The Rational Addiction, Health Information and Dynamic Demand of Energy Drinks

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[Preliminary and Incomplete]

1. Introduction

During the past decade, there have been increasing health concerns over the consumption of energy drinks. Energy drinks are highly caffeinated beverages and, if consumed excessively, could cause adverse consequences such as anxiety, headaches, nausea, restlessness, and an increase in the risk of hypertension and cardiovascular disease (Nurminen et al., 1999; Nawrot et al., 2003; Heckman, 2010; Mesas et al., 2011). Besides, energy drinks also contain other noncaffeine simulants and additives such as guarana and taurine, which are not fully known for their long-term effects of consumption with caffeine together (Reissig, 2009). The FDA Adverse Event Reporting System (FAERS) reports that more than 300 cases that claim "adverse events" possibly tied to energy drinks or energy shots between 2004 and 2012, including more than 20 extreme cases of death.

Despite the potential negative health effects, energy drink market has grown exponentially. Between 2008 and 2015, the total volume consumption and volume consumption per capita of energy drinks increased with an average annual growth rate of 13.3% and 11.6%, respectively. Males between the age of 18 and 34 years old consume the most energy drinks, and nearly one-third of teens between 12 and 17 years drink them regularly.

The rapid growth and the health concerns give rise to an interesting question: why do consumers make this food consumption decision that is suboptimal from the health perspective? That is if energy drinks have potential adverse health effects, why would consumers consume them more? There are be two possible explanations. First, consumers could be addicted to energy drinks due to the presence of the high caffeine content, which is an addictive psychoactive chemical and

could cause behavioral symptoms such as the inability to quit and use despite harm. Therefore, the addiction behavior would result in repeated and increasing purchases of energy drinks because the current consumption could raise the purchase probability in future. Second, consumers may be unaware of the negative effects of energy drinks due to the lack of health information. Although there have been discussions about the potential health risk of energy drinks, it is only recently that the mainstream media started to report the safety issues of energy drinks widely. Therefore, consumers may ignore or underestimate the "health cost" of consuming them.

Based on these possible reasons, this paper tests addiction behavior in the consumption of energy drinks and estimates the impact of health information on energy drinks' demand using the model of rational addiction. Following the approach of Becker et al (1994), I first test the rational addiction of energy drinks' consumption by estimating the reinforcement effect, which is the influence of past consumption on current consumption. I then quantify the impact of health information on consumption in the framework of rational addiction. The data used is a pseudo-panel of per-capita energy drinks consumption of 206 designated market areas in 48 quarters. Results show there is addiction behavior in consumption of energy drinks. Accessing to more health information negatively affects the consumption of energy drinks even with the existence of addiction behavior, but the effect is decreasing over time.

This study is important for research that evaluates the effects of policies aiming to improve the healthfulness of consumers' diet. Especially for energy drinks, a number of consumer groups are proposing for regulating energy drinks. Ignoring the addiction would lead to inaccurate estimation of short- and long-run responses of consumption to policy changes. Besides, this paper also shed light on the importance of health campaign or public education type of policies in enhancing the consumers' healthy eating behaviors.

2. Model Specification

Following Becker et al (1994), thereafter BGM, I assume the consumer's problem is to maximize the sum of lifetime utility given by:

$$V = \sum_{t=0}^{\infty} \beta^{t-1} U(C_t, C_{t-1}, Y_t, e_t) \quad (1)$$

such that

$$\sum_{t=0}^{\infty} \beta^{t-1}(P_t C_t + Y_t) = A^0 \text{ and } C_0 = C^0 \quad (2)$$

where $\beta = 1/(1+r)$ and r is discount rate, C_t is the volume of energy drinks consumed in period t, C_{t-1} is the volume of energy drinks consumed in period *t-1*, Y_t is the consumption of a non-addictive good and is treated as the numeraire, e_t reflects the impact of measured and unmeasured life-cycle variables on utility, P_t is the price of energy drinks at time t, C^0 is the initial consumption level at time zero. A^0 is the present value of wealth. Assuming the utility function is quadratic and solving the first-order conditions for C_t, then the following first-difference equation is obtained as:

$$C_t = \theta C_{t-1} + \beta\theta C_{t+1} + \theta_1 P_t + \theta_2 e_t + \theta_3 e_{t-1} \quad (3)$$

where current energy drinks consumption is a function of past and future energy drinks consumption, current price. θ measures the effect of an increase in past or future consumption on the current consumption. If θ is positive, forces that increase past or future consumption, such as lower past or future price, also increase current consumption (Becker et al, 1994). Therefore, this is the evidence of addictive behavior. The larger the value of θ, the greater is the degree of reinforcement or addiction.

