mathematics

MDPI

Article

Consumer Sentiment and Luxury Behavior in the United States before and after COVID-19: Time Trends and Persistence Analysis

Berta Marcos Ceron [1] and Manuel Monge [2,*]

[1] Faculty of Social Science, Universidad de Salamanca, E-37007 Salamanca, Spain; berta.marcos@ufv.es
[2] Faculty of Law, Business and Government, Universidad Francisco de Vitoria, E-28223 Madrid, Spain
* Correspondence: manuel.monge@ufv.es

Abstract: This paper analyzes the stochastic properties of consumer sentiment to understand how they affected the luxury sector in the United States before and after COVID-19. The results were derived using fractional integration methodologies and suggest that, before the pandemic episode, both variables were expected to be mean reverting and the shocks were transitory, having similar behavior. However, after the appearance of COVID-19, results suggest that consumer sentiment recovered before the luxury sector. Results from the use of cointegration methodologies show that the effects of COVID-19 disappeared in the short-run. Finally, the sentiment of consumers acts as a leading indicator of the behavior of the luxury sector according to wavelet analysis. Thus, an increase in consumer sentiment implies an increase of 3.6% in the luxury sector.

Keywords: luxury sector; consumer sentiment; fractional integration; FCVAR model; wavelet analysis

MSC: 62P20; 62P25; 91B70; 91B84

check for updates

Citation: Marcos Ceron, B.; Monge, M. Consumer Sentiment and Luxury Behavior in the United States before and after COVID-19: Time Trends and Persistence Analysis. *Mathematics* **2023**, *11*, 3612. https://doi.org/10.3390/math11163612

Academic Editors: Emanuel Guariglia and Massimiliano Ferrara

Received: 11 July 2023
Revised: 16 August 2023
Accepted: 18 August 2023
Published: 21 August 2023

1. Introduction

Economic crises are not uncommon occurrences in the economic system and are often influenced by psychosocial behavior. The process that explains the occurrence and onset of a crisis was initially proposed by British economist John Maynard Keynes [1]. Keynesian theory focused on the role of aggregate demand and how it influences economic growth and stability. Later, economists such as Joseph A. Schumpeter [2] and Milton Friedman [3] further developed the theory of economic crises. Schumpeter emphasized the role of innovation and creative destruction in the economy, while Friedman's theory highlighted the role of monetary policy in the occurrence of economic crises.

First, a state of economic boom fosters consumption, which in turn influences people's well-being. Second, a period of strong speculation follows the pattern observed by Walter Bagehot: "People are all the more gullible the happier they are" (see [4]). Third, the high speculation phase always ends with a violent shock of depression and economic restructuring.

Economic and financial crises have a negative impact on consumer sentiment, which translates into a decrease in consumption and greater sensitivity to prices (see [5]).

In [6], the authors showed that these crises generate uncertainty, which leads to a decrease in consumer confidence and increased saving.

Shocks appear with a sudden, violent upheaval, without warning of their arrival. A shock is an escalation of events in which little or no information is available. Shocks not only influence the economy, but also the behavior, feelings, attitudes, motivations, emotions, and expectations of people (see [7,8]).

Research conducted by [9] revealed that unexpected events such as climatic disasters, wars, and pandemics have a significant impact on the emotional and economic state of consumers. Resilience and previous experiences are the factors that affect the consumer's sentiment and behavior.

According to [10], after these shocks, people can use consumption to reestablish their identity and new social relationships.

COVID-19 was not the first world-wide crisis faced by luxury brands, but it has had a significant impact on the economy and people's lives, including on the sentiment and behavior of consumers. In the previous global financial crisis in 2008, the luxury industry was affected and experienced an 8% overall decline. The industry had to adopt suitable strategies to overcome the crisis, according to their own brand identity (see [11–13]; among others), being faithful to their brand image and not diluting their brands (see [14]).

Various studies have evaluated how COVID-19 has affected consumers' perceptions and attitudes and their purchasing behavior.

In [15], the author identified that economic uncertainty and health insecurity caused by the pandemic led to a decrease in the consumption of non-essential goods. On the other hand, reference [16] observed an increase in the consumption of essential products and online purchases, due to restrictions on movement and closure of commercial activity.

Reference [17] identified that uncertainty, perception of severity, perception of scarcity, and anxiety are significant factors that influence consumer purchasing behavior.

Some studies, such as the one conducted by [18], affirm how the COVID-19 pandemic has impacted consumer behavior and led to significant changes in the perception and purchase of products, while the study developed by [19] includes a change in spending patterns and willingness to pay for certain products.

Before the pandemic, the luxury sector was experiencing an increase in demand for products and a greater availability of online options. However, the pandemic has led to a decrease in demand and a shift in consumers' values and priorities. According to a study by [20], the pandemic has led to a change in the perception of luxury and has affected the demand for luxury products.

During the pandemic, consumers adopted a more cautious stance and prioritized safety and convenience in their purchases. According to [21], the pandemic led to an increase in online shopping and a decrease in physical store purchases. Furthermore, consumers sought more accessible and practical luxury products. After the pandemic, it is expected that consumer sentiment and behavior in the luxury sector will continue to evolve.

Reference [22] demonstrates how the luxury sector has had to quickly adapt to respond to this crisis in order to remain relevant to consumers.

Digitization in the luxury sector has been the subject of interest in recent years and has become even more important in the context of the COVID-19 pandemic. According to a study by [23], the pandemic has driven innovation and adoption of digital technologies in the luxury sector, such as the option to make purchases online and the offer of personalized attention through chatbots and virtual advisors, which has led to an increase in customer satisfaction and online sales.

According to [24], after the pandemic, digitalization is expected to continue to be an important aspect in the luxury sector. Digitalization will allow luxury brands to improve their ability to personalize and offer a unique experience to their customers, which in turn will increase customer loyalty and satisfaction.

There is limited literature that examines how consumer sentiment and behavior has been affected in relation to the luxury sector before, during, and after the COVID-19 pandemic in the United States.

Some authors, such as [25], have used market studies and consumer surveys to investigate how the pandemic has affected consumer perception and behavior regarding "masstige" luxury products, and how these have evolved in the post-COVID era.

Other authors, such as [26], have also analyzed the impact of "sustainable trends" on the stimulation of luxury goods purchases through surveys.

