CHANGES IN E-COMMERCE
CONSUMER BEHAVIOR IN THE
COVID-19 OUTBREAK

by

Yuliia Dehtiarova

A thesis submitted in partial fulfillment of
the requirements for the degree of

MA in Economic Analysis.

Kyiv School of Economics

2021

Thesis Supervisor: ________________________ Professor Olga Kupets

Approved by ____
Head of the KSE Defense Committee, Professor

____

____

____

Date ____________________________

Kyiv School of Economics

Abstract

CHANGES IN E-COMMERCE
CONSUMER BEHAVIOR IN THE
COVID-19 OUTBREAK

by Yuliia Dehtiarova

Thesis Supervisor: Professor Olga Kupets

The outbreak of COVID-19 shook the world in 2020 and forced people to change their lifestyles including the way they purchase goods and services, with a dramatic increase in online shopping.

This thesis focuses on studying the consumers' online purchasing behavior for durable goods before and during the outbreak of COVID-19 using the dataset for the multi-category store provided by REES46 Marketing Platform from Kaggle.com. In particular, we look at the effects of price, weekend, and brand on the probability of purchase in October-November 2019 as opposed to March-April 2020.

The estimation results show that in the majority of product categories consumers were not likely to buy cheaper goods in the same product category in the outbreak of COVID-19 in comparison to October-November, 2019. Besides, consumers changed their preferences in terms of brand selection while buying goods from the "Appliances" category. Also, consumers were more likely to do online shopping during weekends with regard to weekdays for the majority of product categories in comparison to October-November, 2019.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGMENTS

I wish to express the greatest gratitude to my thesis supervisor Professor Olga Kupets for her continuous support, invaluable expertise, meaningful feedback, and guidance through the process of thesis writing. Her professional advice made a significant contribution to the progress of this paper.

I also wish to thank all research workshop professors, who were reviewing this paper and listening to the presentations during Research Workshops. They all contributed to thesis advancement by providing suggestions and comments.

Special thanks go to REES46 Marketing Platform who provided the dataset for this study through Kaggle.com and made the current study data-driven. Moreover, I appreciate the consultation on how to work with Big Data from my friend Dima Gumenyuk.

I am also grateful to the whole KSE community and McKinsey & Company who granted my study and gave me the possibility to finish an MA degree at KSE. Moreover, thanks to all of my groupmates for making the education process unforgettable.

Finally, special appreciation is said to my family: parents Iryna and Viktor as well as grandmother Olha for their patience and belief in the great result.

LIST OF ABBREVIATIONS

COVID-19. COronaVIrus Disease 2019.

FMCG. Fast-Moving Consumer Goods.

UK. United Kingdom.

USA. United States of America

Chapter 1

INTRODUCTION

The fast spread of the COVID-19 forced governments to the least popular measure – countries lockdown which included the prohibition of tourism, international travel, eating in restaurants, and even ban for leaving home. This situation has also shown the importance of digitalization of country processes and entering or advancing the era of the digital economy. Safety is of great importance during such an unpredictable and dangerous situation and digital processes reduce the risk of being infected. People started to be more careful and changed the way they behave. Many of them made a digital step forward – they moved partially or completely to online shopping. For example, the study done by McKinsey (2020) for the US market showed that consumers are accelerating the adoption of digital channels, especially in the grocery industry, where around 30% of consumers from the studied sample used digital technologies in this sector for the first time. The same trend was evidenced in the Ukrainian e-commerce industry according to the research done by NAI Ukraine (2020). E-commerce in Ukraine has grown by about 45% in one year and was accounted for 8% of the total number of sales. The growing popularity of e-commerce increases monopolistic competition among producers of goods and services.

Brand diversity is a good example of monopolistic competition. For producers, this competition can be a driver for improving their brands in terms of product category diversification, presentation, and consumer perception. Knowledge of how consumers choose specific products allows producers to be among winners in monopolistic competition. Moreover, firms are interested in the lowest possible elasticity of the offered products, as consumers in that way will not stop preferring such products to other positions offered. That is why producers are concentrated on building consumers' loyalty to brands even during the pandemic, such as COVID-19.

Now, the impact of the pandemic is studied on different spheres of life including consumer behavior and the economy in general. The study done for Jordan in 2020 showed that consumer preferences during COVID-19 shifted to e-payment methods and online shopping (Hashem, 2020). Another study also approves that there is a notable change in buyer's mentalities and their shopping habits including cost awareness, preference inclination for neighbourhood items, and the emotional move towards internet business (Veeragandham et al., 2020). The changes in consumer behavior were also observed in research done for Iran which explored the effects of the COVID-19 pandemic on online consumption. A large drop in online transactions for durable goods during the lockdown was noted (Hoseini and Valizadeh, 2021). Researchers also compare online and offline consumer behavior patterns which help to evaluate the effect of technologies on the behavior patterns (Díaz et al., 2017) especially during crisis times such as COVID-19.

This thesis contributes to the academic literature focused on studying e-commerce consumer behavior during COVID-19. The effects which influence the decision of a consumer to buy durable goods during the COVID-19 pandemic are still poorly studied and described in the literature. Studies about consumer "purchase" decisions for durable goods are mostly related to normal times and concentrated on the effects which generally influence the likelihood of purchase, for example, brand and price which is also a focus of this research. However, this study also explores the effect of weekends (Saturday and Sunday) on a consumer's decision about the purchase.

The thesis is focused on studying the consumers purchasing behavior before (October-November, 2019) and during the outbreak of COVID-19(March-April, 2020) in the sphere of e-commerce. The main question raised in this paper is: "How has the e-commerce consumer buying behavior changed in the outbreak of COVID-19?". The main hypotheses to be tested are listed below:

- Consumers are more likely to buy cheaper goods in the same product category during the outbreak of COVID-19 in comparison to October-November, 2019;
- Consumers are more likely to do online shopping during weekends in the outbreak of COVID-19 in comparison to October-November, 2019;
- Consumers did not change their preferences in terms of brands selection while buying goods from the "Appliances" category during the outbreak of COVID-19 in comparison to October-November, 2019.

To test the hypotheses, we use the e-commerce consumer behavior data from a multi-category store extracted from Kaggle.com and apply the logit model. It is important to stress that having data specifics, the individual user behavior is not studied here. The general consumer pattern of online purchases before and during COVID-19 is the focus of this research.

The rest of the study is structured as follows: Chapter 2 is concentrated on the literature overview with the accent on consumers behavior theory as well as COVID-19 and other crises effects on consumer behavior; Chapter 3 provides data description; Chapter 4 describes study methodology and model specification; Chapter 5 offers the estimation results and discusses the main outcomes of changes in the e-commerce consumer behavior in the outbreak of COVID-19 pandemic; Chapter 6 draws conclusions and provides ideas for further research.

Chapter 2

LITERATURE REVIEW

Pandemics, such as COVID-19 influence local economies as well as the whole world economy. It changes the lifestyle and human behavior. Moreover, in the 21st century in the era of digitalization, it forces individuals, businesses, and governments to digital transformation processes. That is why in this chapter we will examine literature with subsections in the following order: consumer behavior theory, COVID-19, and other crises effects on consumer behavior.

2.1 Consumer behavior theory

Consumer behavior is actively observed both in traditional and behavioral economics. In terms of consumer behavior, traditional economics studies are concentrated mostly on rational decision-making whereas behavioral economics studies emotionally biased or irrational consumer behavior. In terms of consumer behavior, academic literature in microeconomics explores consumer preferences, utility, budget constraints, substitution and income effects, etc.

Engel, Blackwell & Miniard (1990: G4), defined consumer behavior as "those actions directly involved in obtaining, consuming, and disposing of products and services, including the decision processes that precede and follow these actions". The scholarly research on consumer behavior has a long history because it was of specific interest for social science researchers (Peighambari et al., 2016), (MacInnis & Folkes, 2010). Peighambari et al. (2016) analyze 12 years of recent scholarly research on consumer behavior in order to synthesize the main behavioral trends including changes in the environment of consumers' decision-making and purchasing process. Among the article topics, it was found that from 1998 to 2009 the topics related to "Purchase Process" were showing growing trend of popularity. The study results also pointed out that around 6.2% of all analyzed articles were devoted to Brand awareness/loyalty. These factors are studied for both types of goods described in academic economic literature – durable and non-durable goods (Pindyck, Rubinfeld, 2009). Durable goods are intended for long-term usage whereas non-durable goods are for one or short-term usage. As for the demand theory, demand for durable goods is more volatile than for non-durable goods. This happens because the demand for durable goods constructs on the basis of consumer's future expectations regarding development and income.

