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THE E-COMMERCE EXPANSION AND WASTE GENERATION IN THE EU: A PANEL VECTOR AUTOREGRESSION APPROACH

Abstract

This research study applies a multi-method framework, combining Panel Vector Autoregression (PVAR), panel threshold models, quantile regressions, and random forest analyses, to investigate how e-commerce (ECOMS) growth affects different waste streams across 27 EU Member States from 2014 to 2023. The research showed that e-commerce expansion strongly amplifies packaging waste generation, whereas total and municipal waste exhibit limited immediate responses. However, threshold analyses suggest that higher unemployment and lower resource productivity can intensify e-commerce's packaging impact, while robust recycling capacity partially mitigates this trend. Quantile regressions further reveal that high-waste countries face particularly pronounced e-commerce effects, underscoring the need for context-specific interventions. These findings highlight the pivotal role of packaging materials in online retail's environmental footprint and emphasize the importance of targeted circular economy measures, such as advanced recycling infrastructure and reduced packaging design, for effectively managing e-commerce-driven waste.

Keywords: *E-commerce, waste generation, packaging waste, panel vector autoregression, circular economy, recycling*

JEL classification: *C33, L81, Q53, Q56*

ЕКСПАНЗИЈА Е-ТРГОВИНЕ И ГЕНЕРИСАЊЕ ОТПАДА У ЕУ: ПРИСТУП ПАНЕЛ ВЕКТОРСКЕ АУТОРЕГРЕСИЈЕ

Апстракт

У овом раду се примењује комплексан методолошки оквир, у оквиру кога се комбинују панел векторска ауторегресија (PVAR), панел праг модели, квантилана регресија и random forest analiza, да би се анализирао утицај

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раста е-трговине (ECOMS) на различите токове отпада у 27 земаља ЕУ у периоду од 2014. до 2023. године. Резултати овог истраживања показују да експанзија е-трговине значајно подстиче генерисање амбалажног отпада, док је утицај на укупни и комунални отпад ограничен на кратке рокове. Међутим, панел праг анализе указују на то да виша незапосленост и нижа продуктивности ресурса могу појачати ефекат е-трговине на амбалажни отпад, одк значајан капацитет за рециклажу делимишно ублажава овај тренд. Квантилна регресија открива да земље са високим нивоом отпада трпе нарочито изражене ефекте е-трговине, наглашавајући потребу за интервенцијама прилагођеним контексту. Ови резултати истичу кључну улогу амбалажног материјала у еколошком отиску онлајн малопродаје и потврђују значај таргетираних мера циркуларне економије, попут напредне рециклажне инфраструктуре и редукованог дизајна амбалаже, за ефикасно управљање отпадом који потиче из е-трговине.

Кључне речи: *е-трговина, генерисање отпада, амбалажни отпад, панел векторска ауторегресија, циркуларна економија, рециклажа*

Introduction

Electronic commerce (e-commerce) has rapidly transformed global consumer behaviors and business strategies, supported by widespread internet connectivity, evolving logistics, and rising consumer demand for on-demand services (Abukhader & Jönson, 2003; Fichter, 2002). However, this digital transition also poses sustainability concerns (Matthews et al., 2001; Yu et al., 2023), including heightened packaging requirements, increased returns, and new waste streams (Bertram & Chi, 2017; Lonn et al., 2002; Stinson et al., 2019). Although e-commerce can reduce inefficiencies in traditional retail (Bertram & Chi, 2017), its net environmental impact remains ambiguous, as improved transport efficiency (Imran et al., 2023) may be offset by resource-intensive packaging (Yu et al., 2023). These challenges are especially pertinent in the European Union (EU), where e-commerce is growing and legislative efforts, such as the 2018 EU Waste Directives and the proposed Packaging and Packaging Waste Regulation (PPWR), aim to curb packaging and municipal waste (European Commission, 2021). Yet, limited longitudinal research has investigated how e-commerce affects multiple waste streams or considered the moderating role of recycling capacity (Siikavirta et al., 2002; Dost & Maier, 2018). Factors like industrial development, resource usage, and regional policies further complicate outcomes (Caiyi et al., 2022; Visser & Lanzendorf, 2004), pointing to a need for integrated and dynamic modeling (Fichter, 2002; Abukhader & Jönson, 2003; Yu et al., 2023).

Accordingly, this paper explores the link between e-commerce expansion and three waste indicators, waste per capita (WASTPC), municipal waste per capita (MWASTE), and packaging waste per capita (PACWASTE), in 27 EU Member States from 2014 to 2023. It examines whether municipal recycling rates (RECMWASTE) moderate these relationships (Jovanović et al., 2023) and investigates how industrial development (INDVA), resource productivity (RESP), and other macro controls interact.

Methodologically, the study applies Panel Vector Autoregression (PVAR), complemented by panel threshold (PTR), quantile regression, and machine learning to uncover dynamic and non-linear processes. PVAR captures feedback loops where rising e-commerce might spur waste and, in turn, provoke changes in online adoption, while threshold and quantile analyses reveal regime-specific effects (Hansen, 1999; Soukiazis & Proença, 2020; Imran et al., 2023). By integrating these approaches, the paper offers fresh evidence on the immediate and lagged impacts of e-commerce on EU waste generation, the mitigating role of recycling, and the implications for circular economy strategies. The next section reviews the related literature, focusing on packaging, municipal waste, and the factors shaping e-commerce's environmental outcomes.

1. Theoretical background

E-commerce has rapidly become central to modern economies and consumer culture, influencing product design, packaging, and shopping patterns (Chen et al., 2020; Fichter, 2002; Yu et al., 2023). As digital retail expands, studies increasingly investigate its short- and long-term repercussions on resource consumption and waste (Abukhader & Jönson, 2003; Bertram & Chi, 2017; Stinson et al., 2019). This section reviews how e-commerce affects waste per capita (WASTPC), municipal waste per capita (MWASTE), and packaging waste per capita (PACWASTE), along with the moderating roles of recycling infrastructure (RECMWASTE), industrial development (INDVA), unemployment (UNEMP), and resource productivity (RESP). It also highlights key methodological approaches in European Union (EU) research.

A recurring debate addresses the efficiency benefits of e-commerce versus its possible environmental drawbacks (Fichter, 2002; Matthews et al., 2001). Improved logistics can reduce greenhouse gas emissions and operational inefficiencies (Chen et al., 2020; Imran et al., 2023), yet the packaging-intensive nature of online sales often creates elevated levels of packaging waste (PACWASTE), stressing local waste-management systems (Bertram & Chi, 2017; Lonn et al., 2002; Yu et al., 2023). Although e-commerce can replace some in-person shopping, it may generate more frequent small-parcel deliveries and increased return shipments, raising total waste (Stinson et al., 2019; Dost & Maier, 2018). Consequently, net impacts on WASTPC or MWASTE often depend on region-specific logistics maturity and consumer behaviors (Caiyi et al., 2022; Visser & Lanzendorf, 2004).

Several contextual factors shape the extent of e-commerce-driven waste. Recycling infrastructure (RECMWASTE) is frequently identified as pivotal in curbing packaging waste, as robust collection and processing systems can recapture materials and minimize landfills (Jovanović et al., 2023; Popović, 2020). In the EU, policies like the 2018 EU Waste Directives and the Packaging and Packaging Waste Regulation (PPWR) emphasize the importance of expanding recycling capacities to manage escalating online-delivery waste (European Commission, 2021; Popović & Milijić, 2021). Meanwhile, industrial development (INDVA) can heighten waste outputs if e-commerce intersects with strong manufacturing sectors (Popović et al., 2022b; Yu et al., 2023), and resource productivity (RESP) can buffer or exacerbate waste generation by influencing how efficiently raw materials are converted into final products (Borjesson Rivera et al., 2014; Popović et al., 2023).