References [27–29], among others, argued that consumer confidence indices are good social indicators that perform well as leading indicators and reproduce subjective opinions about material living conditions; as such, they are sensitive to real changes in the economy. Additionally, they reflect the general course of business activity and of consumer expenditure.

On the other hand, luxury goods and services are those consumer goods that are defined as discretionary goods [30,31]. These authors argued that spending on some durable and luxury goods (discretionary goods) reflects the flexibility in expenditure. This occurs because these discretionary goods are sometimes limited by the purchasing power of consumers. According to [32], these purchases can be advanced or delayed, making durable expenditures particularly volatile. In contrast, expenditures on necessities do not vary according to consumer attitudes.

In line with the previous statements, this paper offers several contributions to the scant literature on time trends and persistence in the luxury sector and consumer sentiment as a leading indicator of consumer expenditure.

After reviewing the literature, this is the first study that analyzes the time series of the luxury market and consumer sentiment and their statistical properties. To do so, first, to understand the behavior of each time series, a univariate analysis was carried out, where long memory techniques were used to provide evidence on the stochastic properties (more specifically, mean reversion and persistence). Finally, considering COVID-19 as a structural break, this research paper aimed to examine the impact of consumer sentiment on luxury market behavior via cointegration and wavelet analysis.

This paper follows the following structure. Section 2 presents the data used in this study. Section 3 describes the methodologies used to carry out the research. The results are discussed in Section 4. Finally, Section 5 presents the concluding remarks.

2. Data

This research paper uses several time series to understand how the behavior and sentiment of consumers affects the behavior of luxury.

The database used to study the behavior of luxury was obtained from the S&P Dow Jones Indices. The S&P Global Luxury Index is based on the 80 largest publicly traded companies that are involved in the production or distribution of luxury goods or the provision of luxury services that meet specific marketability requirements.

The consumer sentiment database is used as a leading indicator of consumer expenditure. This database is maintained by the University of Michigan and adopted by the Federal Reserve Bank of St. Louis. The Consumer Sentiment Index is based on the consumer confidence level measured in at least 500 monthly telephone interviews in United States. These monthly surveys ask about the economy, personal finances, business conditions, and buying conditions, among others things.

The data used to carry out this research paper have a monthly frequency, from January 1998 to July 2022, as represented in Figure 1.

In order to avoid the spread of the COVID-19 pandemic at the beginning of 2020, Figure 1 shows how the effects of the global lockdown, social distancing, and other measures affected consumers and their use of the Internet to make their purchases (see [33]). The result of this business landscape resulted in a transformation during the quarantine period, accelerating the development of digital commerce with a new digitally immersed consumer ([34,35], among others). Due to the COVID-19 situation, some shopping categories accelerated offerings in the direction of experience categories (see [36]), such as luxury.

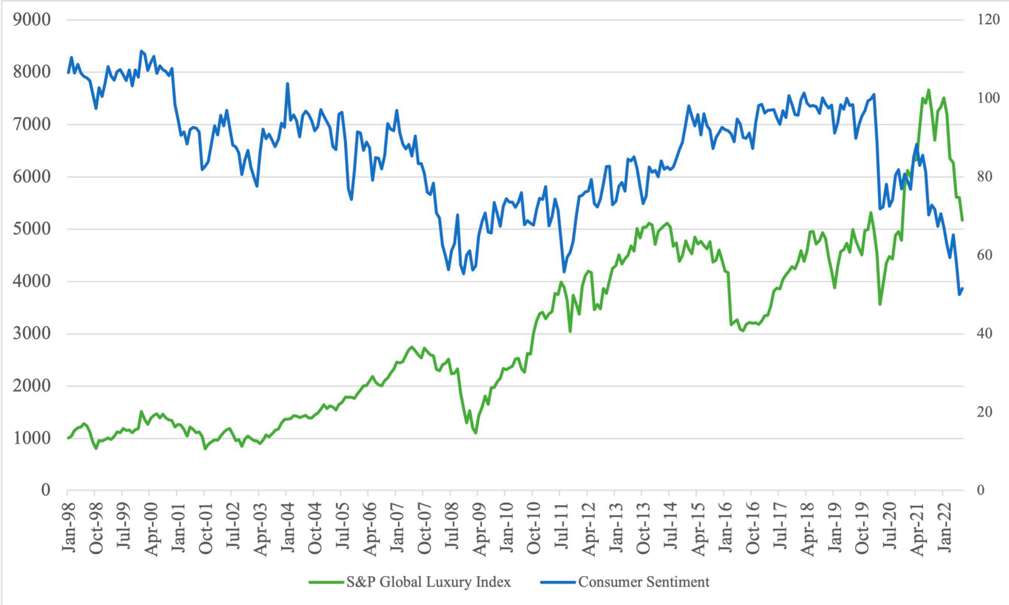

Figure 1. Global Luxury Index vs. Consumer Sentiment Index.

3. Methodology

3.1. Unit Root Methods

Unit roots can be tested in many different ways. For this research, the ADF test based on [37] was used. Many other tests are available with a greater power to calculate unit roots. For instance, Phillips and Perron present a non-parametric estimate of the spectral density of u_t at the zero frequency (see [38]). In addition, the methodology based on KPSS (see [39]) and ERS (see [40]) considered deterministic trends, and obtained the same results.

3.2. ARFIMA (*p*, *d*, *q*) Model

Once tested using standard unit root tests and finding that the time series are not stationary, a more advanced methodology was employed.

Based on the idea introduced by [41–45], any point on a real line does not necessarily have to be an integer value to achieve stationarity $I(0)$. Thus, the number of differences could be fractional $I(d)$.

As indicated by [46–48] and others, unit root methods have very low power to determine whether the data used in the analysis are a long memory process or are fractionally integrated. Therefore, it makes sense to use fractional numbers and fractionally integrated methods to make the time series stationary $I(0)$.

This advanced methodology also allows us to capture and determine when observations are far apart in time but highly correlated, thereby measuring the degree of persistence.

