2019

The Effect of the Online Experience on Household Consumption Expenditure in the European Union

Mark Gallo

The Effect of the Online Experience on Household Consumption Expenditure in the European Union

Mr. Mark Gallo
Economics Department, Pace University, NYC
Dr. Anna Shostya
May 9, 2019
May 23, 2019

Abstract

This study aims to explore the elements of the online user experience that have helped firms like Apple, Alphabet, Microsoft, Amazon, and Facebook become world giants in terms of market capitalization. I use data from Eurostat to investigate the impact of mobile device usage, social media participation, usage of online communal learning sites, customer product reviews, and the national presence of Amazon Prime on final consumption expenditures of households in the European Union. I employ Expected Utility Theory as a theoretical framework to explain consumer behavior associated with online purchases and online sources for product information. I seek to answer the following questions: How does the presence of the resources allotted by the world's wealthiest retailer influence purchasing? Does the use of online social media reflect consumers' buying habits? And finally, what are some potential benefits and challenges associated with an online consumption experience? I use the Ordinary Least Square method to estimate a linear model, in which median net income and gross domestic product are held as control variables. I expect mobile device usage, social media participation, usage of online communal learning sites, and the presence of Amazon Prime to have a positive effect on the consumption expenditures.

Table of Contents

Introduction

In 2016, consumers began product searches on Amazon 55% of the time and those who did not use Amazon were most likely to use Google; These firms control more than 80% of the initial product search market (Galloway, 2018). The acceptance of the online experience, as well as the market power exhibited by the fields largest firms, inspired us to develop this research. This paper examines the relationship between online experience and consumption in the European Union. I observed the European Union's 28 member countries, Turkey, and Macedonia in the year 2016. Data from Eurostat are used to construct a measure for how much of an impact the online experience has played on consumption. This appears to be the most comprehensive dataset available regarding the online experience and European consumption. Geographical data were taken from the 2015 Amazon Investor Relations Report in order to study the impact that the presence of Amazon prime had on European consumption. This is the most comprehensive, available data regarding Amazon.

This paper proceeds as follows. The theoretical framework will discuss why the rates of consumption for those who participate online may be impacted by the online experience. The following section will discuss the relevant literature regarding online participation and consumption. I will then describe the data and methodology, followed by the empirical results. My findings will be presented with robustness checks and an analysis of the model's outputs.

Finally, I will complete my discussion of how expected utility theory can be used to better understand the online experience before proceeding to this paper's conclusion.

Theoretical Framework

In this paper I utilize expected utility theory, coupled with discounted utility modeling, to gain a better understanding as to why the online experience may impact consumption. R.A. Briggs, of Stanford University, suggests that expected utility theory can be used to assign value to one's economic decisions (2014). Expected utility theory assumes rational actors understand how much risk is associated with their economic decisions. These models sought to understand how people consume given the option to delay gratification. George Lowenstein, of the Royal Economic Society, observed that when given the opportunity to obtain an optimal outcome multiple times, those studied chose to maximize their utility with a minimal time delay (Lowenstein, 1987). My research observes Europeans who have used the internet to obtain product information before making a purchase. According to Eurostat data, in 2016, 71% of Europeans reported daily internet use (Eurostat, 2016). Internet speeds in Europe are fast and have been getting faster, so I chose to consider Lowenstein's findings when conducting my analysis (Fastmetrics, 2016).

The initial product search market contains two leading players, Amazon and Google (Galloway, 2018). Consumers appear to be gravitating toward a digital business ecosystem, like the one that Amazon provides. Digital business ecosystems rely on the rationality of the consumer and promote a transition toward a knowledge economy (Nachira, 2006). According to

Avinash Dixit, Susan Skeath, and David Reiley's text "Games of Strategy," rational behavior is: "perfectly calculating a pursuit of a complete and internally consistent objective (payoff) function" (Dixit, 2015, p.707). According to Philippe Mongin, expected utility theory states that the decision maker chooses between risky or uncertain prospects by comparing his expected utility values. This process can be applied when choosing whether to use Amazon or Google to gain product knowledge because it is challenging to conclude that the information one receives is comprehensive. Such values are determined by multiplying the probability of receiving a certain amount of utility by the utility's innate value. Such theory inherently addresses the risks associated with economic decision making and looks to determine what would be the most rational approach (Mongin, 1997). Internet users must have faith in the firms that are providing them with the information needed to draw rational conclusions. I elected to observe this phenomenon using expected utility theory because information obtained online is not always trustworthy. I infer that expected utility values track trust. This paper will observe the role of these firms in the market by studying the impact of the information they provide. I will look to quantify this impact through regression analysis.

Literature Review

Purchasing figures appear to signal that the European Union has shown increased interest in online consumption, with 2017 online spending growing to 534 billion euros, a 73.94% increase from 2013. It should be noted that during this period the European Central Bank (ECB) was actively pursuing expansionary monetary policy measures (Ecommerce News Europe, 2017). The onset of the economic collapse of 2009 pushed the ECB to gradually lower its

Refinancing Tender Rate, the rate of interest banks must pay when borrowing from the ECB, to its current measure of 0.00% (European Central Bank, 2018). Given poor economic conditions, I chose to consider if cheaper prices online could have inspired a shift to online spending, as lower prices and greater transparency of transactions have the potential to inspire a shift to online spending. The law of demand suggests that when holding all other factors constant, as the price of a normal good falls the quantity demanded of said good increases (Investopedia, 2018).

However, a market study conducted by Alberto Cavallo of Harvard University proved otherwise. Cavallo conducted research of 56 large multi-channel retailers in 10 countries and concluded that prices levels are identical 72% of the time. In the United Kingdom, the figure increased to 90%. Cavallo believes that retailers chose to match prices in physical and online locations in an effort to please customers (Cavallo, 2017). He continues to develop this theory by noting how the broad acceptance of smartphones, which as of 2017 were owned by 64.7% of Europeans, has made it easier to conduct price comparisons (Statista, 2018).

