Cache Me If You Can: Rational Addiction To The Leisure Activity Of Geocaching

Kristina Shoyleva* and Daniel K.N. Johnson**

Abstract

This paper tests whether geocaching, a real-world treasure hunt activity using GPS devices and clues provided by other participants, can be modeled as an addictive pursuit. Using over 36 million online activity logs posted by more than 675,000 users in 2010, we find strong evidence that the activity follows a pattern of rational addiction. The result has implications not only for this activity, but for a host of other social activities that increasingly blur the edges between online and real-world communities and activities.

Keywords: addiction, geocaching, online, rational, myopic

I. Introduction

Geocaching is a new but popular activity that is best described as a modern-day treasure hunt. Participants hide containers for other players to find, noting the latitude and longitude on a dedicated website maintained by member subscription fees. Containers (known as caches) range from tiny pill bottles to full-sized garbage cans, and are similar only in that they represent a 'find' for the retrieving player who signs their name on the enclosed logbook. At their discretion, players (or cachers) may log their finds on the website as well, and often take that opportunity to post notes about the location, about their challenges in retrieving or locating the cache, or about their traveling companions. Many caches contain 'swag' or loot left by previous players (ranging from mp3 players to commemorative pins to toy cars and bottle caps). Other caches include 'travel bugs', items that are electronically tagged and request that the finder move it to the next cache and note its movement on the website. Some caches are encoded with complicated ciphers and riddles, while some require players to find an item in each of the fifty states). Some caches require the player to be physically present at a particular time, in order to meet other players. In short, the game can be as simple and local, or as complex and global, as the player wishes it to be.

As a pioneer in this hybrid online/real world activity, the company Groundspeak's website, geocaching.com, lists over 1.4 million cache locations, in virtually every nation, and boasts over 4 million registered users (Groundspeak, 2011). It aims to appeal to a varied customer base, from those interested in family-oriented outdoor activity, to active orienteering adventurers. Their strategy of awarding accomplishments with electronic medallions (e.g. a find in a new state, a find on a particular date) and their detailed online public presentation of those accomplishments (e.g. summaries for other users of how many finds each other player found) are similar to the strategies of other social networking activities such as foursquare.com, Gowalla.com and SCVNGR.com. All seem to draw strength from the potentially addictive properties of the activity, making revenues not only by subscription but through advertisers who expect repeated viewing by users, and by sales of ancillary equipment (e.g. GPS units, commemoratives for accomplishments). With the assistance of groundspeak.com, in this paper we test the applicability of rational addiction models to explain the behavioral patterns of their users. The results will be interesting not only for the nascent industry, but for other firms navigating the growing field that bridges online and real-world activity.

II. Literature

Within economics, addiction models traditionally follow one of two paths, a) myopic if the addict's current behavior is highly predictable using past behavior alone, or b) rational if the addict's current behavior takes into account not only past but anticipated future behavior.

Myopic:
$$C_t = \alpha + \beta_1 C_{t-1} + \beta_2 C_{t-2}$$
 (1)
Rational: $C_t = \alpha + \beta_1 C_{t+1} + \beta_2 C_{t-1} + \beta_3 C_{t-2}$ (2)

The assertion is usually made that myopic patterns exist when addict's are unaware of their dependence, while rational patterns reflect a more insightful (albeit still dependent) addict. Addiction is identified as a statistically significant positive value for each β in the tested model.

^{*}Kristina Shoyleva is a graduate of Colorado College, email Kristina.Shoyleva@gmail.com.

^{**}Daniel K.N. Johnson is the Gerald L. Schlessman Professor of Economics and Director of the Innovative Minds Program at Colorado College, 14 Cache La Poudre Street, Colorado Springs, CO, 80903, USA, email djohnson@ColoradoCollege.edu, tel 719-389-6654.