Before buying some goods or services users typically search the Internet for possible variants. Jun and Park (2016) study the correlation between purchase behavior and search activity. Their findings show that for non-durable goods "search traffic can be a significant predictor of purchases, depending on both price and frequency of purchases". On the other hand, for new products among durable goods when traffic shows a growing interest, it is not necessary a strong indication of actual purchases. In terms of product quality, Kalita et. al. (2004) came to the conclusion that it does not matter whether the firms sell durable or non-durable goods, they signal quality through price.

What influences purchases of durable and non-durable goods? For non-durable goods, the study by Manandhar (2019) stated that the consumers' "buy" decision was influenced by perceived quality. However, it was also found that there were no significant differences in terms of "buy" decisions regarding consumers' income level and age. As for durable goods, brands, quality, price, quantity, mode of purchase influence consumers' "buy" decisions (Rajeswari, Pirakatheeswari, 2014). According to their study, among the factors studied, the "Price" factor has the most significant influence on the "buy" decision. The second place took the "Quality" factor and the "Brand" was ranked third followed by "Model/Design".

2.2 COVID-19 and other crises effects on consumer behavior

As stated in Valaskova et al., (2015) and in Mehta et al (2020) there are several approaches which explain consumer behavior including sociological, economic and psychical-based approach. This applies both to normal and crisis times.

Pandemics cause the crisis and during such periods because of negative economic environments, consumers have to cut down on their expenses and concentrate mainly on responsible consumption. During crises, consumers' behavioral pattern changes. For example, Mehta et al (2020) showed the changes in consumer behavior patterns caused by lockdown periods during the COVID-19 pandemic. Other researchers, for example, Amalia and Ionut (2009) do agree that crises influence consumer behavior and Mansoor (2011) states that as a result of economic recession, consumers simplify their demand, less willing to charity actions, and change brands for those with lower prices.

During crises such as COVID-19, consumers may fall into a panic-buying trap despite simplifying their demand for goods meaning over-purchasing without scarcity in supply (Bentall et al, 2020). Naeem (2021) applied a consumer panic buying theory to analyze the role and impact of social media on 'people's collective response' to the COVID-19 pandemic and study how people's panic buying reactions are shaped.

Panic buying during crises mostly refers to FMCG, but ordinary purchase patterns regarding FMCG are also observed in the literature. For example, O'Connell et al (2020) studied household scanner data that covers FMCG (i.e. grocery products, including food, alcohol, and non-foods) during the first phase of the pandemic in the UK. They found an increase in demand for 30 categories in the four weeks up to 23 March in 2020 relative to 2019 in the UK. Such results may signal effect of COVID-19 crisis on the whole retail industry.

The COVID-19 pandemic drastically hit the retail industry. The number of offline consumer visits in the USA decreased severely and forced to close for the period of a pandemic or even shut down forever (Chetty et al. 2020, Tucker and Yu, 2020). However, the COVID-19 pandemic has a positive and significant impact on consumer's online buying behavior (Nguyen et al., 2020). Based on the secondary sales data for durable goods from Samsung, Ali (2020) stated that under circumstances and restrictions caused by COVID-19, consumers in Iraqi had to adopt technologies and change their lifestyle habits. The results of the study have shown that offline sales decreased by 14%, whereas online sales had an increase of 700% (Ali, 2020). According to the research done by McKinsey (2020), COVID-19 pushed both companies and consumers to adopt digital technologies and the same trend was evident in academic studies. Sheth (2020) stated that digital technology modifies existing consumer habits so that boosting digital transformations lead to new consumption habits. Researchers compare online and offline consumer behavior patterns which help to evaluate the effect of technologies on the behavior patterns (Díaz et al., 2017). Digital transformations and technologies not only influence consumer's online buying behavior but also conducts a significant cost saving to the producers, for example, in terms of procurement processes (Jarach, 2002). The research literature also point out the effect of the COVID-19 on the e-commerce consumer behavior.

The impact of digitalization on consumer behavior forced companies to design new diversified digital-penetration business models (Πασπαλάκης et al, 2018). Digital technologies forced more than 60% of customers to interact through multiple channels, irrespective of time, place, device, or medium (The digital, p. 11). Ovodenko et al (2020) conclude that direct channels in business-consumer communication and a simplified system of distribution are sone of the major benefits of e-commerce. Reinartz et al (2017) state that digitalization needs occurrence, shopping, and consumption move much closer in time and space; in particular, for consumers shopping became ‘an ambient activity that is executed everywhere and anytime’.

To sum up, the studies in the area of consumer behavior for durable and non-durable goods are done both for normal and crisis periods. As for durable goods, it was found that brand and price are among the top-3 factors which influence the consumer buying decision. However, consumers tend to adapt their preferences including online buying behavioral patterns and lifestyle habits to crisis conditions. We can also conclude that goods producers were hit by the pandemic as well and had to put efforts towards digitalization and making their businesses partially or completely online.

Chapter 3

DATA DESCRIPTION

To answer the main research question and test the hypotheses stated in this paper, the dataset on the e-commerce consumer behavior for the multi-category store provided by REES46 Marketing Platform was extracted from Kaggle.com. This chapter is designed to describe the dataset variables, their limitations as well as to show patterns in consumer behavior.

3.1 Raw data overview & dataset limitations

Kaggle.com is a platform that gives users an opportunity to find and publish various datasets, explore and build models as well as participate in online data science challenges.

The raw dataset analyzed in this study includes 285 million observations and 9 variables: event_time, event_type, product_id, category_id, category_code, brand, price, user_id, user_session (Table 1).

The dataset used in this research has important limitations, in particular:

- Only 7 months available for analysis (October 2019 – April 2020);
- Only durable goods are available in terms of goods type;
- Some characteristics, such as country name is encrypted and is not available due to privacy policy and terms of dataset provision;
- Incorrect labeling may appear sometimes;
- Product description which may signal about the quality of a good is not available in the dataset;

Table 1. Variables description

Variable name	Variable value example	Description
brand	samsung	The brand name of the product. The variable values can be missed.
category_code	furniture.kitchen.chair	Product's category taxonomy, meaning category code name, subcategory name, and product name (if applicable). Usually present for meaningful categories and skipped for different kinds of accessories. The variable values can be missed.
category_id	2053013558920217191	Product's category ID
event_time	2019-11-01 00:00:01 UTC	Time in Coordinated Universal Time (UTC) when the event happened. Event means one row in the dataset and can also be called "user's event".
event_type	purchase	The event can be of one of the following types: • view - a user viewed a product • cart - a user added a product to the shopping cart • remove_from_cart - a user removed a product from the shopping cart • purchase - a user purchased a product
price	732.07	Price of a product
product_id	1306894	The ID of a product
user_id	520772685	Permanent user ID
user_session	816a59f3-f5ae-4ccd-9b23-82aa8c23d33c	Temporary user's session ID. Same for each user's session. It changed every time user comes back to the online store from a long pause.

Source: Kaggle.com

3.2 Patterns in consumer behavior

This sub-chapter is designed to answer the main research question "How has the e-commerce consumer buying behavior changed during the outbreak of COVID-

19?" through descriptive statistics of trends in the e-commerce consumer buying behavior in October-November, 2019 comparing to March-April, 2020. The descriptive statistics here describe purchases by consumers, except Figure 1 and Figure 2, where cart events are also included. Descriptive patterns here are done on the cleaned and prepared for analysis dataset. As the methodological approach to this study is not the focus of this chapter, the methodology of data cleaning and preparation is described in Chapter 4.

Figure 1 shows overall consumer activity (aggregated purchase and cart events) in multi-category online-store during October-November, 2019 (4.1 MLN user's events) comparing to March-April, 2020 (6.8 MLN user's events).

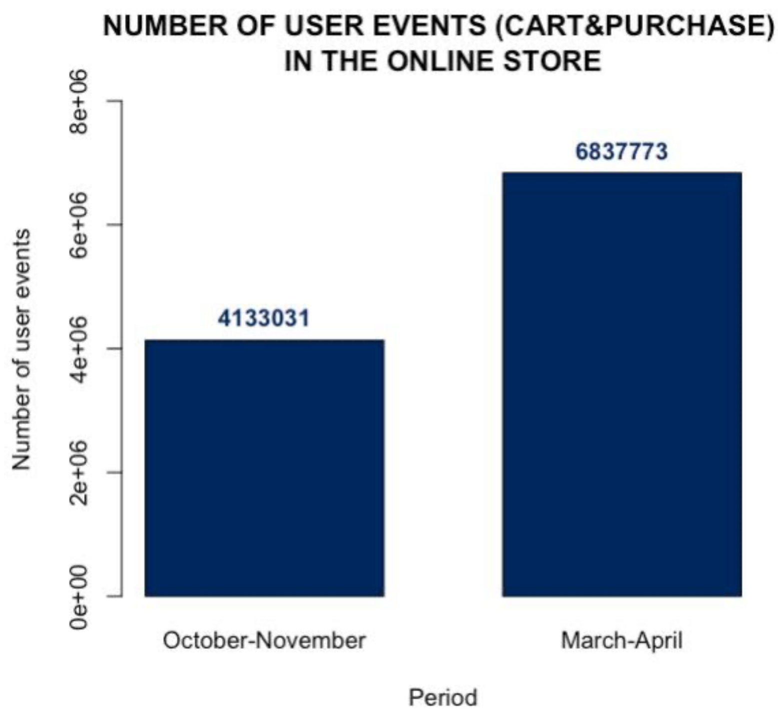

Figure 1-Number of total user events (cart & purchase), October-November, 2019 and March-April, 2020

Online users' activity during the period of a pandemic outbreak is more than 1.6 times higher than before (Figure 1). Consumers increased their intentions to buy more than 1.7 times. Intention to buy a product means that the product was added to the cart but was not finally purchased. The number of intentions to buy in October-November, 2019 refers to around 2.9 MLN, whereas during the outbreak of pandemic - around 5.1 MLN (Figure 2).

