



Designing a Roadmap for Effective and Sustainable Strategies for Assessing and Addressing the Challenges of EU Agriculture to Navigate within a Safe and Just Operating Space

Spatial and Panel Data Analysis of Food Loss and Waste Drivers Across the EU Supply Chain

Discussion paper

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Spatial and Panel Data Analysis of Food Loss and Waste Drivers Across the EU Supply Chain

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Abstract:

Reducing food waste has become a central objective within EU food system policy, particularly under the Farm to Fork Strategy and Sustainable Development Goal 12.3. While policy discussions often concentrate on consumer behaviour, food waste in fact emerges from interactions between technological conditions, structural characteristics of agri-food systems, and demand-side dynamics across multiple supply chain stages. This paper provides an empirical assessment of these drivers across EU Member States, with the aim of supporting evidence-based policy design and improving the representation of food waste in forward-looking modelling exercises. Using harmonised EU food waste data for 27 Member States over the period 2013–2022, we estimate fixed-effects panel regressions separately for four supply chain stages: Primary Production (PP), Processing and Manufacturing (PM), Retail Distribution (RD), and Households (HH). The analysis is preceded by a comprehensive spatial autocorrelation diagnostic. Key findings show that food waste does not exhibit significant spatial clustering at the national level, and that determinants differ substantially across stages. At the household level, income displays an inverted-U relationship with food waste, with an implied turning point near €48,972, while education, household composition and unemployment are robust additional drivers. Upstream stages are governed primarily by production scale and logistics-related variables. Main results are confirmed across multiple robustness checks.

Keywords: food loss and waste, safe and just operating space, drivers, panel data, spatial autocorrelation.

1. Introduction

Food waste has emerged as one of the defining sustainability challenges of the 21st century. In the European Union, an estimated 57.6 million tonnes of food were wasted in 2022 — roughly 127 kg per capita — generating costs exceeding €130 billion and representing a considerable obstacle to achieving SDG Target 12.3, which calls for a 50 per cent reduction by 2030 (Stenmarck et al., 2016). The EU regulatory framework has progressively formalised these commitments, most recently through the revision of the Waste Framework Directive (European Council, 2025), which requires Member States to achieve a 10 per cent reduction in processing and manufacturing waste and a 30 per cent reduction at retail, food service, and household stages by 2030, relative to the 2021–2023 baseline.

Despite growing empirical literature on food waste determinants, most existing studies rely on cross-sectional designs, aggregate measures, and often focus on a single stage of the supply chain. Moreover, the spatial dimension of food waste — whether countries with similar levels tend to cluster geographically — has received limited analytical attention. From our perspective, addressing these gaps is not only academically necessary, but also practically relevant: without stage-specific evidence, there is a real risk that policy instruments will be misallocated or that the same interventions will be applied indiscriminately across very different structural contexts.

This paper attempts to fill these gaps by providing: (i) the first comprehensive spatial diagnostic of food waste distributions across all EU Member States over a 20-year panel; (ii) stage-specific fixed-effects panel regressions with a food waste dataset longer than any previously used for this purpose (Ferrer-Pérez and Philippidis, 2025); and (iii) empirically grounded elasticities suitable for use as inputs in forward-looking simulation frameworks such as MAGNET (Bartelings and Philippidis, 2024; Philippidis et al., 2025).

The remaining sections are structured as follows. Section 2 reviews the relevant literature. Section 3 describes the data. Section 4 presents the methodology. Section 5 reports and discusses the empirical results, including robustness checks and marginal effects. Section 6 presents discussion and concluding remarks.

2. A brief literature review

Research on food loss and waste has grown considerably over the past decade, yet the empirical literature remains fragmented across supply chain stages and rarely adopts a comparative multi-country panel perspective.

At the primary production stage, losses are primarily driven by price volatility, labour availability, and cold-chain infrastructure constraints. Minor et al. (2020) identify these as the principal determinants of on-farm and pre-retail losses in fresh produce supply chains, findings broadly

consistent with the EU context. At processing and retail stages, the literature converges on logistics quality and demand forecasting as the dominant factors, with transport inefficiencies and handling failures accounting for a disproportionate share of waste (e.g., Gunders, 2012). Segrè et al. (2014) offer a complementary macroeconomic perspective, linking infrastructure development, urbanisation, and trade integration to cross-country variation in food loss rates.