Within Europe's legislative framework, ambitious targets aim to reduce municipal and packaging waste (European Commission, 2021). The PPWR proposal seeks tighter design standards, extended producer responsibility, and recycling mandates to diminish the adverse effects of e-commerce packaging (Popović et al., 2023; Yu et al., 2023). Although uniform EU-level directives can foster convergence in recycling practices (Chen et al., 2020; Popović et al., 2022a), variations remain in data accuracy, enforcement, and circular model adoption across Member States (Popović & Milijić, 2021). Research further demonstrates that the interplay between digital consumption and sustainability remains contingent on local institutional frameworks and consumer norms (Visser & Lanzendorf, 2004).

A notable dimension is the temporal aspect of e-commerce's environmental impacts. Yu et al. (2023) argue that while short-term efficiency gains might briefly limit emissions, packaging waste can escalate long-term. Imran et al. (2023) similarly note that frequent deliveries and reverse logistics can dilute initial environmental improvements. Hence, short-run benefits may give way to surging waste pressures, particularly for packaging. Advanced econometric methods, panel vector autoregression (PVAR), threshold models, and quantile regressions help capture these dynamics (Holtz-Eakin, Newey, & Rosen, 1988; Koenker & Bassett, 1978; Hansen, 1999). Researchers also apply machine-learning tools (Breiman, 2001; Popović et al., 2023) to reveal non-linearities and gauge variable importance.

Beyond environmental metrics, e-commerce's waste challenges intersect with broader social and economic dimensions (Popović, 2020; Popović et al., 2022b). Industry 4.0 tools, robotics, AI, and digital platforms may boost efficiency yet potentially increase consumption or exacerbate inequalities (Fichter, 2002; Abukhader & Jönson, 2003). The EU's circular economy frameworks emphasize linking digitalization with well-structured policies to reduce single-use materials and encourage product-service models (Popović & Milijić, 2021; Popović et al., 2023). Nevertheless, effective outcomes depend on institutional backing, cultural acceptance, and technological readiness across diverse Member States.

Overall, the literature indicates that e-commerce has mixed effects on waste streams, with packaging being a chief concern. Contextual factors like RECMWASTE, INDVA, and RESP, combined with policy environments, shape the net outcome. Empirical gaps persist, especially regarding dynamic effects, threshold behaviors, and multi-country analyses applying advanced methods such as PVAR, panel thresholds, and machine learning, topics the following sections address in detail.

2. Research design and methodology

The primary objective of this study is to investigate how the expansion of e-commerce (ECOMS) affects different waste streams, namely waste per capita (WASTPC), municipal waste per capita (MWASTE), and packaging waste per capita (PACWASTE), across European Union (EU) Member States. In addressing this objective, the research also explores whether factors such as recycling infrastructure (RECMWASTE) and industrial development (INDVA) moderate e-commerce's influence while considering distributional heterogeneities and any potential spatial effects. Building on literature that identifies a shortage of multi-country, longitudinal analyses, this study adopts a multi-stage research design (see Figure 1) integrating Panel Vector Autoregression (PVAR), panel threshold regression (PTR), quantile regression, and machine learning checks.

A single overarching question guides the inquiry:

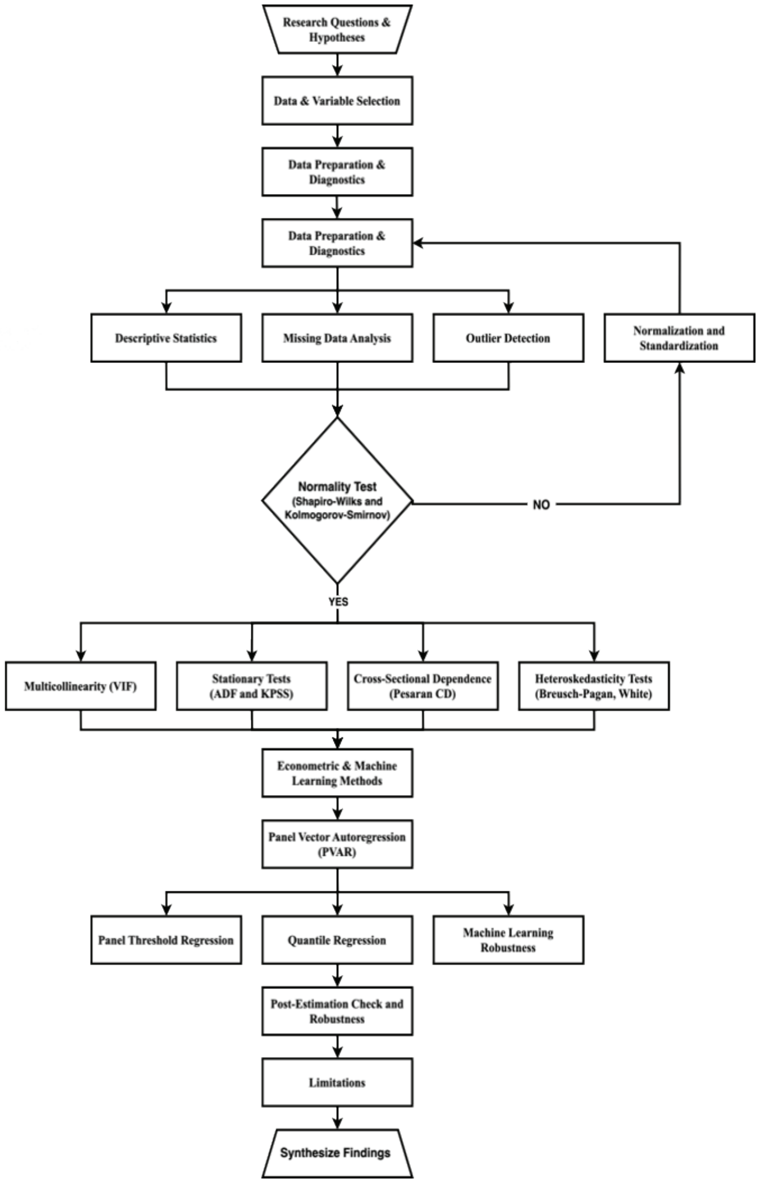
- RQ (Main): How does the expansion of e-commerce (ECOMS) influence waste generation in EU countries, and what contextual factors moderate this relationship?

To delve deeper, five supporting questions are examined:

- RQ1 (Short vs. Long-Run Effects): Are the immediate (short-run) impacts of e-commerce on waste different from the lagged (long-run) impacts?
- RQ2 (Recycling Infrastructure): Does a higher recycling rate (RECMWASTE) moderate or dampen the association between e-commerce and waste generation?
- RQ3 (Threshold Effects): Are there non-linearities or threshold points, such as in RECMWASTE or INDVA, beyond which the effect of e-commerce on waste intensifies?
- RQ4 (Spatial Spillovers): Does e-commerce expansion in one country produce cross-border effects on waste due to shared logistics networks, thereby suggesting spatial interdependence?
- RQ5 (Temporal Dynamics): Does the rise in packaging waste taper off or change character over time (as policies and consumer practices evolve)?

Five hypotheses address these questions:

- H1 (Direct Impact): E-commerce expansion (ECOMS) correlates positively with waste indicators (WASTPC, MWASTE, PACWASTE).
- H2 (Role of Recycling): Higher recycling capacity (RECMWASTE) moderates the positive impact of e-commerce on waste, reducing its magnitude.
- H3 (Threshold Effect): Beyond certain threshold values of RECMWASTE or INDVA, the effect of e-commerce on waste shifts, thus indicating non-linear behaviors.
- H4 (Spatial Spillovers): E-commerce growth in one country triggers adjacent or cross-border effects on waste due to integrated supply chains, thereby confirming spatial dependence.
- H5 (Temporal Dynamics): The initial surge in waste due to e-commerce packaging diminishes over time, suggesting changing consumer and policy responses.



Source: Own design.

A balanced panel of 27 EU Member States (2014–2023) provides 270 country-year observations. Core variables, WASTPC, MWASTE, PACWASTE, ECOMS, RECMWASTE, INDVA, UNEMP, and RESP, are compiled from Eurostat (2024) and World Bank (2024). Waste indicators capture different dimensions (total, municipal, and packaging), while e-commerce penetration (ECOMS) reflects the percentage of enterprises (≥10 employees) conducting online sales. All variables are cleaned and checked for outliers. Skewness is mitigated, and comparability is enhanced through Z-score standardization and/or Box-Cox transformations (Borjesson Rivera et al., 2014).

