[**Supplementary information**]

Hidden heterogeneity in low-carbon cities via demand-sensitive carbon intensity

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Supplementary Note 1: Low-voltage behind-the-meter PV estimation

This Supplementary Note describes the methodology used to decompose aggregated low-voltage (LV) smart meter data into electricity demand and behind-the-meter photovoltaic (PV) generation at the municipal level. The objective is not to reconstruct household-level power flows, but to provide a transparent and internally consistent estimation framework that enables large-scale, spatio-temporal comparison of carbon intensity (CI) and demand-sensitive carbon intensity (SCI) across municipalities.

Estimating the latent components underlying aggregated electricity measurements is commonly referred to as *energy disaggregation* [1], and a wide range of methodological approaches have been proposed in the literature [2, 3]. With respect to behind-the-meter PV generation, existing studies have addressed diverse spatial scales and aggregation levels, including individual consumers [4–7], groups of consumers [8, 9], and single areas or communities [10–12]. These studies differ in data requirements, modeling assumptions, and target applications, reflecting the inherent trade-offs between estimation accuracy and scalability. In this study, we adopt a municipality-scale approach that leverages smart meter data and satellite-based solar irradiance information to enable temporally and spatially consistent estimation across a large number of locations. The overall framework follows the approach proposed in [13], with several simplifying assumptions introduced to ensure robustness under limited spatial resolution and aggregated smart meter observations, and applicability at the municipal scale.

The notation used in this Supplementary Note follows that introduced in the main text. The aggregated LV electricity demand measured by smart meters, $c^{\mathrm{LV}}_{m,t}$, represents net electricity consumption at customer meters and therefore implicitly includes the effect of behind-the-meter PV self-consumption as shown in Eqs. (3) and (4). We consider that LV customers consist of two groups: pure consumers (without PV systems) and prosumers equipped with rooftop PV. Let N^{Υ}_{m} and N^{Π}_{m} denote the numbers of consumers and prosumers in municipality m, respectively. We assume that the per-household electricity demand profile is statistically identical between consumers and prosumers in expectation; i.e., differences in aggregated LV demand dynamics arise from the presence of PV generation rather than systematic differences in underlying consumption behavior. This assumption does not imply identical behavior at the household level, but allows systematic differences in aggregated LV demand dynamics across municipalities to be interpreted primarily in relation to PV penetration, rather than unobserved behavioral heterogeneity. Under this assumption, the counterfactual LV demand in the absence of PV generation can be expressed as

$$\tilde{c}^{\mathrm{LV}}_{m,t} = \left(N^{\Upsilon}_{m} + N^{\Pi}_{m}\right) d_{m,t}, \tag{1}$$

where $d_{m,t}$ denotes the representative per-household demand profile in municipality m. The observed LV demand $c^{\mathrm{LV}}_{m,t}$ is then given by

$$c^{\mathrm{LV}}_{m,t} = \tilde{c}^{\mathrm{LV}}_{m,t} - s^{\mathrm{PV}}_{m,t}, \tag{2}$$

where $s^{\mathrm{PV}}_{m,t}$ represents behind-the-meter PV self-consumption. Under this formulation, behind-the-meter PV self-consumption is reflected as a reduction in the observed LV electricity demand. Gross LV PV generation, denoted by $g^{\mathrm{PV,LV}}_{m,t}$, is estimated independently from electricity demand following the framework of [13]. Solar irradiance data are obtained from the Himawari-8/9 geostationary meteorological satellites [14, 15], and spatially averaged over 1-km satellite observation meshes contained within each municipality. The effective LV PV capacity within each municipality is treated as an implicit variable and estimated through a fitting procedure [13]. Specifically, PV generation is reconstructed such that the combination of (i) PV-derived reverse power flow $\{e^{\mathrm{PV,LV}}_{m,t}; t\}$ observed by smart meters, (ii) estimated PV self-consumption $\{s^{\mathrm{PV,LV}}_{m,t}; t\}$, and (iii) aggregated LV forward power flow yields a total electricity demand profile that is consistent with observed smart meter data at the municipal level. Under this formulation, the spatially averaged solar irradiance serves as an exogenous driver of PV output, while the effective PV capacity within each municipality is inferred as the solution to the fitting problem. This approach ensures consistency between estimated PV generation, self-consumption behavior, and observed power flows, without relying on externally reported residential PV capacity statistics. The primary methodological difference from [13] lies in the use of municipality-averaged irradiance over satellite meshes, rather than site-specific irradiance information, reflecting the spatial resolution of the available smart meter data. This averaging approach is adopted to ensure consistency with the spatial resolution of the available smart meter statistics and to maintain computational tractability at the national scale. Behind-the-meter PV self-consumption is determined by comparing estimated PV generation with aggregated LV demand. When $g_{m,t}^{\mathrm{PV,LV}} \leq c_{m,t}^{\mathrm{LV}}$, all PV generation is assumed to be self-consumed within the municipality. When $g_{m,t}^{\mathrm{PV,LV}} > c_{m,t}^{\mathrm{LV}}$, PV generation is proportionally allocated to self-consumption, and the surplus is assumed to be exported to the grid. This allocation scheme ensures energy balance between demand, PV generation, and grid exchange at the municipal level, while avoiding the need for household-level operational modeling.