In order to gain a more objective understanding as to why consumers may be enticed to increase the quantity of purchases as a result of their online experience, one may look to utilize expected utility theory. Cavallo claims that prices online are set to match prices in-store in order to increase transparency. He infers that the limitation of customer confusion will deter customers from switching to a competing seller. Through my understanding of expected utility theory I concluded that, once uncertainty is accounted for, consumers will make decisions that net the best-expected gain in marginal utility (Mongin, 1997). Cavallo's understanding does appear to coincide with such theory because he accounts for the uncertainty associated with a consumer's decision-making process. He insinuates that the selling of identical products at different price points, only because they were bought through different platforms could spur customer backlash and cause the retailer to garner a negative reputation. According to the laws of game theory, from which expected utility theory is derived, a rational consumer's pursuit of maximum utility will not be deterred by the rationality, or lack of rationality, of his seller (Dixit, 2015).

An economically rational buyer would be incentivized to choose whichever good provided the greatest marginal utility. In the given scenario the discount provided online would be the necessary choice. Such a conclusion is drawn through an understanding of game theory, which theorizes that all players should seek to maximize their marginal benefits while accounting for the strategies taken by their opponents (Dixit, 2015). Because it is assumed that the seller has been presented identical products at different price points, the buyer's incentive to maximize utility is derived from the realization of the lesser price. This is because the goods are otherwise identical. The usage of such a pricing strategy places the seller in a risk trap because he is now at the mercy of the buyers' rationality.

Expected utility theory suggests that when determining strategies, all players must account for potential risks when looking to maximize utility. Having consistent pricing limits a seller's risk because it no longer puts him at the mercy of the buyers' rationality. Sellers who understand expected utility theory infer that the risk associated with buying an identical product at a higher cost would be too substantial for a buyer to ignore when looking to maximize his utility. Purchasers would be incentivized to utilize the platform that provides the lowest prices while sellers would be incentivized to match prices across all platforms in an effort to cater to market demand (Cavallo, 2017).

If one is to utilize Cavallo's research to infer that price differentiation between physical stores and stores online is not persistent and is unlikely to play a substantial role in determining purchase behavior, then expected utility theory would suggest one study factors that explain the uncertainty and risk associated with obtaining information online.

The onset of the online experience was associated with risk in various forms, particularly security, privacy, and reliability (Ling, 2010). Security became a prime concern of early users because of the inherent risks associated with storing sensitive financial information, like credit card and social security numbers, online. Chen and Barnes cite privacy as one's ability to trust the enterprise receiving his financial information (Chen & Barnes, 2007). The consumer who is willing to share such information puts his faith in the receiving party and must trust that it will not use his financial information for anything other than the agreed upon transaction.

Developing trust online is critical for retailers and some have an easier time developing trust than others. According to a study conducted by Koufaris and Hampton-Sosa, consumers are more likely to trust large companies when distributing financial information (Koufaris & Hampton-Sosa, 2004). This conclusion is based on the idea that well-known companies have garnered the trust of a large sample of people and have showcased that they are capable of protecting sensitive information. Consumers who have developed this understanding may be more likely to trust a well-known industry leader while online but may struggle to find security when looking to make purchases from smaller companies who have yet to develop a sound reputation.

Trust for smaller firms can be developed, but according to the research conducted by Laroche, Yang, McDougall, and Bergeron, it takes time (Laroche et al., 1996). They conclude that in order for sellers to gain trust online they must provide a consistent and positive experience for their customer. Ling concludes that doing so allows customers to utilize their previous shopping experiences to develop trust for a retailer. This theory is substantiated by research conducted by Seckler, who determined that as people gain experience shopping online they begin to shop online at an increasing rate. Seckler found that as shoppers became more comfortable with the tools used to shop online they became more likely to use them (Seckler, 2000). Psychological studies appear to bolster such claims. In 1994 Dabholkar concluded that individuals rely heavily on expectancy-value models, insinuating that those who have less experience online are more likely to run into problems, which are likely to deter them from conducting a purchase as a result of their online experience (Dabholkar, 1994). Such conclusions are drawn under the assumption that consumers had an otherwise positive experience while online.

Ling cites that, for online consumers, perceived elements of risk are: security, privacy, and reliability. In an effort to remedy potential risks one may be inclined to observe the impact that trust plays on determining how risk averse a consumer is.

A study conducted by Juan Carlos Burguillo utilized trust-based modeling and the multi-criteria crowdsourced data provided through platforms like Expedia and TripAdvisor to determine whether or not large sums of voluntary customer feedback could significantly explain which hotels tourists chose to book. He concludes that not only have crowdsourced customer reviews showcased a direct relationship to where tourists choose to stay, but also that trust has a relevant and significant impact on user-based recommendations (Burguillo, 2017).

Through Burguillo's study, one can infer that large pools of trusted customer feedback play a significant role when seeking to explain why a customer may choose to make a certain transaction. Such an inference is supported through psychological studies. David Hamilton and Jeffrey Sherman of the University of California at Santa Barbara concluded that group perception promoted conclusions that sought to resolve inconsistencies in the information acquired, and that such perceptions were more likely to exist when critiquing an individual being as opposed to a group of beings (Hamilton & Sherman, 1990). The conclusions drawn by Hamilton and Sherman appear to bolster Burguillo's claims while providing the necessary support to infer that consumer trust can be developed through the use of large sums of voluntary consumer feedback.

Mark de Bruijn, a Vice President of Marketing at SAP, was interviewed for the 2018 European E-commerce Report, during which he stated that over 50% of consumers use social media to submit complaints, post reviews, or provide responses to purchases made (de Bruijin, 2018). De Bruijn subscribes to the belief that retailers must research their social media presence and look to develop a strong, data-driven understanding of their demographics to compete in the digital economy. Such claims are supported through a study conducted by Sumit Chaturvedi, Sachin Gupta, and Devendra Singh Hada for the International Review of Management

Marketing. They concluded that, for consumers in Rajasthan, India, the usage of Facebook showcased a significant effect on the buying behaviors for those shopping for apparel online. However, trust was discovered to be the most significant factor when looking to explain consumption as a result of online participation (de Bruijin, 2018).

