The Paradox of Energy Consumption Decrease in the Transition Period towards a Digital Society

Corina Pelau [1],* and Carmen Acatrinei [2],*

[1]   UNESCO Department for Business Administration, Bucharest University of Economic Studies, 010374 Bucharest, Romania

[2]   Marketing Department, Bucharest University of Economic Studies, 010374 Bucharest, Romania

*   Correspondence: corina.pelau@fabiz.ase.ro (C.P.); carmen.acatrinei@mk.ase.ro (C.A.); Tel.: +40-745-581208 (C.P.); +40-744-896556 (C.A.)

Abstract: The digital transformation era is in full motion, steadily making its way into common households, triggering changes in behavior as well as consumption patterns. While some changes can occur only within the context of the household mean income, such as the upgrade of appliances or devices, correlated with a personal preference in adopting such tools and technologies, there is one area that must keep with the pace of change, regardless of the household's subjective criteria: energy consumption. The objective of this paper is to analyze the impact of digitalization on the household energy consumption, with the intent to understand trends, anticipate future changes as well as impact energy consumption efficiency. The results of the panel regressions based on the quantity of consumed energy and the popularity of several internet activities have revealed an inverse relation. The increased number of consumers doing certain internet activities such as: internet calling, reading online newspapers, activities on social media networks and uploading content online determine a lower energy consumption for that economy. There was no significant evidence for the relation between the energy consumption and internet activities such as: reading e-mails, searching for, doing internet banking and online purchases.

Keywords: energy consumption; energy transition; online activities; consumption pattern

1. Introduction

One of the current buzzwords across business ecosystems is "digitalization". The advances made in the field of technology are changing the way companies see themselves and market their products [1]. It is no surprise that such extensive transformation is now trickling into our day to day activities, whether in the workplace or in the safety and comfort of our own homes. The technology changes are disruptive and while policies are struggling to keep the pace, companies have quickly adapted and they have transformed their products to be consumption-ecosystem focused, with interdependencies that evolve after a product is sold and it is being consumed [2].

Energy efficiency is characterized both by the use of more efficient energy sources, but also by a more responsible behavior of the consumer [3–5]. Especially in a digitalized world, where most of the activities of the consumer are done in correspondence with electronic devices [5,6], it is important to analyze the impact of this development on the energy consumption. Especially the economic development has triggered higher standards of living, associated with an increased energy consumption [7–9]. In this paper we focus on the influence of the increased spread of online activities on the total energy consumption. It has been analyzed whether the consumers' online activities and their constant connection to their electronic devices, are affecting the quantity of energy consumed.

2. Literature Review

2.1. The Transition towards the Digitalization of the Consumer Behavior

Digital technology is affecting all aspects of our lives, from the way we work, to the way we travel and the way we consume information. Several activities of the everyday life of consumers have switched to digitalization and they are done with the help of electronic device. Nowadays consumers do shopping with the help of e-commerce by purchasing their goods online, they write e-mails and not classical postcards or letters and they make their payments through online banking, even the traditional way of talking on the phone is being replaced by internet or video-calls.

Newspapers and magazine subscriptions are almost an image of the past, most publications being forced to share content online and via email rather than in the old traditional format. With media moving to the digital world, there must be a certain adaptation of the format of the content as well. Search engine optimization, as well as an increased competition in the market, with online publishing costs being significantly lower compared to paper equivalent, are pushing the way in which information is prepared for consumption to be organized, reported and indexed in a different, more time efficient manner. With the move towards greener living, households are now cutting costs and perceived CO_2 emission by letting go of their paper subscriptions and opting for digital media instead [10]. However, while easily considering the substances used by print media, such as paper, plastic and rare metals, each with its own associated waste costs, we fail to recognize the environmental impact of our digital media. This type of media, contrary to initial beliefs, does not come bill-free as it retains its own energy costs related either to devices consuming such products (from manufacturing to daily usage) all the way to server farms which store and catalogue the content. This resource usage, while physically hidden as it does not land on our doorstep every day with a printed cost on the front page, is nevertheless present and can account for a hefty energy bill spread amongst the consumer population [10,11].

The social life of the consumers happens nowadays with the help of social media. Household members of most ages are now online, using social media to either keep in touch with their loved ones or simply to pass the time in a pleasant and mildly interactive manner. Social media networks can be used in several ways to communicate or to organize group activities, to offer several services and to inform about the existence of social activities [12]. The penetration of social media in daily lives is undeniable. The interest and use of social media have changed the way in which energy is consumed not only within households but also on a round the clock basis. Charging stations are a common sight in most airports, usually presenting one every few seats near each gate area. Airplanes are now providing under the seat charging power outlets while cafes are a common place for using personal or work laptops, therefore requiring device charging stations in convenient locations. Consumers also charge portable batteries to ensure they are constantly connected to their social platform, whether work or leisure related, or both.

Blockbuster's shutdown [13] was the definitive marker of streaming content taking ownership of the entertainment industry. Individuals and families can now purchase online a movie in a matter of minutes and watch it in the comfort of their homes, in opposition to a few years ago, when a movie was only available in cinemas or at video-rentals. Online streaming content has replaced other entertainment possibilities such as cinema [14] and it has increased an incentive to spend more time at home in front of the computer rather than outside. The access to digital content on demand has results in a higher household electricity consumption. Depending on the type of device and its electricity efficiency class [15], it can increase the monthly electricity bill.

2.2. Factors Affecting Energy Consumption

There are several factors that affect the overall energy consumption of a society. Economic development, technological progress or situational factors like the inequality of opportunity are just some of the factors that affect the amount of consumed energy. Several researches have shown that

economic development impacts the growth of energy consumption [7–9]. More developed societies have a higher living standard and therefore, have the tendency to consume more. Consumers and households with a lower income level have a lower energy consumption, but also a lower number of oportunities for switching to more efficient energy sources [16]. The increase of the purchasing power has an influence on the consumer choice to buy energy intensive household products. This increase of the number of products has also led to an increased energy consumption [17]. This result is also confirmed by Liu et al. who has stated that the nowadays technological change is focused on energy saving and higher efficiency and has consequently a decreasing effect on the energy consumption [7]. Despite the increasing energy consumption caused by economic development, there is also an increased interest to buy energy from more qualitative sources such as clean energy or renewables [17].

