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Article

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Journal of Applied Economics

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Suggested Citation: Fahmy, Hany (2020) : Is the sharing economy causing a regime switch in consumption?, Journal of Applied Economics, ISSN 1667-6726, Taylor & Francis, Abingdon, Vol. 23, Iss. 1, pp. 281-298, https://doi.org/10.1080/15140326.2020.1750121

This Version is available at:
https://hdl.handle.net/10419/314092

Journal of Applied Economics

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/recs20

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To cite this article: Hany Fahmy (2020) Is the sharing economy causing a regime switch in consumption?, Journal of Applied Economics, 23:1, 281-298, DOI: 10.1080/15140326.2020.1750121

To link to this article: https://doi.org/10.1080/15140326.2020.1750121

Published online: 05 May 2020.

JOURNAL OF APPLIED ECONOMICS
2020, VOL. 23, NO. 1, 281–298
https://doi.org/10.1080/15140326.2020.1750121

Routledge
Taylor & Francis Group

ARTICLE

Is the sharing economy causing a regime switch in consumption?

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ABSTRACT

The recent rise of digital technology has enabled the development of various online platforms that gave rise to the so-called sharing economy. Academics suggest that this economy is causing a switch in consumer behaviour. This paper attempts to test this hypothesis by fitting a smooth transition autoregressive model to the cycle of the proportion of e-commerce to personal consumption in the U.S. between 1999 and 2019. The analysis reveals that the sharing economy, driven by the diffusion of digital technology, is causing consumption to transition smoothly, but frequently, between two regimes between 1999 and 2013. In the later period, however, it displays a stable regime due to the slow diffusion of digital technologies over this period. We conclude that, indeed, the sharing economy is causing a regime switch in consumption, and the dynamic behaviour of this regime switching is consistent with the behaviour of the diffusion process of digital technologies.

ARTICLE HISTORY
Received 7 November 2019
Accepted 24 March 2020

KEYWORDS
Sharing economy; digital technology; technological diffusion; regime switching models; smooth transition regression

1. Introduction and literature review

The rise of digital online platforms can be traced back to the mid 1990s with the introduction of the first commercial web browsers; Netscape in 1994 and Microsoft's Internet Explorer in 1995. Since the late 1990s, there has been an increasing trend of disruptions caused by the use of online platforms in executing various activities. In particular, the recent rise of digital online platforms, e.g., Uber and Airbnb, has resulted in a variety of sharing consumption activities. This new form of consumption has established a new economy known as the sharing economy.

The literature on the subject defines consumption activities pertaining to the sharing economy as collaborative consumption (Bostman & Rogers, 2010; Bostman, 2013), or access-based consumption (Bardhi & Eckhardt, 2012; Belk, 2014), or connected-consumption activities (Schor & Fitzmaurice, 2015). In a broad sense, the sharing economy is defined as an activity facilitated by digital online platforms where people rent their skills (such as driving) and make their resources (such as properties or cars) available for money. In this paper, we will adopt this broad definition to describe peer-to-peer activities that are made possible by digital technology. We will refer to these activities as the sharing economy.

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Recent studies on the sharing economy argue that this emerging phenomenon is causing a noticeable change in consumer behavior (see, for instance, Eckhardt, Belk, & Devinney, 2010; Ozanne & Ballantine, 2010; Piacentini et al., 2012). This change in behavior was attributed to different factors. Albinsson and Perera (2012), Belk (2010), and Bostman and Rogers (2010), for instance, attributed such an increasing change in attitudes towards sharing activities to the growing concern about climate change and the urge to social connectedness and communal consumption. Bray, Johns, and Kilburn (2011) and Eckhardt et al. (2010) argue that consumers are turned away from traditional to sharing activities due to economical and institutional reasons. Other authors, from different disciplines, gave different motives.[1] But, setting the motives aside, the consensus among the previous studies seems to be centered on the observation that the sharing economy is causing a *regime switch* in traditional consumption behavior, e.g., using Uber or lyft instead of traditional taxi or using Airbnb instead of renting.

To assess the empirical validity of the effect of this new sharing phenomenon, i.e., to assess whether or not the sharing economy, which is driven by digital technology, is causing a regime switch in consumption habits in the U.S., one, ideally, ought to examine the effect of a digital technology index on the U.S. personal consumption expenditures. Furthermore, in order to capture the effect of the digital technology on consumption spending, this technology index should go far back to the mid or late 1990s; the period that witnessed the beginning of the rise of digital platforms. Unfortunately, the development of technology indices that capture the state of technological advancement is recent and the data do not go far back in time. For instance, the Digital Economy and Society Index (DESI), which measures Europe's digital performance, was developed in 2015. The World Bank's Digital Adoption Index (DAI) has two observations available for most countries: 2014 and 2016. The Bureau of Economic Analysis has recently developed a data set on the digital economy in hopes of assessing and measuring its impact on the economy. Although the data estimates go far back to 1997, the data set, however, only includes goods and services that are primarily digital and excludes all e-commerce peer-to-peer transactions, i.e., it excludes the sharing economy.

Due to the unavailability of a proper digital index and since our intention is to capture the change in U.S. consumer habits following changes of digital technology, we have decided to study the regime switch in the proportion of e-commerce consumption to personal consumption expenditures time series.[2] The U.S. Census Bureau defines e-commerce sales as sales of goods and services where an order is placed by the buyer or price and terms of sale are negotiated over an internet, extranet, electronic data interchange network, electronic mail, or other online system. Thus, the *cycle* of this time series ought to capture fluctuations in the sharing economy due to digital technological changes over time.

Changes in digital technology reflect the invention of new products and the diffusion of these inventions over time. An invention of a new technology is a single event or jump over time. The diffusion of this technology is, however, a slow continuous process. It proceeds slowly at first, accelerates, then slows down in the end due to imitation, new inventions, or because the population becomes saturated (see, for instance, Griliches, 1957; Gort & Klepper, 1982; Mansfield, 1961). The previous empirical studies, among many others,

[1]For a recent survey, see Hamari, Sjoklint, and Ukkonen (2016) and the references therein.
[2]I am indebted to an anonymous referee for the suggestion to use this particular time series.

showed that the diffusion curve is an S-shaped one. More recently, Comin and Hobjin (2004) examined the diffusion of more than 20 technologies across 23 countries of the world's leading industrial economies and documented the same S-shape pattern. Figure 1, which is reproduced from Comin and Hobjin's (2004) Historical Cross-Country Technology Adoption (HCCTA) data set, shows the adoption rates (measured as percentage of U.S. households) for 5 key information and communication technologies that are relevant for the sharing economy; namely, cellular phone, internet, computer, social media and amazon prime users. Aside from Amazon prime users, which is relatively new, notice how these technologies witness an increasing adoption rate during the early period of their diffusion between 1999 and 2013. In the later period between 2013 and 2019, however, the diffusion process of these four technologies slows down as shown from the slow increase in their adoption rates that is depicted in Figure 1. Observe how the four curves are increasing at diminishing rates over this period. This regime will persist until new inventions or innovations enter the market. This, in turn, will potentially lead to a new regime and, hence, creating a cycle.