Social media usage, customer reviews, mobile device usage, price comparisons, the usage of communal learning sites, and the presence of Amazon Prime, variables which have been the basis for previous papers, will be the crux of this research. My objective is to determine how much of an effect these factors have on consumer behavior in an effort to explain the economic impact of the online experience.

Data and Methodology

In an order to verify that the online experience is playing an influential role in the economy and leading to variations in the rate at which consumers buy products, a cross-sectional model was crafted to observe what factors affect the rate at which the European population consumed goods in 2016. Percentages will be used to measure how much a population, in a given country in Europe, has purchased goods as explained by digital platform participation rates. The natural log of final consumption expenditure was chosen to be the dependent variable. Thirty observations were considered for the model, twenty-eight of which were the member countries of the European Union. The final two observations were of Macedonia and Turkey, which have been working to join the European Union since 2004-2005 (Ciddi, 2018). The following hypotheses were designed to present my models:

- H_0: No variables regarding online participation affect the rate at which people in Europe consume goods.

- H_1: At least one variable regarding online participation affects the rate at which people in Europe consume goods.

The literature suggests that trust is the most critical element when observing purchasing within the digital economy. So, I chose to observe independent variables that demonstrate social aspects of the online experience that depend on trust. A description of the variables used for this study has been presented on the following page and is referred to as Table 1. The coefficient expectations and sources have been listed as well. Stephanie Dutchen, of Harvard University, claims that for a society to thrive in the digital economy mutual trust must be persistent (Dutchen, 2018). Eight variables were expected to demonstrate a significant role in analyzing how much the internet experience may affect the purchase of goods. Two additional economic variables were introduced to the model to be held as constants when observing the impact that the online experience may have on consumption. These variables were: median net equivalised income and gross domestic product. A statistical summary of all the variables addressed in this paper has been presented on the following page and has been labeled Table 2. Upon this project's conception, the impact of social media usage inspired the most interest. Social media usage has boomed in recent years and so has the number of advertisements users see. The work of Scott Galloway of New York University was influential when choosing to observe social media usage. Galloway's book, *The Four: The Hidden DNA of Amazon, Apple, Facebook, and Google*, cites that Facebook has a user population that is larger than that of China, with more

Table 1: Expectations and Variable Descriptions

Variable	*Expectation*	Description	Source
Consumption	Dependent Variable	Final consumption expenditure (2016)	Eurostat
PrWiki	Positive	Proportion of population that uses wiki based knowledge sharing tools (2016)	Eurostat
PrSocial	Positive	Proportion of population that uses any social media (2016)	Eurostat
PrSocial.1	Negative	Proportion of population that uses only one type of social media (2016)	Eurostat
PrSocial.2	Positive	Proportion of population that uses two or more social media (2016)	Eurostat
CustomerRv	Unsure	Proportion of population that used customer reviews before purchasing (2016)	Eurostat
Income	Positive	Median Equivalised Net Income (2016)	Eurostat
Amazon	Positive	Dummy Variable: Acess to Amazon Prime (2016)	Amazon I.R. Report
MobilePhone	Positive	Individuals used the mobile phone network to access internet (2016)	Eurostat
MobilePC	Positive	Individuals used non-phone smart device to access internet (2016)	Eurostat
GDP	Positive	Gross Domestic Product (2016)	Eurostat

than two billion users. His work claims that Facebook has created a thriving online society that people enjoy, as they have chosen to spend almost an hour a day on Facebook (Galloway, 2018). Users trust the social media platforms they subscribe to, and with such a large population of people choosing to log into social media, advertisers shifted their focus. As of 2017, Instagram, a company owned by Facebook, had two million active monthly advertisers (Instagram for Business, 2018). The presence of marketers in a digital ecosystem with a growing population inspired the need to include a national presence on social media in the construction of my model.

Social media usage was measured using data from Eurostat to construct three variables, each of which describes a different type of European user who is between the ages of sixteen and seventy-four. This was done to explore how digital literacy can affect a population's rate of consumption. My first variable was the percentage of a nation's population that used social media in any form. This variable was labeled PrSocial and implies no limitation on social media usage. The second was the percentage of a population who chose to participate on social media in only one form and was labeled PrSocial.1. This variable was chosen to demonstrate unsophisticated proficiency on social media. This observation assumes that users who subscribe to only one form of social media will participate in social interaction online at a lesser rate. I infer from the literature that those who participate less online will struggle to utilize the consumption resources that are available on various social media platforms. The final social media variable was the percentage of a population that uses social media in at least two forms. This variable was identified as PrSocial.2. It is meant to represent those who show a greater degree of competence

Table 2: Summary of Statistics

Variable	*Range*	Mean	Standard Deviation
Consumption	4360 - 831000000	574367.6667	1507125.371
PrWiki	10-80	40.03	18.51
PrSocial	25-71	46.23	12.64
PrSocial.1	15-49	26.73	7.59
PrSocial.2	11-90	27.33	21.09
CustomerRv	5-39	21.6	9.26
Income	0.23 -4.15	1.5	0.99
Amazon	0-1	0.2	0.4

when using social media. Those who subscribe to multiple social media platforms are assumed to exhibit greater comfort when participating online. PrSocial and PrSocial.2 are expected to produce a positive coefficient. This is expected because those who spend more time logged in are likely to encounter a greater number of advertisements. PrSocial.1 is expected to showcase a negative coefficient. These expectations consider the claims cited by Dabholkar which asserted that those who participate in the online experience at greater rates were less likely to run into issues when conducting themselves online (Dabholkar, 1994).

