mathematics

MDPI

Article

Consumer Sentiment in the United States and the Impact of Mental Disorders on Consumer Behavior—Time Trends and Persistence Analysis

Jesús Tomás Monge Moreno [1] and Manuel Monge [2,*]

[1] Faculty of Nursing and Physiotherapy, University of the Balearic Islands, 07800 Eivissa, Spain; j.monge@uib.es
[2] Faculty of Law, Business and Government, Universidad Francisco de Vitoria, 28223 Madrid, Spain
* Correspondence: manuel.monge@ufv.es

Abstract: This paper analyzes the stochastic properties in clinical disorders to understand how they have manifested in consumer sentiment in the USA since 1990. The results obtained via fractional integration methodologies exhibit a high degree of persistence, finding non-mean reversion behavior in all of the time series analyzed, except for depressive disorder. Using a causality test, we find that mental and substance use disorders, anxiety disorder, schizophrenia, and alcohol use disorder influence consumer sentiment. Focusing on the cointegrating part, we conclude that an increase in the previously cited mental disorders produces a decrease in the Consumer Sentiment Index.

Keywords: mental disorders; consumer sentiment; consumer expectation; mean reversion; persistence; fractional integration; causality test; FCVAR model

MSC: 62M10; 91B70; 62P20

check for updates

Citation: Monge Moreno, J.T.; Monge, M. Consumer Sentiment in the United States and the Impact of Mental Disorders on Consumer Behavior—Time Trends and Persistence Analysis. *Mathematics* **2023**, *11*, 2981. https://doi.org/10.3390/math11132981

Academic Editor: Manuel Alberto M. Ferreira

Received: 7 June 2023
Revised: 29 June 2023
Accepted: 30 June 2023
Published: 4 July 2023

1. Introduction

The field of consumer behavior has revealed countless insights into purchase preferences, messaging responses, and other tactical pieces of information that marketers can use to shape their products and promotions and drive higher sales. However, it is not well known how mental disorders affect the expectation of consumption.

Experiences, tendencies, and genetics affect individuals and their perceptions, thoughts, behaviors, and choices. But, sometimes, dysfunctional and maladaptive cognitions and behaviors are shown by individuals, which increase the level of clinical concern.

Faced with this reality, and following the research initiated by the Professor of Marketing Steven S. Posavac at Vanderbilt University in the psychological subfield dubbed "Clinical Consumer Psychology", we carry out this research paper to understand how a given clinical disorder may manifest in consumer sentiment.

Before delving into the issue, it is worth contextualizing what is referred to when talking about mental health. The World Health Organization (WHO) define the term mental health as the condition of well-being in which an individual can use his or her abilities, recover from daily routine stress, be productive, and contribute to the community. So, any issue related to intellectual fitness is defined as a mental disorder.

There are several recognized mental issues such as humor issues (e.g., despair), anxiety and stress, problems caused by drug and alcohol use (i.e., drug dependence), personal problems such as extreme mood swings (e.g., bipolar), and delusional disorders, among others.

Related to anxiety, Ref. [1] suggest that although there are multiple variants of anxiety disorders, one commonality is that individuals in an anxious state are motivated to seek amelioration of their distress. Also, marketing themes could help to reduce the source of anxiety or how it is received. Ref. [2] argue in their research paper that negative emotional states can be relieved through the act of purchasing.

Ref. [3] conducted a study focused on anxiety, depression, and stress and the relationship with consumer behavior, stating that they are the most prevalent mental health problems. There has been other research linking anxiety to consumer sentiment (see [4,5]). There are other stressor factors, for example, military members and their experiences, that are associated with materialism and excessive buying. So, this behavior of excessive buying surges as a method or strategy to reduce tension and deal with stressful events (see [6,7]). This is due to people's need for control over their environment, and individuals may try to gain control over other domains (see [2,8], among others). Ref. [6] argued that people buy things more than usual, which influences negative feelings like fear, panic, and feelings of uncertainty.

Along the lines indicated above, Ref. [9] points out that clinical symptoms are reinforced, maintained, or exacerbated by consumption. Consumption by consumers along a clinical dimension is used to improve and reduce feelings of distress.

Ref. [10] stated that other personality disorder symptoms affect consumer processes. Ref. [11] examined whether the magnitude of certain tendencies in consumer judgment and choice covary with the presence or extent of clinical phenomena, such as schizophrenia. They demonstrated that errors in reasoning, holding false beliefs, and overconfidence in schizophrenics produce the tendency to jump to conclusions.

Other related studies about clinical pathologies such as gambling, substance addiction, compulsive buying behavior, and disordered eating behavior, among others, were studied by [12], [13], [14], [15], [16], [17], [18], [19], among others.

