Conference Paper

Assessment of the Impact of COVID-19 on Grocery Retail in Ukraine

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Abstract

The coronavirus crisis affected the development of the global financial system: for some industries, the impact was extremely negative, reducing the market value of specific companies by more than 50%. However, the effect of the crisis on non-cyclical industries such as retail is not easy to assess. The resilience of companies strongly depends on the flexibility and multi-format qualities of the business model and the ability to innovate. For specific market players, the crisis period has become a window of opportunity to increase market share. For grocery retail in Ukraine, enormous challenges driven by COVID-19 influenced the acceleration of the transition from traditional sales channels to online shopping and led to an unexpected sharp growth of convenience and hard-discount store sectors. Consumers had to learn to live with the new reality that changed their shopping behaviors; a large proportion of them started to shop for groceries via online channels that they had never used before. A significant number of consumers are going to stick to online channels even after the reopening of brick-and-mortar stores. The objective of this research was to explore how COVID-19 affected the dynamics of the grocery retail market using economic-mathematical modeling. In employing Machine Learning methods, the authors offered an approach to assess the effects of the restrictions that the Ukrainian government imposed to localize the spread of COVID-19. The effects on consumer behavior metrics were modeled and interpreted according to local retailers' business models, the location qualities of brick-and-mortar stores, and potential shifts towards digital sales channels in specific regions.

Keywords: COVID-19 economic effect, grocery retail, consumer behavior, digital transformation

jel CLASSIFICATION codes: C13, C22, L81

1. Introduction

The coronavirus pandemic led to a significant shock in the world economy in 2020, as companies were forced to reduce their activity, and the government increased spending on supporting the health care system. As a result, Ukraine's gross domestic product (GDP) in 2020 decreased by 4.0%, according to the State Statistics Service, while in developed European countries, the declines of GDP were more significant: in Germany – by 5,0%, in France – by 8.3%, in the UK – by 9.9% [1]. However, in June 2020, the IMF predicted a drop in the national GDP of Ukraine by 8.2% and made an overly pessimistic forecast for an economy with such a structure.

The decline of the agricultural sector by 11.5% led to 1.0% GDP of Ukraine loss (out of 4.0%) due to the last year's snowless winter and, as a result, the drought in 2020 (Figure 1). The possible colossal drop in cash flows was reduced by the fact that prices for Ukrainian main export products rose to ten-year highs. As a result, domestic goods' sales to foreign markets in monetary terms fell by only 1.7%, while imports fell significantly – by 11.0%.

The decline in the transport and logistics sector by 16.4% led to GDP losses of 1.1% (Figure 1). The HoReCa (Hotel – Restaurant – Catering/Café) sector suffered the most – its gross value added in 2020 decreased by 28.5%. However, the contribution of this industry to the negative dynamics of GDP was limited to 0.18% [2].

Despite the primarily negative dynamics, several industries showed growth in 2020. One of the factors holding back the fall of GDP was construction. The industry's main driving force was the program "Big Construction", which has added 1.5% of the positive dynamics of GDP.

The public administration, real estate, IT, healthcare, and financial services sectors offset a 0.4% drop in GDP. However, the wholesales & retail industry contributed the most significant positive impact – 0.7% on GDP dynamics. Traditionally for Ukraine, the engine of the economy remained consumer demand: the increase in real wages by 10.1% and the inability to spend money abroad led to the rise in retail trade by 10.7%.