To empirical implement and estimate the effects of health information, I write a variant of (3) as follow:

$$C_{it} = \delta_0 + \delta_1 C_{it-1} + \delta_2 C_{t+1} + \delta_3 P_{it} + (\gamma_1 + \gamma_2 Trend) * Health_t + \lambda' X_{it} + \alpha_i + \mu_{it} \quad (4)$$

where the subscript *i* denotes the *i* th designated market areas (DMAs) and the subscript t denotes the *t*th quarter. C_{it} is the consumption of energy drinks in *i*th designated market areas at quarter t, P_{it} is the sale weighted price of energy drinks in *i*th designated market areas at quarter t. $Health_t$ is the negative health information of energy drinks at quarter *t*. I use the number of news talking about health concerns about energy drinks at quarter t in the U.S. as a proxy. Because its effect may vary across time, I incorporate the $Trend$ as an interaction term. X_{it} are demographic information of *i*th DMA at quarter t such as the percentage of households having children, the average household income, and the average age of male head et cetera. α_i is the fixed effect of DMA.

To estimate the equation (4), it is worthy to note that C_{it-1} and C_{it+1} are endogenous because e_t affects utility in each period and affects consumption at all dates through the optimizing. Therefore, I use lagged and future prices as instruments following BGM. The estimation is conducted by fixed-effects IV regression.

3. Data

I use Nielsen Consumer Panel Dataset to collect the purchase information of energy drinks, including brand names, prices, package sizes, purchase quantity, and purchase date. The Nielsen Consumer Panel Data represents a longitudinal panel of approximately 40,000-60,000 U.S. households who continually provide information to Nielsen about their households, what products they buy, as well as when and where they make purchases. The data sample in this paper covers the household purchase information from January 1, 2004 to December 31, 2015. Nielsen filters households that do not report their transactions regularly, and periodically adds new households

to replace the ones who leave (Petruzzello, 2015). Therefore, not every household has full purchase records during the sample period, but only around 15% of all households report their transactions regularly. Therefore, instead of using household level data, I construct a pseudo-panel data, the quarterly per-capita volume purchase for every DMAs, to study the consumption patterns of energy drinks in different DMAs over time.[1]

Figure 1 shows the per-capita volume purchase of energy drinks of all DMAs. There is an upward trend for per-capita purchase volume from 2004 to 2015, indicating the potential of addiction because the current consumption could raise the purchase probability in future. To further show evidence of addictive behavior, I made a descriptive analysis following the approach used by Gordon and Sun (2015). They show the evidence of addiction in cigarette using the probability that a purchase quantity of one consumer ($q_{i,t}$) is smaller, equal, or greater than her previous quantity ($q_{i,t-1}$). The probability of increasing purchase quantities for a consumer is $T_i^{-1}\sum_{T_i} I\{q_{i,t-1} < q_{i,t}\}$ where T_i is the number of purchase occasions and $I\{\}$ is an indicator function. Because the rational addiction model implies that addicted consumers are more likely to increase their successive purchase quantities due to the reinforcing effect, the addictive behavior would exist if the probability of increasing purchase quantity will exceed the probability of decreasing purchase quantity. Table 1 shows the descriptive analysis of the addiction of energy drinks. For both household level and DMA level data, the probability of increasing purchase is significantly higher than the probability of decreasing purchase, showing the evidence that consumers are more likely to increase their successive purchase quantities due to the reinforcing effect and the potential of the existence of addictive behavior.

[1] Because the consumption data is unobservable, the purchase information is used instead. The assumption here is consumers consume all energy drinks purchased in a period without stockpiling.

The consumers' demographic information could also influence their rational addition behavior due to the expectation of future. For example, younger unmarried people would consider the future adverse consequences less serious than the older married individuals. Therefore, to use this information, I calculate the average households' demographic characteristics for each DMA. Table 2 shows the information.

Health information is collected from LexisNexis Academic database. I keep the news talking about the health concerns of energy drinks in the U.S.. The quarterly number of news are shown in Figure 2. The number of news increases over time and had a substantial growth after 2010.

4. Results

Since the addiction behavior could be the myopic addiction, in which individuals do not consider the effects of their current consumption on future utility, I first test for the forward-looking behavior. To do that, I regress the current consumption on previous consumption, current price, and future price. The results are shown in the model (1) in Table 3. The previous consumption significantly influences current consumption, indicating the reinforcement effect. More importantly, the coefficient of future price is negative and significant, indicating the future price also significantly affect current consumption. In another word, consumers are not myopic, but forward-looking.

