

The Impact of Technological Factors Based on the Smart Grid in the Electricity Market on Greenhouse Gas Emissions

Yuanyuan SUN

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1. Introduction

With the rapid development of society, environmental challenges have become increasingly urgent. Greenhouse gas emissions have led to significant issues, including ecosystem degradation, global temperature rise, and an increase in natural disasters. In response to escalating global warming, nations worldwide have adopted various measures to reduce greenhouse gas emissions, frequently emphasizing the concept of a “carbon-neutral society.” This vision aims to achieve “net zero” greenhouse gas emissions, a primary goal outlined in the Paris Agreement¹⁾, which targets full carbon neutrality by 2050. The 159 signatory countries of the Paris Agreement are pursuing diverse strategies to meet this target. Investments in smart grid have become a key focus for reducing environmental impacts. For instance, Landis Gyr’s Capital Markets Day report (2020) projected that Europe’s smart grid adoption rate would reach approximately 70% by the end of 2023, with full installations in the Netherlands and the United Kingdom completed by 2022. In the United States, the IEI report (2016) indicated that by 2018, 70% of states had deployed smart meters, with particularly high adoption in states such as California, Texas, Illinois, and Florida.

In Japan, smart grid is crucial for integrating renewable energy sources and enabling next-generation vehicles to use storage batteries for electricity discharge. Smart meter deployment, allocated across the regional power companies, allows consumers to monitor electricity usage in real time, promoting energy-saving behaviors. For utility companies, this detailed usage data facilitates diverse pricing options and improves demand forecasting, enabling optimized electricity generation and storage. These measures reduce energy consumption and CO₂ emissions.

While full-scale smart meter deployment is ongoing, field experiments demonstrate their potential. For

1) The Paris Agreement is an international effort, shared by all countries, to keep the global average temperature increase well below 2° C above pre-industrial levels and to aim to limit it to 1.5° C.

instance, Ida, Tanaka, and Ito (2017) found that smart meters encouraged energy-saving behaviors. However, limited database availability restricts empirical research on smart grid. As adoption expands, the demand for research on their impact on greenhouse gas emissions grows. Quantifying these contributions is critical for establishing long-term decarbonization targets and crafting effective policies. Comparing field experiment outcomes with empirical research is also invaluable.

This study evaluates the impact of smart grid on CO₂ emissions, focusing on technological factors such as photovoltaic (PV), energy-efficient appliances, and hybrid and electric vehicles. PV reduce reliance on fossil fuels by enabling residential self-generation, lowering energy purchased from utilities, and cutting CO₂ emissions. Similarly, energy-efficient appliances, including refrigerators and lighting, contribute to energy savings and emission reductions. Hybrid and electric vehicles, which replace gasoline with electricity, further reduce operational CO₂ emissions. Our findings confirm that widespread smart meter adoption reduces CO₂ emissions, with PV having the most significant negative impact on emissions. Conversely, electric vehicles exhibit a positive correlation with emissions, likely due to a rebound effect. Additionally, energy-efficient appliances show an inverse U-shaped relationship with emissions, reducing CO₂ above a certain threshold.

This paper is organized as follows: Section 2 outlines the structure and environmental impacts of technologies like hems and PV, focusing on smart grid. Section 3 reviews relevant literature on smart grid and related technologies domestically and internationally. Section 4 details the research model, data, and estimated results. Finally, Section 5 summarizes the conclusions, discusses policy implications, and highlights study limitations.

2. Introduction of Smart Grid

2.1 Smart Meters and Related Technologies in Smart Grid

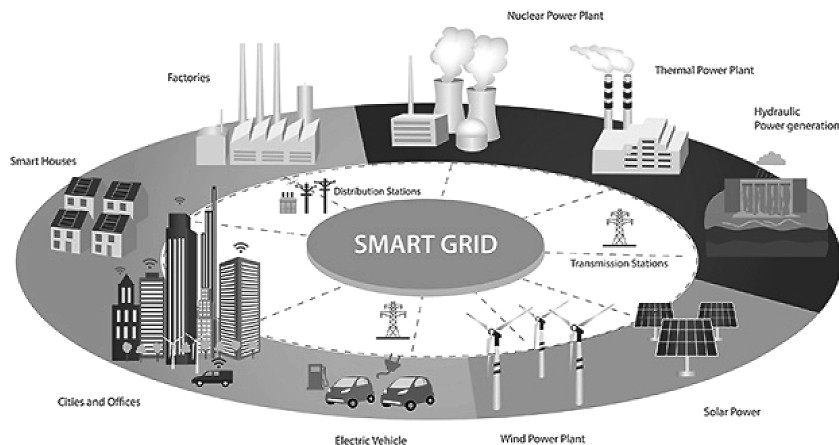
The concept of the smart grid was first introduced in the United States since power outages and blackouts cause approximately 150 billion in losses annually. Additionally, Obama administration set a goal for 25% of the total electricity supply to come from renewable energy sources by 2025. To address the challenges of strengthening the power grid and expanding renewable energy, the U.S. began adopting smart grid early on and the Energy Independence and Security Act of 2007 included smart grid as a distinct item. Subsequently, in 2009, President Obama announced a total of 3.429 billion in grants for the Smart Grid Investment Grant Program. This funding primarily included the installation of smart meters. Based on the smart grid, the implementation of distributed power sources, such as renewable energy, was also promoted.²⁾

2) Referred to Takayama (2010)

In March 2011, because of the Great East Japan Earthquake, power supply system in Japan underwent significant changes. The shift moved from a centralized power supply from traditional electric utilities to a decentralized power supply, including PV generation. With the development of ICT, demand response measures such as peak time shifting have also become more important for consumers' electricity use. In other words, unlike traditional power grid, a two-way power grid can be controlled from both the supply and demand sides to optimize electricity usage. Starting in 2014, smart meters began to be introduced into households. This plan is for the ten regional power companies to install smart meters in households within their regions from 2014 to 2024. The ten regions include Hokkaido, Tohoku, Kanto, Chubu, Hokuriku, Kansai, Chugoku, Shikoku, Kyushu, and Okinawa.³⁾

Smart grid is a power network that aims to achieve power supply system with high efficiency, high quality, and high reliability. The next-generation energy system uses communication networks and information systems to control the balance of electricity flow and volume from both the supply and demand sides, optimizing power usage. Figure 1 shows the conceptual diagram of smart grid.