Beyond the studies on economic drivers, there is a related strand that explores the environmental consequences of food waste, including its climate, water, and energy footprints (e.g., Silvennoinen et al., 2022; Slorach et al., 2020; Gracia-de-Rentería and Ferrer-Pérez, 2025), underscoring the policy relevance of understanding what drives waste generation in the first place.

The household stage has attracted the most extensive econometric literature. Income tends to correlate positively with waste volumes, though the relationship with waste ratios is more ambiguous (e.g., Koivupuro et al., 2012; Secondi et al., 2015). Following the Environmental Kuznets Curve framework (e.g., Grossman and Krueger, 1995; Mazzanti and Zoboli, 2009), we test for an inverted-U income–waste relationship at each stage. Education, household composition, and unemployment are consistently identified as additional robust drivers (e.g., Stefan et al., 2013; Quested et al., 2011, Ferrer-Pérez and Gracia-de-Rentería, 2025).

The spatial dimension (Anselin, 1988) of food waste remains largely unexplored. Thaore et al. (2024) find no study applying spatial autocorrelation methods at the national scale within a multi-country panel, which directly motivates our spatial diagnostic step. Finally, the estimated elasticities produced here respond to a practical need identified in recent ex-ante modelling studies: Barrera and Hertel (2021) provide global estimates of the macroeconomic consequences of food waste reductions, while Bartelings and Philippidis (2024) formalise waste behaviour within the MAGNET computable general equilibrium model. Building on this, Philippidis et al. (2025) show that simulation results in the MAGNET model are highly sensitive to the behavioural parameters assumed at each supply chain stage.

3. Data

The empirical analysis draws on a constructed European Food Loss and Waste panel dataset (Ferrer-Pérez and Philippidis, 2025), integrating harmonised food loss and waste estimates from the JRC food waste accounting database (EC, 2026) for 27 EU Member States across 2003–2022, disaggregated by four supply chain stages and nine food groups. The estimation focuses on the 2013–2022 window, a period for which measurement approaches are considered substantially more consistent and reliable (De Laurentiis et al., 2024).

We first construct the dependent variable for each stage: total food loss or waste per capita (FLpc or FWpc, in kg per person per year). Then, we calculate the Log-transformation of levels of

endogenous variables to address skewness and allow coefficient interpretation as approximate elasticities. We also use a ratio (defined as food waste ratio (FWR) as a share of food available at that stage) as a robustness check that controls for cross-country differences in food supply scale.

Observed explanatory variables, according to relevant literature presented in the previous section, are drawn from Eurostat and the World Health Organisation (WHO). For the PP stage, we include the agricultural output value at producer prices (AGRIOUT, in million purchasing power standards), total agricultural labour input (AGRILAB, in thousand annual work units), output price indices (PIAP), and input price indices for current consumption (Input1) and agricultural investment goods (Input2). For the PM stage, variables include the labour cost index at manufacturing (LCIMAN section C from NACE), the volume index for transport and storage (TaS), the labour cost index for transportation (LCIT), production price and volume indices for the food manufacturing industry (IPRI2021, IPI2021), and the energy price index (EnergyPriceIndex). As for the RD stage, variables include the labour cost index for retail and distribution (LCIRD sections G-J from NACE rev2) and for transport and storage (LCITS section H521 from NACE rev2). We also considered annual detailed enterprise statistics for warehousing and storage services such as the Gross investment in tangible goods in million euros (GrossInv), the number of enterprises (Enterprises) and the apparent labour productivity (AppLabProd). For the HH stage, we use GDP per capita in constant prices (GDPpc), median age (MEDIANAGE), average household size (AVGHHSIZE), healthy life expectancy at birth (HLEAB), educational attainment (EDUC), household composition indicators by number of children (Child1–Child4), total unemployment rate (UNEMPLOY), income inequality (INCQ), and obesity prevalence (BMI30). All continuous variables are log-transformed (prefix L_) except MEDIANAGE and MEDIANAGEsq, which enter in levels to capture a potential non-linear age effect.