The previous observation suggests that the diffusion process of digital technology, which is captured by the e-commerce consumption, can be described as a smooth transition process between multiple equilibria. Therefore, one can capture the effect of digital technology on consumption in the U.S. by fitting a smooth transition autoregressive (STAR) model to the cycle of the proportion of e-commerce consumption to personal consumption. More specifically, the objective of this paper is to test whether or not the sharing economy, which is driven by digital technology, is causing a regime switch in U.S. consumption over the period between 1999 and 2019. We also seek to characterize the dynamics of these consumption regimes if they exist.

The STAR model, which is due to Granger and Teräsvirta (1993) and Teräsvirta (1994), has been used extensively in the regime-switching literature. For instance,

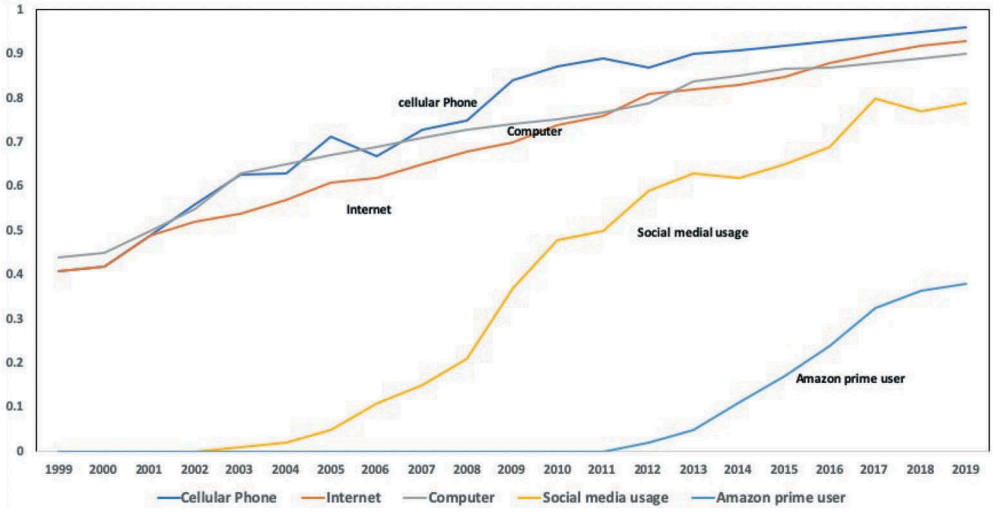

Figure 1. Adoption rates (measured as percentage of U.S. households) for cellular phone, internet, computer, social media usage and amazon prime users from the period in between 1999 and 2019.

Teräsvirta and Anderson (1992) used this model to capture the nonlinear dynamics of business cycles. Lutkepohl, Teräsvirta, and Wolters (1999) fitted STAR models to money demand functions. Sarantis (2001) used STAR models to explain the cyclical behavior in stock markets. More recently, Fahmy (2011; 2014; 2019) studied the nonlinearity and asymmetric behavior of commodity prices using smooth transition regression models with exogenous variables.[3] The econometric analysis of STAR models consists of two stages: specification and nonlinearity testing, and estimation and evaluation. Moreover, as opposed to other regime-switching models, e.g., pure threshold models and Markov switching models, these models have the flexibility of describing time series that can move from one regime to the other such that the transition is *smooth*. This feature fits particularly well in our implicit modelling of the diffusion process, which is captured by the cycle of e-commerce consumption in our analysis.

The remainder of the paper is organized as follows: Section 2 explains the regime-switching model entertained in this paper, the methodology, and the data set used. Section 3 discusses the estimation results. Finally, Section 4 concludes.

2. Econometric analysis and methodology

2.1. The data

In this paper, the data generating process, W_t, is the proportion of the quarterly e-commerce retail sales, *ECRS*, time series to the quarterly, seasonally adjusted, personal consumption expenditures, *PCE*, time series; that is, $W_t = \left(\frac{ECRS}{PCE}\right)_t$. Both time series are obtained from the U.S. Census Bureau over the period between the fourth quarter of 1999 and the first quarter of 2019. Since our intention is to model the cyclical behavior of W_t, we ought, first, to extract the cycle of the time series using Box and Jenkins' (1970) difference stationary approach, where the first difference of the logarithm of W_t, i.e. $\Delta \log(W_t)$, is regressed on a constant and an error term. The least squares residuals obtained from the previous regression, denoted by C_t, represent the quarter-to-quarter cycle of W_t between 1999 and 2019. Both time series W_t and C_t are plotted in Figure 2.

In the data investigation stage, stationarity tests are crucial in ensuring the adequacy of fitting a nonlinear regime-switching model to C_t. The stationarity of C_t is confirmed, at the 5% level of significance, by the augmented Dickey and Fuller (1979) test, Phillips and Perron (1988) test, and the Kwiatkowski et al. (1992) test. The test statistics are shown in Table 1. The time series passes the three stationarity tests and, thus, is adequate for nonlinearity analysis, which we now turn to.

2.2. The STAR model

The general STAR model of order p for C_t is expressed as follows:

$$C_t = \mathbf{\Phi}' z_t + \mathbf{\Theta}' z_t G(s_t; \gamma, \mathbf{c}) + \varepsilon_t, \quad t = 1, 2, ..., T, \tag{1}$$

[3]For a recent literature survey on STAR models, see van Dijk, Teräsvirta, and Franses (2002).

