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The Impact of TFP Improvement on CO_2 Intensity*

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Abstract

This study examines the relationship between total factor productivity (TFP) and CO_2 intensity at manufacturing installations and investigates the channels underlying this relationship. Previous studies suggest that higher TFP is associated with lower CO_2 intensity, but relatively little is known about whether this relationship operates primarily through improvements in energy efficiency or through the decarbonization of the energy used in production. By combining multiple Japanese government statistical datasets on installations' business activities, CO_2 emissions, and energy consumption, this study distinguishes between these two channels. The results show that higher TFP is associated with substantially lower CO_2 intensity. This relationship is driven primarily by lower energy intensity, whereas the association between TFP and the carbon intensity of energy is relatively weak. These findings suggest that improvements in productivity are associated mainly with more efficient energy use rather than with the decarbonization of the energy consumed in production.

Keywords: CO2 intensity, decarbonization, Energy use, Manufacturing sector, TFP
JEL classification: Q40, Q54, D24

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This study utilizes the micro data of the questionnaire information based on the "Census of Manufacture", and "Economic Census for Business Activity" which are conducted by the Ministry of Economy, Trade and Industry (METI), and the Ministry of Internal Affairs and Communications (MIC). To construct the panel data set based on these statistics, this study utilizes the Kougyou Toukei converter, which is provided by RIETI. Also, this study utilizes the "Current Survey of Energy Consumption in the Selected Industries" and "Structural Survey of Energy Consumption" constructed by METI. CO_2 emissions data is provided by the Ministry of the Environment (Data from "Greenhouse Gas Emissions Calculation, Reporting and Publication System").

1. Introduction

Reducing CO_2 emissions has become a major managerial challenge for firms. This is particularly true in the European Union, where explicit carbon-pricing mechanisms require firms to account for the costs associated with their CO_2 emissions in their business decisions. As the global economy moves toward decarbonization, firms are increasingly expected to pursue growth strategies that explicitly incorporate the need to reduce CO_2 emissions.

A substantial body of research has examined the relationship between firms' economic performance and CO_2 emissions. In particular, whether improvements in total factor productivity (TFP) can be reconciled with reductions in CO_2 emissions is an important question from both academic and policy perspectives.

Previous studies have provided considerable evidence that improvements in firms' TFP reduce the CO_2 intensity of production (Forslid et al., 2018; Belloc et al., 2025). However, reductions in total CO_2 emissions will not be achieved if the scale effect, whereby higher TFP expands output and thereby increases emissions, outweighs the emission reductions generated by the technique effect through changes in energy use (Copeland and Taylor, 1994). Even amid the recent strengthening of CO_2 regulations, evidence suggests that the scale effect may continue to outweigh the technique effect (Rottner and von Graevenitz, 2024). Nevertheless, firm-level microdata have not yet been used sufficiently to clarify how improvements in TFP alter energy use and, consequently, the components of the technique effect.

By matching microdata on manufacturing installations across multiple Japanese government statistical surveys, this study constructs a dataset that combines data on TFP, CO_2 emissions, and energy use, and examines how improvements in TFP affect CO_2 intensity at the manufacturing installation. The contribution of this study is that we examine whether the reduction in CO_2 intensity associated with higher TFP operates through lower energy intensity or lower carbon intensity of energy. Using installation-level data on energy consumption, we further decompose the technique effect and examine whether the relationship between TFP and CO_2 intensity operates primarily through lower energy intensity or through a lower carbon intensity of energy.

The results show that, among Japanese manufacturing installations during the sample period from 2007 to 2019, TFP is associated with substantially lower energy intensity, suggesting that the relationship between TFP and CO_2 intensity operates primarily through improvements in energy efficiency. By contrast, the association between TFP and the carbon intensity of energy is limited.

The remainder of this paper is organized as follows. Section 2 discusses the relationship between this study and the existing literature. Section 3 describes the data and empirical framework. Section 4 presents the estimation results, and Section 5 examines their robustness. Section 6 discusses the findings and concludes.