So, the mathematical notation of the fractional model used that is ARFIMA (p, d, q) model is the following:

$$(1-L)^d x_t = u_t,\ t = 1,\ 2, \qquad (1)$$

From Equation (1), x_t denotes the integrated $I(d)$ process of the time series, d represents any real value, the lag operator $(Lx_t = x_{t-1})$ is represented by L, and the $I(0)$ covariance stationary process is represented by u_t, where the spectral density function displays a type of time dependence in the weak form and is positive and finite at the zero frequency. Therefore, it can be stated that if u_t is $ARMA\ (p,\ q)$, x_t is $ARMA(p,\ d,\ q)$. $(1-L)^d$ is a polynomial expressed in terms of binomial expansion.

Table 1 presents a guide to the interpretation of the different values of d.

A higher value of d means a higher degree of persistence, which means a higher level of association between the observations of the series.

To determine the appropriate AR and MA orders in the models $(p,\ q \leq 2)$, the Akaike information criterion and Bayesian information criterion were used (see [49,50]).

Table 1. Interpretation of the results of 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 nonstationary
$d < 1$	x_t is mean reverting
$d \geq 1$	x_t is not mean reverting

3.3. FCVAR Model

To check the relationship of the variables in the long term, this research paper follows [51], and used the multivariate Fractional Cointegrated VAR (FCVAR) model.

The starting point to understand the FCVAR model is the non-fractional CVAR model. If a time series Y_t, where $t = 1, \ldots, T$ is a p-dimensional $I(1)$ time series, then the CVAR model is as follows:

$$\Delta Y_t = \alpha\beta' Y_{t-1} + \sum_{i=1}^{k} \Gamma_i \Delta Y_{t-i} + \varepsilon_t = \alpha\beta' L Y_t + \sum_{i=1}^{k} \Gamma_i \Delta L^i Y_t + \varepsilon_t \quad (2)$$

Δ^b and $L_b = 1 - \Delta^b$ are necessary to derive the FCVAR model because these terms are the fractional counterparts to replace the difference and lag operator Δ and L in (2). We then obtain the following:

$$\Delta^b Y_t = \alpha\beta' L_b Y_t + \sum_{i=1}^{k} \Gamma_i \Delta L_b^i Y_t + \varepsilon_t \quad (3)$$

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

$$\Delta^d X_t = \alpha\beta' L_b \Delta^{d-b} X_t + \sum_{i=1}^{k} \Gamma_i \Delta^b L_b^i Y_t + \varepsilon_t \quad (4)$$

where ε_t is the K-dimensional identically distributed error term with a zero mean and constant variance–covariance matrix $(\varepsilon_t \sim iid(0, \Omega))$. α and β are the framework of hypothesis testing on long-run parameters. These terms are $p \times r$ matrices where $0 \leq r \leq p$. The β matrix represents the long-term equilibria in terms of cointegration. Γ_i controls the short-term behavior of the variables. α indicates the deviation from the equilibria and the speed in the adjustment. The FCVAR model provides 2 additional parameters compared to the CVAR model. The parameter d represents the order of fractional integration of the observable time series in a multivariate context. The parameter b is the degree of fractional cointegration and represents the reduction in the fractional integration order of $\beta\prime X_t$ compared to X_t itself. Depending on this value, we observe the following cases: (a) a non-stationary, although mean reverting, case occurs when the equilibrium errors are in the range $(0, \frac{1}{2})$; (b) a stationary case occurs when the equilibrium errors are fractional and less than 1/2; (c) when $d = b = 1$, the FCVAR model is reduced to the CVAR model.

3.4. Wavelet Analysis

Continuous wavelet transform (CWT) is a time–frequency domain methodology based on two tools, and has the advantages of: (1) no stationarity requirement and (2) the ability to find structural changes due to the interaction of the time and frequency decomposition of both time series. These tools are wavelet coherency and wavelet phase difference (the authors of this study have used continuous wavelet transform (CWT) in several research papers, such as [52–55]).

These methodologies are very relevant since, by definition, a time series is an aggregation of components operating on different frequencies. So, the most important information is hidden in the frequency content of the signal.

Finally, the research carried out by [56–59] suggests that misleading results will be found if we apply a typical cross-correlation to study statistical relationships between two multifractal time series.

To measure the correlation of time series and to identify hidden patterns and/or information in the time–frequency domain, wavelet coherency is used. The mathematical notation of $WT_x(a,\tau)$, which is the wavelet transform of a time series $x(t)$, is as follows:

$$WT_x(a,\tau) = \int_{-\infty}^{+\infty} x(t)\frac{1}{\sqrt{a}}\psi^*\left(\frac{t-\tau}{a}\right)dt \tag{5}$$

From Equation (5), $WT_x(a,\tau)$ is the map on the time and frequency of the original time series onto a function of τ and a. The Morlet wavelet was chosen in this research paper as the mother wavelet (ψ) because it is a complex sine wave within a Gaussian envelope, allowing measurement of the synchronism between time series (see [60]).

To understand how one time series interacts with the other, wavelet coherence is employed. This is defined as follows:

$$WCO_{xy} = \frac{SO(WT_x(a,\tau)WT_y(a,\tau)^*)}{\sqrt{SO\left(|WT_x(a,\tau)|^2\right)SO\left(|WT_y(a,\tau)|^2\right)}} \tag{6}$$

From Equation (6), SO represents the operator in time and scale that smooths the calculus. This is very important because, without it, the wavelet coherency always has a value of one for all times and scales ([61]). Aguiar-Conraria's website (https://sites.google.com/site/aguiarconraria/joanasoares-wavelets, accessed on 10 June 2023) provides the MATLAB code for the CWT.

4. Empirical Results

Table 2 presents the results of the expected consumption and the luxury sector once a univariate analysis is conducted based on the standard unit root tests (ADF, PP, and KPSS). Considering the original time series and the periods before and after COVID-19, the results suggest a non-stationary $I(1)$ behavior.

Table 2. Unit root tests.

