Intertemporal Dependence in Alcohol Consumption Data: Evidence of Rational Addiction?

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Abstract

Intertemporal patterns in alcohol consumption for the United States are analyzed at the national, regional, and state level. We address shortcomings of linear time series models by employing nonlinear estimation techniques. Our findings are consistent with the theoretical model of cyclical rational addiction, with periodicity generally between 6 and 16 years. Further examination shows a positive relationship between average volume of consumption and intertemporal cycle period.

JEL classification: D91, D12.
Keywords: alcohol consumption, mutual information, cyclical rational addiction.

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1 Introduction

Alcohol consumption is of particular interest to economists and other social scientists for many reasons, including its purported habit-forming nature, its effects on health and well-being, and the often-idiosyncratic ways in which its use has been regulated and restricted. Recent studies related to the economic analysis of alcohol have included the latest changes in market structure for beer (Carroll 2000), theoretical treatments of 'addictive' substance use (Becker and Murphy 1988; Grossman 2004; Smith and Tasnádi 2007), estimates of demand elasticities (Gallet 2007; Fogarty 2006; and Fogarty 2010), and longitudinal consumption studies (Johansson et al. 2007; Nelson 2006; and Rojas and Peterson 2008). Though there is good reason to expect interesting dynamics in alcohol demand, relatively little is known about the dynamic properties of aggregate consumption data in this market. A better understanding of these dynamics could help in isolating risk factors for dependency and better inform policies aimed at reducing the various negative externalities associated with alcohol abuse.

New modeling techniques and improved data quality hold great promise in the analysis of consumption data. In a recent meta-analysis, Fogarty (2010) suggests that as modeling procedures become more sophisticated, more accurate statistics are estimated and new patterns in alcohol consumption may be found. One particular finding of the meta-analysis is that temporal changes exist in elasticity estimates. This finding deserves a more in-depth examination, and intertemporal dependency offers a foundation for testing new and existing theories of consumption.

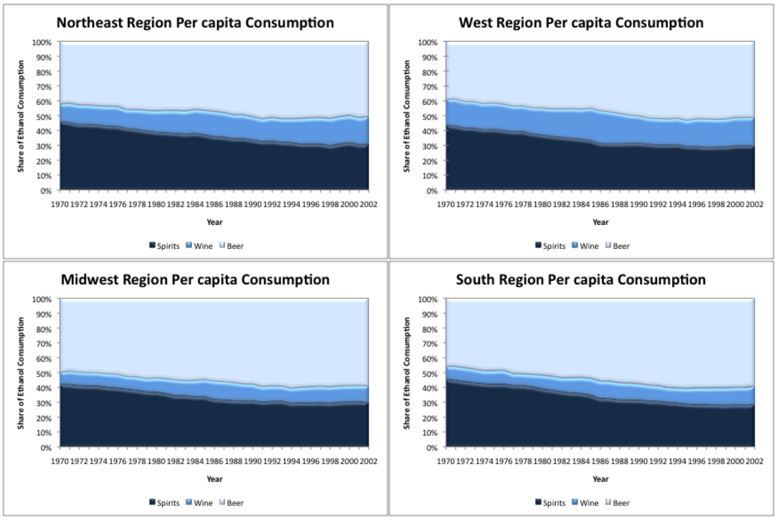
The goal of this paper is to analyze intertemporal patterns in alcohol consumption for the United States at multiple levels of aggregation. To accomplish this goal we examine patterns in alcohol consumption and time-related dependencies for the United States, the four census regions of the United States, and the states individually using nonlinear econometric techniques. This approach provides an alternative means to investigate patterns of intertemporal alcohol dependencies, which would not necessarily be possible with standard time series or systems analysis tools. Annual aggregate ethanol consumption data is obtained from OECD Health Data 2007 and the National Institute of Alcohol Abuse and Alcoholism. Our national data covers 1934-2005, while regional data ranges from 1970-2002. We use ethanol (alcohol equivalent) consumption, as opposed to beverage consumption, to allow for direct comparisons between beverages.

The structure of the paper is as follows; section 2 examines basic trends in alcohol consumption at various levels of aggregation. In Section 3 we specify information-theoretic methods for examining time series. Section 4 applies information theory to the patterns of consumption and examines the differences between linear and nonlinear time series analysis. Section 5 discusses the theoretical implications of our findings, with final remarks in Section 6.

2 Basic trends in alcohol consumption and policies

Figure 1 shows total ethanol consumption in the United States since the end of prohibition. In addition to allowing comparisons across beverages, measuring alcohol consumption as gallons of ethanol consumed per capita takes advantage of the meticulous record-keeping requirements imposed by alcohol-content taxation.

Figure 1: Regional Ethanol Consumption Share by Beverage



Our next level of disaggregation is to the four regions defined by the U.S. Census Bureau: West, Midwest, South, and Northeast. Table 1 shows the distinct patterns in consumption for these four regions between 1970 and 2002. Those Americans that live from the Rocky Mountains to the west drink more alcohol, on average, than any other region in the United States. While the Southern states drank the least in the early 1970s, they surpassed their Northeastern counterparts and approached the national average by 2002.