© Centre for Promoting Ideas, USA

Becker and Murphy (1988) introduced the traditional model of addiction, a model subsequently expanded and tested by many scholars including Becker et al. (1991). Dockner and Feichtinger (1993). Orphanides and Zervos (1995), Baltagi and Griffin (2001), Fenn et al. (2001), and Grubert and Köszegi (2001). Clearly, other factors may also play a role, including the price of the activity (Becker et al., 1981; Fenn et al., 2001), genetic and socio-cultural attributes of the potential user (Dell et al., 1981; Goldman et al., 2006; Li et al., 2008), and surrounding environmental factors including peer pressure (West et al., 1999; Vink et al., 2003). The nature of the substance clearly matters as well, but most research has justifiably focused on substance dependencies to tobacco, alcohol and illicit drugs, leaving a fairly disparate literature that tests addiction to leisure activities (and most of that literature focuses on gambling, e.g. Hartley and Farrell, 2002).

For example, Pierce et al. (1993) show that female dancers are more likely to develop an addiction to dancing than other female athletes to the sports they practice. Griffiths (2000) and Block (2008) both demonstrate strong evidence that addictive models hold for internet and computer usage (although Griffiths confirms that verifiable Internet Addictive Disorder, defined as the excessive usage of the internet leading to the deterioration of one's life, is rare). There is a fine line dividing an addict from the business world's goal of the 'loyal customer'. Studies of brand loyalty abound in the marketing literature (e.g. Tsao et al., 2009; Hansen and Singh, 2008), and in fact dovetail nicely with the expanding literature on compulsive buying (e.g. Ridgway et al., 2008). Future research might consider how marketing models apply to the dataset explored here.

III. Data

Groundspeak provided us with data on all finds logged by players between January 1 and November 16 of 2010, representing 36,045,971 records posted by 677,671 players. Included in each record is a unique identifier for the player, the date, the precise geographic coordinates of the find, and some select details about the find (e.g. degree of difficulty of the terrain, degree of challenge in the clues provided). The average player logged 53.2 finds over the sample period, while the median player logged only 9 finds. Clearly, there is a long upper tail to the distribution of players, with almost fifteen percent of players (99,864) logging only once but four players logging in excess of 7000 finds. The most active player logged 10,117 finds during the period. There is great diversity not only in volume, but in frequency of activity. Roughly one percent of all players (8,437) were active in every month of our sample, with 39% (263,972 players) active during only one month. The same pattern is visible at the weekly and daily levels of time aggregation. Sixteen players were active on each and every one of the 319 days in our sample, while 173,061 players (25.5%) were active for one day only.

On days when a player was active, the average player logged 3.92 finds, but the average player was only active on 13.6 days. Furthermore, the activity is prone to 'streaks', i.e. of all active days recorded, 83.1% occurred on a day consecutive to another active day (while clearly the other 16.9% of active days were isolated, without finds on adjacent days). Each of these facts lead us to believe that addiction may be a powerful explanatory model: players tend to be highly active or completely inactive, and active players tend be active for prolonged periods rather than intense and isolated bursts.

IV. Model and estimation

Our model is based on the classical rational addiction model constructed by Becker et al. (1991) as expanded by Fenn et al. (2001). We use no additional control variables, since the use of user-created screen names prevent us from knowing anything about the players other than their activity level, so the equations are estimated as in equations (1) and (2) above, using random-effects and fixed-effects models. We suspect that fixed effects might be more appropriate, allowing effects to reflect the underlying differences between players. In addition, autocorrelation is better treated with fixed effects, and a Hausman test confirms this as the better choice of model. Because the frequency of this addictive activity has not been tested before, we aggregated activity into three different time-based units (days, weeks, and months), testing each variant. Since the data are effectively counts of activity, we also estimated the model using a negative binomial and a Poisson approach.

Finally, we tested our model using only players who are substantially more active than the average player. We did this to allay the concern that a disproportionate level of inactivity (zero usage) in consecutive periods might be swamping the effects that might be seen among truly active players. Specifically, we considered a subset of players who logged more than nine times in a single month (i.e., players who in one month log more than the median player's annual total). All results are corrected for heteroskedasticity using White-corrected robust standard errors. Due to computational constraints, we separated the weekly dataset into four mutually exclusive and exhaustive random samples, each comprised of roughly 170,000 players (and therefore, roughly 7.5 million observations).

For the same reason, we separated the daily dataset into 20 mutually exclusive and exhaustive random samples, each of 24,000 players (and therefore roughly 7.5 million daily observations). Analyses on each sample confirm the same results as those presented below.