To the best of our knowledge, this is the first paper that analyzes the statistical properties of mental disorders and consumer sentiment in the USA under the assumption of a time series analysis. Therefore, we consider it pertinent that clinical professionals, economists, politicians, and other practitioners and professionals understand how and which mental health problems directly affect consumer behavior. So, the key objectives of our study are twofold. First, we carry out a univariate analysis to understand the behavior of each time series. Second, our intention is to examine whether the impact of mental disorder behavior on consumer sentiment is temporary or permanent, and the relationship in the long term. We also want to measure, in percentage terms, how much it has an effect.

The structure of this paper is as follows. Section 2 describes the data used for this study. In Section 3, we present the methodology applied and the results. Section 4 presents the conclusions.

2. Data

The database associated with the prevalence of mental health disorders and the associated diseases was provided by the Institute for Health Metrics and Evaluation, https://ourworldindata.org/mental-health (accessed on 25 October 2022).

This database of mental illnesses collects the diagnoses of psychological and behavioral symptoms of people. These diseases are measured and quantified based on medical and scientific criteria of observation, analysis of the symptoms in the affected people, and the context of their symptoms.

The mental illnesses used in this study are accurately defined by the International Classification of Diseases (ICD) and the Diagnostic and Statistical Manual of Mental Disorders (DSM), and are quantified based on the criteria included in these manuals by healthcare professionals with training and experience in recognizing mental illnesses.

The mental illnesses that we analyze in this research paper are depression, anxiety, bipolar, eating disorders, schizophrenia, alcohol use disorder, and drug use disorder.

On the other hand, to understand what impact mental health has on consumer sentiment, we used the Consumer Sentiment Index. This database is adopted by the Federal Reserve Bank of St. Louis and was constructed by the University of Michigan. The Index of Consumer Sentiment is based on monthly surveys (at least 500 phone interviews across the continental USA) of consumer confidence levels about the economy, personal finances, business conditions, and buying conditions in the USA.

The database has a yearly frequency from 1990 to 2019.

3. Methodology and Results

3.1. Unit Root Methods

Following ref. [20], for the statistics and econometrics, we used single- or multi-equation regression models of time series to form modeling variables and their interrelations.

It is important to determine the behavior of each time series, analyzing and determining the stationarity in order to be able to work with them.

The fundamental assumption to use these types of models is to conclude whether the process follows non-stationary $I(1)$ behavior when it contains a unit root or whether it is stationary $I(0)$ when it does not.

Until the 1980s, deterministic functions of time were applied, imposing that the residuals on the regression model were $I(0)$ stationary. With the research paper carried out by [21], there was a consensus about the non-stationary component of most series and the use of unit roots or first differences $I(1)$ was the way to go.

For this reason, we determined the integration order of each time series using standard unit root tests. The best known and most widely used unit root test is the Dickey–Fuller test (see [22]). If a non-systematic component in Dickey–Fuller models is autocorrelated, the augmented Dickey–Fuller test is constructed [23]. Many other tests have been considered due to the greater power, such as Phillips [24] and Phillips and Perron [25], in which a non-parametric estimate of spectral density of u_t at zero frequency is used. The methodology based on Kwiatkowski et al. [26] has been used to analyze the deterministic trend.

To analyze the statistical properties of the time series related to the seven mental disorders and the Consumer Sentiment Index, we used the three standard unit root/stationary tests (the augmented Dickey–Fuller (ADF) test, the Phillips Perron (PP) test, and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test). The results obtained suggest that all time series have $I(1)$ non-stationary behavior. Therefore, we must consider performing first differences to convert the time series into $I(0)$ stationary.

3.2. ARFIMA (p, d, q) Model

Once we had tested that the time series were not stationary using standard unit root tests, we employed a more advanced methodology. To achieve stationarity $I(0)$, the number of differences does not necessarily have to be an integer value, since it can be any point on the real line and therefore be fractional $I(d)$. This idea was introduced by [27], [28–30], and [31].

According to [32], [33], and [34], the unit root methods have very low power under fractional alternatives.

For this reason, we used fractional integrated methods with the purpose of making the time series stationary $I(0)$, differentiating the time series with a fractional number. Another feature of the I(d) models is that they can be used to determine and capture the persistence of the observations. This is when observations are far apart in time but are highly correlated.

The fractional integrated method that we used in this research paper was the *ARFIMA* (p, d, q) model, where the mathematical notation is as follows:

$$(1-L)^d x_t = u_t, t = 1, 2, \tag{1}$$

In Equation (1), x_t refers to the time series that has an integrated process of order d $(x_t \approx I(d))$, d refers to any real value, L is the lag-operator $(Lx_t = x_{t-1})$, and u_t refers to I(0), which is the covariance stationary process where the spectral density function is positive and finite at zero frequency and it displays a type of time dependence in the weak form. Therefore, we can state that if u_t is $ARMA\ (p, q)$, x_t is $ARMA\ (p, d, q)$.