Another important observation to note at this stage is the relative similarities between the West and Northeast Region as well as those exhibited between the South and Midwest Regions. These similarities are most apparent in figure 2, the share of beverages in total alcohol consumption by region. The percentage of

Table 1: Average per capita gallons of ethanol consumption (Decade x Region x Beverage)

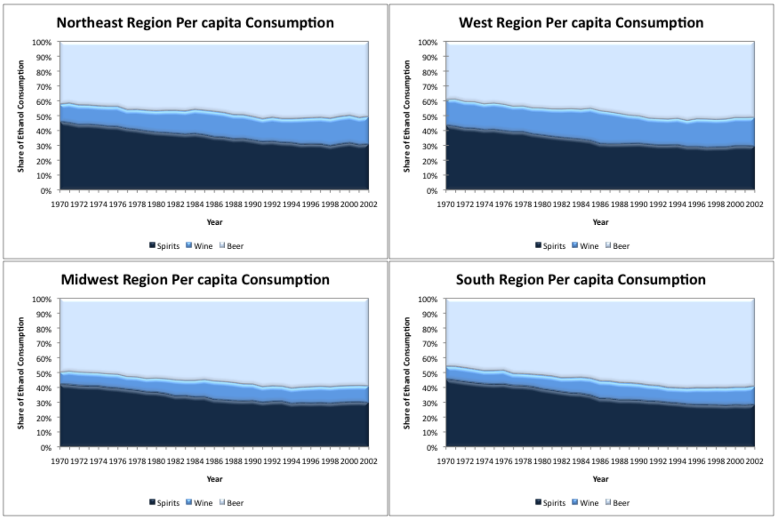
70's Average Per capita Ethanol Consumption				
Region	**Spirits**	**Wine**	**Beer**	**All**
Northeast	1.1840	0.3614	1.2280	2.7734
Midwest	0.9967	0.2198	1.2923	2.5088
South	1.0141	0.2043	1.1654	2.3838
West	1.2596	0.5508	1.3188	3.1293
80's Average Per capita Ethanol Consumption				
Region	**Spirits**	**Wine**	**Beer**	**All**
Northeast	0.9786	0.4201	1.2735	2.6723
Midwest	0.8291	0.2702	1.3861	2.4855
South	0.8603	0.2566	1.3414	2.4584
West	1.0093	0.6012	1.4135	3.0241
90's Average Per capita Ethanol Consumption				
Region	**Spirits**	**Wine**	**Beer**	**All**
Northeast	0.6750	0.3580	1.1149	2.1481
Midwest	0.6530	0.2288	1.3014	2.1832
South	0.6437	0.2330	1.3086	2.1854
West	0.7061	0.4305	1.2463	2.3829
00's Average Per capita Ethanol Consumption				
Region	**Spirits**	**Wine**	**Beer**	**All**
Northeast	0.6538	0.3878	1.0839	2.1255
Midwest	0.6558	0.2377	1.2939	2.1874
South	0.6101	0.2546	1.2902	2.1548
West	0.6753	0.4361	1.1819	2.2933

total alcohol consumption as beer is about 10% larger for the South and Midwest regions than for the West and Northeast regions, where wine is more dominant. For spirits, not only has volume decreased, the regional difference has also decreased from nearly 0.3 gallons in 1970 to 0.05 gallons in 2002.

3 Methods

It is well known that when dependence between random variables is the result of some process that is either nonlinear or of some complicated nature (e.g., non-Gaussian), traditional time series routines that are functions of the correlation coefficient will not capture that dependence (Maasoumi and Racine 2002; Granger, Maasoumi, and Racine 2004). For such cases two techniques are commonly used. The first is the mutual information function, an entropy measure of time dependency (Fraser and Swinney 1986). The second is the BDS test, which tests directly whether a time series is independent and identically distributed (Brock et

Figure 2: Regional Ethanol Consumption Share by Beverage



al. 1991).

3.1 The Mutual Information Function

The mutual information function is a nonlinear analogy to the autocorrelation function in that it tests for dependence between lagged values of a time series (Tsay, 2002). Unlike the autocorrelation function, the mutual information function tests for both linear and nonlinear dependence, making it a more robust test of persistent intertemporal behavior (Fraser and Swinney, 1986). Furthermore, the autocorrelation function hinges on estimating the sample moments of a time series. Entropy dependence measures generally make no assumptions about moments or underlying distributions of a time series; they are only limited by the probability density estimation technique used.

The mutual information function is based upon Shannon's entropy (see Shannon and Weaver, 1949) and defined as the combination of joint and marginal probabilities of the outcomes from an event in a sequence while increasing the time lag between components:

$$I(X_t, X_{t-\tau}) = \sum_{n-\tau} \sum_{n-\tau} P(X_t, X_{t-\tau}) \log \left[\frac{P(X_t, X_{t-\tau})}{P(X_t)P(X_{t-\tau})} \right] \tag{1}$$

For the standard definition of probabilistic independence, the argument $\log[\bullet]$

will equal zero if the vectors are perfectly independent, and will tend to infinity as they become more dependent.

This measure of dependence is independent of the coordinates of x because the probability density functions are dimensionless. Since the mutual information function is based upon joint probability density functions, it is a global measure of dependence and not a function of the individual time vectors (Fraser and Swinney 1986). The time lag that yields the first local minimum of the mutual information function is of interest here. It is an indicator of the time it takes for the system dynamics to complete one full cycle[4].