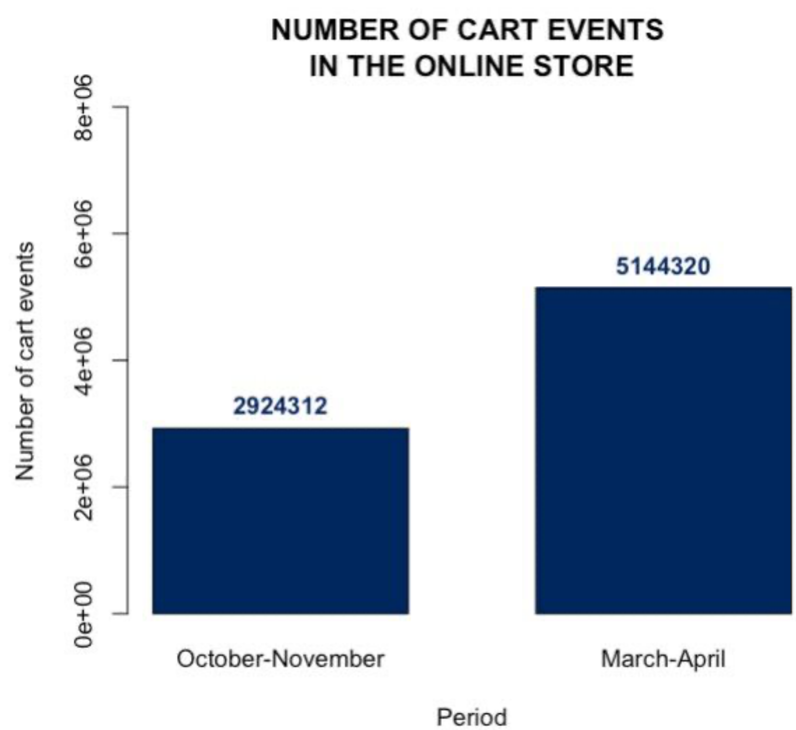

Figure 2-Number of cart events, October-November, 2019 and March-April, 2020

The number of consumer purchases in March-April, 2020 is around 1.4 times more than in October-November, 2019. This refers to more than 1.7 MLN and around 1.2 MLN purchases of durable goods respectively (Figure 3).

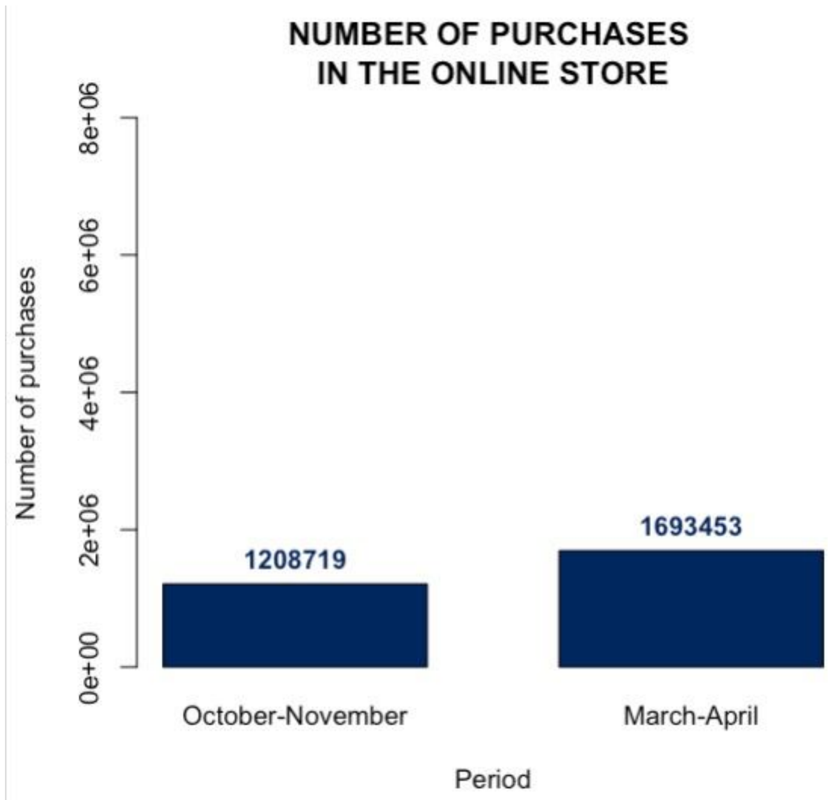

Figure 3-Number of purchases, October-November, 2019 and March-April, 2020

The most popular categories of goods purchased by consumers include accessories, apparel, appliances, computers, furniture, goods for auto, goods for kids, goods for sport (Figure 4). Consumers bought around 1.8 times more appliances during COVID-19, which can be a result of lockdowns. According to Figure 3, the top-3 bought categories are appliances, apparel, and goods for sport, however, the buying pattern is different for October-November, 2019 and March-April, 2020. The appliances category remained to be the most popular among consumers before and during the pandemic. Also, as people probably started spending more time sitting at home and limit social contacts, the demand for furniture increased more than 10 times, for goods for kids – more than 5 times and for goods for sport – more than 45 times.

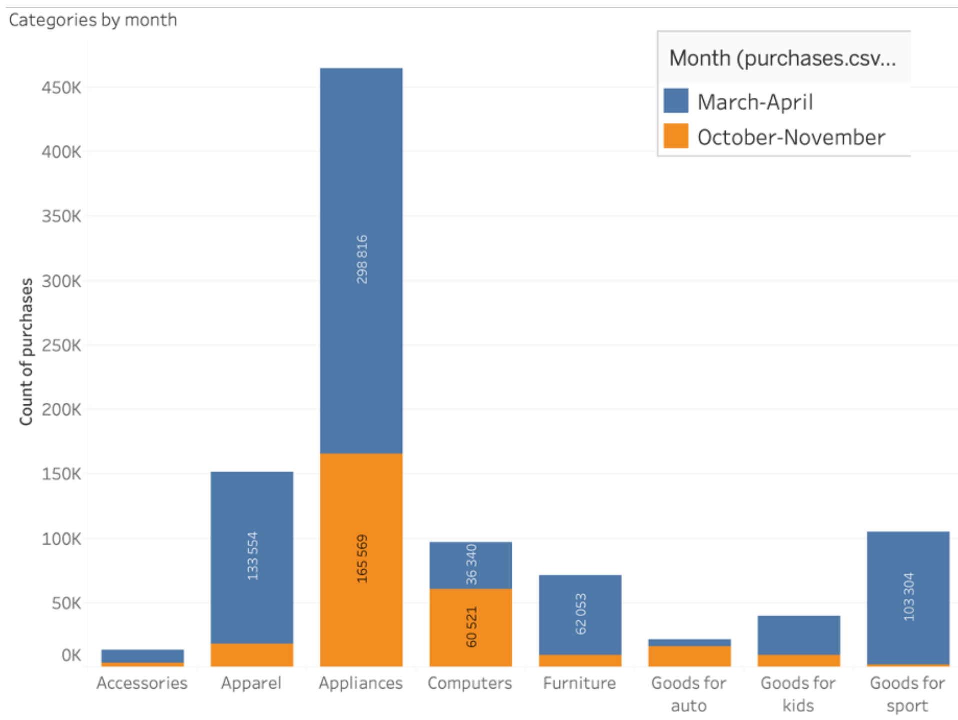

Figure 4. Product categories bought by consumers in October-November, 2019 and March-April,2020

In terms of the subcategories in top-3 product categories bought by consumers, kitchen and personal appliances, as well as shoes and bicycle, were the most popular subcategories during the COVID-19 outbreak (Figure 5).