	ADF			PP		KPSS	
	(i)	**(ii)**	**(iii)**	**(ii)**	**(iii)**	**(ii)**	**(iii)**
			Original Data				
Consumer Sentiment	−1.1776	−2.3556	−2.5834	−1.8882	−2.1751	1.0441	0.6348
S&P Global Luxury Index	0.3653	−1.1097	−2.922	−1.1529	−3.0762	4.2981	0.1902
			Before COVID-19				
Consumer Sentiment	−0.7182	−2.7378	−2.6408	−2.3794	−2.2876	1.0815	0.8833
S&P Global Luxury Index	0.6615	−0.923	−2.4503	−0.9626	−2.5643	3.9953	0.2517
			After COVID-19				
Consumer Sentiment	−0.9442	−0.0163	−1.4899	−1.0651	−1.8857	0.7051	0.2296
S&P Global Luxury Index	0.2907	−2.0361	0.1709	−1.2629	0.1109	0.6285	0.2365

Following the results presented in Table 2, as mentioned in the Methodology section regarding the lower power of unit root tests, the next step is to employ fractional alternatives as ARFIMA (p, d, q) models to study the persistence of the time series, as previously mentioned.

Table 3 displays the results of the best models using the ARFIMA (p, d, q) methodology taking into account Sowell's maximum likelihood estimator [62].

Table 3. Results of long memory tests.

Data Analyzed	Sample Size (Days)	Model Selected	d	Std. Error	Interval	$I(d)$
			Original Time Series			
Consumer Sentiment	295	ARFIMA (2, d, 2)	0.95	0.193	[0.63, 1.27]	$I(1)$
S&P Global Luxury Index	295	ARFIMA (2, d, 2)	0.22	0.193	[−0.10, 0.54]	$I(0)$
			Before COVID-19			
Consumer Sentiment	266	ARFIMA (2, d, 2)	0.95	0.108	[0.77, 1.13]	$I(1)$
S&P Global Luxury Index	266	ARFIMA (2, d, 2)	0.93	0.054	[0.84, 1.02]	$I(1)$
			After COVID-19			
Consumer Sentiment	29	ARFIMA (1, d, 2)	0.79	0.436	[0.07, 1.50]	$I(1)$
S&P Global Luxury Index	29	ARFIMA (1, d, 1)	1.10	0.319	[0.57, 1.62]	$I(1)$

Table 3 displays the fractional parameter d and the AR and MA terms obtained using Sowell's maximum likelihood estimator [62] of various ARFIMA (p, d, q) specifications with all combinations of $p, q \leq 2$, for each time series.

Table 3 presents the fractional parameter (d) results. Focusing on the original time series, it is noted that the original time series of consumer sentiment and luxury index are lower than 1 in both cases $(d < 1)$. These results suggest that both time series are expected to be mean reverting and the shocks will be transitory, where consumer sentiment $(d = 0.95)$ will take longer to recover its original trend than the luxury sector $(d = 0.22)$. Hypothesis $I(1)$ cannot be rejected for the expected consumption variable.

Before the pandemic episode, both variables behaved similarly. On the contrary, after the appearance of COVID-19, consumer sentiment $(d = 0.79)$ recovered its trend faster than the luxury sector $(d = 1.10)$, which will need extraordinary measures to return to its original trend.

According to [15], the economic uncertainty and health insecurity caused by the pandemic have led to a decrease in consumption. References [17,18] stated that uncertainty, perception of severity, perception of scarcity, and anxiety are significant factors that influence consumer purchasing behavior. The research conducted by [19] includes a change in spending patterns and willingness to pay for certain products.

Once the univariate analysis was performed, it became interesting to discover if both time series have a relationship or have any effect on the other. Thus, Table 4 displays the results obtained using Granger causality via a VAR model test to examine the interactions between consumer sentiment and the luxury index in the United States. The Granger test consists of a vector autoregressive representation (VAR) consisting of the two series as follows:

$$CS_t = \alpha_1 + \sum_{i=1}^{n} \beta_i Lux_{t-i} + \sum_{j=1}^{m} \delta_j CS_{t-j} + \epsilon_{CS_t} \tag{7}$$

$$Lux_t = \alpha_2 + \sum_{i=1}^{n} \theta_i Lux_{t-i} + \sum_{j=1}^{m} \psi_j CS_{t-j} + \epsilon_{Lux_t} \tag{8}$$

where CS is the consumer sentiment and Lux is the luxury index, and it is assumed that both ϵ_{Lux_t} and ϵ_{CS_t} are uncorrelated white noise error terms. The maximum number of lags for each variable is represented by the letters m and n in Equations (7) and (8). Before applying these to derive causality results using the VAR methodology, it is important to validate the following assumptions: First, it is important to make sure that the variables are either integrated of order zero or one to apply the VAR model. Second, the ordinary least squares method can be used to estimate the level and the first difference relationship between variables. Finally, if it is an integrated time series of order zero $I(0)$, it is not expected to have long run relationships.

Table 4. Results of Granger causality test.

Direction of Causality	Lags [1]	Prob.	Decision	Outcome
d_CS → d_Luxury	2	0.0434	Reject null	Consumer sentiment causes luxury sector behavior
d_Luxury → d_CS	2	0.4660	Do not reject null	Luxury sector does not cause consumer sentiment

[1] We used the Akaike Information Criterion to detect the number of lags.

For this study, the two Granger causality test hypotheses were tested. The first hypothesis is $H_0 : \sum_{i=1}^{n} \beta_i = 0$ (consumer sentiment does not influence luxury) and $H_1 : \sum_{i=1}^{n} \beta_i \neq 0$ (luxury influences consumer sentiment) and the second hypothesis is $H_0 : \sum_{j=1}^{m} \psi_j = 0$ (luxury does not influence consumer sentiment) and $H_1 : \sum_{j=1}^{m} \psi_j \neq 0$ (luxury influences consumer sentiment).

Table 4 presents the Granger causality results when causality runs from consumer sentiment to luxury and vice versa. From the results, it is observed that consumer sentiment in United States has a direct influence on luxury behavior.

In order to be more precise and following the results obtained in the Granger section, the Fractional Cointegrating VAR (FCVAR) model is used to understand the interactions and the relationship of both time series in the long run. The results are summarized in Table 5.

Table 5. Results of the FCVAR model.