Figure 1 Conceptual diagram of smart grid



Source: LESSMARTGRIDS⁴⁾

An essential component of the smart grid is the installation of smart meters in households. Once installed, smart meters enable instantaneous measurement of electricity consumption and transmission of this data to the utility. Smart meters automatically measure electricity consumption at 30-minute intervals and transmit this data to the management system in real time. These features allow both consumers and utilities to understand real-time electricity demand. The visualization of electricity consumption through smart meters can encourage consumers to adopt energy-saving behaviors.

3) Referred to Ministry of Economy, Trade and Industry

4) LES SMART GRIDS is a French-speaking reference site on smart grids. <https://les-smartgrids.fr/economies-smart-grids-france/>

When think about benefits of smart grid, households can access information on power supply and demand or the amount of PV generated at home, allowing them to use electricity efficiently. They can also automatically use smart appliances at optimal times. In the future, it is expected that electric vehicle batteries will become widespread, allowing households to store electricity generated by PV and use it when needed. This management approach is also being applied in factories and buildings. By efficiently using the electricity stored in decentralized power sources (such as PV), peak-time power consumption can be reduced. From the supply side, by understanding consumer power usage patterns, power companies can efficiently predict future power demands and procure power effectively. In other words, the use of ICT allows both the supply and demand sides to use electricity stably and efficiently.

In short, with the proliferation of smart grid, not only the power industry but also the integration of renewable energy sources such as PV, smart appliances, and electric vehicles is becoming increasingly widespread. This integration can achieve energy savings and be environmentally friendly.

For example, the adoption of renewable energy sources with a low environmental impact, such as PV, is being promoted. PV generation uses solar panels to absorb sunlight and generate electricity, thus eliminating the concern of greenhouse gas emissions. Hybrid and electric vehicles offer similar benefits. Hybrid cars typically have two or more power sources: a gasoline engine and an electric motor. The mechanism of hybrid cars uses the electric motor at low speeds and switches to the gasoline engine at high speeds, optimizing fuel consumption. This design helps reduce CO₂ emissions compared to traditional gasoline cars. Electric vehicles are environmentally friendly as they are powered solely by electricity, without using gasoline. Specifically, according to the study by Ida et al. (2014), the introduction of smart meters, PV generation, and electric vehicles has a greenhouse gas reduction effect.

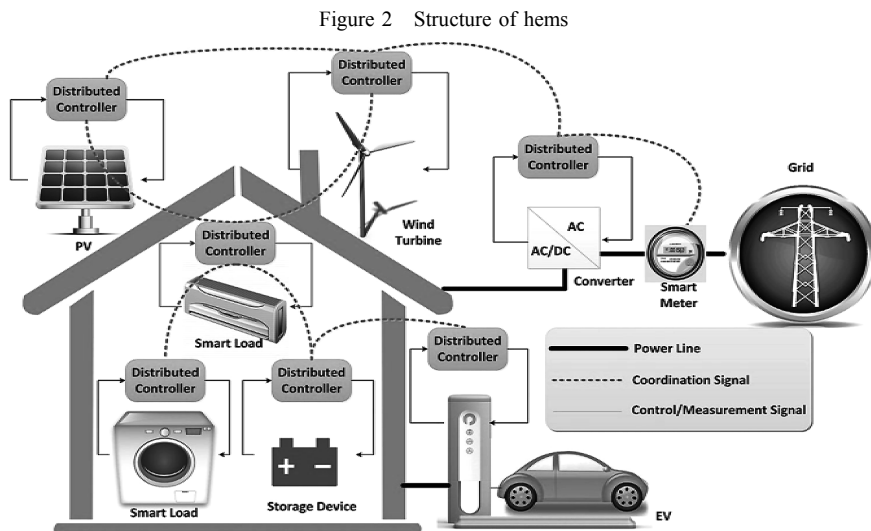
In recent years, the energy-efficient appliances (refrigerators, air conditioners, televisions, and lighting fixtures) have significantly improved, contributing to energy savings at home. By using energy-efficient appliances, the amount of electricity required to be generated at power plants can be reduced, thus lowering the use of fossil fuels. As a result, it is expected that greenhouse gas emissions will be reduced, contributing to the improvement of the global environment.

2.2 Hems in the Smart Grid

Smart meters and Hems are crucial components in the configuration of smart grid. With the introduction of smart meters and Hems, an increased interest in energy conservation among electricity consumers is also an expected role of the smart grid. While the discussion on smart meters was covered in section 2.1, this section will explain the mechanisms of Hems.

Hems stands for “Home Energy Management System” and means that a system designed to measure and manage electricity, gas, and water usage in homes, providing support and advice for saving resources. Hems can control smart meters, smart appliances, PV and energy devices, and electric vehicles.

This means that it cannot only monitor electricity consumption and generation but also track the energy usage of individual appliances. Regarding the functions of Hems, firstly, it enables the visualization of energy consumption in households, gradually increasing consumer awareness of daily energy usage and leading to energy conservation. Secondly, by connecting household appliances to Hems, users can efficiently manage each device smartly through a single control panel. Thirdly, by networking electrical appliances, users can control them remotely via a smartphone even when they are away from home. Lastly, Hems can integrate not only electricity but also gas and water usage, allowing users to monitor consumption levels and usage times. Figure 2 illustrates this mechanism.



Source: Solar choice⁵⁾

3. Literature review

Since the implementation of smart grid in Japan has been relatively slow, as a result, there are not many directly related empirical studies. Therefore, we will first present research directly on smart grid in Japan and abroad.