With this evidence, I then run the rational addiction model. Model (3) and model (2) in Table 3 show the results of rational addiction model with and without considering the change in

demographic characteristics. The coefficients of lag consumption and lead consumption are positive and significant for both models. This means consumers are rational addictive when consuming energy drinks. That is, previous consumption will increase the current consumption through reinforcement effect, and consumers also consider the effects of their current consumption on future utility. However, one concern of this results is that the coefficients result in an unreasonable discount value. Grossman and Chaloupka (1998) suggest that it may be caused by the data that is not rich enough to pin down the discount factor with precision. However, with the positive and significant coefficients, the rational addiction model is accepted. As for the demographic characteristics, the consumption is significantly lower when the DMAs have more households having children, being married, having older female heads, and have college-educated female heads.

Lastly, based on the rational addiction model with demographic information, I incorporate the health information into the estimation. Table 4 shows the results. The coefficient of the number of news is significantly negative, indicating an increase of health information, or learning the health risk of energy drinks, negatively influence the consumption of energy drinks. However, this effect is decreasing over time. One possible reason is that consumers are more sensitive to the increase of health information when health information is at a relatively low level, at the beginning of the sample period. With more health information exposure, consumers are less responsive to the additional information.

5. Conclusion

Given the rapid growth of energy drink market and the rising health concerns of excessive caffeine intake, this paper tests addiction behavior in the consumption of energy drinks and estimates the

impact of health information on energy drinks' demand using the model of rational addiction. Following the approach of Becker et al (1994) and using the pseudo-panel of per-capita energy drinks consumption of 206 designated market areas in 48 quarters, I find there is addiction behavior in consumption of energy drinks. Moreover, accessing more health information, or learning the health risk of energy drink, negatively affects the consumption of energy drinks even with the existence of addiction behavior. However, the effect is decreasing over time. This probably caused by the sensitivity of consumers' responses to the increase of health information. That is, with more health information exposure, consumers are less responsive to the additional information. Therefore, policymakers should take into account the addictive behavior of energy drinks consumption when considering potential regulations on energy drinks. In addition, health campaign, or public education type of policies, is important to influence the energy drinks' consumption.

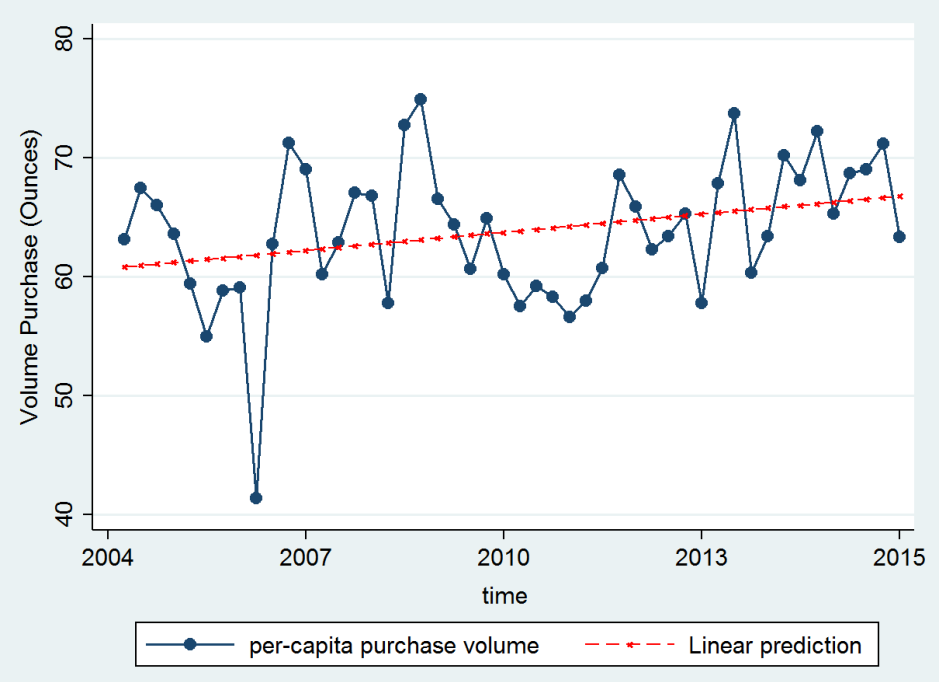

Figure 1. Change of Per-capita Purchase Volume

Table 1. Descriptive Analysis of Addiction Behavior

	Household Level	DMA level
Increasing	0.36	0.54
Decreasing	0.25	0.45
Diff: Increasing-Decreasing	0.11	0.09
t value	57.72	75.87