	$d \neq b$	Cointegrating Equation Beta	
		Consumer Sentiment	Global Luxury Index
Panel I: Consumer Sentiment vs. Global Luxury Index	$d = 1.083\ (0.145)$ $b = 0.546\ (0.278)$	1.000	0.016
	$\Delta^d\left(\begin{bmatrix} C.S. \\ Luxury \end{bmatrix} - \begin{bmatrix} 105.673 \\ 940.931 \end{bmatrix}\right) = L_d \begin{bmatrix} -0.151 \\ -4.030 \end{bmatrix} \nu_t + \sum_{i=1}^{2} \hat{\Gamma}_i \Delta^d L_d^i (X_t - \mu \Big) + \varepsilon_t$		
Panel II: Consumer Sentiment vs. Global Luxury Index "After COVID-19"	$d = 1.459\ (0.000)$ $b = 1.459\ (0.000)$	1.000	0.036
	$\Delta^d\left(\begin{bmatrix} C.S. \\ Luxury \end{bmatrix} - \begin{bmatrix} 103.352 \\ 4993.441 \end{bmatrix}\right) = L_d \begin{bmatrix} -0.027 \\ -3.584 \end{bmatrix} \nu_t + \sum_{i=1}^{2} \hat{\Gamma}_i \Delta^d L_d^i (X_t - \mu \Big) + \varepsilon_t$		

According to the results obtained using the FCVAR model, the focus is on two terms, i.e., the integration term (d) and cointegration term (b), and also the beta term to analyze the behavior of the time series.

Panel I displays the results regarding the long-term relationship between consumer sentiment in the United States and the global luxury index. The order of integration of the individual series is 1.083 and the reduction in the degree of integration in the regression is 0.546. Because $d - b = 0.537$, the cointegration result suggests that the error correction term follows a non-stationary process, although it is mean reverting, and the shock duration is long-lived.

Panel II displays the results that correspond to the period "after COVID-19". The order of integration of the individual series is 1.459, and the same magnitude is obtained in the reduction in the degree of integration in the cointegrating regression. These results imply $I(0)$ cointegrating errors. Therefore, although the individual series apparently shows $I(1)$ behavior, the results of the cointegration analysis hypothesis on the effects of the shock show that they disappear in the short-run and cannot be rejected. On the other hand, the results suggest that an increase in the variable "Consumer Sentiment" produces an increase in the "Luxury Index" (cointegrating equation beta equal to 0.036).

Finally, a multivariate analysis based on the time–frequency domain was performed to understand the correlation that exists between both variables, consumer sentiment and the luxury sector, considering COVID-19. In addition, this methodology is able to detect structural changes in the whole sample.

Figure 2 displays several results. Wavelet coherency is represented in section (a). This result identifies the main regions with statistically significant coherency, indicating when and at which frequencies the interrelations between time series occur and when they are the strongest. These regions are located at cycles that correspond to the 1–12 frequency band (low frequencies that correspond to short term) and the 12.5–32 frequency band (high frequencies that correspond to long term), starting at 1998 in all the series.

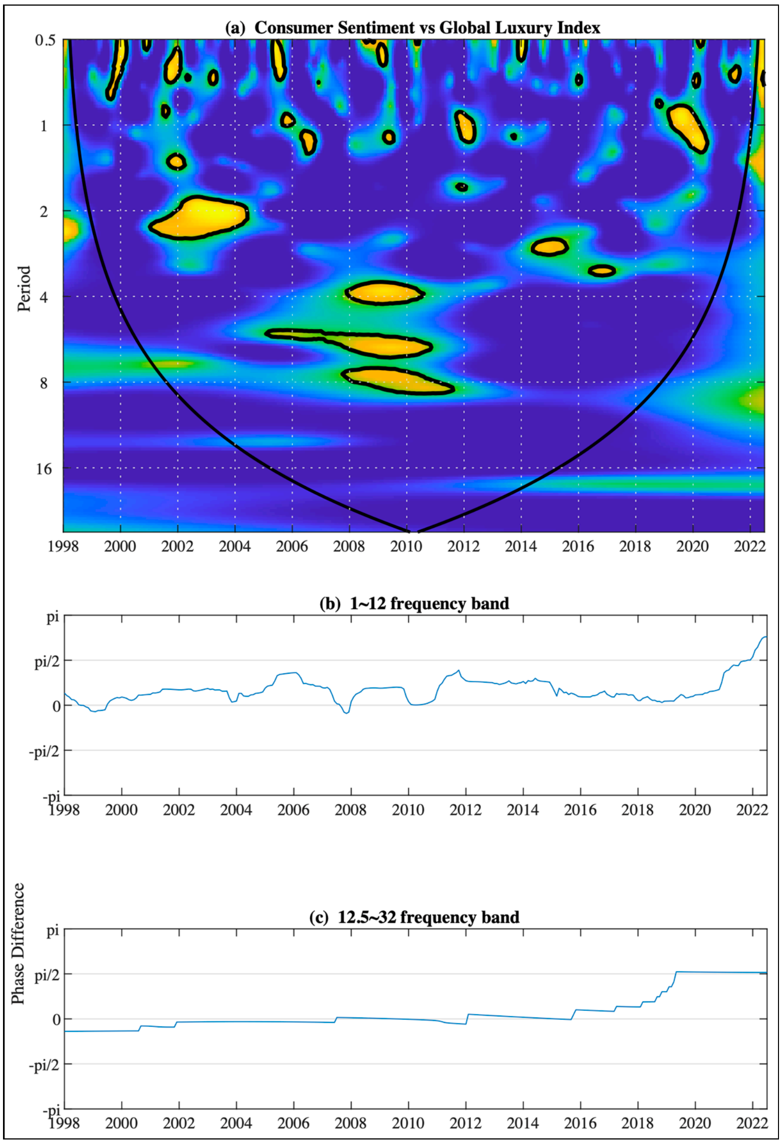

Figure 2. Wavelet coherency and phase-difference analysis.

The region that corresponds to the coronavirus episode has been identified in the 0.8–1.4 frequency band. Once this region is located in the indicated frequency band, the partial difference in the 1–12 frequency band in section (b) is used to determine the impact and importance of the shock of one variable in relation to the other. For the results previously obtained at the 5% significance level, the phase difference is within $\left[0, \frac{\pi}{2}\right]$. This means that, at this frequency, there is a positive correlation between consumer sentiment and the luxury index. Economically, this means that consumer sentiment acted as a leading indicator of the behavior of the luxury sector in the short term during the COVID-19 period.

Consumption or expected consumption under the assumption of natural disasters have been less studied. Many studies, such as [9,10,63–66], indicate compulsive and impulsive behavior regarding consumption.

