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Towards a Circular Economy: Analyzing Food Waste Convergence in Indonesia's Municipalities

Putriesti Mandasari

Department of Agribusiness, Universitas Sebelas Maret (UNS), Surakarta 57126, Indonesia

ABSTRACT

To date, food waste remains a critical issue in most developing countries, where capacities differ among municipalities. This study examines whether food waste convergence occurs among Indonesian municipalities that experience persistent disparities in infrastructure, governance, and fiscal capacity. Using a β-convergence framework (unconditional and conditional) and panel data from 345 observations (2020–2023), this study examines whether areas with a higher initial level of food waste reduce food waste more rapidly, whether socioeconomic characteristics influence convergence, and whether convergence patterns differ across municipal classifications. Results show strong evidence of convergence and confirm that convergence persists even after controlling for GRDP per capita, poverty rate, and recycling rate. However, not all those factors significantly affect convergence, suggesting the influence of institutional and behavioral dynamics. The study also identifies heterogeneity in convergence speeds, where municipalities with higher population densities, larger environmental budgets, or stronger development indicators converge more quickly than their counterparts. This study presents a novel application of β-convergence modeling for municipal food waste analysis, offering empirical insights into circular economic development from a local perspective. Its policy importance lies in identifying where convergence is lacking and why. These findings offer a diagnostic tool to help local governments allocate resources more effectively and prioritize lagging municipalities in food waste reduction efforts.

Keywords: Food Waste; β-Convergence; Municipal; Indonesia; Circular Economy

*CORRESPONDING AUTHOR:
Putriesti Mandasari, Department of Agribusiness, Universitas Sebelas Maret (UNS), Surakarta 57126, Indonesia;
Email: putriesti_mandasari@staff.uns.ac.id

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1. Introduction

The global food system faces dual crises of excessive waste and growing resource scarcity. Nearly a third of global food is wasted annually, contributing up to 10% of total greenhouse gas (GHG) emissions [1, 2]. While food loss occurs along the supply chain, food waste is particularly pronounced at the municipal level, where it constitutes 30–40% of total municipal solid waste (MSW) [3, 4]. This volume of organic waste not only strains local waste management systems but also hampers sustainability and circularity goals by contributing to methane emissions and resource inefficiency. In landfills, food waste decomposes into methane—a greenhouse gas many times more powerful than carbon dioxide [2, 3, 5, 6]. Poorly managed food waste leads to economic losses, environmental degradation, and public health risks due to methane emissions from landfills [7, 8].

These challenges are particularly critical in developing countries like Indonesia, which ranks among the world's top producers of food waste. In Indonesia, the yearly estimated amount of food waste per capita is 300 kg [9, 10]. Most of this waste ends up in poorly managed landfills. In turn, it contributes to environmental degradation and intensifies food insecurity. Additionally, food waste also carries significant economic and social costs. The economic loss due to food waste in Indonesia from 2000 to 2019 is estimated at IDR 213–551 trillion (USD 14.9-38.5 billion) per year [11]. Moreover, food waste exacerbates food insecurity by diverting edible surplus from redistribution to those in need [12]. Limited investment in waste processing infrastructure, weak policy enforcement, and low public awareness in Indonesia further complicate municipal-level responses [13, 14]. Moreover, despite the existence of innovative technologies such as bioconversion, their implementation remains limited [14, 15]. Therefore, addressing food waste at the municipal level presents an environmental improvement, opens circular economic opportunities, and reduces long-term economic and social burdens.

Despite growing awareness and waste management strategies, food waste levels remain uneven across regions, with municipalities playing a key role in determining the effectiveness of reduction efforts [16]. However, most existing research on food waste focuses on household behavior, supply chains, or national-level policies [17, 18], with less attention on how waste is generated, reduced, and managed at the municipal level [13, 19]. This oversight is particularly problematic in Indonesia, where municipalities play an important role in waste governance. Yet, they operate under diverse economic, institutional, and geographic constraints [20, 21]. While some local governments have demonstrated progress, it remains unclear whether such improvements are widespread or if disparities in food waste reduction are widening [17]. In particular, there is a lack of understanding regarding whether municipalities with high food waste levels are catching up with those that perform better over time. Therefore, it raises the following questions: (1) Do Indonesian municipalities with higher initial food waste levels exhibit faster reductions over time? (2) Do structural and institutional variables influence the rate of food waste convergence? and (3) Does the speed of convergence vary across municipalities with different socioeconomic and geographic characteristics?

Understanding these dynamics is essential to designing an effective policy for waste management that aligns with Indonesia's sustainability goals and the SDG target to reduce 50% of food waste by 2030. Reaching this goal will require dramatic changes in behavior, policies, and analytical capacity to track progress and develop new strategies. Growing pressure to reduce food waste as part of circular economic goals has intensified the need for more adaptive and data-driven municipal strategies. Yet, policy designs often lack clear benchmarks to assess whether interventions are closing the gap between high- and low-performing municipalities. Without subnational-level evidence, it is challenging to determine whether interventions work where they are most needed.

This gap highlights the need for a convergence analysis to investigate if areas with high food waste are catching up to those with lower levels. Some municipalities have made strong progress due to improved funding, policies, and community involvement, while others continue to fall behind due to weaker resources and limited public awareness [22, 23]. Meanwhile, convergence theory—originally applied in economic growth literature—offers a valuable framework for assessing whether municipalities with higher initial food waste levels are catching up with better-performing regions. Applying convergence analysis to food waste enables researchers to determine whether progress is evenly distributed across municipalities or concentrated in already well-performing areas. Incorporating convergence analysis into this landscape offers an actionable approach to evaluating whether municipal food waste improvements are equitably distributed. It also identifies where policy support is most needed to bridge institutional and performance gaps.

Although β-convergence has been applied to ecological footprints, emissions, and energy efficiency [24], its application to food waste remains limited. To date, no studies have examined food waste convergence across municipalities in Indonesia, despite the country's wide regional disparities. Developing countries are known to have highly decentralized waste governance and pronounced institutional disparities [25, 26]. Even fewer studies have disaggregated this analysis further to examine heterogeneity based on population density, geography, institutional investment, or recycling infrastructure [24, 27, 28]. Disaggregating convergence by geographic, structural, and institutional variables allows for the identification of whether institutional and socioeconomic conditions influence convergence speeds differently.