The empirical strategy proceeds in two steps. First, we test for spatial autocorrelation using global Moran's I statistics and Local Indicators of Spatial Association (LISA), computed on a row-standardised inverse-distance weights matrix. Second, in the absence of significant global spatial effects, we estimate two-way fixed-effects panel regressions of the form

To test the aforementioned EKC hypothesis of a non-linear income–waste relationship we include the log GDP per capita and its squared term. The GDP variable is mean-centred before squaring to reduce collinearity between the linear and quadratic terms and to make the coefficient on the linear term more interpretable as the slope at the sample mean. While this procedure is a statistical convenience employed for the PP and HH stages, where we formally test the EKC hypothesis, the interpretation of the implied turning point should remain anchored in the distribution of observed GDP levels. Thus, we report the turning-point in euros to aid practical reading. For the two

remaining stages (PM and RD), we do not expect significance of the EKC hypothesis, and GDP enters the model primarily as a control variable.

4. Methodology

The empirical analysis focuses on the period 2013–2022. Although the original sample includes earlier observations, recent methodological assessments indicate that food loss and waste estimates become substantially more reliable from 2013 onwards (De Laurentiis et al., 2024). Restricting the estimation window therefore prioritises data comparability and measurement consistency over longer time coverage.

4.1. Spatial Autocorrelation

Before estimating panel regressions, we test for spatial autocorrelation in food waste per capita (FWpc) across EU Member States for each year from 2003 to 2022.

We first assess whether food waste exhibits systematic geographic clustering across Member States. For this purpose, we compute global Moran’s I on a row-standardised inverse-distance spatial weights matrix and complement it with Local Indicators of Spatial Association (LISA) to detect country-level outliers. A positive significant Moran’s I test statistic may indicate that nearby countries tend to have similar waste levels. In contrast, a globally insignificant Moran’s I combined with only sporadic LISA outliers suggests that spatial dependence is not a dominant feature of the full panel and that country fixed effects can better capture time-invariant cross-country heterogeneity.

4.2. Panel Data Regression

Given the absence of significant global spatial autocorrelation (confirmed in the results section), we estimate stage-specific the following fixed-effects (FE) panel regression model, whose general specification is:

$$\ln(Y_{it}) = \alpha_i + \gamma_t + \beta X_{it} + \varepsilon_{it} \quad (1)$$

where Y_{it} denotes the endogenous variables depending on the stage: food waste per capita ($FWpc_{it}$) or food loss per capita ($FLpc_{it}$). Also, α_i captures country fixed effects that absorb all time-invariant heterogeneity (climate, geography, institutional quality), γ_t captures year fixed effects in specifications that include them, X_{it} is the vector of stage-specific drivers, and ε_{it} is the error term. Standard errors are clustered at the country level in robustness specifications to account for serial correlation within panels.

For the EKC hypothesis, we include the linear and quadratic terms of log GDP per capita, centred at the sample mean. A statistically significant negative linear term and positive quadratic term, combined with a turning point within the observed range of the data, would confirm an inverted-U relationship between income and food waste.

Robustness checks are implemented for each stage: i) inclusion of year fixed effects (Year) and ii) adding one-period lag GDP (L.L_GDPpc) to address potential reverse causality. Also, clustered standard errors at the panel level has also been performed but results are omitted to ease exposition. Similarly, to the regressions for the food waste ratio (FWR) as the dependent variable, a separate set of regressions was estimated but not reported here for brevity.

5. Results and discussion

5.1. Country Rankings by supply chain stage

To contextualise absolute waste levels, we computed country rankings by food loss and waste per capita for each year. At the household stage, Poland, Spain, Lithuania, Latvia, Belgium and Ireland consistently rank among the top ten highest food waste per capita countries throughout the period (see Table 1). At the PP stage, Ireland, Denmark, the Netherlands, Spain and Greece rank highest in food loss per capita, reflecting the large agricultural sectors in these economies (see **¡Error! No se encuentra el origen de la referencia.**). At the PM stage, Greece, Denmark, Italy, and Portugal are consistently prominent (see **¡Error! No se encuentra el origen de la referencia.**). In the RD stage, the ranking is dominated by Spain, Portugal, Ireland and the Netherlands reflecting both the scale of their retail sectors and the structural characteristics of their logistics systems (see **¡Error! No se encuentra el origen de la referencia.**).