The digital economy contains an abundance of free product information and it can be used to make more informed purchases. The rapid growth of Amazon, which is notorious for its transparency regarding product information, showcases how in demand information is amongst consumers. In an effort to analyze the online experience provided through applications like Wikibuy and sites like Amazon, Google Reviews, Yelp, and Expedia the percentage of a population in a given European country that uses customer reviews before making almost any purchase online, was included in the construction of the model. I included the percentage of the population that uses wiki-based learning devices in the model as well. This is because wikis provide platforms for people to discuss product pricing and quality. The qualities of a wiki are fairly similar to those of customer reviews. In order to study each element of the online experience individually, a variable called PrWiki was created, as well as CustomerRv. To be relevant in the digital economy retailers rely on mutual trust (Kourfaris & Hampton-Sosa, 2004). The usage of customer reviews removes the responsibility of demonstrating trust from the firm and places it in the hands of consumers. Consumers instead rely on the commentary of customers who choose to share their purchase experience. I was unable to come to a consensus on this variable’s expected coefficient. Studies of customer reviews have found that a review’s impact appears to be dependent on the product in question and the quality of the review (Hawkin, 2007). In the European Union one out of four consumers who shop online claim to use customer reviews before making a purchase (Eurostat, 2018). The use of research methods provides consumers with additional information and can help consumers determine whether or not they wish to partake in a transaction. In order to observe the impact that customer reviews have on consumption, the variable was included in the creation of the model.

According to the literature, the presence of Amazon has shifted where consumers choose to buy goods (Galloway, 2018). This shift lead to the inclusion of a dummy variable designed to express the impact of Amazon Prime on a given county. Amazon Prime is not available in all the countries that Amazon ships goods to, and those who don’t have access to Prime are not able to use the benefits that come with a subscription. The most noteworthy being Amazon’s famed free two-day shipping. The shipping is not actually free, it is included with the cost of a subscription, the price of which varies per country (Hankin, 2018). This variable was included to analyze the impact that the presence of Amazon Prime can have when it provides a country access to its full range of services. These services include cheaper and faster shipping, access to streaming content, and order tracking. All of which are provided through Amazon’s website.

In an effort to address the growing use of smart, mobile devices, two variables were used in the construction of the model (Statista, 2018). The first of the two is labeled MobilePhone. This variable was chosen to show how access to cellular data on mobile phones may affect the rate of consumption in a given country. The variable is a measure of the percentage of a countries population that has used a mobile phone to connect to the internet through their cellular provider's network. The second variable was called MobilePC. It was chosen to analyze those who utilize devices like laptops or tablets to access the internet while away from home. Due to the growing market for advertising on mobile devices, I elected to consider how their use may impact consumption (EMarketer, 2018). Such devices are an extension of the internet experience and this extension is what inspired their inclusion in the model.

Empirical Results

Our model's original equation has been presented below:

$$Ln(Consumption) = \beta_0 + \beta_1 PrWiki + \beta_2 PrSocial + \beta_3 PrSocial.1 + \beta_4 PrSocial.2 - \beta_5 CustomerRv + \beta_6 Income + \beta_7 Amazon + \beta_8 MobilePhone + \beta_9 MobilePC + \beta_{10} GDP + \varepsilon$$

$$Ln(Consumption) = 12.425 + 0.017PrWiki + 0.020PrSocial - 0.125PrSocial.1 + 0.006PrSocial.2 - 0.062CustomerRv + 0.715Income + 0.235Amazon - 0.005MobilePhone + 0.005MobilePC + 1.251GDP + \varepsilon$$

The regression analysis has been presented on the following page in Table 3. Our first model produced an adjusted r-squared of 0.752 signaling that 75.2% of the variation in the natural log of consumption can be explained by the variation of the model's independent variables. The percentage of those who use Wiki-based learning sites, the percentage of those who use only one form of social media, the percentage of those who always check customer reviews before making a purchase, net equivalized income, and gross domestic product were observed to be significant. However, access to Amazon Prime, the percentage of those who use social media in any form, those who use social media in two or more forms, those who use mobile phones to access the internet, and those who use non-phone smart devices to access the internet lacked significance to the model. Before reducing the model, the correlation matrix was observed to see if any of the independent variables were highly correlated with one another. This is known as serial correlation and can lead to an artificially inflated r-squared value. Upon consulting the correlation matrix, which can be viewed in the appendix, it was observed that

Table 3: Results

	Dependent variable:			
	log(Consumption)			
	(1)	(2)	(3)	(4)
PrWiki	0.017*	0.018*	0.018**	0.018**
	(0.010)	(0.009)	(0.008)	(0.008)
PrSocial	0.020			
	(0.023)			
PrSocial.1	−0.125***	−0.102***	−0.101***	−0.106***
	(0.039)	(0.028)	(0.027)	(0.026)
PrSocial.2	0.006	0.007	0.007	
	(0.008)	(0.007)	(0.007)	
CustomerRv	−0.062***	−0.056***	−0.057***	−0.059***
	(0.021)	(0.019)	(0.018)	(0.017)
Income	0.715**	0.786***	0.793***	0.802***
	(0.288)	(0.218)	(0.205)	(0.204)
Amazon	0.235	0.159		
	(1.080)	(1.000)		
MobilePhone	0.005	0.006		
	(0.031)	(0.023)		
MobilePC	0.005			
	(0.034)			
GDP	1.251**	1.291**	1.355***	1.353***
	(0.521)	(0.493)	(0.207)	(0.207)
Constant	12.425***	12.530***	12.582***	12.965***
	(0.926)	(0.865)	(0.809)	(0.701)
Observations	30	30	30	30
R^2	0.837	0.830	0.829	0.823
Adjusted R^2	0.752	0.766	0.785	0.786
Residual Std. Error	0.802 (df = 19)	0.779 (df = 21)	0.746 (df = 23)	0.745 (df = 24)
F Statistic	9.772*** (df = 10; 19)	12.839*** (df = 8; 21)	18.645*** (df = 6; 23)	22.276*** (df = 5; 24)
Note:				*p<0.1; **p<0.05; ***p<0.01

MobilePC exhibited a fairly strong correlation to net equivalised income, with the two exhibiting a correlation of 0.78. However, net equivalised income was to be held as an economic control variable. It exhibited significance to the model as well, so I elected to keep it in the model and remove MobilePC. I also observed that PrSocial and PrSocial.1 were highly correlated. Upon viewing the regression outputs, I deduced that PrSocial.1 showed significance to the model, while PrSocial did not. This observation inspired the removal of PrSocial from the model in order reduce the possibility that our model contains multicollinearity. The removal of these variables did not drastically affect our r-squared value. This allowed us to infer that they were insufficiently impacting the model and rationalized their removal.