This study addresses that gap by analyzing food waste convergence across Indonesian municipalities between 2020 and 2023 using a β-convergence panel regression framework. Specifically, the goals of this study are threefold: (1) Investigating whether municipalities with high initial levels of food waste are reducing waste more quickly than others (β-convergence); (2) Assessing the extent to which structural (Gross Regional Domestic Product (GRDP), poverty) and institutional (recycling systems) factors influence convergence; and (3) Examining heterogeneity in convergence speed based on key municipal characteristics: geographic location (Java vs. non-Java), population density, environmental budget, and Human Development Index (HDI) score.

This study makes contributions to the literature and offers relevant policy recommendations. First, it introduces the β-convergence framework into municipal food waste research in a developing country. The analysis captures not only unconditional convergence (i.e., whether high-waste municipalities are catching up overall), but also conditional convergence that accounts for structural and institutional differences across regions. Second, it explores heterogeneity in convergence speeds across socioeconomic and geographic subgroups. In terms of policy relevance, this study provides a practical tool for identifying gaps in convergence and uncovering their underlying causes, thereby enabling municipalities to design more targeted and effective interventions. As cities worldwide transition toward circular models, this tool is increasingly vital for aligning sustainability goals with on-the-ground realities.

2. Literature Review

2.1. β-Convergence

β-convergence has served as a foundational concept for understanding how poorer regions or economies catch up with richer ones over time [29, 30]. The framework is typically applied to assess whether disparities in income, productivity, or development indicators narrow as lagging regions grow at a faster rate than leading ones. To capture β-convergence, a wide range of econometric approaches has been used across various sectors, including agriculture [30], innovation [31], and supply-demand dynamics [32]. Over time, the β-convergence model has evolved beyond macroeconomic contexts to encompass a diverse range of applications, including regional innovation [31], health expenditures [33], and income inequality [34]. Two core variants—unconditional and conditional β-convergence—distinguish whether convergence occurs irrespective of structural characteristics or is dependent on them [32, 35]. Recent developments reflect the framework's flexibility and relevance in cross-disciplinary studies.

Despite its strengths, the β-convergence framework has its limitations. Findings from prior applications are often context-specific. For example, while developed countries may show rapid convergence due to established waste infrastructures, developing regions like Indonesia face challenges such as limited budgets, weak institutional frameworks, and public unawareness[13, 22]. Moreover, convergence studies often overlook behavioral and cultural dimensions of food waste, which may significantly influence outcomes but are challenging to quantify.

Applying the β-convergence framework to food waste provides a novel lens through which to evaluate regional disparities in waste reduction efforts. The approach assumes that municipalities with higher initial food waste levels should, over time, reduce waste more rapidly than those with lower starting points. This could potentially lead to convergence in food waste performance. This framing aligns with evidence that regions with significant waste burdens often adopt more aggressive interventions—including technological upgrades, regulatory reforms, and public awareness campaigns—to achieve waste reduction[36]. Furthermore, the framework can uncover how differences in institutional strength, economic capacity, and policy uptake influence the speed and direction of convergence[36]. Thus, β-convergence provides an empirical method for tracking progress and identifying structural or institutional determinants that either promote or hinder convergence in food waste reduction across municipalities.

The novelty of applying β-convergence to food waste lies in its interdisciplinary dimensions—blending environmental sustainability with economic growth theory. This approach enables researchers not only to test whether convergence is occurring but also to investigate the structural and institutional variables that drive it. This study addresses a critical gap by extending β-convergence into municipal food waste governance—an underexplored area despite its centrality to circular economy goals and SDG 12.3.

2.2. Food Waste Convergence

Several studies suggest that regions with higher initial levels of waste tend to adopt more aggressive interventions to reduce food waste more effectively, such as improved waste sorting, composting infrastructure, or public engagement programs[17, 37, 38]. This behavior aligns with the β-convergence hypothesis, which posits that entities with poorer initial conditions improve at a faster rate, thereby narrowing disparities over time[30]. Case studies from cities like Milan and Mouans-Sartoux demonstrate how strong policy frameworks and local innovation in high-waste contexts can yield rapid waste reduction[12]. In addition, public pressure and resource constraints in high-waste municipalities can prompt stronger policy responses and investment in technologies such as anaerobic digestion or composting[16, 18]. These concentrated efforts enable faster progress compared to municipalities where baseline waste levels are already low, making it harder to achieve marginal gains. Accordingly, the first hypothesis proposed is:

H1. *Municipalities with higher initial levels of food waste reduce their food waste faster over time ($\beta < 0$), indicating unconditional convergence.*

2.3. Structural and Institutional Factors

GRDP plays a key role in shaping food waste convergence. Municipalities with higher GRDP per capita may experience increased food consumption and waste levels due to greater purchasing power[39, 40]. Economic capacity, as reflected by higher GRDP, can also enable better waste infrastructure, policy enforcement, and public education efforts that accelerate waste reduction. In contrast, lower-GRDP regions might exhibit lower waste generation due to financial constraints and often lack the resources for long-term solutions[23, 41–43]. This suggests that GRDP per capita influences how quickly municipalities converge in food waste levels, highlighting the role of economic structure in convergence analysis[44, 45].

Next, poverty levels may also shape municipal food waste levels. In high-poverty municipalities, food is often treated as a scarce resource, leading to more conservative consumption and lower levels of waste[23, 41]. In this setting, every bit of food holds significant value, leading individuals and families to adopt more frugal consumption patterns[23, 41]. Without food-sharing systems, some areas may experience both food insecurity and food waste, which exacerbates regional inequality[45]. Therefore, poverty rate serves not only as a structural constraint, but also as a key variable in determining whether food waste convergence unfolds.