Country\Year	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Belgium	6	8	9	6	9	9	3	3	1	1
Croatia	.	.	.	10	.	8	6	4	8	7
Denmark	9	9	9	10	10
Estonia	.	10	6	.	10
Ireland	8	6	8	8	7	4	8	10	4	3
Latvia	3	2	1	3	3	6	10	.	.	9
Lithuania	1	4	5	5	5	5	4	6	6	4
Netherlands	7	7	7	9	6	7	9	7	5	6
Poland	2	1	2	1	1	1	2	2	2	2
Portugal	10	.	10	7	8	10	7	5	7	8
Romania	4	3	3	4	4	3	5	8	.	.
Spain	5	5	4	2	2	2	1	1	3	5

Table 1 Top 10 Countries by Food Waste per capita at HH stage (2013–2022)

5.2. Spatial Autocorrelation Analysis

5.2.1. Household stage

Table 2 reports Moran's I statistics for food loss/waste per capita at each stage (HH, PP, PM, RD) across selected years. A first surprising result is that food loss/waste does not show significant spatial clustering at the national level within the EU

Table 2 Moran's I test of HH, PM, RD, PP Food Loss/Waste per capita

Year	Stage	Moran's I	p-value
2003	HH	-0.0273	0.7679
2005	HH	-0.0279	0.7680
2007	HH	-0.0226	0.7250
2010	HH	-0.0285	0.7740
2013	HH	-0.0301	0.7870
2016	HH	-0.0277	0.7650
2019	HH	-0.0158	0.6140
2022	HH	-0.0137	0.5880
2003	PP	-0.0127	0.503
2010	PP	-0.0028	0.359
2013	PP	-0.0321	0.872
2022	PP	-0.0279	0.783
2003	PP	-0.0127	0.503
2016	PM	0.0557	0.019
2017	PM	0.0550	0.021
2021	PM	0.0452	0.037
2013	RD	-0.0284	0.802
2019	RD	0.0005	0.322
2022	RD	-0.0444	0.882

Note: Showed only some years of the sample

This pattern suggests that similarities in food waste levels across EU countries are not primarily driven by geographic proximity. Rather, national economic structures, institutional arrangements, and domestic behavioural patterns appear to be the dominant reference scale for policy intervention. From a governance perspective, this finding reinforces the case for country-specific food waste reduction strategies, rather than approaches based on regional groupings.

See for instance in Figure 1 the spatial distribution of HH food waste for years 2013 and 2022 in the sample. Despite differences in absolute levels, no systematic geographic clustering is apparent in either year, consistent with the Moran's I results.