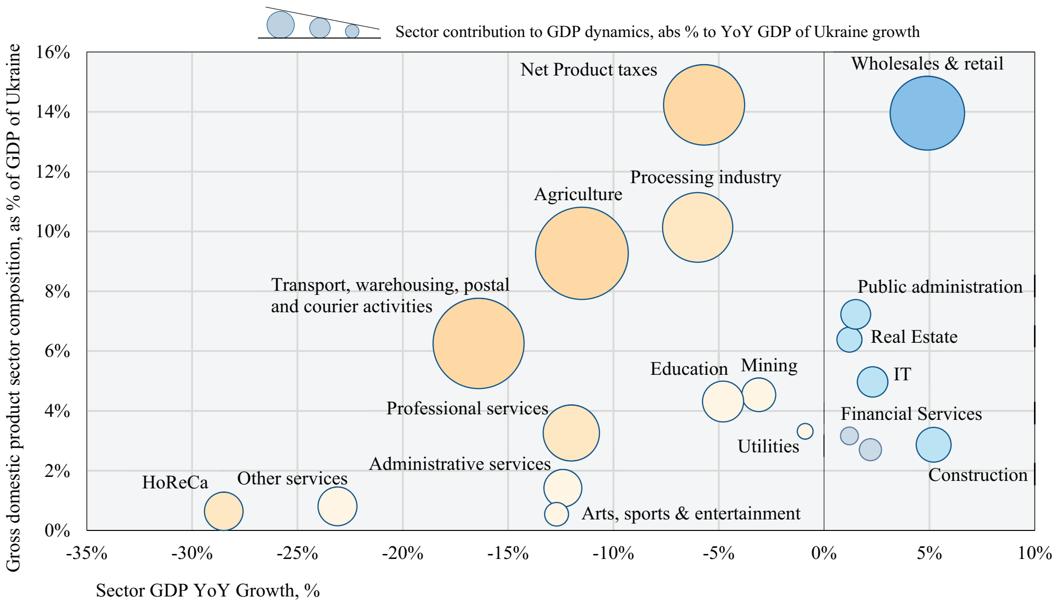

Figure 1: Sector contribution to 2020 GDP Dynamics of Ukraine. (Source: compiled by the author based on [3].)

Consumer habits are the most important external factor for retail planning and strategy formulation. Last year's pandemic globally changed the lives of consumers, including Ukrainians. Among the main trends and changes, the most noticeable were the following: temporary closure of stores or significant reduction in traffic due to the closure of malls where the point is located. The structure of consumption has changed; in particular, irrational mass purchases of certain groups of goods often occur. The crisis caused by the pandemic is also causing a change in the income of the population both around the world and in Ukraine. Thus, in America, consumers are reducing their expenses by almost 40% and, most importantly, plan to continue to reduce costs in the near future [4]. In Ukraine, this figure is not so homogeneous, as 43% of low-income respondents indicated that they significantly reduced their expenses, while among the representatives of the above-average consumer category, 25% remained within this point.

Due to the pandemic, buying processes have changed – previously conservative in terms of food retail, Ukrainian consumers quickly became accustomed to online shopping, which provoked and supported the active development of delivery services and general digitalization of retail. Thus, the pandemic affected the change in purchasing activity of Ukrainians not only in the minimum year, but also with the potential for this trend: 39% of respondents said that they intended to shop offline, rather than quarantine, and 32% of respondents planned and suggested the next one-two years more to buy in online stores [5].

COVID-19 is changing interactions with consumers at most points of contact: retailers now have to reinvent shopping, provide a highly hygienic environment through the physical changing of the store, enhance their own digital capabilities, work deeply with loyalty programs, and understand where and how they engage its customer and reimagine value for money. Thus, pandemic impact touched as operational as sales and marketing functions.

Even the processing of data for consumer interaction has changed. Previously, the primary purpose of the analysis was collecting consumer insights in real-time and accurate planning. Now, a very volatile market requires retailers to forecast accurately and replace marketing models with those that provide for consumer insights, or rather, form them through an experience that is unusual and uncommon for them [4].

In general, the trend of business development in a pandemic is such that now businesses that survive in these crisis conditions find themselves a wholly renewed and long-term adapted ecosystem with radically different approaches to stores, supply chain management, marketing, e-commerce, and operations. In this way, companies gain significant competitive advantages and increase their flexibility for consumers after the pandemic.

The main objective of the research is to build a tool that allows identifying critical structural changes for grocery supermarket chains to adapt to market trends and behavioral changes. Furthermore, the insights derived from the Ukrainian retail market analysis may be helpful to build a corporate strategy for the global grocery retail companies to remain competitive and adjust the expansion processes according to the local needs of the target audience.

2. Approach to COVID-19 Impact Assessment

2.1. Data Preparation Overview

Assessing the effect of the coronavirus crisis on the development of the retail market in Ukraine is a rather complex task. The grocery retail market in Ukraine demonstrates a high level of diversity and concentration in each region. At each oblast level, competition continues between local players, which create a personalized offer for residents' purchasing power, and national supermarket chains with more significant investment resources and new personal experience.