Lastly, the recycling rate reflects municipal performance in managing solid waste. Regions with higher recycling rates typically demonstrate more effective systems for sorting, collecting, and processing food waste, which in turn supports faster reduction in overall waste levels [46]. Recycling initiatives often coincide with public awareness and supportive regulations that strengthen convergence outcomes. Conversely, municipalities with poor recycling infrastructure may fall behind due to limited coverage, low participation rates, or weak policy enforcement [41, 47]. Thus, the recycling rate acts as an institutional indicator that can accelerate or hinder food waste convergence efforts across municipalities. Thus, the second hypothesis is formulated as follows:

H2a. *GRDP per capita significantly influences the rate of food waste convergence.*

H2b. *Poverty rate significantly influences the rate of food waste convergence.*

H2c. *Recycling rate significantly influences the rate of food waste convergence.*

2.4. Municipal Heterogeneity

Municipalities can have different food waste convergence rates based on their geographical location. Java, as the economic and governance center, benefits from more advanced infrastructure, greater fiscal capacity, and stronger institutional frameworks that support effective food waste management [21, 48]. Regions in Java are more likely to implement food waste policies through collaborative efforts involving municipalities, local businesses, and community networks [49]. The presence of a more mature food service sector and public awareness campaigns further accelerates the adoption of sustainable waste practices. In contrast, many non-Java municipalities experience slower progress due to limited waste management infrastructure, low administrative capacity, and geographic isolation, which pose logistical challenges for food waste collection, redistribution, and treatment [20, 50]. These differences highlight that geographic location is not only a spatial distinction but also a proxy for disparities in readiness and capacity to engage in food waste reduction, potentially slowing convergence between regions.

Population density is another structural characteristic that may differentiate the speed of food waste convergence across municipalities. High-density urban areas typically face greater pressure to manage waste efficiently due to high waste volumes, limited landfill capacity, and increased visibility of environmental problems [51]. Densely populated municipalities are also more likely to attract funded pilot projects and private-sector collaborations, which further support convergence [52]. On the other hand, low-density municipalities tend to experience slower adoption of advanced waste practices due to dispersed settlements, higher per-unit service costs, and weaker public engagement [53]. As a result, municipalities with higher population density may progress more rapidly in aligning with national food waste targets, while low-density areas face structural barriers that delay convergence.

Environmental budget levels may also differentiate the capacity of municipalities to implement effective food waste management strategies. High-budget municipalities are more likely to invest in technologies such as composting, anaerobic digestion, and digital tracking systems, which accelerate waste reduction [52, 54]. They also tend to support public campaigns and provide institutional support that boosts community participation. In contrast, municipalities with limited environmental budgets often rely on outdated landfill practices and face difficulties in sustaining long-term initiatives [55, 56]. These financial constraints can hinder their ability to converge with better-funded counterparts, leading to slower reductions in food waste.

HDI reflects social and economic conditions that may shape the pace of convergence in food waste. Municipalities with high HDI typically have better education systems, stronger healthcare, and greater access to public services, all of which contribute to higher awareness and better implementation of sustainable practices [42]. These areas are more likely to support food recovery, promote behavior change, and adopt innovative waste reduction strategies. On the other hand, lower-HDI regions may struggle with poor infrastructure and limited educational opportunities, making it more challenging to reduce waste effectively [45]. This suggests that

HDI levels may influence the rate at which municipalities achieve national goals for reducing food waste. This leads to the formulation of the third research hypothesis:

H3a. *The convergence speed varies across geographic location (Java vs non-Java).*

H3b. *The convergence speed varies across population density (high vs low).*

H3c. *The convergence speed varies across budget levels (high vs low).*

H3d. *The convergence speed varies across HDI levels (high vs low).*

3. Materials and Methods

3.1. Empirical Model

The concept of β-convergence originates from growth economics, aiming to assess whether poorer areas generally grow faster than the richer ones, thereby reducing disparities over time [29]. The model tests whether the change in an outcome variable—typically in log-difference form—is negatively associated with its lagged level, indicating convergence. The β-convergence framework has been extended to non-economic indicators, including environmental performance and public policy outcomes such as carbon emissions and waste management [57]. Its flexibility has enabled researchers to assess how environmental burdens evolve across regions with varying starting conditions.

In this study, the β-convergence approach is adapted to examine whether Indonesian municipalities with higher initial levels of food waste experience faster reductions over time. This framework enables the identification of long-term trends in performance equalization and supports a dynamic assessment of local policy outcomes. Equations (1) and (2) represent the foundational logic of the model, where a significant negative coefficient on the lagged food waste variable implies convergence. Following empirical precedents in regional economic studies [29], this study focuses on whether disparities in municipal food waste are narrowing over the observed period.

Following prior empirical studies [58], the unconditional β-convergence model is estimated using a fixed-effects panel regression (equation 3). Thus, the model controls unobserved time-invariant municipal characteristics, μ_i, and common shocks across years, δ_t. This method isolates the within-municipality variation in food waste changes, improving the precision of the convergence estimates.

$$logFW_{it} - logFW_{i(t-1)} = \alpha + \beta logFW_{i(t-1)} + \varepsilon_{it} \quad (1)$$

$$\Delta logFW_{it} = \alpha + \beta logFW_{i(t-1)} + \varepsilon_{it} \quad (2)$$

$$\Delta logFW_{it} = \alpha + \beta logFW_{i(t-1)} + \mu_i + \delta_t + \varepsilon_{it} \quad (3)$$

$$\Delta logFW_{it} = \alpha + \beta logFW_{i(t-1)} + \gamma' X_{it} \quad (4)$$

To better capture the variations between municipalities, the analysis used a conditional β-convergence model. This approach includes key characteristics—such as the GRDP per capita, poverty levels, and recycling rates—as control variables in the analysis (see equation (4)). Including these covariates allows for a more precise estimation of the convergence process by isolating the effect of initial food waste levels from other factors influencing waste dynamics [58].