Ida et al. (2014) analyzed the adoption of smart devices such as smart meters, PV generation, and electric vehicles based on consumer preferences and willingness-to-pay (WTP) and concluded that they have a reduction effect on greenhouse gas emissions. Carroll et al. (2014) concluded that the installation of smart meters stimulated consumers' energy-saving behavior and thus had a positive effect. Date et al. (2015) aimed to examine the environmental and economic impacts of smart grid implementation in resi-

5) Solar choice is an organization that since 2008 has been helping Australian households and businesses make informed decisions when purchasing sustainable infrastructure. <https://www.solarchoice.net.au/blog/home-energy-management-systems-a-smart-way-to-save/>

dential and commercial areas. They predicted electricity demand and evaluated the CO₂ reduction effects. Their results showed that residential areas showed a significant reduction in CO₂ emissions due to the introduction of PV systems, while commercial areas showed a smaller reduction.

As the adoption of smart grid progresses, other technologies also contribute to energy conservation and CO₂ reduction in conjunction. Examples include PV generation, electric vehicles, and energy-saving home appliances. Unlike smart grid, these technologies were introduced earlier, so it is true that there are more related papers on them compared to smart grid.

Hondo and Baba (2008) surveyed 200 households in Iida city, Japan, that had installed PV systems. Through questionnaire surveys, they found that households with PV systems had increased awareness of environmental issues and engaged in more environmentally friendly behaviors in their daily lives. Matsui et al. (2012) conducted empirical experiments to test the effects of visualizing electricity consumption data on consumers' energy conservation behaviors. They insisted that electricity data visualization is associated with energy conservation. Their findings provide valuable insights.

Aoki et al. (2022) discussed that CO₂ emissions are determined by carbon intensity and energy efficiency, and that reducing CO₂ emissions requires improvements in carbon intensity and energy efficiency. Liang et al. (2022) used data collected from smart meters to analyze the effect of combining two technologies, PV generation and electric vehicles, on reducing consumers' electricity usage. The results showed that users who only used electric vehicles, without PV, had higher electricity usage compared to non-electric vehicles users. It was also found that consumers who used both PV and electric vehicles reduced their electricity usage.

Furthermore, there are also papers that do not specifically refer to which technology but generally discuss the elements of technology that have a reducing effect on CO₂ emissions. Bindi (2019) examined the role of technological innovation in reducing per capita CO₂ emissions and greenhouse gas emissions and found that it played an important role in reducing demand. Wu et al. (2021) analyzed the impact of internet development and technological advancements on energy conservation and emission reduction in urban areas of China. The results showed that advancements in internet technology can improve energy savings and reduce emissions. Tan and Cao (2023) came to a similar conclusion in their study. According to their research, green technologies have an effective impact on reducing CO₂ emissions.

With the proliferation of smart grid, the introduction of smart meters into households only began in 2014, and the installation process is not yet complete. As a result, directly related empirical research is limited. Previous studies have primarily focused on analyzing the impact of individual technology on greenhouse gas emissions. However, evaluating the environmental impact of smart grid is considered highly important. Understanding these impacts may be crucial for building future energy policies and long-term CO₂ reduction goals. Therefore, this study analyzes the spread of smart grid by incorporating multiple interconnected technological elements into a single model. This approach can yield more reli-

able results and provide insights into the individual effects. Based on these, various energy policies and recommendations can be formulated.

4. Regression Analysis

4.1 Model

The original model was proposed by Ehrlich and Holdren (1971). It suggests that society's impact on the environment is determined by population and individual effect. And then Dietz and Rosa (1997) developed the Impact = Population $\times$ Affluence $\times$ Technology (IPAT) model to examine the influence of population, technology, and affluence on a country's CO₂ emissions. Subsequently, various researchers have used this model to investigate factors that affect CO₂ emissions. For example, recent studies such as Tan and Cao (2023) have used the IPAT model as a basis to examine the impact of green technological innovation on CO₂ emissions in G7 and BRICS countries.

In the paper of Dietz and Rosa (1997), the IPAT model is represented by the following equation (1):

$$I = P \times A \times T \quad (1)$$

In equation (1), I represent the impact on CO₂. P is the population of a country or region. A represents economic activity per person, while T represents the environmental impact per unit of economic activity, which is determined by the technology used for the production of goods and services. To facilitate the econometric estimation, we modified the IPAT model developed by Dietz and Rosa (1997) and fitted it into the model presented in equation (2).

$$I_i = \alpha P_i^b A_i^c T_i^d e_i \quad (2)$$

In equation (2), I , P , A , and T represent environmental impact, population, wealth, and technology, respectively. The index i denotes a single entity. The parameters α , b , c , and d can be estimated using statistical methods. α is a constant that scales the model. b , c , and d are coefficients that determine the effects on population, wealth, and technology. The term e represents random error term.

Based on equation (2), we constructed the following logarithm estimation model (3) which the effects of smart meters alone. With the integration of various technology elements associated with the widespread adoption of smart grid, such as PV generation, electric vehicles, and energy efficiency, in addition to smart meters, model (4) aims to verify the separate effects on CO₂.

$$\ln(CO_2)_{it} = \alpha + \beta_1 Smartmeter_{it} + \beta_2 \ln GDP_{it} + \beta_3 \ln Pop_{it} + \mu_i + \varepsilon_{it} \quad (3)$$

$$\ln(CO_2)_{it} = \alpha + \beta_1 Smartmeter_{it} + \beta_2 PV_{it} + \beta_3 Energyefficiency_{it} + \beta_4 \ln EV_{it} + \beta_5 \ln GDP_{it} + \beta_6 \ln Pop_{it} + \mu_i + \varepsilon_{it} \quad (4)$$

The dependent variable on the left-hand side represents CO₂ emissions. On the right side, the independent variables include *Smartmeter*, which represents the installation rate of smart meters in households, which means that the diffusion of smart grid. *PV*, which represents the installation rate of residential PV systems. *Energyefficiency*, which represents the energy efficiency of the residential sector. In this study, residential energy efficiency is used as an indicator that reflects the performance of appliances. *EV* refers to the number of subsidies for green cars, including electric vehicles and hybrid vehicles. It is believed that as the number of subsidies increases, the number of electric vehicles will also increase. In short, the number of subsidies is linked to the adoption rate of electric vehicles. Since it is difficult to obtain data on the adoption rate of that, this study uses the number of electric vehicles subsidies as a proxy variable for the adoption rate of electric vehicles. *GDP* is calculated using prefectural income by region blocks. *Pop* is the population in ten region blocks. μ_i is the individual effects, ε_{it} is the error term, and α is the constant. Here, *i* refers to region blocks (Hokkaido, Tohoku, Kanto, Chubu, Hokuriku, Kansai, Chugoku, Shikoku, Kyushu, and Okinawa) and *t* corresponds to years. The estimation of this study covers the years from 2007 to 2020. In the estimation of this model, we expect that technological factors such as smart meters will have a negative impact on CO₂ emissions.