From Equation (1), the polynomial $(1-L)^d$ is expressed in terms of binomial expansion, where for all real d, x_t depends not only on a finite number of past observations but also on the whole of its history. So, a higher value of d implies a higher level of association between the observations of the series.

Depending on the value of the parameter d, we can differentiate between various cases. Table 1 summarizes the different results of d:

Table 1. Interpretation of the results of $\boldsymbol{d}$ for the *ARFIMA* model.

$d = 0$	x_t process is short memory
$d > 0$	x_t process is long memory
$d < 0.5$	x_t is covariance stationary
$d \geq 0.5$	x_t is non-stationary
$d < 1$	x_t is mean-reverting
$d \geq 1$	x_t is not mean-reverting

Table 2 displays the fractional parameter d and the AR and MA terms obtained using Sowell's [35] maximum likelihood estimator for various $ARFIMA\ (p, d, q)$ specifications with all combinations of $p, q \leq 2$, for each time series. To select the appropriate AR and MA orders in the model, we used the Akaike information criterion [36] and Bayesian information criterion [37].

Table 2. Results of long memory tests.

Data Analyzed	Sample Size (Year)	Model Selected	d	Std. Error	Interval	$I(d)$
Mental Health Time Series						
Mental and substance use disorders	30	*ARFIMA* $(2, d, 0)$	1.26	0.241	[0.87, 1.66]	$I(1)$
Anxiety disorders	30	*ARFIMA* $(2, d, 1)$	0.65	0.402	[−0.01, 1.31]	$I(0), I(1)$
Depressive disorders	30	*ARFIMA* $(2, d, 0)$	0.31	0.277	[−0.15, 0.77]	$I(0)$
Bipolar disorders	30	*ARFIMA* $(0, d, 0)$	0.97	0.160	[0.71, 1.23]	$I(1)$
Eating disorders	30	*ARFIMA* $(0, d, 2)$	1.16	0.189	[0.85, 1.47]	$I(1)$
Schizophrenia	30	*ARFIMA* $(0, d, 0)$	1.15	0.133	[0.93, 1.37]	$I(1)$
Alcohol use disorders	30	*ARFIMA* $(1, d, 0)$	1.35	0.163	[1.09, 1.62]	$I(1)$
Substance use disorders	30	*ARFIMA* $(1, d, 0)$	1.38	0.141	[1.15, 1.61]	$I(1)$
Consumer Sentiment Time Series						
Consumer Sentiment Index	30	*ARFIMA* $(0, d, 0)$	0.95	0.168	[0.68, 1.23]	$I(1)$

The first results that we found were that the estimates of d in all cases were fractional, with a high degree of persistence.

We observe from Table 2 that the mental and substance use disorders, bipolar disorders, eating disorders, schizophrenia, alcohol use disorders, and substance use disorders present a non-mean-reverting behavior for these variables, where the parameter d is higher than 1 and the confidence intervals suggest $I(1)$ behavior. So, we can conclude that the shocks in these mental diseases will not be transitory. Therefore, shocks are expected to be permanent, causing a change in trend, and therefore extraordinary measures will be required to reverse the situation and recover the original trend.

For the case of anxiety disorder, apparently the parameter d is equal to 0.65, but due to the high value that we obtain in the standard error, the interval is very wide and we cannot reject the $I(0)$ and $I(1)$ hypotheses.

Finally, in the cases of depressive disorders and Consumer Sentiment Index, although the parameter d is lower than 1 ($d < 1$) and apparently shows a mean-reverting behavior, the confidence interval indicates that we cannot reject the $I(1)$ hypothesis for these variables.

3.3. Granger Causality Test

Next, once we studied the statistical properties of each time series, we proposed the Granger causality test between each mental disorder and consumer sentiment in the

USA, which involved as a first step in the estimation the following vector autoregressive representation (VAR) model:

$$MD_t = \alpha_1 + \sum_{i=1}^{n} \beta_i CS_{t-i} + \sum_{j=1}^{m} \delta_j MD_{t-j} + \epsilon_{MD_t} \quad (2)$$

$$CS_t = \alpha_2 + \sum_{i=1}^{n} \theta_i CS_{t-i} + \sum_{j=1}^{m} \psi_j MD_{t-j} + \epsilon_{CS_t} \quad (3)$$

where MD is each mental disorder and CS is the consumer sentiment, and it is assumed that both ϵ_{MD_t} and ϵ_{CS_t} are uncorrelated white noise error terms (see [38]). The letters m and n in Equations (2) and (3) represent the maximum number of lags for each of the variables.

The application of the VAR methodology is based on the following validations. First, VAR can only be applied when all of the variables are either integrated of order zero or one. Second, one can estimate the level and the first difference relationship between variables using the ordinary least squares method. Third, variables are not expected to have long run relationships since they are integrated of order zero.

