At what lag should economic indicators be applied to predict sales in a transformed economy? Is it worthwhile when e-tailing?

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Abstract

Making strategic decisions in retailing is associated with analysing sales development, which can indicate the current trends in consumer demand. Determining retail sales indicators is a valuable step towards better prediction and helps to make strategic decisions more realistic. However, the question is to what extent the general assumption of profitability of using retail sales indicators can be applied in the case of a transformed economy. This paper aims to provide information on the possibility of using selected economic indicators to predict sales in the environment of a transformed economy. The paper analyses the joint time series development of retail sales in the Czech Republic. The Johansen cointegration test has been performed to determine whether retail sales show long-term cointegration with the set of selected indicators. The results establish GDP, total employment, gross wage, and consumer data as leading indicators of retail sales at different levels of delays. In contrast, in the case of online retail sales, no significant influence of the observed factors has been found. The findings suggest that if managers choose to plan their online retail processes based on retail sales estimates, they must respond to changes in these indicators much faster than managers in offline environments.

Key words

transformed economies, retail industry, retail sales, economic indicators, cointegration

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Introduction

Retail sales are an important part of the state economy because they reflect the current condition of the market and the development of selected time series. Frumkin (2000)

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considered retail sales to be a key indicator of consumer spending. Therefore, there is a positive correlation between retail sales and overall performance (Pícha et al., 2013). Over time, researchers have examined many different factors that can affect retail sales, including the weather (Starr, 2000), price anchors (Anderson and Simester, 2003), customer satisfaction (Gómez et al., 2004), online reviews (Floyd et al., 2014), and prediction methods and models (Aras et al., 2017; Chong et al., 2021). Although numerous prediction methods have been developed, finding representative predictors by means of which to achieve good performance is still challenging, and economic indicators are still used to link to the condition of an economy when predicting retail sales (Wang, 2022).

Retailers attempt to engage consumers by implementing a variety of technologies and business models (Kita et al., 2022) in the buying process. The aim of these technologies and tools is to facilitate decision making through visual display and menu decisions, consumption and engagement big data collection, analytics and profitability (Grewal et al., 2017). Despite brick-and-mortar retail still dominating the way customers shop, the rapid growth of e-commerce is rapidly changing customer shopping habits and determining the future of retail (Ratchford et al., 2022).

Customers do not make their purchase decisions based only on a functional, physical, or economic need for a purchase. For example, one analyses the influence of rationality and irrationality (emotions) on the purchasing decision-making process (Matušínská and Zapletalová, 2021). Babin et al., (1994) identified two dominant customer-shopping motives (hedonic and utilitarian) in traditional retail, which influence customer purchasing decisions as well. Later, it was found that these shopping motives also influenced customers in the online environment (Childers et al., 2001). The hedonic motive increases sales in traditional retail, as customers are motivated by the physical environment itself, the ability to see products, and social gatherings. Customers with a utilitarian motive prefer to buy online to avoid unscheduled purchases. This situation may increasingly negatively affect the number of sales in traditional retail due to the coming digitalisation of the retail format. Therefore, this study also focuses on the use of economic indicators to predict sales in the case of e-tailing.

In the 1990s, many Eastern European countries began to transform their economies. The economic system has gradually changed from a CPE to a market economy. This caused the law of supply and demand to suddenly come into effect and change the way customers shop. Therefore, the motivation for this paper is to compare whether the generally accepted relationships between economic indicators and retail sales (Cai and He, 2014; Mitchell et al., 2005) can also be applied in the transformed Czech economy. Retail sales reflect the state of the economy and are important in the analytical part of the creation of strategic plans by business organisations. Therefore, this paper is also intended for business organisation managers to enable them to examine how economic indicators can predict the development of retail sales and online retail sales. In addition, the theory of dividing economic indicators into groups (leading, lagging, coincident) for sales forecasting was specified more than 30 years ago (Burstiner, 1991); therefore, the motivation for writing this article was to check whether the general assumptions of the relationship between selected economic indicators and sales development are still valid. Furthermore, the development of the Internet and the possibility of online shopping is also important here; as such, we also looked at whether economic indicators can be used to predict online sales or whether the environment is so different that the relationship is not proven. For these reasons, the authors of the paper have formulated the following research questions, which will be verified using data from the Czech Republic, as an example of a transformed economy, for the period 2001-2019.

RQ 1: How do lagged economic indicators reflect the development of retail sales in the Czech Republic?
RQ 2: Is it appropriate to use such lagged economic indicators for predictions in the online environment as well?