Data diagnostics consider normality, using Shapiro–Wilk and Kolmogorov–Smirnov tests, revealing significant skewness that justifies transformations. Variance Inflation Factors (VIF) remain below 3.5, indicating no severe multicollinearity. Augmented Dickey-Fuller (ADF) and KPSS tests confirm that most transformed series achieve stationarity, while Pesaran's CD test shows minimal cross-sectional dependence for this sample. Finally, heteroscedasticity (Breusch–Pagan, White tests) and serial correlation checks (including Wooldridge's test) prompt the use of robust errors or feasible generalized least squares in subsequent estimations (Soukiazis & Proença, 2020; Imran et al., 2023).

PVAR is employed to capture dynamic interdependencies, following Holtz-Eakin, Newey, and Rosen (1988) and Arellano and Bover (1995). E-commerce (ECOMS) and each waste indicator (WASTPC, MWASTE, or PACWASTE) are modeled as endogenous, incorporating exogenous controls (RESP, UNEMP, INDVA). The specification:

$$\boldsymbol{y_{i,t}} = \boldsymbol{A(L)\,y_{i,t-1}} + \boldsymbol{x_{i,t}\,\Gamma} + \boldsymbol{\epsilon_{i,t}} \qquad (1)$$

- $y_{i,t}$ *- vector of multiple endogenous variables*
- *$A(L)$ - matrix of lag operators*
- $x_{i,t}$ *- matrix of exogenous regressors*
- *Γ – matrix of corresponding coefficients*
- $\epsilon_{i,t}$ *– residual*

allows short-run shocks to e-commerce or waste to propagate over time, while the Bayesian Information Criterion (BIC) determines the optimal lag length. Impulse Response Functions (IRFs) illustrate short-run vs. long-run adjustments, and Variance Decompositions (FEVD) indicate the relative contribution of e-commerce shocks to waste or vice versa.

To test H3, panel threshold regressions (PTR) detect non-linear regime changes for e-commerce–waste linkages once RECMWASTE or INDVA crosses an estimated threshold (Hansen, 1999). Potential spatial dependence (H4) is explored via Pesaran's CD test and, where relevant, spatial autoregressive models. Quantile regressions (Koenker & Bassett, 1978) reveal distributional nuances, clarifying whether high-waste vs. low-waste contexts respond differently to e-commerce expansions. Finally, random forest regressors (Breiman, 2001) are a robustness check, capturing potential non-linearities unaccounted for in conventional parametric approaches (Popović et al., 2023).

Various robustness checks complement the core analysis. Alternative waste indicators, such as MWASTE and PACWASTE, replace WASTPC to verify consistency, while additional interaction terms assess whether industrial development or resource productivity modifies e-commerce's impact. Structural breaks around major policy shifts are briefly examined. Granger causality tests further clarify directionality: e-commerce might drive waste, yet rising waste and subsequent policies might also dampen or reshape online retail.

Hence, this multi-method design, PVAR, PTR, quantile regressions, and machine learning, aims to address identified gaps by capturing both dynamic (short-run vs. long-run) and distributional (low-waste vs. high-waste) characteristics. The subsequent section presents the empirical results, detailing how e-commerce relates to waste in the EU and examining implications for circular economy strategies, especially regarding packaging reduction, recycling, and labor-market transitions.

3. Research results

This section presents the empirical findings derived from a multi-stage framework encompassing descriptive analyses, Panel Vector Autoregression (PVAR) models (A–C, D, and Scenarios E–F), panel threshold regressions, quantile regressions, and machine learning robustness checks. The overarching goal is to clarify how e-commerce (ECOMS) expansion affects waste per capita (WASTPC), municipal waste per capita (MWASTE), and packaging waste per capita (PACWASTE) in EU Member States, alongside potential moderating factors such as recycling infrastructure (RECMWASTE) and industrial development (INDVA).

3.1. Descriptive statistics and data diagnostics

Table 1 displays the mean, standard deviation, and range for eight variables (N=270). Notable points include significant heterogeneity in waste indicators. Waste per capita (WASTPC) averages 6,333 kg but can rise to almost 24,872 kg, highlighting substantial cross-country differences. E-commerce adoption (ECOMS) ranges between ~7.2% and ~42.5% of enterprises (≥10 employees), reflecting varying degrees of digital market maturity. Municipal waste per capita (MWASTE) also varies widely (247–844 kg), as does packaging waste per capita (PACWASTE) (48–246 kg).

Table 1: Descriptive Statistics

Variables	Count	Mean	St. Dev.	Min	25%	50%	75%	Max
WASTPC	270	6333.19	5589.82	879.00	2482.75	4297.00	7783.50	24872.00
ECOMS	270	21.28	7.74	7.20	15.23	20.10	26.55	42.50
MWASTE	270	510.96	130.81	247.00	425.25	488.00	589.50	844.00
PACWASTE	270	147.42	46.25	48.33	114.87	152.79	175.36	246.14
RECMWASTE	270	38.52	14.98	9.10	29.18	39.70	49.50	70.30
RESP	270	1.84	1.12	0.30	0.95	1.46	2.65	5.46
UNEMP	270	7.46	4.06	2.02	5.03	6.56	8.50	26.71
INDVA	270	22.45	6.21	9.97	18.94	22.07	26.67	41.49

Source: Own calculations.

A balanced panel with no missing observations strengthens the dataset's robustness. Potential outliers in WASTPC, RESP, UNEMP, and INDVA were verified and retained to capture true variation. Shapiro-Wilk and Kolmogorov-Smirnov tests (Table 2) reveal significant skewness, prompting Box-Cox transformations and z-score standardization (Borjesson Rivera et al., 2014). Variance Inflation Factors (VIF) remain below 3.5, indicating minimal multicollinearity (Soukiazis & Proença, 2020).

Table 2: Normality Check

Variable	Shapiro-Wilk Statistic	Shapiro-Wilk p-value	Kolmogorov-Smirnov Statistic	Kolmogorov-Smirnov p-value
Original Dataset				
WASTPC	0.7884	0.0000	0.2221	0.0000
ECOMS	0.9772	0.0003	0.0711	0.1244
MWASTE	0.9575	0.0000	0.1223	0.0006
PACWASTE	0.9823	0.0020	0.0504	0.4838
RECMWASTE	0.9772	0.0003	0.0654	0.1898
RESP	0.9282	0.0000	0.1382	0.0001
UNEMP	0.8194	0.0000	0.1647	0.0000
INDVA	0.9837	0.0036	0.0466	0.5848

Source: Own calculations.

Augmented Dickey-Fuller (ADF) and KPSS tests (Table 3) confirm that most variables approach stationarity once standardized, while Pesaran's CD test shows weak cross-sectional dependence.

Table 3: Augmented Dickey-Fuller (ADF) and KPSS Tests Results

Variable	ADF Stat	ADFp-value	ADF Lags	KPSS Stat	KPSS p-value	KPSS Lags
WASTPC_z	-2.7982	0.0585	10	0.1240	0.1000	10
ECOMS_z	-5.0563	0.0000	0	0.0945	0.1000	9
MWASTE_z	-4.2920	0.0005	0	0.5201	0.0371	9
PACWASTE_z	-3.7724	0.0032	0	0.2607	0.1000	10
RECMWASTE_z	-4.3792	0.0003	0	0.0599	0.1000	9
RESP_z	-3.6440	0.0050	10	0.0904	0.1000	10
UNEMP_z	-4.8897	0.0000	10	0.0863	0.1000	9
INDVA_z	-3.2895	0.0154	10	0.0958	0.1000	9

Source: Own calculations.

Heteroscedasticity, identified by Breusch–Pagan and White tests (Table 4), led to the use of robust standard errors or feasible generalized least squares. Serial correlation was addressed via system GMM or robust covariance estimators (Imran et al., 2023).