Following the information and entropy literature we apply nonparametric estimation using kernel density approximations as a method for estimating the mutual information function. In addition to being less computationally burdensome than the traditionally used histogram methods (see Dionísio et al. 2006), under appropriate conditions, the nonparametric method of estimating the mutual information function is also asymptotically efficient. By using kernel weights, the possible inefficiencies encountered with the histogram method of estimating the mutual information function are minimized (Pagan and Ullah 1999).

3.2 The BDS Test

The BDS statistic tests a univariate time series, Xt, for independence. Where n is the sample size, m is the embedding dimension, and ε is a predetermined distance, the BDS test statistic is as follows:

$$w_{m,n}(\varepsilon) = \sqrt{n-m+1}\frac{c_{n,m} - c_{1,n-m+1}^{m}(\varepsilon)}{\sigma_{m,n}(\varepsilon)} \tag{2}$$

where

$$c_{m,n}(\varepsilon) = \frac{2}{(n-m+1)(n-m)} \sum_{s=m}^{n} \sum_{t=s+1}^{n} \prod_{j=0}^{m-1} I_\varepsilon(X_{s-j}, X_{t-j}) \tag{3}$$

and

$$I_\varepsilon(X_{s-j}, Xt-j) = \begin{cases} 1 & if\ x|X_{s-j}, X_{t-j}| < \varepsilon \\ 0 & otherwise \end{cases} \tag{4}$$

Under the null hypothesis of an independent and identically distributed time series, the statistic has an asymptotic distribution N(0,1). In most practical applications the BDS test is used as a residual test for models with an additive error

[4]If the global minimum of the mutual information function were used as the time lag of interest, it is likely (given a sufficiently large data set) that the nonlinear system will have already completed a full cycle, so that the estimate would include redundancy of the system. This could force the enveloping of dynamical structure.

term. If the null hypothesis is rejected then the model insufficiently describes the dependent variables. The BDS test is not a test for deterministic chaos like those that use the mutual information function, but in fact the opposite. Using the BDS test in conjunction with the mutual information function provides an accurate description of the underlying structure of a time series, be it linear or not. This method of trend analysis helps to identify the foundation of said structure while remaining independent of restrictive assumptions (Brock et al. 1991).

4 Nonlinear Trends in Alcohol Consumption

4.1 United States

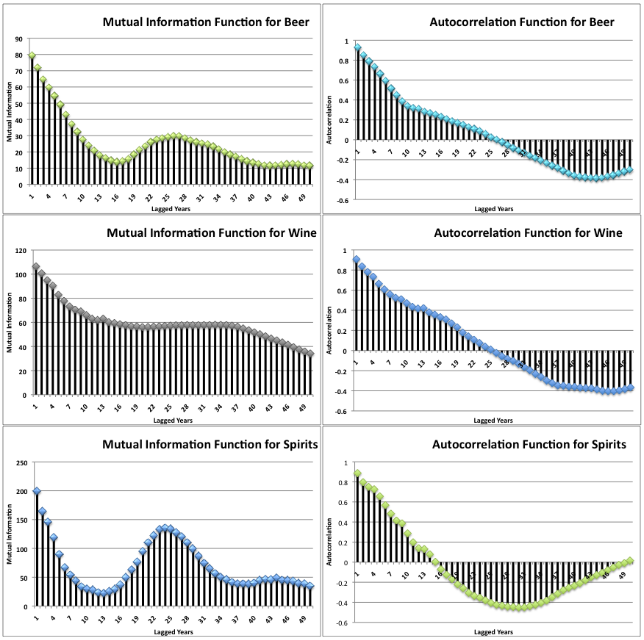
Employing information-theoretic techniques allows for the isolation of dependency patterns that might have otherwise gone unseen, it also helps to identify differences in the dynamics across beverages. Indeed, for our nationally aggregated data, the mutual information function shows an explicit minimum dependency at lag 16 for beer and lag 13 for spirits, whereas the information statistic for wine decreases steadily with no real apparent minimum (figure 3).

Compared to the traditionally used autocorrelation function where independence of beer consumption, defined by a zero correlation, is at about lag 27 for beer, lag 15 for spirits, and lag 25 for wine, these findings are somewhat surprising. If the autocorrelation function were to be used to assess United States intertemporal alcohol consumption patterns, the conclusion would be made that beer and wine exhibit the most similar patterns while spirits appears to follow a different behavioral structure altogether. In contrast, when accounting for nonlinear dynamics, we find that it is in fact beer and spirits that behave more similarly, and wine that exhibits the longer-run dependency structure.

Although the linear autocorrelation function is widely used, the presence of strong non-linear effects can easily be seen in figure 3 (Fogarty 2010; Tsay 2002). It stands to reason then, that those models used to estimate elasticities and other metrics used for the purpose of alcohol-related policy might have critical bias.