This paper aims to provide information on the possibility of using selected economic indicators to predict sales in the environment of a transformed economy. The first part presents the main theoretical background of the economic indicators, while the second part characterises the selected research method to determine which economic indicators have long-term relationships with the development of retail sales. The next part describes the selected procedures, and the results of the research are discussed. The last part of the paper summarises the proven relationships between economic indicators and retail sales and concludes the core findings.

1. Literature review

1.1 The economic indicators of retail sales development

Retail is undoubtedly an important branch of the national economy, and the development thereof is historically related to the development of the economy, in the sense of observing the economic conditions of the country (Sagaert et al., 2018). Retail sales of consumer goods can reflect consumer demand, and are also an important indicator by means of which the government may study social and economic trends (Shen et al., 2019). Within the industry itself, in recent years, two forms (online and offline) of trading operate side by side or together, which increases the importance of omnichannel marketing strategies (Timoumi et al., 2022). The offline environment has historically consisted of a network of stores where buying and selling are done physically, and this form of selling is still dominant. In the online environment, all activities supporting market transactions, including marketing, customer support, delivery, and payment, are provided within e-commerce (Schniederjans et al., 2013; Turban et al., 2017). Retail, whether bricks-and-mortar or online, depends on the purchasing power of the population. Although retail has several functions within the logistics chain, its main objective is to sell goods to the final consumer to meet their needs; in the omnichannel context, shoppers are still ‘kings’ and ‘queens’ with the final decision-making power (Mimoun et al., 2022).

The purchasing power of the population can be affected by several factors, such as income, the prices of products, savings, or the availability of credit. Retail sales are a significant indicator that reflects the development of household consumption related to the factors mentioned. As household expenditures represent a component of Gross Domestic Product (GDP), this indicator can influence the movements of other economic entities and consequently the development of other indicators of economic development (Pícha et al, 2013). Creating a retail sales prediction is an important part of strategic business management. Forecasts are used to provide funds for investments and operations of retail units and to measure the required amount of material and goods. Retailers perceive sales forecasting to be important because it helps practitioners achieve better financial budgeting, operation planning, and inventory policies (Ma and Fildes, 2021). Companies perform the statistical analysis of demand. Companies derive their retail sales from historical sales (Zhang et al., 2020), analysing time series (Sagaert et al., 2018), and econometric analyses (Gao et al., 2018).

These analyses measure the impact of causal factors (such as prices) on the development of retail sales, also known as an indicator.

The available studies also examine the factors that affect retail sales while taking the location of sales into account. These factors include, for example, those acting on retail sales according to the size of the settlement unit, which is addressed in a study by Walter et al. (2018). Country-specific studies are also emerging. Sales forecasts cover both total retail sales and a particular product range. Liu et al., (2021) base their research on the fact that total retail sales of consumer goods are not only an important indicator by which to measure consumption levels, but also an important indicator of the national economy and the healthy development thereof, and a basis for corporate decision making. Often, this includes strategic commodities, energy, or agricultural products. Predictions for different sales channels are addressed, as are distribution channels in offline and online environments.

The development of e-commerce inspires the study of e-commerce, as sales are increasing year-on-year around the world and the Czech Republic. In addition to GDP, Jiao's (2021) study also works with other indicators that influence the development of online sales, such as the number of Internet users or the expenditure of urban and rural residents and their association with retail sales. A study by Xu et al., (2020) even addresses 15 variables acting in the online environment on apparel sales in their regression model.

Retail sales indicators are economic categories that can reflect retail sales development. For this reason, companies use them for strategic planning. Unfortunately, in practice, the most challenging discipline is the identification of effective predictors and their associated temporal causalities (time lags) (Wang, 2022). These economic indicators can be divided into leading indicators (Feizabadi, 2020; Sagaert et al., 2018), coincident and lagging indicators (Feizabadi, 2020).

1.2 Leading, coincident and lagging indicators

Leading indicators predict the subsequent development of retail sales. Retail sales are influenced by the movement of leading economic variables, either up or down; thus, leading indicators predict changes in sales activity. Burstiner (1991) states that the leading indicators are labour productivity, monetary policy, and consumer expenditure. Some authors, such as Ring (1984) and Gale (1996), when dealing with household incomes and their impact on retail sales development, address the issue of the level of retail sales and their impact thereon.

The next group is coincident indicators, which are economic indicators that change at the same time as retail sales. The coincident indicators are the gross domestic product and company profits (Burstiner, 1991). Other experts deal with the relationship between retail sales and GDP (see, e.g. Mitchell et al., (2005)). According to them, retail sales are an important indicator in macroeconomic policymaking due to their availability, as data are recorded monthly, while GDP is quarterly. Based on research by Kim et al., (2006), it is clear that both sales and business developments are closely correlated with GDP as the main indicator of economic development. Therefore, it is necessary to monitor the development of GDP when estimating the development of sales. Future estimated revenue is the basis for determining profit margins and other economic indicators needed for managers to make decisions. Other authors look at the structure of GDP and the components which it is affected by. Retail sales are a part of household consumption, which is one of the most important components of GDP. Cai and He (2014) also assessed the relationship between GDP and other indicators, including sales development.