The two Granger causality hypotheses that were tested for each mental disease in this study are as follows. The first hypothesis was $H_0 : \sum_{i=1}^{n} \beta_i = 0$ (mental disease does not influence consumer sentiment) and $H_1 : \sum_{i=1}^{n} \beta_i \neq 0$ (mental disease influences consumer sentiment), and the second hypothesis was $H_0 : \sum_{j=1}^{m} \psi_j = 0$ (consumer sentiment does not influence mental disease) and $H_1 : \sum_{j=1}^{m} \psi_j \neq 0$ (consumer sentiment influences mental disease) (see [38]).

Table 3 presents the Granger causality results when causality runs from each mental disorder to consumer sentiment, and vice versa. We observe from the results that there are four mental disorders (mental and substance use disorders, anxiety, schizophrenia, and alcohol use disorder) that have a direct influence on consumer sentiment. Therefore, there is a unidirectional causality running from mental and substance use disorders, anxiety, schizophrenia, and alcohol use disorder to consumer sentiment. For the rest of the mental disorders, we do not find relevant significant cases and there is no causality between them.

Table 3. Results of Granger causality test.

Direction of Causality	Lags [1]	Prob.	Decision	Outcome
Mental and substance use disorders → Consumer Sentiment Index	3	0.0246	Reject null	Mental and substance use disorders influence Consumer Sentiment Index
Consumer Sentiment Index → Mental and substance use disorders	3	0.2535	Do not reject null	Consumer Sentiment Index does not influence mental and substance use disorders
Anxiety disorder → Consumer Sentiment Index	9	0.0000	Reject null	Anxiety disorder influences Consumer Sentiment Index
Consumer Sentiment Index → Anxiety disorder	9	0.2858	Do not reject null	Consumer Sentiment Index does not influence anxiety disorder
Depressive disorder → Consumer Sentiment Index	2	0.5171	Do not reject null	Depressive disorder does not influence Consumer Sentiment Index
Consumer Sentiment Index → Depressive disorder	2	0.4195	Do not reject null	Consumer Sentiment Index does not influence depressive disorder
Bipolar disorder → Consumer Sentiment Index	1	0.9210	Do not reject null	Bipolar disorder does not influence Consumer Sentiment Index
Consumer Sentiment Index → Bipolar disorder	1	0.4771	Do not reject null	Consumer Sentiment Index does not influence bipolar disorder
Eating disorders → Consumer Sentiment Index	1	0.8963	Do not reject null	Eating disorders do not influence Consumer Sentiment Index
Consumer Sentiment Index → Eating disorder	1	0.5036	Do not reject null	Consumer Sentiment Index does not influence eating disorders

Table 3. *Cont.*

Direction of Causality	Lags [1]	Prob.	Decision	Outcome
Schizophrenia → Consumer Sentiment Index	9	0.0182	Reject null	Schizophrenia influences Consumer Sentiment Index
Consumer Sentiment Index → Schizophrenia	9	0.9980	Do not reject null	Consumer Sentiment Index does not influence schizophrenia
Alcohol use disorder → Consumer Sentiment Index	9	0.0000	Reject null	Alcohol use disorder influences Consumer Sentiment Index
Consumer Sentiment Index → Alcohol use disorder	9	0.4464	Do not reject null	Consumer Sentiment Index does not influence alcohol use disorders
Substance use disorders → Consumer Sentiment Index	9	0.5773	Do not reject null	Substance use disorders do not influence Consumer Sentiment Index
Consumer Sentiment Index → Substance use disorders	9	0.0604	Do not reject null	Consumer Sentiment Index does not influence substance use disorders

[1] We used the Akaike information criterion to detect the number of lags.

On the other hand, there is no causality between consumer sentiment and each mental disorder.

3.4. FCVAR Model

In order to understand and to check the relationship between multiple variables in the long term, we followed the model introduced by [39] which was further expanded by [40]. The model is called the fractional cointegrated vector autoregressive (FCVAR) model and it is a step ahead of the cointegrated vector autoregressive (CVAR) model proposed by [41].

To understand the FCVAR model, first it is necessary to present the non-fractional CVAR model.