4.2 Data

The variables used in this study, their data sources and calculation formulas are summarized in Table 1 below.

Table 1 The variables and data sources

Variable name	Variable	Source
<i>CO₂</i>	CO ₂ emissions from the household sector by region blocks	Ministry of the Environment-Estimation of CO ₂ emissions by sector
<i>Smartmeter</i>	Smart meter installation rate in household (unit: %)	METI—Agency of Natural Resources and Energy
<i>PV</i>	Installation rate of PV systems in households (unit: %)	METI Agency of Natural Resources and Energy-Act on Special Measures Concerning the Promotion of Utilization of Renewable Electric Energy, Website for Information Disclosure ⁶⁾
<i>Energyefficiency</i>	Energy efficiency in the household sector $\frac{P_M M}{P_E E_h} \cdot \frac{P_E}{P_M}$ 7)	$P_M M$ and $P_E E_h$ is coming from household survey in Ministry of Internal Affairs and Communications. P_E and P_M is coming from CPI in Ministry of Internal Affairs and Communications.

6) <https://www.fit-portal.go.jp/PublicInfoSummary>

7) This formula was taken from Aoki et al. (2022). In this study, P_M is the nominal price of energy-using goods ↗

<i>EV</i>	Number of subsidies granted for electric and hybrid vehicles by prefecture	Next Generation Vehicle Promotion Center
<i>GDP</i>	Prefectural income for each region	Cabinet Office
<i>Pop</i>	Population in the region blocks	Statistics Bureau of Japan

4.3 Descriptive Statistics

The descriptive statistics are summarized in Table 2 for the logarithmized data used in this study.

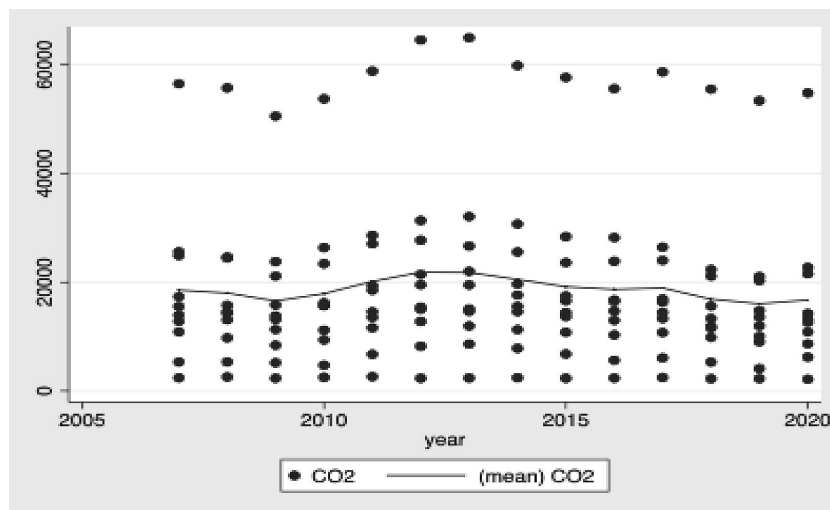
Table 2 Descriptive statistics of the variables

Variable	Obs	Mean	Std. Dev.	Min	Max
$\ln CO_2$	140	9.535	.829	7.675	11.082
Smartmeter	140	.182	.261	0	.925
PV	140	.011	.011	0	.042
EV	120	2235.992	2618.841	14	14282
Energyefficiency	140	.408	.114	.178	.641
$\ln GDP$	130	17.292	1.049	15.104	19.262
$\ln Pop$	140	15.965	.921	14.133	17.61

4.4 Time Series Scatter Plots for the Technological Factors

In this study, time series scatter plots and average polyline for CO_2 and the technological factors of smart meter, PV generation, electric vehicles, and energy efficiency are created and presented in Figure 3 to Figure 7.

Figure 3 Time series scatter plot and average polyline of CO_2



and P_E is the nominal price of energy. E_h represents the energy consumption in household, and M represents the input quantity of energy-using goods. The calculation process is described in Appendix A.

Figure 4 Time series scatter plot and average polyline of smart meter installation rate