The circumstances and the geographical coordinates are another important factor that affect the consumption of energy. The circumstance and the environment, defined as the inequality of opportunity, in which an individual has lived, also impact the energy consumption. Several researches conducted in China have shown difference in the energy consumption in urban and rural areas [18–21]. The energy production in the rural areas is based more on local resources, in comparison to urban areas [19]. The geographic region is another factor that determines high differences for energy consumption and the preference for cleaner energy sources [21,22]. The organization of municipalities, their area and the number of inhabitants play also an important role for energy efficiency [23].

There are proven links between the level of awareness regarding the environment and the actions taken to conserve energy [24–27], but awareness alone is not sufficient to trigger a pro- environmental behavior [28,29] and therefore reduce the energy consumption in a household. Awareness of level of energy consumption is related to a reduction in consumption over time. In several studies in Japan and Holland [30] it was concluded that households will reduce their energy consumption between 5% and 9% when they are made aware of their consumption levels. Understanding the amount and the way in which energy is used, helps decision makers to educate consumers and to raise the awareness regarding a more efficient energy consumption.

2.3. Consumer Behavior and Energy Consumption

One of the main factors that can influence domestic energy consumption is human behavior coupled with the physical properties the household, number of occupants, degree of education as well as level of income [30–33]. Several authors point out that the behavior of the consumer has an important role on an increased resource efficiency and consequently on the decrease of energy consumption [3–5]. According to Chen a lower energy consumption can be achieved only by a radical change in the values and the behavior of the energy users [3].

Energy consumption is another important topic when speaking about pro-environmental behaviour. The consumed energy is influenced by the used equipment and by its maintenance, the behaviour of the user and by other general conditions [5,6]. Several equipment used in the household and at work, such as lighting system, refrigerator efficiency, computer (monitor and desktop) as well as other types of equipment have an impact on the overall energy consumption [6].

Kuo et al point out the importance of the influential attributes on the consumption of energy [34]. The introduction of smart-meters and other digital devices that can measure the consumed energy, may determine a change in the behavior of the consumers and to eliminate outdated behavior [34,35]. Newer technologies include mobile phone applications [36] and energy efficiency measurement with the help of the internet of things [37]. The installation of smart meters would allow a reduction in personnel required in order to read the household meters, it would eliminate the adjustment bills that are now being received by all households (adjustment bills are an estimate of consumption, and a credit or debit note is issued to the consumer at specific time throughout the year based on the real consumption volume), and will help identify loss of energy along the network. Overall, such measure would decrease costs and ensure an optimal consumption and distribution of energy [35].

Home energy management systems represent the future trend towards an increased energy efficiency. Despite the increased awareness regarding responsible energy saving, there are still some behavioral changes that should be triggered [38–40]. According to a research conducted by Nilson et al. the main reasons for resistance to change of behavior are related to the preservation of the consumer's comfort and their well-deserved value of life [38]. Several studies have tried to estimate the future energy consumption, based on the behavior of the consumer. Interesting topics in this sense is impact of the transportation behaviour on the energy consumption [41] and the structure of energy types [19].

3. Methodology of Research

3.1. Hypotheses

The objective of our research is to determine the impact of the consumers' online activities on the overall energy consumption in an economy. One may say that with the increased use of the computer the energy consumption should increase, but because of the more efficient electronic devices and of the automated process, the energy consumption will actually decrease. There are several factors related to the online behavior of the consumers that may determine a reduced energy consumption [42–45]. On one hand on the consumer side, the frequent use of online activities may determine individuals to have higher expectations regarding the performance of the used devices. Consumers who are using daily the internet will expect and demand devices with high speed internet, big storage capacities and efficient energy consumption, so the popularity of the internet activity will trigger the use of high performance devices from a superior energy class. Moreover, there are researches that show that an average level of computer and internet skills (user of advanced internet activities) have a positive influence on the recycling rate [46,47] and on the pro-environmental behavior. On the other hand, the interest of consumers for online activities has determined the producers of electronic devices to develop more efficient products that are energy efficient and more environmental-friendlier. With the development of intelligent and more performant devices, the producers also focus on creating products with superior energy classes. This fact is sustained both by the legislation which increased the standards for the energy class of products and by the consumers who demand lower energy costs for the lifetime value of products. Moreover the automated processes facilitated by electronic intelligent systems reduces the effort and energy involved in certain processes. Therefore, we formulate the following hypotheses in order to sustain our objective:

Hypothesis 1. The consumers' online activities have an impact on the energy consumption.

Hypothesis 2. An increased interest for online activity of the consumers influences in a decreasing way the quantity of consumed energy.

In order to test these hypotheses, we have analyzed the influence of eight different online activities of consumers on the total energy consumption. If at least one of the analyzed activities has an influence on the energy consumption, our hypotheses are confirmed. Therefore, for these activities, we have formulated the following sub-hypotheses:

Hypothesis 2.i: There is a positive or negative relation between the consumers online activity i and the quantity of consumed energy, where i = 1, . . . , 8 and i includes the following activities: {online purchases; writing and checking e-mails; internet calls via telephone or video-chat; social media networks activity; content upload on the internet; information search; online newspaper reading; internet banking}.

The influence of the mentioned consumers' online activities has been tested with the help of panel data analysis. For each of the online behavior patterns, there have been tested models with one or more variables.

3.2. Panel Regression Models with the Energy Consumption as Dependent Variable

The relation between the energy consumption and the consumers' online activities have been developed in the following panel regression model:

$$
\begin{aligned}
E_{Cons,it} = {}& \beta_1\, X_{o\_purch,it} + \beta_2\, X_{e\text{-}mail,it} + \beta_3\, X_{o\_calls,it} + \beta_4\, X_{s\_net,it} + \beta5\, X_{c\_upload,it} + \beta_6\, X_{info,it} \\
& + \beta_7\, X_{o\_news,it} + \beta_8\, X_{i\_banking,it} + \beta_{9c}\, C_{GDPPC,it} + \beta_{10c} C_{temp,it} + c
\end{aligned}
\tag{1}
$$

where i = online activity and t = time.