Let Y_t, $t = 1, \ldots, T$ be a p-dimensional $I(1)$ time series. The CVAR model is as follows:

$$\Delta Y_t = \alpha\beta' Y_{t-1} + \sum_{i=1}^{k} \Gamma_i \Delta Y_{t-i} + \varepsilon_t = \alpha\beta' L Y_t + \sum_{i=1}^{k} \Gamma_i \Delta L^i Y_t + \varepsilon_t \tag{4}$$

To derive the FCVAR model, we need Δ^b and $L_b = 1 - \Delta^b$, which are the fractional counterparts to replace the difference and lag operator Δ and L in (4). We then obtain the following:

$$\Delta^b Y_t = \alpha\beta' L_b Y_t + \sum_{i=1}^{k} \Gamma_i \Delta L_b^i Y_t + \varepsilon_t \tag{5}$$

which is applied to $Y_t = \Delta^{d-b} X_t$, such that

$$\Delta^d X_t = \alpha\beta' L_b \Delta^{d-b} X_t + \sum_{i=1}^{k} \Gamma_i \Delta^b L_b^i Y_t + \varepsilon_t \tag{6}$$

where ε_t is a term with mean zero and variance–covariance matrix (Ω) that is p-dimensional independent and identically distributed; α and β are $p \times r$ matrices where $0 \leq r \leq p$. The relationship in the long-term equilibria in terms of cointegration in the system is due to the matrix β. Controlling the short-term behavior of the variables is due to parameter Γ_i. Finally, the deviations from the equilibria and their speed in the adjustment are due to parameter α.

In contrast to the CVAR model, there are two additional parameters in the FCVAR model. The order of fractional integration of the observable time series is represented by the parameter d. The degree of fractional cointegration, that is, the reduction in the fractional integration order of $\beta\prime X_t$ compared to X_t itself, is represented by the parameter b.

The relevant ranges for b are $\left(0, \frac{1}{2}\right)$, whereby in which case the equilibrium errors are a fraction of order greater than 1/2 and therefore non-stationary, although mean-reverting, and $\left(\frac{1}{2}, 1\right]$, whereby in which case the equilibrium errors are fractional of the order less than 1/2 and are stationary [42]. Note that for $d = b = 1$, the FCVAR models are reduced to the CVAR model, which is thus nested in the FCVAR model as a special case.

As an intermediate step toward the final model, we consider a version of model (4) with $d = b$ as an assumption of no persistence in the cointegration vectors and a constant mean term for the cointegration relations. That is to say the following:

$$\Delta^d X_t = \alpha(\beta' L_d X_t + \rho') + \sum_{i=1}^{k} \Gamma_i \Delta^d {L_d}^i X_t + \varepsilon_t \quad (7)$$

The simple model considered is the following:

$$\Delta^d (X_t - \mu) = L_d \alpha \beta' (X_t - \mu) + \sum_{i=1}^{k} \Gamma_i \Delta^d {L_d}^i X_t + \varepsilon_t \quad (8)$$

where μ represents the level parameter that shifts each of the series by a constant to avoid the bias related to the starting values in the sample ([40]). $\beta'\mu = -\rho\prime$ represents the mean stationary cointegrating relations.

The asymptotic analysis in [43] shows that the maximum likelihood estimators of $(d, \alpha, \Gamma, \ldots, \Gamma_2)$ are asymptotically normal, while the maximum likelihood estimator of (β, ρ) is asymptotically mixed normal when $d_0 < 1/2$ and asymptotically normal when $d_0 > 1/2$.

The results of the FCVAR model are summarized in Table 4.

Table 4. Results of the FCVAR model.

	$d \neq b$	Cointegrating Equation Beta	
		Var1	**Var 2**
Panel I: Mental and substance use disorders (Var1) vs. Consumer Sentiment Index (Var2)	$d = 1.525(0.424)$ $b = 1.525(0.352)$	1.000	–0.146
	$\Delta^d\left(\begin{bmatrix} \textit{Mental and substance use disorders} \\ \textit{Consumer Sentiment} \end{bmatrix} - \begin{bmatrix} 15.465 \\ 76.697 \end{bmatrix}\right) = L_d \begin{bmatrix} -0.008 \\ 1.931 \end{bmatrix} \nu_t + \sum_{i=1}^{2} \hat{\Gamma}_i \Delta^d L_d^i (X_t - \mu) + \varepsilon_t$		
Panel II: Anxiety (Var1) vs. Consumer Sentiment Index (Var 2)	$d = 1.239(0.424)$ $b = 1.239(0.210)$	1.000	–0.050
	$\Delta^d\left(\begin{bmatrix} \textit{Anxiety} \\ \textit{Consumer Sentiment} \end{bmatrix} - \begin{bmatrix} 5.606 \\ 72.983 \end{bmatrix}\right) = L_d \begin{bmatrix} -0.062 \\ 1.204 \end{bmatrix} \nu_t + \sum_{i=1}^{2} \hat{\Gamma}_i \Delta^d L_d^i (X_t - \mu) + \varepsilon_t$		
Panel III: Schizophrenia (Var 1) vs. Consumer Sentiment Index (Var2)	$d = 0.058(0.192)$ $b = 0.058(0.003)$	1.000	–0.002
	$\Delta^d\left(\begin{bmatrix} \textit{VSchizophrenia} \\ \textit{Consumer Sentiment} \end{bmatrix} - \begin{bmatrix} 0.472 \\ 78.812 \end{bmatrix}\right) = L_d \begin{bmatrix} 2.929 \\ 360995.240 \end{bmatrix} \nu_t + \sum_{i=1}^{2} \hat{\Gamma}_i \Delta^d L_d^i (X_t - \mu) + \varepsilon_t$		
Panel IV: Alcohol use disorders (Var 1) vs. Consumer Sentiment Index (Var2)	$d = 0.954(0.000)$ $b = 0.954(0.000)$	1.000	–0.085
	$\Delta^d\left(\begin{bmatrix} \textit{Alcohol use disorders} \\ \textit{Consumer Sentiment} \end{bmatrix} - \begin{bmatrix} 3.154 \\ 92.281 \end{bmatrix}\right) = L_d \begin{bmatrix} -0.05 \\ 3.309 \end{bmatrix} \nu_t + \sum_{i=1}^{2} \hat{\Gamma}_i \Delta^d L_d^i (X_t - \mu) + \varepsilon_t$		