Of course, it should be noted that COVID-19 has led to the launch of various forms of quarantine. At the beginning of the pandemic, restrictive measures on public transport, visits to food establishments, entertainment events, and non-food outlets, including shopping malls, were introduced throughout Ukraine. On July 22, 2020, adaptive quarantine was launched in Ukraine. Such COVID-19 prevention and control measure specifies appropriate geographical zones depending on the level of pandemic spread:

- **Green zone:** restrictions on the number of passengers in transport, 50% occupancy of cinemas, the mandatory wearing of a mask/respirator in public buildings;
- **Yellow zone:** all restrictions that apply to the green zone and a ban on visiting social protection institutions;
- **Orange Zone:** all restrictions that apply to the yellow zone and a ban on accommodation (except hotels), entertainment and restaurants at night, scheduled hospitalization of patients; the activities of gyms, sports clubs, cultural events, with a limit of 1 person per 20 square meters and less than 100 people.
- **Red zone:** all previous restrictions and a ban on public transport in the normal mode, the activities of restaurants and malls, visits to educational institutions.

After analyzing the choice of a possible format for the study of quarantine's impact to ensure the bias of assessments and based on covariance analysis, the entire period of all-Ukrainian lockdown and red zone periods in some regions during the adaptive quarantine were selected. Other constraint formats do not provide sufficient periods to assume that their impact assessments are sustainable.

The daily time series of sales for each store individually for the period from January 1, 2018, to March 31, 2021, was used to assess the impact of COVID-19. To do this, data from six national chains of grocery stores, which represent mini-markets, convenience stores, soft discounters, supermarkets, premium markets, and hypermarkets, was used. The retail formats of stores were classified by the range of characteristics: size, type of location, assortment, and price formation (Table 1).

The grocery retail chain's antifragility to COVID-19 is driven by the ability to transform rapidly and the high diversification of the store format portfolio. However, on each store's level, a range of endogenous and exogenous factors may influence the revenue dynamics during lockdowns specifically. Endogenous factors can be described by service drivers: operational efficiency of personnel and the ad-hoc accessibility metrics

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(Out-of-Stock and Out-of-Shelf rates), which directly affect the store guest's satisfaction (Customer Satisfaction Index).

However, exogenous factors have even more influence. Among the most influential are the following factors: seasonality of sales during the day, week, month, year, the growth cycle stage of the store, weather conditions. Seasonality patterns can be fully explained by the store location features: regional pattern (higher sales in the southern region and suburbs during summer and in large cities and the west during winter), the presence of infrastructure facilities within a radius of the location, as well as business centers, malls, and other entertainment facilities. The classification will also include indicators of whether the point-of-sale can be considered a convenience store or a destination store, average price of real estate, total number of flats within a radius of the location.

Table 1: Descriptions of grocery retail formats on the Ukrainian market.

Dimensions	Size	Location	Assortment	Price	Ukraine grocery retail chains
Mini-market	0–150 m^2	Close to home, objects of transport infrastructure	Limited assortment, focused on specific product group	Low - upper-medium	Kolo, Foody, Rukavychka
Soft Discounter	150–500 m^2	Outskirts, roadside, seldom close to home	Narrow, specific (category stores): 2,000–5,000 SKU	Low, dominated by Private Labe	ATB, Thrash!
Convenience	200–800 m^2	Close to home	Narrow: 3,000–10,000 SKU	Medium - upper medium	Fora, ATB, Thrash!
Super	600–5,000 m^2	Malls (destination stores) or traffic roadside	Medium-wide (Full fresh line): 8,000–30,000 SKU	Medium-High	Silpo, Fora, Novus, VK Group, Varus
Premium	600–5,000 m^2	Malls (destination stores) or city center	Wide - specific wide: 8,000–30,000 SKU	High	Silpo, Good Wine
Hyper	3,000+ m^2	Outskirts (destination stores), rarely malls	Wide: 20,000–60,000 SKU	Medium	Fozzy Cash & Carry, Auchan, Metro

Source: compiled by the author based on [6].

2.2. Identification of COVID-19 impact using Machine Learning methods

In order to most accurately determine the impact of the launch of strict quarantine restrictions, several transformations were implemented: data cleaning from anomalies and seasonal decomposition of sales dynamics.

1. To avoid taking into account days when shops were closed entirely or were affected by unforeseen and unsystematic events (refitting periods, closure of shopping malls or subways due to suspected mines, closure of roads for repairs), the data were cleared of outliers. To achieve this goal, a number of anomaly identification methods based on clustering were used.