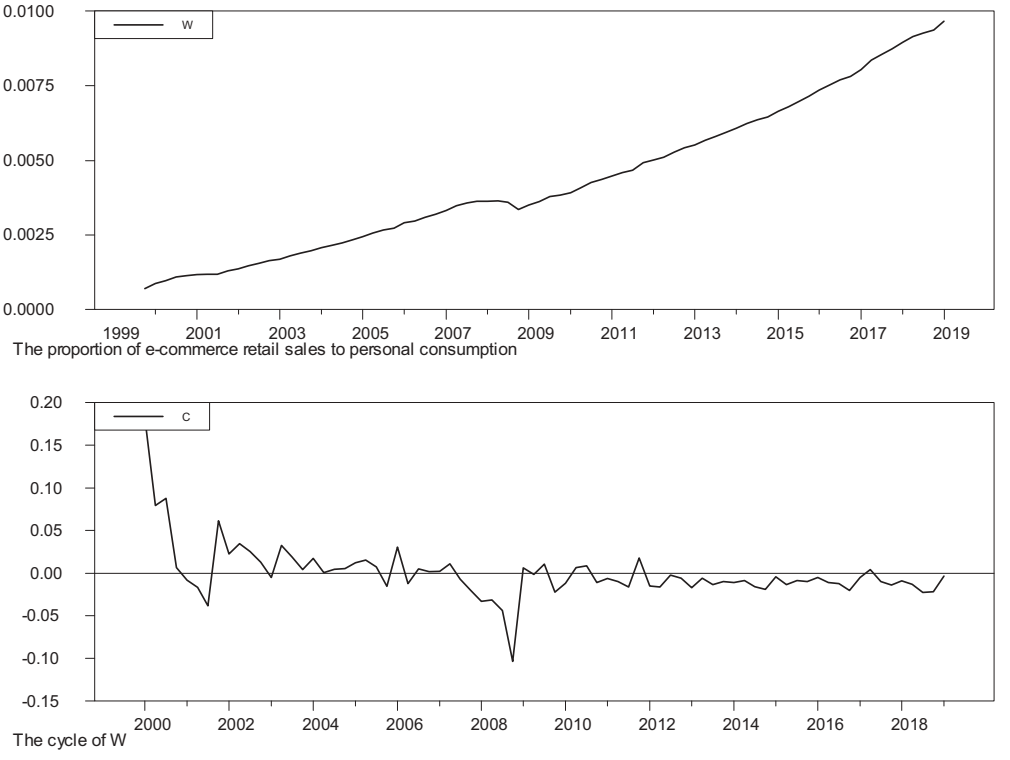

Figure 2. The proportion of U.S. e-commerce retail sales to personal consumption expenditures, $W_t = \left(\frac{ECRS}{PCE}\right)_t$, from Q4 1999 to Q1 2019 (top panel) and its cycle, C_t, over the same period (bottom panel).

Table 1. The stationarity of the cycle of the proportion of U.S. e-commerce retail sales to personal consumption expenditures.

Time Series	ADF(k)	PP	KPSS
C_t	− 5.83(2)	− 8.6	0.95

ADF, PP, KPSS are respectively the augmented Dickey and Fuller (1979), the Phillips and Perron (1988), and the Kwiatkowski et al. (1992) test statistics with a constant. k is the number of lags of the ADF test. The 5% critical value is −2.9 for ADF and PP and 0.46 for KPSS.

where $z_t = (1, C_{t-1}, ..., C_{t-p})' = (1, \widetilde{z}_t')'$ is a vector of autoregressive lags of C_t, $\mathbf{\Phi} = \left(\phi_0, \phi_1, ..., \phi_p\right)' = \left(\phi_0, \widetilde{\mathbf{\Phi}}'\right)'$ and $\mathbf{\Theta} = \left(\theta_0, \theta_1, ..., \theta_p\right)' = \left(\theta_0, \widetilde{\mathbf{\Theta}}'\right)'$ are parameter vectors, T is the sample size, $\varepsilon_t \sim i.i.d.(0, \sigma^2)$, and $G(s_t; \gamma, \mathbf{c})$ is a logistic transition function of the threshold/transition variable s_t. It is a bounded function, between 0 and 1, of the continuous transition variable s_t and continuous everywhere in the parameter space for any value of s_t. The transition variable could be an element of the lags of the dependent variable, i.e., $s_t = C_{t-d}$ where $d > 0$ is a delay parameter or a linear time trend t; that is, the transition set Ω is

$$\Omega = \{C_{t-1}, C_{t-2}, ..., C_{t-p}, t\}. \tag{2}$$

The logistic function $G(\cdot)$ is defined in general as

$$G(S_t; \gamma, \mathbf{c}) = \left(1 + \exp\{-\gamma \prod_{j=1}^{k}(s_t - c_j)\}\right)^{-1}, \qquad \gamma > 0, \tag{3}$$

where γ is the slope of the function, and $\mathbf{c} = (c_1, ..., c_k)'$ is a vector of location parameters such that $c_1 \leq \cdots \leq c_k$. Given such definition, the STAR model defined in Equation (1) is often referred to as the logistic smooth transition autoregression (LSTAR) model. The transition function in Equation (3) is a monotonically increasing function of the transition variable s_t. The restrictions $\gamma > 0$ and $c_1 \leq \cdots \leq c_k$ are identifying restrictions. The choice of k determines the behavior of the logistic transition function. When $k = 1$, the parameters vectors change monotonically as a function of s_t from $\mathbf{\Phi}$ to $\mathbf{\Phi} + \mathbf{\Theta}$. This implies that the LSTAR model of order 1, or LSTAR(1), is capable of characterizing the time series C_t whose dynamic properties are different in an upper regime from what they are in a lower regime such that the transition between the two regimes is smooth. The logistic function in the LSTAR(1) model takes the form

$$G(s_t; \gamma, c) = (1 + \exp\{-\gamma(s_t - c)\})^{-1}, \qquad \gamma > 0. \tag{4}$$

Note that when $s_t < c$, i.e., when $s_t \to -\infty,\ G(\cdot) = 0;$ this defines the lower regime. On the other hand, when $s_t > c,$ i.e. when $s_t \to +\infty,\ G(\cdot) = 1$ and the time series is in the upper regime. The LSTAR(1) function in (4) is plotted in Figure 3, where the threshold $c = 0.5$ and the slope $\gamma = \{3, 100\}$ for the solid and the dashed lines, respectively.

In the LSTAR model with $k = 2$, or LSTAR(2), the parameter vectors change symmetrically around the midpoint $\bar{c} = \frac{c_1 + c_2}{2}$, where the logistic function attains its minimum value. The LSTAR(2) model is a three-regime switching regression model in which the dynamics of the two outer regimes, associated with large and small values of s_t, are the same while the behavior in the transition period, i.e., the middle (ground) regime, is different. The second-order logistic function in the LSTAR model takes the form

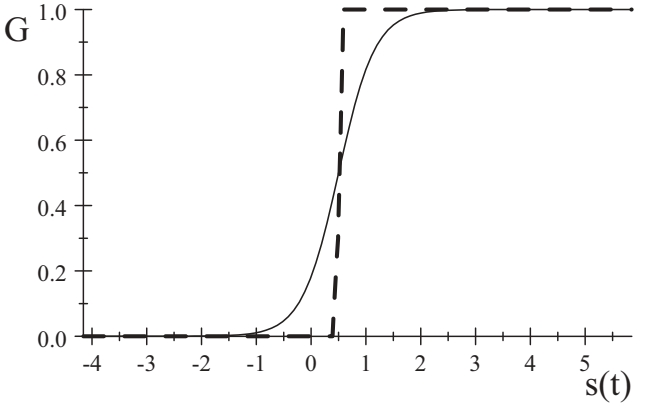

Figure 3. The smooth transition logistic function of order 1 with a moderate slope $\gamma = 3$ (the solid line) and with a larger slope $\gamma = 100$ (the dashed line). The threshold value $c = 0.5$..

