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The evolution of e-commerce sector during the COVID-19 pandemic in Europe

Examiners: Professor, Kaisu Puumalainen
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ABSTRACT

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In 2020, the world encountered a severe pandemic, COVID-19 that shocked the structures of societies and economies. Both companies and consumers experienced various governmental restrictive measures. More than two years later since the pandemic began, online shopping has proven itself as a sustainable solution in a world that is adapting to new practices. In order to find out the European-wide effects of the pandemic, the text examines the growth of e-commerce business during the COVID-19 pandemic in 20 countries. This master's thesis is a partial replication of the research conducted by Szász et al. (2022), but with a different research design and newer statistical data. The research objective is to find out with quantitative methods how the pandemic has affected the growth of the e-commerce sector. The included variables are governmental stringency index, unemployment and COVID-19 cases. Monthly data of the variables are collected from Eurostat, Ecommerce Europe and Our World in Data databases. In addition, countries are compared on the evolution of the e-commerce sector during the pandemic. Firstly, the total market share growth of the e-commerce sector is presented and secondly, monthly variation in e-commerce volume is shown. A panel regression analysis is conducted based on the collected variables to see how much the governmental stringency index, unemployment and COVID-19 cases correlate with the growth of e-commerce euro volume. As a result of the regression, the answers to the research questions were obtained. Governmental restrictive measures and COVID-19 cases had a significantly increasing effect on the e-commerce sector. Implications of the analysis show that governmental restrictions speed up the digital transition of consumers moving to online services. To prepare for societal threats in the future, governments should create long-term strategies for restrictive measures. This would be done to avoid overcompensation where companies would be put in unequal positions and also provide stability for consumers.

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Vuonna 2020 maailmaa kohtasi yhteiskunnan rakenteita ja taloutta rikkova pandemia, COVID-19. Sekä yritykset että kuluttajat kokivat tahoillansa erilaisia toimintaa rajoittavia toimenpiteitä valtioiden toimesta. Nyt kun pandemian alusta on kulunut yli kaksi vuotta, verkkokauppaliiketoiminta on osoittautunut kestäväksi ratkaisuksi uusiin käytäntöihin mukautuvassa yhteiskunnassa. Pandemian euroopanlaajuisten vaikutusten selvittämiseksi tekstissä tutkitaan verkkokauppaliiketoiminnan kasvua COVID-19 pandemian aikana 20 maassa. Työ on osittainen replikaatio Szászin ym. (2022) tutkimuksesta, mutta eriävällä tutkimusasetelmalla ja uudemmalla tilastodatalla. Tavoitteena on selvittää kvantitiivisin menetelmin, kuinka pandemia on vaikuttanut verkkokaupan kasvuun. Sisällyttämällä muuttujat valtiollisten rajoitustoimien indeksistä, työttömyydestä ja koronatapauksista, saadaan yhtenäinen kuva yhteiskunnallisella tasolla. Näistä muuttujista kerätään kuukausitason tiedot valituille maille Eurostat-, Ecommerce Europe- ja Our World in Data -lähteistä. Lisäksi kuvataan maiden verkkokauppaliiketoiminnan markkinaosuuden kasvua COVID-19-pandemian aikana, ja vertaillaan kuukausittaista volyymivaihtelua. Kerätyistä muuttujista tehdään paneeliregressioanalyysi, jolla nähdään kuinka paljon valtiollisten rajoitustoimien indeksi, työttömyys ja COVID-19-tapaukset korreloivat verkkokauppaliiketoiminnan euromääräinen volyymin kanssa. Paneeliregression tuloksena saatiin vastaukset tutkimuskysymyksiin. Sekä valtioiden asettamilla rajoituksilla että COVID-19-tartunnoilla on ollut verkkokauppaliiketoimintaa kohtaan merkittävästi lisäävä vaikutus. Yhteiskunnalliset rajoitukset nopeuttavat kuluttajien siirtymistä sähköisiin kauppapalveluihin. Tulevien uhkien varalta hallitusten tulisi laatia pitkän aikajänteen strategia, jotta rajoitustoimenpiteillä ei syntyisi ylikompensaatiota, jolloin eri yritykset joutuvat eriarvoisiin asemiin, ja myös vakauttaa markkinoita kuluttajille.

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1 INTRODUCTION

In Spring 2020 the world was introduced with a new pandemic that will have long-lasting global implications. The outbreak was due to a novel coronavirus named SARS-CoV-2 that causes the COVID-19 disease and it originated from Wuhan, China, sometime in late 2019 (WHO, 2020). Only few European countries had infections by February 2020. Sharp rises in infections started in March and April. Initially, Italy had the highest infections rates, only for Spain to surpass it in April (Mogi & Spijker 2022). To date, there have been more than 600 million confirmed cases, over 6,5 million confirmed deaths and over 12 800 million vaccine doses administered (Worldometer 2022).

Martin-Neuninger & Ruby (2020) and Shankar et al. (2021) explain that the pandemic has since caused world-wide disruption in economies due to increased uncertainty, regulations and volatility in consumer behavior. As the pandemic has progressed, both businesses and consumers have faced the need to constantly adapt to dynamic regulations. Not all businesses could keep up with a drastically changing society, which has caused some of them unable to adapt to close their doors either momentarily or permanently.

As will be explaiend later, With the aid of flexible online shopping channels, the e-commerce sector has proved to be an invaluable factor in supporting the economy with the aid of flexible online shopping channels. Lund et al. (2021) estimate that the e-commerce sales grew up to 400% compared to before the COVID-19 outbreak. In Europe, the e-commerce sector has experienced growth during the pandemic in online shopper amounts and revenues.

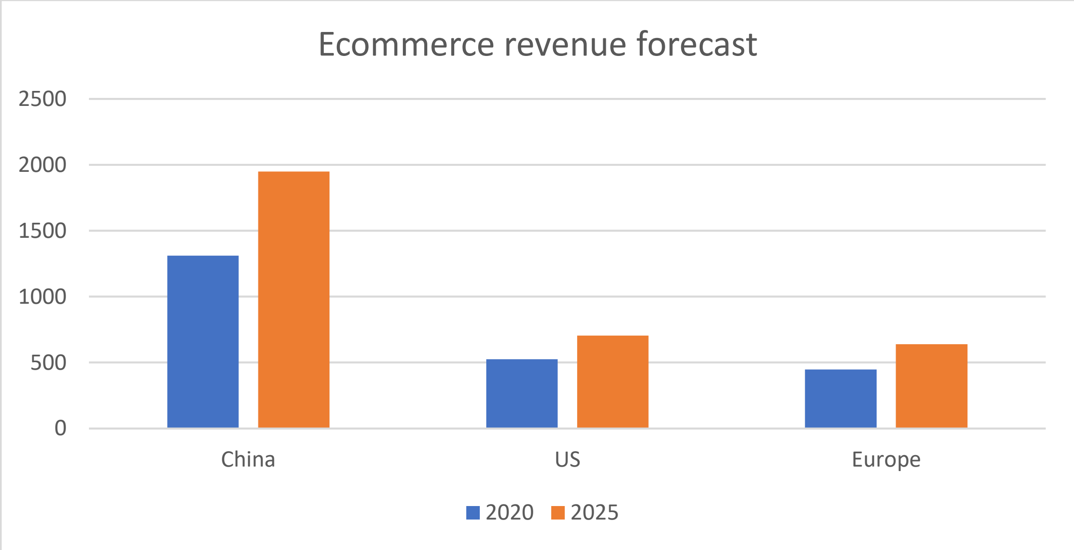

Figure 1. Global e-commerce revenue forecast in billions of euros (Statista 2021).

Since the outbreak of COVID-19 in 2020, global economies have experienced a rapid shift to orient themselves to digital platforms. Figure 1 shows that the e-commerce market in China is expected to grow 32,7% until 2025, the United States by 25,6% and Europe by 29,8%. In their research, Szász et al. (2022) have shown that the online sales of European countries rose during the first wave of the pandemic. In addition, they found indications that the markets experienced a level shift during the pandemic era, taking online sales to new permanent highs.

1.1 Background for thesis and relevance

Since the Dot-Com bubble burst 20 years ago, e-commerce has been a fast-developing sector. Research interest has been tremendous and therefore, more studies have been conducted in the field. There has been academical calls for studies to inspect the evolution of e-commerce. (Bai & Li 2022.) Few could anticipate the short-timescale outcome of the COVID-19 pandemic. No industry was spared from the effects, since businesses were required to take a new approach protecting assets and company profits. Government actions against outbreaks have greatly affected consumer behavior by increased online sales (Chang and Meyerhoefer 2021).