The reduction of the model produced the following equation which is referred to in Table 3 as Model 2:

$$Ln(Consumption) = \beta 0 + \beta 1PrWiki + \beta 2PrSocial.1 + \beta 3PrSocial.2 - \beta 4CustomerRv$$
$$+ \beta 5Income + \beta 6Amazon + \beta 7MobilePhone + \beta 8\ GDP + \boldsymbol{\varepsilon}$$

$$Ln(Consumption) = 12.530 + 0.018PrWiki - 0.102PrSocial.1 + 0.007PrSocial.2 -$$
$$0.057CustomerRv + 0.786Income + 0.159Amazon + 0.006MobilePhone + 1.291GDP + \boldsymbol{\varepsilon}$$

The second regression analysis produced an adjusted r-squared of 0.766. PrSocial.2 and MobilePhone remained insignificant. When determining how to reduce the model further it was observed that PrSocial.2 had a t-value of 0.914, while MobilePhone had much lower t-value of 0.265. In order to determine which variable was lacking the necessary explanatory power to remain in the model, the absolute values of the t-values were observed with regard to their proximity to two. The absolute values were compared to two because a t-value of two represents two standard deviations from the mean. When a t-value is produced whose absolute value is greater than two one is able to reject the null hypothesis and conclude with 95% confidence that our variable's presence in the model is not lacking significance. As a result, MobilePhone was removed in order to create the third model because its absolute t-value was further below two. The regression output showcased a decrease in our r-squared by 0.001. This allowed us to rationalize the construction of the third model, which has been produced below:

$$Ln(Consumption) = \beta 0 + \beta 1PrWiki + \beta 2PrSocial.1 + \beta 3PrSocial.2 - \beta 4CustomerRv + \beta 5Income + \beta 7GDP + \boldsymbol{\varepsilon}$$

$$Ln(Consumption) = 12.582 + 0.018PrWiki - 0.101PrSocial.1 + 0.007PrSocial.2 - 0.057CustomerRv + 0.793Income + 1.355GDP + \boldsymbol{\varepsilon}$$

Regressing the third model showed an adjusted r-squared of 0.785. It was observed that PrScocial.2 produced a positive coefficient, while PrSocial.1 produced a significant and negative coefficient. This aligns with that literature regarding digital literacy. Those who were more accustomed to social media and have multiple ways to access the services appear to inspire an increase in the rate of consumption, while those who were less active, inspired the consumption rate to decline.

Removing those who use social media in two or more forms produced the final model, which is presented below:

$$Ln(Consumption) = \beta 0 + \beta 1 PrWiki + \beta 2 PrSocial.1 - \beta 3 CustomerRv + \beta 4 Income + \beta 5 GDP + \varepsilon$$

$$Ln(Consumption) = 12.965 + 0.018 PrWiki - 0.106 PrSocial.1 - 0.059 CustomerRv + 0.802 Income + + 1.353 GDP + \varepsilon$$

The final regression, seen on Table 3 as Model 4, produced an adjusted r-squared of 0.786. All the variables present in the model exhibit significance. 78.6% of the variation in the log of consumption can be explained by the variations of the independent variables presented in the final equation.

Due to the comparison of digital literacy occurring as expected, I concluded that the third model was of the greatest interest. I ran a Breusch-Pagan test and plotted the model's residuals and fitted values. Running these tests made it clear I could proceed under the assumption that heteroscedasticity of residuals was not present, as there was no signal that the residuals exhibited unique variances. Upon observing a p-value for Breusch-Pagan test of 0.4311 I concluded I could not reject the test's null hypothesis that homoscedasticity, or constant residual variance, was present. Plotting the residuals and fitted values supported the results provided through the Breusch-Pagan test, as the test's fitted line plot remained flat. Our graphical and statistical outputs are provided in the appendix.

The independent variables in our third model have inspired the following conclusions. A 1% increase in a European country's population that uses communal learning sites produced a 0.018% increase in the rate of household consumption expenditures, holding social media usage, customer reviews, net equivalised income, and GDP constant. The aligns with the literature that suggests consumers can develop trust for services through the usage of publically curated product information (Hamilton & Sherman, 1990). The information provided on wiki-based learning sites can vary and new wikis are being created for consumers all the time. Wikibuy is an example of how wikis are starting to impact how I shop. Wikibuy is an application that, when used with Google chrome provides, "a community of over 1 million users who share prices and coupons found in real-time while they shop. When the community knows a lower price is available at another store, you'll be notified, automatically, right in your browser " (Chrome Web Store, Wikibuy). New tools like Wikibuy may explain why the coefficient is so close to zero, yet remains positive. An increase in information does appear to spur a higher rate of consumption however the realization of lower prices may reduce its impact.

At the 99% level of significance, a 1% increase in the percentage of the population that uses only one social media platform resulted in a 0.106% decrease in consumption while holding the model's remaining variables constant. While a 1% increase in the percentage of the population that uses social media in at least two forms resulted in a 0.007% increase in the rate of consumption, holding the models remaining variables constant. Despite this variable not showcasing significance, I felt it produced the most interesting model. This model allowed us to compare the coefficients regarding those who use social media in only one form to those who use it in two or more. My comparison aligns with the literature review and bolsters the statements made by Dabholkar who makes claim that those who spend less time online are more likely to be deterred from consuming as a result of their online experience (Dabholkar, 1994). My expectations for this variable proved to be accurate. The understanding that those who are less digitally literate are likely to consume less as a result of the online experience has been supported by my findings.