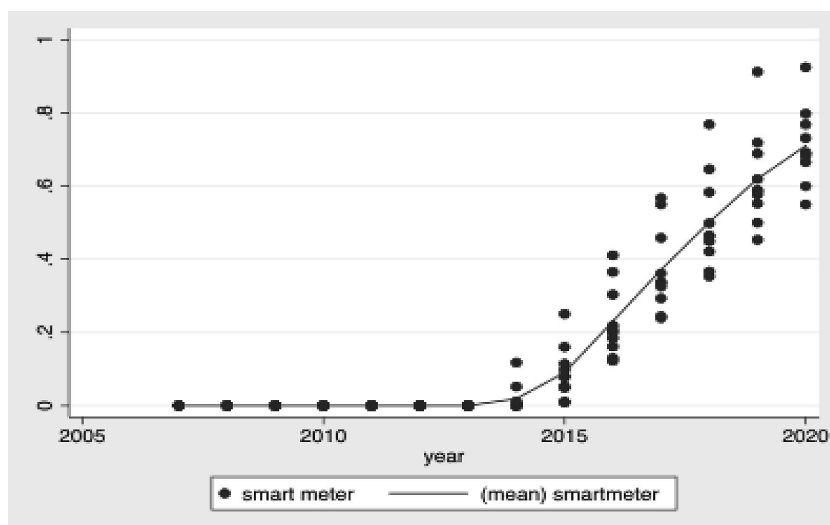


Figure 5 Time series scatter plot and average polyline of PV installation rate

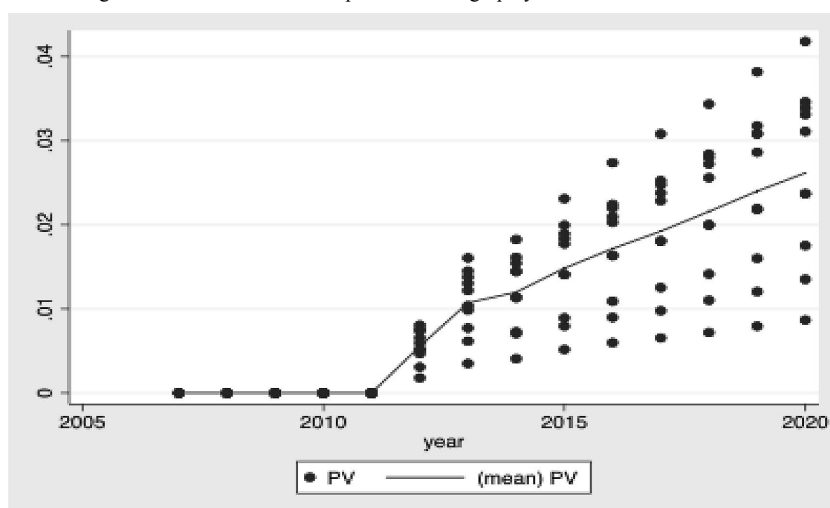


Figure 6 Time series scatter plot and average polyline of the subsidies number of electric vehicles

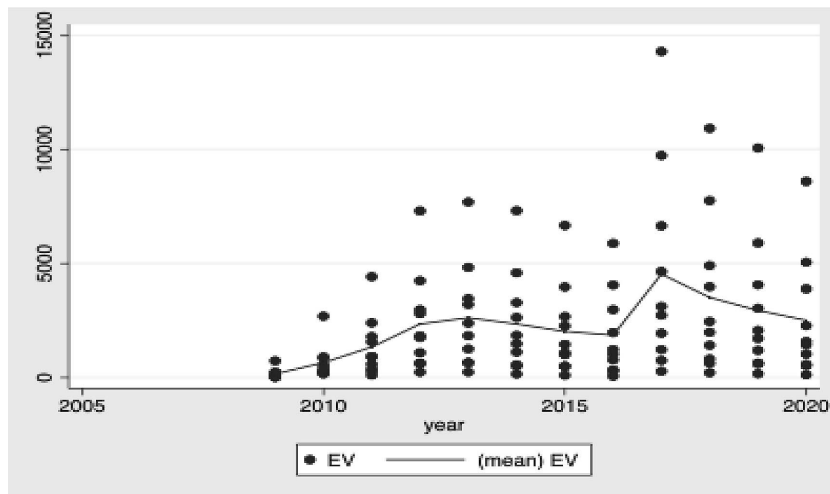
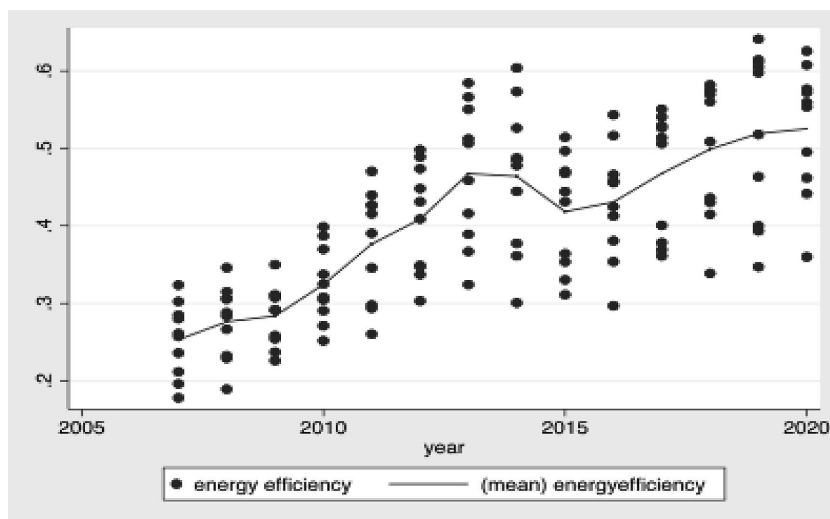


Figure 7 Time series scatter plot and average polyline of energy efficiency



Since 2013, CO₂ emissions have exhibited a clear downward trend, likely reflecting the effects of improved energy efficiency, the adoption of renewable energy, and the increasing prevalence of smart grid technologies. The penetration rate of smart meters has shown steady growth since 2014, while the installation rate of PV has consistently risen since 2012. EV adoption has also demonstrated an overall upward trajectory since 2016, with a slight decline observed in 2017. This drop may be attributed to waning consumer interest following the initial surge in EV adoption. Additionally, the energy efficiency of home appliances has shown a general upward trend, indicating significant advancements in energy-saving technology.

4.5 Hausman test

This study uses panel data, which allows for the presence of either fixed or random effects. The choice between the two is determined using the Hausman test.

The Hausman test calculates the probability of having the null hypothesis that “the random effects model is preferable” and the alternative hypothesis that “the fixed effects model is preferable”. If the probability is greater than 10%, the null hypothesis is not rejected. If it is less than 10%, the null hypothesis is rejected and the alternative hypothesis is adopted. After testing the model (3) and model (4) this study, the P value is close to zero, so the null hypothesis is rejected with 1% significant level. This means that the fixed effects model is appropriate for model (3) and model (4).

4.6 Estimation Results

The estimation results for model (3) and model (4) are shown in Table 3 and Table 4, respectively. Specifically, model (3) shows the effect of smart meters alone, while model (4) demonstrates the combined effects of multiple technological factors such as smart meters, PV generation, electric vehicles, and energy-efficient appliances.