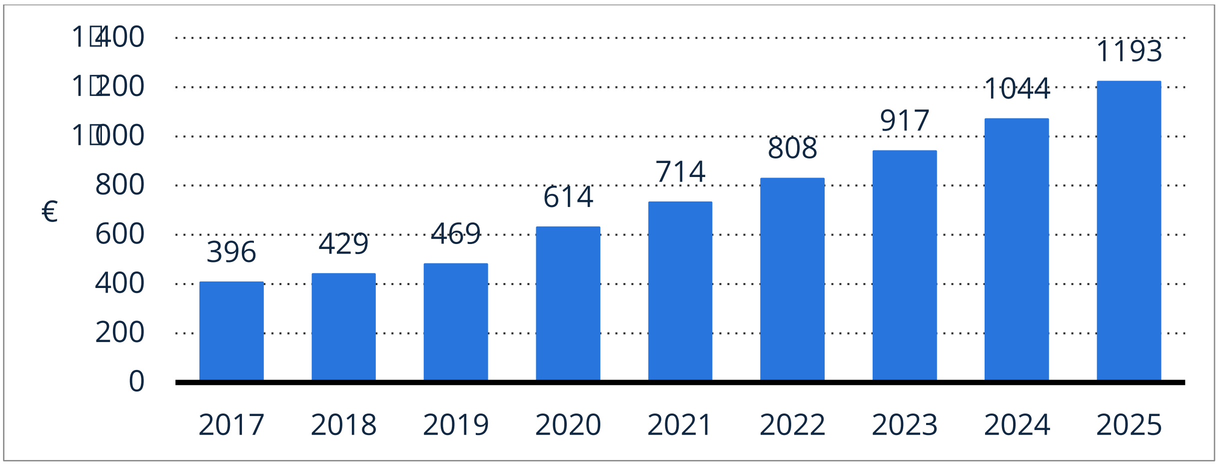

Figure 2. Retail e-commerce revenue in billions of euros in Europe between 2017-2025 (Statista 2022).

Globally, e-commerce has seen large growth in recent years. Even since the Dot-Com bubble in the early 2000s, there has been a steady growth while slowly expanding and stealing market share from retail (Szász et al. 2022). As you can see in Figure 2, the e-commerce market was already on the rise pre-pandemic and experienced a significant growth during the first year of the pandemic.

This master's thesis is a replication in part of the previously introduced quantitative research that was originally released in the Spring of 2022 by Szász et al (2022). The objective was to study short-term drivers and long-term implications of the COVID-19 pandemic. Different timespans were examined, but mostly there was a focus on the period during the pandemic, between January 2020-2022, in other words, two complete years. Firstly, the group investigated the growth of online retail in selected European countries and the permanence of the level shift the markets experienced. Secondly, it was examined how consumer behavior changed as months progressed. The authors created a model to track the movement of citizens in relation to online sales and another model to compare the governmental restrictions and online sales. The results showed that:

1. COVID-19 boosted online sales turnover.
2. The short-term evolution of online sales is significantly explained by governmental stringency and by the consumers' time spent around their homes.
3. In the future, tracking customer movement outside brick-and-mortar stores could prove useful for managers in sudden pandemic developments and as well as post-pandemic.

Governments, consumers and companies have had troubles adapting to the aggressive nature of the pandemic. There is a clear need for monitoring societal transformation as well during the pandemic as after it.

1.2 Objective of research

Szász et al. (2022) came to a conclusion that overall, the online sales in Europe have benefited from COVID-19. But it was left to be seen, was the shift only momentary or permanent. Since the pandemic can cause rapid movements in society even on a monthly basis (as seen later), it is important to track the variations in behavior.

Therefore, this master's thesis takes a quantitative approach to solving the main research question:

"How did the spread of the COVID-19 pandemic impact on the evolution of e-commerce in Europe?"

The main research question is a modification of one of the research questions in the previous work made by Szász et al. (2022). The group researched long-term effects that COVID-19 had on European online sales. They included every 27 EU member states in the work, and due to that fact, the main data for online sales gathered from Eurostat was not up-to-date for all included countries and therefore was missing data. Also, the timeline extended from January 2020 to January 2022, so two whole years were under inspection. This master's thesis provides newer data points with modified variables to probe the effects of COVID-19 in the evolution of e-commerce in Europe. The timeline has been extended from January 2020 to August 2022 by excluding some European countries that lack the needed data from the months in 2022. By gathering data from three main sources, a customized dataset will be formed to accommodate all relevant variables to solve the question above. These variables will be explained more in detail later in the text.

Moreover, there are 3 sub questions which aim to support the goal of the main research question:

1. ***What effect did government stringency have on e-commerce sales?***

Governmental pressure to keep the pandemic on a leash has resulted in companies having to experience temporary shutdowns and lay-offs. In turn, consumers have had to turn to online channels to purchase products and services. To observe governmental responses to the pandemic, The Oxford COVID-19 Government Response Tracker was created (Hale et al. 2021). One element of the tracker is the stringency index that this master's thesis focuses on. The index was created by aggregating different response metrics and it uses a scale of 0 being the lowest and 100 being the highest level, for example a total temporary lockdown. In other words, the index takes into account different government actions and policies, such as: workplace and school closures, restrictions or cancellations in events with large amounts of people, travel bans and so on.

2. ***What effect did unemployment have on e-commerce sales?***

Unemployment is an important societal indicator to measure buying power. Since the pandemic broke out, there have been industry-wide lockdowns and company closures. Employed have become unemployed, or they have fewer hours to work now. (Mittal 2021). The more there is employment, the more citizens earn income to have a positive impact on the economy. The disposable income of EU citizens fell by 9,3 percent in 2020 due to the COVID-19 pandemic (Almeida et al. 2021). When COVID-19 began having an effect in Europe, companies were forced to let personnel go or furlough them temporarily (The Economist 2020.) Bauer gives an example from Germany that by April 2020, up to 60% of new unemployment was due to shutdowns the government imposed (Bauer 2021).

3. ***What effect did COVID-19 cases have on e-commerce sales?***

Including COVID-19 cases during the pandemic era is crucial in itself. Infection cases are directly responsible for different mechanics of the society. The specification for this variable in this text is cumulative with the amount corresponding per million people. Since there are multiple countries under examination, it is good for the validity for the results that the data is homogenized. Our World In Data (2022) provides all needed data for cumulative COVID-19 cases.

Together, these research questions form a collective that aims to gauge societal phenomena and to look for correlations between the variables. Variable details and how the data was collected will be explained in the methodology section later on in this text.

1.3 Exclusions and limitations

A previous research was conducted by Szász et al. (2022). The group concluded that the pandemic generated a window of opportunity for online retailers to capitalize and grow their market shares during the pandemic in Europe. This master’s thesis will use the publication as a starting point with differing parameters and newer e-commerce volume data. Since the objectives of the original research were multifaceted with varying level of scopes, a decision was made to include some elements and exclude others. Next, the exclusions are presented.

The European Union is used as the center point of view. But due to the fact that not all countries have reported data, they have been left out of the dataset and examination. Countries included are Austria, Belgium, Bulgaria, Czechia, Greece, Croatia, Denmark, Finland, France, Germany, Italy, Lithuania, Netherlands, Norway, Spain, Poland, Portugal, Romania, Sweden, and Turkey. In addition, EU-27 (includes all EU member states) as a collective was included in the country comparison section.

European countries that were not included are as follows: Albania, Bosnia and Herzegovina, Cyprus, Estonia, Hungary, Ireland, Latvia, Luxembourg, Malta, Slovenia, Montenegro, North Macedonia, Serbia, Slovakia, Switzerland (and United Kingdom). The exclusion resulted from the fact that none of the aforementioned countries had up-to-date monthly e-commerce data in Eurostat.

The empirical section uses custom a dataset of panel data with cross-sectional and time series elements, that starts from January 2020 since the COVID-19 pandemic began spreading until August 2022. In this time period, there are 32 months which are used to describe the data. Similar to the research done by Szász et al. (2022), this master’s thesis also uses Eurostat for monthly retail index turnover volume for selected countries with the parameter “Retail sale via mail order or via internet”. The euro volume collected from Ecommerce Europe is combined with the index to create an estimation of sales for each country. This helps analyzing and comparing the countries with each other.

1.4 Literature review

Considering how reliant on e-commerce channels both businesses and consumers have become during the COVID-19 pandemic, researchers in many different localities have conducted groundwork of different scopes and localities. This section covers the most important research topics across different continents. Studies discussed in this section are centered around the e-commerce sector and that are the most relevant for this master's thesis.

In the United States, Hwang et al. (2020) collaborated with an art supply manufacturer and found out that having online channels is crucial during a pandemic. Stay-at-home orders combined with brick-and-mortar store closures led to increased online revenues. In another study, Kirk and Rafkin (2020) inspected social-distancing rules during the first pandemic wave and discerned different consumer behavior patterns.

In Asia, researchers have shown great interest in the effects of COVID-19, possibly due to strict governmental measures to limit movement. The talking point has been mainly how online grocery shopping has been reshaped by difficult circumstances. In China, the changes in online shopping were researched by multiple research groups. Topics included keywords such as panic buying (Hao et al. 2020; Li et al. 2020), lockdown behavior (Gao et al 2020), community-based ordering (Guo et al. 2020) and digital engagement during the pandemic (Jiang and Stylos 2021). It was discovered that the pandemic setting increases the drive for consumers to purchase food online, especially young people who live in big cities. Moreover, the more there are COVID-19 cases, the bigger the probability of online food shopping. Li et al. (2020) and Hao et al. (2020) studied what effects online channels impose on the population.

In Europe, there has been a clear emphasis on the regulative side, such as social-distancing rules and travel restrictions. For example, in Belgium, Beckers et al. (2021) investigated the first wave of the COVID-19 pandemic. They found out that restrictions increased online orders. During the first months of the pandemic, half of retailers who did not already use an online channel for sales, opened one. New problems can result from governmental regulations. In France, Guthrie et al. (2021) researched the healthcare sector and the new ways consumers have problems adapting to a new context, which can lead to panic buying.