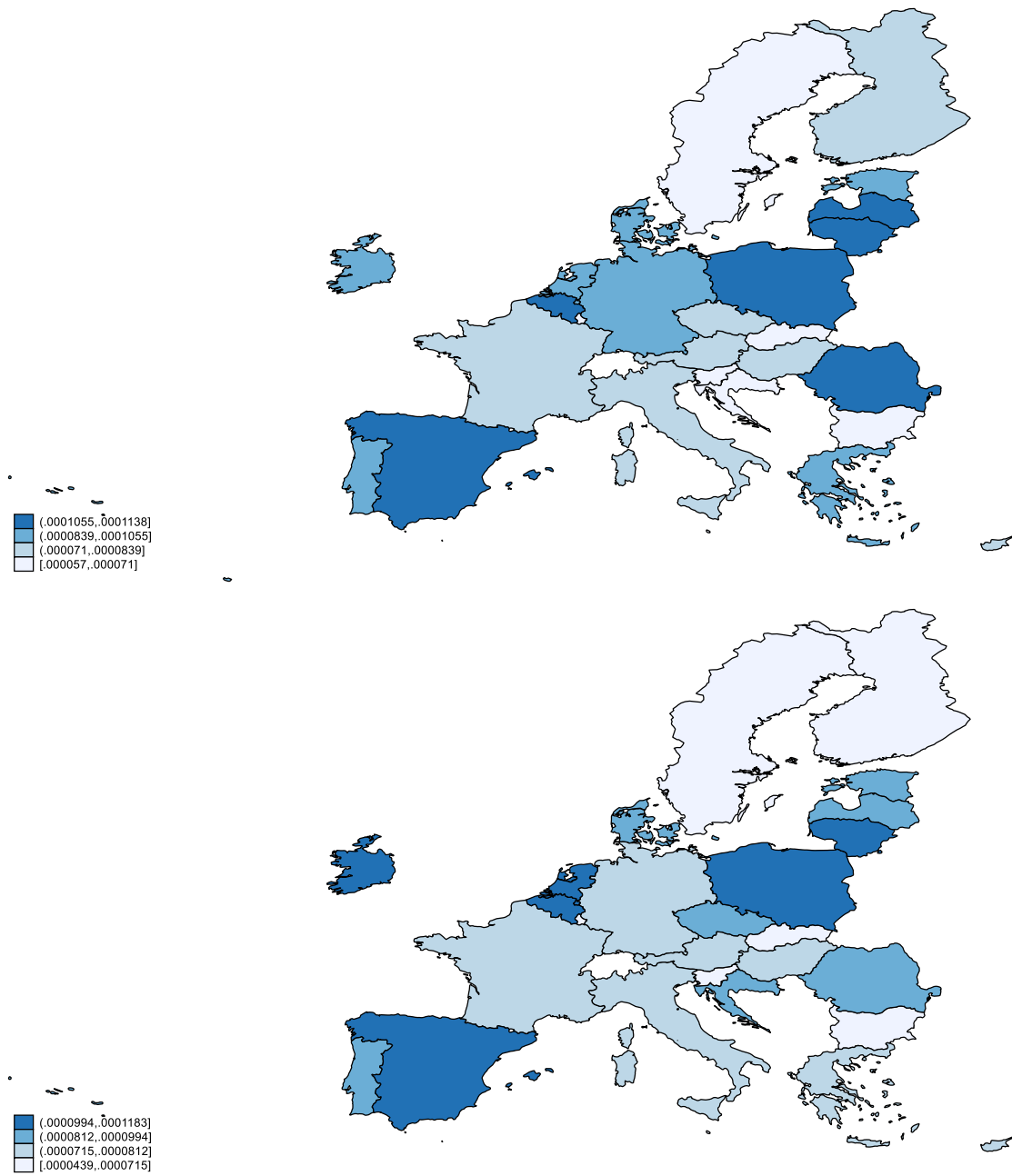


Figure 1 Spatial distribution of household food waste in 2013 (upper panel) and 2022 (lower panel)

So, we can conclude from our spatial diagnostics that standard panel fixed-effects models are appropriate for all supply chain stages.

5.3. Panel data regression analysis

In this section we have conducted the panel regression analysis for each supply chain stage in turn but for brevity and to ease exposition, we only show the results for the household stage given the richness of its findings¹.

5.3.1. Household stage (HH)

The household regressions deliver the richest set of results and the most direct policy lessons. **¡Error! No se encuentra el origen de la referencia.** reports the results. In the baseline fixed-effects specification for log household food waste per capita ($N = 215$), the centered log GDP per capita terms produce a statistically significant inverted-U profile: the linear term is negative (-0.303 , $p < 0.001$) and the quadratic term is positive (0.233 , $p < 0.001$). Using the standard formula and re-expressing the turning point on the euro scale yields $\approx \text{€}48,972$. This value is above the sample mean and above the GDP per capita of most Member States, implying that the majority of countries in the sample remain on the rising segment of the curve. Robustness checks (clustered SE, inclusion of year fixed effects, and a lagged-GDP specification) preserve the EKC coefficients in sign and significance, although point estimates vary modestly across specifications.

