_t = conw1 if weeknumber ==1
replace con_t = conw2 if weeknumber ==2
replace con_t = conw3 if weeknumber ==3
replace con_t = conw4 if weeknumber ==4
replace con_t = conw5 if weeknumber ==5
replace con_t = conw6 if weeknumber ==6
replace con_t = conw7 if weeknumber ==7
replace con_t = conw8 if weeknumber ==8
replace con_t = conw9 if weeknumber ==9
replace con_t = conw10 if weeknumber ==10
replace con_t = conw11 if weeknumber ==11
replace con_t = conw12 if weeknumber ==12
gen con_tminus1 = conw1 if weeknumber ==2
replace con_tminus1 = conw2 if weeknumber ==3
replace con_tminus1 = conw3 if weeknumber ==4
replace con_tminus1 = conw4 if weeknumber ==5
replace con_tminus1 = conw5 if weeknumber ==6
replace con_tminus1 = conw6 if weeknumber ==7
replace con_tminus1 = conw7 if weeknumber ==8
replace con_tminus1 = conw8 if weeknumber ==9
replace con_tminus1 = conw9 if weeknumber ==10
replace con_tminus1 = conw10 if weeknumber ==11
replace con_tminus1 = conw11 if weeknumber ==12
```

```
gen con_tminus2 = con1 if weeknumber ==3
replace con_tminus2 = conw2 if weeknumber ==4
replace con_tminus2 = conw3 if weeknumber ==5
replace con_tminus2 = conw4 if weeknumber ==6
replace con_tminus2 = conw5 if weeknumber ==7
replace con_tminus2 = conw6 if weeknumber ==8
replace con_tminus2 = conw7 if weeknumber ==9
replace con_tminus2 = conw8 if weeknumber ==10
replace con_tminus2 = conw9 if weeknumber ==11
replace con_tminus2 = conw10 if weeknumber ==12
gen con_tplus1 = conw2 if weeknumber ==1
replace con_tplus1 = conw3 if weeknumber ==2
replace con_tplus1 = conw4 if weeknumber ==3
replace con_tplus1 = conw5 if weeknumber ==4
replace con_tplus1 = conw6 if weeknumber ==5
replace con_tplus1 = conw7 if weeknumber ==6
replace con_tplus1 = conw8 if weeknumber ==7
replace con_tplus1 = conw9 if weeknumber ==8
replace con_tplus1 = conw10 if weeknumber ==9
replace con_tplus1 = conw11 if weeknumber ==10
replace con_tplus1 = conw12 if weeknumber ==11
drop conw1
drop conw2
drop conw3
drop conw4
drop conw5
drop conw6
drop conw7
drop conw8
drop conw9
drop conw10
drop conw11
drop conw12
drop con1
drop con2
drop con3
drop con4
drop con5
drop con6
drop con7
drop con8
drop con9
drop con10
drop con11
drop con12
xtset accountid weeknumber
```

```
set matsize 800
* Hausman test
xtreg con_t mhi con_tminus1 con_tminus2 con_tplus1, fe vce (cluster accountid)
estimates store fixed
xtreg con_t mhi con_tminus1 con_tminus2 con_tplus1 week1 week2 week3 week4
week5 week6 week7 week8 week9 week10 week11 if addict ==1, re
hausman fixed ., sigmamore
* Regression
xtreg con_t mhi con_tminus1 con_tminus2 con_tplus1, fe vce (cluster accountid)
* Test: autocorrelation
findit xtserial
net sj 3-2 st0039
net install st0039
xtserial con_t mhi con_tminus1 con_tminus2, fe vce(cluster accountid)
```

WORKS CONSULTED

Becker, Gary S., Michael Grossman, and Kevin M. Murphy. “Rational Addiction and the Effect of Price on Consumption.” *The American Economic Review* 81, no. 2, (1991): 237-241.

Block, Jerald J. “Internet Addiction.” *American Journal of Psychiatry* 165 (2008): 306-307.

Chaloupka, Frank J. and Rima Nai. “International Issues in the Supply of Tobacco: Recent Changes and Implications for Alcohol.” *Addiction* 95, no.12s4 (2000): 477–489.

Caldwell, Dave. “Modern Treasure Hunts for the Whole Family.” *New York Times,* 2010. Available at:
http://www.nytimes.com/2010/12/10/technology/10geocache.html

Dell, Lynn J. Dell, Mary F. Ruzicka, and Anthony T. Palisi. “Personality and Other Factors Associated with the Gambling Addiction.” *Substance Use & Misuse* 16 no. 1 (1981): 149-156.

Drukker, David M.. "Testing for Serial Correlation in Linear Panel-data Models." *The Stata Journal* 3 no. 2 (2003): 168–177.

Fenn, Aju J. and John R. Schroeter. “Cigarettes and Addiction Information: New Evidence in Support of the Rational Addiction Model.” *Economic Letters* 72, no. 1 (2001): 39.