As discussed before, Szász et al. (2022) researched the European Union to find out the short- and long-term effects of COVID-19 in socio-economic context. Also, they examined online shopping behavior during governmental lockdowns and other measures to limit in-store visiting. And lastly, Dannenberg et al. (2020) focused on Germany to find out how the COVID-19 has sped up the transition to the digital age.

1.5 Thesis structure

In the first chapter, the author introduced the preliminary setting for the thesis by providing research objectives and background information. Moreover, literature review gives an overview of the most important researches around the subject.

The theoretical framework provides key information by laying out the key concepts that will be reflected upon across the text. Main focus points in this master's thesis are centered around the evolution of retail and how it has slowly transformed to digital platforms, consumer behavior during the COVID-19 period and governmental factors to understand before delving into analyzing the results.

The methodology section covers all the information needed to understand how data was collected and to make it presentable with describing and summarization. Empirical findings offer answers to the main and sub research questions that were set during introduction. Country comparisons are presented in visual and compact form and panel regression analysis is also presented.

The results are then discussed and are reflected to academical theory. Lastly, the master's thesis is concluded with reflections to existing literature and other implications that have arisen during the analysis period.

2 THEORETICAL FRAMEWORK

In this section, the main concepts used in this master's thesis are explained. Keywords, such as e-commerce, online channels and consumer behavior will be explained. In addition, new phenomena in these concepts that appeared during the COVID-19 pandemic are introduced, such as panic buying. The benefit of theoretical framework is that is serves as a lens when inspecting different topics (National University Library 2022). This section helps analyzing events that have passed and provides a specific angle to view subjects.

2.1 The digitalization of commerce

In the 1970s, the first delivery services were created to shorten the time of delivery. In the 1990s, computers started to have large-scale adoption globally and the World-Wide Web was developed. Also, payment systems such as PayPal were established. With multiple advancements in the technological sector, e-commerce became reality. (Ingene 2014). Fan et al. (2020) also say that as time has passed and more technological improvements have been made in the internet infrastructure, the threshold to sell products and services to consumers has been lowered. The advancement of internet technology result in consumers to use e-commerce platforms in order to buy and interact with products (Wagner et al. 2020a). Lastly, the advent of e-commerce platforms have enabled to generate more sales (Lee et al. 2018).

While the online systems have developed, traditional retailing has been evolved, especially with the help of the advancements in internet technology. Bourlakis (2009) contends that generally the main elements in the shopping experience have been sensory based, such as touch and smell. There also can be a possibility to trial a product and this can give a boost in confidence in the company and the product itself. With online elements, the shopping experience has transformed, and consumers do not have these kinds of options and may just return a product back to the store if it is not to their liking. What comes to shopper profiles, traditional retailing has been a favorite of so-called 'social shoppers', while online buyers prefer convenience or they like testing new ways to shop. With digitalization as a global trend, Drobyazko (2020) talks about the digital economies which consist of demand and need for technologies, products and services. Traditional economy is transformed to create resources instead of consuming. Digitalization transforms markets and one result of it is e-commerce. Now, it is an essential part of a modern society.

2.1.1 E-commerce classifications

E-commerce enables consumers to purchase goods and services from a retailer on the internet. The prevalence of the business sector has increased over time, since consumers find the way of shopping online easier. However, Chiu et al. (2014) remind that to understand consumer intentions and lure potential customers and retain them later on, online sellers need to give guarantees, such as fulfilling orders and data privacy. These guarantees go hand-in-hand with frequently informing the consumers of the benefits of shopping online. These benefits include the convenience of shopping anywhere you are, better pricing and a broader range of products at sale.

Holdofr and Haasis (2014) state that, as the availability of the internet increases, e-commerce becomes an option for more consumers. A benefit of e-commerce platforms is that the interaction between consumers and companies increase. This can result in more shopping behavior and thus generate economic benefits (Wang & Herrando 2019). Artene (2014) asserts that due to the growing demand for e-commerce, eventually consumers will only use online platforms for shopping instead of going to brick-and-mortar stores. The author continues by saying that due to aggressively dynamic online environment, companies need to be swift with responding to changes to stay competitive.

E-commerce comes in different forms and business models. Two most relevant models for this research are B2C (business-to-consumer) and B2B (business-to-business). According to Paul George (2019), in the B2C model, consumers purchase products on e-commerce platforms. There are different types of platforms to suit the needs of diverse consumer needs. Many factors have an influence on the buyers' needs, such as the simplicity of e.g. website design. When visiting these sites, consumers usually already have a goal in mind to buy a certain product conveniently and without a hassle. Laudon (2016) explains that, whereas B2C refers to companies selling products and services to consumers, B2B focuses on other businesses. So far it is the most popular model in the e-commerce sector and it still has more growth potential. Alsaad et al. (2021) agree that B2B faces significant use and popularity.

They list that e-commerce brings benefits to B2B, such as decreasing costs, speeding decision-making and improving internal bureaucracy.

2.1.2 The importance of online channels

When trying to pinpoint what one means with online channels, they are defined as a category that includes all devices that are enabled by the internet. These could include mobile devices. With them, consumers can interact with online platforms and buy products and services. Also, mobile applications e.g. provide a 'touchpoint' with consumers that the seller can leverage. (Wagner et al. 2020b.)

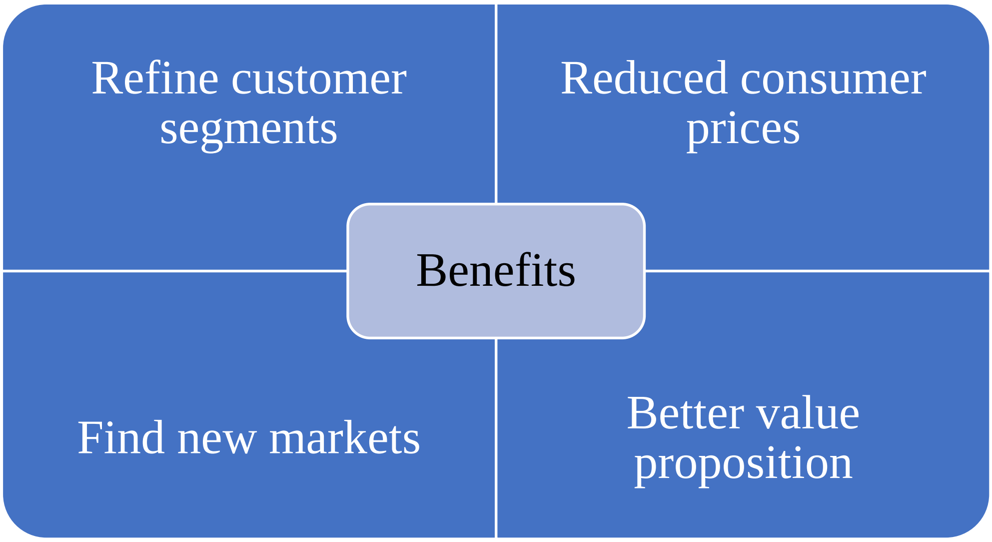

Figure 3. Online channel benefits (Xie et al. 2016).

As you can see in figure 3, there are four benefits according to Xie et al. 2016). When companies include online selling channels in their operations, more market expansion is enabled and consumer segmentation can be fine-tuned. In addition, depending on distribution channels and other factors, products can be lower-priced compared to competitors with no online selling channels. And lastly, the value proposition and brand integrity can be better. Consumers have realized the advantages online shopping brings. According to Lim (2015), the online shopping experience is more convenient, better priced and tailored to individual needs. Also, consumers overcome time and spatial barriers and have more information to make purchase decisions.

Tian et al. (2013) posit that due to growing interest for the internet technology, companies and individuals are becoming more involved with e-commerce. Since the digital world can accommodate more real users, there are big amounts of sellers and buyers interacting with each other. The intricate e-commerce market is always changing because of these interactions. Since the progress is ever-changing, new applications for e-commerce have been found to significantly influence the economy. According to Eurostat (2022b), shopping online has never been as popular as it is now. The survey included 16-74-year-olds, of which 74% had bought products or services online in the last 12 months. Compared to the 2016 survey, there was an increase of 11 percentage points.

2.2 Previous research in country-level context

As shown by Szász. et al. (2022) in their research, the interest in online shopping has increased steadily for the last 20 years in Europe with the COVID-19 pandemic providing a boosting effect. The research group concluded that multiple European countries, including the biggest ones such as France and Germany had experienced a level shift in online retail sector.

Globally, studies have been conducted that have encompassed whole ecosystems. Pantano et al. (2020) inspected consumer behavior in the retail area on a macro-level but included some example countries, such as UK and China. The main focus was providing a commentary or a synthesis of the current situation and challenges in both online and offline retail sector.

Gu et al. (2021) studied online consumer behavior in pandemic context due to the increasing relevancy of the e-commerce sector. The group created a survey among online shoppers in top 10 countries based on market growth to understand decision-making process and their changes. It was found that consumer behavior changes during times where there are fast changes, such as the COVID-19 pandemic. Results indicated increased web traffic on online grocery stores and consumers becoming more experienced to make faster purchase decisions.

Kwok et al. (2022) examined the impact of the COVID-19 pandemic on the business sector and e-commerce in Asia. By providing case analyses for countries such as Malaysia and India, the purpose was to look at different industries and document the changes in the business environments.

Scutariu et al. (2021) carried out a study to understand how e-commerce companies act during the pandemic. There were a total of 31 European countries included in the country-level analysis. Some companies were fast to adapt by recreating e.g. strategies and processes. Others have experienced the pandemic too disrupting and business cannot operate any more in traditional ways.