The panel regression model (1) has the energy consumption as dependent variable and the different online activities of consumers as independent variables. The online activities tested in this model are: online purchases; writing and checking e-mails; internet calls via telephone or video-chat; social media networks activity; content upload on the internet; information search; online newspaper reading; internet banking. For each of the independent variables there has been defined a β_i coefficient, i = 1, . . . , 8, for which the significance has been tested. The model also includes the control variable gross domestic product per capita (GDPPC) with the β_{9c} coefficient, the yearly average temperature with the β_{10c} coefficient and the constant c. For these variables there have been tested several panel regression models with random effect. In the following parts of the paper, it can be observed that the independent variables are grouped into two categories based on the correlations between them and have been tested separately. This grouping of the independent variables, does not affect the overall model. The variables that are not included in a group will have the β coefficient equal to zero ($\beta_g = 0$).

3.3. Data Collection

The detailed definition of the variables used for the application of the panel regression model can be observed in Table 1.

For most of the variables there have been used data from the Eurostat Database (2019) [48–50] for the following 29 countries: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, The Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden and United Kingdom. The temperature data have been collected from the World Bank Group (2019) [51]. The data has been collected for the period 2010–2016. A brief description of all variables can be observed in Table 1.

For the dependent variable energy consumption there has been used the Eurostat (2019) indicator which describes the quantity of electricity and heat used by end consumers at home. This indicator has been calculated in kg/capita for the used oil equivalent. For the independent variables regarding the online behavior of consumers, there has been also used a Eurostat (2019) indicator describing the percentage of people who have done a certain internet activity. For all variables included in the model, the percentage has been related to the total population.

The model contains the control variables gross domestic product per capita (GDPPC) provided by Eurostat (2019) [50] and the yearly average temperature provided by the World Bank Group (2019) [51]. Initially the model has been tested with two other control variables, namely daily computer use and internet access of households. Because of the inter-correlations between the independent variables and these control variables, they have not been included in the final model.

Table 1. Definition of variables.

Variable Code	Variable Name	Description
ECons	Energy consumption *	Describes the quantity of electricity and heat used by the final consumers at home, excepting energy used for transportation. The quantity is expressed in kg/capita for the oil equivalent.
Xo_purch	Online purchases-commerce *	Describes the percentage of individuals from the total population, who have used the internet for online purchases.
Xe-mail	E-mails *	Describes the percentage of individuals from the total population, who have used the internet for sending e-mails.
Xo_calls	Internet calls (telephone or video) *	Describes the percentage of individuals from the total population, who have used the internet for internet calls via telephone or video-chat.
Xs_net	Social networks *	Describes the percentage of individuals from the total population, who have used the internet for social networking activities, for creating user profile, posting messages or other contributions.
Xc_upload	Content upload *	Describes the percentage of individuals from the total population, who have used the internet for the uploading self-created content on the internet.
Xinfo	Information search *	Describes the percentage of individuals from the total population, who have used the internet for searching information about products and services.
Xo_news	Online Newspaper *	Describes the percentage of individuals from the total population, who have used the internet for reading or downloading online newspapers or news.
Xi_banking	Internet Banking *	Describes the percentage of individuals from the total population, who have used the internet for internet banking.
CGDPPC,it	GDPPC *	This variable describes the gross domestic product per capita at market prices.
Ctemp	Temperature **	Describes the yearly average temperature for the analyzed country

* Source: Eurostat Database (2019); ** World Bank Group (2019).

3.4. Correlation between the Variables

The correlation matrix presented in Table 2 shows that there are strong correlations between some of the independent variables. For instance, variables such as online purchases and e-mail regarding (0.898) or information search and e-mail reading (0.917) or internet banking and information search (0.819) have shown high correlations. For this reason it is inadequate to test their influence on the dependent variable energy consumption in a combine model. Therefore, the independent variables have been grouped into two groups and their influence has been tested separately. Because of the high correlations between them, some of the independent variables had the tendency to cancel their influence on the dependent variable.

Table 2. Correlation between the variables.

Variable Name	Energy Consumption	Online Purchases	E-mails	Internet Calls	Social Networks	Content Upload	Information Search	Online Newspaper	Internet Banking	GDPPC	Temperature
Energy consumption	1.000										
Online purchases	0.614	1.000									
E-mails	0.760	0.898	1.000								
Internet calls	0.193	0.207	0.266	1.000							
Social networks	0.448	0.680	0.709	0.560	1.000						
Content upload	0.169	0.444	0.428	0.386	0.593	1.000					
Information search	0.659	0.858	0.917	0.299	0.697	0.493	1.000				
Online Newspaper	0.618	0.559	0.702	0.472	0.652	0.355	0.743	1.000			
Internet Banking	0.686	0.744	0.851	0.311	0.629	0.409	0.819	0.699	1.000		
GDPPC	0.647	0.766	0.745	0.172	0.584	0.411	0.662	0.461	0.558	1.000	
Temperature	−0.759	−0.426	−0.567	−0.235	−0.312	0.030	−0.456	−0.539	−0.612	−0.352	1.000

The variables in group 1 are e-mail reading, internet calls and online newspaper. The correlation matrix for these variables and the control variable GDPPC can be observed in Table 3. As it can be observed, between these variables there are acceptable correlations that do not affect the panel regression model in a significant way.

Table 3. Correlation between the variables in group 1.

Variable Name	E-mails	Internet Calls	Online Newspaper	GDPPC	Temperature
E-mails	1.000				
Internet calls	0.322	1.000			
Online newspaper	0.693	0.567	1.000		
GDPPC	0.729	0.094	0.441	1.000	
Temperature	−0.550	−0.172	−0.467	−0.360	1.000

The second group of variables includes online purchases, social networks activities, content upload on the internet and internet banking. As the correlation matrix in Table 4 shows, there are acceptable correlation between the independent variables in group 2. Consequently, the variables can be used in the panel regression model.

Table 4. Correlation between the variables in group 2.