An anomaly in our approach is considered a multivariate outlier - a combined extraordinary sales level on a specific day of the week. To detect them, the following algorithms were used [7]:

- ***k*-Nearest Neighbors Detector**: for each observation, the distance to its *k*-th nearest neighbor signals of a possible outlying score;
- **Isolation Forest:** performing data partitioning in the form of a set of trees allows to check how isolated the observation is in the structure;
- **Angle-Based Outlier Detection (ABOD):** the relationship between each observation and its neighbor in the form of the variance of its weighted cosine scores helps to detect the outlying score;
- **Histogram-based Outlier Detection:** deriving of the outlier score by building histograms;
- **Local Correlation Integral (LOCI):** identification of anomalies based on clusters, their diameters, and their inter-cluster distances.

Finally, the anomalies probability scores of five models (Figure 2) are ensembled to receive the weighted probability to consider the point as an outlier. After the revision that anomaly observation does not lay in the horizon of holidays or lockdown periods, the data will be cleaned. Using time-series modeling, these points will be filled with unbiased forecasts.

2. To clear the assessment of the effect from substantial seasonal shifts, holidays, and trend differential change, a seasonal series decomposition was proposed. For such an assessment, a method of decomposition based on the fbprophet algorithm was used.

The model was implemented using the open-source libraries in Python. The core of the algorithm lies on a decomposable time-series model with three components: trend, seasonality, and holidays [8]:

$$y(t) = g(t) + s(t) + h(t) + r(t) + e_t, \tag{1}$$

where $g(t)$ - non-periodic trend component, $s(t)$ – seasonality component (weekly, monthly, yearly periodicity), and $h(t)$ – holidays effect component and $r(t)$ – regressor, e_t - the error term, which represents any idiosyncratic changes which the model does not