3.2. Research Procedures

This study sequentially applies the procedures as shown in **Figure 1**. First, the data are collected and prepared for further analysis. The analysis utilized annual panel data at the municipal level covering the period from 2020 to 2023, resulting in 355 observations. Although the original dataset spanned from 2019 to 2023, the estimation began in 2020, as the first-difference transformation was applied to the dependent variable. For subgroup or heterogeneity analyses, the number of observations decreased slightly to 345 due to missing values in specific variables across certain municipalities. All data used in this study were retrieved from publicly accessible sources. Municipal-level food waste and recycling data were obtained from the Ministry of Environment and Forestry's Solid Waste Information System

(SIPSN), available at *https://sipsn.menlhk.go.id.* Socioeconomic indicators such as GRDP per capita, poverty rate, and HDI were sourced from Statistics Indonesia via *https://www.bps.go.id.*

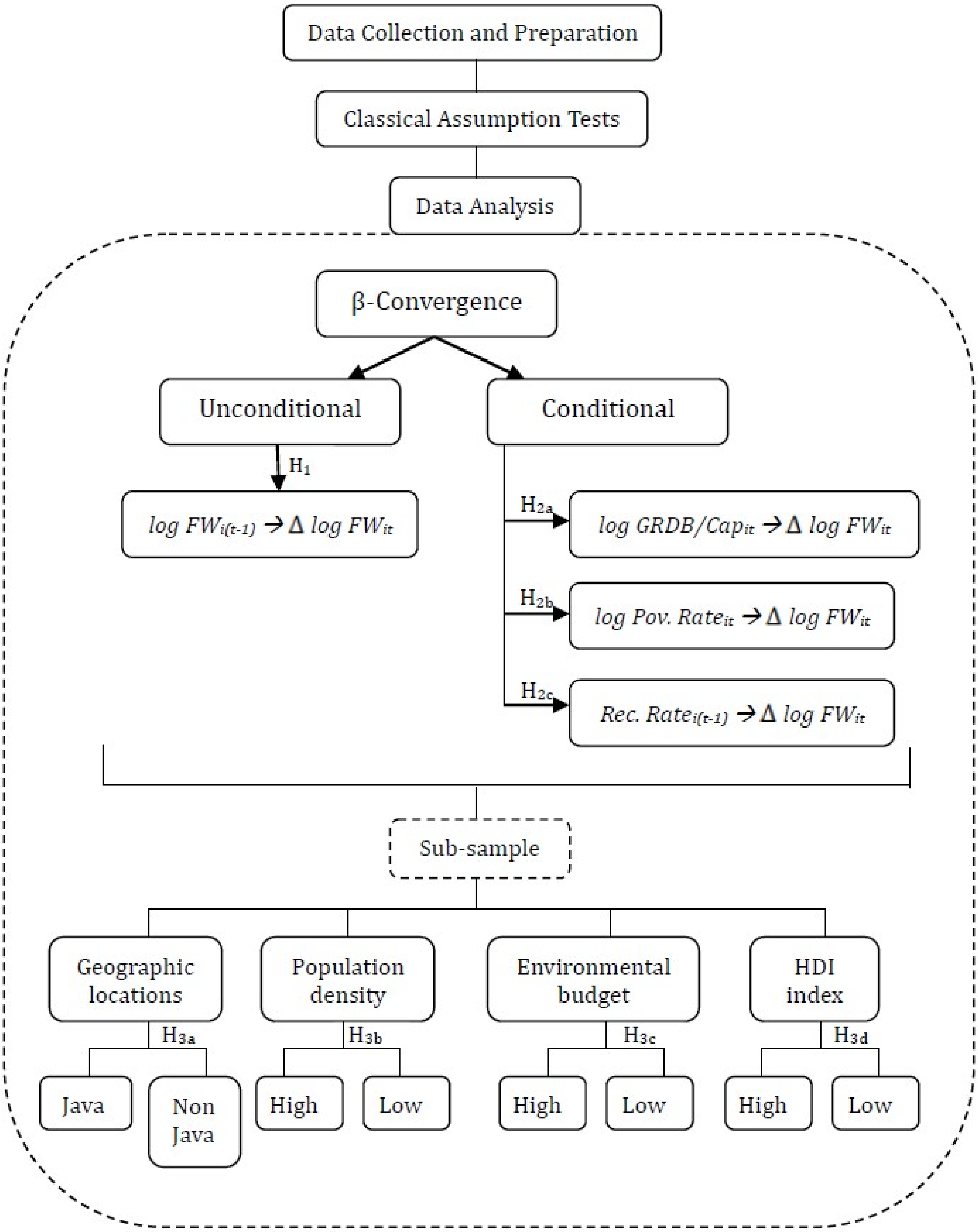

Figure 1. Research Framework.

Second, the selected variables were tested against classical assumptions to ensure their validity. **Table 1** summarizes the variables used in the model, all of which were selected based on their theoretical and empirical relevance to convergence studies and municipal solid waste management. The key explanatory variable, lagged log food waste, captures convergence dynamics, while GRDP per capita, poverty rate, and recycling rate serve as controls. The inclusion of control variables aims to capture the complexity of food waste performance at the municipal level. Statistics indicate that variations exist between different municipalities. For example, the standard deviation of the recycling rate emphasizes major differences in how waste is managed across various areas, with some municipalities reporting no recycling at all. Similarly, the poverty rate varies slightly, reflecting the different economic situations of local populations.

Table 1. Descriptive Statistics.