Table 4: Breusch-Pagan and White Tests

Metric	Breusch-Pagan Test	White Test
LM Statistic	99.1023	193.2545
LM p-value	1.65×10^{-18}	8.65×10^{-24}
F-value	21.7046	16.8354
F p-value	4.92×10^{-23}	2.59×10^{-46}

Source: Own calculations.

Overall, this dataset provides a solid basis for subsequent analyses. It contains no missing values, accommodates outliers legitimately, and satisfies transformations to handle skewness. Stationarity checks, low VIFs, and minimal cross-sectional dependence reinforce its suitability for PVAR, panel threshold, quantile regressions, and machine learning (Matthews et al., 2001). The next subsections detail the PVAR results, followed by threshold and quantile findings and robustness checks.

3.2. PVAR Results: Models A, B, and C

This section presents the Panel Vector Autoregression (PVAR) estimations for three two-variable models that pair e-commerce (ECOMS) with different waste indicators. Model A analyzes e-commerce and waste per capita (WASTPC), Model B examines e-commerce and municipal waste per capita (MWASTE), and Model C focuses on e-commerce and packaging waste per capita (PACWASTE). Each model employs two lags, determined by the Bayesian Information Criterion (BIC), to capture dynamic feedback in the connection between e-commerce and waste.

3.2.1. Lag selection

All three two-variable PVAR systems underwent an internal lag selection procedure. Table 5 shows that a 2-lag specification generally outperforms a 1-lag model in each scenario, as reflected in lower BIC values. This result suggests meaningful dynamic effects across two periods.

Table 5: Lag Selection

Model	Lags	RSS	Num. Params	Nobs	LLF	AIC	BIC
A	1	25.9545	6	243	-73.0409	158.0819	179.0402
A	2	20.5291	10	216	-52.3197	124.6395	158.3923
B	1	37.7344	6	243	-118.51	249.0194	269.9778
B	2	32.8734	10	216	-103.168	226.3368	260.0895
C	1	28.4769	6	243	-84.3098	180.6196	201.578
C	2	23.3144	10	216	-66.0605	152.1211	185.8739

Notes: RSS (Residual Sum of Squares); LLF (Log Likelihood Function); AIC (Akaike Information Criterion); BIC (Bayesian Information Criterion);

Source: Own calculations.

3.2.2. Model A (WASTPC & ECOMS)

Model A explores how e-commerce (ECOMS) and waste per capita (WASTPC) influence each other. Table 6 summarizes the key coefficients.

Table 6: PVAR Results for Model A (WASTPC & ECOMS)

Dep. Var.	Regressor	Coeff.	t-stat	p-value
WASTPC_z	$WASTPC_{t-1}$	1.1812	12.1413	0.0000
WASTPC_z	$ECOMS_{t-1}$	0.0164	0.7434	0.4582
WASTPC_z	$WASTPC_{t-2}$	-0.4607	-5.6554	0.0000
WASTPC_z	$ECOMS_{t-2}$	-0.0058	-0.3368	0.7367
WASTPC_z	$WASTPC_{t-1}$	-0.1368	-0.6459	0.5192

WASTPC_z	$ECOMS_{t-1}$	0.6337	7.9014	0.0000
WASTPC_z	$WASTPC_{t-2}$	0.2267	1.0327	0.3031
WASTPC_z	$ECOMS_{t-2}$	0.1672	1.9829	0.0489

Source: Own calculations.

- WASTPC displays strong inertia (coefficient ~1.1812), with a partial mean-reversion term at the second lag (–0.4607, p<0.001).
- ECOMS does not significantly predict short-run variations in WASTPC, implying that online retail may not alter total waste per capita immediately.
- ECOMS primarily depends on its own history (coefficient ~0.6337), suggesting an internal momentum in e-commerce growth.

Granger Causality. Table 7 shows no robust evidence of short-run causality in either direction, with p-values over 0.50.

Table 7: Model A Granger Causality Tests

Dependent Variable	Causal Variable	Test Statistic	p-value
WASTPC_z	ECOMS_z	0.7372	0.6917
ECOMS_z	WASTPC_z	1.2144	0.5449

Source: Own calculations.

Impulse Response Functions (IRFs). Table 8 suggests a mild (and sometimes negative) WASTPC response to an e-commerce shock, whereas WASTPC shocks do not strongly affect ECOMS beyond the initial lag.

Table 8: Model A: Selected IRF (5-period horizon)

Horizon	IRF (ECOMS→WASTPC)	IRF (WASTPC→ECOMS)	Lower B. (ECOMS)	Upper B. (ECOMS)	Lower B. (WASTPC)	Upper B. (WASTPC)
0	0.00	0.00	0.0000	0.0000	0.0000	0.0000
1	0.02	-0.14	-0.5351	0.2619	1.0144	1.3539
2	0.03	-0.25	-1.0072	0.4696	1.0277	1.8312
3	0.04	-0.35	-1.4843	0.6766	1.0410	2.4754
4	0.05	-0.44	-1.9482	0.8466	1.0541	3.3453
5	0.07	-0.55	-2.4862	1.0580	1.0640	4.5206

Source: Own calculations.

Forecast Error Variance Decomposition (FEVD). Table 9 confirms that 99% of WASTPC's variance is self-driven, while ECOMS shocks account for only ~1%. Overall, Model A indicates limited immediate effects of e-commerce on total waste per capita.

Table 9: FEVD for Model A (Selected Horizons)

Horizon	FEVD (WASTPC from WASTPC)	FEVD (WASTPC from ECOMS)	FEVD (ECOMS from WASTPC)	FEVD (ECOMS from ECOMS)
0	1.0000	0.0000	0.0000	1.0000
1	0.9998	0.0002	0.0445	0.9555
2	0.9995	0.0005	0.2788	0.7212
3	0.9994	0.0006	0.6613	0.3387
5	0.9992	0.0008	0.9741	0.0259

Source: Own calculations.

3.2.3. Model B (MWASTE & ECOMS)

In Model B, e-commerce (ECOMS) pairs with municipal waste per capita (MWASTE). Table 10 highlights the main coefficients.

Table 10: PVAR Results for Model B (MWASTE & ECOMS)

Dep. Var.	Regressor	Coeff.	t-stat	p-value
MWASTE_z	$MWASTE_{t-1}$	0.7211	7.1086	0.0000
MWASTE_z	$ECOMS_{t-1}$	0.0114	0.2016	0.8405
MWASTE_z	$MWASTE_{t-2}$	-0.0578	-0.9458	0.3455
MWASTE_z	$ECOMS_{t-2}$	0.0491	0.7786	0.4372
ECOMS_z	$MWASTE_{t-1}$	0.0302	0.3610	0.7185
ECOMS_z	$ECOMS_{t-1}$	0.6367	7.7125	0.0000
ECOMS_z	$MWASTE_{t-2}$	0.0127	0.1662	0.8682
ECOMS_z	$ECOMS_{t-2}$	0.1537	1.7088	0.0892

Source: Own calculations.

- MWASTE strongly depends on its previous value (~0.7211), consistent with entrenched municipal waste patterns.
- ECOMS lags do not significantly predict MWASTE, suggesting that short-term changes in e-commerce do not alter municipal waste generation.
- As in Model A, ECOMS remains largely self-driven (Coefficient ~0.6367).

Granger Causality. Table 11 indicates no significant short-run predictive power from ECOMS to MWASTE or vice versa.

Table 11: Model B Granger Causality Tests

Dependent Variable	Causal Variable	Test Statistic	p-value
MWASTE_z	ECOMS_z	1.93714	0.3796
ECOMS_z	MWASTE_z	0.56683	0.7532

Source: Own calculations.

Impulse Responses and FEVD. Tables 12 and 13 show minimal MWASTE response to e-commerce shocks, with MWASTE's own history explaining ~99% of its variance. Thus, e-commerce exhibits little immediate impact on municipal waste in Model B.

