THE IMPACT OF E-COMMERCE ON TRADITIONAL TRADE: A CROSS-COUNTRY STOCK INDEX ANALYSIS

ВПЛИВ ЕЛЕКТРОННОЇ КОМЕРЦІЇ НА ТРАДИЦІЙНУ ТОРГІВЛЮ: МІЖКРАЇНОВИЙ АНАЛІЗ ФОНДОВИХ ІНДЕКСІВ

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The rapid expansion of e-commerce has intensified the need to assess its impact on traditional retail and financial markets. This study aims to examine the relationship between traditional retail and e-commerce using stock indices from China, the United States, and India. The research applies an econometric framework, including the Augmented Dickey-Fuller test, Johansen cointegration analysis, VAR/VECM models, Granger causality tests, impulse response functions, and forecast error variance decomposition. The results reveal that the interaction between traditional retail and e-commerce differs across countries, reflecting variations in market maturity and digitalisation. E-commerce indices exhibit higher volatility, while traditional retail indices remain more stable and retain a dominant role in explaining short-term market dynamics. The findings provide a basis for evaluating the effects of digital transformation on retail markets and may support investment analysis, policy development, and strategic decision-making.

Key words: *e-commerce, traditional trade, stock indices, digital economy, time series, VAR model, VECM model.*

Стрімкий розвиток електронної комерції є одним із ключових чинників трансформації сучасної світової економіки. Поширення цифрових платформ, мобільної комерції та електронних платіжних систем зумовлює необхідність оцінювання впливу цих процесів на традиційну торгівлю, що набуває особливої актуальності в умовах цифровізації економіки. Метою дослідження є аналіз впливу розвитку електронної комерції на традиційну торгівлю шляхом дослідження взаємозв'язку між фондовими індексами, які характеризують традиційний роздрібний сектор та сектор електронної комерції в Китаї, США та Індії. Для досягнення поставленої мети використано комплекс економетричних методів. Зокрема, здійснено попередню обробку часових рядів, проведено тестування стаціонарності за допомогою розширеного тесту Дики-Фуллера, визначено наявність довгострокових взаємозв'язків із використанням тесту Йогансена, побудовано моделі векторної авторегресії (VAR) та векторної моделі корекції похибки (VECM), виконано тест Грейнджера на причинність, а також аналіз функцій імпульсного відгуку та декомпозиції дисперсії похибки прогнозу. Результати дослідження свідчать про наявність взаємозв'язку між традиційною торгівлею та електронною комерцією в усіх досліджуваних країнах, проте характер і сила цього взаємозв'язку суттєво відрізняються залежно від рівня розвитку цифрової економіки та особливостей національних ринків. Встановлено, що фондові індекси електронної комерції характеризуються вищою волатильністю та більшою чутливістю до зовнішніх шоків порівняно з індексами традиційної торгівлі. З іншого боку, традиційний сектор у більшості випадків зберігає провідний вплив на короткострокову динаміку цифрового сегмента, тоді як довгострокові взаємозв'язки мають специфіку, характерну для певної країни. Практична цінність отриманих результатів полягає у можливості їх використання для оцінювання наслідків цифрової трансформації роздрібної торгівлі, прогнозування динаміки фондових ринків, розроблення стратегій розвитку підприємств роздрібної торгівлі та електронної комерції, а також формування управлінських рішень і державної політики у сфері цифрової економіки.

Ключові слова: *електронна комерція, традиційна торгівля, фондові індекси, цифрова економіка, часові ряди, VAR-модель, VECM-модель.*

Problem statement. Over the past decades, e-commerce has fundamentally transformed the global trade system, leading to a gradual transition from traditional retail to digital platforms. According to Insider Intelligence (eMarketer), by the end of 2025, global online retail sales will reach $6.42 trillion, accounting for 20.5% of total global retail sales. Other estimates predict global online sales will grow to $8.3 trillion, a 55.3% increase compared to 2021. Such trends indicate a deep digital transformation of the consumer market, accompanied by changes in consumer behaviour, logistics processes, marketing strategies, and the competitive environment.

Under these conditions, an urgent scientific and practical task is to assess the impact of e-commerce development on traditional trade. One of the most representative tools for such analysis is stock indices, which reflect not only market capitalisation and investor expectations, but also the performance of companies in the relevant sectors of the economy, which makes it possible to detect both short-term market fluctuations and long-term structural changes.

Of particular interest is the comparative analysis of China, the USA and India, which represent different models of e-commerce development. China is the world leader in online sales and the level of digital integration, the USA is characterised by high innovation and the decisive influence of global digital corporations, while India demonstrates one of the highest growth rates of e-commerce due to

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active digitalisation and the development of digital payment systems. Studying the relationship between the development of e-commerce and the dynamics of stock indices in these countries is important for understanding structural changes in traditional trade and forming sound economic forecasts.

Analysis of recent research and publications. Analysis of modern scientific research shows that the problem of the impact of e-commerce on the development of traditional trade is considered in several interrelated directions.