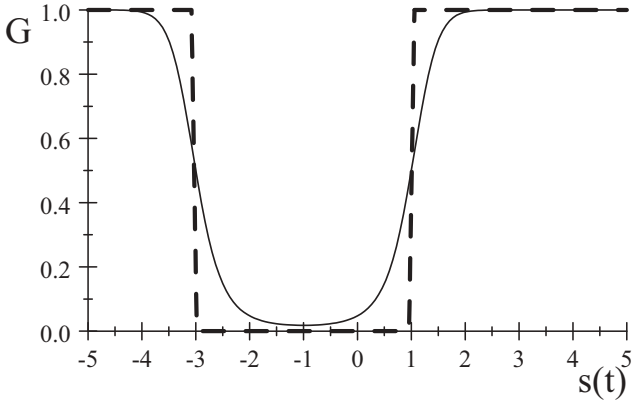

Figure 4. The smooth transition logistic function of order 2 with a moderate slope $\gamma = 1$ (the solid line) and with a larger slope $\gamma = 100$ (the dashed line). The threshold values are $c_1 = -3$ and $c_2 = 1$..

$$G(s_t; \gamma, c_1, c_2) = (1 + \exp\{-\gamma(s_t - c_1)(s_t - c_2)\})^{-1}, \qquad \gamma > 0, c_1 \leq c_2, \tag{5}$$

where $\gamma > 0$ and $c_1 \leq c_2$ are identifying restrictions as mentioned before. The second-order logistic function in Equation (5) is plotted in Figure 4, where $c_1 = -3, c_2 = 1$ and $\gamma = \{1, 100\}$ for the solid and dashed lines, respectively. Observe how the functions change symmetrically around the midpoint $\bar{c} = \frac{c_1 + c_2}{2} = -1$.

Notice that, unlike the first-order logistic function, the second-order function is not zero at the minimum; it achieves a minimum value

$$G_{\min} = \frac{1}{1 + \exp\{-\gamma \tilde{c}\}}, \tag{6}$$

where $\tilde{c} = c_1 c_2 - \bar{c}^2$ and $\bar{c} = \frac{c_1 + c_2}{2}$, when the transition variable s_t equals to $\bar{c}$. To facilitate the interpretation of the regimes of the LSTAR(2) model, we can apply the following reparameterization to the logistic function G in Equation (5): Let

$$G = G_{\min} + \widetilde{G} \times (1 - G_{\min}), \tag{7}$$

where

$$\widetilde{G} = \frac{G - G_{\min}}{(1 - G_{\min})}. \tag{8}$$

Substituting Equation (7) in Equation (1) and reparameterizing the STAR model yields

$$C_t = \mathbf{\Lambda}' z_t + \mathbf{\Gamma}' z_t \widetilde{G} + \varepsilon_t, \tag{9}$$

where $\mathbf{\Lambda} = \mathbf{\Phi} + \mathbf{\Theta} G_{\min}$ and $\mathbf{\Gamma} = (1 - G_{\min})\mathbf{\Theta}$. After this reparameterization, we can observe three regimes displayed by the logistic function in Equation (5) depending on the value taken by the transition variable: a ground (middle) regime and two outer regimes. The middle regime is realized when the transition variable takes a value in between the two threshold parameters, i.e., when $c_1 \leq s_t \leq c_2$. In particular, when the transition variable takes the value of any of the thresholds, i.e., when $s_t = c_1$ or $s_t = c_2$, then $G = \frac{1}{2}$. When the transition variable takes a weighted average of both threshold

values; that is, when $s_t = \overline{c} = \frac{c_1+c_2}{2}$, then $G = G_{\min}$ and $\widetilde{G} = 0$. Thus, in this case, the STAR model in Equation (9) is reduced to the autoregressive model

$$C_t = \mathbf{\Lambda}^{'} z_t + \varepsilon_t. \tag{10}$$

On the other hand, the two outer regimes are achieved when $s_t \to \pm\infty$, which, in turn, implies that $G = 1$ in Equation (5) or $\widetilde{G} = 1$ in Equation (8). In such case, from the reparameterization in Equation (9), the behavior of C_t in the outer regimes is described by the following autoregressive model

$$C_t = \left(\mathbf{\Lambda}^{'} + \mathbf{\Gamma}^{'}\right) z_t + \varepsilon_t. \tag{11}$$

In this paper, we shall follow the modelling framework proposed by Granger and Teräsvirta (1993), Teräsvirta (1994), and Eitrheim and Teräsvirta (1996), which consists of two stages. The first stage is the specification and nonlinearity testing stage, in which the delay parameter of the nonlinear model is determined by suggesting and testing a linear model against the STAR model fitted to C_t. If the null hypothesis of linearity is rejected, a short sequence of F tests is conducted to decide the type of the nonlinear model (LSTAR(1) or LSTAR(2)). The specified model is estimated and evaluated in the second stage. In the following section, we discuss the nonlinearity testing, estimation and evaluation of the LSTAR model in Equation (1), and present the empirical findings of the analysis.

3. Empirical results

3.1. Stage 1: specification, nonlinearity testing and model selection

In this stage, we begin by specifying an adequate linear autoregressive model of order m, $AR(m)$, for C_t, where m is the value that minimizes the Akaike (1974) information criterion (AIC) or the Bayesian information criterion (BIC). The resulting autoregressive model acts as the *starting* model for nonlinearity analysis. The AIC for C_t was minimized at a lag order 4 whereas the BIC was minimized at a lag of order $m = 2$. However, when estimating the preliminary $AR(4)$ as suggested by the AIC, the coefficients of the third and fourth lags of C_t were insignificant and, therefore, the $AR(2)$ model, that was suggested by the BIC, was considered as the starting linear model for the nonlinearity analysis. Before accepting the suggested $AR(2)$ model as the starting point of the analysis, preliminary diagnostic tests were applied to the model in order to ensure its adequacy as a starting linear model. In particular, the Ljung and Box (1978) test of no serial correlation of order $q = 1$ up to $q = 4$ in the residuals and Engle's (1982) Lagrange multiplier (LM) test of no autoregressive conditional heteroskedasticity (ARCH) of order $v = 1$ up to $v = 4$ in the residuals were considered. The p values of both tests are denoted by $Q(q)$ and $LM_{ARCH(v)}$ respectively. The estimated $AR(2)$ and the preliminary misspecification tests results are reported as follows:

$$C_t = \underset{(0.20)}{-0.003} + \underset{(0.04)}{0.23}\, C_{t-1} + \underset{(0.009)}{0.22}\, C_{t-2} + \widehat{\epsilon}_t, \tag{12}$$

$$Q(1) = 0.89, \quad Q(4) = 0.96,$$

$$LM_{ARCH(1)} = 0.06, \qquad LM_{ARCH(4)} = 0.43,$$

$$JB = 0.10, \qquad K_3 = 0.016, \qquad K_4 = 5.5,$$

where $\widehat{\epsilon}_t$ is the series of residuals, K_3 and K_4 are the skewness and Kurtosis, respectively, JB is the p value of the Jarque and Bera (1987) test of normality, and the values in parentheses beneath the estimated parameters are p values corresponding to the standard individual t tests of significance. Judging by the p value of the Ljung and Box (1978) test, the null hypothesis of no serial correlation of order $q = 1$ up to $q = 4$ in the residuals series was not rejected at the 5% level of significance. Also, judging by the p value of Engle's (1982) test, the null hypothesis of no ARCH of order $v = 1$ up to $v = 4$ was not rejected at the 5% level of significance. Finally, the null hypothesis of normality of errors was not rejected at the 5% level of significance as seen from the p value of the JB test. Notice that, other than the insignificant constant drift coefficient, the model passes all preliminary diagnostic tests, and therefore, can act as a good starting model for the nonlinearity analysis.