The results presented in this paper contribute to the previous literature to help understand the behavior of consumer sentiment in a pandemic episode and how this affects a specific sector such as luxury.

5. Conclusions

Some studies have analyzed how the COVID-19 pandemic has impacted consumer behavior and shown how this event has caused a significant change in the perception and purchase of products (see [18]). In addition, this pandemic has changed the pattern of spending and the willingness to pay for certain products (see [19]).

The luxury sector has historically been resistant and resilient to economic fluctuations and has proven to be a key driver of economic growth (see [67]).

Before the pandemic, the luxury sector was experiencing an increase in demand for products and a greater availability of online options. However, with the arrival of the pandemic, this sector has been one of the hardest hit. Store closures, decreased tourism, and economic uncertainty have negatively impacted luxury businesses. The pandemic led to a decrease in demand and a shift in consumers' values and priorities. According to a study by [20], the pandemic led to a change in the perception of luxury, affecting the demand for luxury products.

Consumer sentiment and behavior changed due to economic uncertainty and health insecurity, causing the consumption of non-essential goods to decline (see [15]), thereby impacting the luxury sector.

There is limited literature that answers how consumer sentiment and behavior have been affected in relation to the luxury sector before, during, and after the COVID-19 pandemic in the United States. For this reason, this paper is the first study that analyzes the statistical properties of the luxury market and consumer sentiment via a time series analysis from January 1998 to July 2022. To do so, methodologies based on fractional integration, fractional cointegration, and wavelet analysis are used.

Using fractional integration methodologies, the results are quite similar. Both variables, consumer sentiment and the luxury sector, are very persistent (d = 0.95 and $d = 0.93$, respectively) and present mean reversion with shocks disappearing in the long run. Once the pandemic had been declared by government authorities in March 2020, a change in trends occurred between both time series. While consumer sentiment presents a behavior similar to that of before the pandemic (d = 0.79), the luxury sector has a permanent component that causes changes in the trend and, therefore, extraordinary measures will be required to reverse the situation and recover the original trend.

These results are in line with the research paper of [22], where it is stated that the brick-and-mortar stores of the luxury brands in some countries rely heavily on overseas consumers. Reference [68] suggests that Chinese tourists alone account for 27 percent of the entire luxury market.

Since the pandemic began, Chinese consumers have had to concentrate their consumption in China due to the spread of the COVID-19 pandemic overseas and the restrictions in global travel. Additionally, the Chinese government adopted new policies related to the import tariffs on luxury products. This caused the gap between the prices of luxury goods in China and those in other countries to gradually decrease.

The Granger causality test suggests that consumer sentiment in the United States has a direct influence on luxury behavior. Following this result, a multivariate analysis using Fractional Cointegrating VAR (FCVAR) model was conducted to understand the interactions and the relationship of both time series in the long run. The results indicate that both time series have the same magnitude, where $d = b = 1.459$. Therefore, although the individual series apparently show $I(1)$ behavior, with the results of the cointegration analysis, the hypothesis that the effects of the shock disappear in the short run cannot be rejected. Additionally, it can be seen that an increase in consumer sentiment implies an increase of 3.6% in the luxury sector.

Finally, a time–frequency analysis based on wavelet analysis was performed to understand the correlation that exists between both variables, i.e., consumer sentiment and the luxury sector. Focusing on the regions that correspond to the coronavirus episode, a positive correlation between both time series is observed. Economically, this means that consumer sentiment acted as a leading indicator of the behavior of the luxury sector in the short term during the COVID-19 period.

A future line of research is the use of other methodologies, such as those proposed by [69–72], in order to expand the literature with the use of methodologies based on the time–frequency domain within the framework of time series.

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

Funding: Prof. Manuel Monge is acknowledge support from an internal Project of the Universidad Francisco de Vitoria.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data used in this research are detailed in Section 2 of this paper. They are open public databases. In any case, the data that support the findings of this study are available on request from the corresponding author.

Conflicts of Interest: All authors have participated in (a) conception and design, or analysis and interpretation of the data; (b) drafting the article or revising it critically for important intellectual content; and (c) approval of the final version. This manuscript has not been submitted to, nor is under review at, another journal or other publishing venue. The authors have no affiliation with any organization with a direct or indirect financial interest in the subject matter discussed in the manuscript.

References

1. Keynes, J.M. *The General Theory of Employment, Interest, and Money*; Harbinger: New York, NY, USA, 1936.
2. Schumpeter, J.A. *Business Cycles*; McGraw-Hill: New York, NY, USA, 1939; Volume 1, pp. 161–174.
3. Friedman, M.; Schwartz, A.J. *A Monetary History of the United States, 1867–1960*; Princeton University Press: Princeton, NJ, USA, 2008; Volume 14.
4. Galbraith, J.K. *Breve Historia de la Euforia Financiera*; Ariel: Barcelona, Spain, 1991.
5. Kaytaz, M.; Gul, M.C. Consumer response to economic crisis and lessons for marketers: The Turkish experience. *J. Bus. Res.* **2014**, *67*, 2701–2706. [CrossRef]
6. Sarmento, M.; Marques, S.; Galan-Ladero, M. Consumption dynamics during recession and recovery: A learning journey. *J. Retail. Consum. Serv.* **2019**, *50*, 226–234. [CrossRef]
7. Bernanke, B.S. Irreversibility, uncertainty, and cyclical investment. *Q. J. Econ.* **1983**, *98*, 85–106. [CrossRef]
8. Reinhart, C.M.; Rogoff, K.S. Is the 2007 US sub-prime financial crisis so different? An international historical comparison. *Am. Econ. Rev.* **2008**, *98*, 339–344. [CrossRef]
9. 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]
10. Kennett-Hensel, P.A.; Sneath, J.Z.; Lacey, R. Liminality and consumption in the aftermath of a natural disaster. *J. Consum. Mark.* **2012**, *29*, 52–63. [CrossRef]