2.3 Consumer behavior during the pandemic

Geel (2002, 2004, 2011) states that technological transitions depend on the development of technology, but they are also affected by socio-technical events. COVID-19 has introduced a new playing field for all actors, including governmental jurisdiction, companies and consumers. Harvard Global Health Institute remarked (2020) that pandemics like COVID-19 could have destabilizing effects on governments and have other severe consequences, such as imposing travel restrictions and other bans. Martínez-López & López López (2021) argue that businesses becoming more digitalized was due to sudden escalation of limitations on our systems because the escalation of the COVID-19 pandemic was so fast. The transformation was further pushed by the worldwide trend of digital transformation. According to the authors, businesses becoming digitalized was always coming, but COVID-19 was the driver for this.

Depending on the shopping situation, consumers tend to decide the price level and format that matches their individual needs. And in the end, consumers are the ones who choose the market format that retailers need to provide. Gauri et al. (2021b.) The COVID-19 pandemic has resulted in narrowing product assortments. There have been up to 40% decreases in assortments since the center point in many companies has shifted only including famous brands and products. Large companies such as Amazon grow even more since they work as platform for other retailers to offer their brands and private labels (Gauri et al. (2021a). But the market does not only consist of large established brands. Small and medium-sized companies support economic activities of societies. The decline in these kinds of companies due to the pandemic can have a substantial effect in total economic activity (Pedauga et al. 2022).

2.3.1 Economic impact in Europe

Estimates of the negative economic effects that COVID-19 has created are substantial (Evans, 2020). The COVID-19 pandemic has caused turmoil in Europe that will consume resources and time to mend. Su et al. (2022) state that since the COVID-19 pandemic was unleashed in Europe in 2020, unemployment spiked and the amount of COVID-19 infections were one direct cause for the increase. Economic activity on the whole was slowed down. This led to less work available on the market, as well as different industries shrinking. Therefore, the fast spread of the virus has set a tremendous challenge for the European economy as the countries struggle to gain an advantage (Demertzis et al. 2020). Ahmad et al. (2021) forecasted, based on a selection of Europe's largest countries (France, Spain, Belgium, Turkey, Italy and Germany) that unemployment will remain higher for the next two years with diminishing results after that.

The Economist (2020) report that when COVID-19 started having major ramifications in the European landscape in March 2020, some companies had to close doors momentarily and order personnel to work from home. To lessen the negative impact of the pandemic, regulators needed to either increase unemployment benefits for now-jobless workers, or pay companies to furlough employees at least temporarily.

Pantano et al. (2020) presented in their research that in emergency situations like COVID-19, many consumers accept steep increases in prices of products and services. With governmental measures to limit interaction such as people gathering in stores, longer queues form outside of stores with longer waiting times. This has led to accessibility to stores being lowered. In fear of being infected, consumers have been looking for different ways to make purchases. Sudden regulatory measures such as lockdowns have had an additional effect to this.

2.3.2 Unusual consumer behavior

Disasters can have an impact on consumer behavior (Ballantine et al. 2014). When consumers experience a change in availability of products or services that they are accustomed to, shift in consumption habits can be manifested. Non-communicable diseases can be a cause for the change (Datta et al 2018).

Psychological fears can cause changes in consumer behavior (Solomon 2020). It is important to understand how this fear can have an effect in purchasing behavior and money-spending. (Khan & Huermovic 2019). Since the outbreak of the pandemic, online purchase amounts have increased among consumers (Tran 2021). Laato et al. (2020) add that buying behavior has changed due to the fact that there is a fear of being infected among consumers. Addo et al. (2020) concludes that even though society has suffered from stress and anxiety, e-commerce platforms serve a special role in perceived safety places. Therefore there has been an increase in consumer shopping behavior. Hall et al. (2021) discovered in their research that during the pandemic, consuming spending patterns varied resulting to temporal displacement of consumption in some product categories. The behavior of consumers spending more money in these categories indicates that there indeed was stockpiling during 2020. Moreover, during lockdowns, the hospitality sector had decline in spending.

Sheth (2020) argues that time and location binds consumption. Lockdowns and other measures limit consumer access to stores. Time and location are now bound and not the other way around. The new address for shopping is at home. Partly due to this, consumers now have more freedom to decide when and where to work and shop. Due to governmental stringency, COVID-19 has managed to disrupt consumer behavior. Consumers have been forced to find new ways to adapt to staying at home for long periods of time. Therefore, the possibility to adopt new technologies has increased, since they bring more convenience to working and consuming. Hwang et al. 2020) states that having an online channel is important during a pandemic such as COVID-19. By having one, it results in higher revenues during events such as lockdowns and national emergencies and temporary store closures. In addition, having existing customers helps increasing chances for continuous online purchases.

During the first wave of the COVID-19 pandemic in the Spring of 2020, there was an initial rush to empty the shelves of important every-day products, according to Google (2020). This kind of panic-induced behavior was manifested in multiple countries in Europe.

Before COVID-19, going into brick-and-mortar stores had an added value of being engaging and entertaining. In the post-pandemic time, consumers need to judge whether it is worth it to physically go to shop. A new economic reality will result from this pandemic. Consumers are expected to shop in new ways. Home delivery services act as one example. With distant working becoming commonplace, more activities are performed at home. Instead of going to the gym, one could order equipment to use at home, and instead of a movie theater, one could watch new movie releases in the comfort of their own home. (Roggeveen & Sethuraman 2020.)

Purchasing decisions are influenced by scarcity. Some consumers experience a thrill by the perception of scarcity. This in turn has an effect whether they want to purchase a product or not. (Wu et al. 2012). Scarcity is an important factor take consider during the pandemic era as it can lead into panic-induced behavior. Hamilton (2019) adds that In order to attract attention of a consumer, one needs to consider the importance of product scarcity. It also increases the perceived value of a product over time.

3 METHODOLOGY

This section provides key methodological concepts. First, background information of the e-commerce field is examined for the selected 20 countries plus EU-27 economic area. Necessary explanations about the used variables will be provided, regarding data gathering and how it was processed and categorized. Also, descriptive statistics will be provided to further understand the composition and structure of the variables. Later, they will be subjected to a multiple-variable panel regression analysis, and its results will be displayed in the section four, empirical findings and analysis.

3.1 Research approach

Creswell (2009) states that when referring to research designs, it is meant that they are the plans that start from broad assumptions and ending with data analysis. There are several phases before one gets to the finish line. He further explains that when one conducts a research using quantitative approach, they first collect the needed data by first recognizing and identifying a sample and population, and then deciding how to gather said data. After this, the data is collected and analyzed.

Van de Ven states (2007) states that when one conducting a research, continuous interaction is needed between theory and empiricism. the analysis yields more profound results in theory and practice. This master's thesis takes a quantitative approach in order to answer the main research question: "How did the spread of the COVID-19 pandemic impact on the evolution of e-commerce in Europe?". Under the main question, there are several supporting sub-questions: 1. What effect did government stringency have on e-commerce sales? 2. What effect did unemployment have on e-commerce sales? And finally, 3. What effect did COVID-19 cases have on e-commerce sales? To find the level of causal relationship answer these questions, different variables need to be considered to generate a reliable and valid result with the least amount of bias possible.

3.2 Data collection

In this section, the process of collecting the required data for analysis will be explained, as well as the used variables. This master's thesis uses panel data with multiple variables that are being monitored over time. The dataset contains a combination of cross-sectional and time series elements. Since the COVID-19 period is being examined, it is important that the data we use is frequent enough to have a detailed overview. In order to do this, different databases were sifted through to find data that would suit the research objectives. To date, the pandemic has lasted 34 months, so the timespan is quite short to be measured yearly or quarterly. Overall, there are 20 countries with each 32 points of observations (a month is a single point) within the time period of January 2020 and August 2022. There are 4 main variables that will be explained after this section.

Main data is collected in combination from:

- Eurostat (2022a) for retail index and unemployment.
- Ecommerce Europe (2016) for e-commerce euro volume.
- Our World In Data (2022) for COVID-19 cases and government stringency index.

The use of cross-country data has increased over time. Focus has been shifted to panel data econometrics with large number of countries and time series being long (Baltagi, B. H. et al. 2021). Das, P. (2019) explains that when talking about panel data, it is a combination of cross-sectional and time series data. It is formed by collecting data with same sample units over periods of time. Panel data can be balanced or unbalanced. Wu, L. & Qiu J. (2021) assert that longitudinal researches have a main advantage. It is that you can take one variable and study the changes is experiences over time. Compared to a dataset that is in the form of time series, many measurements can be observed instead of just single long series. According to Baltagi, B. H. (2021), panel data helps controlling individual heterogeneity, is more informative since there is lesser amounts of collinearity in variables, is better when studying different societal factors such as unemployment and is better than cross-sectional or time series data at detecting hidden effects.

Hsiao (2003a) explains that panel data provides many observations for one sample of individuals over time and it has become a popular form of categorizing data. Panel data enables larger points of data, reducing collinearity within explanatory variables. This results in better econometric estimates, which cannot be done if one were to use only cross-sectional or time series data.

In this research, after all the essential data was collected from databases it was compiled into one unified custom dataset in Stata. Next, the collected data is explained more in-depth.

3.2.1 E-commerce volume

To gather detailed turnover data for online sales, Eurostat was deemed to be the most suitable option. It provided month-to-month index data for all the selected countries and the EU-27 area. As mentioned before, since not all countries provide the necessary statistics, it also affected the selection process during the preliminary stages of this master's thesis.