The first direction focuses on assessing the role of digital trade and e-commerce in ensuring economic growth and sustainable development. Shubai W., Meilin W., & Yujing W. substantiated the positive impact of digital trade on achieving sustainable development goals and identified the countries where this effect is most pronounced [1]. Bocean C.G., Scrioșteanu A., Gîrboveanu S., Mitrache M., Băloi I.C., et al. proved that e-commerce is a catalyst for digital transformation and sustainable socio-economic development [2].

The second direction covers the analysis of factors driving digital trade and the transformation of international trade. Alkhaifi F. proposed a conceptual approach to assessing the impact of e-commerce on trade, highlighting the key role of technological infrastructure, government regulation, and reduced transaction costs [3]. Wang H. found that the development of the digital economy and investment in research and development increase countries' competitiveness in international trade [4]. Kuang Z., Yu J., Gao Q., & Gu L. proved that the deepening of digital trade rules, despite their positive effects, can restrain the structural modernisation of exports due to requirements for data management and privacy protection [5]. Ali Y., Wei L., & Khan H. confirmed the decisive importance of digital innovation capacity, digital skills, and institutional quality for digital trade development [6].

The third direction examines the transformation of business models and traditional trade under the influence of digitalisation. Al-Ababneh H.A., Alrhaimi S.A., Al Adwan M.N., Al Refai Mohammed N., Sarıhasan I., Vasudevan A., & Mohammad S.I. proved that the evolution of e-business from online trading to digital platforms has led to the formation of new business models and competitive advantages [7]. Wang Y. & Wang W. substantiated the need to adapt classical theories of international trade to the digital economy [8]. Bhagat S., Ravi S.S., & Sankar M. identified the factors behind the transformation of traditional retail and established the key advantages of modern retail formats and e-commerce [9]. In addition, Martínez-Falcó J., Marco-Lajara B., & Sánchez-García E. showed that digital technologies and e-commerce are fundamentally changing the mechanisms of international trade by increasing the efficiency of cross-border operations [10].

Despite numerous scientific studies, the quantification ща the impact of e-commerce development on traditional trade using stock indices as indicators of market dynamics remains understudied. Most studies focus on individual aspects of digital trade, its impact on economic growth, sustainable development, or international competitiveness, whereas comparative analysis of the relationships between traditional trade and e-commerce across different countries remains insufficiently explored. This determines the relevance of the present study.

Research objectives. The objectives of the study are to assess the relationship between traditional trade and e-commerce based on the analysis of stock indices of China, the USA and India, identify short-term and long-term dependencies between them, determine causality and assess market shock transmission mechanisms.

Main results and their justification. To achieve the article objective, the following research methodology was proposed. The study began with data preprocessing, which included the stock index time series representing traditional retail and e-commerce in China, the United States, and India. To ensure comparability, all series were standardised to a daily frequency, while missing observations caused by non-trading days were filled using linear interpolation. To stabilise variance and facilitate economic interpretation, all time series were transformed into natural logarithms. Stationarity was then tested using the Augmented Dickey-Fuller (ADF) test, and non-stationary series were differenced until stationarity was achieved. The optimal lag length for the models was determined using the following criteria: AIC (Akaike Information Criterion), HQIC (Hannan–Quinn Information Criterion), SBIC (Schwarz/Bayesian Information Criterion), and FPE (Final Prediction Error). They help identify the lag structure that provides the best balance between model accuracy and complexity.

Long-run relationships between traditional retail and e-commerce indices were examined using the Johansen cointegration test. This test is essential for identifying whether the variables share a common stochastic trend, which would justify the use of a Vector Autoregressive Model (VAR) or a Vector Error Correction Model (VECM) in the presence of cointegration. Depending on the results, a VAR or a VECM were estimated. Granger causality tests were subsequently applied to identify the direction of predictive relationships between the variables. Finally, Impulse Response Functions (IRFs) and Forecast Error Variance Decomposition (FEVD) were employed to evaluate the dynamic effects of shocks and the relative contribution of each variable to the system's overall variability.

All statistical calculations, model construction, and econometric analysis were performed using Stata 19 software.

To implement the methodology, two stock indices have been selected for the USA, China and India: one representing the traditional retail sector and the other representing the e-commerce sector (Table 1) [11]. The selection was guided by several key criteria: representativeness, ensuring that the indices accurately reflect the performance of the respective sectors; data availability, allowing for consistent and reliable time-series analysis; and cross-country comparability, which is essential for drawing meaningful conclusions in a global context. The research period covers the interval from January 5, 2015, to July 17, 2025 (for the INQQ The India Internet ETF index – from April 7, 2022; for the ProShares Online Retail ETF – from July 17, 2018), determined by the availability of complete historical data on the platform.

The analysis began with the construction of logarithmic time series plots for stock indices representing traditional retail and e-commerce sectors in China, the United States, and India (Figure 1). The results reveal clear differences between traditional and digital markets. In China, the CSI Overseas China Internet Index (lch_csi) displays higher volatility and a strong upward trend until 2021, followed by a decline, reflecting the rapid expansion of the digital sector and subsequent market correction. In contrast, the Shanghai Composite Index (lch_ssec) remains relatively stable throughout the period. A similar pattern is observed in the United States. The ProShares Online Retail ETF (lus_onln) increased sharply until early 2021 before declining and fluctuating, likely reflecting the pandemic-driven boom in online retail followed by market normalisation. Meanwhile, the Dow Jones Retailers Index (lus_djusrt) demonstrates gradual and stable growth, indicating the resilience of the traditional retail sector.