11. Raggio, R.D.; Leone, R.P. Chasing brand value: Fully leveraging brand equity to maximise brand value. *J. Brand Manag.* **2009**, *16*, 248–263. [CrossRef]
12. Halliburton, C.; Kellner, K. Are Luxury Brands Really Immune to Financial Recession. In A Comparative Empirical Investigation of Luxury and Non-Luxury Brands in the Downturn. 2012. Available online: www.marketing-trends-congress.com (accessed on 28 July 2023).
13. Som, A.; Blanckaert, C. *The Road to Luxury: The Evolution, Markets, and Strategies of Luxury Brand Management*; John Wiley & Sons: Hoboken, NJ, USA, 2015.
14. Kapferer, J.N.; Bastien, V. The specificity of luxury management: Turning marketing upside down. *J. Brand Manag.* **2009**, *16*, 311–322. [CrossRef]
15. Sheth, J. New areas of research in marketing strategy, consumer behavior, and marketing analytics: The future is bright. *J. Mark. Theory Pract.* **2021**, *29*, 3–12. [CrossRef]
16. Gu, S.; Ślusarczyk, B.; Hajizada, S.; Kovalyova, I.; Sakhbieva, A. Impact of the COVID-19 pandemic on online consumer purchasing behavior. *J. Theor. Appl. Electron. Commer. Res.* **2021**, *16*, 2263–2281. [CrossRef]
17. Omar, N.A.; Nazri, M.A.; Ali, M.H.; Alam, S.S. The panic buying behavior of consumers during the COVID-19 pandemic: Examining the influences of uncertainty, perceptions of severity, perceptions of scarcity, and anxiety. *J. Retail. Consum. Serv.* **2021**, *62*, 102600. [CrossRef]
18. Pan, T.; Shu, F.; Kitterlin-Lynch, M.; Beckman, E. Perceptions of cruise travel during the COVID-19 pandemic: Market recovery strategies for cruise businesses in North America. *Tour. Manag.* **2021**, *85*, 104275. [CrossRef] [PubMed]
19. Kumar, P. Luxury consumption amidst the COVID-19 pandemic. *Mark. Intell. Plan.* **2023**, *41*, 62–82. [CrossRef]
20. Choi, Y.H.; Lee, K.H. Changes in consumer perception of fashion products in a pandemic—Effects of COVID-19 spread. *Res. J. Costume Cult.* **2020**, *28*, 285–298. [CrossRef]
21. Grechi, D.; Pezzetti, R.; Pavione, E.; Gazzola, P. The Impact of COVID-19 on the Fashion Industry: A Generation Survey. In Proceedings of the STRATEGICA 2021—Shaping the Future of Business and Economy, Bucharest, Romania, 21–22 October 2022; pp. 285–296.
22. Xie, J.; Youn, C. How the luxury fashion brand adjust to deal with the COVID-19. *Int. J. Costume Fash.* **2020**, *20*, 50–60. [CrossRef]
23. Chung, M.; Ko, E.; Joung, H.; Kim, S.J. Chatbot e-service and customer satisfaction regarding luxury brands. *J. Bus. Res.* **2020**, *117*, 587–595. [CrossRef]
24. Holmqvist, J.; Wirtz, J.; Fritz, M.P. Luxury in the digital age: A multi-actor service encounter perspective. *J. Bus. Res.* **2020**, *121*, 747–756. [CrossRef]
25. Wang, Z.; Yuan, R.; Luo, J.; Liu, M.J. Redefining "masstige" luxury consumption in the post-COVID era. *J. Bus. Res.* **2022**, *143*, 239–254. [CrossRef]
26. Pencarelli, T.; Ali Taha, V.; Škerháková, V.; Valentiny, T.; Fedorko, R. Luxury products and sustainability issues from the perspective of young Italian consumers. *Sustainability* **2019**, *12*, 245. [CrossRef]
27. Zagórski, K.; McDonnell, J.S. "Consumer Confidence" Indexes as social indicators. *Soc. Indic. Res.* **1995**, *36*, 227–246. [CrossRef]
28. Song, M.; Shin, K.S. Forecasting economic indicators using a consumer sentiment index: Survey-based versus text-based data. *J. Forecast.* **2019**, *38*, 504–518. [CrossRef]
29. Jain, P.K.; Pamula, R.; Srivastava, G. A systematic literature review on machine learning applications for consumer sentiment analysis using online reviews. *Comput. Sci. Rev.* **2021**, *41*, 100413. [CrossRef]
30. Zagorski, K. Hope factor, inequality, and legitimacy of systemic transformations: The case of Poland. *Communist Post-Communist Stud.* **1994**, *27*, 357–376. [CrossRef]
31. McDonnell, J.S. *The Differential Effects of Community Perceptions of Inflation and Unemployment on Consumer Confidence: An International Assessment*; University of Melbourne, IAESR: Melbourne, VIC, Australia, 1994.
32. Pickering, J.F. *The Acquisition of Consumer Durables—A Cross-Sectional Investigation*; Associated Business Programs: London, UK, 1977.
33. Alessa, A.A.; Alotaibie, T.M.; Elmoez, Z.; Alhamad, H.E. Impact of COVID-19 on entrepreneurship and consumer behaviour: A case study in Saudi Arabia. *J. Asian Financ. Econ. Bus.* **2021**, *8*, 201–210.
34. Tran, L.T.T. Managing the effectiveness of e-commerce platforms in a pandemic. *J. Retail. Consum. Serv.* **2021**, *58*, 102287. [CrossRef]
35. Xayrullaevna, S.N.; Pakhritdinovna, K.D.; Anvarovna, B.G. Digitalization of the economy during a pandemic: Accelerating the pace of development. *J. Crit. Rev.* **2020**, *7*, 2491–2498.
36. Im, J.; Kim, H.; Miao, L. CEO letters: Hospitality corporate narratives during the COVID-19 pandemic. *Int. J. Hosp. Manag.* **2021**, *92*, 102701. [CrossRef]
37. Dickey, D.A.; Fuller, W.A. Distribution of the estimators for autoregressive time series with a unit root. *J. Am. Stat. Assoc.* **1979**, *74*, 427–431.
38. Phillips, P.C.; Perron, P. Testing for a unit root in time series regression. *Biometrika* **1988**, *75*, 335–346. [CrossRef]
39. 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]