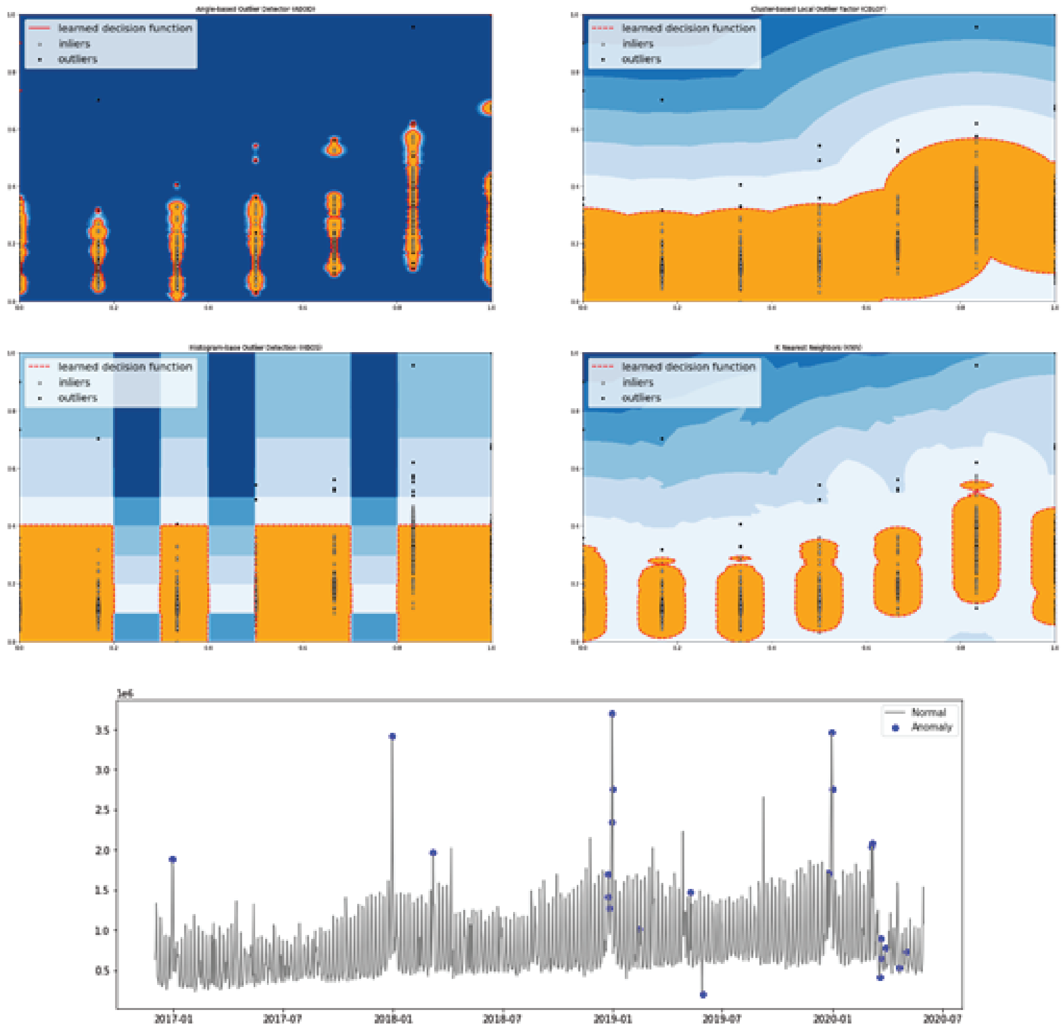

Figure 2: Anomalies Detection. (Source: compiled by the author based on Python PyOD library.)

accommodate. The multiplicative approach and the log transformation to identify the value of components were used to model the seasonality.

The non-periodic trend component is modeled using the modified logistic growth model in the form [9]:

$$g(t) = \frac{c(t)}{1 + e^{-(b+a(t)^T \delta)(t-(m+a(t)^T \gamma))}} \tag{2}$$

The limiting value $c(t)$ is not constant as the store's traffic can be driven by the district property development or the income growth of residents.

The growth rate $b + a(t)^T \delta$ can also change in time as the store can be refitted, or some competitors can exit the local market busting sales growth dramatically. So the changepoints for the trend reversal are defined to incorporate a varying rate to fit the historical data. The constant growth rate for the period before changepoint is described by b parameter and $a(t)^T \delta$ stand for the shift of the growth rate, where $a(t)^T$ is a binary operator for time events when the acceleration/deceleration $\delta \in \mathbb{R}$ occurs. The binary operator for time events can be described by the vector:

$$a_i(t) = \begin{cases} 1, & t \geq \tau_i \\ 0, & t < \tau_i \end{cases}, \quad i = \overline{1, n} \tag{3}$$

As a result, after i changepoints, the growth rate is adjusted to $b + \sum_{i:t \geq \tau_i} \delta_i$. At the point where the growth rate is adjusted, the offset parameter $m + a(t)^T \gamma$ can be described by the formula:

$$\gamma_i = \left(s_i - m - \sum_{l<i} \gamma_l \right) \left(1 - \frac{b + \sum_{l<i} \delta_l}{b + \sum_{l \leq i} \delta_l} \right) \tag{4}$$

Such a trend model described above effectively fits the historical data; however, it can make an incorrect extrapolation for the future by extending the generative model based on short observation periods forward. Such risk is mitigated by simulation of future changepoints to match the historical average frequency of changepoints.

The sales dynamics of grocery retail stores have a range of multi-period seasonalities, as were described earlier. The most effective way to create a flexible model for periodic effects is to decompose seasonalities in the form of Fourier series without an intercept term [10]:

$$s(t) = \sum_{n=1}^{N} \left(a_n cos(2\pi nt) + b_n sin(2\pi nt) \right) \tag{5}$$

The seasonal component can be transformed to the form:

$$s(t) = X(t) \beta^T, \tag{6}$$

where $X(t) = [cos(2\pi t), \ldots, sin(20\pi Nt)]$ – matrix of seasonality vectors for each t and $\beta = [a_1, b_1, \ldots, a_N, b_N]$ – the vector of parameters. AIC, as a model selection procedure, was used to choose the optimal parameters.

The third component, which influences the store's sales, is holiday shocks, which sometimes do not have a periodic pattern (for example, Easter, local events) or, on the contrary, can be easily recognized (New Year's Eve, Christmas). The model is similar to the seasonal component:

$$h(t) = Z(t) \kappa^T, \tag{7}$$

where $Z(t)$ – binary matrix of holiday events for each t and κ – the vector of parameters. The holiday effect includes additional surrounding days as the major sales shock occurs during the week before a specific event.