The dataset "turnover and volume of sales in wholesale and retail trade" (Eurostat 2022a) was selected for its expansive parameters to choose from. Information is provided for all of retail, and it had to be narrowed down only to online sales. That is why "retail sale via mail order houses or via internet" was chosen. The data is seasonally and calendar adjusted data, the unit of measure is index 2015=100, and the business trend indicator is index of delated turnover. There are a total of 21 geopolitical entities, which are Austria, Belgium, Bulgaria, Czechia, Greece, Croatia, Denmark, Finland, France, Germany, Italy, Lithuania, Netherlands, Norway, Spain, Poland, Portugal, Romania, Sweden, and Turkey and EU-27. Due to the fact that COVID-19 is in focus and the newer the data the better, the timeline starts from January 2020 ending in August 2022 and it is on a month-to-month basis. At first, September 2022 was also included, but due to missing data for some countries, it eventually was left out.

As mentioned, the data offers only index numbers and not real euro volume amounts. Also, the numbers are country-bound, meaning that an index number for one location could not be compared with another. For this, a way was needed to be found to be able to do comparisons between locations not only relying on index numbers. By using the index 2015=100, the e-commerce euro volume amounts needed to be found for the year 2015 for each location. The most suitable data was offered by Ecommerce Europe (2016) for their collection of B2C e-commerce sales in Europe. Euro volume was then collected for each location. By using the index numbers that were previously gathered for each month, the estimated euro volume was calculated. During the calculations, inflation was presumed to be negliglible.

3.2.2 Government stringency index

One of the variables used in the master's thesis is the so-called 'government stringency index' (Our World In data 2022). The index is a part of a larger indicator, which is called The Oxford COVID-19 Government Response Tracker (Hale, T. et al. 2021). To understand how societies react to the pandemic, government stringency index will be used as an explanatory variable. The stringency index was created by aggregating different response metrics and it uses a scale of 0 being the lowest and 100 being the highest. In other words, the index takes into account different government actions and policies, such as: workplace and school closures, restrictions or cancellations in events with large amounts of people, travel bans and so on.

The data for the stringency index is only available on a day-to-day-basis. Due to all other variables used in month-to-month form, the raw data file had to be downloaded and disseminated to smaller pieces. For each country, the stringency daily data was added up for each month, and then arithmetically divided with each day to generate a mean.

3.2.3 Cumulative COVID-19 cases

COVID-19 cases can provide information regarding how a society functions under duress. COVID-19 daily-based data was first collected for each country. Closer classification is "Daily new confirmed COVID-19 cases per million people". (Our World In Data 2022). Since multiple countries are being compared, the infections need to be unified, and absolute numbers will have a lesser meaning in the analysis. In the dataset, daily cases were collected and added together to compile cumulative data on a monthly basis.

3.2.4 Unemployment percentage

To gauge societal effects, unemployment was considered as a fitting indicator for seeing changes in society. And if we refresh what Mittal (2021) stated earlier, is that unemployment is an important societal indicator to measure buying power. After the outbreak in 2020, there have been severe problems with industries forced to lock down and companies close their doors. Therefore also is more unemployment and fewer work hours left. Unemployment data was gathered from Eurostat and the dataset contains harmonized unemployment percentages for each selected country. Moreover, all population is included with the parameters "under and over 25-year-old-males" and "under and over 25-year-old females". The minimum and maximum ages are 15-74. The data is seasonally adjusted, but not calendar adjusted.

3.3 Descriptive statistics

Previous sections discussed the process of collecting all the required information to create a custom dataset. In this section, the used variables are described more profoundly how they exist in the dataset that was used. Mann (2010) explains that datasets are large in their original form. The information they contain should be condensed to a more manageable form. This can be done with descriptive statistics.

Code name	**Description**	**Measure of unit**
ecom_e	e-commerce volume per country	billions of euro
stringency	government stringency index per country	0-100 with 100 being the strictest
unem	harmonized unemployment	percentage of population
covid_mc	cumulative COVID-19 cases	per million people

Table 1. Description of variables used.

Code names were created for the main variables, since it is easier to handle the Stata software this way (Table 1). As explained before, they use different measures of unit. Going through from top to bottom, "ecom_e" corresponds 'e-commerce volume', "stringency" corresponds 'government stringency index per country', "unem" corresponds 'harmonized unemployment' and lastly, "covid_mc" corresponds 'cumulative COVID-19 cases'.

Code name		Mean	Std. dev.	Minimum	Maximum	Skewness	Kurtosis	Observations
ecom_e	*overall*	26.74	33.40	0.41	143.30	1.90	5.62	N = 608
	between		34.02	0.48	116.89			n = 19
	within		4.15	1.74	53.14			T= 32
stringency	*overall*	44.76	22.36	0	95.44	-0.16	2.11	N = 608
	between		6.33	37.01	57.93			n = 19
	within		21.49	-13.17	103.18			T= 32
unem	*overall*	6.82	3.42	1.80	20.20	1.39	4.91	N = 608
	between		3.38	2.61	15.31			n = 19
	within		0.92	3.60	11.70			T= 32
covid_mc	*overall*	109264.40	134898.30	0	556453.70	1.52	4.49	N = 608
	between		34254.46	52317.53	155012.50			n = 19
	within		130706.20	-45748.18	522093.60			T= 32

Table 2. Descriptive statistics of variables used.

There are four main variables that are used during analysis. Above is presented their main characteristics. All values have been shortened to show 2 decimals. To create a strong balance withing the dataset, Turkey was left out since it had missing months for unemployment percentages. All variables share month-to-month level in data reporting, which means that there are 32 months overall with 19 months per variable, which totals to 608 observations per variable. The ecom_e variable has an overall mean of 26.74 and the standard deviation in within group is lower than the standard deviation between groups. The mean value for the stringency variable is 44.76 and it has a lower variation in within groups than between the group. The overall mean for unem is 6.82 and the variation between the group is lower than within the group. The skewness value shows that the distribution is positively skewed of all the variables, and the kurtosis value is higher than the given range, which indicates that the distribution is leptokurtotic and does not show normal behavior, nor does the data normally distribute. This is because COVID-19 cumulative cases start from 0, and as the infections progress over time, the larger the total value becomes for each country.

To give a sense of the scale of the data, a short comparison of the differences in maximum and minimum values of the variables is presented. The e-commerce euro volume (ecom_e), Croatia had the lowest amount of 0.41 BN€ and France had the highest amount of 143.3 BN€. Multiple countries had a stringency index of 0 during the first one or two months of the pandemic in 2020, but none had 0 after that. Czechia held the lowest unemployment percentage of 1.8 and Greece had the highest with a percentage of 20.2. Multiple countries had no COVID-19 during the first or the second month of 2020 when the pandemic statistics were established. However, as the outbreak has progressed, Denmark holds the most infection cases until August 2022 with 556 453 cases per million people.

3.3.1 Correlation matrix

To better see the relationship of the variables, correlation matrix was used. It is arranged in the order of columns and rows to list coefficients that correlate with each other. Correlation matrix is used to indicate association among a pair of variables. (Hadd & Rodgers 2021.)

	ecom_e	**stringency**	**unem**	**covid_mc**
ecom_e	1	0.10**	-0.18	0.03
stringency	0.10**	1	0.24**	-0.47**
unem	-0.18	0.24**	1	-0.16**
covid_mc	0.03	-0.47**	-0.16**	1
				** = 1% significant

TABLE 3. Correlation matrix of the main variables.

Above is shown the correlation between two variables. All numbers vary between -1 and 1. A variable has a perfectly positive linear correlation (1) with itself. The closer to zero the correlation is, the weaker it is between variables (Krehbiel 2004). Table 3 shows that the relationship between unemployment and government stringency index has the most positive correlation at 0,24. The strongest negative linear correlation is between cumulative COVID-19 cases and government stringency index with -0,47. Other variables share a weak connection with each other.

3.4 Panel regression

Regression analysis is a common analytical process in which the relationship among variables is calculated (Huarng 2015). Since the dataset contains both cross-sectional and time-series data, it was decided that formatting the dataset into long-panel form was the most suitable option. When analyzing this kind of data, panel data regression can be a powerful way of measuring independent variables against a dependent variable (Brugger 2021). When doing a regression analysis, it is normal to assume that the factors affecting the value of the dependent variable could be explained by random disturbances. When analyzing multiple individual units in time series data, it can be supposed that variables that were omitted can affect individual units and time periods. (Hsiao 2003b.) According to Gujarati & Porter (2010), regression analysis uses a dependent variable against independent variables to understand their relationship with one another.

3.4.1 Model specifications

There are different kinds of regression models to analyze panel data with. The two most meaningful for this research are discussed. The first one is fixed effects model (FE). According to Zulfikar (2018), FE has parameters that are fixed or not random, which means that the variables it uses are constant. These variables could be for example age or sex, since there is no constant variation. Since the variables can have non-directly observable factors, the FE model can help solve that. In addition to the FE, random effects model (RE) estimates panel data to see, whether there are variable that could be connected between time and individuals. Main benefit of the RE model is that it leaves out heteroscedasticity.

To test the appropriateness of the regression models, a Hausman test can be used to test whether the null hypothesis (H0) imposed by the orthogonality conditions of the RE estimator are proper. If the results of slope parameters show that both random effect and fixed effect models, there is no profound difference in using either one. In the case of infringing the so-called 'orthogonality assumption', random effect estimate results diverge significantly from fixed effect estimates. (Baum 2006.)