40. Elliot, G.; Rothenberg, T.J.; Stock, J.H. Efficient tests for an autoregressive unit root. *Econometrica* **1996**, *64*, 813–836. [CrossRef]
41. Adenstedt, R.K. On large-sample estimation for the mean of a stationary random sequence. *Ann. Stat.* **1974**, *2*, 1095–1107. [CrossRef]
42. 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]
43. Granger, C.W. Long memory relationships and the aggregation of dynamic models. *J. Econom.* **1980**, *14*, 227–238. [CrossRef]
44. Granger, C.W. Some properties of time series data and their use in econometric model specification. *J. Econom.* **1981**, *16*, 121–130. [CrossRef]
45. Hosking, J.R. Modeling persistence in hydrological time series using fractional differencing. *Water Resour. Res.* **1984**, *20*, 1898–1908. [CrossRef]
46. Diebold, F.X.; Rudebush, G.D. On the power of Dickey-Fuller tests against fractional alternatives. *Econ. Lett.* **1991**, *35*, 155–160. [CrossRef]
47. Hassler, U.; Wolters, J. On the power of unit root tests against fractional alternatives. *Econ. Lett.* **1994**, *45*, 1–5. [CrossRef]
48. Lee, D.; Schmidt, P. On the power of the KPSS test of stationarity against fractionally-integrated alternatives. *J. Econom.* **1996**, *73*, 285–302. [CrossRef]
49. Akaike, H. Maximum likelihood identification of Gaussian autoregressive moving average models. *Biometrika* **1973**, *60*, 255–265. [CrossRef]
50. Akaike, H. A Bayesian extension of the minimum AIC procedure of autoregressive model fitting. *Biometrika* **1979**, *66*, 237–242. [CrossRef]
51. Johansen, S.; Nielsen, M.O. Likelihood inference for a fractionally cointegrated vector autoregressive model. *Econometrica* **2012**, *80*, 2667–2732. [CrossRef]
52. Zhou, W.X. Multifractal detrended cross-correlation analysis for two nonstationary signals. *Phys. Rev. E* **2008**, *77*, 066211. [CrossRef]
53. Podobnik, B.; Stanley, H.E. Detrended cross-correlation analysis: A newmethod for analyzing two nonstationary time series. *Phys. Rev. Lett.* **2008**, *100*, 084102. [CrossRef] [PubMed]
54. Gu, G.F.; Zhou, W.X. Detrending moving average algorithm for multifractals. *Phys. Rev. E* **2010**, *82*, 011136. [CrossRef] [PubMed]
55. Jiang, Z.Q.; Zhou, W.X. Multifractal detrending moving-average cross-correlation analysis. *Phys. Rev. E* **2011**, *84*, 016106. [CrossRef]
56. Monge, M.; Gil-Alana, L.A. Spatial crude oil production divergence and crude oil price behaviour in the United States. *Energy* **2021**, *232*, 121034. [CrossRef]
57. Monge, M.; Poza, C.; Borgia, S. A proposal of a suspicion of tax fraud indicator based on Google trends to foresee Spanish tax revenues. *Int. Econ.* **2022**, *169*, 1–12. [CrossRef]
58. Monge, M. Bunker fuel, commodity prices and shipping market indices following the COVID-19 pandemic. A time-frequency analysis. *Int. Econ.* **2022**, *172*, 29–39. [CrossRef]
59. Monge, M.; Rojo, M.F.R.; Gil-Alana, L.A. The impact of geopolitical risk on the behavior of oil prices and freight rates. *Energy* **2023**, *269*, 126779. [CrossRef]
60. Aguiar-Conraria, L.; Soares, M.J. The continuous wavelet transform: Moving beyond uni- and bivariate analysis. *J. Econ. Surv.* **2014**, *28*, 344–375. [CrossRef]
61. Aguiar-Conraria, L.; Azevedo, N.; Soares, M.J. Using wavelets to decompose the time-frequency effects of monetary policy. *Phys. A Stat. Mech. Appl.* **2008**, *387*, 2863–2878. [CrossRef]
62. Sowell, F. Maximum likelihood estimation of stationary univariate fractionally integrated time series models. *J. Econom.* **1992**, *53*, 165–188. [CrossRef]
63. Weinberger, M.F.; Wallendorf, M. Intracommunity gifting at the intersection of contemporary moral and market economies. *J. Consum. Res.* **2012**, *39*, 74–92. [CrossRef]
64. Markhvida, M.; Walsh, B.; Hallegatte, S.; Baker, J. Quantification of disaster impacts through household well-being losses. *Nat. Sustain.* **2020**, *3*, 538–547. [CrossRef]
65. Martin, A.; Markhvida, M.; Hallegatte, S.; Walsh, B. Socio-economic impacts of COVID-19 on household consumption and poverty. *Econ. Disasters Clim. Chang.* **2020**, *4*, 453–479. [CrossRef]
66. Hall, M.C.; Prayag, G.; Fieger, P.; Dyason, D. Beyond panic buying: Consumption displacement and COVID-19. *J. Serv. Manag.* **2020**, *32*, 113–128. [CrossRef]
67. Savelli, E. Role of brand management of the luxury fashion brand in the global economic crisis: A case study of Aeffe group. *J. Glob. Fash. Mark.* **2011**, *2*, 170–179. [CrossRef]
68. D'Arpizio, C.; Levato, F.; Fenili, S.; Colacchio, F.; Prete, F. *Luxury after COVID-19: Changed for (the) Good*; Bain & Company: Boston, MA, USA, 2020.
69. Guariglia, E.; Silvestrov, S. Fractional-Wavelet Analysis of Positive definite Distributions and Wavelets on D'(C) D'(C). In *Engineering Mathematics II: Algebraic, Stochastic and Analysis Structures for Networks, Data Classification and Optimization*; Springer International Publishing: Berlin/Heidelberg, Germany, 2016; pp. 337–353.

70. Yang, L.; Su, H.; Zhong, C.; Meng, Z.; Luo, H.; Li, X.; Tang, Y.Y.; Lu, Y. Hyperspectral image classification using wavelet transform-based smooth ordering. *Int. J. Wavelets Multiresolution Inf. Process.* **2019**, *17*, 1950050. [CrossRef]
71. Guariglia, E.; Guido, R.C. Chebyshev Wavelet Analysis. *J. Funct. Spaces* **2022**, *2022*, 5542054. [CrossRef]
72. Zheng, X.; Tang, Y.Y.; Zhou, J. A framework of adaptive multiscale wavelet decomposition for signals on undirected graphs. *IEEE Trans. Signal Process.* **2019**, *67*, 1696–1711. [CrossRef]