The proposed decomposition does not aim to reconstruct exact household-level power flows. Instead, it provides a transparent and internally consistent approximation of LV behind-the-meter behavior suitable for large-scale comparative analysis of CI and SCI.

Supplementary Note 2: High-voltage PV self-consumption approximation

This Supplementary Note explains the approximation used to estimate self-consumption of PV generation at the high-voltage (HV) level, where direct behind-the-meter measurements are unavailable. This approach leverages observed reverse power flows and institutional information on feed-in tariff (FIT) participation to ensure consistency between PV generation, electricity demand, and grid exchanges at the municipal scale.

Under the current institutional framework in Japan, PV generation at the HV level is largely connected under the FIT scheme, implying that a substantial fraction of generated electricity is exported to the grid. Consequently, significant self-consumption is expected mainly from non-FIT PV installations. Based on this observation, the effective self-consumption rate is estimated by combining (i) observed HV PV reverse power flows, $\{e_{m,t}^{\mathrm{PV,HV}}; t\}$, (ii) publicly available municipality-level FIT certification data [16], published by Agency for Natural Resources and Energy, METI, on the number and capacity of PV installations, and (iii) aggregated HV demand measurements, $\{d_{m,t}^{\mathrm{HV}}; t\}$. Specifically, the relationship between certified FIT PV capacity and the annual maximum observed PV reverse power flow is used to estimate an average capacity-to-output conversion factor at the municipal level. Deviations between predicted and observed reverse power flows are interpreted as potential self-consumption. This estimate is further adjusted by the proportion of non-FIT installations, yielding an effective self-consumption rate for HV PV generation. The estimated self-consumption rate is applied to time-resolved PV reverse power flow data to reconstruct total HV PV generation, including both exported and self-consumed components. The self-consumed portion is then added to observed HV demand to obtain an approximation of net electricity demand behind the meter. This procedure ensures consistency between PV generation, demand, and observed power flows at the municipal level.

While this approach does not resolve facility-level operational behavior, it explicitly accounts for institutional constraints imposed by the FIT scheme and leverages observed power flow data. Given the objective of characterizing relative differences in CI and SCI across municipalities, the proposed approximation is considered sufficient for the purposes of this study.

Supplementary Note 3: Emission factors and CO_2 accounting assumptions

This Supplementary Note documents the emission factors and CO_2 accounting assumptions underlying the CI and SCI calculations presented in **Methods** of the main text. In this study, emission factors are defined on the supply side based on system-level generation characteristics and technology-specific literature, while electricity quantities are derived on the demand side from municipal-level smart meter data under the municipal energy boundary defined in the main text. These elements are combined through a consistent accounting framework to enable comparative analysis across municipalities and time periods. Accordingly, the emission factors adopted in this study are not intended to represent exact marginal or real-time system emissions, but rather to provide a transparent and internally consistent basis for comparing relative emission levels and demand-sensitive emission responses across municipalities.

Sources and rationale of emission factors

The emission factors used in this study are summarized in Table 2 of the main text. These values are derived from existing literature and publicly available sources, and are used to characterize the carbon intensity of electricity supplied from the power grid operated by each TSO. Time-varying grid emission factors determined by the generation mix within each TSO service area are publicly available via Zenodo [17], and readers are referred to that dataset for detailed temporal profiles. This subsection provides supplementary explanations of the rationale and assumptions underlying the emission factors adopted in this study.

For thermal power generation, utility-specific CO_2 emission factors are derived based on the fuel composition ratios (coal, oil, and LNG) publicly disclosed by each TSO. In the published statistics, thermal power generation is categorized not only into coal-fired, oil-fired, and LNG-fired plants, but also includes an additional category labeled as "other thermal power." This category is interpreted as mixed-fuel thermal generation rather than single-fuel dedicated plants. Accordingly, for each utility, the emission factor associated with "other thermal power" is estimated as a weighted

Supplementary Table 1 Utility-specific CO_2 emission factors for thermal power generation derived from fuel composition ratios.

TSO	Coal (%)	Oil (%)	LNG (%)	CO_2 emission factor (kg-CO_2/kWh)
Hokkaido Electric Power Network	65.7	18.6	15.7	0.851
Tohoku Electric Power Network	52.7	1.4	45.9	0.782
TEPCO Power Grid	25.3	0.0	74.7	0.686
Chubu Electric Power Grid	24.7	1.4	74.0	0.687
Chugoku Electric Power T & D	61.7	3.3	35.0	0.816
Shikoku Electric Power T & D	71.4	4.8	23.8	0.851

average of fuel-specific emission factors, using the utility-specific shares of coal-, oil-, and LNG-fired thermal generation. Fuel-specific emission factors for coal-fired and LNG-fired thermal power are summarized in Table 2, adopted from Refs. [18, 19]. The aggregated emission factor for each utility is then calculated as the weighted average of all thermal categories, taking into account both single-fuel and mixed-fuel thermal generation. Supplementary Table 1 summarizes the resulting utility-specific emission factors. For example, for TEPCO Power Grid, the thermal power emission factor is calculated as $(0.943 \times 0.253) + (0.599 \times 0.747) = 0.686$ kg-CO_2/kWh, based on the reported coal and LNG composition ratios, where oil-fired generation is negligible [20].