After the results had been obtained in the causality tests, we wanted to understand the relationship that exists in the long term between mental illness and consumer sentiment. To do this, we used the FCVAR model to obtain four different results (from Panel I to Panel IV).

We are going to focus on two terms, the integrating and cointegrating part $(d \neq b)$ and the beta term, to analyze the behavior of the time series.

In Panel I and II, we observe that the order of integration of individual series into a cointegrating system is $d = 1.525$ and $d = 1.239$, respectively. The reduction in the degree of integration in the cointegrating regression is $b = 1.525$ and $b = 1.239$. These results imply $I(0)$ cointegrating errors, which means that the error follows a stationary process and the duration of any shock in this relationship will be short-lived.

From Panel III and IV, where we analyze the long-term relationship between schizophrenia and alcohol use disorders in consumer sentiment, we observe that the order of integration of the individual series is lower than 1 in these two cases $(d < 1)$, obtaining the same magnitude in the reduction in the degree of integration in the cointegrating regression. Again, these results imply that the error correction term follows a stationary process $(d - b = 0)$.

On the other hand, if we observe the cointegrating equation beta from several panels, the results suggest the following: (1) an increase in mental and substance use disorders produces a decrease (-0.146) in the Consumer Sentiment Index; (2) an increase in anxiety disorder produces a decrease (-0.050) in the Consumer Sentiment Index; (3) an increase in schizophrenia produces a decrease (-0.002) in the Consumer Sentiment Index; and (4) an increase in alcohol use disorders produces a decrease (-0.085) in the consumption expectation in the USA.

4. Concluding Comments

The World Health Organization (WHO) defines the term mental health as the condition of well-being in which an individual can use his or her abilities, recover from daily routine stress, be productive, and contribute to the community. So, any issue related to intellectual fitness is defined as a mental disorder.

Thus, in mental health, it is important to keep in mind that experiences, tendencies, and genetics affect individuals and their perceptions, thoughts, behaviors, and choices. However, sometimes, dysfunctional and maladaptive cognitions and behaviors are manifested by individuals, which increase the level of clinical concern and affect their mental health.

Because of these situations, consumption and the feeling that it produces in people with a mental health problem could have significant repercussions. Thus, following the research line initiated by Professor Steven S. Posavac at Vanderbilt University in the psychological subfield called "Clinical Consumer Psychology", the goal is to understand how a certain clinical disorder has manifested itself in consumer sentiment in the USA since 1990.

So, in conducting a univariate analysis using long memory tests, we have demonstrated that that there is a high degree of persistence in mental disorders and the Consumer Sentiment Index $(d > 1)$, except for depressive disorder $(d = 0.31)$. So, shocks in each mental disorder and in the expected consumer will not be transitory.

Once we had obtained long memory results, we analyzed, using the Granger causality test, the influence of each mental disorder on consumer sentiment behavior. The results suggest that four mental disorders (mental and substance use disorders, anxiety, schizophrenia, and alcohol use disorder) have a direct influence on consumer sentiment.

Finally, focusing on the FCVAR model, we conclude that an increase in cases of any mental and substance use disorders, anxiety, schizophrenia, and alcohol use disorder produces a decrease in the Consumer Sentiment Index $(\beta = -0.146, \beta = -0.050, \beta = -0.002$, and $\beta = -0.085)$.

According to [44], with our results, we demonstrate that there are other clinical phenomena, such as those that we have analyzed in this research paper, that are related to tendencies in consumer judgement and decision making.