To extract the influence of regressor – red zone quarantine and competitors opening/closure in our case – exact the same algorithm as for the holidays is implemented. The result of extraction will allow us to measure the pure decomposed influence of COVID-19 prevention and control measures on sales of a specific class of stores. The result of described decomposition is represented in Figure 3.

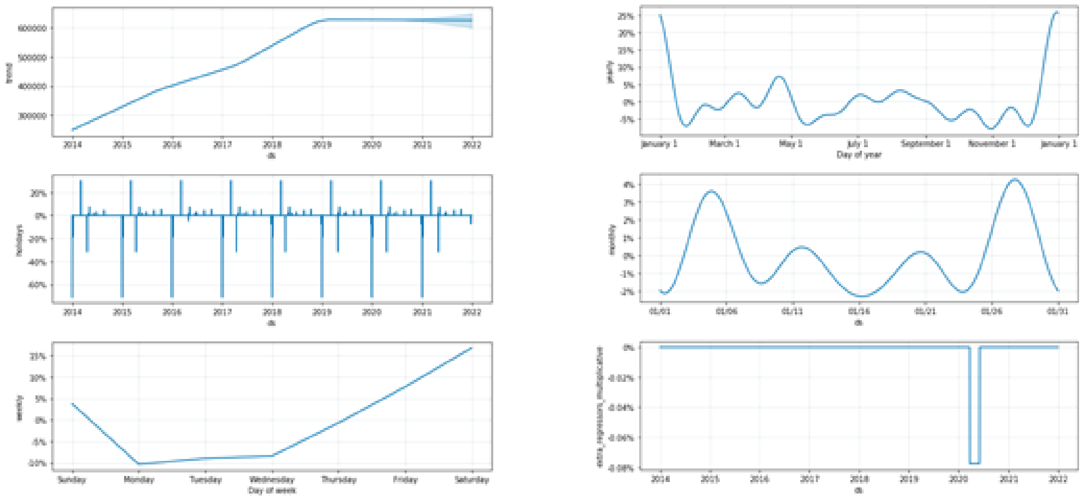

Figure 3: Seasonal Decomposition Results. (Source: compiled by the author based on Python fbprophet library.)

Stan's L-BFGS approach is implemented to fit the model's parameters and minimize mean absolute percentage error (MAPE) as a target metric [11]. The cross-validation was used for tuning hyperparameters of the model, such as changepoint, seasonality, and holiday prior scales. The creation of a grid of the parameters, with parallelization over cutoffs, helped to identify the optimal model for each store. The parameters were evaluated based on average RMSE over a 15% horizon random sample of all historical observations.

The model training gave a result of 14.3% MAPE on the test dataset for all of the 586 stores. The result of forecasts is represented in Figure 4.

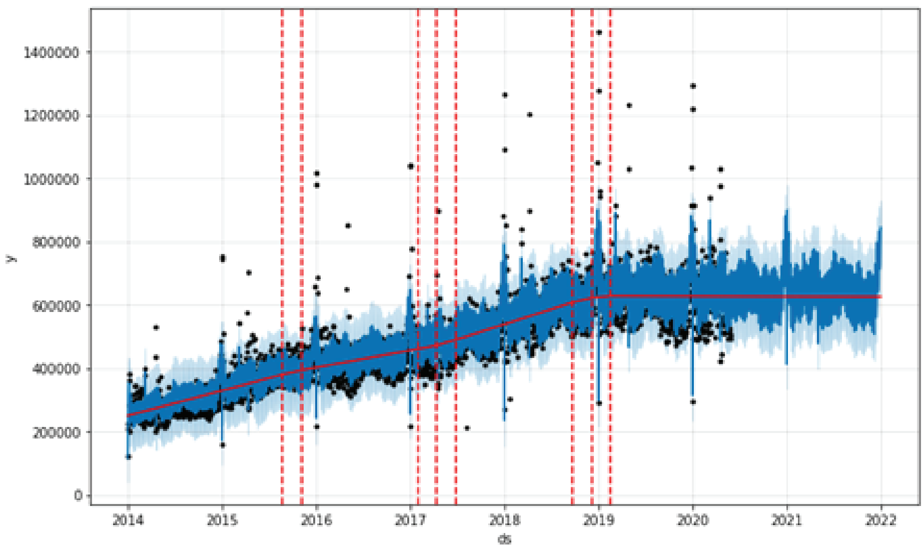

Figure 4: Example of forecasting the sales dynamics of the specific supermarket. (Source: compiled by the author based on Python fbprophet library.)