Variable	Definition and Unit	Obs.	Mean	Std. Dev.	Min.	Max.
∆log Food Waste	Year-to-year change in municipal food waste (log)	345	0.105	0.551	–1.616	4.625
Log Food Waste (t–1)	Volume of municipal food waste in the previous year (log)	345	14.533	1.368	9.469	17.879
Log GRDB per Capita	Gross Regional Domestic Product per capita (log)	345	16.806	1.109	14.165	20.134
Log Poverty Rate	Percentage of the population living below the poverty line (log)	345	–1.616	1.128	–3.902	1.558
Recycling Rate (t–1)	Proportion of municipal solid waste that was recycled in the previous year (%)	345	0.097	0.112	0	1.192

To ensure the appropriateness of including these variables simultaneously, correlation and multicollinearity diagnostics were conducted. **Table 2** shows that the pairwise correlations among explanatory variables are relatively low, with the highest correlation (0.377) occurring between log poverty and log GRDP per capita. Meanwhile, the recycling rate (t–1) shows negligible correlation with the other variables, suggesting its inclusion does not distort the model. **Table 3** further confirms the absence of multicollinearity, as all variance inflation factor (VIF) values are well below the conventional threshold of 10, with the highest VIF being 1.820. These findings suggest that the independent variables add distinct information to the model without multicollinearity problems. As such, the inclusion of these variables in the conditional convergence model is statistically sound and theoretically defensible. Meanwhile, to ensure robust inference, the analysis employs variance-covariance estimation (VCE), clustering the standard errors at the municipal level. This adjustment corrects for potential within-municipality heteroskedasticity and serial correlation within municipalities.

Table 2. Correlation.

Variable	Log Food Waste (t–1)	Log GRDB per Capita	Log Poverty Rate	Recycling Rate (t–1)
Log Food Waste (t–1)	1			
Log GRDB per Capita	0.238	1		
Log Poverty Rate	0.157	0.377	1	
Recycling Rate (t–1)	0.036	0.008	0.042	1

Table 3. VIF.

Variable	VIF	1/VIF
Log Food Waste (t–1)	1.070	0.936
Log GRDB per Capita	1.280	0.784
Log Poverty Rate	1.820	0.548
Recycling Rate (t–1)	1.010	0.989

Third, the unconditional and conditional β-convergence models were analyzed. The analysis was also applied to various subsamples to explore heterogeneity in convergence patterns across municipal characteristics. These include location (Java vs. non-Java), population density (high vs. low), environmental budget (high vs. low), and human development index (HDI) level (high vs. low). The "high" and "low" categories were determined using the sample mean as the threshold. Municipalities with values above the average were classified as "high," while those at or below the mean were classified as "low." This binary classification offers an interpretable and straightforward method for distinguishing differences in convergence dynamics across various socioeconomic and institutional backgrounds, with sufficient observations in each group to support reliable statistical inference.

4. Results

4.1. Unconditional Convergence

Table 4. Unconditional β-convergence Estimates of Municipal Food Waste (2020–2023).

△log Food Waste	Unconditional			
	(1)	**(2)**	**(3)**	**(4)**
log Food Waste (t–1)	−0.358*** (0.078)	−0.357*** (0.077)	−1.021*** (0.081)	−1.049*** (0.079)
Constant	5.303*** (1.149)	5.339*** (1.152)	14.926*** (1.173)	15.290*** (1.148)
Municipal FE	-	-	√	√
Year FE	-	√	-	√
Obs.	355	355	355	355
R2 Within	0.734	0.716	0.734	0.751
Wald χ^2	21.000***	21.560***	-	-
F Statistics	-	-	159.600***	43.840***

Standard errors clustered at the municipal level are in parentheses. ***: $p < 0.01$.

The initial analysis tests whether β-convergence in food waste exists across Indonesian municipalities without controlling for other socioeconomic characteristics. As shown in **Table 4**, Models (1) to (4) sequentially incorporate time and municipality fixed effects to examine the robustness of the convergence pattern. Model (1) begins with a basic regression without fixed effects. The result reveals a significant negative relationship between the lagged log of food waste and its change over time, suggesting a tendency toward convergence. Yet, including just the year fixed effects in Model (2) results in a slightly weaker fit. When the municipality fixed effect is added in Model (3), the β coefficient becomes more negative, confirming the presence of convergence. Model (4), which includes both fixed effects, produces the most consistent estimate, indicating that municipalities with higher initial food waste levels reduced their waste more rapidly over time. This supports Hypothesis 1 and confirms that β-convergence in municipal food waste occurred during the observed period.

Across all four models in **Table 4**, the β coefficient indicates a negative and highly significant effect at the

1% level. The results consistently indicate the presence of unconditional convergence. The magnitude of the coefficient becomes notably larger when municipality fixed effects are included, as seen in Models (3) and (4). This implies that unobserved, time-invariant municipal characteristics play an important role in explaining initial disparities in food waste levels. The within R^2 improves from 0.716 in Model (2) to 0.751 in Model (4), reflecting better model fit when both municipal and year fixed effects are accounted for. These findings suggest that convergence in municipal food waste is not solely a result of common national trends but is also shaped by persistent, locality-specific factors. Overall, the estimates provide strong baseline evidence that food waste disparities across Indonesian municipalities narrowed during the observed period, consistent with β-convergence theory.

4.2. Conditional Convergence Based on Local Socioeconomic Factors

Table 5 shows results from the conditional β-convergence models, which incorporate control variables into the main model. Models 5–7 particularly emphasize how different factors within municipalities (e.g., GRDP per capita, poverty, and recycling rates) affect the convergence of food waste. Across all three models, the coefficient in lagged food waste remains negative and statistically significant, reinforcing the presence of convergence even after accounting for differences in economic and institutional conditions.

Table 5. Conditional β-convergence Estimates of Municipal Food Waste (2020–2023).

△log Food Waste	**Conditional**		
	(5)	**(6)**	**(7)**
log Food Waste (t–1)	−1.051*** (0.080)	−1.052*** (0.082)	−1.053*** (0.081)
Log GRDB per Capita	0.151* (0.085)	0.149* (0.079)	0.146* (0.081)
Log Poverty Rate	-	0.011 (0.046)	0.011 (0.047)
Recycling Rate (t–1)	-	-	−0.109 (0.258)
Constant	12.806*** (1.648)	12.887*** (1.561)	12.957*** (1.597)
Municipality FE	√	√	√
Year FE	√	√	√
Obs.	345	345	345
R2 Within	0.765	0.764	0.764
F Statistics	34.740***	31.270***	31.270***

Standard errors clustered at the municipal level are in parentheses. ***: $p < 0.01$, *: $p < 0.10$.