Variable Name	Online Purchases	Social Networks	Content Upload	Internet Banking	GDPPC	Temperatures
Online purchases	1.000					
Social networks	0.681	1.000				
Content upload	0.441	0.587	1.000			
Internet Banking	0.742	0.625	0.410	1.000		
GDPPC	0.766	0.587	0.407	0.555	1.000	
Temperature	−0.424	−0.308	0.028	−0.612	−0.349	1.000

4. Results and Discussion

4.1. Desriptive Statistics of Variables

The statistical variation of the variables can be observed in Table 5, based on data from the Eurostat Database (2019). The dependent variable energy consumption per capita has an average value of M_{ECons} = 582.1 kg in oil equivalent and a standard deviation SD_{ECons} = 195.6. The smallest energy consumption Min_{ECons} = 164 kg in oil equivalent has been registered in Malta, in 2014, while the highest value Max_{ECons} = 1084 kg in oil equivalent has been achieved in Finland in 2010. The two online activities with the highest standard deviations are online purchases (SD_{o_purch} = 19.0) and internet banking ($SD_{i\_banking}$ = 23.5), showing the highest differences of behavior for the European consumer. The most popular internet activity is e-mail reading having a mean of the variables of $M_{e\text{-}mail}$ = 66.5 and a standard deviation $SD_{e\text{-}mail}$ = 15.3. The least popular online activity is content upload having a mean of variables of M_{c_upload} = 27.3. The information about the other variables can be found in Table 3. The following panel regression models have been developed based on these variables.

Table 5. Statistical variation of variables.

Variable	Mean	Standard Deviation	Minimum	Maximum
Energy consumption	582.1	195.6	164	1084
Online purchases	33.4	19.0	2	78
E-mails	66.5	15.3	31	93
Internet calls	30.6	10.5	10	58
Social networks	48.8	11.2	25	76
Content upload	27.3	10.5	0	51
Information search	61.4	15.2	26	88
Online Newspaper	53.8	16.4	17	92
Internet Banking	56.4	23.5	6	94
GDPPC	104.2	71.0	20.4	336
Temperatures	10.2	4.2	−0.02	21

4.2. Panel Regression Models for the Variables in Group 1

Based on the correlation matrix and the relations between the variables, they have been divided into two groups. In the first group of variables, there have been included the e-mail reading and writing, internet calls, online newspaper and information searching on the internet. For these independent variables, there have been tested two combined and four ceteris paribus (one for each variable) panel regression models, having the energy consumption as dependent variable and the GDPPC as control variable. The results of these panel regression models can be observed in Table 6.

Table 6. Panel regression for the variables in group 1.

	Dependent Variable: Energy Consumption					
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
E-mails	0.275 (0.30)	-	−1.237 ** (−2.47)	-	-	-
Internet calls	−1.359 *** (−2.78)	−1.286 *** (−3.15)	-	−1.45 *** (−5.18)	-	-
Online Newspaper	−0.504 (−1.04)	−0.212 *** (−0.63)	-	-	−0.975 *** (−4.14)	-
Information search	0.453 (0.81)	-	-	-	-	−0.925 *** (−2.74)
GDPPC	0.296 (1.61)	0.336 * (1.94)	0.390 ** (2.08)	0.317 ** (1.84)	0.387 ** (2.21)	0.403 ** (2.25)
Temperature	−42.39 *** (−15.13)	−42.12 *** (−16.65)	−46.65 *** (−17.82)	−42.73 *** (−17.19)	−43.51 *** (−17.20)	−46.22 *** (−19.12)
Constant	1007.2 *** (19.75)	1028.7 *** (28.54)	1099.3 *** (25.48)	1030.7 *** (28.65)	1038.9 *** (28.58)	1069.5 *** (27.42)
Random effect	Yes	Yes	Yes	Yes	Yes	Yes
Wald-chi2	438.14 ***	466.34 ***	403.20 ***	473.24 ***	443.82 ***	415.59 ***
R-sq	0.671	0.6565	0.624	0.653	0.645	0.632
Rho	0.950	0.951	0.945	0.952	0.948	0.944
Observations	171	199	174	201	201	202

Note: * represents $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; values between parentheses represent z-values.

Model 1 describes the panel regression having the dependent variable energy consumption, all four independent variables regarding the percentage of consumers doing online activities and the control variables GDPPC and yearly average temperature. As it can be observed in Table 6, the variable with the most significant influence on the dependent variable is internet calls ($\beta_3 = -1.359$, $z = -2.78$, $p = 0.005$). This variable has an inversed influence on the energy consumption by having negative values for the β-coefficient ($\beta_i < 0$). The control variable GDPPC ($\beta_{9c} = 0.296$, $z = 1.61$, $p = 0.107$) has an average significance, while the control variable average temperature ($\beta_{10c} = -42.39$, $z = -15.13$, $p = 0.000$) and the constant c = 1007.2 (z = 19.75, $p = 0.000$) have also significant values. In this combined

model, there is no significant influence from the variables online newspaper reading ($\beta_7 = -0.504$, $z = -1.04$, $p = 0.296$), e-mail reading ($\beta_2 = 0.275$, $z = 0.30$, $p = 0.761 > 0.1$) and information search ($\beta_6 = 0.453$, $z = 0.81$, $p = 0.416 > 0.1$). The model has a good significance overall, having Wald-chi2 = 438.14 ($p = 0.000$) and an R-square = 0.671.

Model 2 includes the dependent variable energy consumption and the two independent variables with higher significances from model 1: internet calls and online newspaper. For this model Wald-chi2 = 466.34 ($p = 0.000$) and R-square = 0.656 show a good significance of the model. The fact that both Wald-chi2 and R-square have lower values in comparison to model 1, shows that the eliminated variables e-mails and information search have their role in the relation. For model 2, the independent variable internet calls ($\beta_3 = -1.286$, $z = -3.15$, $p = 0.002$) as well as the control variables GDPPC ($\beta_{9c} = 0.336$, $z = 1.94$, $p = 0.052$), average temperature ($\beta_{10c} = -42.13$, $z = -16.65$, $p = 0.000$) and the constant c (c = 1028.7, $z = 28.54$, $p = 0.000$) have significant values. In opposition to this, the independent variable online newspaper ($\beta_7 = -0.212$, $z = -0.63$, $p = 0.526 > 0.1$) does not have a significant value.

In model 4, there is presented the relation between the dependent variable energy consumption and the independent variable internet calls. This model shows a high significance having the highest Wald-chi2 = 473.24 ($p = 0.000$) among the ceteris paribus models and a high value for R-square ($R^2 = 0.653$). The β-coefficient for the independent variable internet calls ($\beta_3 = -1.453$, $z = -5.18$, $p = 0.000$) shows also a high significance of the model. Moreover, for all three models including the variable internet calls the β-coefficient has kept the negative sign, showing that with an increase of percentage of people doing this activity, the energy consumption decreases.