In India, the India Internet ETF (lind_inqq) exhibits relatively stable dynamics with minor fluctuations, suggesting the gradual development of the country's digital economy. At the same time, the Nifty 50 index (lind_nsei) maintains a stable upward trajectory, reflecting the strength of the broader stock market.

Thus, e-commerce indices exhibit greater volatility and more pronounced growth-decline cycles than traditional retail indices, highlighting higher sensitivity to external shocks and the rapid pace of digital transformation. In contrast, traditional retail indices demonstrate greater stability, reflecting the gradual development of mature market sectors. This observation is consistent with previous studies suggesting that digital markets are characterised by higher growth potential and greater sensitivity to external shocks than traditional retail sectors [2; 7].

Stationarity was tested using the Dickey-Fuller test, which detects the presence of a unit root. The results are presented in Table 2.

All time series are non-stationary at levels, as the p-values exceed 0.05. After first differencing, the null hypothesis of a unit root is rejected for all series, indicating that they are integrated of order one (I(1)).

The next step involves determining the optimal number of lags for the vector models. The results are presented in Table 3.

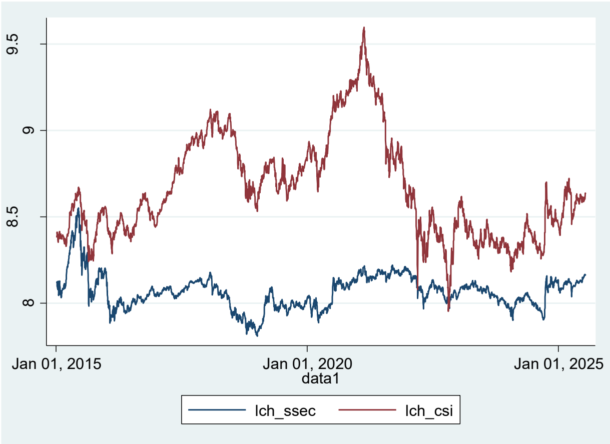
Given that AIC and FPE tend to select a higher number of lags to preserve as much information as possible, greater emphasis was placed on the more conservative HQIC and SBIC criteria. Accordingly, the optimal lag length for each pair of indices was determined using the Hannan–Quinn Information Criterion (HQIC) and the Schwarz Bayesian Information Criterion (SBIC). For the pair lch_ssec and lch_csi, both criteria selected lag 3. For lus_spret

Table 1

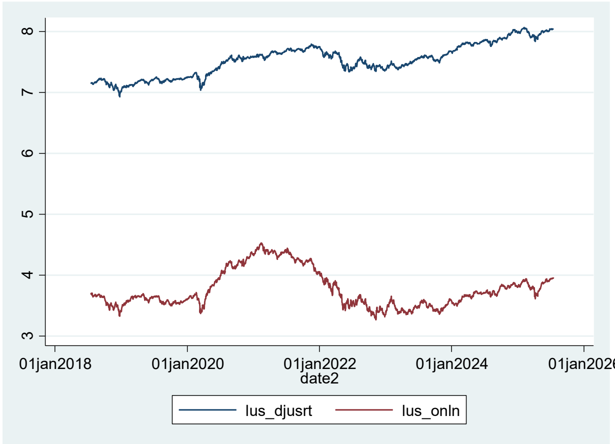
Stock indices representing traditional trade and e-commerce in China, USA and India

Country	Index	Symbol	Trade type	Description
China	Shanghai Composite Index (SSEC)	*ch_ssec*	Traditional Trade	One of China's main stock indices, covering companies listed on the Shanghai Stock Exchange
	CSI Overseas China Internet Index	*ch_csi*	E-Commerce	Tracks the performance of Chinese internet companies listed abroad
USA	Dow Jones Retailers (DJUSRT)	*us_djusrt*	Traditional Trade	Represents U.S. companies primarily engaged in traditional retail operations, including department stores, supermarkets, and specialty retailers
	ProShares Online Retail ETF (ONLN)	*us_onln*	E-Commerce	An ETF investing in companies that derive most of their revenue from online sales
India	Nifty 50 (NSEI)	*ind_nsei*	Traditional Trade	A benchmark index of India's top 50 companies across various sectors. Its choice is justified because India does not have a highly specialized retail index and the Nifty 50 is the most liquid and representative
	INQQ The India Internet ETF (INQQ)	*ind_inqq*	E-Commerce	A thematic ETF investing in leading Indian companies in the digital economy: online commerce, online payments, cloud services, etc.