Table 12: Model B: Selected IRF (5-period horizon)

Horizon	IRF (ECOMS → MWASTE)	IRF (MWASTE → ECOMS)	Lower Bound (ECOMS)	Upper Bound (ECOMS)	Lower Bound (MWASTE)	Upper Bound (MWASTE)
0	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
1	0.0302	0.7211	-0.1224	0.1673	0.5018	0.8852
2	0.0410	0.5203	-0.1664	0.2282	0.2546	0.7800
3	0.0419	0.3756	-0.1604	0.2464	0.1327	0.6855
4	0.0380	0.2713	-0.1470	0.2322	0.0671	0.6031
5	0.0324	0.1961	-0.1309	0.2180	0.0352	0.5317

Source: Own calculations.

Table 13: FEVD for Model B (Selected Horizons)

Horizon	FEVD (MWASTE from MWASTE)	FEVD (MWASTE from ECOMS)	FEVD (ECOMS from MWASTE)	FEVD (ECOMS from ECOMS)
0	1.0000	0.0000	0.0000	1.0000
1	0.9998	0.0002	0.0022	0.9978
2	0.9991	0.0009	0.0101	0.9899
3	0.9982	0.0018	0.0255	0.9745
5	0.9961	0.0039	0.0859	0.9141

Source: Own calculations.

3.2.4. Model C (PACWASTE & ECOMS)

Model C pairs e-commerce (ECOMS) with packaging waste per capita (PACWASTE). Unlike WASTPC or MWASTE, PACWASTE demonstrates a stronger linkage to e-commerce. Table 14 presents the key results.

Table 14: PVAR Results for Model C (PACWASTE & ECOMS)

Dep. Var.	Regressor	Coeff.	t-stat	p-value
PACWASTE_z	$PACWASTE_{t-1}$	0.5420	5.8150	0.0000
PACWASTE_z	$ECOMS_{t-1}$	0.0737	2.6240	0.0094
PACWASTE_z	$PACWASTE_{t-2}$	0.2543	3.0592	0.0025
PACWASTE_z	$ECOMS_{t-2}$	0.0227	0.7671	0.4440
ECOMS_z	$PACWASTE_{t-1}$	0.2354	1.5825	0.1152
ECOMS_z	$ECOMS_{t-1}$	0.5836	6.9648	0.0000
ECOMS_z	$PACWASTE_{t-2}$	0.0891	0.5951	0.5525
ECOMS_z	$ECOMS_{t-2}$	0.0921	1.0120	0.3129

Source: Own calculations.

- PACWASTE Persistence. $PACWASTE_{t-1}$ has a strong positive effect (~0.5420), indicating high persistence.

- E-Commerce Influence. $ECOMS_{t-1}$ is significantly positive (~0.0737, p=0.0094) for PACWASTE, suggesting that rising e-commerce quickly elevates packaging waste.

Table 15 shows Granger causality in both directions (p<0.01), implying a feedback loop where e-commerce growth drives packaging waste, and rising packaging waste may reinforce e-commerce logistics.

Table 15: Model C Granger Causality Tests

Dependent Variable	Causal Variable	Test Statistic	p-value
PACWASTE_z	ECOMS_z	11.8385	0.0027
ECOMS_z	PACWASTE_z	9.3951	0.0091

Source: Own calculations.

IRFs and FEVD. Tables 16 and 17 reveal that e-commerce shocks can explain up to 22% of PACWASTE variance by horizon 5. This stands in contrast to WASTPC or MWASTE, where e-commerce accounted for ≤2%.

Table 16: Model C: Selected IRF (5-period horizon)

Horizon	IRF (ECOMS → PACWASTE)	IRF (PACWASTE → ECOMS)	Lower Bound (ECOMS)	Upper Bound (ECOMS)	Lower Bound (PACWASTE)	Upper Bound (PACWASTE)
0	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
1	0.2354	0.5419	-0.0369	0.5081	0.3587	0.7151
2	0.2650	0.3111	-0.0415	0.5651	0.1421	0.5306
3	0.2279	0.1881	-0.0354	0.5219	0.0596	0.3978
4	0.1773	0.1187	-0.0304	0.4596	0.0287	0.3096
5	0.1314	0.0774	-0.0251	0.3811	0.0131	0.2382

Source: Own calculations.

Table 17: FEVD for Model C (Selected Horizons)

Horizon	FEVD (PACWASTE from PACWASTE)	FEVD (PACWASTE from ECOMS)	FEVD (ECOMS from PACWASTE)	FEVD (ECOMS from ECOMS)
0	1	0	0	1
1	0.9819	0.0181	0.14	0.86
2	0.9337	0.0663	0.3541	0.6459
3	0.8744	0.1256	0.4989	0.5011
5	0.8209	0.1791	0.5826	0.4174

Source: Own calculations.

Hence, Model C offers robust evidence of a direct and short-run e-commerce impact on packaging disposal. In practical terms, these findings highlight that online retail fosters a significant increase in packaging materials, corrugated cardboard, plastics, protective wraps, and so forth, which manifest as higher packaging waste in the short to medium term.

Overall, Model C indicates a short-run, bidirectional nexus between e-commerce and packaging waste. These findings highlight that online retail more immediately affects packaging streams than total or municipal waste, underscoring the importance of targeted policy measures for packaging-intensive channels.

3.3. PVAR extensions: Models D, scenario E, and scenario F

Beyond the two-variable setups in Models A, B, and C, the analysis expands to Model D, a principal-component–based index, and two multi-variable scenarios (E and F). These extensions investigate how e-commerce (ECOMS) might indirectly influence additional waste variables, industrial development, resource productivity, and labor market conditions. They follow the PVAR approach described earlier but vary in endogenous and exogenous variables.

3.3.1. Model D: PCA-based index (INDEX) and E-commerce (ECOMS)

Model D condenses four standardized waste and recycling measures, WASTPC_z, MWASTE_z, PACWASTE_z, and RECMWASTE_z, into a single principal component (INDEX). This aggregated index gauges a country's combined waste–recycling performance. Once again, Bayesian Information Criterion (BIC) was consulted to decide on lags. Table 18 (mentioned below) shows that a 2-lag specification yields a consistently lower BIC, reinforcing the earlier choice of two lags.

Table 18: Lag Selection Model D

Model	Lags	RSS	Num. Params	Nobs	LLF	AIC	BIC
D	1	33.1829	6	243	-102.893	217.7852	238.7436
D	2	27.5942	10	216	-84.2619	188.5238	222.2766

Source: Own calculations.

Table 19 (presented next) shows that INDEX remains highly dependent on its own first lag (~0.6705, p<0.001). By contrast, e-commerce exerts only a modest and statistically insignificant short-run effect on this composite index (coefficient ~0.0539, p≈0.19). In the ECOMS equation, however, e-commerce strongly depends on its own lag (~0.6162, p<0.001), mirroring the momentum seen in earlier models.

Table 19: PVAR Results for Model D (INDEX & ECOMS)

Dep. Var.	Regressor	Coeff.	t-stat	p-value
MWASTE_z	$INDEX_{t-1}$	0.6705	7.8441	<0.0010
MWASTE_z	$ECOMS_{t-1}$	0.0539	1.3242	0.1871
MWASTE_z	$INDEX_{t-2}$	0.1072	1.5405	0.1251
MWASTE_z	$ECOMS_{t-2}$	0.0231	0.5063	0.6133
ECOMS_z	$INDEX_{t-1}$	-0.0603	-0.5525	0.5813
ECOMS_z	$ECOMS_{t-1}$	0.6162	7.6459	<0.0010
ECOMS_z	$INDEX_{t-2}$	0.1642	1.7005	0.0907
ECOMS_z	$ECOMS_{t-2}$	0.1279	1.4023	0.1625

Source: Own calculations.