In addition to the different significant lag estimated by the mutual information function and the autocorrelation function, the shape of the mutual information function suggests an extremely cyclical pattern for both beer and spirits indicated by the traditional peak and trough shape. We can infer from the information statistic that the consumption of spirits behaves according to some cyclical pattern with the cycle period being indicated by the first minimum, 13 years, and the amplitude being measured by the height of the second maximum. The apparent cyclical pattern for beer, while not as prominent as that for spirits, has a period

Figure 3: Mutual Information and Autocorrelation Functions for United States Alcohol Consumption by Beverage



of 16 years.

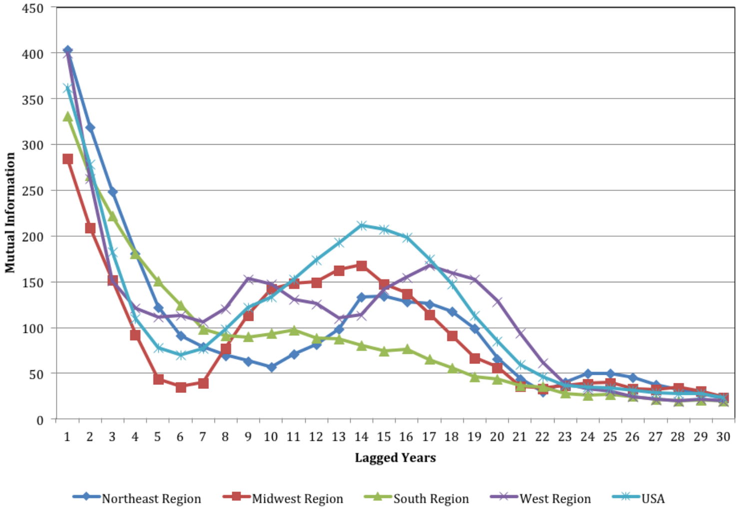
4.2 U.S. Census Regions

There are striking contrasts among regional intertemporal dependencies for both the regions and the alcohol types. For beer, while consumption volumes are similar across all regions, the Midwest and South Regions exhibit different intertemporal dependencies; see table 2 and figure 4. The similarities in consumption levels may lead one to hypothesize that they have similar behavioral patterns in consumption; however, the cycle period and the cycle amplitude defined by the mutual information function contrast this statement and suggest very different behavioral patterns. Indeed, the differences between those regions that exhibited similar volumes of consumption are profound when comparing intertemporal dependencies. For instance, in the western region, dependencies are much longer lived for both wine and spirits than for beer, i.e. the smallest first minimum lag is 5 years for beer while the smallest for wine and spirits is 11 years. This means that the cyclical behavioral consumption pattern for drinking beer repeats much faster than that for spirits and wine at the regional level.

Table 2: First minimum lagged year of the mutual information function for regional ethanol consumption)

First Minimum of the Mutual Information Function				
Ethanol	Beer	Spirits	Wine	All
Northeast Region	10	13	6	7
Midwest Region	6	18	15	14
South Region	9	19	16	7
West Region	5	11	11	10
USA	6	20	6	7

Figure 4: Mutual Information Function for Regional Ethanol Consumption (Beer)



The relationship between level of consumption and intertemporal dependency may lend some evidence supporting the notion that habit formation is more likely to occur in areas where general consumption is larger (see, e.g., Lee and Smith 2008). At the regional level we can see this relationship with wine. The West Region consistently consumes the most wine per capita (table 2). Like beer at the national level, wine in the West Region controls a larger share of alcohol consumption and exhibits a greater initial level of intertemporal dependency. It appears that as consumption volume increases, a larger cyclical effect is found. To further examine the relationship between the mutual information function and consumption levels we need to turn our focus to state alcohol consumption.

4.3 State-by-State

At the state level, it becomes apparent that the variability of dependence between the regions is large. Consider the volume of ethanol consumed as wine (see table 3) in the following four States (Regions): California (West), Delaware (South), District of Columbia (South), and Mississippi (South). The District of Columbia has consistently consumed the most wine per capita, whereas Delaware's consumption has increased throughout the sample period to be among the top ten wine consumer states.

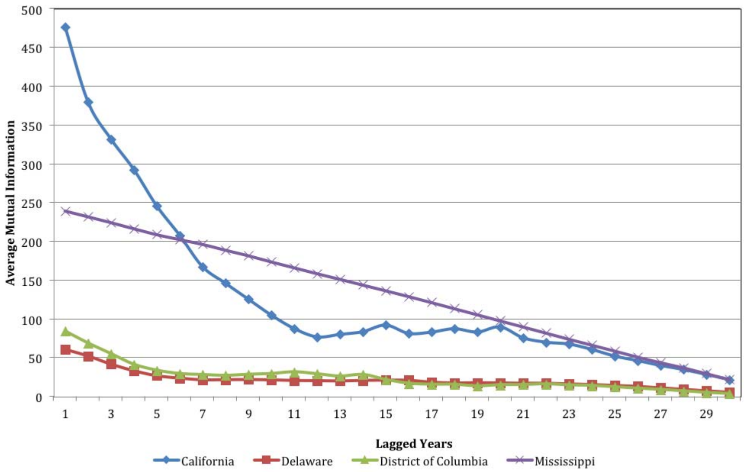
Table 3: Average per capita gallons of ethanol consumption by state and beverage 1970-2002