Source: collected by the authors from [11]



(a)



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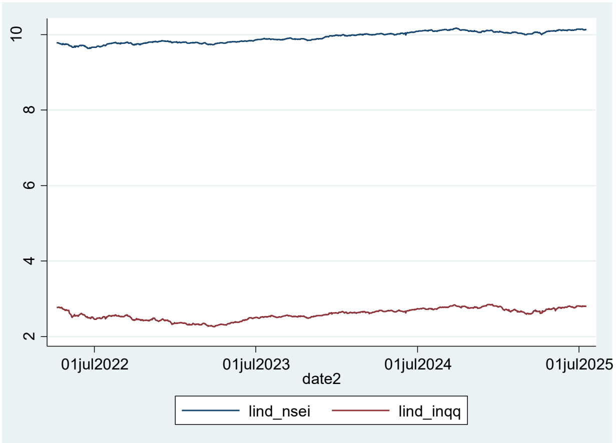

(c)

Fig. 1. Retail and E-commerce Index Dynamics (2016–2025): (a) China; (b) USA; (c) India

Source: constructed by the authors

Table 2

Dickey-Fuller test results for assessing the stationarity of index time series

Index	Original level time series		After first-order differencing.	
	Z(t)	p-value	Z(t)	p-value
lch_ssec	-2.854	0.110	-55.985	0.000
lch_csi	-1.927	0.319	-55.573	0.000
lus_djusrt	-0.520	0.888	-62.019	0.000
lus_onln	-1.258	0.648	-48.880	0.000
lind_nsei	-0.046	0.962	-55.895	0.000
lind_inqq	-1.023	0.745	-32.242	0.000

Source: calculated by the authors

Table 3

Determination of the optimal number of lags for the models

Index pair	Optimal Lag (p-value)			
	FPE	AIC	HQIC	SBIC
lch_ssec & lch_csi	7 (0.014)	7 (0. 014)	3 (0.000)	3 (0.000)
lus_djusrt & lus_onln	2 (0.022)	2 (0.022)	1 (0.000)	1 (0.000)
lind_nsei & lind_inqq	4 (0.015)	4 (0. 015)	2 (0.000)	2 (0.000)

Source: calculated by the authors

and lus_ibay, lag 1 was identified as optimal (with lag 2 as an alternative), while for lind_nsei and lind_inqq, lag 2 was selected. Therefore, all subsequent analyses are based on these optimal lag lengths.

Long-term equilibrium relationships were then examined using the Johansen cointegration test, which identifies the number of cointegrating vectors (Table 4).

The results indicate long-term equilibrium relationships in two of the three analysed pairs. Specifically, cointegration was not confirmed for lus_djusrt–lus_onln, supporting the use of a VAR model in first differences. In contrast, one cointegration vector was identified for lch_ssec–lch_csi and lind_nsei–lind_inqq, justifying a VEC model to analyse the relationship between traditional retail and e-commerce. The identified cross-country differences in long-run relationships suggest that the effects of digital transformation depend on national market structures and institutional conditions, as emphasised in previous studies [4; 6].

Accordingly, a VEC model was constructed for the stock indices representing traditional retail and e-commerce in China, with the results presented in Table 5.

Both equations demonstrate statistically significant error correction coefficients, indicating a mechanism that restores equilibrium after short-term deviations. In the short term, both variables exhibit interdependence: the lagged values of the e-commerce index have a positive and statistically significant effect on the traditional retail index, while the influence of the traditional index on e-commerce is negative. This may suggest competition or capital reallocation between the sectors. The lagged coefficients confirm substantial short-term effects.

At the same time, the cointegration equation reveals that the long-term relationship between

Table 4

Johansen cointegration test results

Variable pair	rank	Trace statistic	5% critical value	Max-eigen statistic	5% critical value	Number of cointegrating vectors
lch_ssec, lch_csi	0	15.282	15.410	11.218	14.070	0
	1	4.063	3.760	4.063	3.760	1
lus_djusrt, lus_onln	0	2.163	15.410	2.022	14.070	0
	1	0.141	3.760	0.141	3.760	0
lind_nsei, lind_inqq	0	17.947	15.410	16.539	14.070	1
	1	1.408	3.760	1.408	3.760	0

Source: calculated by the authors

Table 5

VEC-model results for China

Dependent variable	Regressor	Coefficient	Std. error	z-statistic	p-value
lchssec	*ECT (L1)*	-0.004	0.001	-3.10	0.002
	lch_ssec (L1)	0.035	0.017	2.02	0.044
	lch_ssec (L2)	0.066	0.017	3.81	0.000
	lch_csi (L1)	0.076	0.009	8.12	0.000
	lch_csi (L2)	0.024	0.009	2.55	0.011
	Constant	-0.000	0.000	-0.15	0.881
lchcsi	*ECT (L1)*	-0.008	0.003	-2.86	0.004
	lch_ssec (L1)	-0.101	0.033	-3.11	0.002
	lch_ssec (L2)	0.078	0.032	2.39	0.017
	lch_csi (L1)	0.113	0.017	6.45	0.000
	lch_csi (L2)	0.002	0.018	0.09	0.930
	Constant	0.000	0.000	0.05	0.963
Cointegrating Equation					
Regressor		**Coefficient**	**Std. error**	**z-statistic**	**p-value**
lch_ssec		1.000 (norm)	–	–	–
lch_csi		0.051	0.097	0.53	0.597
Constant		-8.515	–	–	–

Source: calculated by the authors

the indices is weak and statistically insignificant, suggesting instability in the relationship or the influence of external factors. Such findings are in line with the view that rapidly evolving digital markets are strongly influenced by regulatory and technological changes, which may weaken stable long-run relationships between traditional and digital sectors [3; 5].