Holding the model's remaining variables constant, a 1% increase in those who always use customer reviews before making a purchase online resulted in a 0.057% decrease in consumption. This finding was significant at the 99% level. I was unsure what to expect for this variable, but my coefficient has showcased a negative relationship between customer reviews and consumption. This seems to suggest that those who use customer reviews were deterred from increasing their purchasing. Additional research regarding the impact of customer reviews may provide the increased insight needed to better understand the impact of customer reviews on consumption.

An increase in net equivalized income by 10,000 euros, holding the models remaining variables constant, resulted in an increase in consumption of 79.3%. This aligns with literature regarding increases in income. According to Tullio Jappelli and Luigi Pistaferri, of Stanford University, in the short term, increases in consumption should track increases in income (Tullio & Pistaferri, 2010). My expectations for this variable coincided with the results, which was expected.

Observing gross domestic product lead us to observe that an increase in a nation's GDP by one million euros increased a countries consumption by 31.5%, holding the model's remaining variables constant. Gross domestic product is a measure of how much a national economy has produced and can grow as a result of increased consumption (Paula-Elena & Maha, 2014). An increase in consumption was expected to be observed upon the inclusion of GDP in the model and my regression analysis is in line with my expectations.

Discussion

My research studied the impact that variables related to the development of trust have on consumption. For a consumer to make a purchase with confidence, he must rely on the trust that he has for his sources of information. Expected utility theory suggests that consumers assign value to economic actions they may take in order to consider risk. This is necessary when obtaining product information online because it is challenging to authenticate online information. I have theorized that, in order to trust online information, consumers should assign expected values to the information they receive and consider these values before making a purchase. My research observed variables that allowed users to provide commentary on products. I believe that these tools help develop trust. If a customer discovers that his sources for product reviews are often credible he would be inclined to assign a higher expected utility value to them. As a result, he would be more incentivized to trust such reviews when making future purchases. This may explain why firms that take advantage of customer reviews, like Amazon, have flourished in the digital age.

The growing population of people using social media to review products may explain why my observations of digital literacy returned mixed results. The advent of social media has provided advertisers with a new ad space that can reach billions of potential buyers. In 2016 there were 2.28 billion social media users and by 2021 the number of people on social media is expected to surpass three billion (Statista, 2018). Social media advertisements are unique, as they are not distributed in the same way traditional print and television ads are. They are distributed based on algorithms that interpret a user's participation on the platform (Wilshire, 2018). This means that the ads one sees are the result of his preferences and tastes, which are determined through his social media activity. Thus, those with greater levels of digital literacy are likely to receive ads that are better tailored to their preferences. However, the econometric analysis found in this paper does not observe the impact of algorithmic advertising. Additional research on new forms of advertising coupled with the findings of this paper may provide the details needed to better understand how consumers are impacted by the advertising present within the online experience.

Conclusion

The internet has become a powerful resource and the data that is available regarding products has never been so vast. In an instant one can determine how much a product costs, what materials were used to make it, how certain products are expected to fit, what colors are available, see products of a similar nature, in both design and pricing, and get products shipped to one's door within a couple of days, or in some cases a couple of hours (Ecommerce News Europe, 2018). This research showcased that the usage of communal learning sites, the population who uses social media on only one platform, the use of customer reviews, net equivalised income, and GDP all exhibited significance when looking to observe what factors influence consumption. These variables require continued study in order to fully understand the impact they will have going forward. Continued development of this research is necessary, as the online experience has continued to shape how people across Europe consume goods. As data continues to develop and become accessible I expect more to be studied, explained, and understood.

References

"2M Monthly Advertisers on Instagram." Instagram for Business. Accessed December 04, 2018. https://business.instagram.com/blog/welcoming-two-million-advertisers/.

A Competitive European Internet Industry. A Socio-Economic Analysis of the European Internet Industry and the Future Internet Public-Private Partnership, ed. RAND Corporation, 57 – 72. Santa Monica: RAND Corporation, 2012.

"Amazon Launches Amazon Prime Now in Italy." Ecommerce News. October 19, 2018. Accessed December 04, 2018. https://ecommercenews.eu/amazon-launches-amazon-prime-now-in-italy/.

"Amazon Now Has Nearly 50% of US Ecommerce Market." EMarketer Retail. Accessed December 04, 2018. https://retail.emarketer.com/article/amazon-now-has-nearly-50-of-us-ecommerce-market/5b48c542ebd4000b2140992.

"Big, Bad Amazon." The Economist. October 20, 2014. Accessed December 04, 2018. https://www.economist.com/free-exchange/2014/10/20/big-bad-amazon.

Briggs, R. A. "Normative Theories of Rational Choice: Expected Utility." Stanford Encyclopedia of Philosophy. August 08, 2014. Accessed December 04, 2018. https://plato.stanford.edu/entries/rationality-normative-utility/.

Burguillo, Juan Carlos. "Trust-based Modelling of Multi-Criteria Crowdsourced Data" *Data Science and Engineering, Springer Link.* Vol. 2. No. 3 (2017): 199-209

Cavallo, Alberto. "Are Online and Offline Prices Similar? Evidence from Large Multi-Channel Retailers." American Economic Review, no. 107(1) (2017): 283 – 302.

Chaturvedi, Sumit, Gupta, Sachin, and Hada, Singh. “Perceived Risk, Trust and Information Seeking Behavior as Antecedents of Online Apparel Buying Behavior in India: An Exploratory Study in Context of Rajasthan” *International Review of Management and Marketing,* 6(4). (2016): 935-943.

Chen, Yu-Hui and Barnes, S. ‘Initial trust and online buyer behavior’, Industrial Management & Data Systems, 107(1), (2007): 21-36

Ciddi, Sinan. "For Turkey and the EU, Partnership May Be Better Than Membership." Stratfor. April 04, 2018. Accessed December 15, 2018. https://worldview.stratfor.com/article/turkey-and-eu-partnership-may-be-better-membership.

"COUNTRY COMPARISON:: GDP (PURCHASING POWER PARITY)." Central Intelligence Agency. Accessed December 04, 2018. https://www.cia.gov/library/publications/the-world-factbook/rankorder/2001rank.html#ch.