V. Results

Virtually every test showed the same results, as shown in Table 1, namely universally strong evidence of rational addiction. Lagged and future activity predict current activity whether we use fixed or random effects, daily or weekly or monthly units of analysis, normal or negative binomial or Poisson distributions, all players or only active players. Table 2 presents the same estimation, considering only the previously defined active sample of players, with virtually identical coefficient estimates. The myopic model (not presented here), fits almost as well, universally confirming addiction but unsurprisingly with slightly lower predictive power.

The only exception is the monthly analysis, which consistently shows strong evidence of rational addiction with a single lag (whether the second lag coefficient is included in the analysis or not), but consistently shows a small but statistically significant negative second lag. That result does not change appreciably when monthspecific indicator variables are used to control for seasonality effects, which we suspected might cause the second lag coefficient to turn negative due to changes in seasons that affect player interest and time availability for the activity. While significant at the individual coefficient and overall model level, the simple addictive explanation proposed clearly explains relatively little of the day-to-day (or week-to-week or monthto-month) variation in each player's activity.

VI. Conclusions

It appears that geocaching, or at least the aspect of it manifested in a player's desire to log their activity online, can be effectively modeled as a rational addiction. That result is unambiguously true whether addiction is measured at the daily, weekly or monthly level, although monthly data seem to have a shorter lag period and therefore more cyclicality involved. In this way, geocaching appears similar to other addictive leisure activities such as gambling or internet usage. While clearly premature to conclude on an appropriate marketing strategy going forward, we would suggest that Groundspeak and other geocaching organizations look to their peers in other addictive leisure industries for ideas. Groundspeak already 'tiers' their players, offering more services to players who play more for a premium membership (as casinos always do). Groundspeak might consider a revenue-sharing or perks-program model for active players, much as gambling establishments offer to frequent visitors.

Obviously, the practice of matching consumer interests with targeted internet advertisements is already in practice (Schwartz et al., 2008), and is evident on the geocaching.com website as well. Since advertising online is often cheaper and more effective that traditional marketing (Kozinets, 2002), an emphasis on wordof-mouth advocacy is frequently beneficial (Hill et al., 2006). Most importantly, Groundspeak (and other purveyors of addictive leisure pursuits) should continue to focus more energy on acquiring new players than on retaining existing players. We have shown not only that the activity is inherently addictive, but that it is virtually equally addictive for highly active players and for the entire population of players. Without more information on marginal costs and revenues, we cannot afford to offer a more specific recommendation.

VII. References

Baltagi, B.J. and J.M. Griffin (2001), "The Econometrics of Rational Addiction: The Case of Cigarettes". Journal of Business & Economic Statistics 19(4): 449-454.

Becker, G.S. and K.M. Murphy (1988), "A Theory of Rational Addiction". The Journal of Political Economy 96(4): 675-700.

Becker, G.S., M. Grossman and K.M. Murphy (1991), "Rational Addiction and the Effect of Price on Consumption". The American Economic Review 81(2): 237-241.

Block, J.J. (2008), "Internet Addiction". American Journal of Psychiatry 165: 306-307.

Dell, L.J., M.F. Ruzicka and A.T. Palisi (1981), "Personality and Other Factors Associated with the Gambling Addiction". Substance Use & Misuse 16(1): 149-156.

Dockner, E.J. and G. Feichtinger (1993), "Cyclical Consumption Patterns and Rational Addiction". The American Economic Review 83(1): 256-263

Fenn, A.J., F. Antonovitz and J.R. Schroeter (2001), "Cigarettes and addiction information: new evidence in support of the rational addiction model". Economic Letters 72(1): 39-45.

Goldman, D., G. Oroszi and F. Ducci (2006), "The Genetics of Addictions: Uncovering the Genes". American Psychiatric Association 4: 401-415.

Griffiths, M. (2000), "Does Internet and Computer "Addiction" Exist? Some Case Study Evidence". CyberPsychology & Behavior 3(2): 211-218.

Groundspeak (2011), Geocaching.com Factsheet. Available at:

http://www.geocaching.com/articles/Brochures/footer/FactSheet_GeocachingCom.pdf

Grubert, J. and B. Köszegi (2001), "Is Addiction "Rational"? Theory and Evidence". The Quarterly Journal of Economics 116(4):1261-1303.