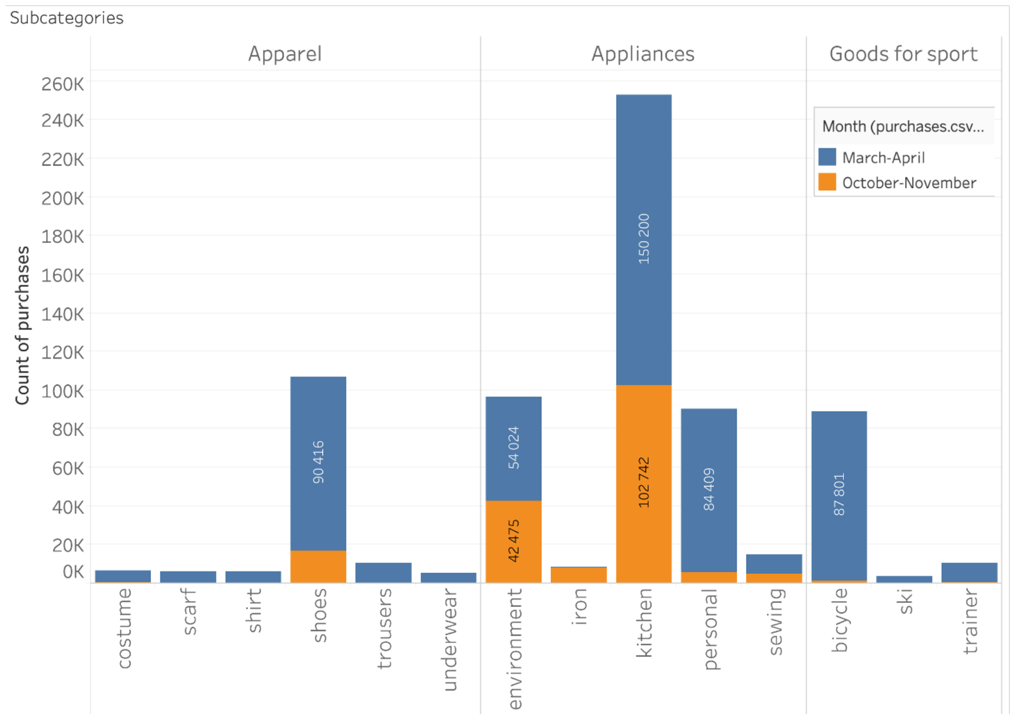

Figure 5. Product subcategories in top-3 product categories bought by consumers, October-November, 2019 and March-April, 2020

What is also important to notice is a consumer-buying pattern by days (Figure 6) and hours (Figure 7). During a pandemic, the most popular buying days were Thursday and Saturday, whereas before the pandemic – Sunday and Monday. However, during COVID-19 on Friday more than 2 times more purchases were made by consumers than before the pandemic (Figure 6). Also, on Monday during the pandemic, the number of purchases decreased by around 1.4 times than before.

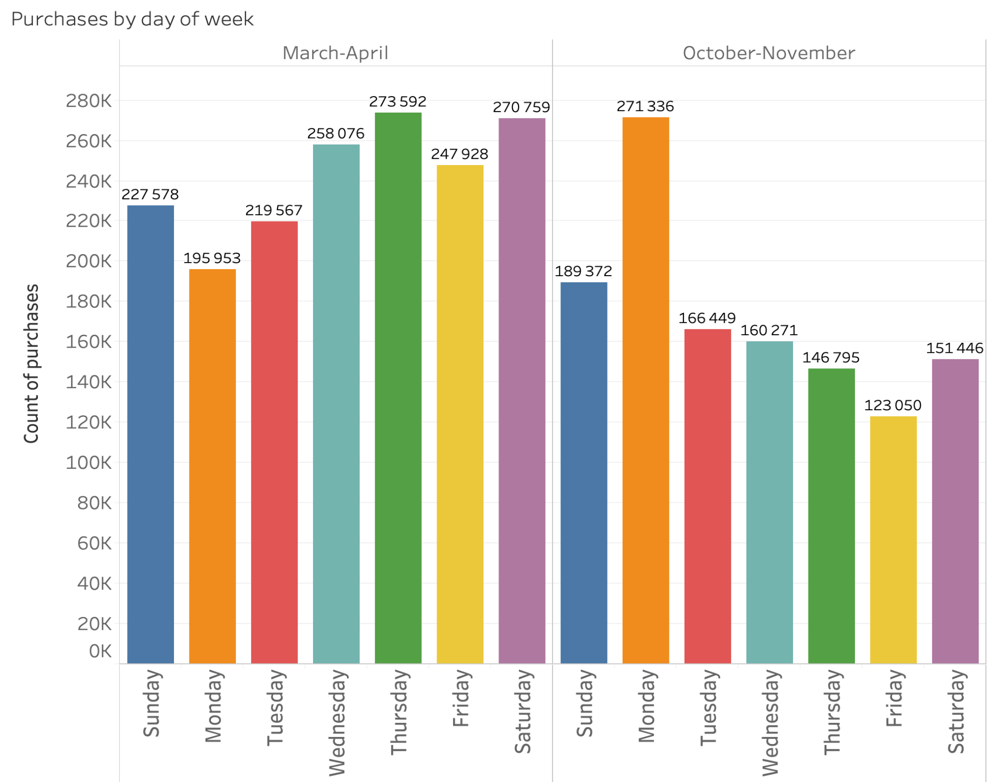

Figure 6. Consumers' buying pattern by day of week in October-November, 2019 and March-April, 2020

The pattern of buying the goods per hour before and during COVID-19 remained almost unchanged (Figure 7).

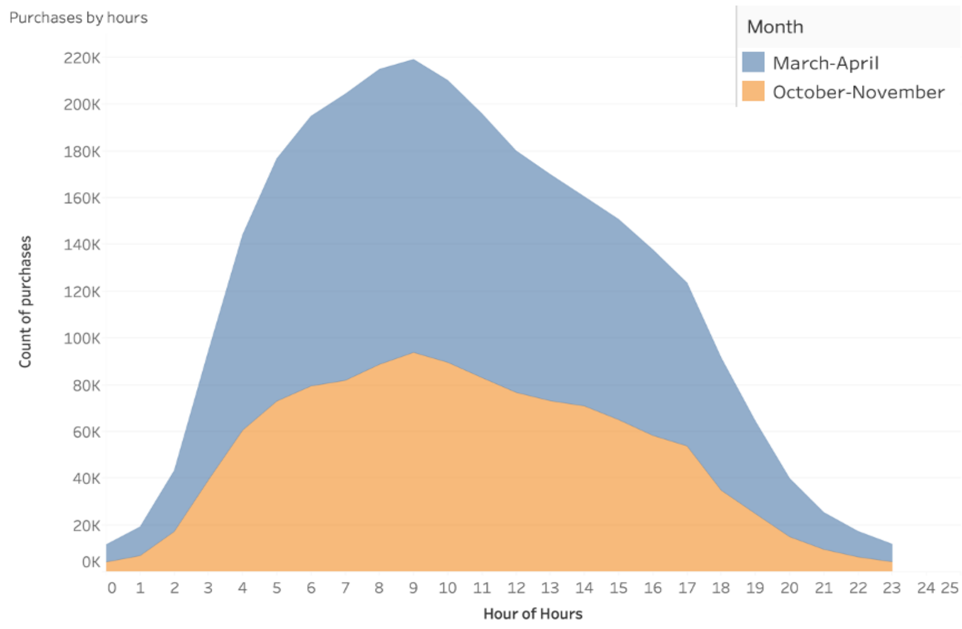

Figure 7. Consumer's buying pattern by hour in October-November, 2019 and March-April, 2020

There are plenty of characteristics that determine product quality including materials used for production, price, brand, etc. Due to dataset limitations, it is impossible to confidently state whether the users started buying products of better or worse quality. However, the average buying price in comparison with the number of purchases can be assessed. The results have shown that during the pandemic the average buying price for apparel and appliances increased around 1.9 and 1.4 times respectively (Figure 8). For furniture and goods for sport, the average buying price dropped more than 2 times despite a vast increase in sales of both categories. In March-April, 2020 computers category became less popular than before and the average buying price dropped around 3 times.