Author Contributions: Conceptualization, J.T.M.M. and M.M.; Methodology, M.M.; Software, M.M.; Formal analysis, M.M.; Investigation, J.T.M.M. and M.M.; Data curation, J.T.M.M. and M.M.; Writing—original draft, J.T.M.M. and M.M.; Writing—review & editing, J.T.M.M. and M.M.; Visualization, J.T.M.M. and M.M.; Supervision, J.T.M.M. and M.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data is available on the links that are indicated in Section 2.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Posavac, S.S.; Posavac, H.D. Adult separation anxiety disorder symptomology and susceptibility to marketing persuasion. *J. Soc. Clin. Psychol.* **2017**, *36*, 158. [CrossRef]
2. Sneath, J.Z.; Lacey, R.; Kennett-Hensel, P.A. Coping with a natural disaster: Losses, emotions, and impulsive and compulsive buying. *Mark. Lett.* **2009**, *20*, 45–60. [CrossRef]
3. Smith, L.; Jacob, L.; Yakkundi, A.; McDermott, D.; Armstrong, N.C.; Barnett, Y.; López- Sánchez, G.F.; Martin, S.; Butler, L.; Tully, M.A. Correlates of symptoms of anxiety and depression and mental wellbeing associated with COVID-19: A cross- sectional study of UK-based respondents. *Psychiatry Res.* **2020**, *291*, 113138. [CrossRef] [PubMed]
4. Cooper, M.A.; Gordon, J.L. Understanding panic buying through an integrated psychodynamic lens. *Front. Public Health* **2021**, *9*, 666715. [CrossRef] [PubMed]
5. Leung, J.; Chung JY, C.; Tisdale, C.; Chiu, V.; Lim, C.C.; Chan, G. Anxiety and panic buying behaviour during COVID-19 pandemic—A qualitative analysis of toilet paper hoarding contents on Twitter. *Int. J. Environ. Res. Public Health* **2021**, *18*, 1127. [CrossRef]
6. Lins, S.; Aquino, S. Development and initial psychometric properties of a panic buying scale during COVID-19 pandemic. *Heliyon* **2020**, *6*, e04746. [CrossRef] [PubMed]
7. Roy, D.; Tripathy, S.; Kar, S.K.; Sharma, N.; Verma, S.K.; Kaushal, V. Study of knowledge, attitude, anxiety & perceived mental healthcare need in Indian population during COVID-19 pandemic. *Asian J. Psychiatry* **2020**, *51*, 102083.
8. Yuen, K.F.; Wang, X.; Ma, F.; Li, K.X. The psychological causes of panic buying following a health crisis. *Int. J. Environ. Res. Public Health* **2020**, *17*, 3513. [CrossRef]
9. Gerrard, Y. TikTok Has a Pro-Anorexia Problem. 2020. Available online: https://www.wired.com/story/opinion-tiktok-has-a-pro-anorexia-problem (accessed on 3 January 2023).
10. Posavac, S.S.; Posavac, H.D.; Gaffney, D.R.; Kardes, F.R. Toward a Clinical Consumer Psychology. *Front. Psychol.* **2022**, *13*, 904843. [CrossRef]
11. Sanchez, C.; Dunning, D. Jumping to conclusions: Implications for reasoning errors, false belief, knowledge corruption, and impeded learning. *J. Personal. Soc. Psychol.* **2021**, *120*, 789. [CrossRef]
12. Levine, M.P.; Harrison, K. Effects of media on eating disorders and body image. In *Media Effects*; Routledge: Oxfordshire, UK, 2009; pp. 506–532.
13. Leeman, R.F.; Potenza, M.N. Similarities and differences between pathological gambling and substance use disorders: A focus on impulsivity and compulsivity. *Psychopharmacology* **2012**, *219*, 469–490. [CrossRef] [PubMed]
14. Brevers, D.; Bechara, A.; Cleeremans, A.; Noël, X. Iowa Gambling Task (IGT): Twenty years after–gambling disorder and IGT. *Front. Psychol.* **2013**, *4*, 665. [CrossRef]
15. Clark, L.; Averbeck, B.; Payer, D.; Sescousse, G.; Winstanley, C.A.; Xue, G. Pathological choice: The neuroscience of gambling and gambling addiction. *J. Neurosci.* **2013**, *33*, 17617–17623. [CrossRef] [PubMed]
16. American Psychiatric Association. *Diagnostic and Statistical Manual of mental Disorders*, 5th ed.; Psychiatric Association: Washington, DC, USA, 2013.
17. Granero, R.; Fernández-Aranda, F.; Mestre-Bach, G.; Steward, T.; Baño, M.; del Pino-Gutiérrez, A.; Moragas, L.; Mallorquí-Bagué, N.; Aymamí, N.; Gómez-Peña, M.; et al. Compulsive buying behavior: Clinical comparison with other behavioral addictions. *Front. Psychol.* **2016**, *7*, 914. [CrossRef] [PubMed]
18. Mandel, N.; Rucker, D.D.; Levav, J.; Galinsky, A.D. The compensatory consumer behavior model: How self-discrepancies drive consumer behavior. *J. Consum. Psychol.* **2017**, *27*, 133–146. [CrossRef]
19. Jones, Z. Rise of the IGaming Industry: Is the United States Ready to Accept Online Casinos? Forbes. 2021. Available online: https://www.forbes.com/sites/zackjones/2021/04/21/the-rise-of-the-igaming-industry-what-is-in-store-forthe-citizens-of-united-states/?sh=796fb8863555 (accessed on 18 May 2022).
20. Box, G.E.P.; Jenkins, G.M. *1970: Time Series Analysis, Forecasting and Control*; Holden-Day: San Francisco, CA, USA, 1970.
21. Nelson, C.R.; Plosser, C.R. Trends and random walks in macroeconmic time series: Some evidence and implications. *J. Monet. Econ.* **1982**, *10*, 139–162. [CrossRef]
22. Dickey, D.A.; Fuller, W.A. Distributions of the estimators for autoregressive time series with a unit root. *J. Am. Stat. Assoc.* **1979**, *74*, 427.
23. Dickey, D.A.; Fuller, W.A. Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica* **1981**, *49*, 10571072. [CrossRef]
24. Phillips, P.C. Time series regression with a unit root. *Econom. J. Econom. Soc.* **1987**, *55*, 277–301. [CrossRef]
25. Phillips, P.C.B.; Perron, P. Testing for a unit root in time series regression. *Biometrika* **1988**, *75*, 335–346. [CrossRef]
26. Kwiatkowski, D.; Phillips, P.C.; Schmidt, P.; Shin, Y. Testing the null hypothesis of stationarity against the alternative of a unit root. *J. Econom.* **1992**, *54*, 159–178. [CrossRef]
27. Adenstedt, R.K. On large-sample estimation for the mean of a stationary random sequence. *Ann. Stat.* **1974**, *2*, 1095–1107. [CrossRef]
28. Granger, C.W. Long memory relationships and the aggregation of dynamic models. *J. Econom.* **1980**, *14*, 227–238. [CrossRef]
29. Granger, C.W. Some properties of time series data and their use in econometric model specification. *J. Econom.* **1981**, *16*, 121–130. [CrossRef]