The last group is of lagging indicators, which evolve with a delay in time after the development of retail sales. The discount rate and the stock/sales ratio are typically lagging indicators of retail sales (Burstiner, 1991). Central banks respond by changing the discount rate to consumer demand and sales developments, indicating the discount rate as a lag. Consequently, this change can be considered a lag indicator as it, in turn, affects household consumption and goods turnover. However, according to Rejnuš (2014), consumer demand is relatively inelastic in terms of interest rates. Rather, non-price characteristics, such as the size of repayments, maturity, etc., determine consumer credit.

1.3 The use of indicators in sales forecasting

Certain patterns in the retail market reflect the economic development of a country and vice versa. Some authors had chosen other indicators that we mentioned earlier, the development of which is related to the development of retail and retail sales. They examine this problem in a broader context and discuss retail and economic levels. For example, Boer (2000) correlates the share of the employment of the population in services (including retail) and the share of the population's expenditure on groceries with the level of retail and the economy.

Existing sales forecasting methods mostly use previous sales data to forecast sales in the next period (Zhang et al., 2020). Sales forecasting is a key component of company planning and control activities, where companies try to forecast sales by tracking one or more indicators (Chen, 2010). For example, macroeconomic conditions, such as the change in the consumer price index (CPI), would not only affect consumers' willingness to buy but would also contain forward-looking environmental information (Zhang et al., 2020). Sagaert et al., (2018) also demonstrate the usefulness of macroeconomic leading indicators for tactical sales forecasting.

The measures implemented within the framework of state economic policy can have a pronounced influence on retail sales. Following the previous example, this could be a positive change in the country's housing policy, which may subsequently affect the sale of building materials and household equipment. Recently, new perspectives on forecasting using previously unused indicators are also evident, such as forecasting building permits with Google Trends (Coble and Pincheira, 2021) and online reviews (Zhang et al., 2020). In reality, regardless of the type of economic indicator (leading, lagging, or coincident), Wang (2022) points out that types of indicator are often mixed together. However, he argues that they need to be identified in order to extract significant predictors before constructing forecasting models.

2. Methodology

The objective of the research is to discover which economic indicators can reflect the development of retail sales. The purpose of the research is also to discern what kinds of economic indicators are examined from the theoretical point of view. On the basis of the research, it is possible to increase the knowledge of whether the economic indicators studied reflect the development of retail sales and whether their use is also appropriate in the case of sales coming exclusively from the online environment. Cointegration analysis was applied to evaluate the data, which was used mainly to analyse the data in financial markets (Shin, 2021) and various econometric analyses. Available studies have looked at, for example, the relationship between government spending and economic growth, the relationship between stock prices and dividends, demand elasticities (Rodrigues and Bacchi, 2017), and price cointegrations between products (Fuhrman et al., 2021).

Six possible economic indicators have been selected for the analysis of the cointegration with retail sales, namely the household final consumption expenditure (HFCE) mentioned in the discussion and the conclusion as consumer data due to the marketing view of the research area in this paper, the unemployment rate (UR), the consumer price index (CPI), gross wages (GW), gross domestic product (GDP), and total employment (TE). The values of the variables have been converted into a percentage change in the time series. The Johansen cointegration test was performed using EViews software to determine whether retail sales have a long-term cointegration with the set of selected indicators.

2.1. Sample

The data for the research was obtained from the Czech Statistical Office. All secondary data are used at a quarterly frequency, covering the period from 2001 (Q1) to 2019 (Q4). The description of the data after their change to a percentage change over time is available in Table 1. If we focus on skewness, it can be said that data are highly skewed only in the case of the CPI. The rest of the data are moderately skewed and some of them (the unemployment rate, gross wages, and GDP) are approximately symmetric. The following table includes a data description of the selected indicators, as well as a data description of the retail sales value (RSV) as a whole and the value of retail sales made on the Internet or via mail-order (IRSV). In other sections of the paper, for the purposes of a better understanding, we use the term retail sales to denote sales for the entire market (including offline sales and sales made via the Internet or mail-order) and online retail sales for sales made via the Internet or mail-order.