State	Beer	State	Wine	State	Spirits	State	All
Utah	0.843	Mississippi	0.100	Utah	0.494	Utah	1.469
Arkansas	1.006	West Virginia	0.103	West Virginia	0.532	Arkansas	1.711
Alabama	1.016	Kentucky	0.114	Arkansas	0.583	West Virginia	1.711
Connecticut	1.031	Arkansas	0.121	Iowa	0.591	Oklahoma	1.826
Oklahoma	1.049	Iowa	0.125	Kansas	0.597	Alabama	1.837
Kentucky	1.064	Utah	0.132	Ohio	0.603	Kentucky	1.837
North Carolina	1.071	Kansas	0.134	Tennessee	0.612	Kansas	1.841
West Virginia	1.076	Tennessee	0.135	Pennsylvania	0.622	Tennessee	1.876
New York	1.102	Oklahoma	0.139	Oklahoma	0.637	North Carolina	2.013
Kansas	1.110	Alabama	0.157	Idaho	0.656	Indiana	2.013
New Jersey	1.114	South Dakota	0.158	Kentucky	0.659	Iowa	2.018
Georgia	1.124	North Dakota	0.158	Texas	0.659	Mississippi	2.030
Tennessee	1.129	Indiana	0.181	Alabama	0.663	Ohio	2.106
Indiana	1.161	Nebraska	0.184	Indiana	0.671	Pennsylvania	2.151
Mississippi	1.215	Ohio	0.203	North Carolina	0.712	Virginia	2.224
Virginia	1.222	Pennsylvania	0.203	Mississippi	0.714	South Dakota	2.277
Maryland	1.228	Wyoming	0.208	Virginia	0.734	Georgia	2.279
Massachusetts	1.241	South Carolina	0.209	Nebraska	0.747	Missouri	2.279
Washington	1.243	Georgia	0.212	Missouri	0.754	Idaho	2.329
California	1.247	Missouri	0.218	Oregon	0.780	Nebraska	2.338
Maine	1.256	Texas	0.220	New Mexico	0.783	South Carolina	2.395
South Carolina	1.261	North Carolina	0.230	Louisiana	0.853	New York	2.447
South Dakota	1.261	Louisiana	0.248	South Dakota	0.859	Michigan	2.448
Oregon	1.265	Minnesota	0.251	Washington	0.859	Maine	2.456
Minnesota	1.274	Michigan	0.265	Montana	0.862	Texas	2.476
Ohio	1.299	Montana	0.269	Michigan	0.876	Louisiana	2.507
Iowa	1.302	Virginia	0.269	Maine	0.898	North Dakota	2.516
Michigan	1.307	Wisconsin	0.277	Hawaii	0.903	Oregon	2.517
Missouri	1.307	New Mexico	0.297	Arizona	0.905	Connecticut	2.524
Rhode Island	1.312	Maine	0.302	South Carolina	0.925	Minnesota	2.540
Idaho	1.324	Maryland	0.316	New York	0.925	Washington	2.566
Pennsylvania	1.326	Illinois	0.338	Rhode Island	0.931	New Jersey	2.579
Illinois	1.334	Idaho	0.349	Georgia	0.942	Maryland	2.631
Delaware	1.375	Delaware	0.357	North Dakota	0.960	Illinois	2.636
North Dakota	1.398	Arizona	0.361	Illinois	0.964	New Mexico	2.648
Florida	1.398	Florida	0.368	California	0.987	Rhode Island	2.701
Louisiana	1.406	Hawaii	0.389	New Jersey	1.004	Montana	2.767
Nebraska	1.407	Colorado	0.400	Minnesota	1.014	Hawaii	2.767
Vermont	1.413	New York	0.420	Wyoming	1.036	Massachusetts	2.769
Colorado	1.418	Connecticut	0.440	Connecticut	1.053	Wyoming	2.782
District of Columbia	1.439	Massachusetts	0.450	Wisconsin	1.060	California	2.850
Alaska	1.472	Alaska	0.454	Colorado	1.061	Arizona	2.857
Hawaii	1.475	Rhode Island	0.458	Massachusetts	1.077	Colorado	2.879
Wyoming	1.538	New Jersey	0.460	Maryland	1.088	Florida	2.921
New Mexico	1.568	Washington	0.464	Vermont	1.139	Delaware	2.972
Arizona	1.592	Oregon	0.472	Florida	1.154	Vermont	3.031
Texas	1.597	Vermont	0.479	Delaware	1.240	Wisconsin	3.064
Montana	1.636	New Hampshire	0.522	Alaska	1.440	Alaska	3.367
Wisconsin	1.727	California	0.617	New Hampshire	2.298	New Hampshire	4.687
New Hampshire	1.867	Nevada	0.723	Nevada	2.355	District of Columbia	4.826
Nevada	1.974	District of Columbia	0.875	District of Columbia	2.512	Nevada	5.052

However, Figure 5 shows that Delaware and the District of Columbia exhibit similar dependency patterns for wine. First, neither area has a high level of predictability or strong cyclical pattern. Second, the mutual information function for both remains relatively constant over time lags. Third, the two time series have similar first minimums of their respective mutual information functions, for example, 7 years for Delaware and 8 years for the District of Columbia (see table

4).