Table 20 shows borderline Granger causality in both directions (ECOMS → INDEX at p≈0.0697; INDEX → ECOMS at p≈0.0499). Impulse responses indicate that an e-commerce shock modestly raises the composite index, yet less dramatically than in the packaging-specific setting (Model C). Forecast error variance decompositions (FEVD) confirm that INDEX is mainly driven by its own past, with e-commerce shocks explaining around 7–12% of its mid-horizon variance. Overall, the aggregated nature of INDEX dampens e-commerce's immediate effect compared to packaging waste, although some two-way interaction may emerge over time.

Table 20: Model D Granger Causality Tests

Dependent Variable	Causal Variable	Test Statistic	p-value
INDEX_z	ECOMS_z	5.3269	0.0697
ECOMS_z	INDEX_z	5.9964	0.0499

Source: Own calculations.

3.3.2. Scenario E: Multi-variable system

Scenario E moves from a two-variable to a five-variable PVAR, incorporating the following as endogenous variables: INDEX (the PCA-based composite of WASTPC, MWASTE, PACWASTE, RECMWASTE), ECOMS RESP (resource productivity), UNEMP (unemployment rate), and INDVA (industrial value added).

To confirm the lag length, Table 21 again points to two lags. This setup explores whether industrial structure, labor dynamics, or resource productivity shape e-commerce's link to a broader waste–recycling context.

Table 21: Lag Selection Scenario E

Model	Lags	RSS	Num. Params	Nobs	LLF	AIC	BIC
Sc. E	60.9292	30	243	-176.725	413.4504	518.2422	60.92921
Sc. E	48.8923	55	216	-146.04	402.0792	587.7195	48.8923

Source: Own calculations.

Table 22 reveals several key insights. The index is highly persistent (~0.7701, p<0.001) but negatively influenced by rising unemployment, while e-commerce (ECOMS) again demonstrates inertia (~0.6897, p<0.001). Resource productivity (RESP) shows significant self-persistence (~0.7032) yet remains largely unaffected by e-commerce or the overall index. Meanwhile, unemployment (UNEMP) is persistent (~0.6765) yet may decline if industrial value added improves and industrial development (INDVA) interacts positively with e-commerce (Coefficient ~0.0561, p≈0.0415). These patterns suggest that labor conditions and industrial factors can indirectly modulate the interaction between e-commerce and waste, although direct e-commerce impacts on the index remain modest.

Table 22: PVAR Results for Scenario E Multi-Variable System

Dep. Var.	Regressor	Coeff.	t-stat	p-value
INDEX	$INDEX_{t-1}$	0.7701	16.1974	<0.0010
INDEX	$ECOMS\_z,_{t-1}$	0.0511	1.7219	0.0866
INDEX	$RESP\_z,_{t-1}$	-0.1274	-1.4068	0.1610
INDEX	$UNEMP\_z,_{t-1}$	-0.0685	-1.9842	0.0485
INDEX	$INDVA\_z,_{t-1}$	-0.0395	-0.7776	0.4377
ECOMS_z	$INDEX_{t-1}$	0.0280	0.4815	0.6306
ECOMS_z	$ECOMS\_z,_{t-1}$	0.6897	11.998	<0.0010
ECOMS_z	$RESP\_z,_{t-1}$	-0.1597	-0.7509	0.4535
ECOMS_z	$UNEMP\_z,_{t-1}$	-0.1715	-3.1956	0.0016
ECOMS_z	$INDVA\_z,_{t-1}$	-0.0908	-0.8107	0.4185
RESP_z	$INDEX_{t-1}$	-0.0157	-0.8202	0.4130
RESP_z	$ECOMS\_z,_{t-1}$	0.0249	1.7080	0.0891
RESP_z	$RESP\_z,_{t-1}$	0.7032	9.1462	<0.0010
RESP_z	$UNEMP\_z,_{t-1}$	-0.0314	-1.8769	0.0619
RESP_z	$INDVA\_z,_{t-1}$	-0.0104	-0.2679	0.7890
UNEMP_z	$INDEX_{t-1}$	-0.1187	-2.2052	0.0285
UNEMP_z	$ECOMS\_z,_{t-1}$	0.0067	0.1572	0.8753
UNEMP_z	$RESP\_z,_{t-1}$	-0.1274	-0.8091	0.4194
UNEMP_z	$UNEMP\_z,_{t-1}$	0.6765	13.1502	<0.0010
UNEMP_z	$INDVA\_z,_{t-1}$	-0.2024	-2.4414	0.0155
INDVA_z	$INDEX_{t-1}$	-0.0171	-0.4374	0.6622
INDVA_z	$ECOMS\_z,_{t-1}$	0.0561	2.0507	0.0415
INDVA_z	$RESP\_z,_{t-1}$	0.1185	0.8940	0.3723
INDVA_z	$UNEMP\_z,_{t-1}$	0.0668	2.2374	0.0263
INDVA_z	$INDVA\_z,_{t-1}$	0.2334	1.6474	0.1010

Source: Own calculations.

3.3.3. Scenario F: Partially exogenous

ScenarioScenario F treats RESP, UNEMP, and INDVA as exogenous, focusing on the two main endogenous variables, INDEX and ECOMS, while holding the others constant. The results broadly mirror Scenario E, implying:

- INDEX retains strong self-dependence (Coefficient ~0.6640), with minimal direct influence from e-commerce.
- ECOMS remains strongly autoregressive, reflecting its inherent momentum.

Although borderline Granger causality hints that e-commerce may influence the index over short horizons, the evidence is not conclusive once lagged index values are considered. Impulse responses confirm that e-commerce explains only around 12% of the index's variance, even by Horizon 5. Hence, structural exogenous factors (labor market, resource use, industrial activity) do not drastically amplify e-commerce's immediate role in shaping a combined waste–recycling index.

Table 23: PVAR Results for Scenario F Partially Exogenous

Dep. Var.	Regressor	Coeff.	t-stat	p-value
INDEX	$INDEX_{t-1}$	0.6640	7.4744	<0.0010
INDEX	$ECOMS\_z,_{t-1}$	0.0566	1.3668	0.1734
INDEX	$INDEX_{t-2}$	0.1029	1.4002	0.1631
INDEX	$ECOMS\_z,_{t-2}$	0.0273	0.6072	0.5445
INDEX	RESP_z	-0.0295	-0.2723	0.7857
INDEX	UNEMP_z	-0.0164	-0.3856	0.7003
INDEX	INDVA_z	-0.0829	-0.8603	0.3908
ECOMS_z	$INDEX_{t-1}$	-0.0608	-0.5514	0.5820
ECOMS_z	$ECOMS\_z,_{t-1}$	0.5975	7.3978	<0.0010
ECOMS_z	$INDEX_{t-2}$	0.1317	1.3348	0.1836
ECOMS_z	$ECOMS\_z,_{t-2}$	0.1223	1.4113	0.1599
ECOMS_z	RESP_z	-0.1112	-0.6218	0.5348
ECOMS_z	UNEMP_z	-0.1185	-1.9481	0.0529
ECOMS_z	INDVA_z	0.1558	1.0834	0.2800

Source: Own calculations.

These larger frameworks underscore that e-commerce exerts a pronounced, direct effect on packaging waste (Model C) but has smaller short-run impacts when aggregated with broader waste or recycling indicators. Model D suggests that packaging stands out among waste streams for e-commerce-driven increases, while the combined index reduces e-commerce's immediate significance. Scenarios E and F further show that industrial development, unemployment, and resource productivity overshadow e-commerce's direct influence, often operating through broader economic or labor-market pathways.

Thus, packaging emerges as the crucial channel for e-commerce-induced waste escalation. This highlights the importance of targeted policy and industrial responses, such as minimizing packaging material and improving recycling, to counteract online retail's environmental costs. The following sections delve into how these findings inform policy design and ongoing circular economy strategies.

3.4. Panel threshold regressions (PTR)

This section examines whether specific economic or labor-market conditions alter the relationship between e-commerce (ECOMS) and waste once a cutoff is crossed in the moderator variable. Three possible thresholds, unemployment (UNEMP_z), resource productivity (RESP_z), and industrial development (INDVA_z), are tested across all three models (A: WASTPC; B: MWASTE; C: PACWASTE). Single-threshold panel threshold regressions (PTR) were run to see how e-commerce's impact shifts under low vs. high regimes of these contextual factors.