For biomass-only power generation, direct CO_2 emissions during combustion are assumed to be zero, following the carbon-neutrality convention. Indirect lifecycle emissions are approximated using the indirect emission component of conventional thermal power generation, resulting in an emission factor of 0.079 kg-CO_2/kWh [19].

For cogeneration systems (CGSs), the allocation of CO_2 emissions between electricity and heat follows the methodology specified by the Agency for Natural Resources and Energy, Ministry of Economy, Trade and Industry (METI) [21]. Specifically, CO_2 emissions are allocated based on the ratio of primary energy required to produce equivalent amounts of secondary energy using conventional systems. In this study, city gas is assumed as the primary fuel [22], and a gas turbine-based CGS is considered, with an electricity generation efficiency of 0.3 and a waste heat recovery efficiency of 0.5.

For electricity supplied via interconnection lines and battery storage systems, the generation mix at the time of reception cannot be uniquely identified. Therefore, a substitute emission factor corresponding to the utility-average emission intensity of the supplying TSO is adopted. The value differs across TSOs; for example, for the TEPCO Power Grid, the fiscal year 2024 average emission factor of 0.575 kg-CO_2/kWh is used [19]. Similarly, for pumped storage power generation, CO_2 emissions associated with pumping electricity consumption and indirect lifecycle emissions from hydroelectric generation are both considered. The emission factor is calculated by adding the indirect hydroelectric emission factor (0.011 kg-CO_2/kWh) to the TSO-specific average emission intensity. For TEPCO Power Grid, this results in a total value of 0.586 kg-CO_2/kWh [19]. TSO-specific emission factors used in the analysis are provided in Supplementary Table 2.

Supplementary Table 2 Utility-specific CO_2 emission factors assigned to interconnection lines (IL), battery energy storage systems (BESS), and pumped storage power generation (PSPG).

TSO	CO_2 emission factor (kg-CO_2/kWh) IL & BESS	PSPG
Hokkaido Electric Power Network	0.519	0.530
Tohoku Electric Power Network	0.555	0.566
TEPCO Power Grid	0.575	0.586
Chubu Electric Power Grid	0.530	0.541
Chugoku Electric Power T & D	0.591	0.602
Shikoku Electric Power T & D	0.506	0.517

Treatment of non-PV sources in CI accounting

In the municipal-level CI accounting framework adopted in this study, electricity supplied to meet municipal demand is classified into three categories that can be explicitly distinguished from municipality-aggregated smart meter statistics: PV generation, grid-supplied electricity, and non-PV local generation collectively referred to as "Other". The "Other" category encompasses distributed generation technologies such as cogeneration systems, small-scale hydropower, biomass-only plants, and battery discharge for which detailed technology-level dispatch information is not available from the aggregated smart meter data. Accordingly, this subsection focuses on the treatment of emission factors associated with "Other" sources, rather than on the allocation of electricity quantities.

As described in the CI formulation in the main text, total electricity consumption within a municipality at time t is decomposed into technology-specific supply components $q^k_{m,t}$, and CI is computed as a demand-weighted average of the corresponding emission factors. Under this formulation, the contribution of non-PV local generation to CI is represented by the term $q^{\mathrm{O}}_{m,t}\alpha^{\mathrm{O}}$, where $q^{\mathrm{O}}_{m,t}$ denotes the electricity supplied by "Other" sources to meet municipal demand, and α^{O} is the associated emission factor. While the magnitude of electricity supplied by non-PV sources directly affects CI, the internal technology-specific composition of this category is not explicitly resolved within the municipal accounting framework.

Rather than attempting to infer the internal mix of non-PV sources, which would require additional assumptions beyond the available data, this study adopts a scenario-based approach to characterize the potential influence of "Other" generation on CI and SCI through alternative choices of α^{O}. Specifically, three representative emission-factor scenarios are considered: (i) a pessimistic scenario assuming CGS as the dominant non-PV source, corresponding to a relatively high carbon intensity typical of gas turbine–based CGS; (ii) a baseline scenario based on the time-varying generation mix of the corresponding transmission system operator (TSO), representing an average system-level emission intensity; and (iii) an optimistic scenario assuming small-scale hydropower as the dominant non-PV source, yielding a comparatively low carbon intensity.

By evaluating CI and SCI under these alternative assumptions, we assess the sensitivity of municipal carbon indicators to uncertainty in the composition of non-PV generation. Municipalities for which CI or SCI exhibits large variation across these scenarios are interpreted as having substantial ambiguity in emission attribution driven by non-PV sources. Such municipalities are excluded from the main CI–SCI analyses and visualizations and are shown separately in gray in the CI–SCI maps. This screening procedure ensures that the subsequent discussion focuses on municipalities where observed differences in CI and SCI primarily reflect demand structure, PV deployment, and operating conditions, rather than unresolved uncertainty in non-PV generation composition.

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