The next step is the analysis of impulse response functions (IRF) and forecast error variance decomposition (FEVD), assessing how short-term shocks in one variable affect the other over time. Table 6 and Figure 2 show the results.

Table 6

Forecast error variance decomposition (FEVD) for China

Response	Impulse	Proportion of explained variance (%)
lch_ssec	*lch_ssec*	100.00
lch_csi	*lch_ssec*	14.95
lch_ssec	*lch_csi*	0.00
lch_csi	*lch_csi*	85.05

Source: calculated by the authors

The chart in the upper left corner demonstrates the response of the e-commerce index to its own shock, which is weak but positive, indicating internal inertia of the sector; this is confirmed by the fact that approximately 85% of the variance of this variable is explained by its own shocks. The upper right chart shows the response of the e-commerce index to a shock in the traditional sector, which is also positive but less pronounced, possibly indicating a limited influence of traditional trade on e-commerce; according to FEVD, this influence amounts to approximately 15%.

The lower left chart demonstrates the response of the traditional index to a shock in the e-commerce sector – it is moderate and positive, however, at the first forecast step this effect is statistically insignificant, as the share of explained variance equals 0%. Finally, the lower right chart shows the response of the traditional index to its own shock, which is the most pronounced among all, indicating strong internal dynamics of this sector, confirmed by 100% of explained variance. Overall, the impulse responses and FEVD results confirm the existence of interconnection between the sectors, with the predominance of the traditional trade's influence on e-commerce in the short term. This result supports

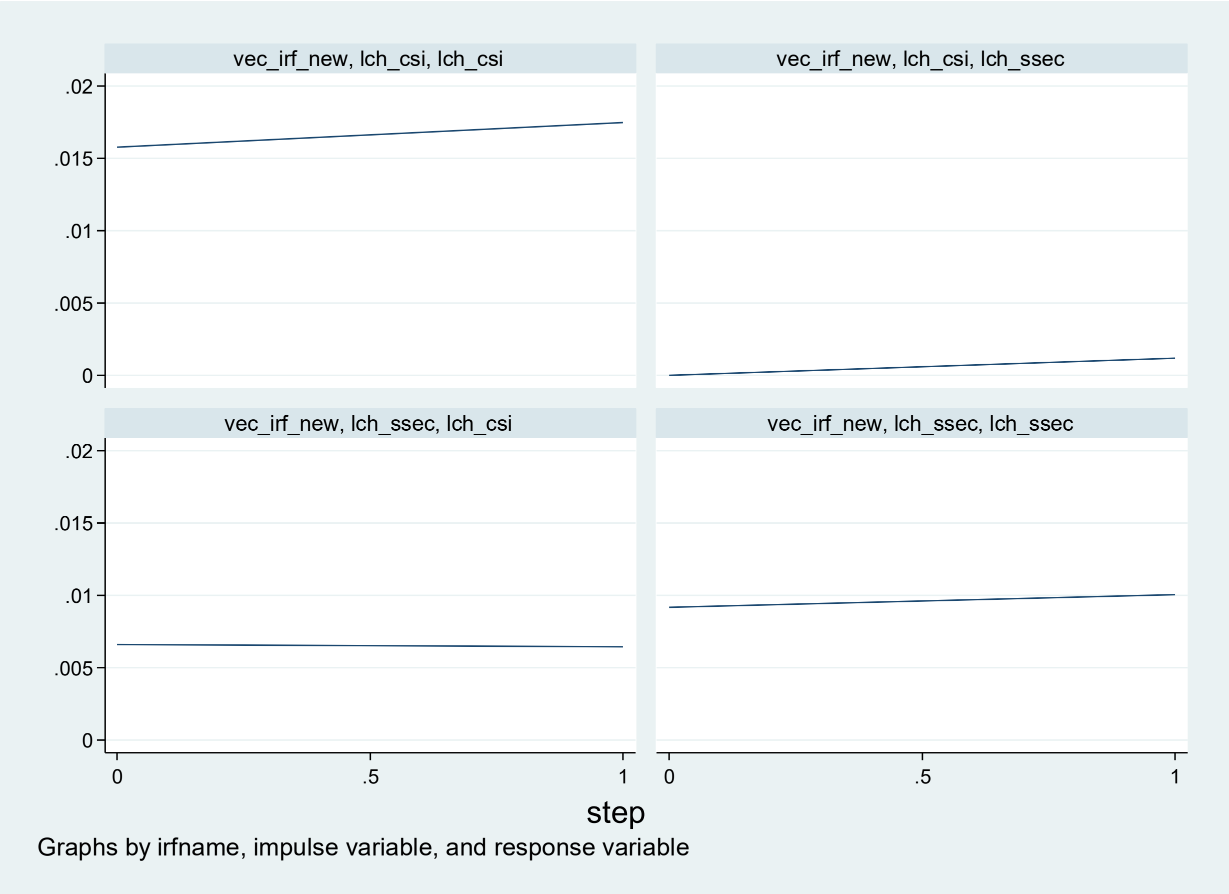

Fig. 2. Impulse response functions for China's VEC model

Source: constructed by the authors

earlier evidence that digital commerce continues to evolve alongside rather than independently from established retail systems, despite its rapid expansion [7; 9].