Figure 5: Mutual Information Function for State Ethanol Consumption (Wine)



This stands in stark contrast to other high wine consumption states such as California. California starts as the state with the highest level of predictability, reaching a first minimum at 12 years. Behavioral patterns of consumption in California are much more cyclical than those in Delaware and D.C. A theoretical model used to estimate parameters such as elasticities will need to account for these findings. We turn our discussion then to the theoretical implications of the intertemporal dependencies found in alcohol consumption.

5 Discussion and Theory

5.1 Cyclical Models of Rational Addiction

Using the findings of the nonlinear trend analysis we can begin to formulate a theoretical model of the underpinnings of alcohol consumption. One finding that appears to have potential at this stage is that of cyclical rationally addictive goods proposed by Dockner and Feichtinger in 1993[5]. Assume that the representative consumer derives utility from consuming some alcoholic beverage, c(t), and that two "stocks" of consumption S_1(t) and S_2(t) where S_1(t) and S_2(t) can, for example, be thought of as a 'cultural stock' and a 'consumption stock,' respectively.

[5]A number of other authors have developed dynamic models of cyclical consumption. See, for example, Wirl (1996, 2002), Behrens et al. (2002), Faria 2003, and Cowan et al. (2004).

Table 4: The first minimum lagged year of the mutual information function by state and beverage

State	Beer MIF	State	Wine MIF	State	Spirits MIF	State	All MIF
Colorado	3	Hawaii	1	Georgia	3	Kentucky	1
Kentucky	4	Wyoming	3	Illinois	3	Pennsylvania	2
Georgia	4	Louisiana	4	Wisconsin	3	Virginia	2
Virginia	4	South Carolina	5	District of Columbia	3	Maine	2
North Dakota	4	Virginia	5	Alabama	4	District of Columbia	2
New Mexico	4	Wisconsin	5	Minnesota	4	Arkansas	3
Utah	5	Maine	5	Alaska	4	Missouri	3
Kansas	5	Rhode Island	5	New Hampshire	4	Minnesota	4
Oregon	5	Vermont	5	Arkansas	5	New Hampshire	4
Minnesota	5	New Hampshire	5	Texas	5	Utah	5
Ohio	5	Iowa	6	Montana	5	Alabama	5
Iowa	5	Indiana	6	Arizona	5	Tennessee	5
Idaho	5	Texas	6	South Carolina	5	Iowa	5
Delaware	5	Montana	6	Missouri	6	Texas	5
Arizona	5	Maryland	6	Hawaii	6	Louisiana	5
Texas	5	Idaho	6	Rhode Island	6	Connecticut	5
Montana	5	Arizona	6	North Dakota	6	Rhode Island	5
Nevada	5	Florida	6	Wyoming	6	Massachusetts	5
Indiana	6	Massachusetts	6	Massachusetts	6	Nevada	5
Maryland	6	Alaska	6	Utah	7	Indiana	6
Massachusetts	6	New Jersey	6	Florida	7	South Dakota	6
Michigan	6	Oregon	6	California	8	South Carolina	6
Illinois	6	Mississippi	7	New Jersey	8	New York	6
Florida	6	Alabama	7	Colorado	8	Michigan	6
Louisiana	6	Nebraska	7	Nevada	8	Oregon	6
Nebraska	6	Ohio	7	Maryland	10	New Mexico	6
District of Columbia	6	Delaware	7	New York	11	Montana	6
Alaska	6	New York	7	Connecticut	11	Hawaii	6
Hawaii	6	Washington	7	Delaware	11	Delaware	6
Wisconsin	6	Tennessee	8	Indiana	12	Wisconsin	6
Connecticut	7	Georgia	8	South Dakota	12	West Virginia	7
Oklahoma	7	Michigan	8	Kansas	14	Kansas	7
Washington	7	Colorado	8	Oklahoma	14	North Carolina	7
California	7	District of Columbia	8	Idaho	14	Georgia	7
Pennsylvania	7	Utah	9	Louisiana	14	Idaho	7
Vermont	7	New Mexico	9	Iowa	15	Washington	7
Wyoming	7	Oklahoma	10	Tennessee	15	Maryland	7
Alabama	8	Nevada	11	Virginia	15	Illinois	7
Tennessee	8	Pennsylvania	12	Nebraska	15	Colorado	7
Maine	8	California	12	Maine	15	Florida	7
Missouri	8	North Carolina	13	Mississippi	16	Ohio	8
South Dakota	9	Connecticut	13	Oregon	16	North Dakota	8
New Hampshire	9	Kansas	14	New Mexico	16	Vermont	8
Rhode Island	10	Minnesota	14	North Carolina	17	Oklahoma	9
Arkansas	11	North Dakota	15	Kentucky	18	New Jersey	9
North Carolina	11	Missouri	15	Washington	18	Mississippi	10
New York	12	Illinois	15	Ohio	19	Nebraska	10
New Jersey	13	West Virginia	17	West Virginia	20	Wyoming	10
West Virginia	15	Arkansas	17	Michigan	20	California	10
South Carolina	18	Kentucky	18	Pennsylvania	21	Arizona	11
Mississippi	20	South Dakota	18	Vermont	24	Alaska	11

Assume then that consumption stock is the measure of past consumption, making current consumption a function of past consumption (perhaps via habit formation or an unobserved learning-by-doing process). Similarly, cultural stock can defined as in Throsby (2001), "...in a broadly anthropological or sociological framework to describe a set of attitudes, beliefs, morals, customs, values and practices which are common to or shared by any group". As with consumption stocks, cultural stocks can make current consumption a function of past consumption, either positively, e.g., social drinking, or negatively, e.g., religious scorn.