Hausman's test uses the null hypothesis to see that there is no correlation between some subject-specific effects that are not observed and the predictor variables that are observed against another hypothesis, which purports that subject-specific effects that are unobserved are, in fact, correlated with predictor variables that are observed. If the null hypothesis is rejected, then it is better to use the fixed effects model. Generally, random effects model is more efficient compared to fixed effects model. (Liu, T. et al. 2020.)

To find out whether there is heteroscedasticity in the regression model, Breusch Pagan test is used (Breusch & Pagan 1979). The test checks for the variance of errors in the regression. There is heteroscedasticity if the variance is dependent on the values of independent variables.

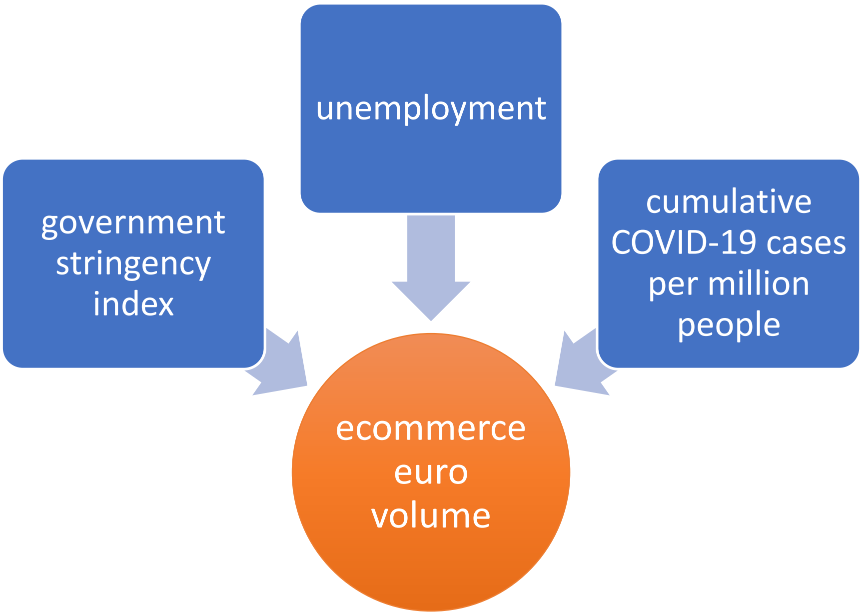

Figure 4. The relationship of the variables.

Dependent and independent variables are result of mathematical modeling (Bierens 2004). To understand how variables correlate with each other in regression analysis, causality is important (figure 4). Dependent variable is the effect and independent variable is the cause. As mentioned before, the aim is to find out how governmental stringency, unemployment and COVID-19 cumulative cases affect the e-commerce euro volume in the selected countries. Figure 4 illustrates the relationship of the used variables in this master's thesis. Independent variables are 'stringency', 'unem' and 'covid_mc' and they are being tested against 'ecom_e', which is a dependent variable.

4 EMPIRICAL FINDINGS AND ANALYSIS

Since some data was either on a daily or annual basis, different measures were taken to homogenize everything in monthly-basis, as discussed in the methodology section. A long-panel custom dataset was formed with four different variables and the statistics of the dataset was described in detail.

In this section, the results of the tests are shown. Firstly, the empirical results are presented, after which discussion follows. The text starts with laying out the results of the panel regression estimates to decide which model would be the most suitable to use. After finding the most suitable regression model, its findings are analyzed.

4.1 Descriptive results

As discussed in the introduction section of the study, the e-commerce industry has been growing its market share and will continue to do so at least until 2027 (Szász et al. 2022, Statista 2022). To perceive how well single countries have performed during the pandemic, a comparison was in the form of time graphs. Collected from Eurostat (2022a), “Retail sale via mail order or via internet” deflated turnover data was used as an index (2015=100) to estimate monthly e-commerce volume in selected countries and overall for EU-27 economic area. In this way, the graphs depict not only the e-commerce growth for single markets in their own vacuums, but since the percentage is based on the euro volume, we can compare countries on the same level. The percentage growth of the volume was calculated based on the change from the previous month.

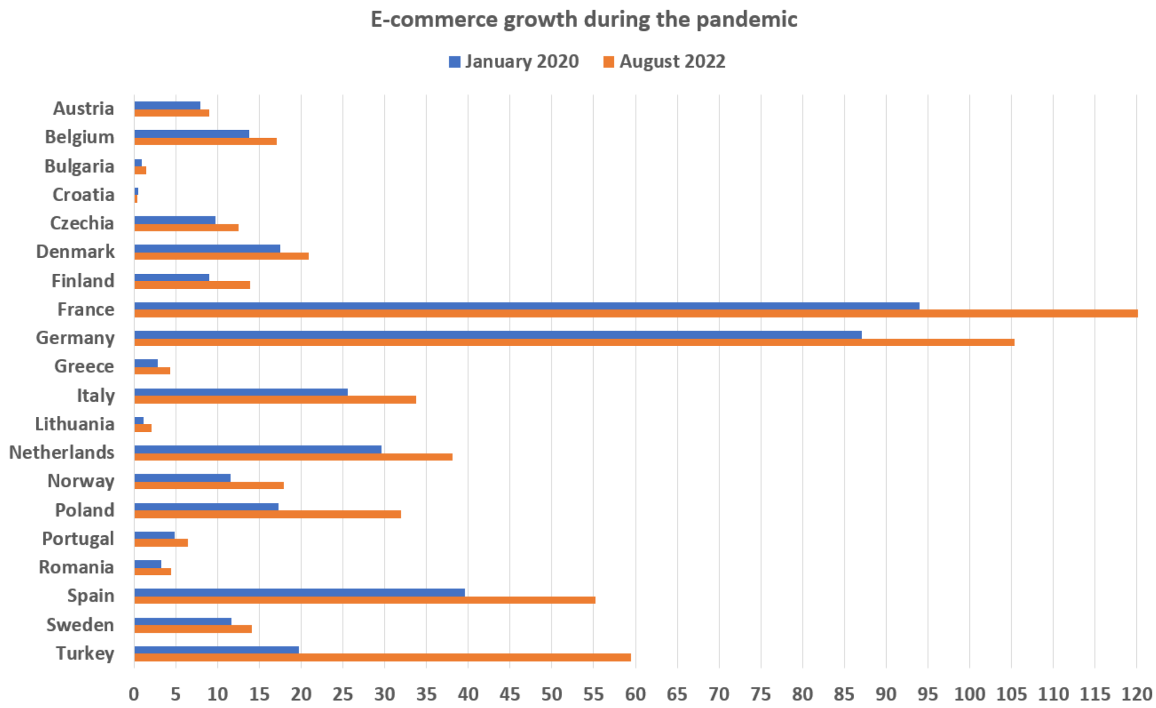

Figure 5. The B2C e-commerce evolution in selected countries in billions of euros (Eurostat 2022a and Ecommerce Europe 2016).

Above you can see the estimated e-commerce growth in 19 European countries plus Turkey. Monthly euro volumes are unavailable for the public, so estimations were made to correspond the real B2C e-commerce values for each country. By using the index 2015=100, the B2C euro volume was collected for each country in 2015 from Ecommerce Europe (2016). Then, by combining the index value and euro amount, the monthly estimated volume was generated.

Figure 5 indicates that the buying behavior has increased. All countries have experienced strong growth since the start of the pandemic, except for Croatia being the only country with a smaller e-commerce market share compared to the start of the pandemic. Unemployment was discussed earlier, and it was concluded that since the COVID-19 began in Europe, unemployment increased and resulted into more furloughs and part-time work. Due to this, there can be less buying power.