For the U.S. stock indices, a VAR model in first differences was constructed, which represents the most appropriate form for identifying the relationship between traditional retail and e-commerce. The results of the model are presented in Table 7.

The analysis confirmed that the U.S. e-commerce index (ONLN) has a statistically significant short-term impact on the dynamics of the traditional retail sector (DJUSRT). The first lag of ONLN exerts a negative influence on DJUSRT, while the second lag has a positive effect – both with a high level of statistical significance. This pattern may indicate a correction effect, where the traditional sector initially reacts to fluctuations in online retail and subsequently adapts to new market conditions. Conversely, DJUSRT also has a significant influence on ONLN: the first lag shows a positive effect, while the second lag is negative. This may suggest a cyclical response of the e-commerce sector to changes in traditional retail. The own dynamics of both indices exhibit strong autocorrelation, which is typical for financial time series. The bidirectional interaction identified for the U.S. market is consistent with studies arguing that mature digital economies exhibit intensive feedback mechanisms between traditional and online retail channels [8; 10].

These relationships are supported by the Granger causality test (Table 8), which confirmed bidirectional causality: the ONLN index Granger-causes changes in DJUSRT, and vice versa, with a stronger effect from the traditional sector. This indicates close interaction between retail channels in the United States and the mutual transmission of information between them.

To gain a deeper understanding of the dynamic interaction between the indices, the IRF and FEVD results are presented in Figure 3.

The results indicate that a shock in the ONLN index causes a short-term positive response in DJUSRT, whereas the reverse effect is relatively weak. This is confirmed by the FEVD: over an eight-period horizon, shocks in DJUSRT explain up to 17% of the variation in ONLN, while the influence of ONLN on DJUSRT remains negligible (approximately 0.3%). These findings suggest that ONLN is becoming increasingly dependent on the dynamics of the broader U.S. retail market, whereas DJUSRT retains a high degree of autonomy, highlighting the dominant role of the broad market index in explaining fluctuations in the sector-specific ETF.

A similar analysis was then conducted for India's traditional retail and e-commerce stock indices, involving the construction of a VECM (Table 9).

In the first-difference equation for the Nifty 50 index, the error correction coefficient is statistically insignificant, indicating that the traditional market does not exhibit a clear response to deviations from long-term equilibrium. At the same time, the lagged INQQ variable has a positive and highly significant effect on the dynamics of the Nifty 50, suggesting a short-term dependence of the traditional market on

Table 7

VAR-model results for the USA

Dependent variable	Regressor	Coefficient	Std. error	z-statistic	p-value
ldowjonesret	*ldowjonesret (L1)*	1.002	0.020	51.04	0.000
	ldowjonesret (L2)	-0.003	0.020	-0.15	0.878
	lonlnetf (L1)	-0.044	0.014	-3.25	0.001
	lonlnetf (L2)	0.045	0.014	3.28	0.001
	Constant	0.005	0.006	0.79	0.431
lonlnetf	*ldowjonesret (L1)*	0.533	0.026	20.27	0.000
	ldowjonesret (L2)	-0.533	0.026	-20.25	0.000
	lonlnetf (L1)	1.014	0.018	55.50	0.000
	lonlnetf (L2)	-0.016	0.018	-0.85	0.393
	Constant	0.003	0.008	0.37	0.708

Source: calculated by the authors

Table 8

Granger causality test results

Dependent variable	Excluded variable	Chi² statistic	Degrees of freedom	p-value	Conclusion
ldowjonesret	*lonlnetf*	10.812	2	0.004	Caused by *lonlnetf*
lonlnetf	*ldowjonesret*	410.750	2	0.000	Caused by *ldowjonesret*