Model 5 describes the ceteris paribus relation between the independent variable newspaper reading and downloading and the dependent variable energy consumption. Similar to model 4, the Wald-chi2 = 443.82 ($p = 0.000$) and R-square ($R^2 = 0.645$) show a good significance of the model. The β-coefficient confirms the relation by having $\beta_7 = -0.975$, $z = -4.14$, $p = 0.000$ for newspaper reading and downloading. For the variable newspaper reading the β-coefficient has a negative sign for all three models. This shows a negative influence on the dependent variable energy consumption.

In model 3, the ceteris paribus relation is presented, having the energy consumption as dependent variable and e-mail reading and writing as single independent variable. For this relation the β-coefficient of the variable e-mail reading ($\beta_2 = -1.237$, $z = -2.47$, $p = 0.013$) shows significant values. The significance is also valid for the entire model having Wald–chi2 = 403.20 ($p = 0.000$) and R-square $R^2 = 0.624$. Despite these values, the β-coefficient does not preserve the same sign throughout the models and by having a confidence interval that includes the value 0. It must be also mentioned that this variable showed the highest correlations with other independent variables (as it can be observed in Table 2). Therefore, it is difficult to evaluate the direction of the relation between the e-mail reading and energy consumption.

The regression presented in model 6, between the dependent variable energy consumption and the independent variable information search on the internet is similar to the one presented in model 3. Wald-chi2 = 415.59 ($p = 0.000$), R-square ($R^2 = 0.632$), as well as the β-coefficient for the independent variable information search on the internet ($\beta_6 = -0.925$, $z = -2.74$, $p = 0.006$) show a good significance. In spite of this result, the β-coefficient does not preserve the sign and the confidence interval includes the value 0. Similar to model 3 it is difficult to analyze the direction between the variables.

4.3. Panel Regression Models for the Variables in Group 2

In this section the panel regression models for the dependent variable energy consumption and the independent variables regarding the online activities through online purchases, social media networks, content upload on the internet and internet banking are presented. Besides these variables, all tested models include the control variable GDPPC. There are presented two combined models and four ceteris paribus models, one for each variable. The results for each of these models can be observed in Table 7.

Table 7. Panel regression for the variables in group 2.

	Dependent Variable: Energy Consumption					
Variables	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**	**Model 12**
Online purchases	0.486 (0.56)	-	−1.449 *** (−4.41)	-	-	-
Social networks	1.228 * (1.89)	−0.838 ** (−2.26)	-	−0.869 *** (−2.91)	-	-
Content upload	−0.139 (−0.31)	-	-	-	−1.095 *** (−2.94)	-
Internet Banking	0.707 (1.05)	−0.025 (−0.05)	-	-	-	−1.059 ** (−2.56)
GDPPC	0.333 (1.52)	0.410 ** (2.10)	0.519 *** (2.86)	0.382 *** (2.04)	0.346 * (1.74)	0.433 ** (2.34)
Temperature	−30.60 *** (−6.69)	−42.97 *** (−12.23)	−43.29 *** (−17.05)	−43.18 *** (−12.55)	−46.35 *** (−17.20)	−46.37 *** (−19.08)
Constant	723.1 *** (8.88)	1016.5 *** (18.82)	1019.1 *** (27.74)	1021.7 *** (21.15)	1048.4 *** (25.98)	1070.9 *** (27.19)
Random effect	Yes	Yes	Yes	Yes	Yes	Yes
Wald-chi2	115.35 ***	196.94 ***	459.52 ***	198.91 ***	359.08 ***	414.83 ***
R-sq	0.703	0.647	0.630	0.643	0.638	0.625
Rho	0.974	0.956	0.951	0.958	0.946	0.946
Observations	86	144	203	145	144	202

Note: * represents $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; values between parentheses represent z-values.

Model 7 describes the panel regression model including all four variables from the second group and the dependent variable energy consumption. The Wald-chi2 = 115.35 ($p = 0.000$) and $R^2 = 0.703$ show a good significance of the model. In spite of this result, no all β-coefficient have had significant values. The social networks ($\beta_4 = 1.228$, z = 1.89, $p = 0.059$) have had a significant value. On the opposite side, the internet banking ($\beta_8 = 0.707$, z = 1.05, $p = 0.296$), the online purchases ($\beta_1 = 0.486$, z = 0.56, $p = 0.577 > 0.1$) and the content upload on the internet ($\beta_5 = -0.139$, z = −0.31, $p = 0.759 > 0.1$) have had lower significance. The control variable GDPPC ($\beta_{9c} = 0.333$, z = 1.52, $p = 0.129 > 0.1$) has had a lower significance in the combined model, while the control variable average temperature ($\beta_{10c} = -30.60$, z = −6.69, $p = 0.000$) and the constant c (c = 723.1, z = 8.88, $p = 0.000$) have been significant.

In model 8 there is presented the panel regression with the dependent variable energy consumption and the two variables with the highest significances from model 7, namely social networks and internet banking. For this model both the Wald-chi2 = 196.94 ($p = 0.000$), the $R^2 = 0.647$ and most of the β-coefficient have shown significant values. The variable activities on social media networks ($\beta_4 = -0.838$, z = −2.26, $p = 0.024$) has a high significance, while the internet banking ($\beta_8 = -0.025$, z = −0.05, $p = 0.963$) is not significant at all. For this model both the control variable GDPPC ($\beta_{9c} = 0.410$, z = 2.10, $p = 0.036$), average temperatures ($\beta_{10c} = -42.97$, z = −12.23, $p = 0.000$) and the constant c (c = 1016.5, z = 18.82, $p = 0.000$) have had significant values.

Model 10 presents the ceteris paribus relation between the energy consumption as dependent variable and the percentage of people doing online activities on social media networks as single independent variable. To these, there are added the control variable GDPPC and average temperature. The overall significance of the model is given by the Wald-chi2 = 198.9 ($p = 0.000$) and the relatively high R-square ($R^2 = 0.643$). The β-coefficient for the variable social media networks is also significant, having $\beta_4 = -0.869$, z = −2.91, $p = 0.004$. Besides, β_4 has a negative value, similar to model 8.