Among non-income covariates, education is strongly and negatively associated with HH food waste ($\text{EDUC} = -0.535$, $p = 0.001$), suggesting that higher educational attainment is linked to lower per-capita waste. Average household size ($\text{AVGHHSIZE} = 0.651$, $p = 0.003$) and the presence of children ($\text{Child1} = 1.318$, $p < 0.001$; $\text{Child2} = 0.714$, $p = 0.003$; $\text{Child3} = 0.127$, $p = 0.048$) are positively associated with waste, consistent with larger and child-bearing households generating more avoidable waste per capita. Median age shows a non-linear pattern (negative linear and positive quadratic terms), hinting at a life-cycle effect. Unemployment enters negatively and robustly (-0.169 , $p < 0.001$), an intuitive result reflecting that constrained household budgets reduce food waste. Clearly, this should be interpreted as a social-policy issue, rather than a viable path toward improved sustainability.

Table 3 Fixed Effects Panel Regression – HH stage

Variable	Estimates	Year FE	Lagged
L_GDPpc	-0.303***	-0.280**	-0.250***
L_GDPpc ²	0.233***	0.242***	0.228***
L1.L_GDPpc	-	-	-0.083
MEDIANAGE	-0.329**	-0.360**	-0.300***
MEDIANAGE ²	0.004**	0.004**	0.004***
L_AVGHHSIZE	0.651**	0.665**	0.628***
L_HLEAB	0.742**	0.725*	0.790*

¹ The others are omitted to ease exposition but available from authors upon request.

L_EDUC	-0.535**	-0.567**	-0.523**
L_Child1	1.318***	1.308***	1.315***
L_Child2	0.714**	0.710**	0.7069
L_Child3	0.127**	0.130**	0.122
L_UNEMPLOY	-0.169***	-0.176***	-0.169***
Year FE	No	Yes	NO
N	215	215	215
Within R ²	0.421	0.444	0.423

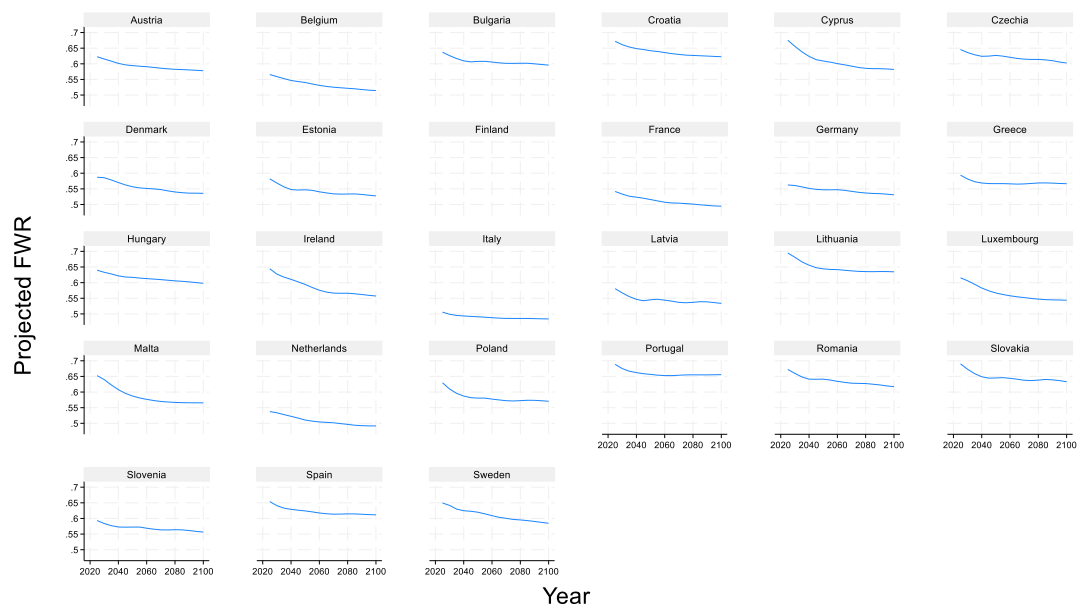
Notes: Ln(FWpc) is the dependent variable. *** p<0.01, ** p<0.05, * p<0.10. In column 2, year fixed effects have been added. In column 3, lagged GDPpc has been added.

5.4. Projections exercise: Food Waste at Household stage toward 2100

To construct long-run household food waste trajectories, we have constructed the Food Waste Ratio (ratio) defined as a share of food available at that stage.