Table 1. Data description

	HFCE	UR	CPI	GW	GDP	TE	RSV	IRSV
Mean	1.137	-0.119	0.401	1.343	0.073	0.168	0.115	17.143
Median	2.465	-0.142	0.333	1.900	0.249	0.209	0.304	16.950
Maximum	7.134	1.385	3.300	11.944	4.428	1.857	4.213	34.200
Minimum	-8.631	-1.033	-0.800	-13.389	-5.698	-2.146	-6.657	1.100
Std. Dev.	4.540	0.445	0.660	6.611	1.590	0.835	1.777	7.702
Skewness	-0.888	0.486	1.495	-0.456	-0.263	-0.737	-0.871	-0.172
Kurtosis	2.378	4.041	7.362	2.519	4.877	3.268	5.253	2.576
Sum	85.266	-8.902	30.067	100.703	5.438	12.621	8.660	685.700
Sum Sq. Dev.	1525.553	14.623	32.249	3234.090	187.009	51.542	233.622	2313.598

Source: own elaboration based on data from the Czech Statistical Office Database, 2020

2.2. Data Analysis

The first step in data processing will be to examine the existence of correlation. Subsequently, a Johansen system cointegration test will be performed to express the linear relationship between the selected economic indicators.

Correlation

To reveal the relatively linear relationship between the monitored variables, we applied correlation analysis. The calculation of the Pearson correlation coefficient is as follows (Brooks et al., 2002):

$$the\ r_{xy} = \frac{\sum(x_i - \bar{x})\,(y_i - \bar{y})}{(n-1)s_x s_y} \qquad (1)$$

where x and y are the sample means of X and Y variables, and sx and sy are the corrected sample standard deviations of X and Y. The Pearson correlation is +1 in the case of a perfect direct linear relationship, −1 in the case of a perfect inverse linear relationship, and some value in the open interval (−1, 1) in all other cases, indicating the degree of linear dependence between the variables. The closer the coefficient is to either −1 or 1, the stronger the correlation between the variables is.

Cointegration analysis

The analysis of the data was divided into three steps (testing stationary, finding lags, finding cointegration) to find answers to the research questions formulated. The first step was to use the Augmented Dickey-Fuller (ADF) test, as one of the best-known and most widely used unit root tests (Artlová and Fedorová, 2016). The intercept was included in the ADF test equation. The second step was to provide a Lag Exclusion Wald test to find lags between economic indicators and retail sales. The results of the test were then used in the Johansen system cointegration test. After testing the data for stationarity and providing the VAR test, the Johansen system cointegration test was performed. The Johansen tests are robust to both skewness and excess kurtosis in cointegration errors. Skewness refers to an asymmetry that deviates from the symmetrical normal distribution in a set of data. Symmetric distributions, including the normal distribution, have skewness values equal to zero. This test was used to find any cointegration between the development of the economic indicators examined in this research and the development of retail sales.

Cointegration means that multiple persistent macroeconomic variables move together at low frequencies, which means that they share common long-term trends and these movements connect with basic economic theories such as balanced economic growth (Stock and Watson, 2017).

The cointegration equation is shown below (Rao, 1994):

$$Y_t = \mathrm{A}_1 Y_{t-1} + A_2\, Y_{t-2} + \cdots + \mathrm{A}_p\, Y_{t-p} + \epsilon_t \qquad (2)$$

The Johansen system cointegration approach was chosen due to the examination of long-term interactions between indicators and retail sales. His reparametrised equation is shown below:

$$\Delta Y_t = \Gamma_1\, \Delta Y_{t-1} + \Gamma_2\, \Delta Y_{t-2} + \cdots + \Gamma_{p-1}\, \Delta Y_{t-p+1} - \psi Y_{t-p} + \epsilon_t \qquad (3)$$

In the Johansen system cointegration, the approach is the coefficient matrix on the lagged level. The rank of ψ can is obtained by computing canonical correlations between ΔY_t and Y_(t-p) (Rao, 1994).

VECM

If the factors are non-stationary and are cointegrated, the method used to investigate the issue of causation is the Vector Error Correction Model (VECM), which is a Vector Autoregressive Model (VAR) in first differences with the addition of a vector of cointegrating residuals. Both VAR and VECM models are useful if the observed data of the pattern tends to have no high fluctuations. Then, the result of the model prediction could not be stationary, not white noise, with data delay, and certainly residual as opposed to normally distributed. To eliminate possible biases, it was necessary to apply all selected methods.

Therefore, this VAR system does not lose long-run information. We apply the following VECM specification:

$$\Delta Y_{it} = \Pi y_{i,t-k} + \Gamma_1 \Delta y_{i,t-1} + \Gamma_2 \Delta y_{i,t-2} + \ldots + \Gamma_{k-1} \Delta y_{i,t-(k-1)} + \mu_{it} \quad (4)$$

where Δyt means the rate of growth or changes, μ_{it} denotes an n×1 vector of unobservable error terms. The variables and Γ in the matrix contain the value of the cointegrating vectors.