The next step in the specification stage is linearity testing. Guided by the lag order of C_t that was suggested by the AIC above, the transition set consists of four lags of C_t and a time trend; that is,

$$\Omega = \{C_{t-1}, C_{t-2}, C_{t-3}, C_{t-4}, t\}. \tag{13}$$

The null-hypothesis of linearity, denoted by H_{0L} in the text, is tested against the alternative of nonlinear STAR model for each transition candidate in the transition set Ω. The test statistic, denoted by F_L, is due to Teräsvirta (1994) and Luukkonen, Saikkonen, and Teräsvirta (1988). It is an LM test with an asymptotic F distribution with $3p$ and $T - 4p - 1$ degrees of freedom when H_{0L} is valid. The test is constructed by replacing the first-order transition function in Equation (4) in the STAR model in Equation (1) by a third-order Taylor approximation about the null hypothesis $\gamma = 0$. This approximation yields

$$C_t = \boldsymbol{\Phi}' z_t + \frac{1}{4}\gamma \boldsymbol{\Theta}' z_t(s_t - c) - \frac{1}{48}\gamma^3 \boldsymbol{\Theta}' z_t(s_t - c)^3 + \varepsilon_t, \quad t = 1, ..., T. \tag{14}$$

Using $z_t = (1, \widetilde{z}_t')'$, $\boldsymbol{\Phi} = \left(\phi_0, \widetilde{\boldsymbol{\Phi}}'\right)$, $\boldsymbol{\Theta} = \left(\theta_0, \widetilde{\boldsymbol{\Theta}}'\right)$, and reparameterizing Equation (14), we obtain

$$C_t = \delta_0 + \delta_1' \widetilde{z}_t + \pi_1' \widetilde{z}_t s_t + \pi_2' \widetilde{z}_t s_t^2 + \pi_3' \widetilde{z}_t s_t^3 + \widetilde{\varepsilon}_t, \tag{15}$$

where $\widetilde{\varepsilon}_t = \varepsilon_t + R(\gamma, c, s_t)$, with R being the remainder from the approximation, and π_j, for $j = 1, 2, 3,$ is of the form $\gamma\widetilde{\pi}_j$, where $\widetilde{\pi}_j \neq 0$ is a function of $\widetilde{\boldsymbol{\Theta}}$. Based on the auxiliary regression in Equation (15), the null hypothesis of linearity H_{0L} is

$$H_{0L} : \pi_1 = \pi_2 = \pi_3 = 0. \tag{16}$$

The test is repeated for each transition candidate in the transition set Ω. If the null hypothesis of linearity is rejected for at least one of the models, the model against which the rejection, measured in p value, is strongest is chosen to be the STAR model to be estimated.

Another purpose of conducting the linearity test is to use the test results for model selection. If linearity is rejected and a transition variable is selected, the next step is to choose a model type. This choice is, again, based on the auxiliary regression in Equation (15). Teräsvirta (1994) showed that when $c = 0$ then $\pi_2 = 0$ when the model is an LSTAR (1), whereas $\pi_1 = \pi_3 = 0$ when the model is an LSTAR(2). The author suggested the following procedure to carry a sequence of F tests based on the auxiliary regression in Equation (15) in order to select the suitable model, i.e., LSTAR(1) or LSTAR(2):

(1) Test the null hypothesis: $H_{04} : \pi_3 = 0$ with an ordinary F test (F_4). A rejection of H_{04} can be interpreted as a rejection of the LSTAR(2) model.
(2) Test the null hypothesis H_{03} that $\pi_2 = 0$ given that $\pi_3 = 0$ using another F test (F_3). Failure to reject H_{03} indicates that the model is an LSTAR(1).
(3) Test the null hypothesis H_{02} that $\pi_1 = 0$ given that $\pi_2 = \pi_3 = 0$ using an F test (F_2). Rejecting H_{02} after accepting H_{03} supports the choice of the LSTAR(1) model. Accepting H_{02} after rejecting H_{03} points to the LSTAR(2) model.
(4) After carrying out the three F-tests and noting which hypotheses are rejected, if the test H_{03} yields the strongest rejection measured in the p value, choose the LSTAR(2) model; otherwise, select the LSTAR(1) model.

The previous sequence of tests was executed for each transition variable in Ω and the results are reported in Table 2. The fourth lag of C_t, tagged with the symbol " $*$ " in the first column of Table 2, is the variable with the strongest H_{0L} rejection (smallest p value) and, therefore, is selected as the transition variable in the STAR model. The corresponding model is an LSTAR(2) model as the p value of the F_3 test is less than the p value of F_2 and F_4. Thus, the LSTAR model suggested for C_t by the previous analysis is

$$C_t = \phi_0 + \phi_1 C_{t-1} + \phi_2 C_{t-2} + (\theta_0 + \theta_1 C_{t-1} + \theta_2 C_{t-2}) G(C_{t-4}; \gamma, c_1, c_2) + \varepsilon_t, \qquad (17)$$

for $t = 1, ..., T$, where $G(c_{t-4}; \gamma, c_1, c_2)$ is the second-order logistic function defined in Equation (5) with $s_t = C_{t-4}$.

3.2. Stage 2: estimation and evaluation

After determining the transition variable and the type of the STAR model, the next step is estimation. The parameters of the STAR model in Equation (17) are estimated using conditional maximum likelihood. Assuming normality of the error term, the log-likelihood function is

Table 2. P values of the F tests sequence applied to the cycle of the proportion of U.S. e-commerce retail sales to personal consumption expenditures.

Ω	F_L	F_4	F_3	F_2	suggested model
C_{t-1}	6.11×10^{-2}	7.78×10^{-2}	1.05×10^{-1}	3.67×10^{-1}	Linear
C_{t-2}	1.6×10^{-2}	9.72×10^{-2}	8.31×10^{-1}	3.64×10^{-3}	LSTAR(1)
C_{t-3}	7.70×10^{-1}	6.79×10^{-1}	3.22×10^{-1}	8.85×10^{-1}	Linear
C^*_{t-4}	1.56×10^{-2}	8.85×10^{-2}	9.53×10^{-3}	5.25×10^{-1}	LSTAR(2)
t	2.84×10^{-1}	3.52×10^{-1}	8.06×10^{-1}	7.87×10^{-2}	Linear

$$
\begin{aligned}
&l(\phi_0, \phi_1, \phi_2, \theta_0, \theta_1, \theta_2, \sigma, \gamma, c_1, c_2) \\
&= -\frac{1}{2}\ln(2\pi) - \frac{1}{2}\ln(\sigma^2) \\
&\quad -\frac{1}{2}\frac{\{C_t - (\phi_0 + \phi_1 C_{t-1} + \phi_2 C_{t-2} + (\theta_0 + \theta_1 C_{t-1} + \theta_2 C_{t-2})G)\}^2}{\sigma^2}.
\end{aligned} \tag{18}
$$

Conditional on starting values of the parameters, the log-likelihood function in Equation (18) is maximized using the iterative Broyden-Fletcher-Goldfarb-shanno (BFGS) algorithm. The estimator of the variance-covariance matrix of the ML estimators is a robust estimator that involves an accurate estimate of the Hessian of the log-likelihood function, which is also obtained from the BFGS algorithm.