Fergusson, David, Michael T. Lynskey, and L John Horwood, 2006. “The Role of Peer Affiliations, Social, Family and Individual Factors in Continuities in Cigarette Smoking between Childhood and Adolescence,” *Addiction* 90, no. 5, (2006): 647–659.

Gardner, R. and P.H. Connell. “Opioid Users Attending a Special Drug Dependence Clinic 1968-1969.” *Bulletin on Narcotics* 23, (1971): 9-15.

Goldman, David, **Gabor Oroszi and Francesca Ducci, 2006. “**The Genetics of Addictions: Uncovering the Genes,” *American Psychiatric Association* 4 (2006): 401-415.

Google Inc. Google.com. Copyright © 2011
http://mail.google.com/support/bin/answer.py?hl=en&ctx=mail&answer=1217362

Griffiths, Mark . “Does Internet and Computer "Addiction" Exist? Some Case Study Evidence.” *CyberPsychology & Behavior* 3, no. 2 (2000): 211-218.
Groundspeak, Geocaching.com. Factsheet, Copyright © 2000-2011. Available at: http://www.geocaching.com/articles/Brochures/footer/FactSheet_GeocachingCom.pdf

Heather, Nick. “Choice, Behavioral Economics, and Addiction.” *Elsevier*, (2003): 150-153.

Hill, Shawndra, Foster Provost, and Chris Volinsky. “Network-Based Marketing: Identifying Likely Adopters via Consumer Networks.” *Statistical Science* 21, no. 2 (2006): 256-276.

Hyman, Steven E. and Robert C. Malenka “Addiction and the Brain: The Neurobiology of compulsion and its persistence.” *Nature Reviews Neuroscience* 2 (2001): 695-703.

Johnson, B.D., P..J. Goldstein and N.S. Dudraine. “What is an Addict? Theoretical Perspectives and Emprirical Patterns of Opiate Use.” *Paper presented at the meeting of the Society for the Study of Social Problems*, Boston. 1979.

Kamen, Gary. “Foundations of Exercise Science.” *Lippincott Williams & Wilkins*, (2001): 227- 229.

Kozinets, Robert V.. “The Field Behind the Screen: Using Netnography for Marketing Research in Online Communities.” *Journal of Marketing Research* 39 no.1 (2002): 61-72.

Li, Chuan-Yun, Xizeng Mao, and Liping Wei. “Genes and (Common) Pathways Underlying Drug Addiction.” *PLoS Comput Biol* 4, no.1 (2008) Available at: http://www.ploscompbiol.org/article/info%3Adoi%2F10.1371%2Fjournal.pcbi.0040002

Lieberman , Marvin B. and David B. Montgomery. “First-Mover Advantages.” *Strategic Management Journal* 9, Special Issue: Strategy Content Research.(1988): 41-58.

Nagle, Jeanne. “Everything you Need to Know about Drug Addiction.” *The Rosen Publishing Group*, (1999): 22.

Narayanan , Suresh and Balasingam Vicknasingam. “Responses to the Illicit Drug Problem: Insights from Supply and Demand Analysis.” *Australian Economic Review* 43, no. 1 (2010): 88–99.

Pierce, Edgar F., Myra L. Daleng, and Robert. W. McGowan “Scores on Exercise Dependence among Dancers.” *Perceptual and Motor Skills* 76, no. 2 (1993): 531-535.

Schwartz, Paul M., Ronald D. Lee, and Ira Rubinstein.”Data Mining and Internet Profiling: Emerging Regulatory and Technological Approaches.” *Law and Technology*

Scholarship, Berkeley Center for Law and Technology, UC Berkeley (2008). Available at: http://escholarship.org/uc/item/2zn4z6q4

Stephen, Andrew T. and Olivier Toubia. "*Deriving Value from Social Commerce Networks*." *Journal of Marketing Research* 47, no. 2 (2010): 215-228
US Census Bureau, 1999. Available at: www.census.gov.

Vink, Jacqueline M., Gonneke Willemsen, and Dorret I. Boomsma. "The Association of Current Smoking Behavior With the Smoking Behavior of Parents, Siblings, Friends and Spouses." *Addiction* 98, no. 7, (2003) 923–931.

Winick, Charles. "Maturing Out of Narcotic Addiction," *Bulletin on Narcotics* 14, no.1 (1962): 1-7.

Waldorf, Dan. "Life without Heroin: Some Social Adjustments during Long-Term Periods of Voluntary Abstention." *Social Problems Journal* 18, no. 2 (1970) 228-243.

West, Ptrick, Helen Sweeting and Russell Ecob. "Family and friends' Influences on the Uptake of Regular Smoking From Mid-adolescence to Early Adulthood," *Addiction* 94, no. 9 (1999): 1397–1411.