3. Research results

First, the correlation between dependent and independent variables is presented in the following table. Correlation analysis is used to express the linear relationship between the selected variables. The results show the strength of the Pearson correlation coefficient. In the case of the dependent variable RSV, a statistically significant relationship was demonstrated only for the GDP indicator. Thus, it can be said that as the RSV indicator increases, the GDP also increases. However, the correlation coefficient can be considered weak. In the case of IRSV, the GDP and UR indicators proved to be statistically significant. The identified links can be perceived as weak when GDP grows with the growth of IRSV and UR decreases. Other resulting links do not indicate statistically significant results. One of the expected reasons is the presence of delays for independent variable indicators. Another reason is the presence of nonlinear relationships between variables.

Table 2. Correlation between dependent and independent variables

	CPI	GDP	GW	HFCE	TE	UR
RSV	-0.1566	**0.3563**	0.0435	-0.0019	-0.0989	0.0094
RSV ONL	-0.0278	**0.2572**	0.0156	0.0531	0.1495	**-0.2312**

Source: own elaboration based on data from the Czech Statistical Office Database, 2020

The second test examines the stationary character of the data using the Augmented Dickey-Fuller (ADF) test. The ADF test is based on the model of the first-order autoregressive process (Box and Jenkins, 1970). The null hypothesis is formulated as the process contains a unit root, and therefore it is non-stationary. The results of the ADF test confirmed the possibility of using cointegration analysis for further data testing. All the examined indicators are stationary at the first difference. Almost all of the indicators are significant at the 1% level; only the GW is significant at the 5% level.

The second step was to analyse the lag lengths in the equations. The Akaike information criterion (AIC) was chosen to find appropriate lags between retail sales and online retail sales values and selected indicators. The testing was set to eight possible delays due to the time series at the quarterly level. Differences in lag lengths of selected indicators were found using the test as shown in Table 3. There is no difference between retail sales and online retail sales value in assumed lag lengths of examined indicators. These outputs were used to perform the Johansen system cointegration test.

Table 3. VAR Lag Akaike information criterion (AIC)

Type of retail sales	Indicators	Lag	AIC
Retail sales (offline and retail sales via the internet or mail-order)	GDP	4	7.198*
	TE	4	5.627*
	GW	4	7.466*
	CPI	4	5.511*
	UR	4	4.575*
	HFCE	4	6.828*
Online retail sales value (via the internet or mail-order)	GDP	4	10.071*
	TE	4	8.424*
	GW	4	10.213*
	CPI	4	8.275*
	UR	4	7.434*
	HFCE	4	9.320*

*indicates lag order selected by the criterion

Source: own elaboration based on data from the Czech Statistical Office Database, 2020

Providing the Johansen system cointegration test was the last step in this research. This test was used to examine the co-integration links between retail sales/online retail sales and selected indicators. First, this test was proved as a whole perception of retail sales value. The test proved cointegration links between retail sales and all examined indicators, as shown in the Table 4.

Table 4. The results of the Johansen system cointegration test (RSV)

Hypothesised No. of CE(s)	Trace Statistic	0.05 Critical Value	Probability	Maximum Eigen-value Statistic	0.05 Critical Value	Probability
None	**195.464**	**125.615**	**0.000**	**68.614**	**46.231**	**0.000**
Max. 1	**126.850**	**95.753**	**0.000**	**44.136**	**40.077**	**0.016**
Max. 2	82.714	69.818	**0.003**	28.757	33.876	0.181
Max. 3	53.957	47.856	**0.012**	23.976	27.584	0.135
Max. 4	29.981	29.797	**0.047**	21.019	21.131	0.052

Source: own elaboration based on data from the Czech Statistical Office Database, 2020

In all cointegrations between retail sales and selected indicators, no more than one cointegration link was found at the significance level of 0.05. Retail sales being delayed by four lags were discovered. Given the delays found, the indicators examined can be considered leading in the context of retail sales.

The next step was to apply the same test to retail sales through the Internet and mail-order field (online retail sales). The results also confirmed all cointegration links between online retail sales and selected indicators. Table 5 shows that one cointegration link was found in all cases at the significance level of 0.05.

Table 5. The results of the Johansen system cointegration test (IRSV)

Hypothesised No. of CE(s)	Trace statistic	0.05 Critical Value	Probability	Maximum Eigen-value Statistic	0.05 Critical Value	Probability
None	**179.582**	**125.615**	**0.000**	**56.132**	**46.231**	**0.003**
Max. 1	**123.449**	**95.753**	**0.000**	**43.443**	**40.077**	**0.020**
Max. 2	**80.006**	**69.818**	**0.006**	28.248	33.876	0.202
Max. 3	**51.757**	**47.856**	**0.020**	23.390	27.584	0.157

Source: own elaboration based on data from the Czech Statistical Office Database, 2020

As in the previous case, online retail sales in cointegration linkage with examined indicators are delayed by four lags, considered leading in the context of retail sales via the Internet and mail-order.