In Model (5), GRDP per capita shows a significant positive association with food waste growth, providing support for H2a. This suggests that economically stronger municipalities tend to experience faster increases in food waste over time, possibly due to higher consumption levels. This finding is consistent with previous research [40, 44] who note that wealth often leads to over-consumption if not managed by strong waste-reduction policies. As for Model (6), the poverty rate is included but is not statistically significant. Model (7) also indicates that the recycling rate has no significant effect on food waste convergence. These findings partially support Hypothesis 2, indicating that while convergence holds after accounting for municipal characteristics, not all socioeconomic variables have a uniform or significant impact on food waste reduction rates.

The consistently significant β-convergence coefficients across all conditional models suggest that municipal food waste convergence is robust to include structural socioeconomic variables. However, the explanatory power of these covariates appears limited, particularly poverty and recycling rates, which vary relatively little across municipalities. These findings show that convergence dynamics are complex [2, 59]. Therefore, more detailed data is needed to truly understand how socioeconomic factors impact convergence.

4.3. Heterogeneity in Convergence Patterns

Table 6 presents the group-specific heterogeneity by looking at the conditional β-convergence model across different types of municipalities. These findings confirm Hypothesis 3, showing that the speed of food waste convergence is not uniform. Instead, it is shaped by local socioeconomic and institutional environments. However, the coefficient estimates for β-convergence remain consistently negative and of comparable magnitude across most subsamples. This implies that the overall convergence effect is irrespective of belonging to certain groups, although convergence speed may differ. This insight reinforces the robustness of the main findings but also generates information on contextual policy implications.

In terms of location, municipalities on Java Island exhibit a stronger convergence pattern than those outside Java, as shown in Models (8a) and (8b). The β coefficient is more negative for Java, suggesting that municipalities in this region—characterized by denser infrastructure, more mature waste management systems, and closer administrative oversight—are reducing food waste more quickly relative to their initial levels. In contrast, non-Java regions may face capacity constraints or slower adoption of circular practices, resulting in more gradual convergence.

Table 6. Subgroup Estimates of Conditional β-convergence in Municipal Food Waste (2020–2023).

△ln FW	**Location**		**Density**		**Environmental Budget**		**Human Development Index**	
	Java	**Non–Java**	**High**	**Low**	**High**	**Low**	**High**	**Low**
	(8a)	**(8b)**	**(9a)**	**(9b)**	**(10a)**	**(10b)**	**(11a)**	**(11b)**
Log Food Waste (t–1)	−1.085*** (0.144)	−1.005*** (0.083)	−1.055*** (0.107)	−0.991*** (0.115)	−1.111*** (0.226)	−1.037*** (0.081)	−1.087*** (0.113)	−0.971*** (0.126)
Log GRDB per Capita	0.181** (0.073)	0.005 (0.254)	0.188** (0.077)	−0.048 (0.223)	0.088 (0.075)	0.236*** (0.077)	0.067 (0.055)	0.217*** (0.064)
Log Poverty Rate	0.149** (0.063)	−0.105 (0.065)	0.091 (0.067)	−0.152** (0.061)	0.007 (0.043)	−0.031 (0.078)	0.007 (0.047)	−0.016 (0.095)
Recycling Rate (t–1)	3.869*** (1.209)	−0.387 (0.287)	2.961*** (0.892)	−0.496* (0.279)	2.396** (1.156)	−0.210 (0.272)	0.504 (0.437)	−0.279 (0.243)
Constant	13.236*** (2.500)	14.236*** (4.865)	12.394*** (2.075)	14.833*** (4.625)	14.988*** (3.886)	11.065*** (1.472)	14.818*** (2.034)	10.491*** (1.560)
Municipal FE	√	√	√	√	√	√	√	√
Year FE	√	√	√	√	√	√	√	√
Obs.	104	233	121	216	93	244	194	143
R^2 Within	0.870	0.741	0.880	0.616	0.835	0.758	0.840	0.635
F Statistics	20.570***	38.730***	30.320***	23.610***	9.060***	37.420***	20.460***	117.980***

'High' and 'low' categories are based on whether values are above or below the sample mean of each respective grouping variable. Standard errors clustered at the municipal level are in parentheses. ***: p < 0.01, **: p < 0.05, *: p < 0.10.

When grouped by population density, high-density municipalities show faster convergence than their low-density counterparts, as reported in Models (9a) and (9b). This rapid convergence could be linked to stronger regulatory enforcement, concentrated public awareness efforts, or economies of scale in waste management services. The recycling rate is particularly important in these regions, suggesting that policies tend to work better in densely populated areas compared to less populated ones.

Regarding environmental budget classifications, municipalities with higher budget allocations demonstrate steeper convergence rates (Model 10a). Meanwhile, those with lower budgets converge more slowly (Model 10b). Having better finances at the municipal level may accelerate local governments' adoption of new waste reduction technologies or create policies that support such efforts.

Finally, differences in convergence speed based on HDI levels are also evident. **Table 6** shows that food waste convergence occurs faster in municipalities with high (Model 11a) than low (Model 11b) levels of HDI. Higher HDI levels may indicate greater institutional capacity and public participation in environmental programs. This municipality type often has better data collection and coordination of actions, which allows for more effective waste management interventions.

Table 6 also shows that the number of observations and the model performance vary between subgroups. Some groups provide relatively balanced observations among the subgroups, while others (e.g., the environmental budget group) provide composition disparities. Meanwhile, the "within R^2" shows higher explanatory power in high-density areas (0.880) and municipalities located on Java (0.870). Lower "within R^2" values, however, occur in low-density (0.616) and low-HDI (0.635) municipalities. Lastly, the F-statistics are highly significant in all models, confirming the joint relevance of the explanatory variables. These findings demonstrate the robustness of the model specifications and highlight the convergence of food waste at the municipal level across various institutional and socioeconomic contexts.