Model 11 describes the panel regression between the energy consumption and the percentage of people uploading content on the internet. This relation has also a high significance, having Wald-chi2 = 359.08 ($p = 0.000$) and a high R-square ($R^2 = 0.638$). The β-coefficient for the variable content upload ($\beta_5 = -1.095$, z = −2.94, $p = 0.003$) has negative values, similar to model 7. Despite the lack of significance of β_5 in model 7, it can be stated that there is a negative influence on the energy consumption.

In model 12, there is presented the ceteris paribus relation having the internet banking as single independent variable. For this variable there is also a significant value for Wald-chi2 = 414.83 (p = 0.000), but it has a lower value for R-square (R^2 = 0.625). The β-coefficient for internet banking (β_8 = −1.059, z = −2.56, p = 0.011) has negative values for model 12, in opposition to model 7 and model 8, where β_8 has positive values. Therefore, it is difficult to affirm the direction of the influence of the internet banking activity on the energy consumption.

Model 9 presents the ceteris paribus influence of the percentage of people doing online purchases on the dependent variable energy consumption. In spite of the significant values for Wald-chi2 = 459.52 (p = 0.000) and of the β-coefficient for online purchases (β_1 = −1.449, z = −4.41, p = 0.000), it is difficult to say if there is really an influence on the energy consumption. On one hand, β_1 does not preserve the same sign across the models, having a confidence interval that includes 0. On the other hand, the R-square (R^2 = 0.6302) has a relatively low value, compared to the other models. Therefore, the influence is difficult to prove.

5. Conclusions

The results of our research show that the percentage of people doing certain online activities has an influence of the total energy consumption at the household level. In a paradoxical way, with an increased percentage of people doing online activities, the energy consumption of the households decreases. At a first sight, it was expected that more internet activities will involve in a greater amount electronic devices, which will have an increasing impact on the energy consumption. The results of the panel regression models show that there is an inversed relation, explained probably by the increased energy efficiency of the devices used by the consumer for the online activities or by changing consumption patterns. Therefore, this topic can be extended in future research in order to determine the mediating factors for this decreasing relation.

The online activities which have the highest and most significant influence on the decreasing values of energy consumption are the internet calls and social media networks. The internet calls have significant β-coefficient in all tested models and besides it preserves the negative sign across models. Therefore, it can be stated that Hypothesis 2.3 is confirmed, regarding the influence of the people doing internet calls on the decreasing energy consumption. The variable social media networks has significant β-coefficients values for all tested models and it has a negative influence in two of the tested models. Moreover, in a panel regression including all eight online activities, it is the variable with the highest significance. Based on these facts, it can be also stated that *hypothesis 2.4 is confirmed* and that the social media activity influences the energy consumption. In spite of the fact that the content uploads does not have a significant β-coefficient in the combined relation, this coefficient had a negative value across models. Taking into consideration the fact that the ceteris paribus relation is significant, there can be stated that Hypothesis 2.5 is partially confirmed and that the uploading of content on the internet has a small influence on the energy consumption. The same situation is valid for online newspaper reading and downloading. For this variable the β-coefficients in all tested models have negative values and the β-coefficient are significant for one combined and the ceteris paribus model. Consequently, it can be also stated that Hypothesis 2.7 is partially confirmed and that the online reading of newspaper has a negative influence on the energy consumption.

For the other variables e-mail reading, information search, internet banking and online purchases, the β-coefficient did not have a constant sign across models, therefore, it is difficult to state their influence on the dependent variable energy consumption. It must be pointed out, that for all ceteris paribus relations the β-coefficients had significant negative values, but in the combined models, these influences have not been preserved. Consequently, based on these results Hypotheses 2.1, 2.2, 2.6 and 2.8 are rejected, regarding the influence of the e-mail reading, information search, internet banking and online purchases on the energy consumption.

Taking into consideration the fact that four of the eight analyzed online activities have an influence on the decreasing energy consumption, it can be stated that an increased interest for online activity of

the consumers has a negative influence on the quantity of consumed energy and therefore Hypothesis 2 is confirmed. Moreover, it can be affirmed that the online activities of the consumer influence the energy consumption and consequently Hypothesis 1 is also confirmed. For future research it will be interesting to define in a more precise way these relations. Online activity is associated with an increased use of electronic devices, so therefore at a first sight it is expected to have a positive relation between online activities and energy consumption.

The limitations of the research refer to the selection of the variables, which present the general behavior of the consumers without any specification regarding the time spent on the internet, the frequency of doing an online activity, the devices used for the online activity and several other details. The variables describe only if a consumers is doing a certain online activity or not. For future research it will be interesting to research the effect of a more detailed behavior on the energy consumption and its implications. Another aspect that needs further analysis is the changing sign of the β-coefficient for the models with more than two variables. This can be explained by the inter-correlations between the variables. Variables with lower influences can affect the overall relation.

The topic of the influence of the information and communication technology sector and the frequent use of the internet on the energy consumption have gained increased attention in the past years [45,47]. Studies from ten years ago, have shown that an increased use of consumer electronic devices such as TVs [52] or others have an impact on the energy consumption. The results of our research have shown that in a time with more modern technologies such as frequent internet use, decreases the energy consumption. Besides knowing this, it is important for future research to investigate more the factors that mediate this paradoxical relation between digitalization and energy consumption. Especially considering the fact that there will be an increased trend towards the use of robots, artificial intelligence and internet of things, it is important to further investigate it. The mediating factors can be the use of the increased energy efficiency class and performance of devices, the consumption patterns or the alternative sources of energy. Consumers who frequently use the internet will also have higher performance expectations from their devices. Therefore, an increased use of the internet will increase the demand for high technologies, having also better energy efficiency classes and more efficient product lifetime costs. Changing consumption patterns can also lead to a reduced energy consumption. Apparently, consumers who have average internet skills and an interest in technologies, have also a pro-environmental behavior. It might be the profile of the internet consumers that determines them to be more careful in their energy consumption and in the types of used energies. It will be also interesting to see how current innovations such as robots, artificial intelligence and internet of things will affect in the future the energy consumption. Only by understanding the context in which frequent internet users consume less energy, it will be possible to apply efficient energy policies with positive and sustainable impact on the environment.