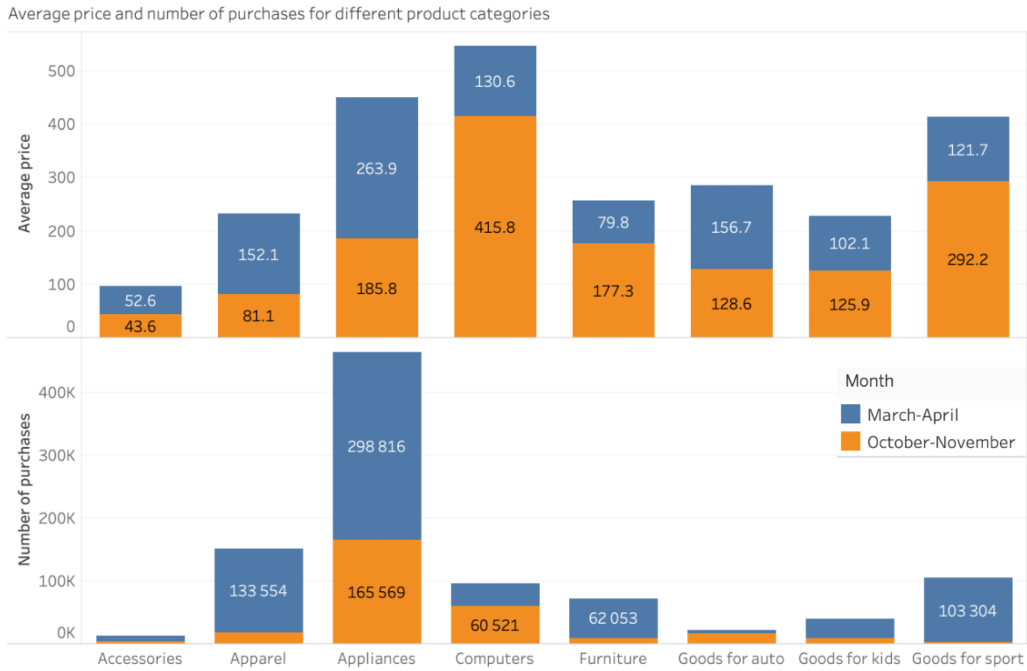

Figure 8. Average product category price comparing to the number of purchases in October-November, 2019 and March-April 2020

This chapter was focused on the descriptive patterns in consumer buying behavior. The next Chapter 4 is focused on the methodological approach to research.

Chapter 4

METHODOLOGY

This chapter is designed to describe model specification methodology as well as data cleaning and preparation.

4.1 Model specification

In traditional academic literature, typically reasons which influence changes in consumer preferences while selecting a particular good are studied (Lautiainen, 2015). As in our study, there are dataset limitations in terms of the available period (October 2019 – April 2020) and as it contains only durable goods which are bought not as frequently as non-durable goods, there is no way and no need in this research to study the purchase behavior for the same consumer. That is why the factors which generally influence the likelihood of consumer buying decisions before and during the COVID-19 outbreak are studied in this research. Hence, logistic regression (logit) which estimates the log odds as a linear combination of the independent variables is built in this study. The general logit model specification is described below,

$$\log\left(\frac{p(X)}{1-p(X)}\right) = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_n x_{ni} + \varepsilon_i \qquad (1)$$

where $p(X)=(x_1 \ldots x_n)$, $\beta_1 \ldots \beta_n$ – coefficients, $x_1 \ldots x_n$ – independent variables, β_0 – intercept and left-hand side represents the odds ratio which reflects the probability of occurrence of a particular event against the probability of that same event not happening.

Logit model specification (2) is designed to test the likelihood of purchasing a product for the hypothesis about price effects and the hypothesis about brand preferences.

$$p(\,IsPurchased = 1|brand, price, day\ of\ week) = \beta_0 + \beta_1 \cdot brand + \beta_2 \cdot price + \beta_3 \cdot day\ of\ week + \varepsilon_i, \tag{2}$$

where ε represents the error term, the dependent variable "IsPurchased" equals 1 if the good was purchased by a consumer. The independent variables, in this case, are represented by brand, price and day of week. The variables brand, and day of the week (values from Sunday to Saturday) are categorical.

To test the hypotheses and answer the research question, we estimate the same logit models separately both for October-November, 2019 and for March-April, 2020 in order to compare results. The expected signs for β_2 during the outbreak of COVID-19 are negative as well as the coefficient magnitude is expected to decrease in each product category comparing to October-November, 2019. Also, for β_1 the expected result is reverse to β_2, meaning a positive sign for both studied periods and the same magnitude. For β_3 the expected sign is positive for both periods. We also expect the difference in terms of the likelihood of purchase between weekdays and weekends.

To test the hypothesis about possible weekend effects on consumer online buying decisions, we have also created an alternative specification (3).

$$p(IsPurchased = 1|brand, price, IsWeekend) = \beta_0 + \beta_1 \cdot brand + \beta_2 \cdot price + \beta_3 \cdot IsWeekend + \varepsilon, \quad (3)$$

where ε represents the error term, the dependent variable "IsPurchased" equals 1 if the good was purchased by a consumer. The independent variables, in this case, are represented by brand, price and "IsWeekend". The variable brand is categorical. The variable "IsWeekend" is binary and assigns 0 for all weekdays and 1 for Saturday and Sunday. The positive sign is expected for β_3 and a higher magnitude of the coefficient in each product category for the period regarding the outbreak of COVID-19 in comparison to October-November, 2019.

4.2 Data cleaning

This subsection describes how the data are cleaned and prepared for the regression model specification described in subsection 4.1. and patterns in consumer behavior described in 3.2.

As the COVID-19 outbreak started in March 2020 and due to dataset limitations, only March-April, 2020 can be considered as the pandemic period in this study. Taking into account this fact, from the available dataset the earliest possible period of 2 months before the pandemic was also extracted. This accounts for October-November, 2019. So, the first step was to unite October, November into one dataset and March, April – to another. After this step, both datasets were cleaned from N/A's, view and remove_from_cart events due to large file sizes and unnecessity in terms of research focus. The datasets are left with cart and purchase events. As consumers at first may add the good to the cart and only then – buy, we had to obtain unique cart events for those goods that were added to the cart but not purchased. Then, unique cart and purchase events were united for each dataset separately. Also, the binary variable "IsPurchased" was created for future regression analysis, assigning 0 for cart events and 1 for purchase events. The next step for each dataset was to split the event_time variable into 2 separate variables: date and time as well as to extract from the newly created variable "date" the day of the week and attach it to the datasets. Moreover, the variable "IsWeekend" was created for future regression analysis, assigning 0 for all weekdays and 1 for Saturday and Sunday. Also, as the variable category_code contains both category and subcategory names as well as product names sometimes, this variable were split into 3 different variables. As product name is a rare case in this dataset, empty spaces for this variable were filled with N/A and are not used further in this study. After defining categories, the separate subsets for each product category were done both for October-November, 2019 and March-April, 2020. The final step of data preparation for regression analysis was brand consolidation. For the dataset in each product category, unpopular brands were grouped together as "other". The descriptive statistics for the cleaned and prepared dataset in each product category can be found in Appendix.

C h a p t e r 5

ESTIMATION RESULTS

The estimation results of the logit models specifications (2), (3) described in Chapter 4 are provided in this chapter using marginal effects of logit models.

Table 2 shows the marginal effects of price on the likelihood of purchasing a product. The first hypothesis stated in this thesis that consumers are more likely to buy cheaper goods in the same product category during the outbreak of COVID-19 in comparison to October-November, 2019 was not confirmed for most product categories. To test the price effects on consumer buying decisions the logit model (2) was built including brand, price, and day of the week as explanatory variables for each of the product categories left after dataset cleaning. In terms of significance, in all categories except Accessories and Goods for sports, the price effect was significant in October-November, meaning that in these 2 categories price had no effect on the likelihood of purchase. These 2 categories have the smallest number of purchases in October-November. On the other hand, in March-April in all the studied categories, price influenced the decision of purchase. As for signs, in all the categories with significant effects, except the Computers and Goods for kids categories, the price impact on the probability of buying is negative before the pandemic. However, surprisingly during the pandemic for all the categories except Accessories were positive, meaning that the increase in price was increasing the probability of purchase. As was stated in the Literature review, during pandemics and other crises, people tend to simplify their demand, but the results of the study have shown a reverse effect. This can be explained mostly by the shift in demand for goods in the same product category, meaning that the type of goods bought by consumers was different in October-November, 2019 comparing to March-April, 2020. Also, due to the fact that during the outbreak of COVID-19, the lockdowns forced people to spend more time at home and change their habitual way of life. Therefore, they probably had to change the ways from where they obtain more joy and utility and in the case of our research, this might have been done through buying more pricy goods. As price is one of the determinants of better quality, we can also assume that those who bought durable goods during pandemic were oriented on the goods of better quality. For the most popular purchase category – Appliances, price effects changed in the following way: increasing price by 1% in the outbreak of COVID-19 was increasing the likelihood of buying a particular good by 1.7 percentage points comparing to the decrease by 2.1 percentage points in October-November, 2019.