30. Granger, C.W.; Joyeux, R. An introduction to long-memory time series models and fractional differencing. *J. Time Ser. Anal.* **1980**, *1*, 15–29. [CrossRef]
31. Hosking, J.R. Modeling persistence in hydrological time series using fractional differencing. *Water Resour. Res.* **1984**, *20*, 1898–1908. [CrossRef]
32. Diebold, F.X.; Rudebush, G.D. On the power of Dickey-Fuller tests against fractional alternatives. *Econ. Lett.* **1991**, *35*, 155–160. [CrossRef]
33. Hassler, U.; Wolters, J. On the power of unit root tests against fractional alternatives. *Econ. Lett.* **1994**, *45*, 1–5. [CrossRef]
34. Lee, D.; Schmidt, P. On the power of the KPSS test of stationarity against fractionally-integrated alternatives. *J. Econom.* **1996**, *73*, 285–302. [CrossRef]
35. Sowell, F. Maximum likelihood estimation of stationary univariate fractionally integrated time series models. *J. Econom.* **1992**, *53*, 165–188. [CrossRef]
36. Akaike, H. Maximum likelihood identification of Gaussian autoregressive moving average models. *Biometrika* **1973**, *60*, 255–265. [CrossRef]
37. Akaike, H. A Bayesian extension of the minimum AIC procedure of autoregressive model fitting. *Biometrika* **1979**, *66*, 237–242. [CrossRef]
38. Asteriou, D.; Hall, S.G. *Applied Econometrics*; Palgrave Macmillan: London, UK, 2015.
39. Johansen, S. A representation theory for a class of vector autoregressive models for fractional processes. *Econom. Theory* **2008**, *24*, 651–676. [CrossRef]
40. Johansen, S.; Nielsen, M.Ø. Likelihood inference for a fractionally cointegrated vector autoregressive model. *Econometrica* **2012**, *80*, 2667–2732. [CrossRef]
41. Johansen, S. *Likelihood-Based Inference in Cointegrated Vector Autoregressive Models*; Oxford University Press: New York, NY, USA, 1996.
42. Dolatabadi, S.; Nielsen, M.Ø.; Xu, K. A fractionally cointegrated VAR analysis of price discovery in commodity futures markets. *J. Futures Mark.* **2015**, *35*, 339–356. [CrossRef]
43. Johansen, S.; Nielsen, M.Ø. The role of initial values in nonstationary fractional time series models. *SSRN Electron. J.* **2012**, 12–18. [CrossRef]
44. Hastie, R.; Dawes, R.M. *Rational Choice in an Uncertain World: The Psychology of Judgment and Decision Making*; Sage Publications: Thousand Oaks, CA, USA, 2009.