Finding good starting values is important for the algorithm to work properly. Starting values are obtained by constructing a grid in γ, c_1 and c_2, estimating the parameters ϕ_0, ϕ_1, ϕ_2, θ_0, θ_1, and θ_2 conditionally on (γ, c_1, c_2), and computing the sum of squared residuals (SSR). The parameter values that correspond to the minimum of that sum are taken as the starting values. To facilitate the construction of an effective grid, we follow Teräsvirta's (1998) suggestion to standardize the exponent of the transition function G by dividing it by k^{th} power of the sample standard deviation of the transition variable, σ^k, in the general LSTAR(k) model. The previous grid search procedure produced the following starting values: $\gamma = 10$ and $c_1 = -0.0296$, and $c_2 = 0.0102$. The minimum SSR corresponding to these starting values is $SSR = 0.014$. The grid is plotted in Figure 5.

The final step in this stage, where the adequacy of the fitted model is considered, is the evaluation step. The misspecification tests for the STAR models that have been considered in Eitrheim and Teräsvirta (1996) and Teräsvirta (1998) will be considered in this

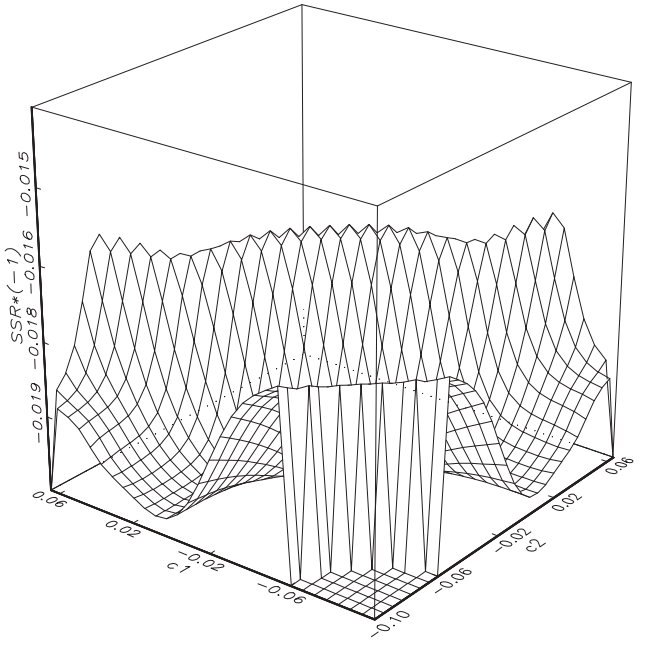

Figure 5. A four-dimension (γ, c_1, c_2, SSR) graphical plot of the grid.

paper. In particular, three tests will be considered. The first test is an LM-type test of no error autocorrelation of order q. The p value of the test is denoted by $LM_{AUTO(q)}$. The second diagnostic test is an LM-type test of no remaining nonlinearity in the fitted STAR model. The p value of this test is denoted by *NRNL*. The test is carried on against C_{t-4}; the transition variable selected in the specification stage.

The best fitted LSTAR(2) model that we managed to obtain after dropping the insignificant drift parameter in the linear part of C_t and θ_2 in the nonlinear part, and the results of Eitrheim and Teräsvirta (1996) and Teräsvirta's (1998) misspecification tests are reported as follows:

$$C_t = \underset{(0.0001)}{0.74}\, C_{t-1} + \underset{(0.008)}{0.24}\, C_{t-2} + \left(\underset{(0.01)}{0.007} - \underset{(0.001)}{0.88}\, C_{t-1}\right) G, \tag{19}$$

where

$$G = \left(\frac{1}{1 + \exp\left\{-\underset{(0.03)}{7.47}\left(C_{t-4} + \underset{(0.0001)}{0.03}\right)\left(C_{t-4} - \underset{(0.0001)}{0.01}\right)/0.0005\right\}}\right) + \hat{\varepsilon}_t, \tag{20}$$

and

$$\overline{R}^2 = 0.76, \qquad \hat{\sigma}^2 = 0.0005,$$

$$LM_{ARCH(1)} = 0.84, \qquad LM_{ARCH(4)} = 0.82,$$

$$LM_{AUTO(1)} = 0.13, \qquad LM_{AUTO(4)} = 0.11, \qquad LM_{AUTO(8)} = 0.37,$$

$$NRNL = 0.2, \qquad JB = 0.001, \qquad K_3 = -0.75, \qquad \text{and } K_4 = 6.29.$$

The figures in parentheses beneath the parameter values and the figures recorded for the misspecification tests are p values. $\hat{\sigma}^2$ is the sample variance of the transition variable C_{t-4} and $\hat{\varepsilon}_t$ is the residual series. The large value of the adjusted coefficient of determination, $\overline{R}^2 = 0.76$, implies that the STAR model was a good fit. The original and fitted series of C_t are plotted in Figure 6 and the second-order logistic function G in Equation (20) is plotted in Figure 7. All parameters are significant. Judging by the p value of the Ljung and Box (1978) test, the null hypothesis of no serial correlation of order $q = 1$, $q = 4$, and $q = 8$ in the residuals series is not rejected at the 5% level of significance. Also, judging by Engle's (1982) test, the null hypothesis of no ARCH of order $v = 1$ up to $v = 4$ was not rejected at the 5% level of significance. The model also passes the test of no remaining nonlinearity as demonstrated by the reported p value of the test. The null hypothesis of normality of errors was rejected at the 5% level of significance as seen from the p value of the Jarque and Bera (1987) test. But, this is due to the existence of large outliers in the third and fourth quarters of 2008 in the time series C_t (see Figures 2 and 6). A quick look at the standardized residuals in Figure 8 also confirms that; one can

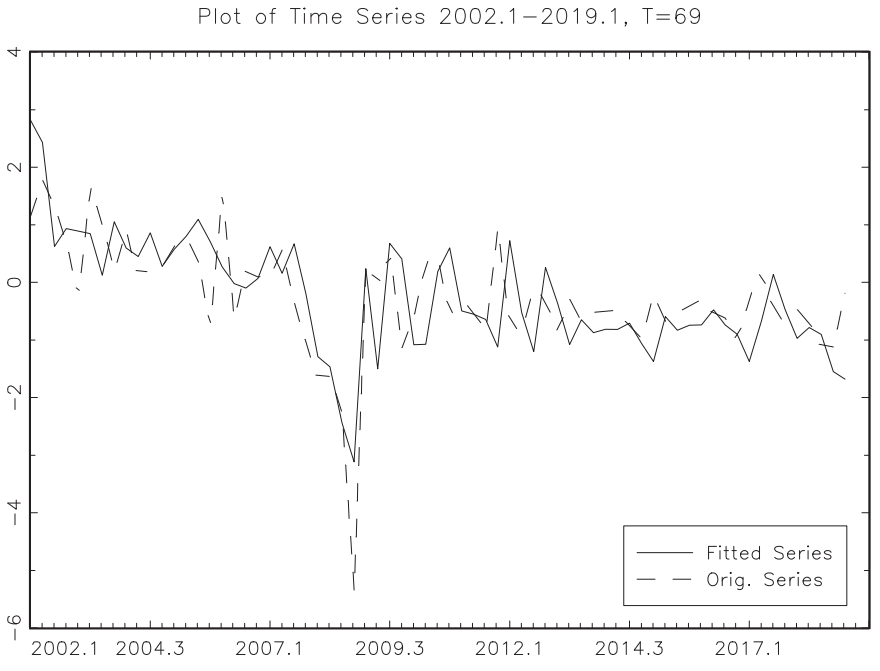

Figure 6. The original and fitted series of C_t..