3. Results of COVID-19 Impact Assessment

Based on the decomposition results and assessment of the effect of quarantine measures at each store's level, it was found that mini-markets, discounters, convenience, and premium formats were flexible enough to adapt and gain additional benefits from the growth of growth the average check (Figure 5). However, the same cannot be mentioned about supermarket chains, which have suffered significant losses due to reduced traffic at their locations. Therefore, let us look at the effects on each format separately.

The positive impact on mini-markets and convenience stores can be characterized by a reduction in customers' day-to-day movements. It is much more efficient for the specific population category to use the closest point-of-sales to get basic-needs products or use specialty stores for specific assortment. In this case, the prior purchases are made in the destination store or are ordered through its courier delivery of a network of stores, specialized online food distributors, or logistics operators such as Glovo or Rocket in Ukraine. Thus, for mini-markets, the main driver of sales growth is an increase in the frequency of purchases, and for convenience stores - the average purchase amount; the effect increases in direct dependence on the population density within the point-of-sale.

For discounters, the sales growth during the pandemic is driven by the redistribution of supermarket traffic towards cheaper promotional purchases with a lower gross margin as buyers' reaction to the uncertainty of their income level and the end of quarantine. It is worth noting that all of the above formats are characterized by a significant increase in the average purchase size, which compensates for the fall in traffic.

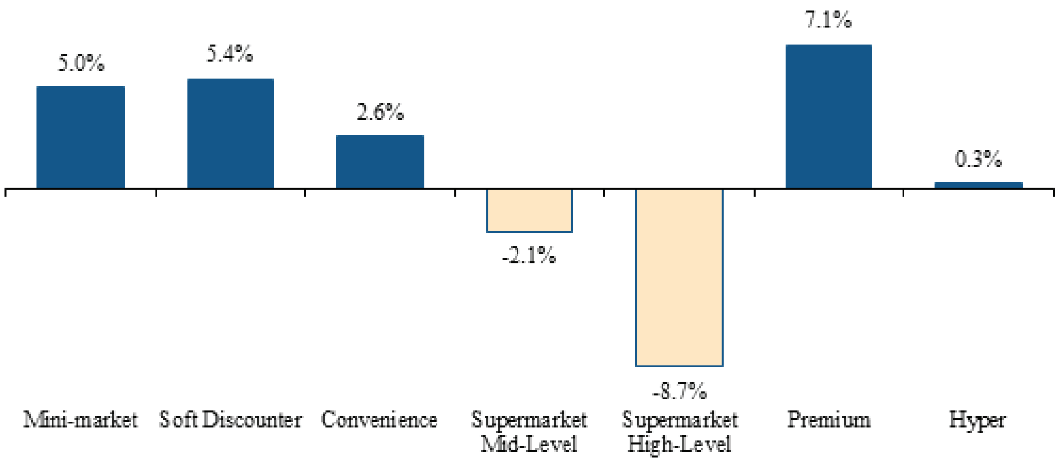

Figure 5: Median impact of COVID-19 on sales dynamics of the stores grouped by format. (Source: compiled by the author.)

For supermarkets, a hard lockdown has resulted in a significant reduction in traffic compared to smaller formats. However, this is mainly due to such a format's traditional location priorities: city centers and busy places such as shopping or business centers. In addition, as a result of the quarantine launching, most entertainment centers were forbidden to visit, which caused the loss of such a portion of traffic that even the average check growth could not compensate for that. For the High-Level supermarkets, the effect is much more critical since such stores are located in the modern shopping malls outside the city with an average area of 35 000 m^2. The relationship of effect on supermarkets sales and size of the mall, where they are located, can be identified in Figure 6.