Table 3 Estimated result for model (3)

ln CO ₂	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Smartmeter	-.25	.082	-3.04	.003	-.412	-.087	***
lnGDP	-.104	.334	-0.31	.756	-.766	.557	
lnPop	-.491	.702	-0.70	.486	-1.881	.899	
Constant	19.219	11.585	1.66	.1	-3.725	42.163	*
Mean dependent var		9.544	SD dependent var				0.830
R-squared		0.186	Number of obs				130
F-test		8.935	Prob > F				0.000
Akaike crit. (AIC)		-186.053	Bayesian crit. (BIC)				-174.583

*** $p < .01$, ** $p < .05$, * $p < .1$

Table 4 Estimated result for model (4)

ln CO ₂	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Smartmeter	-.268	.079	-3.38	.001	-.425	-.111	***
PV	-7.705	2.658	-2.90	.005	-12.982	-2.428	***
lnEV	.088	.017	5.25	0	.054	.121	***
Energyefficiency	.586	.275	2.13	.035	.041	1.132	**
lnGDP	-.239	.388	-0.62	.539	-1.008	.531	
lnPop	.598	.856	0.70	.487	-1.103	2.298	
Constant	3.416	13.19	0.26	.796	-22.773	29.606	
Mean dependent var		9.549	SD dependent var				0.832
R-squared		0.586	Number of obs				110
F-test		22.147	Prob > F				0.000
Akaike crit. (AIC)		-210.854	Bayesian crit. (BIC)				-191.950

*** $p < .01$, ** $p < .05$, * $p < .1$

The results presented in Table 3 indicate the effects when only smart meter adoption is considered. The findings show that the proliferation of smart meters reduces CO₂ emissions by 0.25%. No significant results were observed for prefectural income or population.

In Table 4, smart meters are identified as a significant driver of CO₂ reduction, exhibiting a negative relationship. Specifically, a 1% increase in the installation rate of smart meters led to an approximate 0.27% decrease in CO₂ emissions, primarily due to consumers' energy-saving behaviors. This highlights the "visibility effect" of smart meters in promoting energy conservation. Additionally, the adoption of residential PV significantly reduced CO₂ emissions, with a 1% increase in PV installation rates resulting in a 7.7% reduction. This is attributed to households generating their own electricity, thereby decreasing their reliance on utility-supplied electricity, and reducing the demand for traditional fossil-fuel-based generation such as thermal power and coal. Comparing the coefficients, renewable energy production and usage had a more pronounced impact on CO₂ reduction than the energy-saving behaviors triggered by smart meter installation.

Conversely, the adoption of electric and hybrid vehicles appears to increase CO₂ emissions, suggesting a rebound effect. Mizobuchi (2011) reported an 18% rebound effect in Japan's passenger car sector, indicating that energy-saving policies for vehicles may fall short of targets. Lower fuel costs for electric vehicles compared to gasoline-powered vehicles likely encourage more driving, increasing total driving distances and electricity consumption. Additionally, higher electricity demand for charging, particularly during nighttime or peak hours, exacerbates power demand fluctuations.

Regarding energy efficiency, a significant positive relationship with CO₂ emissions was observed, indicating another possible rebound effect. When consumers replace older appliances with energy-efficient ones, the reduced cost of energy services may lead to increased usage, partially offsetting the expected energy savings. Studies such as Awan et al. (2017) suggest an inverted U-shaped relationship between energy efficiency and CO₂ emissions, necessitating the inclusion of a quadratic term in the model to capture this dynamic.

Lastly, societal aging may indirectly influence CO₂ emissions through slower adoption of energy-efficient technologies among older populations. Dividing the population into age groups—youth (ages 15-34) and elderly (ages 65 and above)—could reveal disparities in technology adoption and their environmental impacts. As aging populations become more prominent, it is essential to investigate their relationship with CO₂ emissions, as highlighted by Kawamura (2011). Thus, the model was revised to incorporate these factors, as outlined in Equation (5).

$$\ln(CO_2)_{it} = \alpha + \beta_1 Smartmeter_{it} + \beta_2 PV_{it} + \beta_3 Energyefficiency_{it} + \beta_4 Energyefficiency_{it}^2 + \beta_5 \ln EV_{it} + \beta_6 \ln GDP_{it} + \beta_7 \ln Young_{it} + \beta_8 \ln Old_{it} + \mu_i + \varepsilon_{it} \quad (5)$$

In the current model, *Pop* was eliminated, and the other explanatory variables were not changed, but a quadratic term for energy efficiency and the elderly and youth population was added to the original model. The reason for this adjustment was the belief that the transition from no energy savings due to poor appliance performance to energy savings would not result in a simple linear increase or decrease in CO₂ emissions. Instead, CO₂ emissions were expected to peak, indicating a quadratic relationship. The estimation results for equation (5) are presented in Table 5 below.

Table 5 Estimation Results for model (5)

ln CO ₂	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Smartmeter	-.211	.077	-2.73	.008	-.365	-.058	***
PV	-8.092	2.597	-3.12	.002	-13.25	-2.934	***
lnEV	.056	.022	2.54	.013	.012	.1	**
Energyefficiency	2.859	1.417	2.02	.047	.045	5.673	**
Energyefficiency ²	-2.571	1.437	-1.79	.077	-5.426	.284	*
lnGDP	-1.968	.509	-3.86	0	-2.98	-.956	***
lnYoung	.416	.406	1.03	.308	-.39	1.221	
lnOld	1.527	.42	3.63	0	.692	2.362	***
Constant	14.282	10.011	1.43	.157	-5.604	34.168	
Mean dependent var		9.545	SD dependent var				0.835
R-squared		0.663	Number of obs				109
F-test		22.418	Prob > F				0.000
Akaike crit. (AIC)		-229.232	Bayesian crit. (BIC)				-205.010