Author Contributions: Conceptualization, C.P. and C.A.; methodology, C.P.; validation, C.P.; formal analysis, C.P. and C.A.; writing—original draft preparation, C.P and C.A.; writing—review and editing, C.P and C.A.; supervision, C.P.

References

1. Westerman, G.; Bonnet, D. Revamping your business through digital transformation. *MIT Sloan Manag. Rev.* **2015**, *56*, 10–13.
2. Subramaniam, M.; Iyer, B.; Venkatraman, V. Competing in digital ecosystems. *Bus. Horiz.* **2019**, *62*, 83–94. [CrossRef]

3. Chen, M.F. Extending the theory of planned behavior model to explain people's energy savings and carbon reduction behavioral intentions to mitigate climate change in Taiwan-moral obligation matters. *J. Clean. Prod.* **2016**, *112*, 1746–1753. [CrossRef]

4. Fisher, J.; Irvine, K. Reducing Energy Use and Carbon Emissions: A Critical Assessment of Small-Group Interventions. *Energies* **2016**, *9*, 172. [CrossRef]

5. Kuo, T.C.; Tseng, M.L.; Lin, C.H.; Wang, R.W.; Lee, C.H. Identifying sustainable behavior of energy consumers as a driver of design solutions: The missing link in eco-design. *J. Clean. Prod.* **2018**, *192*, 486–495. [CrossRef]

6. Yoon, Y.R.; Moon, H.J. Energy consumption model with energy use factors of tenants in commercial buildings using Gaussian process regression. *Energy Build.* **2018**, *168*, 215–224. [CrossRef]

7. Liu, X.; Zhou, D.; Zhou, P.; Wang, Q. Factors driving energy consumption in China: A joint decomposition approach. *J. Clean. Prod.* **2018**, *172*, 724–734. [CrossRef]

8. Qiu, H.; Yan, J.; Lei, Z.; Sun, D. Rising wages and energy consumption transition in rural China. *Energy Policy* **2018**, *119*, 545–553. [CrossRef]

9. Tang, E.; Peng, C.; Xu, Y. Changes of energy consumption with economic development when an economy becomes more productive. *J. Clean. Prod.* **2018**, *196*, 788–795. [CrossRef]

10. Fortunati, L.; O'Sullivan, J. Situating the social sustainability of print media in a world of digital alternatives. *Telemat. Inform.* **2019**, *37*, 137–145. [CrossRef]

11. Voineagu, V.; Vasilache, S.N.; Serban, D.; Cristache, A.E.; Begu, L.S. An analysis of the Romanian e-commerce trade trends in European perspective. *Econ. Comput. Econ. Cybern. Stud. Res.* **2016**, *50*, 235–252.

12. Dabija, D.C.; Babut, R.; Dinu, V.; Lugojan, M.I. Cross-Generational Analysis of Information Searching based on Social Media in Romania. *Transform. Bus. Econ.* **2017**, *16*, 248–270.

13. Stern, J. Blockbuster to Shut Down all Remaining Stores. 2013. Available online: https://abcnews. go.com/Technology/blockbuster-shut-remaining-stores-dvd-mail-service/story?id=20805588 (accessed on 3 January 2019).

14. Arnold, A. Convenience vs. Experience: Millennials Love Streaming but Aren't Ready to Dump Cinema Just Yet. *Forbes*. 2017. Available online: https://www.forbes.com/sites/andrewarnold/2017/10/26/millennials-love-streaming-but-arent-ready-to-dump-cinema-just-yet/#3a2d6c776311 (accessed on 3 January 2019).

15. Bagher, A.M.; Vahid, M.M.A.; Mohsen, M. A Review of Challenges in Display Technology. *Int. J. Electr. Compon. Energy Convers.* **2017**, *3*, 26–39. [CrossRef]

16. Damette, O.; Delacote, P.; Del Lo, G. Households energy consumption and transition toward cleaner energy sources. *Energy Policy* **2018**, *113*, 751–764. [CrossRef]

17. Zhang, M.; Bai, C. Exploring the influencing factors and decoupling state of residential energy consumption in Shandong. *J. Clean. Prod.* **2018**, *194*, 253–262. [CrossRef]

18. Muhumuza, R.; Zacharopoulos, A.; Mondol, J.D.; Smyth, M.; Pugsley, A. Energy consumption levels and technical approaches for supporting development of alternative energy technologies for rural sectors of developing countries. *Renew. Sustain. Energy Rev.* **2018**, *97*, 90–102. [CrossRef]

19. Niu, S.; Lia, Z.; Qiu, X.; Dai, R.; Wang, X.; Qiang, W.; Hong, Z. Measurement of effective energy consumption in China's rural household sector and policy implication. *Energy Policy* **2019**, *128*, 553–564. [CrossRef]

20. Yang, R.; He, J.; Li, S.; Su, W.; Ren, Y.; Li, X. Different effects of main influence factors on household energy consumption in three typical rural villages of China. *Energy Rep.* **2018**, *4*, 603–618. [CrossRef]

21. Shi, X. Inequality of opportunity in energy consumption in China. *Energy Policy* **2019**, *124*, 371–382. [CrossRef]

22. Pelau, C.; Pop, N.A. Implications for the energy policy derived from the relation between the cultural dimensions of Hofstede's model and the consumption of renewable energies. *Energy Policy* **2018**, *118*, 160–168. [CrossRef]

23. Segador-Vegas, C.; García-Sanz-Calcedo, J.; Encinas-Martín, D. Determination of the Energy Behaviour in Municipalities with Fewer than 6000 Inhabitants in Badajoz (Spain). *Energies* **2018**, *11*, 2287. [CrossRef]

24. Vicente-Molina, M.A.; Fernández-Sáinz, A.; Izagirre-Olaizola, J. Environmental knowledge and other variables affecting pro-environmental behaviour: Comparison of university students from emerging and advanced countries. *J. Clean. Prod.* **2013**, *61*, 130–138. [CrossRef]

25. Mainieri, T.; Barnett, E.; Valdero, T.; Unipan, J.; Oskamp, S. Green buying: The influence of environmental concern on consumer behaviour. *J. Soc. Psychol.* **1997**, *137*, 189–204. [CrossRef]

26. Kennedy, E.H.; Beckley, T.M.; McFarlane, B.L.; Nadeau, S. Why we don't walk the talk: Understanding the environmental values/behaviour gap in Canada. *Hum. Ecol. Rev.* **2009**, *16*, 151–160.