Hansen, K. and V. Singh (2008), "Research Note: Are Store-Brand Buyers Store Loyal? An Empirical Investigation". *Management Science* 54(10): 1828-1834.

Hartley, R. and L. Farrell (2002), "Can Expected Utility Theory Explain Gambling?" *The American Economic Review* 92(3): 613-624.

Hill, S., F. Provost and C. Volinsky (2006), "Network-Based Marketing: Identifying Likely Adopters via Consumer Networks". *Statistical Science* 21(2): 256-276.

Kozinets, R.V. (2002), "The Field behind the Screen: Using Netnography for Marketing Research in Online Communities". *Journal of Marketing Research* 39(1): 61-72.

Li, C.-Y., X. Mao and L. Wei (2008), "Genes and (Common) Pathways Underlying Drug Addiction". *PLoS Comput Biol* 4(1):e2.

Orphanides, A. and D. Zervos (1995), "Rational Addiction with Learning and Regret". *The Journal of Political Economy* 103(4):739-758.

Pierce, E.F., M.L. Daleng and R.W. McGowan (1993), "Scores on Exercise Dependence among Dancers". *Perceptual and Motor Skills* 76(2): 531-535.

Ridgway, N.M., M. Kukar-Kinney and K.B. Monroe (2008), "An Expanded Conceptualization and a New Measure of Compulsive Buying". *The Journal of Consumer Research* 35(4):622-639.

Schwartz, P.M., R.D. Lee and I. Rubinstein (2008), "Data Mining and Internet Profiling: Emerging Regulatory and Technological Approaches". *University of Chicago Law Review* 75(1): 261-285.

Tsao, H.-Y., P.-C. Lin, L. Pitt and C. Campbell (2009), "The Impact of Loyalty and Promotion Effects on Retention Rate". *The Journal of the Operational Research Society* 60(5): 646-651.

Vink, J.M., G. Willemsen and D.I. Boomsma (2003), "The Association of Current Smoking Behavior With the Smoking Behavior of Parents, Siblings, Friends and Spouses". *Addiction* 98(7): 923–931.

West, P., H. Sweeting and R. Ecob (1999), "Family and friends' Influences on the Uptake of Regular Smoking From Mid-adolescence to Early Adulthood". *Addiction* 94(9): 1397–1411.

	Daily units		Weekly units		Monthly units	
Variable	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Constant	0.174	(40.14) ***	0.318	(26.65)***	2.645	(72.45)***
C _{t+1}	0.133	(16.05)***	0.231	(30.54) ***	0.133	(29.62)***
C _{t-1}	0.127	(16.26)***	0.219	(32.75)***	0.312	(50.15)***
C _{t-2}	0.036	(6.47)***	0.121	(30.95) ***	-0.056	(32.18)***
Observations		7,908,833		7,376,048		6,099,039
Player-groups		24,949		171,536		677,671
Adjusted R ²		0.083		0.346		0.386
F-statistic		397.64***		769.07***		1332.71***

Table 1: Rational addiction estimation results, fixed effects, full population

*** represents 99% confidence, ** represents 95% confidence, * represents 90% confidence. The weekly (daily) results represent the third (eighth) of four (twenty-nine) samples but are highly representative of the other samples as well.

Table 2: Rational addiction estimation results, fixed effects, active sample

	Daily units		Weekly units		Monthly units	
Variable	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Constant	0.352	(39.79)***	0.820	(25.64)***	6.365	(72.05)***
C _{t+1}	0.133	(15.99)***	0.234	(30.01)***	0.134	(29.54)***
C _{t-1}	0.128	(16.19)***	0.221	(32.14)***	0.313	(50.00) ***
C _{t-2}	0.036	(6.44)***	0.123	(30.78)***	-0.056	(32.06) ***
Observations		3,748,525		2,539,666		2,376,468
Player-groups		11,825		59,062		264,052
Adjusted R ²		0.076		0.319		0.359
F-statistic		395.05***		755.02***		1326.14***

*** represents 99% confidence, ** represents 95% confidence, * represents 90% confidence. The weekly (daily) results represent the third (eighth) of four (twenty-nine) samples but are highly representative of the other samples as well.