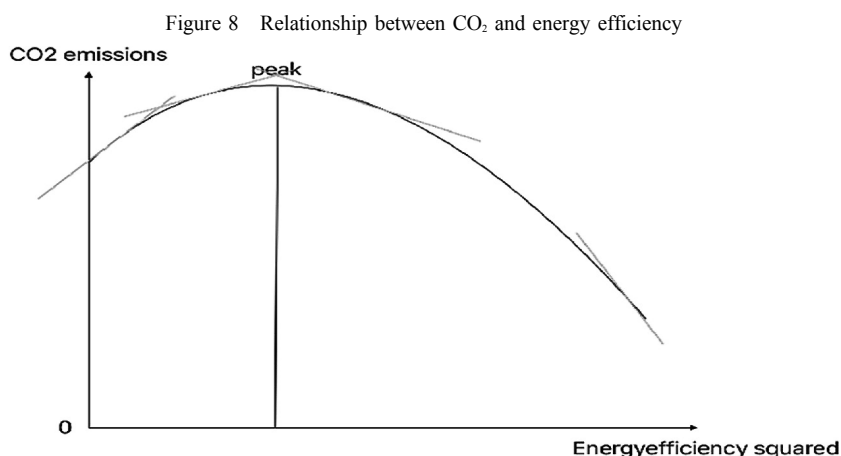
*** $p < .01$, ** $p < .05$, * $p < .1$

The estimation results of the revised model indicate that both the linear and quadratic terms of energy efficiency are statistically significant. While the signs and significance of other explanatory variables remain unchanged, their coefficient values have decreased. This suggests that including the squared term for energy efficiency diminishes the apparent effect of all technological factors. Notably, the impact of PV installations increased slightly from 7.7% to 8.1%, demonstrating their growing importance in reducing CO₂ emissions.

From an age group perspective, the younger population showed a positive but statistically insignificant relationship with CO₂ emissions. Conversely, the elderly population exhibited a significant increase of approximately 1.5% in CO₂ emissions. This result may be due to the elderly's limited adoption of energy-efficient technologies or difficulty implementing energy-saving measures, potentially driven by financial constraints or perceived shorter time horizons, which contribute to their higher emissions.

In addition, GDP was found to have a significant negative effect on CO₂ emissions, highlighting evidence of decoupling. LIU (2021) attributes this to Japan's sustained improvements in the energy efficiency of fossil fuels, particularly coal, following the oil crises. These advancements provide Japan with substantial potential for decarbonization, suggesting that greenhouse gas emissions can be reduced alongside economic growth through technological innovation and targeted energy policies.

The relationship between energy efficiency and CO₂ emissions follows a convex quadratic pattern, where the linear term of energy efficiency is positively associated with CO₂ emissions, and the quadratic term is negatively associated. The turning point of this quadratic function is approximately 0.556, derived from the formula $\frac{-2.86}{2 \times (-2.57)} \approx 0.556$. As shown in Figure 8, this turning point serves as a threshold: when energy efficiency is below this value, improvements do not lead to energy savings, and CO₂ emissions increase. However, once energy efficiency surpasses the threshold, energy savings accelerate, resulting in a significant reduction in emissions. This dynamic is depicted in Figure 8, where the slope of the blue line steepens after the peak, indicating increased CO₂ reduction as energy efficiency improves.



For model (4), it was hypothesized that the passage of time might capture improvements in CO₂ reduction technologies, heightened societal awareness of CO₂ reduction, or advancements in policies, indicating a potential time effect. However, estimation results showed that most outcomes were statistically insignificant (Appendix B). This suggests that as the smart grid evolves, a time trend may already be embedded within the associated technological factors. Thus, this study concludes that explicitly including a time effect is unnecessary.

5. Conclusion

This study employed a fixed-effects model rooted in the theoretical framework of the IPAT equation to estimate the factors influencing CO₂ emissions from 2007 to 2020. The primary focus was on the smart grid, supplemented by additional technological variables using OLS estimation.

The analysis revealed that the diffusion of smart meters significantly reduced CO₂ emissions, primarily through the visualization of electricity consumption, which promotes energy-saving behaviors among consumers. Similarly, the adoption of PV was associated with a decrease in CO₂ emissions, as these sys-

tems reduce reliance on utility-supplied electricity. Energy efficiency exhibited an inverted U-shaped relationship with CO₂ emissions: initial improvements in energy efficiency led to increased emissions, but after reaching a threshold, further advancements resulted in significant reductions. However, the expansion of electric and hybrid vehicles appeared to produce a rebound effect, leading to higher CO₂ emissions. Additionally, GDP was negatively correlated with CO₂ emissions, reflecting the role of technological advancements and energy policies in decoupling economic growth from carbon emissions.

Furthermore, the results for population and the younger age group were not statistically significant, making it difficult to establish a clear relationship with CO₂ emissions. However, an increase in the elderly population was found to be associated with higher CO₂ emissions. This could be attributed to factors such as the elderly's lower incentive to adopt energy-saving technologies, more time spent at home during retirement, and increased electricity consumption. To address this issue, we recommend strengthening energy-saving initiatives targeted specifically at the elderly population. Additionally, the government could consider fully subsidizing the installation of solar panels for seniors.

In this study, we analyzed the combined impact of four technological factors on CO₂ emissions: smart meters, PV solar installations, electric and hybrid vehicles, and the adoption of energy-efficient appliances. The most significant effect was observed from PV solar installations, which reduced CO₂ emissions by approximately 8%. In contrast, smart meters contributed only a modest reduction of 0.21% in CO₂ emissions, despite their widespread adoption. The government's response to the limited impact of smart meters will be crucial moving forward. Furthermore, by the end of 2020, only 6.9% of households nationwide had installed PV solar systems, likely due to the high initial installation costs.

We propose several solutions regarding smart meters and PV installation. First, efforts should focus on enhancing the CO₂ reduction effectiveness of smart meters. By integrating big data analytics and AI technologies to analyze real-time data from smart meters, we can offer optimized energy consumption strategies to both consumers and utility companies. This would encourage more energy-efficient behaviors, thereby improving CO₂ emissions reductions. Second, the widespread adoption of PV solar systems should be expedited. This can be achieved by encouraging consumers to purchase PV solar installations. We recommend additional tax incentives for companies in PV system to increase competition among solar panel manufacturers. This would drive down the cost of solar systems and make them more affordable. The government could also provide subsidies for PV installations above the typical value, using a combination of funds and vouchers. These vouchers could have expiration dates, motivating consumers to install PV systems sooner. These measures aim to accelerate the adoption of PV, making them more financially accessible to both businesses and consumers.