Before turning to the results, Table 23 summarizes the key findings across Models A, B, and C, listing the best threshold and slope changes ($\beta 1$, $\beta 2$) under each moderator.

Table 23: Panel Threshold Regressions (PTR) Summary

Model	Yvar	Xvar.	TH Var.	Best TH	Param α	Param β1	Param β2	SR
A	WASTPC_z	ECOMS_z	RESP_z	-0.134	-0.005	-0.173	0.047	9.712
A	WASTPC_z	ECOMS_z	UNEMP_z	0.704	0.010	0.003	0.247	9.615
A	WASTPC_z	ECOMS_z	INDVA_z	-0.022	0.003	0.094	-0.016	9.756
B	MWASTE_z	ECOMS_z	RESP_z	-0.064	0.008	0.450	0.176	35.108
B	MWASTE_z	ECOMS_z	UNEMP_z	-0.097	0.030	0.107	0.391	35.008
B	MWASTE_z	ECOMS_z	INDVA_z	0.269	-0.001	0.236	0.454	35.817
C	PACWASTE_z	ECOMS_z	RESP_z	0.083	-0.007	0.342	0.485	13.167
C	PACWASTE_z	ECOMS_z	UNEMP_z	0.524	0.014	0.330	0.552	12.954
C	PACWASTE_z	ECOMS_z	INDVA_z	0.104	-0.003	0.328	0.530	12.936

Source: Own calculations.

1. Model A (WASTPC_z, ECOMS_z):
- Unemployment Threshold (~ 0.7042): E-commerce's slope rises from near zero to about +0.2468 in the higher unemployment regime, although the overall residual sum of squares (SSR) shift is modest.
- RESP or INDVA: Splits here yield slope changes in the range of $\beta 1 \approx -0.17$ vs. $\beta 2 \approx +0.05$, mostly borderline significant.
- High unemployment or lower resource productivity can amplify e-commerce's effect on total waste per capita, albeit less strongly than in packaging contexts.

2. Model B (MWASTE_z, ECOMS_z):
- Unemployment Threshold (~ -0.0972): Once unemployment dips below this level, the slope for e-commerce on MWASTE rises from about +0.1074 to +0.3909. Regions with lower unemployment appear more susceptible to short-run connections between e-commerce and MWASTE.
- Though earlier PVAR models found little short-run e-commerce influence on municipal waste, PTR suggests that under certain labor conditions, such as high employment, MWASTE may climb in tandem with e-commerce, likely reflecting higher consumption in more stable job markets.

3. Model C (PACWASTE_z, ECOMS_z):
- Unemployment Threshold (~ 0.5245): E-commerce's slope on packaging waste jumps from +0.0144 in the lower unemployment regime to +0.3302 in the higher unemployment regime, indicating a significant threshold change.
- Packaging Sensitivity: Packaging waste responds strongly to e-commerce expansion when unemployment is elevated, possibly due to shifting consumer habits or more frequent home deliveries in precarious labor contexts. The jump dwarfs that seen in total or municipal waste, underscoring packaging's vulnerability to online retail growth.

Across these threshold tests, H3 (Threshold Effect) is partly confirmed: e-commerce can exert a stronger influence on waste under specific labor or industrial conditions. The largest threshold effect surfaces in Model C, aligning with previous findings that packaging is the most e-commerce-sensitive stream (Caiyi et al., 2022). Policy or managerial actions, such as targeted recycling incentives or packaging regulations, may be especially crucial where unemployment or industrial structures exacerbate packaging inflows.

3.5. Quantile regressions

Quantile regressions next assess how e-commerce's impact on waste varies across the distribution, particularly among low- vs. high-waste countries. This approach moves beyond mean-based estimations to reveal differing effects along various percentiles.

Before detailing results, Table 24 (mentioned below) lists the quantile regression outcomes for Models A (WASTPC), B (MWASTE), and C (PACWASTE), with slopes at quantiles $\tau \in \{0.10, 0.25, 0.5, 0.75, 0.9\}$.

Table 24: Quantile Regressions

Model	Quantile	Yvar	Xvar	Param Const	Param Slope
A	0.1	WASTPC_z	ECOMS_z	-0.2055	0.0258
A	0.25	WASTPC_z	ECOMS_z	-0.0747	0.0304
A	0.5	WASTPC_z	ECOMS_z	0.0075	0.0063
A	0.75	WASTPC_z	ECOMS_z	0.0850	0.0694
A	0.9	WASTPC_z	ECOMS_z	0.1948	0.0717
B	0.1	MWASTE_z	ECOMS_z	-0.3819	0.2840
B	0.25	MWASTE_z	ECOMS_z	-0.1256	0.1661
B	0.5	MWASTE_z	ECOMS_z	0.0118	0.1590
B	0.75	MWASTE_z	ECOMS_z	0.1504	0.2301
B	0.9	MWASTE_z	ECOMS_z	0.3049	0.3554
C	0.1	PACWASTE_z	ECOMS_z	-0.2678	0.3451
C	0.25	PACWASTE_z	ECOMS_z	-0.1356	0.3716
C	0.5	PACWASTE_z	ECOMS_z	-0.0008	0.3523
C	0.75	PACWASTE_z	ECOMS_z	0.1361	0.3735
C	0.9	PACWASTE_z	ECOMS_z	0.2703	0.4284

Source: Own calculations.

1. Model A (WASTPC): At lower quantiles (τ=0.10,0.25,0.50), e-commerce's slope hovers near zero. At upper quantiles (τ=0.75,0.90), however, it rises (0.069–0.072), implying a "rebound" effect in high-waste settings (Fichter, 2002).
2. Model B (MWASTE): Positive slopes across all quantiles, growing from ~0.284 at τ=0.10 to ~0.355 at τ=0.90. This suggests that in higher MWASTE contexts, e-commerce has an even stronger positive correlation with municipal waste, an effect that average-based panel estimates might miss.
3. Model C (PACWASTE): E-commerce strongly correlates with packaging waste from low (τ=0.10) to high (τ=0.90) quantiles, with slopes around 0.345–0.428. High-waste countries thus see an even steeper e-commerce effect, echoing earlier packaging-focused PVAR findings.

3.6. Machine learning robustness checks

Random forest regressions were performed on WASTPC_z, MWASTE_z, and PACWASTE_z using e-commerce, recycling, industrial value added, and unemployment as features. Table 25 reports MSE and R-squared, whereas Table 26 shows feature importance.

Table 25. Machine Learning (Random Forest) Model Performance

Target	Mean Squared Error (MSE)	R-squared
WASTPC_z	0.219028	0.761683
MWASTE_z	0.349699	0.703557
PACWASTE_z	0.102336	0.894982

Source: Own calculations.

Table 26. Machine Learning (Random Forest) Feature Importance

Target	Feature	Importance
WASTPC_z	ECOMS_z	0.149054
WASTPC_z	RECMWASTE_z	0.233295
WASTPC_z	INDVA_z	0.413758
WASTPC_z	UNEMP_z	0.203893
MWASTE_z	ECOMS_z	0.085691
MWASTE_z	RECMWASTE_z	0.372636
MWASTE_z	INDVA_z	0.373102
MWASTE_z	UNEMP_z	0.168571
PACWASTE_z	ECOMS_z	0.157299
PACWASTE_z	RECMWASTE_z	0.501397
PACWASTE_z	INDVA_z	0.233315
PACWASTE_z	UNEMP_z	0.107988

Source: Own calculations.

1. Model Performance: Packaging waste (PACWASTE_z) yields the highest R^2 (~0.89). For total and municipal waste, industrial value added (INDVA_z) and recycling rates (RECMWASTE_z) appear slightly more important than e-commerce (ECOMS_z).
2. Partial Dependence Insights: Incremental e-commerce growth notably increases packaging waste, more so than total or municipal waste. Random forest results confirm that packaging is highly sensitive to online retail, while broader waste categories are shaped by factors like recycling infrastructure or industrial composition (Yu et al., 2023).