Table 2. Marginal effects of price on the likelihood of purchasing a product

	October-November		March-April	
Category	Coefficient	Std	Coefficient	Std
Accessories	-0.011	(0.007)	-0.010***	(0.003)
Apparel	-0.025***	(0.0009)	0.019***	(0.0008)
Appliances	-0.021***	(0.001)	0.017***	(0.0007)
Computers	0.004***	(0.001)	0.018***	(0.002)
Furniture	-0.007*	(0.003)	0.017***	(0.001)
Goods for auto	-0.009.	(0.005)	0.028***	(0.005)
Goods for kids	0.015***	(0.003)	0.020***	(0.002)
Goods for sport	-0.011	(0.009)	0.031***	(0.001)
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				

Note: This is the marginal effects of price for logit model designed for several product categories in the extended model which include brand, price and day of week as explanatory variables and variable "IsPurchased" as dependent variable.

Table 3 shows the marginal effects of weekends on the likelihood of purchasing a product with respect to weekdays. Variable "IsWeekend" equals 1 if Saturday or Sunday is the day of purchase and equals 0 for all other days of the week. The second hypothesis stated in this thesis that consumers are more likely to do online shopping during weekends in the outbreak of COVID-19 in comparison to October-November, 2019 was confirmed for most product categories. To test the effects of the weekends (Saturday and Sunday) on consumer buying decisions the logit model (3) was built including brand, price, and IsWeekend as explanatory variables for each of the product categories left after dataset cleaning. In all categories except for Accessories, Goods for kids, and Goods for sports the effect of weekends was significant in October-November 2019, meaning that in these 3 categories weekends had no effect on the likelihood of purchase. During the outbreak of COVID-19, consumers were indifferent to weekdays only when buying items from the "Goods for auto" category. Also, during this period in comparison to October-November, 2019 consumers were more likely to buy goods from "Accessories", "Apparel", "Appliances", "Furniture", "Goods for sport" and "Goods for kids" categories during the weekends in comparison to weekdays.

As during the pandemic, the effect of weekdays on the likelihood of purchase has not increased only for the "Computers" and "Goods for auto" category, we can conclude that our hypothesis fails to reject. The primary expectation of higher buying probability during Saturday and Sunday was grounded by the fact that during the pandemic, people spent at home more time than before. For example, they might have changed their working style to remote (work from home) mode. However, as behavioral changes are not always easily perceived in terms of mental adjustments, after a long working week people might need to obtain more joy and happiness and this can probably be done by buying something new online. Among all the categories, during COVID-19 the highest increase in the likelihood of purchase had Appliances (3.2 p.p.) and Furniture (3 p.p.) categories during the weekends in comparison to weekdays. However, comparing before the pandemic purchases during the weekends with regard to weekdays, the highest increase in the probability of buying had "Computers" category (3.6 p.p.), whereas the lowest one - "Furniture" category (-2.7 p.p.). Such a difference in buying probabilities in the "Furniture" category can be explained by the need for particular goods for more comfortable home-sitting.

Table 3. Marginal effects of weekends on the probability of purchase

	October-November		April-March	
Category	Coefficient	Std	Coefficient	Std
Accessories	-0.010	(0.012)	0.014*	(0.006)
Apparel	0.007***	(0.002)	0.023***	(0.002)
Appliances	0.008***	(0.002)	0.032***	(0.001)
Computers	0.036***	(0.003)	0.014***	(0.004)
Furniture	-0.027***	(0.007)	0.030***	(0.003)
Goods for auto	0.009.	(0.005)	0.010	(0.009)
Goods for kids	0.006	(0.007)	0.027***	(0.004)
Goods for sport	0.007	(0.015)	0.022***	(0.002)
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				

Note: This is the marginal effects of weekends (Saturday and Sunday), which is represented by "IsWeekend" variable. "IsWeekend" equals 1 if the day of purchase is Saturday or Sunday. The base for this regression - all weekdays. The effects are described for several product categories in the extended model which include brand, price, and "IsWeekend" as explanatory variables and variable "IsPurchases" as a dependent variable.

Table 4 shows the marginal effects of brands on the likelihood of purchasing a product. The third hypothesis stated in this thesis that consumers did not change their preferences in terms of brand selection while buying goods from the "Appliances" category during the outbreak of COVID-19 in comparison to October-November, 2019 was not confirmed for the vast majority of categories. To test this hypothesis the logit model (2) was built including brand, price, and day of the week as explanatory variables for the "Appliances" category. This category was chosen based on the perception that in terms of safety people started to be more cautious, spend more time at home, and were in need of home appliances. We dived deeper to compare the general pattern of consumer preferences regarding brand selection before and during the pandemic. "Braun" was chosen as the base brand in the regression model and all the results for the specified hypothesis are interpreted with respect to this brand. Table 4 indicates that during pandemic appliances by several brands like Acer, Huter, Kivi, Lucente, Phoenix, Pulser, Sony, and Torrent appeared to be bought by consumers. This can be because goods of such brands were simply not supplied by the online store before the pandemic or were not in demand by consumers. In terms of significance, the results from Table 4 shows that the vast majority of studied brands except for Asel, Bosh, Delonghi, Haier, Lg, Phillips, Scarlett, Vitek appeared to be significant during both October-November, 2019 and March-April, 2020. This means that all studied brands except listed ones influenced the likelihood of purchase before the pandemic as well as during it. In October-November, 2019 negative influence on the probability of the decision about had such brands as Atlant, Hansa, Janome, Karcher, Maxwell, Panasonic, and Xiaomi, however, in April negative influence on the probability of buying a good were observed for the vast majority of brands. Only Beko, Haier, Kivi, Lucente, Phoenix, and Tefal had positive effects. Before the pandemic, if the good from Appliances category was of brand "Beko", the probability of purchase were increasing by 6.1 percentage points with regard to

“Braun”, which is the highest result. On the other hand, during the pandemic among the leaders was the brand “Lucente” with the highest influence on the likelihood of purchase, increasing it by 8.4 percentage points.

Table 4. Marginal effects of brands on the probability of purchase in the logit model designed for the “Appliances” category

	Dependent variable:			
	IsPurchased			
	October-November		March-April	
	Coefficient	Std	Coefficient	Std
Acer	-	-	-0.045***	(0.008)
Arg	0.047***	(0.009)	0.001	(0.006)
Artel	0.045***	(0.008)	-0.032***	(0.005)
Asel	-0.004	(0.010)	-0.086***	(0.006)
Atlant	-0.020*	(0.009)	-0.099***	(0.008)
Beko	0.061***	(0.007)	0.013*	(0.006)
Bosh	0.009	(0.007)	-0.016**	(0.006)
Dauscher	0.040***	(0.008)	-0.017*	(0.007)
Delonghi	-0.010	(0.011)	-0.072***	(0.009)
Elenberg	0.057***	(0.007)	-0.052***	(0.009)
Haier	0.006	(0.009)	0.044***	(0.07)
Hansa	-0.018*	(0.009)	-0.042***	(0.009)
Huter	-	-	-0.123***	(0.008)
Indesit	0.042***	(0.007)	-0.029***	(0.006)
Janome	-0.020*	(0.008)	-0.057***	(0.006)
Karcher	-0.068***	(0.009)	-0.014.	(0.008)
Kitfort	0.030*	(0.012)	-0.035***	(0.008)

Table 4 - Continued

	Dependent variable:			
	IsPurchased			
	October-November		March-April	
	Coefficient	Std	Coefficient	Std
Kivi	-	-	0.042***	(0.009)
Lg	-0.003	(0.007)	-0.044***	(0.005)
Lucente	-	-	0.084***	(0.006)
Maxwell	-0.051***	(0.010)	-0.046***	(0.007)
Midea	0.027***	(0.007)	-0.044***	(0.006)
Other	-0.003	(0.006)	-0.054***	(0.005)
Panasonic	-0.055***	(0.012)	-0.023**	(0.007)
Phillips	0.022**	(0.008)	-0.007	(0.006)
Phoenix	-	-	0.020**	(0.007)
Polaris	0.015.	(0.008)	-0.016*	(0.006)
Pulser	-	-	-0.060***	(0.007)
Redmond	0.023**	(0.008)	-0.051***	(0.006)
Samsung	0.022***	(0.006)	-0.025***	(0.005)
Scarlett	-0.012	(0.009)	-0.030***	(0.007)
Sony	-	-	-0.075***	(0.008)
Tefal	0.043***	(0.008)	0.042***	(0.008)
Torrent	-	-	-0.062***	(0.006)
Vitek	-0.005	(0.007)	-0.026***	(0.006)
Xiaomi	-0.064***	(0.008)	-0.075***	(0.005)
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				

Note: This is the marginal effects of brands in the "Appliances" category in the extended model which include brand, price, and day of the week as explanatory variables and variable "IsPurchased" as a dependent variable. The reference brand is "Braun".