Source: calculated by the authors

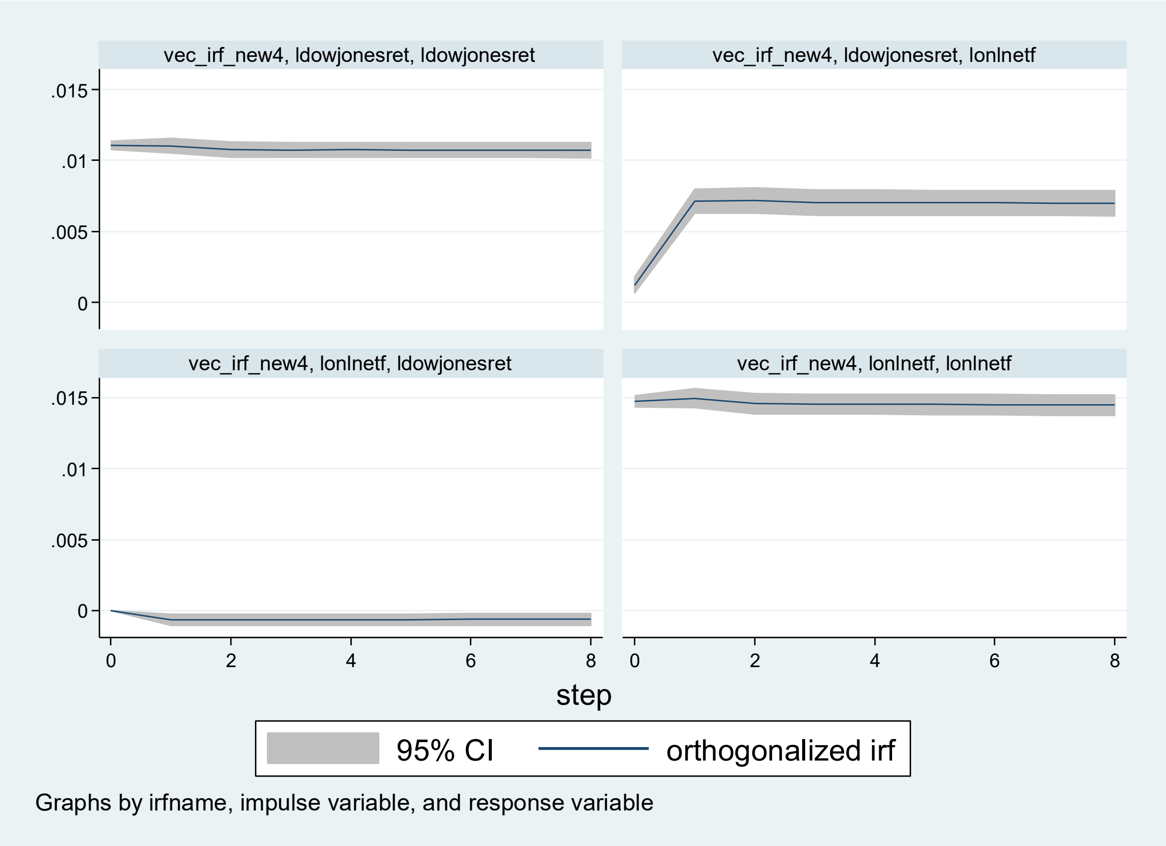

Fig. 3. Impulse response functions for the USA's VAR model

Source: constructed by the authors

Table 9

VEC-model results for India

Dependent variable	Regressor	Coefficient	Std. error	z-statistic	p-value
lindnsei	*ECT (L1)*	0.001	0.002	0.66	0.509
	lind_nsei (L1)	-0.046	0.032	-1.42	0.155
	lind_inqq (L1)	0.125	0.019	6.26	0.000
	Constant	0.000	0.000	1.70	0.089
lindinqq	*ECT (L1)*	0.013	0.003	3.87	0.000
	lind_nsei (L1)	0.141	0.052	2.72	0.006
	lind_inqq (L1)	-0.006	0.032	-0.19	0.851
	Constant	-0.000	0.000	-0.11	0.912
Cointegrating Equation					
Regressor		**Coefficient**	**Std. error**	**z-statistic**	**p-value**
lind_nsei		1.0000 (norm)	–	–	–
lind_inqq		-0.890	0.136	-6.53	0.000
Constant		-7.624	–	–	–

Source: calculated by the authors

the technology sector. In the INQQ equation, the error correction coefficient is positive and statistically significant, indicating the presence of a mechanism that restores equilibrium in the internet sector. Additionally, the lagged Nifty 50 variable positively affects INQQ, whereas the lagged INQQ variable is not statistically significant. This suggests that the technology sector is partly driven by the dynamics of the broader market.

The cointegration equation confirms a long-term relationship between the indices. The coefficient for INQQ is negative and statistically significant, indicating an inverse relationship between the index levels in the long run. A more in-depth analysis was conducted using impulse response functions (Figure 4) and forecast error variance decomposition (Table 10).

Table 10

Forecast error variance decomposition (FEVD) for India

Response	Impulse	Proportion of explained variance (%)
ind_nsei	*ind_nsei*	100.00
ind_inqq	*ind_nsei*	21.35
ind_nsei	*ind_inqq*	0.00
ind_inqq	*ind_inqq*	78.65

Source: calculated by the authors

In particular, the dynamics of the Nifty 50 index are entirely driven by its own shocks, indicating the dominance of internal factors within the traditional sector. In contrast, the INQQ index shows sensitivity to changes in the traditional market: over 21% of its forecast error variance is explained by shocks in the Nifty 50. At the same time, the impact of INQQ on Nifty 50 at the first step is zero, which aligns with the results of the impulse response functions. This suggests that in the short term, the traditional market influences the technology sector, but not vice versa.

Overall, the obtained empirical results generally confirm the conclusions of previous studies regarding the growing importance of e-commerce for retail transformation, while also demonstrating that the strength and direction of this relationship vary substantially across countries depending on the maturity of their digital economies [2; 8; 10].