Figure 2 presents the change in food waste by subgroup—geographic location, population density, environmental budget, and HDI—providing a visual overview of the average trends. Although the figure does not directly show convergence, it helps illustrate broader trends and subgroup differences that contextualize the regression-based findings. In each panel, municipalities classified with "higher" characteristics—Java (a), high density (b), high budget (c), and high HDI (d)—generally display more fluctuation but a sharper reduction in food waste by 2023 compared to their counterparts. These trends visually reinforce the β-convergence findings discussed in **Tables 4–6**, where higher initial food waste levels were associated with faster declines. Notably, the sharper year-on-year drop in Java and high-density municipalities supports the regression evidence that convergence occurs more rapidly in well-resourced and administratively stronger areas.

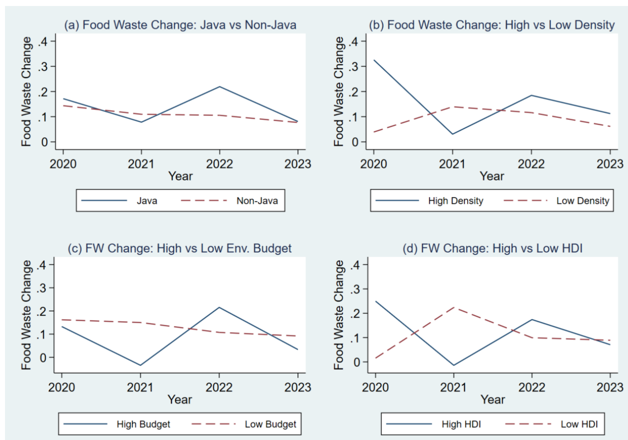

Figure 2. Average change of food waste ($\Delta ln\ FW_t = ln\ FW_t - ln\ FW_{t-1}$) by group: (**a**) Location (Java vs. Non-Java); (**b**) Density (High vs. Low); (**c**) Environmental Budget (High vs. Low); and (**d**) Density (High vs. Low).

Interestingly, all subgroups show a moderate increase in food waste change in 2022, following the decline in 2021. This pattern likely reflects the national post-COVID recovery, as pandemic-related mobility restrictions and disruptions in food service sectors eased. This recovery may lead to increased food consumption and, subsequently, higher food waste generation. Municipal systems may have struggled to immediately recalibrate, especially in rapidly growing urban centers. However, the regression models address this systemic shock by including year-fixed effects, which absorb national-level influences that impact all municipalities in the same period. As a result, the β-convergence estimates remain unbiased, and the subgroup comparisons continue to reflect genuine differences in municipal capacity and structural characteristics.

The disparities between the high and low groups by 2021–2023 also illustrate the heterogeneity in the regression-based subsample analysis (**Table 6**). However, local municipalities with low budgets and a low HDI index showed a slower, yet steadier, decrease in food waste. In other words, high-budget and high-HDI areas experienced greater changes, notably improved institutional responsiveness. These trends help justify claims of non-uniform convergence, driven by governance, fiscal investment, and development levels. The visual patterns offer a complementary perspective on the regression results, illustrating the dynamics of food waste change over time within each group.

5. Discussion

This study introduces the β-convergence model into municipal food waste analysis within a developing country context—an application that has been underexplored in existing literature. While prior studies, such as those by Tonini et al. [60] and Campoy-Muñoz et al. [61] focus on environmental impacts or economic simulations of waste reduction at macro levels, this study employs a granular, municipal-level approach to measure the speed of food waste improvements. The integration of socioeconomic variables into a conditional β-convergence model also adds methodological novelty, bridging environmental convergence theory with public policy and waste system design.

Unlike prior studies that examine convergence at the national level [62, 63] or in the context of emissions or ecological indicators [24], this study provides a novel municipal-level analysis of food waste convergence in a developing country context. This research confirms the β-convergence model in the context of Indonesian municipal food waste. The results show that municipalities with higher initial levels of food waste tend to reduce their waste more rapidly. Furthermore, the analysis reveals that structural factors—particularly GRDP per capita—influence the speed of convergence, while other variables such as poverty rate and recycling rate show limited effects. Importantly, the convergence process is not uniform; it varies across municipalities with different socioeconomic and institutional profiles. Therefore, policymakers should implement food waste minimization strategies suited to local settings, rather than based on a single template. This way, they can support circular economy transitions with more impactful and context-specific food waste management.

This research complements Cheng et al. [28], who emphasized regional disparities in solid waste generation across China and highlighted the importance of location-specific policy responses. While Cheng et al. [28] found persistent inequality in waste outcomes between provinces, this study shows that convergence is evident at the municipal level in Indonesia, suggesting effective horizontal policy harmonization. Furthermore, the persistence of convergence after accounting for both municipal and year fixed effects indicates that Indonesia's efforts to strengthen local waste governance—through regulation, performance evaluation, and standardized reporting [64] —may have contributed to a national trend of catching up among lagging regions. In this regard, the findings extend the understanding of convergence beyond emissions to include material waste flows, reinforcing the potential for decentralized waste management reforms to produce measurable environmental convergence.

In the conditional models, the β-convergence coefficient confirms that convergence continues even after accounting for municipal differences in income, poverty, and recycling behavior. GRDP per capita shows a positive association with food waste growth, aligning with Environmental Kuznets Curve (EKC) logic, where waste tends to increase with rising income until a threshold is reached [24, 60]. This pattern supports previous findings in the U.S. [65], Europe [24, 60], and China [28]. In these contexts, economic development initially leads to increased waste generation. Over time, this trend begins to reverse as environmental awareness [24], technological adoption [60], and market structures [66] evolve.

However, this study finds that poverty rate and recycling rate do not significantly affect convergence speed. One plausible explanation, as noted by Grazhdani[67], is that household-level recycling and socio-environmental behavior are difficult to capture accurately using aggregated municipal indicators. Similarly, Gu[68] observed discrepancies in waste generation behaviors between household types in China, suggesting that socioeconomic predictors are more effective when disaggregated. The limited impact of the recycling rate may also reflect underdeveloped waste separation systems in many Indonesian municipalities[64], where community participation and recycling infrastructure remain uneven. Municipal recycling success depends on stable logistics and market linkages, which are often lacking in lower-income municipalities[26]. Inconsistencies in the local implementation of food waste collection and treatment policies often neutralize the expected gains from household-level awareness or infrastructure presence[25]. Therefore, while income levels influence convergence, deeper behavioral and institutional drivers likely underlie the municipal disparities in waste dynamics.