Dabholkar, P. ‘Incorporating choice into an attitudinal framework: analyzing models of mental comparison processes’, Journal of Consumer Research, 21(1), (1994): 100-118

de Bruijn, Mark. Ecommerce Europe. EuroCommerce. European Ecommerce Report 2018 Edition.

Diacon, Paula-Elena, and Liviu-George Maha. "The Relationship between Income, Consumption and GDP: A Time

Series, Cross-Country Analysis." October 30, 2014. https://ac.els-cdn.com/S2212567115003743/1-s2.0-S2212567115003743-main.pdf?_tid=f3cc7c3d-1d46-41b0-aa89-8e129b5e2b7a&acdnat=1543889148_4e5a00c69f2f8cc88c6e7dc73f9acb7e.

Dixit A., Skeath S., and Reiley D. *Games of Strategy Forth Edition.* New York: W.W. Norton & Company, 2015

Dutchen, Stephanie "Trust Me, I'm Your Smartphone." Paying for Health Care with Time | Harvard Medical School. Accessed December 04, 2018. https://hms.harvard.edu/magazine/connections/trust-me-im-your-smartphone

Editors, EMarketer. "Mobile Ad Spending to Surpass All Traditional Media Combined by 2020 - EMarketer Trends, Forecasts & Statistics." EMarketer. October 16, 2018. Accessed December 04, 2018. \https://www.emarketer.com/content/mobile-ad-spending-to-surpass-all-traditional-media-combined-by-2020.

Elliot, S. and Fowell, S. 'Expectations versus reality: A snapshot of consumer experiences with internet retailing', International Journal of Information Management, 20(5), (2000): 323-336.

Eurosystem, European Central Bank. "Key ECB Interest Rates" European Central Bank. Accessed October 10, 2018.https://www.ecb.europa.eu/stats/policy_and_exchange_rates /key_ecb_interest_rates/html/index.en.html

Europe, Ecommerce News. "Ecommerce in Europe was Worth €534 billion in 2017." *Ecommerce News Europe*.

July 2, 2018. Accessed October 6, 2018. https://ecommercenews.eu/ecommerce-in-europe-was-worth-e534-billion-in-2017/

Eurostat**,** V1 E-sales and turnover from e-sales, 2008 to 2016, EU28 (% enterprises, % total turnover), Accessed October 6, 2018. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=File:V1_E-sales_and_turnover_from_e-sales,_2008_to_2016,_EU28_(%25_enterprises,_%25_total_turnover).png#filelinks

"Fiber Optic Internet." Fastmetrics Inc. ISP. Accessed December 15, 2018. https://www.fastmetrics.com/internet-connection-speed-by-country.php#average-speed-interne.

Lowenstein, George. "Anticipation and the Valuation of Delayed Consumption." Jstor. Accessed December 2, 2018. https://www-jstor-org.rlib.pace.edu/stable/pdf/2232929.pdf?refreqid=excelsior:1972b37d50ee4eea008a3db3cbc6d590

Hamilton, D. and Sherman. S. “Perceiving individuals and groups: Expectancies, dispositional inferences, and causal attributions” *Journal of Personality and Social Psychology* (1999): 181-190.

Hankin, Lisa. "The Effects of User Reviews on Online Purchasing Behavior across Multiple Product Categories." May 2007. https://www.ischool.berkeley.edu/sites/default/files/lhankin_report.pdf.

Hoorens, Stijn. “The Future Contribution of the European Internet Industry Under the Three Scenarios” In *Towards*

"Household Internet Access in the European Union (EU28) 2007-2017 | Statistic." Statista. Accessed December 04,

2018. https://www.statista.com/statistics/377585/household-internet-access-in-eu28/.

Investopedia, "Cost-Benefit Analysis" Investopedia. Accessed October 14, 2018. https://www.investopedia.com/terms/c/cost-benefitanalysis.asp

Investopedia, "Law of Demand*" Investopedia*. Accessed October 13, 2018. https://www.investopedia.com/terms/l/lawofdemand.asp

Jappelli, Tullio, and Luigi Pistaferri. "The Consumption Response to Income Changes." 2010. https://web.stanford.edu/~pista/ann_rev.pdf.

Koufaris, M. and Hampton-Sosa, W. 'The development of initial trust in an online company by new customers', Information & Management, 41(3), (2004): 377-397.

Kowalczyk, Piotr. "How Much Does Amazon Prime Membership Cost in Your Country? (comparison)." Ebook Friendly. January 21, 2018. Accessed December 04, 2018. https://ebookfriendly.com/amazon-prime-membership-price-comparison/.

Laroche, M., Kim, C. and Zhou, L. 'Brand familiarity and confidence as determinants of purchase intention: an empirical test in a multiple brand context', Journal of Business Research, 37(2), (1996): 115-120.

Lecher, Colin. "Amazon Is Facing an EU Antitrust Probe into Its Collection of Sales Data." The Verge. September 19, 2018. Accessed December 04, 2018.

https://www.theverge.com/2018/9/19/17879480/amazon-eu-data-collection-probe.

Lieber, Ethan. “Online vs. Offline Competition” *Oxford Handbook of the Digital Economy*. (2011): 1-29.

Ling, Kwek Choon. “The Effects of Shopping Orientations, Online Trust and Prior Online Purchase Experience toward Customers’ Online Purchase Intention” *International Business Research* Vol.3, No. 3 (2010): 63-76.

Mongin, Philippe. “Expected Utility Theory” *Handbook of Economic Methodology,* (1997): 2-11.

"Number of Social Media Users Worldwide 2010-2021." Statista. Accessed December 04, 2018. https://www.statista.com/statistics/278414/number-of-worldwide-social-network-users/.

Nachira, Francesco. "Digital Business Ecosystem." 2006. Accessed December 2, 2018. http://www.digital-ecosystems.org/events/2006.06-sardegna/nachira-sardegna-ict.pdf.

Pace University Library Remote Database Authentication. Accessed December 04, 2018. https://www-statista-com.rlib.pace.edu/statistics/203722/smartphone-penetration-per-capita-in-western-europe-since-2000/.