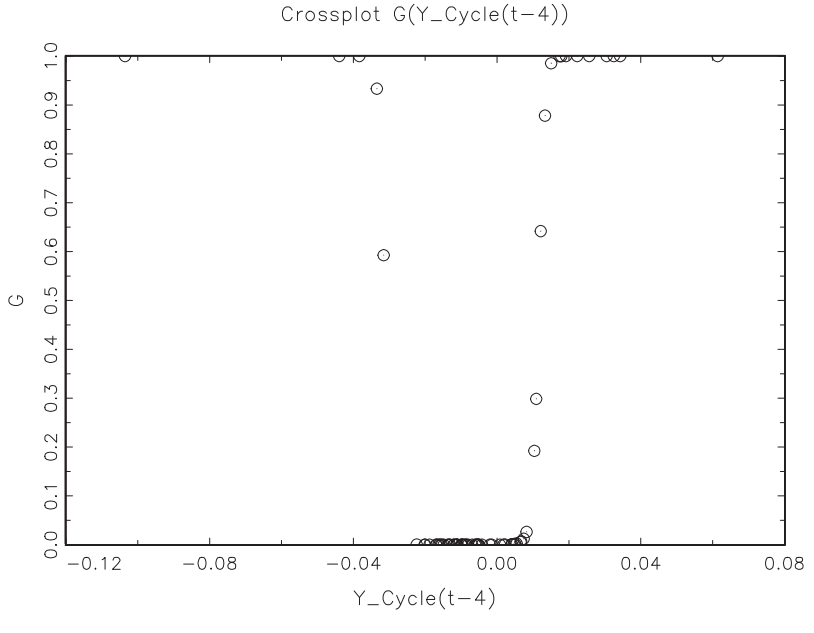

Figure 7. A dot plot of the transition function *G*. Each dot corresponds to one observation.

notice that around these outliers the absolute value of the standardized residuals is greater than three. These outliers correspond to the period of recession that followed the housing bubble of 2008 in the U.S.

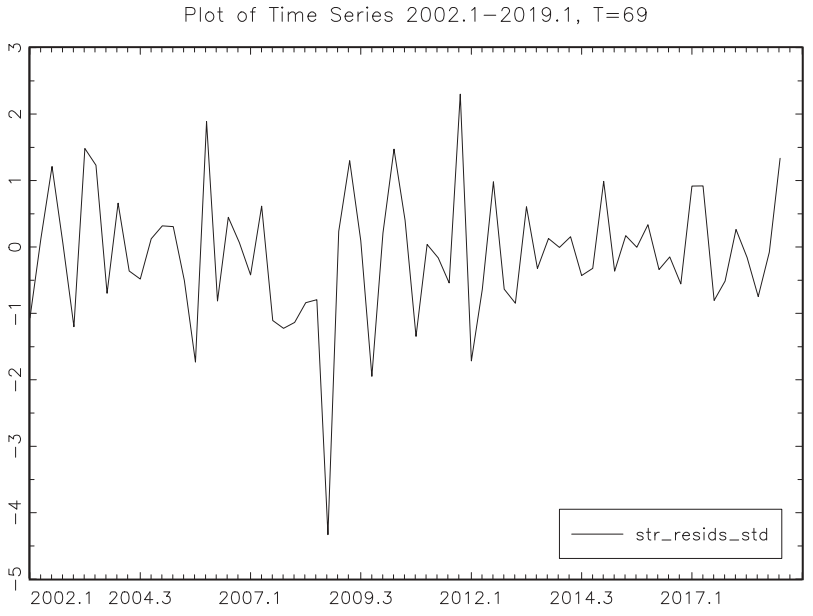

Figure 8. A plot of the standardized residuals series of the LSTAR(2) fitted to C_t..

3.3. Dynamic analysis

The two estimated threshold values are $c_1 = -3\%$ and $c_1 = 1\%$. These threshold values define the ground regime, where the growth rate of the fourth lag of the cycle of the proportion of e-commerce consumption to personal consumption, C_{t-4}, is in between −3% and 1%. When the transition variable takes an average value of these two thresholds, i.e., if $C_{t-4} = \bar{c} = \frac{c_1+c_2}{2} = -1\%$, then the transition function $\widetilde{G} = 0$ in the reparameterized STAR model in Equation (9). The behavior of C_t in this ground regime is, therefore, characterized by the following AR model:

$$C_t = \boldsymbol{\Lambda}' z_t + \varepsilon_t = (\boldsymbol{\Phi} + \boldsymbol{\Theta} G_{\min})' z_t + \varepsilon_t, \tag{21}$$

or equivalently, using the suggested LSTAR(2) model for C_t in Equation (17),

$$C_t = \theta_0 G_{\min} + (\phi_1 + \theta_1 G_{\min}) C_{t-1} + \phi_2 C_{t-2} + \varepsilon_t, \tag{22}$$

where

$$G_{\min} = \frac{1}{1 + \exp\{-\gamma \tilde{c}\}/\sigma^2} = \frac{1}{1 + \exp\{-7.47(0.0097)/0.0005\}} = 0.0025. \tag{23}$$

Therefore, using the estimated results in Equations (19 and 20), in the ground regime, the cycle of the proportion of e-commerce consumption to personal consumption is characterized by the following AR(2) process:

$$C_t = 0.00002 + 0.74 C_{t-1} + 0.24 C_{t-2} + \hat{\varepsilon}_t. \tag{24}$$

On the other hand, when $C_{t-4} \to \pm\infty$, $G = 1$ in Equation (19) and the model is reduced to the following AR(2) process:

Table 3. Dynamic analysis of the cycle of the proportion of U.S. e-commerce retail sales to personal consumption expenditures.