For better visual comparison the graph for marginal effects of brands on the probability of purchase in the logit model designed for the "Appliances" category was built. The graph visualizes data from Table 4. From Figure 9, it is clearly observed that both consumer groups which were buying durable goods before or during the pandemic had the same preference patterns only for brand "Tefal" almost for all brands the preferences were fluctuating. Such results can be explained by the fact, that as durable goods are not bought often, the individual preferences of consumers from the sample may differ. However, the hypothesis was formed from the initial assumption that the most well-known brands have built customer loyalty and that they will be preferred despite differences in consumer sample.

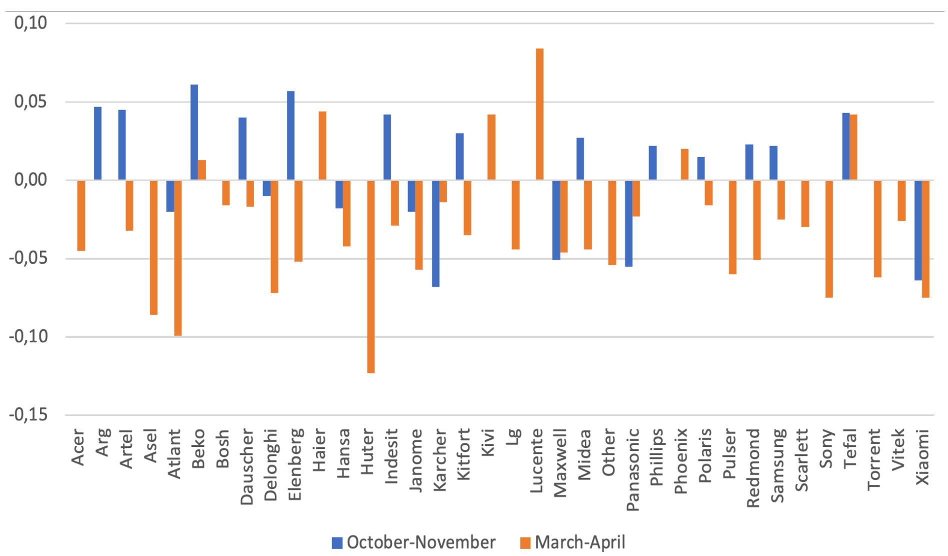

Figure 9.Marginal effects of brands on the probability of purchase in the logit model designed for the "Appliances" category

Chapter 6

CONCLUSIONS

In this study, we investigate the changes in e-commerce consumer behavior in the outbreak of the COVID-19 pandemic. In particular, we look at the effects of price, weekend, and brand on the probability of purchase. For this, we use the dataset on the e-commerce consumer behavior for the multi-category store provided by REES46 Marketing Platform and obtained through Kaggle.com. Due to dataset limitations, the studied period for the COVID-19 outbreak includes only March-April, 2020, and compared to the 2-months period of October-November, 2019 before the pandemic.

The results of the study showed that in the outbreak of COVID-19 the e-commerce consumer buying behavior is different than before the pandemic. First of all, consumers not only started buying online more around 1.4 times but also increased their intentions to buy more than 1.7 times. The most popular categories bought during the pandemic were Appliances, Apparel, and Goods for sports. Among these categories, only Appliances were top-1 category before COVID-19. At the same time, the most popular subcategories during March-April, 2020 included kitchen appliances, shoes, and bicycles. As for the average buying price for apparel and appliances, it increased around 1.9 and 1.4 times respectively. For furniture and goods for sport, the average buying price dropped more than 2 times despite a vast increase in sales of both categories.

The hypotheses that during the COVID-19 outbreak in comparison to the before pandemic period, consumers are more likely to buy cheaper goods in the same product category as well as that consumers did not change their preferences in terms of brands selection while buying goods from the "Appliances" category were not confirmed for the vast majority of categories and brands respectively. The traditional theory of consumer behavior during crises was built based on offline behavioral patterns, however taking into account the fact that lifestyle processes including patterns of purchases are moving online, the theory might be revised. For example, there exists a general perception is that during crises consumers limit their spending, however, our research showed the positive effect of price on the likelihood of purchase. Probably, the preferences changed to those goods which give more utility and might be of better quality or it may happen due to the shift in demand for goods in the same product category.

Another hypothesis that during the COVID-19 outbreak in comparison to the before pandemic period, consumers are more likely to do online shopping during weekends was confirmed for the majority of product categories. This may be explained by the fact that after a long working week people might need to obtain more joy and happiness by buying something new online because of unavailability of habitual ways of getting utility of processes and goods. The results of this study can be useful for the researches who study online consumer behavior in the sphere of e-commerce.

This thesis is an introduction to the possibilities for future economic research related to the topic. Among the possible extensions, first of all as the store offers only durable goods it would be great to obtain the broader period of transaction – at least for several years or, alternatively, conduct a similar research but for non-durable goods. This will also open an opportunity to build a representative difference in difference regression model to study shifts in demands in the same product categories. Also, using the same dataset – market basket analysis can be done to search for the link between product categories, subcategories and product names. Moreover, as county here is encrypted due to privacy policy, the similar research can be done for Ukraine to make more precise conclusions using dataset from largest Ukrainian e-commerce online platforms.

WORKS CITED

Ali, B. J. 2020. "Impact of COVID-19 on consumer buying behavior toward online shopping in Iraq". *Economic Studies Journal*, 18(42), 267–280. Retrieved from https://www.asjp.cerist.dz/en/article/134070

Amalia, P. and P. Ionut 2009. "Consumers' reaction and organizational response in crisis context", Uni. Of Oradea. *The Journal of the Faculty of Economics*, 1(5), pp. 779-782.

Bentall RP, A. Lloyd, K. Bennett, R. McKay, L. Mason, J. Murphy, et al. 2021 "Pandemic buying: Testing a psychological model of over-purchasing and panic buying using data from the United Kingdom and the Republic of Ireland during the early phase of the COVID-19 pandemic". *PLoS ONE* 16(1): e0246339. https://doi.org/10.1371/journal.pone.0246339

Binita Manandhar. 2019. "Consumer Buying Behavior for Nondurable Goods. *Management Dynamics*. Vol. 22, No. 1: 47-68 DOI: https://doi.org/10.3126/md.v22i1.30238 URL: https://www.nepjol.info/index.php/md/article/view/30238/24232

Chetty, R., J.N. Friedman, N. Hendren, and M. Stepner. 2020. "Real-time economics: A new platform to track the impacts of COVID-19 on people, businesses, and communities using private sector data". Working paper. URL: https://opportunityinsights.org/wp-content/uploads/2020/06/Short_Covid_Paper.pdf

Consumer behavior theory. n.d. P.36-95, URL: https://repository.up.ac.za/bitstream/handle/2263/29162/02chapter2.pdf?sequence=3&isAllowed=y

Díaz, Asunción & Gómez Rico, Mar & Molina Collado, Arturo. 2017. "A comparison of online and offline consumer behaviour: An empirical study on a cinema shopping context". *Journal of Retailing and Consumer Services*. 38. 44-50. 10.1016/j.jretconser.2017.05.003.

Engel, J.F., RD. Blackwell, and P.W. Miniard. 1990. *Consumer Behavior*. Sixth Edition. The Dryden Press, Chicago

Hashem, T.N. 2020. "Examining the Influence of COVID 19 Pandemic in Changing Customers' Orientation towards E-Shopping". *Modern Applied Science*. Vol. 14, No. 8 (August): 59:76. https://doi.org/10.5539/mas.v14n8p59

Hoseini, M., and A. Valizadeh. 2021. "The effect of COVID-19 lockdown and the subsequent reopening on consumption in Iran". *Rev Econ Household*. DOI: https://doi.org/10.1007/s11150-021-09557-8

J.Singh, n.d. Brief Notes on Demand for Durable Goods, at www.economistsdiscussion. URL: https://www.economicsdiscussion.net/notes/brief-notes-on-demand-for-durable-goods/928

Jarach, D. 2002. "The digitalisation of market relationships in the airline business: the impact and prospects of e-business". *Journal of Air Transport Management*, Elsevier. Vol. 8(2), pages 115-120. DOI: 10.1016/S0969-6997(01)00039-4 URL: https://ideas.repec.org/a/eee/jaitra/v8y2002i2p115-120.html

Kalita, J.K., S. Jagpal and D.R. Lehmann. 2004. "Do high prices signal high quality? A theoretical model and empirical results". *Journal of Product & Brand Management,* Vol. 13 No. 4, pp. 279-288. DOI: https://doi.org/10.1108/10610420410546989 URL:https://www.emerald.com/insight/content/doi/10.1108/10610420410546989/full/html

Lautiainen, Tanja. 2015. "Factors affecting consumers' buying decision in the selection of a coffee brand." URL: https://core.ac.uk/download/pdf/38124382.pdf

MacInnis, D. J., and V. S. Folkes. 2010. "The disciplinary status of consumer behavior: A sociology of science perspective on key controversies". *Journal of Consumer Research*, 36, 899-914.