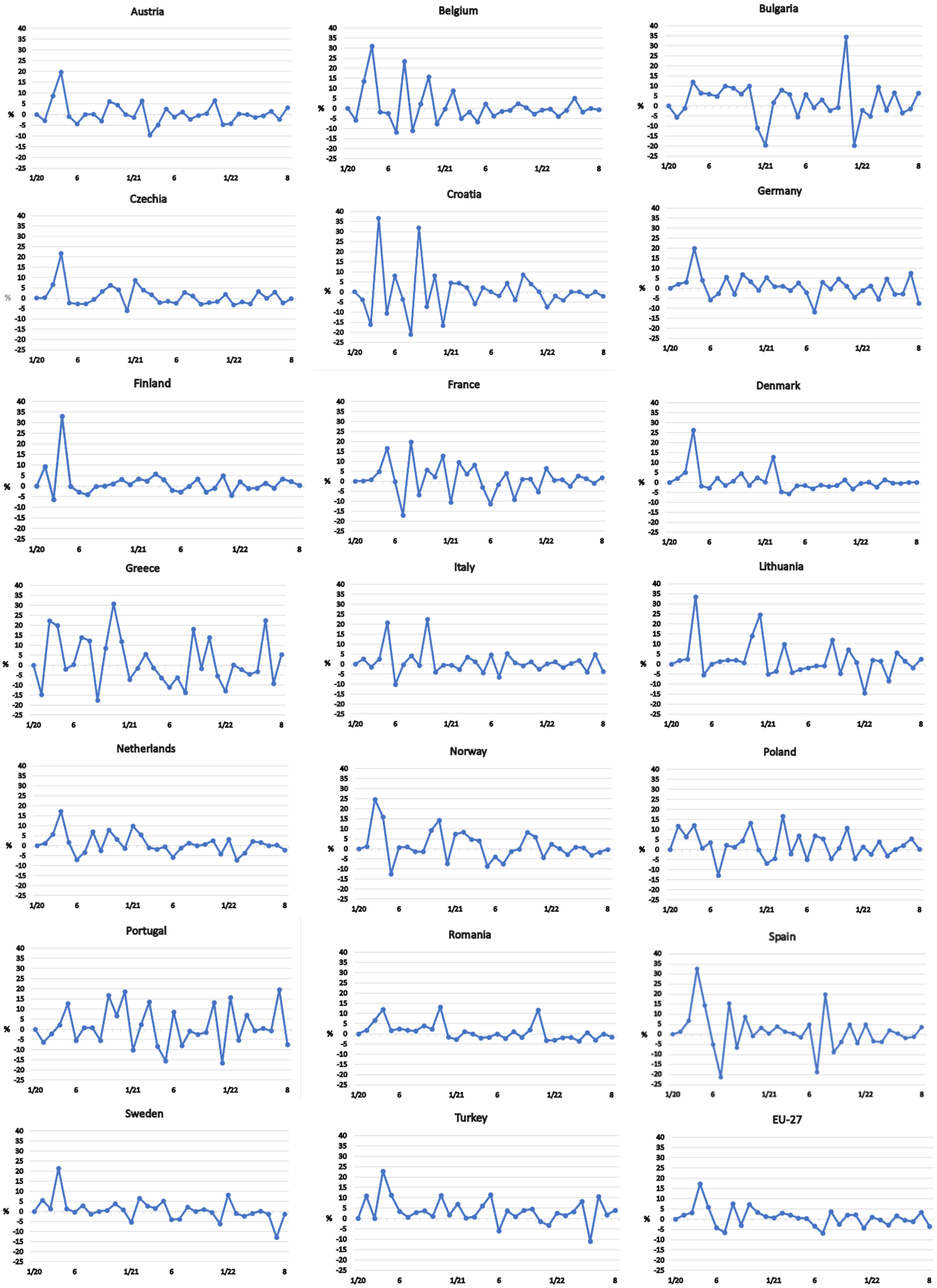

Figure 6. Overview of selected countries and the EU-27 area.

Stockpiling and panic buying behavior was reported in the early 2020 by researchers in China (Hao et al. 2020; Li et al. 2020). In addition, the data provided by Google (2020) showed earlier that multiple European countries experienced initial rushes to empty shelves. In the comparison above, it shows anomalous monthly changes in e-commerce volume (figure 6). Sharp changes could present this behavior, since the largest spikes in volume happened during the first six months into the pandemic.

Surprisingly, the highest volume increase in one month happened in Croatia (36,58%) even though it was the only country that had a negative growth during the COVID-19 pandemic. Lithuania (33,3%) and Finland (33,03%) had the second and third most monthly changes in volume. Considering only countries with the largest population, Spain is the leader (32,7%), then Turkey (22,83%) and then Italy (20,75%). Comparing January and June 2020, the following countries experienced at least one month of growth equal or higher than 20%: Austria, Denmark, Finland, Greece, Lithuania, Norway, Spain, Sweden and Turkey.

4.2 Estimation tests

During the process of preliminary testing, Stata software was used. It provided comprehensive tools for creating the long-panel dataset as well as the needed analyses. Before it could be decided which panel data regression model was the most suitable candidate, all the issues in the dataset could be ironed out so that there would be no room for errors. Overall in the final regression analysis, there are 19 countries overall that are being examined. For having a balanced dataset, it was crucial that the variables contained the same amount of information for each country.

Given the main research problem: “How did the spread of the COVID-19 pandemic affect on the evolution of e-commerce in Europe?”, it is natural that ecom_e is used as the dependent variable to which the other variables will be reflected upon. Other variables used in panel regression are stringency, unem and covid_mc, which were chosen as independent variables. Group variable was “location” and the timeline was set as month.

Hausman test						
Variable	**fixed coef.**	**random coef.**	**difference**	***s*td. err.**		
stringency	0.077	0.077	0.000	0.000		
unem	0.351	0.346	0.005	0.021		***Chi2(2)*** *= 0.09*
covid_mc	1.14e-5	1.14e-5	7.91e-09	9.45e-08		***p>Chi2*** *= 0.956*

Table 4. Hausman test results.

As discussed before, Hausman's test can help determining whether random effects or fixed effects model is a more suitable option for panel data. First, the Hausman's test was done. Table 4 shows the results of the analyses. In the fixed effect estimator, the fixed coefficient was consistent under H0 and Ha. In the random effects estimator, the coefficient was inconsistent under Ha and efficient under H0.

Hausman test suggests that the individual effects are uncorrelated with the other variables in the model with a p-value of 0.956, in where p>0.05. The null hypothesis (H0) is not rejected and therefore, we can conclude that the random effects model is more appropriate than the fixed effects model for this dataset.

To test whether there is heteroscedasticity, the Breusch Pagan test was conducted. The chi square test statistic is 26.20 with one degree of freedom. The results show that p>chi2 equals 0,000. In order to reject the null hypothesis (H0), the result needs to be p<0.05. Therefore, the null hypothesis (H0) is rejected, which indicates there is no heteroscedasticity and there are random differences. Since the null hypothesis is rejected, random effects model should be used over pooled OLS.

Additional 5 estimator tests were conducted, which included pooled OLS, population-averaged, between, fixed effects and first-differences. The results of those can be seen in appendix X. Of these estimator results, random effects results were included, since it was the most relevant for the work. The closer results of the model are presented in the next section after this one.

4.3 Random effects model

After concluding the preliminary estimator tests, it is found that the random effects panel regression model is the most suitable to use with the given dataset. To refresh, Hausman test rejected the null hypothesis with P<0.956. In addition, Breusch Pagan test also rejecting the null hypothesis indicated that there are unobserved random effects in the data.
Below you can see the equation used to formulate the used model:

$$y_{it} = \alpha_0 + \beta_1\, {}_{stringency\ it} + \beta_2\, {}_{unem\ it} + \beta_3\, {}_{covid\_mc\ it} + \gamma_{it} + \varepsilon_{it}$$

With the components consisting of:

y_{it}:	e-commerce euro volume (BN€)
${}_{stringency\ it}$:	government stringency index (0-100)
${}_{unem\ it}$:	unemployment among the population (%)
${}_{covid\_mc\ it}$=	COVID-19 cumulative cases (per 1MM people)
γ_{it}=	random effect coefficient
ε_{it}=	error term
The $\beta_1\ \beta_2\ and\ \ \beta_3$	estimated parameters of the model.

The equation of the model is as follows:

$$y_{it} = 19.683 + 0.0772x_{stringency\ it} + 0.346x_{unem\ it} + 0.00001x_{covid\_mc\ it}$$

Note: ecom_e is dependent variable	coefficient	std. err.	p-value	observations
stringency	0.077 (8.65)**	0.008	0.000	608
unem	0.346 (1.60)	0.215	0.109	608
covid_mc	1.14e-5 (7.27)**	1.57e-06	0.000	608
_cons	19.683* (2.40)*	8.196	0.016	608
sigma_u	35.135	** = 1% significant		
sigma_e	3.908	* = 5% significant		
rho	0.986	(t-values in brackets)		
R^2				
(within)	0.143			
(between)	0.0101			
(overall)	0.010			
Wald chi2(3)	98.76			
P>F	0.000			

Table 5. Random effects panel regression model results.

The results of the random effects panel regression can be seen above. The independent variable was ecom_e and independent variables were stringency, unem, covid_mc. In the random effects model configuration, the GLS model was used. Table 5 shows that each variable had 608 observations. The group variable was set for 'location', which corresponds countries in the dataset and the time was set as 'month'. We can see that the R^2 value is higher within compared to between. The R^2 within variation is 0.143, which shows weak positive correlation between the dependent variable and the regression model. Wald chi squared has three degrees of freedom with a value of 98.76.
The p-value for the model is <0.01, which indicates that the null hypothesis cannot be rejected and the model is suitable to use.

Government stringency index (stringency) had a positive effect on the dependent variable e-commerce (ecom_e) with a coefficient of 0.077, which is is highly significant at 1 percent level, since p-value is less than 1 percent. Also, the coefficient of unemployment (unem) was positive but insignificant with a value of 0.345. This was due to the p-value being greater than the 5 percent level of significance. The coefficient of COVID-19 cumulative cases per million (covid_mc) showed a positive correlation with e-commerce with the value 1.14e-5, which is highly significant at 1 percent due to the p-value being 0.01.

5 DISCUSSION

To answer the main research question: “How did the spread of the COVID-19 pandemic impact on the evolution of e-commerce in Europe?”, we need to first discuss the results of the panel regression analysis in the context of the sub-questions of this master’s thesis. The section is divided into four different parts. The first three parts discuss the results in the context of the sub-research questions. Lastly, the main research question is discussed.

5.1 RQ1: Governmental stringency

The first sub-question of this study was: “What effect did government stringency have on e-commerce sales?”. According to the results of the panel regression analysis, governmental stringency index had a significant positive effect on the growth of e-commerce. The result was expected, since the COVID-19 pandemic began, governmental measures to control the outbreak have been harsh, depending on the country. These measures could include lockdowns, stay-at-home orders, school closures, flight bans and other restrictions. Since consumers have spent even long periods of time at home without access to stores, they have had to turn to online channels to purchase products and services.