However, there are limitations to this study. First, as mentioned in Section 2.2, Home Energy Management Systems (Hems), promoted by smart grid, influence energy efficiency and, consequently, CO₂ emissions. Due to insufficient data on current adoption rates, evaluating the effect of hems is currently

not feasible. Once relevant data becomes available, estimation will be necessary. Second, this study focuses only on households, but it is essential to consider the lifecycle CO₂ emissions of products in future analyses. It is crucial to account for changes in CO₂ emissions associated with the manufacturing and disposal of products such as electric vehicles and solar panels when discussing overall societal CO₂ emissions.

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Data Availability

CO₂ emissions from the household sector

https://www.env.go.jp/policy/local_keikaku/tools/suikai.html

Smart meter installation rate in household

https://www.emsc.meti.go.jp/activity/emsc_electricity/pdf/0006_06_02.pdf

Installation rate of PV systems in households

<https://www.fit-portal.go.jp/PublicInfoSummary>

Household survey in Ministry of Internal Affairs and Communications.

<https://www.stat.go.jp/data/kakei/rank/singleyear.html>

CPI in Ministry of Internal Affairs and Communications

<https://www.stat.go.jp/data/cpi/>

Number of subsidies granted for electric and hybrid vehicles

<https://www.cev-pc.or.jp/tokei/koufu.html>

Prefectural income by region

https://www.esri.cao.go.jp/jp/sna/sonota/kenmin/kenmin_top.html

Population by region

<https://www.stat.go.jp/data/jinsui/2022np/index.html>

Declarations

Competing interests There is no competing interest of personal or financial nature to disclose.

Ethical approval Not applicable as no animal or human subjects were involved.

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Appendix A

On this page we consider a model with three goods: energy, energy-using goods, and non-energy-using goods. A household derives utility from the consumption of energy-using goods and non-energy-using goods. Energy-using goods, such as automobiles that require gasoline or electrical appliances that require electricity, do not have utility solely from ownership; they require energy input to be used. Non-energy-using goods, such as desks or chairs, do not require energy input for consumer use.

We model energy-using goods as perfect complements with energy. Therefore, the utility C received by the household can be assumed to follow a Leontief type utility function given by

$$C = \min\{B_E E_h, M\} \quad (1)$$

Here, B_E represents the energy efficiency of the goods, E_h represents the household's energy consumption, and M represents the input quantity of energy-using goods. The energy efficiency of electrical appliances is primarily determined by firms through product development and design, leaving little room for households to change it. Therefore, assuming that C remains constant, we vary the input ratio of E_h and M , thereby assuming equation (1). Assuming that B_E is given and reflects product performance, households act while taking B_E as given.

Next, we assume that the utility derived from energy-using goods and non-using goods is given by

$$U = U(C, G) \quad (2)$$

C represents the consumption of energy-using goods, and G represents the consumption of non-energy-using goods.

Under the given assumptions, the budget constraint for the household can be defined as follows.

$$P_E E_h + P_M M + P_G G = I \quad (3)$$

The expenditure on energy consuming goods includes the cost of purchasing goods ($P_M \times M$) and the cost of energy ($P_E \times E_h$). Where P_M is the nominal price of energy-using goods and P_E is the nominal price of energy. In addition, the expenditure on non-energy-using goods is represented by $P_G \times G$. Specifically, P_G represents the nominal price of non-energy-using goods, such as furniture like desks and chairs.

Therefore, the household chooses E_h , M and G to maximize the utility function (2) under the constraints of equations (1) and (3). The prices (P_E , P_M , P_G) and the energy efficiency B_E of the household are assumed to be given. Assuming a Leontief utility function for energy and energy-using goods, the optimal consumption of these goods is determined by maximizing:

$$C = B_E E_h = M \quad (4)$$

Equation (4) implies that it can also be expressed as

$$B_E = \frac{M}{E_h} \quad (5)$$

Multiplying both the numerator and the denominator of equation (5) by $P_E \times P_M$, we obtain the result in equation (6).

$$B_E = \frac{P_M \times M}{P_E \times E_h} \times \frac{P_E}{P_M} \quad (6)$$

In other words, the household's energy efficiency, denoted as B_E , can be determined using the ratio of nominal expenditures on energy-using goods to energy $((P_M \times M) / (P_E \times E_h))$ along with their relative prices (P_E / P_M) . In this paper, B_E is assumed to be constant, so it is an exogenous variable.

Regarding the calculation described in equation (6), let's explain the data. $P_M \times M$ represents expenditure on energy-using goods (equipment items), while $P_E \times E_h$ represents expenditure on energy. P_E is the price index for energy, while P_M is the price index for non-energy goods (consumer goods).

Appendix B

The result of table 1 below shows the estimation results for putting time effect into the model (4) in 4.1 that combines multiple technology factors.

Table 1 Estimation results with time effect

ln CO ₂	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Smartmeter	.514	.173	2.97	.004	.17	.858	***
PV	-14.49	2.82	-5.14	0	-20.098	-8.883	***
lnEV	.002	.04	0.05	.961	-.078	.082	
Energyefficiency	.688	.311	2.21	.03	.07	1.306	**
lnGDP	.501	.594	0.84	.401	-.679	1.682	
lnPop	-1.858	.987	-1.88	.063	-3.82	.104	*
2010	.034	.075	0.45	.651	-.116	.184	
2011	.129	.103	1.25	.214	-.076	.333	
2012	.254	.124	2.05	.043	.008	.499	**
2013	.268	.132	2.03	.045	.006	.531	**
2014	.218	.126	1.73	.088	-.033	.469	*
2015	.161	.121	1.33	.189	-.081	.402	
2016	.07	.125	0.56	.575	-.178	.319	
2017	.001	.167	0.01	.994	-.331	.334	
2018	-.194	.178	-1.09	.281	-.548	.161	
2019	-.317	.199	-1.59	.116	-.713	.08	
Constant	30.256	12.38	2.44	.017	5.637	54.876	**
Mean dependent var		9.549	SD dependent var				0.832
R-squared		0.744	Number of obs				110
F-test		15.221	Prob > F				0.000
Akaike crit. (AIC)		-243.611	Bayesian crit. (BIC)				-197.703

*** $p < .01$, ** $p < .05$, * $p < .1$

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