Conclusions. The study assessed the impact of e-commerce on traditional retail by analysing stock indices representing both sectors in China, the USA, and India using cointegration analysis, VAR/VECM models, Granger causality tests, impulse response functions, and forecast error variance decomposition. The results indicate that e-commerce and traditional retail are interconnected across all three countries; however, the strength and direction of this relationship vary depending on the level of digital economy development. E-commerce indices were found to be more volatile and more responsive to external shocks than traditional retail indices, reflecting the dynamic nature of digital markets.

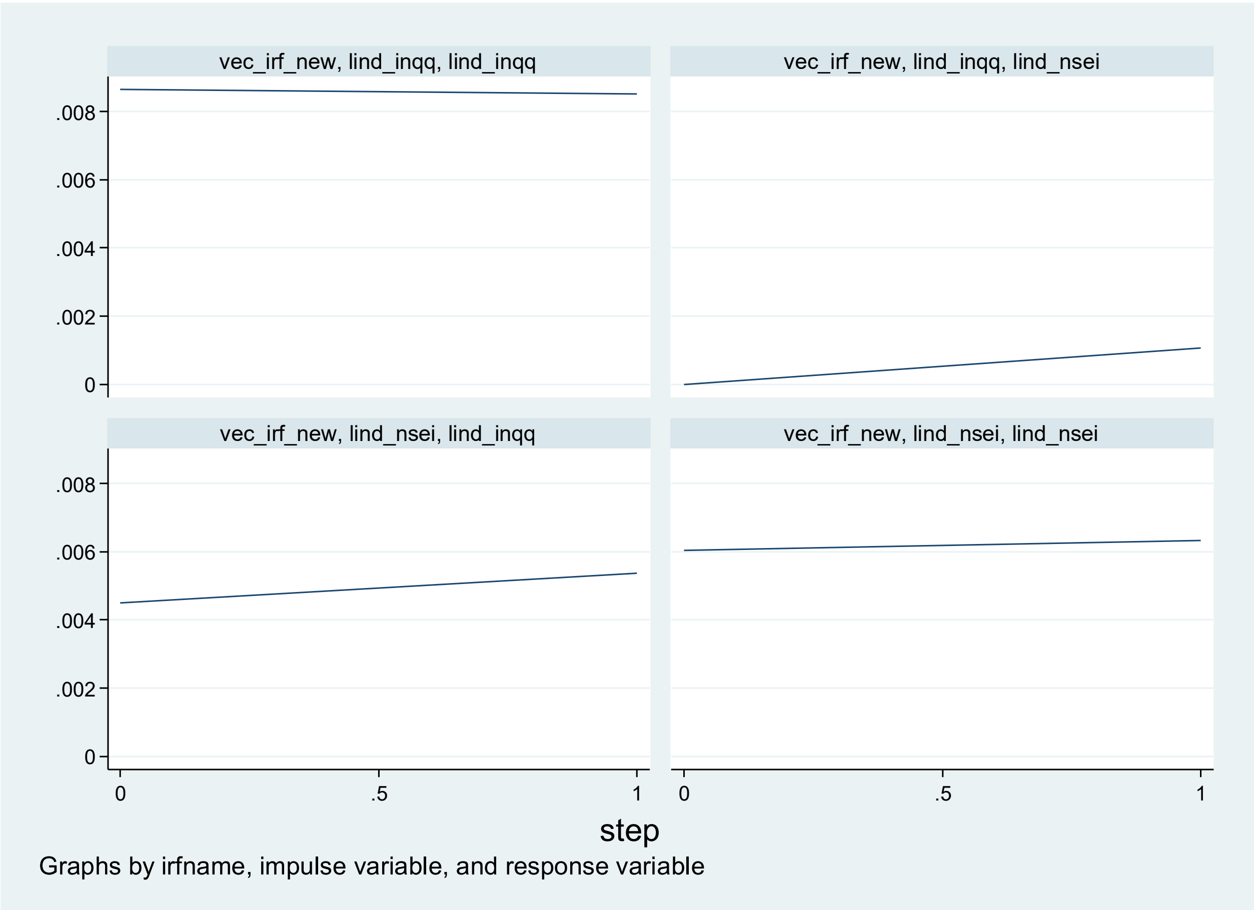

Fig. 4. Impulse response functions for India's VEC model

Source: constructed by the authors

The econometric analysis revealed differences in long-term relationships between the sectors. Cointegration was confirmed for China and India, indicating the existence of long-run equilibrium relationships, whereas no cointegration was identified for the USA, suggesting that interactions between the sectors are primarily short-term. At the same time, impulse response and variance decomposition analyses showed that traditional retail indices retain a dominant role in explaining the short-term dynamics of e-commerce indices, while the reverse influence remains limited. The Granger causality results additionally confirmed significant predictive relationships between the sectors, particularly in the U.S. market.

Overall, the findings demonstrate that the influence of e-commerce on traditional retail is country-specific and depends on market maturity, the level of digitalisation, and the structural characteristics of national economies.

Prospects for further research include expanding the sample of countries, incorporating macroeconomic and institutional factors into the models, and analysing the impact of major external shocks, such as technological innovations, regulatory changes, and global economic crises, on the interaction between traditional retail and e-commerce. Such an approach would provide a more comprehensive understanding of the mechanisms underlying the transformation of retail markets in the digital economy.

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