Thus, machine learning checks reinforce the main econometric findings: e-commerce is a key predictor for packaging, but not the sole driver of overall waste streams. This underscores the need for targeted interventions, such as reusable packaging and more advanced recycling, to curb e-commerce-driven waste surges.

3.7. Comparisons to prior studies and summary of key findings

This multi-method, multi-country approach extends beyond single-model or single-nation analyses (e.g., Stinson et al., 2019). While e-commerce's net impact can be partially offset by logistical efficiencies, the packaging domain proves particularly susceptible, aligning with earlier studies (Bertram & Chi, 2017; Yu et al., 2023). Threshold tests show that factors like unemployment and resource productivity can amplify e-commerce's impact, especially on packaging waste, whereas quantile regressions reveal that high-waste countries experience stronger correlations between e-commerce and waste. Finally, random forests confirm packaging as the most e-commerce-sensitive stream, while total and municipal waste hinge more on macro-structural variables like industrial value added (Fichter, 2002).

Overall, e-commerce demonstrates limited short-run effects on total or municipal waste but exerts a robust, often threshold-dependent influence on packaging waste. This finding holds key policy implications: legislation might prioritize packaging regulations, recycling enhancements, or industrial transitions in regions where labor-market or structural conditions heighten e-commerce's environmental footprint.

4. Discussion

This study's findings depict a complex interplay between e-commerce (ECOMS) and various waste indicators in the European Union (EU), relying on a Panel Vector Autoregression (PVAR) framework complemented by panel threshold regressions (PTR), quantile regressions, and machine learning. By investigating whether e-commerce directly affects waste per capita (WASTPC), municipal waste per capita (MWASTE), and packaging waste per capita (PACWASTE), it also examines how recycling infrastructure (RECMWASTE), industrial development (INDVA), and resource productivity (RESP) might moderate these relationships. The results underscore how contextual factors shape diverging outcomes for different waste streams.

PVAR Models A (WASTPC & ECOMS) and B (MWASTE & ECOMS) show that e-commerce exerts negligible short-run effects on total or municipal waste per capita. These results echo Fichter's (2002) assertion that partial offsets, such as optimized logistics, can limit e-commerce's direct impacts on broad waste indicators. By contrast, Model C (PACWASTE & ECOMS) indicates a pronounced positive correlation, with e-commerce shocks explaining up to 22% of PACWASTE variance. This finding confirms that H1 applies most strongly to packaging waste, likely due to the resource-intensive nature of shipping materials (Bertram & Chi, 2017; Yu et al., 2023).

Subsequent analyses (Model D, Scenario E/F) reinforce that e-commerce's clearest short-run environmental effects center on packaging rather than entire waste streams. Although there is no explicit interaction term between e-commerce and recycling, machine learning feature importances highlight RECMWASTE's role in shaping overall waste outcomes. Particularly in packaging, strong recycling capacity (Popović & Milijić, 2021) could partially mitigate e-commerce-driven inflows, offering limited support for H2. Nevertheless, advanced recycling alone does not negate e-commerce's impact on packaging.

Panel threshold regressions confirm that in specific labor or industrial contexts, e-commerce-induced waste surges intensify. PACWASTE again exhibits the most pronounced threshold jump, from roughly +0.0144 to +0.3302 in higher unemployment settings, suggesting that precarious labor markets may amplify e-commerce's packaging footprint (Bertram & Chi, 2017; Caiyi et al., 2022). This supports H3, particularly for packaging scenarios, although municipal waste sees a smaller threshold effect. Meanwhile, limited cross-sectional dependence (Pesaran CD) implies that e-commerce expansion in one Member State does not significantly affect neighboring waste levels, undercutting H4.

Regarding timing, short-run IRFs suggest no immediate surge in total or municipal waste, while packaging sees a marked rise after 2–3 periods. Model C's impulse responses and random forest partial dependence both confirm that packaging implications do not disappear over time, signaling a persistent e-commerce effect. Thus, H5 is partially supported: although no long-run cointegration tests were performed, multi-lag PVAR results imply that packaging inflows can persist unless moderated by regulation. The EU's Packaging and Packaging Waste Regulation (PPWR) may eventually curb such effects, but near-term policies remain crucial.

These outcomes align with previous literature (Matthews et al., 2001; Bertram & Chi, 2017; Yu et al., 2023), emphasizing packaging as e-commerce's primary environmental liability, while broad waste indicators (WASTPC, MWASTE) see muted direct impacts. In line with Fichter (2002), partial logistical efficiencies can neutralize some net increases in total waste. However, threshold analyses highlight how labor-market vulnerabilities (e.g., higher unemployment) can exacerbate packaging streams. This dynamic intersects with structural factors, such as industrial composition and resource productivity, that shape the distribution and magnitude of e-commerce-driven waste (Visser & Lanzendorf, 2004).

Quantile regression findings reinforce these insights, revealing that high-waste countries exhibit a stronger correlation between e-commerce and waste, particularly for packaging. Meanwhile, multi-variable PVAR expansions (Scenario E/F) show that industrial value-added and unemployment constrain or redirect e-commerce's environmental impacts, overshadowing them for total or municipal waste in certain contexts (Imran et al., 2023; Popović et al., 2023). Consequently, no uniform e-commerce effect applies across all Member States; policies must adapt to local labor and industrial structures.

From a policy standpoint, packaging stands out as the key domain for targeted interventions. As e-commerce fuels short-to-medium-term packaging increases, especially where unemployment is high, policymakers might prioritize measures such as:

- Stricter EU-level standards (PPWR) and extended producer responsibility (EPR) schemes to curtail single-use plastics.
- Enhanced recycling capacities, ensuring efficient collection and reuse.
- Incentives for minimal-packaging design, biodegradable materials, or reusable shipping containers.

Although e-commerce alone does not dominate broader waste trajectories, contextual forces (industrial composition, labor markets) play critical roles in fueling consumption or shaping disposal patterns. Future studies should address data granularity, such as subnational or firm-level, to uncover finer-scale variations in returns and reverse logistics.

More advanced threshold or spatial models (Durbin) may also clarify how regional trade corridors transmit e-commerce-related waste. Finally, researchers could explore whether policy-driven design changes weaken e-commerce's packaging footprint over time.

Overall, these findings highlight e-commerce's nuanced environmental imprint in the EU. Although total and municipal waste often see moderate short-run changes, packaging emerges as the domain of immediate concern, magnified by specific economic conditions. By emphasizing context-dependent strategies, particularly in packaging management, this research informs policymakers and industry stakeholders seeking to reconcile digital market growth with sustainable waste outcomes.

Conclusion

This paper has provided new insights into how e-commerce expansion affects waste generation across the European Union (EU), focusing on total, municipal, and packaging waste. By employing a multi-method approach, Panel Vector Autoregression (PVAR), panel threshold regression, quantile regression, and machine learning, this study has shown that e-commerce's most immediate impact emerges in packaging waste, while total and municipal waste exhibit weaker short-run responses. These findings highlight that packaging streams, rather than aggregated or municipal indicators, serve as the primary channel through which digital commerce exerts short-term pressure on waste.

The research further reveals that certain contextual factors, such as unemployment levels or industrial composition, can magnify the packaging-specific effects of e-commerce. Meanwhile, higher recycling capacity demonstrates the potential to moderate packaging inflows but does not fully negate e-commerce's role in boosting packaging waste. Overall, the results imply that policymakers and industry actors aiming to mitigate the environmental footprint of online retail should consider targeted measures for packaging materials, especially in labor contexts prone to greater e-commerce-driven surges.

Future studies could explore subnational heterogeneities, more fine-grained data on reverse logistics, and longer time horizons to capture how shifts in policy or consumer behavior might alter the packaging-intensive nature of e-commerce. Despite certain limitations regarding data granularity and cross-border analyses, this work advances the literature by delineating the varied, context-dependent pathways through which digital retail can shape waste patterns within the EU's complex policy and economic landscape.

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