27. Oberst, C.A.; Schmitz, H.; Madlener, R. Are Prosumer Households That Much Different? Evidence from Stated Residential Energy Consumption in Germany. *Ecol. Econ.* **2019**, *158*, 101–115. [CrossRef]

28. Zsóka, A.; Szerényi, Z.M.; Széchy, A.; Kocsis, T. Greening due to environmental education? Environmental knowledge, attitudes, consumer behaviour and everyday pro-environmental activities of Hungarian high school and university students. *J. Clean. Prod.* **2013**, *48*, 126–138. [CrossRef]

29. Bamberg, S.; Möser, G. Twenty years after Hines, Hungerford and Tomera: A new meta-analysis of psycho-social determinants of pro-environmental behaviour. *J. Environ. Psychol.* **2007**, *27*, 14–25. [CrossRef]

30. Pothitou, M.; Kolios, A.; Varga, L.; Gu, S. A framework for targeting household energy savings through habitual behavioural change. *Int. J. Sustain. Energy* **2016**, *35*, 686–700. [CrossRef]

31. Jensen, J.O. Measuring consumption in households: Interpretations and strategies. *Ecol. Econ.* **2008**, *68*, 353–361. [CrossRef]

32. Vassileva, I.; Dahlquist, E.; Wallin, F.; Campillo, J. Energy consumption feedback devices' impact evaluation on domestic energy use. *Appl. Energy* **2013**, *106*, 314–320. [CrossRef]

33. Yohanis, Y.G. Domestic energy use and householders' energy behaviour. *Energy Policy* **2012**, *41*, 654–665. [CrossRef]

34. Kuo, C.F.J.; Lin, C.H.; Lee, M.H. Analyze the energy consumption characteristics and affecting factors of Taiwan's convenience stores-using the big data mining approach. *Energy Build.* **2018**, *168*, 120–136. [CrossRef]

35. Fahim, M.; Sillitti, A. Analyzing Load Profiles of Energy Consumption to Infer Household Characteristics Using Smart Meters. *Energies* **2019**, *12*, 773. [CrossRef]

36. Lee, S.; Go, M.; Ha, R.; Cha, H. Provisioning of energy consumption information for mobile ads. *Pervasive Mob. Comput.* **2019**, *53*, 49–61. [CrossRef]

37. Chen, X.; Li, C.; Tang, Y.; Xiao, Q. An Internet of Things based energy efficiency monitoring and management system for machining workshop. *J. Clean. Prod.* **2018**, *199*, 957–968. [CrossRef]

38. Nilsson, A.; Wester, M.; Lazarevic, D.; Brandt, N. Smart homes, home energy management systems and real-time feedback: Lessons for influencing household energy consumption from a Swedish field study. *Energy Build.* **2018**, *179*, 15–25. [CrossRef]

39. Dumitru, I.; Popescu, I.C.; Veghes, C.; Kailani, C. Marketing communication as a vector of the Romanian small businesess' sustainable development. *Amfiteatru Econ.* **2013**, *15*, 671–686.

40. Paunescu, C.; Acatrinei, C. Managing Maturity in Process-Based Improvement Organizations: A perspective of the Romanian Companies. *J. Bus. Econ. Manag.* **2012**, *13*, 223–241. [CrossRef]

41. Nematchoua, M.K.; Orosa, A.; Reiter, S. Energy consumption assessment due to the mobility of inhabitants and multiannual prospective on the horizon 2030–2050 in one Belgium city. *Energy* **2019**, *171*, 523–534. [CrossRef]

42. Mashhadi, A.R.; Behdad, S. Discriminant effects of consumer electronics use-phase attributes on household energy prediction. *Energy Policy* **2018**, *118*, 346–355. [CrossRef]

43. Tjorring, L.; Jensen, C.L.; Hansen, L.G.; Andersen, L.M. Increasing the flexibility of electricity consumption in private households: Does gender matter? *Energy Policy* **2018**, *118*, 9–18. [CrossRef]

44. Tjorring, L. We forgot half of the population! The significance of gender in Danish energy renovation projects. *Energy Res. Soc. Sci.* **2016**, *22*, 115–124. [CrossRef]

45. Morley, J.; Widdicks, K.; Hazas, M. Digitalisation, energy and data demand: The impact of Internet traffic on overall and peak electricity consumption. *Energy Res. Soc. Sci.* **2018**, *38*, 128–137. [CrossRef]

46. Serban, D.; Pelau, C.; Dinca, V. Panel data analysis for measuring the impact of e-skills on the ecological behavior of individuals. *Econ. Comput. Econ. Cybern. Stud. Res.* **2019**, *53*, 57–74. [CrossRef]

47. Bastida, L.; Cohen, J.J.; Kollmann, A.; Moya, A.; Reichl, J. Exploring the role of ICT on household behavioural energy efficiency to mitigate global warming. *Renew. Sustain. Energy Rev.* **2019**, *103*, 455–462. [CrossRef]

48. [Dataset] Eurostat: Final Energy Consumption in Households per Capita [sdg_07_20]. 2019. Available online: https://ec.europa.eu/eurostat/web/products-datasets/-/sdg_07_20 (accessed on 27 January 2019).

49. [Dataset] Eurostat: Individuals—Internet Activities [isoc_ci_ac_i]. 2019. Available online: https://ec.europa.eu/eurostat/web/products-datasets/-/isoc_ci_ac_i (accessed on 6 February 2019).

50. [Dataset] Eurostat: Main GDP Aggregates per Capita [nama_10_pc]. 2019. Available online: https://ec.europa.eu/eurostat/web/products-datasets/-/nama_10_pc (accessed on 6 February 2019).

51. [Dataset] World Bank Group. Climate Change Knowledge Portal. 2019. Available online: https://climateknowledgeportal.worldbank.org/download-data (accessed on 23 March 2019).

52. Crosbie, T. Household energy consumption and consumer electronics: The case of television. *Energy Policy* **2008**, *36*, 2191–2199. [CrossRef]