To determine the number of cointegration vectors affecting the dependent variables RSV and RSV_ONL, it is necessary to reject the null hypothesis in both analysed tests Trace Statistic and Maximum Eigenvalue Statistic. After comparing their values with the critical field at the 5% level of significance, it is possible to see that the variables RSV and IRSV always have one cointegration vector at most. The direction of the relationship and the standard errors of individual factors can be seen in the following cointegration equation. The delay is determined to be four quarters.

Cointegration Equation: (standard error in parentheses)

$$\underset{}{RSV} = -0.286 + \underset{(0.352)}{0.863\ CPI} - \underset{(0.262)}{0.906\ GDP} - \underset{(0.278)}{1.123\ GW} + \underset{(0.348)}{1.412\ HFCE} - \underset{(0.749)}{1.631\ TE} - \underset{(0.782)}{0.505\ UR}$$

$$RSVONL = -12.89 + \underset{(5.722)}{18.44CPI} + \underset{(3.990)}{14.14GDP} + \underset{(4.907)}{34.86\ GW} - \underset{(6.180)}{53.46\ HFCE} + \underset{(11.642)}{23.61TE} + \underset{(12.269)}{8.84UR}$$

The results of the cointegration equation show that the factors CPI and HFCE affect the development of the RSV value in the same direction and the factors GDP, GW, TE, and UR in the opposite direction. Completely different causal relationships are achieved in the RSV_ONL analysis. The increase in the IRSV values is caused by an increase in the CPI, the GDP, the GW, the TE, and the UR, and a decrease in the HFCE.

The highest values of standard errors and variances are identified for the factors UR and TE; conversely, the lowest values are identified for the GDP and the GW. For a correct discussion of the results of the Johansen cointegration test, it is necessary to create a vector error correction model which captures how individual factors contribute to the long-term equilibrium state of the dependent variable. Based on the results of T-Statistics, it is then possible to determine the statistical significance of the observed factor. The overall correctness of the model with the dependent variable RSV is confirmed by the F-statistic result. The model explains more than 66% of the total variability and deviations from the average value. In contrast, the model results for the IRSV cannot be considered statistically significant. The following tables present the results of the VECM in terms of RSV (Table 6) and IRSV (Table 7).

Table 6. VECM results (RSV)

Coefficient	Error Correction	Standard Errors	T-Statistics
CointEq1	**-1.161321**	**(0.29317)**	**[-3.96131]**
D(CPI(-1))	0.596410	(0.47767)	[1.24859]
D(CPI(-2))	0.950415	(0.56824)	[1.67255]
D(CPI(-3))	0.560050	(0.63854)	[0.87708]
D(CPI(-4))	0.582558	(0.57037)	[1.02137]
D(GDP(-1))	**-0.898918**	**(0.23735)**	**[-3.78734]**
D(GDP(-2))	**-0.872740**	**(0.20684)**	**[-4.21950]**
D(GDP(-3))	**-0.427182**	**(0.18340)**	**[-2.32920]**
D(GDP(-4))	-0.210682	(0.14587)	[-1.44433]
D(GW(-1))	**-1.189579**	**(0.29996)**	**[-3.96577]**
D(GW(-2))	**-0.865729**	**(0.27313)**	**[-3.16970]**
D(GW(-3))	-0.486222	(0.24808)	[-1.95993]
D(GW(-4))	-0.125035	(0.15428)	[-0.81042]
D(HFCE(-1))	**1.290302**	**(0.39108)**	**[3.29930]**
D(HFCE(-2))	**0.968349**	**(0.32578)**	**[2.97245]**
D(HFCE(-3))	0.563230	(0.27121)	[2.07674]
D(HFCE(-4))	0.101513	(0.23004)	[0.44129]
D(TE(-1))	**-2.272249**	**(0.65949)**	**[-3.44546]**
D(TE(-2))	**-2.382179**	**(0.63547)**	**[-3.74871]**
D(TE(-3))	**-1.346151**	**(0.58846)**	**[-2.28758]**
D(TE(-4))	**-1.392452**	**(0.48323)**	**[-2.88153]**
D(UR(-1))	-0.047293	(0.70840)	[-0.06676]
D(UR(-2))	-1.049445	(0.94039)	[-1.11597]
D(UR(-3))	-0.412521	(0.80609)	[-0.51176]
D(UR(-4))	0.262979	(0.71337)	[0.36864]
R-squared	**0.6662**	**F-statistic**	2.7531

Source: own elaboration based on data from the Czech Statistical Office Database, 2020

The resulting values of the VECM could explain the behaviour of the selected factors to the dependent variable. According to the results of the statistical significance of the cointegration equation, the VECM corrected the long-run relationship in four cases (the GDP, the GW, the HCFE, and the TE). Only the TE indicator was able to equilibrate the dependent variable in all four delayed quarters. The GDP factor explains the behaviour of the RSV in three quarters and GW and the HFCE factors in two quarters.