McKinsey & Company. 2020. "How COVID-19 has pushed companies over the technology tipping point—and transformed business forever". URL: https://www.mckinsey.com/business-functions/strategy-and-corporate-finance/our-insights/how-covid-19-has-pushed-companies-over-the-technology-tipping-point-and-transformed-business-forever

McKinsey&Company. 2020. "The COVID-19 recovery will be digital: A plan for the first 90 days". URL: https://www.mckinsey.com/business-functions/mckinsey-digital/our-insights/the-covid-19-recovery-will-be-digital-a-plan-for-the-first-90-days

Mansoor D. 2011. "The Global Business Crisis and Consumer Behavior: Kingdom of Bahrain as a Case Study". *International Journal of Business and Management.* Vol. 6, No. 1; January 2011, pp. 104-115;

Mehta, S., T. Saxena, and N. Purohit. 2020. "The New Consumer Behavior Paradigm amid COVID-19: Permanent or Transient?". *Journal of Health Management.* Vol. 22, issue 2, page(s): 291-301. Article first published online: July 30, 2020; Issue published: June 1, 2020 DOI: https://doi.org/10.1177/0972063420940834 URL: https://journals.sagepub.com/doi/10.1177/0972063420940834

Naeem, M. 2021. "Do social media platforms develop consumer panic buying during the fear of Covid-19 pandemic". *Journal of Retailing and Consumer Services.* Vol. 58, 102226. DOI: https://doi.org/10.1016/j.jretconser.2020.102226

Nguyen, Hoang Viet, Hiep Xuan Tran, Le Van Huy, Xuan Nhi Nguyen, Minh Thanh Do, and Ninh Nguyen. 2020. "Online Book Shopping in Vietnam: The Impact of the COVID-19 Pandemic Situation". Publishing Research Quarterly, 10: 1–9.

O'Connell, M., Á. De Paula, and K. Smith. 2020. "Spending dynamics and panic buying during the COVID-19 first wave". URL: https://voxeu.org/article/spending-dynamics-and-panic-buying-during-covid-19-first-wave

Ovodenko, A.A., G.Yu., Peshkova, and O.V. Zlobina. 2020. "Digital Evolution of Consumer Behavior and its Impact on Digital Transformation of Small and Medium Business Sustained Development Strategy". *Advances in Economics, Business and Management Research*. Vol. 156. 2nd International Scientific and Practical Conference on Digital Economy (ISCDE 2020). URL: https://doi.org/10.2991/aebmr.k.201205.071

Peighambari, K., S. Sattari, A. Kordestani, and P. Oghazi. 2016. "Consumer Behavior Research: A Synthesis of the Recent Literature". SAGE Open April-June 2016: 1–9 DOI: 10.1177/2158244016645638 URL: https://journals.sagepub.com/doi/pdf/10.1177/2158244016645638

Pindyck, Robert S., and Daniel L. Rubinfeld. 2009. *Microeconomics*. Upper Saddle River, N.J.: Pearson/Prentice Hall.

Rajeswari, R., P. Pirakatheeswari. 2014. "A Study on Consumer Behavior and Factors Influencing the Purchase Decision of Durable Goods with Reference to Salem District". *International Research Journal of Business and Management*. Vol. 7, No. 11 P. 10-18. URL: http://irjbm.org/irjbm2013/Nov2014/Paper2.pdf

Retail real estate market report. 2020. NAI Ukraine. https://naiukraine.com/wp-content/uploads/2020/11/Rynok-torgovoj-nedvyzhymosty-1.pdf

Reinartz, W. and M. Imschloß. 2017. "From Point of Sale to Point of Need: How Digital Technology Is Transforming Retailing". *The Future of Retailing*. Vol. 9, No. 1. P.43-47. doi 10.1515/gfkmir-2017-0007. URL: https://www.nim.org/sites/default/files/medien/2327/dokumente/reinartz_imschloss_vol_9_no_1_english_.pdf

Seung-Pyo Jun, Do-Hyung Park. 2016. "Consumer information search behavior and purchasing decisions: Empirical evidence from Korea". *Technological Forecasting and Social Change*. Vol. 107, Pages 97-111. DOI: https://doi.org/10.1016/j.techfore.2016.03.021. URL: https://www.sciencedirect.com/science/article/pii/S0040162516300026

Sheth, J. 2020. "Impact of Covid-19 on consumer behavior: Will the old habits return or die?". Jun 4. doi: 10.1016/j.jbusres.2020.05.059. URL: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7269931/

The digital transformation of customer services. Our point of view. Deloitte. URL: https://www2.deloitte.com/content/dam/Deloitte/nl/Documents/consumer-business/deloitte-nl-the-digital-transformation-of-customer-services.pdf

Tucker, Catherine E. and Yu, Shuyi, "The Early Effects of Coronavirus-Related Social Distancing Restrictions on Brands (April 1, 2020)". Available at

SSRN: https://ssrn.com/abstract=3566612 or http://dx.doi.org/10.2139/ssrn.3566612

Valaskova, K., K. Kramarova, and V. Bartosova. 2015. "Multi criteria models used in Slovak consumer market for business decision making". *Procedia Economics and Finance*, 26, 174–182. URL: https://doi.org/10.1016/s2212–5671(15)00913–2

Veeragandham, M., N. Patnaik, R. Tiruvaipati, and M. Guruprasad. 2020. "Consumer Buying Behavior towards E-Commerce during COVID-19", *International Journal of Research in Engineering, Science and Management* 3, no. 9 (September): 78-82. https://doi.org/10.47607/ijresm.2020.292

What is Panic Buying? 2020. CFI. URL: https://corporatefinanceinstitute.com/resources/knowledge/other/panic-buying/

Πασπαλάκης, E., and Evangelos P. 2018. "The impact of digital technology on consumer behavior and business operations. Case study". 131p. URL: http://dione.lib.unipi.gr/xmlui/handle/unipi/11773

APPENDIX

Table 5. Descriptive statistics for IsPurchased, IsWeekend and Price variables in each product category

	October-November, 2019			March-April, 2020		
	IsPurchased	IsWeekend	IsWeekend	IsPurchased	IsWeekend	price
Variable type in regression	dependent	Independent	Independent	dependent	Independent	Independent
Accessories						
Number of observations	7,861			31,678		
min	0	0	1.30	0	0	0.37
mean	0.4221	0.2857	47.13	0.3141	0.2897	57.79
max	1	1	648.67	1	1	2566.72
Apparel						
Number of observations	47,950			374,922		
min	0	0	3.73	0	0	0.27
mean	0.3725	0.324	83.01	0.3562	0.2708	145.31
max	1	1	913.79	1	1	2573.81
Appliances						
Number of observations	422,420			769,432		
min	0	0	3.35	0	0	0.58
mean	0.392	0.2707	198.33	0.3884	0.277	256.59
max	1	1	2574.04	1	1	2574.04
Computers						
Number of observations	148,518			95,464		

Table 5 - Continued

	October-November, 2019			March-April, 2020		
	IsPurchased	IsWeekend	IsWeekend	IsPurchased	IsWeekend	price
Variable type in regression	dependent	Independent	Independent	dependent	Independent	Independent
min	0	0	1.25	0	0	1.13
mean	0.4075	0.2638	429.80	0.3807	0.2836	128.24
max	1	1	2574.04	1	1	2574.04
Furniture						
Number of observations	24,586			177,023		
min	0	0	5.12	0	0	0.20
mean	0.3884	0.2854	189.29	0.3505	0.2786	72.12
max	1	1	2500.48	1	1	2574.04
Goods for auto						
Number of observations	40,839			15,244		
min	0	0	5.15	0	0	1.22
mean	0.4036	0.275	130.05	0.3403	0.2771	132.47
max	1	1	978.15	1	1	2448.94
Goods for kids						
Number of observations	22,387			83,257		
min	0	0	0.90	0	0	1.29
mean	0.4291	0.2846	128.17	0.3612	0.2806	98.87
max	1	1	2391.31	1	1	2573.81

Table 5 - Continued

	October-November, 2019			March-April, 2020		
	IsPurchased	IsWeekend	IsWeekend	IsPurchased	IsWeekend	price
Variable type in regression	dependent	Independent	Independent	dependent	Independent	Independent
Goods for sport						
Number of observations	5,349			274,126		
min	0	0	3.86	0	0	0.25
mean	0.3804	0.2722	306.27	0.3768	0.285	115.09
max	1	1	2573.81	1	1	2573.81