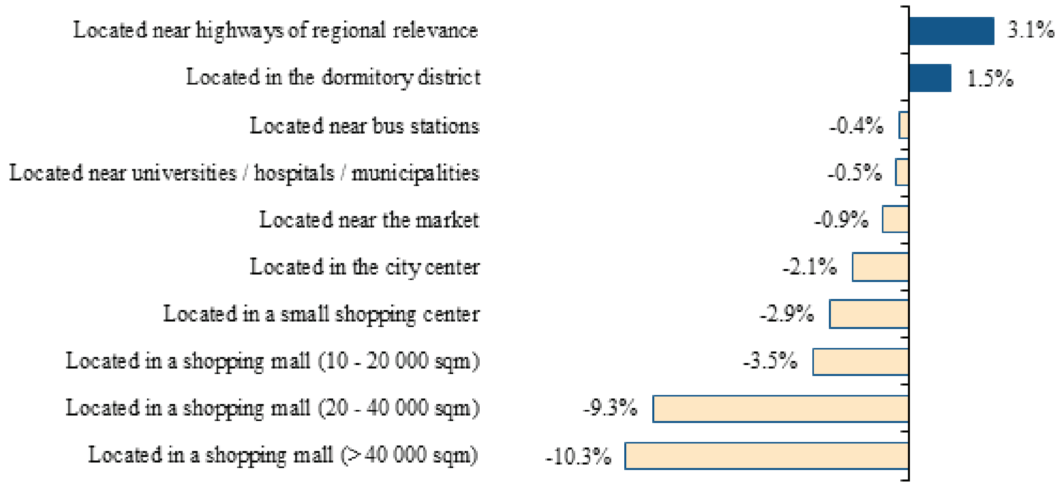

Figure 6: Median impact of COVID-19 on sales dynamics of the stores grouped by location parameters. (Source: compiled by the author.)

The premium segment has a separate loyal target audience. The quarantine measures do not particularly affect their purchasing power and behavioral characteristics as buyers of the premium food segment. Insurance against potentially extended stays at home during a hard lockdown and the replacement of restaurant services have led to a significant increase in the average shopping basket of the premium format target audience with a slight loss of visit frequency.

Hypermarkets can be identified as the only format not affected by the launch of the red zone quarantine. Business representatives of the HoReCa sector, who had to reduce the volume of purchases, were replaced by buyers who accepted the price benefit of such a format.

The flow has moved from the supermarket segment towards such formats as mini-market, discounter, and convenience stores, but the way out of the quarantine has shown that this trend can be reversed. The biggest potential threat or an opportunity to boost sales to all formats is the online delivery segment, which has grown from 0% to 5% of the total sales of the brick-and-mortar grocery retail chains in 2020.

4. Conclusion

Ukraine's GDP in 2020 decreased, but not as much as the GDP of other European countries, including Germany or France. In a certain way, this is due to the structure of Ukraine's GDP and the fact that consumer demand is the main engine of the Ukrainian economy. Considering this factor and the fact that part of the demand of Ukrainians, who often travel, in 2020 was realized in the domestic market, it is pretty logical that the wholesale and retail industry had a positive effect on GDP for 0,7%. Moreover, this indicator is the largest among other Ukrainian industries representing the retail sector as the most prospective during the COVID-19 crisis.

Nevertheless, just like any other industry, wholesale and retail are going through tough times. At the exact moment, the difficulties (changes in consumer preferences, the closure of retail outlets, the requirement for digitalization), which the players of this market face, to a certain extent, catalyze the development of this industry. Thus, companies capable of surviving the crisis caused by the global pandemic will significantly improve their competitive position for the market in the future.

To evaluate the impact of COVID-19, six grocery store chains of various formats were analyzed. As a result, the main factors of changes were discovered, among which are both endogenous and exogenous. A range of Machine Learning methods was used to clear data: clustering anomaly identification methods, a seasonal series decomposition based on a fbprophet algorithm. The recommended approach to the assessment of COVID-19 impact on sales dynamics was quite effective in recognizing consumer behavioral patterns in such a period of transformations. The influence of various grocery retail formats and brick-and-mortar location characteristics was identified.

Our research insights may be helpful for grocery retail companies to build a corporate strategy to remain competitive in the market. The insights gained from the COVID-19 impact assessment approach proposed in the article helped determine that companies focusing on traditional supermarket sector development should expand into affordable convenience-store segments during a period of hard lockdown. To avoid potential loss of target audience, companies should avoid expansion into shopping malls or business centers but focus on residential areas and locations on roads of regional relevance. Current locations in the grocery retail company portfolio that face government restrictions can be used to expand e-commerce infrastructure: dark stores or pickups. Ongoing monitoring will allow companies to adapt quickly by changing corporate strategy, maximizing operating income, and optimizing investment budgets.

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