Page, Vanessa. "Digital Native." Investopedia. May 24, 2018. Accessed December 04, 2018. https://www.investopedia.com/terms/d/digital-native.asp.

Seckler, V. (2000). ‘Survey says Web apparel buys doubled’, Women Wear Daily, 12, July, pp.2.

Sharma, Rakesh. "Perfect Competition." Investopedia. November 13, 2018. Accessed December 04, 2018. https://www.investopedia.com/terms/p/perfectcompetition.asp.

Statista, “Smartphone user penetration as percentage of total population in Western Europe from 2011 to 2018*”. Statista The Statistics Portal. Accessed October 5, 2018. https://www.statista.com/statistics/203722/smartphone-penetration-per-capita-in-western-europe-since-2000/

"Star Ratings." Driver Requirements | How To Drive With Uber | Uber. Accessed December 04, 2018. https://www.uber.com/drive/resources/how-ratings-work/.

“trust.” *Merriam-Webster.* 2018. https://www.merriam-webster.com (14 October 2018)

"Trust Me, I'm Your Smartphone." Paying for Health Care with Time | Harvard Medical School. Accessed December 04, 2018. https://hms.harvard.edu/magazine/connections/trust-me-im-your-smartphone.

Vincent, James. "Amazon Will Change Its Ebook Contracts with Publishers as EU Ends Antitrust Probe." The Verge. May 04, 2017. Accessed December 04, 2018. https://www.theverge.com/2017/5/4/15541810/eu-amazon-ebooks-antitrust-investigation-ended.

Weber, K. and Roehl, W. ‘Profiling people searching for and purchasing travel products on the World Wide Web’, Journal of Travel Research, 37(3), (1999): 291-298

Weissman, Cale Guthrie. "How Has Technology Changed The Way We Trust?" Fast Company. February 14, 2017. Accessed December 04, 2018. https://www.fastcompany.com/3068057/how-has-technology-changed-the-way-we-trust.

"Why Is Competition Policy Important for Consumers?" Together Against Trafficking in Human Beings. Accessed December 04, 2018. http://ec.europa.eu/competition/consumers/why_en.html.

W. (n.d.). Wikibuy. Retrieved March 23, 2019, from https://chrome.google.com/webstore/detail/wikibuy/nenlahapcbofgnanklpelkaejcehkggg?hl=en-US

Wiltshire, Emma. "The Current State of Social Media Algorithms [Infographic]." Social Media Today. April 26, 2018. Accessed December 04, 2018. https://www.socialmediatoday.com/news/the-current-state-of-social-media-algorithms/522260/.

"Your Key to European Statistics." Together Against Trafficking in Human Beings. Accessed December 04, 2018. https://ec.europa.eu/eurostat/data/database.

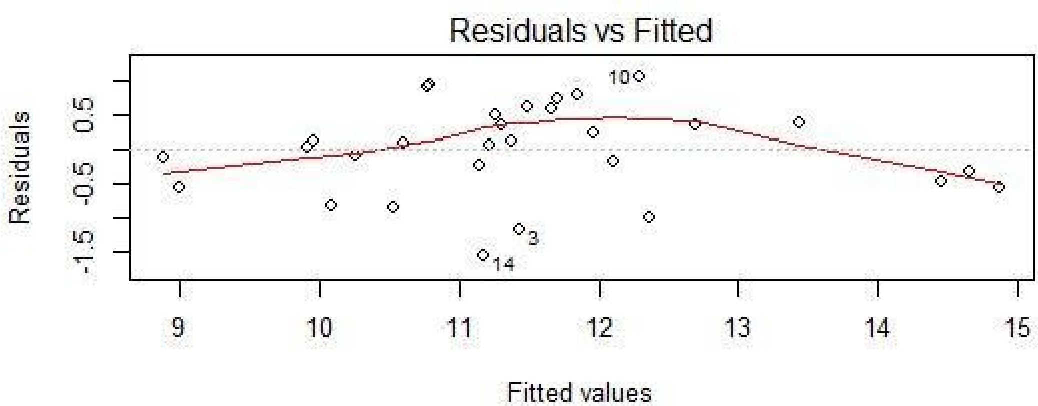
Appendix

1.

Correlation Matrix

	Consumption	PrSocial	PrSocial.1	MobilePC	CustomerRv	PrWiki	Income	Amazon	GDP	MobilePhone	PrSocial.2
Consumption	1	-0.010	-0.140	0.030	0.190	0.100	0.100	0.610	1	-0.080	-0.070
PrSocial	-0.010	1	0.790	0.620	0.230	0.390	0.680	-0.060	-0.010	0.340	-0.200
PrSocial.1	-0.140	0.790	1	0.540	-0.080	0.230	0.590	-0.250	-0.130	0.410	-0.220
MobilePC	0.030	0.620	0.540	1	0.380	0.420	0.780	-0.020	0.030	0.620	-0.190
CustomerRv	0.190	0.230	-0.080	0.380	1	0.340	0.360	0.350	0.19	-0.010	-0.200
PrWiki	0.100	0.390	0.230	0.420	0.340	1	0.280	0.030	0.110	0.300	-0.230
Income	0.100	0.680	0.590	0.780	0.360	0.280	1	0.170	0.100	0.340	-0.190
Amazon	0.610	-0.060	-0.250	-0.020	0.350	0.030	0.170	1	0.600	-0.150	-0.120
GDP	1	-0.010	-0.130	0.030	0.190	0.110	0.100	0.600	1	-0.080	-0.070
MobilePhone	-0.080	0.340	0.410	0.620	-0.010	0.300	0.340	-0.150	-0.080	1	-0.080
PrSocial.2	-0.070	-0.200	-0.220	-0.190	-0.200	-0.230	-0.190	-0.120	-0.070	-0.080	1

2.



3.

```
> lmtest::bptest(model.3)

        studentized Breusch-Pagan test

data:  model.3
BP = 5.9298, df = 6, p-value = 0.4311
```