This study also finds evidence of heterogeneity in convergence patterns. Although convergence holds across all subsamples, municipalities in Java, high-density areas, and those with larger budgets or higher HDI levels demonstrate faster convergence. These results show that municipalities with more "superior" characteristics tend to experience faster convergence than their counterparts. The variation in convergence speeds underscores the significance of municipal-level capacity in translating national policy into operational outcomes. Municipalities with higher resource capacities might be better able to develop and enforce interventions. On the other hand, regions with resource limitations may struggle to reduce waste over time consistently. Thus, capacity, governance, and socio-institutional readiness are crucial for accelerating improvements in environmental performance.

For example, faster convergence in Java compared to non-Java regions reflects better administrative capacity, infrastructure access, and data reporting systems—factors that Kurniawan et al.[64] emphasized as critical for zero-waste program implementation in urban Indonesia. The role of population density is similarly significant, as noted in Tonini et al.[60], who emphasize that food waste is highly sensitive to urban structure and the reach of policy. Urban density facilitates economies of scale in waste collection, monitoring, prevention, and enforcement, all of which may explain the sharper decline in food waste among densely populated municipalities[27, 28, 60].

Additionally, convergence is faster in municipalities with greater environmental budgets, where the recycling rate becomes statistically significant. This aligns with Cobo et al.[69] and Allevi et al.[70], who demonstrated that well-funded municipal programs in the waste sector resulted in more efficient system optimization and better integration with circular economy goals. At the country level, failing to invest in local food systems results in longer-term environmental burdens[62]—a lesson underscored by slower convergence in low-budget municipalities.

Municipalities with higher HDI levels also converge more quickly, likely due to stronger institutions and community participation. This supports insights from Castillo-Giménez et al.[24], who observed that governance and institutional maturity drive the success of EU waste treatment performance. These municipalities may also have better access to public services and waste-related education, which can accelerate behavioral shifts. In contrast, low-HDI areas have limited educational access and administrative bottlenecks that slow convergence[45], despite national targets. Overall, the results confirm that enabling conditions—financial, infrastructural, and social—facilitate convergence in reducing food waste.

This convergence also aligns with circularity goals described by Cobo et al.[69], where systems transition from linear to circular models, enabling waste reduction through integrated municipal action. In Indonesia's case, the findings suggest convergence may reflect the scaling of decentralized waste systems (e.g., via the national SIPSN platform) combined with data standardization efforts. Thus, the municipal-level convergence adds empirical weight to global goals of harmonized food waste management under frameworks like Sustainable Development Goal (SDG) 12.3., which ensures production and consumption sustainability.

The findings provide scientifically supported policy recommendations to reduce food waste at both the local and national levels. First, the heterogeneity of these convergence speeds exhibited across subsamples suggests the importance of context-specific interventions. The convergence framework allows policymakers to identify which municipalities are falling behind and why. By identifying which and why convergence is lagging, this research provides a diagnostic framework for allocating resources and interventions. Municipalities with slow convergence—particularly those with low HDI, limited budgets, or non-Java status—require targeted interventions such as fiscal transfers, technical assistance, and community engagement programs [69, 71]. Therefore, the convergence rate can serve as a diagnostic and monitoring tool, complementing existing metrics like recycling rates or landfill volumes. In addition, the convergence framework can also serve as a dynamic indicator of how quickly municipalities improve over time. While traditional tools measure environmental impact at a fixed point, the convergence rate captures whether lagging municipalities are catching up, thus offering insight into the progress of sustainability interventions. Second, policymakers should incentivize circular economy adoption through performance-linked grants, as fiscal support leads to waste behavior changes [71]. The fiscal incentive is even more effective when complemented with strategies, regulations, and market behaviors [66].

6. Conclusions

This work offers strong support for β-convergence in Indonesian municipal food waste. The findings indicate that municipalities with higher initial waste levels experience faster reduction rates in food waste relative to those with lower initial levels. The analysis confirms unconditional convergence and shows that food waste convergence persists even after accounting for structural municipal characteristics such as GRDP per capita, poverty rate, and recycling rate. Notably, the analysis reveals heterogeneity in convergence speeds across geographic regions, levels of population density, environmental endowments, and human development. The variation in convergence speeds reflects disparities in local capacities to plan, fund, and implement effective waste reduction strategies.

These findings have significant implications for circular economic practices and sustainable governance. The food waste convergence trend suggests that waste monitoring may help narrow performance gaps between higher- and lower-performing municipalities. However, the unequal speed of the convergence across municipal groups highlights the need for more municipal-specific policy responses. High-performing municipalities benefit from stronger institutions, better infrastructure, and fiscal capacity—factors that should guide capacity-building in lagging municipalities.

The study contributes methodologically by applying a conditional β-convergence framework to municipal food waste data. Furthermore, the framework provides a replicable model for other developing countries seeking to achieve the SDG 12.3 targets. It also advances the literature by integrating structural and institutional dimensions into the analysis of food waste performance. In addition, the findings provide policymakers with a tool to identify where support is most needed and monitor progress toward accelerating food waste convergence toward sustainability.

While the analysis provides robust findings, the convergence framework assumes linearity, which may oversimplify the policy response in complex municipal systems. Despite its linearity assumption, the β-convergence model remains theoretically grounded and empirically practical for municipal-level policy analysis. Future research should explore nonlinear models and consider household or sectoral-level food waste dynamics. It would also be valuable to integrate behavioral and institutional indicators more explicitly, following approaches used in circular economy adoption studies [61].

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Data Availability Statement

All data used in this study are publicly available. Municipal waste data are available through the Ministry of Environment and Forestry website, https://sipsn.menlhk.go.id., while socioeconomic indicators (e.g., GRDP per capita, poverty rates) are accessible from Statistics Indonesia, https://www.bps.go.id.

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Conflicts of Interest

The author declares no conflict of interest.

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