If the consumer's utility function follows that specified in Dockner and Feichtinger (1993):

$$U_t = U(c(t)), S_1(t), S_2(t)) \tag{5}$$

the variations in cyclical patterns found in the information statistic suggest what Dockner and Feichtinger called 'partially addicted' behavior, where the cultural stock, S_1(t), negatively impacts consumption c(t) and consumption stock, S_2(t), positively impacts c(t). We can then hypothesize the relative size of the stocks of consumption by examining the relative period and amplitude of the consumption cycle through the mutual information function, and suggest future research into this area to confirm our hypotheses.

5.2 The BDS Test

The presence of important nonlinear processes can be verified with the BDS test. The null hypothesis of the BDS test is that the error terms of a linear model are both independently and identically distributed. If the null hypothesis is rejected then one can conclude that the time series has some underlying form of time dependence. The test statistic has a standard normal distribution, however p-values are bootstrapped to ensure efficiency, so the estimated z-statistic needs to be above 1.96 for the null hypothesis to be rejected at the 5% level (Belaire-Franch and Contreras 2002).

Consider again the cases of Delaware and D.C. For both the Delaware and District of Columbia time series for wine consumption, the z-statistics are above 16 for every embedding dimension tested (table 6). Therefore, the null hypothesis is rejected for both series at the 1% level. We can conclude then that while the two series do not appear to be cyclical, they are time dependent. This suggests, within the context of the two-stock rational addiction model, that the consumption stock might be relatively larger than the cultural stock and/or the cultural stock might be positively related to consumption resulting in the positive consumption trend.

The effects of the hypothesized relatively large consumption stock and small cultural stock can be contrasted with those apparent in the state of Mississippi. Not surprisingly given the state's demographics, the mutual information function for Mississippi is nearly a straight line that begins at a relatively large level of dependence. Mississippi is consistently one of the bottom states in terms of wine consumption. The linear decrease in mutual information is due to the consistent drinking pattern over time and is typical of states with similar demographics. Furthermore, this pattern in intertemporal dependence does not exist for beer and spirits, with few exceptions. This is consistent behavior for an individual whose utility function is defined as above with a relatively large negatively impacted consumption level through the cultural stock. Confirming with the BDS test, the null hypothesis is rejected at the 5% level with a z-statistic above 3.4 for every embedding dimension tested (table 5). We can conclude that the time series for wine consumption in Mississippi is time dependent.

Table 5: Regression results for the first minimum of the mutual information function vs. ethanol consumption

Model 1: First Min. of the MIF vs. Consumption 1970-2002					
Regression Statistics					
R Square	0.123				
Adjusted R Square	0.104				
Observations	48				
	df	***SS***	***MS***	***F***	***Significance F***
Regression	1.000	31.204	31.204	6.445	0.015
Residual	46.000	222.713	4.842		
Total	47.000	253.917			
	Coefficients	***Standard Error***	***t Stat***	***P-value***	
Intercept	1.571	1.886	0.833	0.409	
Consumption 1970-2002	1.957	0.771	2.539	0.015	

Model 2: First Min. of the MIF vs. Consumption 1970-1974					
Regression Statistics					
R Square	0.110				
Adjusted R Square	0.091				
Observations	48				
	df	***SS***	***MS***	***F***	***Significance F***
Regression	1.000	28.035	28.035	5.710	0.021
Residual	46.000	225.882	4.910		
Total	47.000	253.917			
	Coefficients	***Standard Error***	***t Stat***	***P-value***	
Intercept	1.398	0.585	2.390	0.021	
Consumption 1970-1974	2.824	1.486	1.900	0.064	

Model 3: First Min. of the MIF vs. Consumption 1998-2002					
Regression Statistics					
R Square	0.083				
Adjusted R Square	0.063				
Observations	48				
	df	***SS***	***MS***	***F***	***Significance F***
Regression	1.000	21.087	21.087	4.170	0.047
Residual	46.000	232.829	5.062		
Total	47.000	253.917			
	Coefficients	***Standard Error***	***t Stat***	***P-value***	
Intercept	2.142	1.049	2.040	0.047	
Consumption 1998-2002	1.616	2.314	0.700	0.488	

5.3 Volume Impacts on Intertemporal Dependency

The first minimum of the mutual information function is generally used as the determinant of intertemporal dependency (Fraser and Swinney 1986). For wine we saw a possible correlation between the volume of consumption and intertemporal dependency. Further investigation into this result finds strong evidence that as the level of ethanol from all beverages consumed increases, the first minimum of the mutual information function increases. In terms of the utility model stated; as the level of consumption stock, S_1(t), increases, the longer the potential period of cycle dynamics.