Table 2. Demographic Information of DMAs

Variables	Mean	Std. Dev.	Min	Max
Percentage of households having children	0.4	0.3	0.0	1.0
Percentage of households married	0.7	0.2	0.0	1.0
Average household income	50833.5	13844.5	4000.0	240000.0
Average age of male head	39.9	10.9	0.0	70.0
Average age of female head	43.5	9.7	0.0	70.0
Percentage of households having male head with college degree	0.5	0.3	0.0	1.0
Percentage of households having female head with college degree	0.6	0.3	0.0	1.0

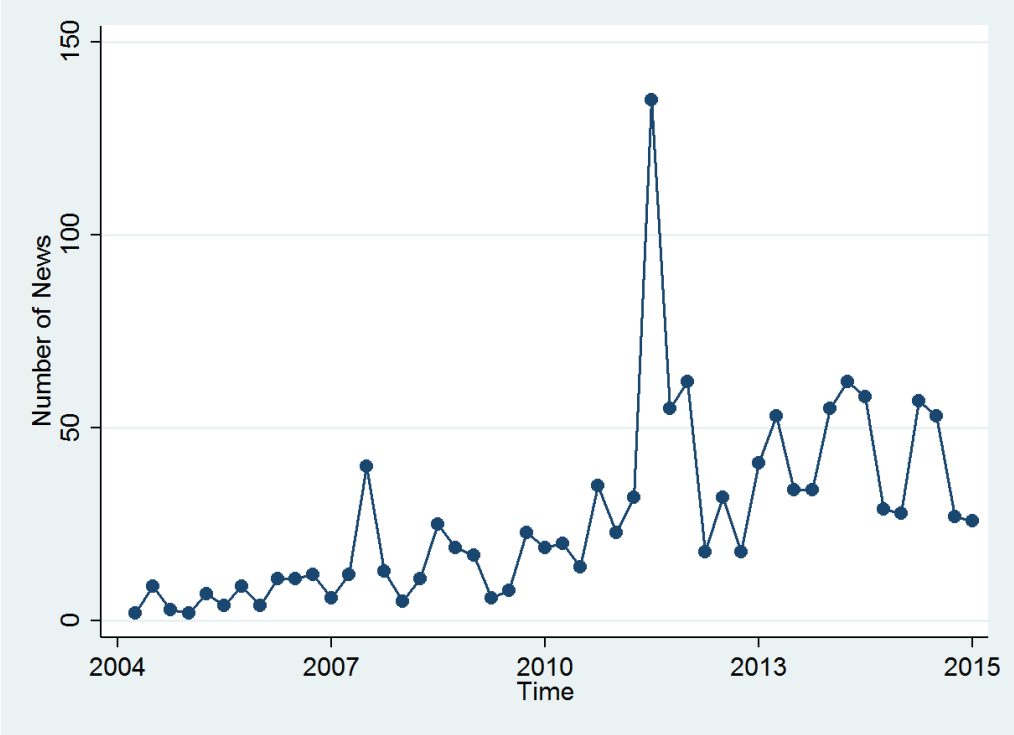

Figure 2. Change of Number of News About Health Concerns of Energy Drinks

Table 3. Rational Addiction of Energy Drinks

	Myopic Addiction	Rational Addiction	
	(1)	(2)	(3)
C_{t-1}	0.198*	0.151*	0.207*
	(0.087)	(0.089)	(0.087)
C_{t+1}		0.298*	0.322*
		(0.079)	(0.077)
P_t	-65.233*	-61.419*	-66.344*
	(6.713)	(6.521)	(6.544)
P_{t+1}	-22.238*		
	(6.222)		
Percentage of			-39.303*
households having children			(3.853)
Percentage of			-16.305*
households married			(4.866)
Average household income			-2.98E-05
			6.77E-05
Average age of male head			-0.079
			(0.101)
Average age of female head			-0.174*
			(0.102)
Percentage of households			-1.859
having male head with college degree			(3.681)
Percentage of households			-8.023*
having female head with college degree			(3.543)
trend	0.210*	0.133*	0.032
	(0.061)	(0.057)	(0.057)
Constant	61.911*	43.087*	85.323
	(6.567)	(6.018)	(9.478)

Table 4. Health information and Rational Addiction of Energy Drinks

	(1)
C_{t-1}	0.167*
	(0.089)
C_{t+1}	0.299*
	(0.079)
P_t	-62.118*
	(6.535)
number of news	-0.229*
	(0.096)
number of news* Trend	0.008*
	(0.003)
Constant	44.771*
	(6.234)

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