5.2 RQ2: Unemployment

COVID-19 has been causing havoc in various industries and sectors since the outbreak. To gauge societal effects, unemployment was considered as a fitting indicator to observe changes in society. Monthly data of unharmonized unemployment percentage was collected. To refresh, the second sub-research question set in the beginning was: “What effect did unemployment have on e-commerce sales?” After the outbreak in 2020, there have been severe problems with industries forced to lock down and companies close their doors. Therefore also is more unemployment and fewer work hours left.

According to the panel regression results, unemployment had only little positive effect on the growth of e-commerce. This was expected since unemployment is an essential indicator to measure buying power, and both unemployment and furloughs have risen since the pandemic started in 2020 (Bauer 2021; Mittal 2021; The Economist 2020).

5.3 RQ3: COVID-19 cases

Changes in consumer behavior during COVID-19 have been a topic of debate in academia, as previously discussed in the literary review section. Many studies found that there was stockpiling and panic buying in 2020. As discussed in the country comparison section, during 2020 most countries experienced high percentage changes in e-commerce volume.

The third sub-research question set in the beginning was that "What effect did COVID-19 cases have on e-commerce sales?". The results of the panel regression analysis shows that COVID-19 cases had a significant positive effect on e-commerce euro volume.

5.4 Main research question and summary

As discussed, the results show that all societal factors that were tested against e-commerce volume have a positive correlation with it. When considering the multi-level perspective, the factors that were researched, relate to the socio-technic regime. On that level, regulations and policies have limited the freedom of individuals and caused a positive effect on e-commerce, since governmental stringency has driven more consumers inside homes to use online services. But at the same time, too stringent measures deplete buying power by creating more unemployment and furloughs.

The main research question was: "How did the spread of the COVID-19 pandemic impact on the evolution of e-commerce in Europe?". To answer this question based on the background research and results, it can be said that overall the impact was positive. Country comparison in section 3.3 shows higher e-commerce volumes in August 2022 compared to January 2020. In addition, panel regression indicates that all three driving forces in the socio-technical regime collectively influenced the growth in e-commerce volume:

- Governments limited freedom of individuals and driving more consumers online and increasing e-commerce sales (tightening in policy regimes and affecting user preferences and markets)
- Governments limited freedom of markets and causing restlessness, such as unemployment, which resulted in slightly increased e-commerce sales (tightening in policy regimes and affecting user preferences and markets)
- COVID-19 cases increased over time and slightly increasing e-commerce sales (landscape development).

6 CONCLUSIONS

The sudden outbreak of the COVID-19 pandemic came as a surprise to everyone. According to the government stringency index (Our World In Data 2022), all European countries have experienced governmental measures to control the fast spread of the pandemic. In this master's thesis, European Union served as the economical center point during research. Countries that were included in panel regression test were Austria, Belgium, Bulgaria, Czechia, Greece, Croatia, Denmark, Finland, France, Germany, Italy, Lithuania, Netherlands, Norway, Spain, Poland, Portugal, Romania and Sweden. Other European countries were left out due to the fact that they did not have up-to-date monthly data. The main data needed for the analysis was collected from Eurostat (2022a), Ecommerce Europe and Our World In Data (2022). The custom dataset contained monthly data from 20 European countries between January 2020 and August 2022, including 32 months' worth of data points for each country. Due to the fact that there was both cross-sectional and time-series data with multiple variables, it was decided that panel regression was a suitable method to analyze the data.

The data was then regressed to see what effect different societal dimensions have on e-commerce euro volume. The results of the panel regression showed that:

- Government stringency index showed a significant positive correlation
- COVID-19 cumulative cases per million people had a significant positive correlation.

6.1 Contributions to theory

Szász et al. (2022) researched the long-term trajectory of online sales pre- and post-COVID-19. They discovered that measures taken by governments to inhibit movement led to higher online sales due to a window of opportunity caused by the COVID-19 pandemic. Dannenberg (2020) argued that the pandemic was able to force open a window of opportunity for digital transition and increase in online trade. This master's thesis further fortifies these results by providing newer data and proving that 19 European countries have increased their e-commerce market share since the pandemic started. When looking at the country comparison graphs in section 3.3, all countries experienced tumultuous time in 2020, but in 2022, the variations in month-to-month timeline have settled down and not returning to pre-pandemic lows.

Geels (2002) created the multi-level perspective (MLP) theoretical model for examining and how technological transformations happen during landscape developments such as the COVID-19 pandemic. This examination happens inside socio-technical dimensions, for example market, user practices and policies. These events can open windows of opportunities for new technology to substitute older technology. This text adopted the multi-level model to observe societal effects on the macro level. The results provided some valuable feedback on how pressure is formed on the socio-technical regime and the impact of landscape developments in different stages of the pandemic.

6.2 Practical implications

As shown by previous studies and this master's thesis, e-commerce and digital platforms experience constant new peaks in user amounts, euro volume and technological advancements. The first two share a strong connection with the COVID-19 outbreak. The COVID-19 pandemic has shown that sudden measures taken to limit the mobility of a society can result in negative repercussions, especially for brick-and-mortar stores, since consumers are unable to visit them. No one knows when the next global emergency arrives and what is the response to it. In the post-COVID-19 era, we should start preparing properly for the next crises. We now know that lockdowns and other strict measures drive more consumers on online platforms and to do e-shopping.

Lastly, governments should use more caution with stringency measures and create a long-term strategy to not let landscape developments put too much pressure on the socio-technical regime. The reaction to global events should be justified without overcompensating some aspects of the society and undercompensating others. To prevent stockpiling and panic buying behavior, a better strategy would also benefit consumers and provide stability.

6.3 Limitations and future directions

Different precautions were taken to make sure that the results are both valid and reliable. The dataset was strongly balanced and only full monthly data was used for each individual country. Initially, Turkey was included but left out due to the fact that the Eurostat database was missing unemployment data. And this leads to another issue. To be able to use new data, a sacrifice had to be made in the country-inclusion process. The research is missing 8 European Union member countries which speaks to the problem of generalizability of the results on the EU level. Even though the results indicate that different factors showed positive correlation with the e-commerce sector, the selection of countries could skew the outcome. Fortunately, Europe's largest countries were included to represent the geography with mostly small countries being left out of the research.

What comes to methodology, using panel regression as an analysis method was appropriate since there are both cross-sectional and time series elements with multiple variables. However, more tests could have been conducted to generate more accurate results. For example, you could separate countries either individually or in groups and regress the data that way. Also, by adding more related variables you could test with broader results. However, important metrics such as GDP, internet penetration and educational attainment only exist as annual data form and may not offer good results after all. Also, the results cannot be fully generalized for the European Union area, since some countries were missing.

Using COVID-19 cumulative cases instead of real amounts could pose a misalignment in the data since it only has growing values. With more time, it could have been tested in the estimator tests which data could had provided a more robust correlation with e-commerce volume.

Also due to time constraints, perfecting the used variables could have added to the validity and reliability of the research. Regarding the government stringency index, there could have been more suitable ways to calculate the monthly average from the daily data. During data collection, to save time, the mean was calculated arithmetically. There could had been months where the index was at e.g. lower values for a long period of time and then having high values for the rest of the month. It is difficult to discern a clear average that would reflect the true 'status quo' in a society. To collect e-commerce euro volume, Statista contained the needed data for most selected countries, but not all. To circumvent this, a more comprehensive database had to be found. Since there are multiple countries that are being compared, Statista was missing total e-commerce volumes for each country, so Ecommerce Europe (2016) had to be used instead for accurate B2C e-commerce euro volumes.

The findings of this master’s thesis could provide clues as to the main propagators of the factors on the multi-level perspective. Research could be conducted in larger ecosystems in e.g. Asia with similar variables to find out whether or not there are cross-sectional elements between Europe and Asia.

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APPENDICES

Appendix 1. Non-included estimates for panel regression.

estimator	R^2	P>F	coefficient		std. err.	p-value	obs.
fixed effects	0,010	0,000	stringency	0,077** (8,63)	0,008	0,000	608
			unem	0,350* (1.62)	0,216	0,106	
			covid_mc	1,14e-5** (7.26)	1,57e-06	0,000	
			_cons	19,653** (12.78)	1,537	0,000	
first-differences	0,033	0,000	stringency	0,041** (4,45)	0,009	0,000	608
			unem	0,013 (0,05)	0,288	0,964	
			covid_mc	4,97e-06 (1)	4,96e-06	0,317	
between	0,016	0,609	stringency	1,938 (1,32)	1,473	0,208	608
			unem	-1,807 (-0,65)	2,761	0,523	
			covid_mc	5,32e-5 (0,22)	0,0002441	0,830	
			_cons	-53,524 (-0,84)	63,685	8,313	
population-averaged		0,000	stringency	0,077* (8,67)	0,009	0,059	608
			unem	0,345* (1,60)	0,215	-0,077	
			covid_mc	1,14e-5** (7,28)	1,57e-06	0,000	
			_cons	19,682 (2,55)	7,722	4,549	
pooled OLS	0,023	0,002	stringency	0,254** (3,65)	0,069	0,000	608
			unem	-0,401 (-0,99)	0,405	0,323	
			covid_mc	2,73e-5** (2,40)	1,14e-5	0,017	
			_cons	15,117** (3,27)	4,625	0,001	
**=1% significance * =5% significance t-value in parentheses							