Table 7. VECM results (IRSV)

Coefficient	Error Correction	Standard Errors	T-Statistics
CointEq1	0.095632	(0.08803)	[1.08633]
D(CPI(-1))	0.797249	(2.20190)	[0.36207]
D(CPI(-2))	2.034786	(2.18877)	[0.92965]
D(CPI(-3))	2.493991	(2.24478)	[1.11102]
D(CPI(-4))	-0.834526	(2.34190)	[-0.35635]
D(GDP(-1))	-1.396686	(1.20102)	[-1.16292]
D(GDP(-2))	-0.978946	(1.07890)	[-0.90735]
D(GDP(-3))	-0.489292	(0.86152)	[-0.56794]
D(GDP(-4))	-0.579056	(0.59076)	[-0.98019]
D(GW(-1))	-2.309066	(2.73314)	[-0.84484]
D(GW(-2))	-1.750291	(2.03985)	[-0.85805]
D(GW(-3))	-1.020064	(1.43024)	[-0.71321]
D(GW(-4))	-0.578083	(0.73239)	[-0.78931]
D(HFCE(-1))	3.957555	(4.06395)	[0.97382]
D(HFCE(-2))	2.934502	(3.00667)	[0.97600]
D(HFCE(-3))	1.252345	(1.93012)	[0.64884]
D(HFCE(-4))	0.527131	(1.10340)	[0.47773]
D(TE(-1))	-2.444500	(3.06931)	[-0.79643]
D(TE(-2))	-1.368637	(2.95083)	[-0.46381]
D(TE(-3))	-0.343509	(2.68909)	[-0.12774]
D(TE(-4))	0.345560	(1.98677)	[0.17393]
D(UR(-1))	0.637761	(3.01237)	[0.21171]
D(UR(-2))	1.409146	(3.76908)	[0.37387]
D(UR(-3))	3.525490	(3.55610)	[0.99139]
D(UR(-4))	0.455222	(3.05458)	[0.14903]
R-squared	**0.3587**	**F-statistic**	**0.7715**

Source: own elaboration based on data from the Czech Statistical Office Database, 2020

The resulting relationships confirmed the influence of individual factors from the Johansen cointegration equations. The results show that the HFCE affects the development of the RSV value in the same direction and the factors GDP, GW, and TE in the opposite direction. TE and GW have mainly exerted the strongest impact on RSV. The influence of the observed factors on the IRSV variable was not demonstrated by the VECM.

4. Discussion

The results show that economic indicators can be used in short-term planning due to the confirmed cointegration links on specific lag length found between retail sales and consumer data (household final consumption expenditure), the unemployment rate, CPI, gross wage, GDP, and the total employment indicator. This answers the first research question in which we aimed to discover the extent to which lagged economic indicators reflect the development of sales in the Czech Republic. In addition, the results of the cointegration equation show that factors including CPI and consumer data affect the development of the retail sales value in the same direction (positive effect) and factors involving GDP, gross wage, total employment, and the unemployment rate in the opposite direction (negative effect). The increase in retail sales value through the Internet or mail-order is caused by an increase in CPI, GDP, gross wage, total employment, the unemployment rate and a decrease in consumer data. The retail sales behind these economic indicators are delayed differently. Thus, the answer to the second research question is that it is not appropriate to use equally lagged economic indicators for the online environment.

The research was the first of its kind to focus on retail sales. In this section, it was found that individual time series have a significant statistical relationship at the 0.05 significance level. The Vector Error Correction Model proved the existence of a long-run relationship between retail sales and certain economic indicators examined (GDP, GW, HCFE, and TE). These variables share a common stochastic trend. Therefore, they are combined in the long term. The cointegration observed between the variables examined assumes different delay values. Retail sales are delayed the most behind total employment (four quarters) and less behind GDP (three quarters), gross wage, and consumer data (household final consumption expenditure) (two quarters). These findings did not prove that the Gross Domestic Product indicator was a similar economic indicator to retail sales, as Burstiner (1991) and Mitchell et al. (2005) claimed. In the case of household final consumption expenditure, the result confirmed the assumption of a leading indicator (Burstiner, 1991). The results indicate that the gross wage and total employment indicators can also be considered leading indicators. Therefore, these indicators examined can predict changes in retail sales activity. We also find the CPI useful as a macroeconomic leading indicator for tactical sales forecasting, as demonstrated by Sagaert et al., (2018), given the observed lag.