Regime	Transition variable	Roots	Stationarity	Model
Ground (mid)	$C_{t-4} = \bar{c} = -1\%$	$\lambda_1 = -0.24;\ \lambda_2 = 0.98$	stationary	AR(2)
Outer	$C_{t-4} \to \pm\infty$	$r_1 = -0.56; r_2 = 0.42$	stationary	AR(2)

$$C_t = 0.007 - 0.14C_{t-1} + 0.24C_{t-2} + \hat{\varepsilon}_t. \tag{25}$$

The roots of the characteristics polynomials corresponding to the AR(2) models in Equations (24 and 25) are summarized in Table 3. The dynamic analysis suggested by Table 3 reveals that, in the ground regime, when $-3\% \leq C_{t-4} \leq 1\%$, the process is stationary since the two real roots lie inside the unit circle. As for the two outer regimes, i.e., when C_{t-4} is above 1% or below -3%, the two real roots are also inside the unit circle and C_t is stationary with a mean $EC_t = 0.8\%$. The transition variable C_{t-4} and the two threshold values $c_1 = -3\%$ and $c_2 = 1\%$ are plotted in the top panel of Figure 9. The transition function G in Equation (20) is plotted in the bottom panel of the same figure. Notice that the transition variable stays most of the time in between the two threshold values, i.e., it stays in the ground regime most of the time. In particular, in the most recent period between 2013 and 2019, the ground regime is dominant. In other words, the fourth lag of the cycle of e-commerce consumption over personal consumption is stable between 2013 and 2019. This is consistent with the recent slowing down of the usage rate of digital information and communication technologies; namely, cellular phone, internet, computer and social media (see Figure 1). The diffusion cycle of

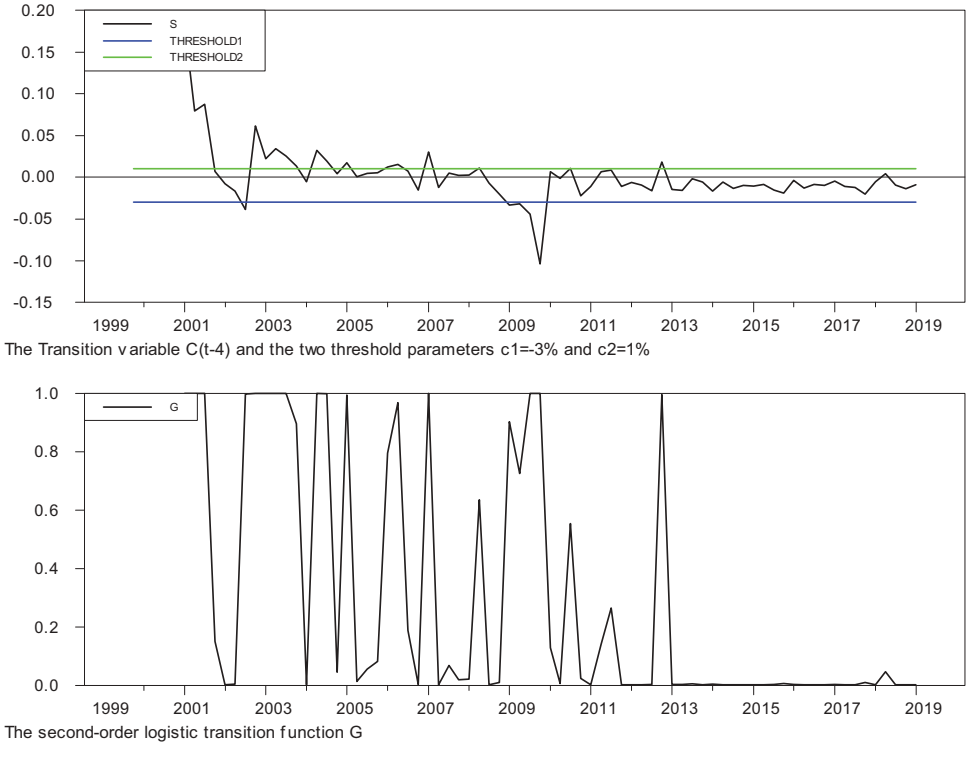

Figure 9. A plot of the transition variable C_{t-4} and the two threshold values $c_1 = -3\%$ and $c_2 = 1\%$ (top panel), and the transition function $G(\gamma, c_1, c_2; C_{t-4})$ (bottom panel) between 1999 and 2019.

these technologies indicate that, currently, consumption is in a mature state. Notice how this regime is different that the earlier period in between 1999 and 2013, where C_{t-4} exhibits frequent transitions from the ground regime to the outer regime and, guided by the estimated slope of the transition function $\gamma = 7.4$, this transition is moderately smooth as shown from the spikes of the transition function depicted at the bottom panel of Figure 9.

To sum up, the sharing economy has been causing disruptions to consumption habits in the period between 1999 and 2013. These disruptions were the result of the acceleration in the diffusion process of digital technologies during this period. In the recent period, however, the sharing economy has been stable. This stability could be attributed to the slow down of the diffusion of digital technology as a result of imitations or because the population has already reached a level of saturation.

4. Conclusion

The recent rise in digital technology has enabled the development of various online platforms that resulted in a variety of peer-to-peer sharing activities. Academics argue that this so-called sharing economy is causing a change in consumer habits. In this paper, we test empirically whether or not the sharing economy, which is motivated by digital technology, is causing a regime switch in personal consumption in the U.S. over the period between 1999 and 2019. To this end, we extract the quarter-to-quarter cycle of the proportion of U.S. e-commerce retail sales to personal consumption, C_t, and fit a proper smooth transition regression model to it.

The results of the econometric analysis show that C_t is pushed by its fourth lag, i.e., by C_{t-4} between two stationary AR(2) regimes; a ground regime and two similar outer regimes. The ground AR(2) regime is characterized as follows: when $-3\% \leq C_{t-4} \leq 1\%$, C_t stays in this regime. In other words, when the fourth lag of the growth of e-commerce sales relative to personal consumption is in between -3% and 1%, C_t is in a ground stable regime. If, however, C_{t-4} is strictly above 1% or strictly below -3%, the growth of e-commerce over personal consumption moves to another stable AR(2) regime. In the early period of the analysis between 1999 and 2013, the time series C_t switches between these two regimes smoothly, but frequently, as shown from the transition function in the bottom panel of Figure 9. More recently, however, in between 2013 and 2019, the growth of e-commerce over personal consumption is more persistent in the ground regime. This recent stabilization of the sharing economy indicates that digital technology has reached a maturity state, where the technological diffusion process slows down. This is consistent with the empirical studies on diffusion and our earlier observation regarding the slow growth of four key information and communication technologies over the period between 2013 and 2019; namely, cellular phone, internet, computer and social media usage. This recent slow down could be due to imitation or because the population is becoming more saturated. Thus, we conclude that, indeed, the sharing economy is causing a regime switch in consumption, and the dynamic behavior of this regime switching is consistent with the general behavior of the diffusion process of digital technology that is documented by empirical studies.

Finally, it is worth noting that the stationarity of C_t in both regimes means that it oscillates between the ground and the outer regimes. It could stay in one regime for a while, but it is bound to visit the other regime eventually. This means that, in the future, new inventions and further innovations in digital technology will most likely cause another cycle of disruptions to personal consumption.

Acknowledgments

I would like to express my gratitude to an anonymous referee for the constructive review and the helpful comments on the earlier version of this paper. All errors remain mine. This paper is supported by a research grant from Royal Roads University.

Disclosure statement

No potential conflict of interest was reported by the author.

Funding

This work was supported by a research grant from Royal Roads University.

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