The way we projected FWR is by modelling its two components separately and then recombining them in a consistent way. Specifically, we estimate fixed-effects panel models for food waste per capita (numerator) and food entering the stage per capita (denominator), both in logs, and recover country-specific effects from the baseline regressions. For the projection exercise, we feed in GDP per capita and population paths from the from the SSP2 scenario (Shared Socioeconomic Pathway 2), while holding all other covariates fixed at their last observed values to avoid imposing assumptions on variables for which no forward-looking data exist. The predicted log values are then transformed back to levels using a Duan (1983)'s smearing correction to limit retransformation bias. Finally, we reconstruct total volumes and compute the ratio as projected waste over projected inflows. This approach ensures internal consistency of the ratio and keeps the projections grounded in the estimated structural relationships, while remaining transparent about the ceteris paribus nature of the exercise.

Figure 2 summarize the results. The figure indicates that, although the food waste ratio declines gradually in many countries, the reduction is not sufficient to close the gap with the target in most cases. This finding points directly to where policy effort must be concentrated: the non-income determinants identified in the model (e.g., education, household composition support, and labour market conditions). These are key levers that policymakers will need to activate deliberately and at scale if the EU's Waste Directive (Directive 2008/98/EC) targets are to be met.



Graphs by Country

Figure 2 Household food waste ratio (FWR) projections toward 2100 under SSP2.

6. Conclusion

This study provides a comprehensive econometric analysis of food waste determinants across the EU supply chain using a harmonised 20-year panel dataset. Our two-step empirical strategy (spatial diagnostics followed by stage-specific fixed-effects regressions) yields robust and policy-relevant findings.

The results show strong stage heterogeneity. First, the absence of spatial clustering implies that the Member State remains the appropriate governance unit for food waste reduction. Policy interventions should be calibrated to national contexts (institutional, structural, and sociodemographic) rather than designed for regional groupings or based on geographic proximity assumptions.

Second, the strong stage-specificity of drivers argues against a one-size-fits-all approach. Measures targeting efficiency at the Primary Production stage will need to operate through different mechanisms than those addressing retail or household waste

Third, our projected household food waste ratio trajectories under SSP2 income scenarios show that income growth alone is insufficient for most EU Member States to achieve the SDG 12.3 50 per cent reduction target by 2030 or even by 2100. Our exercise reinforces the conclusion that the non-income determinants identified in the model are the key levers that policymakers must deliberately activate. Consequently, policy mixes will need to combine technological innovation,

structural adjustments along supply chains, and demand-side instruments such as education campaigns, labelling improvements, and targeted household-level interventions.

Several limitations should be acknowledged. First, the analysis is restricted to the post-2013 period, reflecting improved harmonisation of EU food waste estimates (EC, 2026). While this enhances comparability, it limits the observation of longer-term structural dynamics. Second, food waste data remain partly model-based, implying potential measurement error that may attenuate estimated elasticities. Third, fixed-effects estimates capture within-country variation and therefore do not directly explain persistent cross-country differences. Fourth, projection exercises rely only on GDP and population scenarios while holding other determinants constant, meaning results should be interpreted as conditional trajectories rather than forecasts. Fifth, the absence of global spatial autocorrelation does not exclude other forms of interdependence such as trade or policy spillovers.

Future work should extend the panel as more harmonised data become available, explore food group heterogeneity in greater detail and model linkages between stages of the supply chain more explicitly.

Declarations

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Conflicts of interest/ Competing interests

The authors have no conflicts of interest to declare that are relevant to the content of this article

Ethics approval/ Consent to participate/Consent for publication

Not applicable to this article as no human participants involved during the current study.

Availability of data and material

Main data used in this study are publicly available from Ferrer Pérez, H., Philippidis, G. (2025). EU Food Loss and Waste (FLW) Panel Data (2003–2022): Estimates and Drivers. [Data set]. BrightSpace Horizon Europe project GA Nr. 101060075.<https://doi.org/10.5281/zenodo.17483053>.

Authors' contributions

Conceptualization, H.F., G.P.; Methodology, H.F., G.P.; Resources H.F., G.P.; Writing – original draft preparation, H.F., G.P.; Writing – review and editing, H.F., G.P.; Funding acquisition, G.P.

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