Based on these findings, retail management should include wages to sales ratios as key performance indicators. The information that retail store management learns from analysing this ratio can lead to many different management decisions. For example, employees with consistently high ratios may become candidates for layoffs, while those with low wages to sales ratios may be promoted or may receive pay rises. Retail businesses of all sizes can use this ratio to track their progress and assess their financial needs and growth.

For additional research and as further contributions to the literature on this topic, other important ratios could be observed. These include sales per hour, which measures average hourly sale rates; items per sale, which reflects how many products a customer is likely to buy in one transaction; or conversion rate, which indicates what percentage of store visitors make purchases.

The difference between the theory of economic indicators was examined, and our research results can be caused by factors that have not been investigated in this research and that reflect the present reality of the Czech economy. For example, the most significant factor that may be linked to the gross wage indicator may be a very low long-term unemployment rate of 2.4% until the beginning of 2020 (CZSO, 2020) in the labour market. The results of examining online retail sales (via the Internet and mail-order) did not show the existence of long-run relationships with GDP, total employment, gross wage, consumer data, CPI, or the unemployment rate. The academic implications are the use of knowledge for discussion among academics and with students in business-oriented seminars.

The implications for practice are the possibility of using the outputs of retail organisations when planning their sales. The research revealed different results for the retail sales (wherein the offline environment prevails) and the value of the online retail sales (via the Internet or mail-order stores), showing that economic indicators can be used to predict retail sales, but only on the retail sales market as a whole. This finding may indicate a faster response in the online environment to changes in the development of the indicators examined. This research result shows that if managers decide to plan processes based on retail sales estimates associated with the analysis of the indicators examined in this research, business planning managers in the online environment have to respond much faster to changes in these indicators than managers in the traditional offline environment.

Conclusions

Retail in eastern Europe and the Czech Republic has changed significantly since 1989. The market environment and competition have contributed to growth, modernisation, and the use of modern technologies. The literature on the economic indicators of retail sales development divided these indicators into leading, coincident, and lagging indicators based on their movement with the development of retail sales. The paper aims to provide information on the possibility of using selected economic indicators to predict sales in the environment of a transformed economy. The Czech Republic was chosen as being representative of a transformed economy. The research in this paper examines the issue of leading indicators (consumer price, total employment, gross wage, the unemployment rate, and consumer data) and a coincident indicator (GDP) with sales development as perceived by Burstiner (1991) and Mitchell et al., (2005).

The Johansen system cointegration test and Vector Error Correction Model were used to answer the research questions. This procedure proved lagged cointegration links between retail sales and GDP, total employment, gross wages, and consumer data, which also answers the first research question. The economic indicators analysed in this paper were found to belong to the leading indicators groups, which means that they evolve ahead of retail sales. In the case of GDP, the result contradicts the claims made by Burstiner (1991) and Mitchell et al., (2005), who consider GDP to be a coincident indicator.

Based on research outputs, it is possible to answer the second research question oriented toward using examined lagged economic indicators for predictions in the online environment. Movements of economic indicators were not proven in the online environment. Therefore, it is not possible to observe these movements. The research findings show that the movements of the indicators analysed are not the same due to online retail sales possibly responding faster to the change in the indicators examined than retail sales, where traditional offline sales prevail. Economic indicators are useful for retail organisations because they can predict the development of retail sales, which can help managers with strategic planning. Therefore, the research focus on economic indicators reflecting retail sales development is significant due to the strategic decision making of managers in retail organisations. Unfortunately, research shows that this only applies to traditional retail organisations operating in the offline market.

This study has certain limitations. Based on the time series analysis, it is based on the breakdown of sales into a trend, a cycle, and the seasonality component. Data from 2020 are no longer included in the study, as there would be a strong seasonal effect due to the COVID-19 pandemic. The trend is a long-term, basic direction of the growth or decline in sales, based on fundamental changes in population, capital formation, and technology. The cycle represents the medium-term development of sales driven by changes in economic and competitive activities. However, cyclical fluctuations are predicted to be strong. Therefore, this study can only reflect the trend of the selected variables. In addition, estimates such as GDP often vary according to the institutions they are provided by, which can reduce the applicability of results abroad. Although the previous sentence says that estimates of some indicators vary depending on the responsible institutions, we would like to attempt subsequent comparative research involving other transformed economies of Central and Eastern Europe and established market economies within the EU, which could reduce the risk of biasing the indicators examined.

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