The District of Columbia, Nevada, and New Hampshire are obvious outliers

Table 6: The BDS test for wine consumption in Delaware, District of Columbia, and Mississippi

BDS test for	Delaware				
Sample:	1970-2002				
Included obs.	33				
Dimension	**BDS Statistic**	**Std. Error**	**z-Statistic**	**Prob.**	**Bootstrap Prob.**
2	0.154657	0.007754	19.94476	0.0000	0.000
3	0.255344	0.012623	20.22792	0.0000	0.000
4	0.315157	0.015396	20.47018	0.0000	0.000
5	0.347100	0.016440	21.11340	0.0000	0.000
6	0.364013	0.016249	22.40230	0.0000	0.000

BDS test for	District of Columbia				
Sample:	1970-2002				
Included obs.	33				
Dimension	**BDS Statistic**	**Std. Error**	**z-Statistic**	**Prob.**	**Bootstrap Prob.**
2	0.127390	0.007596	16.77147	0.0000	0.000
3	0.206594	0.012301	16.79497	0.0000	0.000
4	0.235118	0.014925	15.75360	0.0000	0.000
5	0.243851	0.015854	15.38123	0.0000	0.000
6	0.232772	0.015588	14.93263	0.0000	0.000

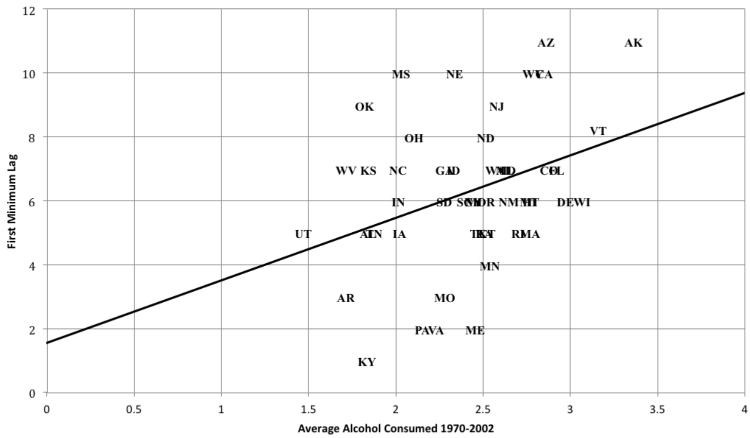
BDS test for	Mississippi				
Sample:	1970-2002				
Included obs.	33				
Dimension	**BDS Statistic**	**Std. Error**	**z-Statistic**	**Prob.**	**Bootstrap Prob.**
2	0.057427	0.012319	4.661619	0.0000	0.004
3	0.069710	0.020105	3.467306	0.0005	0.028
4	0.106549	0.024592	4.332674	0.0000	0.012
5	0.130044	0.026340	4.937132	0.0000	0.004
6	0.143202	0.026117	5.483165	0.0000	0.004

when examining per capita consumption. The volume consumed may not be indicative of the permanent residents of the District of Columbia due to high numbers of non-resident workers (who may nevertheless contribute to per capita consumption totals). In Nevada, tourism is by far the biggest contributor to alcohol consumption; therefore, per capita consumption, once again does not necessarily reflect the behavior of permanent residents. As for New Hampshire, the state-run liquor commission has pursued an aggressive marketing campaign and sells retail at 'wholesaler's price' to increase sales for the state by attracting neighboring state's residents to purchase (NH Liquor Commission). It is for these reasons that these three states are left out of the simple linear regression described below.

Those areas of the United States that consume on average large levels of alcohol exhibit relatively more predictable behavior i.e., a larger first minimum lagged year. Figure 6 plots the average level of ethanol consumption versus the first minimum of the mutual information function for each state. The positive relationship apparent in the graph is confirmed through simple linear regression. See table 6 for regression results for the model:
First Minimum of the Mutual Information Function = 1.9572 Average Ethanol Consumed + 1.5709.

The model was obtained by the ordinary least squares method and has an Adjusted R-square of 0.1038 and an F-value of 6.445. The constant term of the regression is statistically not significantly different from zero but the Average Ethanol Consumed coefficient is, at the 5% level. In general, when average per capita ethanol consumption increases by one gallon, intertemporal dependency increases by 1.957 years. The cyclical period of consumption increases with the volume of consumption. The use of average ethanol consumption over the entire period was checked for consistency by regressing the First Minimum of the Mutual Information Function on Average Ethanol Consumed in the two periods from 1970-1974 and 1998-2002. In both cases a statistically significant positive relationship was found between time lag and volume, see table 6.

Figure 6: The first minimum of the mutual information function vs. ethanol consumption



6 Final Remark

Examining intertemporal dependence we find alcohol consumption to exhibit cyclical behavior. Further examination showed that as the volume of consumption increased so did the cycle period. This result suggests that the theoretical model of cyclical rational addiction developed by Dockner and Feichtinger (1993) is a good fit when modeling aggregate alcohol consumption. We also found that those states that had more 'cultural stock', i.e. a larger religious population, more strict regulation, and/or a larger contingency of non-resident drinkers, were less likely to exhibit cyclical behavior. While the nonlinear methods used have suggested some general trends, further study is needed to confirm specific theoretical assumptions.

It is clear that consumption habits are evolving over time and it appears that static changes in consumption do not exist for any of the beverage types.

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