2. Previous studies

Previous studies have examined the relationship between productivity measures, such as TFP and labor productivity, and CO_2 intensity. The studies have generally found that productivity improvements are associated with lower CO_2 intensity and greater energy efficiency. Using Swedish firm data, Forslid et al. (2018) show that higher TFP is associated with greater energy efficiency and lower CO_2 intensity. Their results indicate that exporting firms tend to be more productive and that more productive exporters achieve lower CO_2 intensity. At the same time, their findings suggest that higher TFP reduce CO_2 intensity independently of firms' export status.

A similar relationship between productivity and CO_2 intensity has also been documented for Japan. Wang et al. (2021), for instance, examine the relationships among labor productivity, CO_2 emissions, and innovation using data on Japanese firms. Their results indicate that improvements in labor productivity are associated with reductions in CO_2 intensity. Overall, the existing literature suggests that improvements in TFP and labor productivity contribute to reducing CO_2 intensity. However, relatively little is known about the specific channels through which improvements in a firm's TFP lead to lower CO_2 intensity.

Belloc et al. (2025) decompose total environmental efficiency (TEE), defined as value added relative to CO_2 emissions, into TFP and environmental factor productivity (EFP), with the latter defined as factor inputs relative to CO_2 emissions, and examine the relationships among these components. Their estimates indicate that a 1% increase in TFP is associated with an approximately 0.6% improvement in TEE. However, they also find that the relationship between TFP and EFP is relatively weak. They therefore conclude that although firms with higher TFP tend to exhibit greater environmental efficiency, they do not necessarily undertake actions that reduce their absolute CO_2 emissions.

As policymakers in many countries increasingly emphasize the need for a large scale energy transition to achieve further reductions in CO_2 emissions, it has become increasingly important to identify the channels through which improvements in TFP affect CO_2 intensity. More detailed empirical analysis of these mechanisms is therefore warranted.

In particular, previous studies using microdata based on firms have focused primarily on the magnitude of the scale effect associated with improvements in TFP and the mechanisms through which this effect arises. By contrast, the components of the technique effect have not been sufficiently examined.

3. Data

3.1 Data for TFP estimation

This study uses data on manufacturing installation from 2000 to 2019 to estimate TFP. With the exception of 2011 and 2015, all data are taken from the "Census of Manufacture" conducted by the

Ministry of Economy, Trade, and Industry (METI) of Japan.

This census covers manufacturing installations with four or more employees, comprising 192,047 installations in 2019. The Census of Manufacture targets installations in the manufacturing industry with more than four employees, mandating all installations to complete and submit the form to the government. However, this study restricts the analysis to installations with 30 or more employees, which are required to complete Form A. Installations with fewer employees than those covered by Form A are required to complete Form B. While Form A contains variables necessary for estimating TFP, including fixed asset, Form B does not include such information. Therefore, the analysis focuses on installations that completed Form A (45,636 installations in 2019). The actual response rate for Forms A and B combined was 95.1% (METI, 2021).

For 2011 and 2015, the study employs data from the "Economic Census for Business Activity", jointly conducted by the METI and Ministry of Internal Affairs and Communications. This census has been conducted every five years since 2012. The census covers all business installations including non-manufacturing sector in Japan. In the years in which the Economic Census for Business Activity is conducted, the Census of Manufacture is not administered. By integrating data from these two censuses, this study compiles a panel dataset from 2000 to 2019 to estimate the TFP of installations.

3.2 Data of CO_2 emissions and energy

In this study, we use manufacturing installation data on CO_2 emissions and energy consumption to examine the effects of TFP on CO_2 intensity, energy intensity, and CO_2 intensity of energy. The CO_2 emissions data are obtained from the "Greenhouse Gas Emissions Calculation, Reporting and Publication System administered by the Ministry of the Environment, Japan". The system started in 2006. This mandatory reporting system covers "Specified Establishments" and "Specified Transport Emitters". The present analysis focuses specifically on manufacturing installations classified as "Specified Establishments".

"Specified Establishments" are operated by business entities that either consume at least 1,500 kiloliters of crude-oil-equivalent energy per year or emit at least 3,000 tonnes of CO_2-equivalent per year for any individual greenhouse gas, with the latter criterion additionally requiring that the business entity regularly employ at least 21 employees in total. The CO_2 emissions reported under this system include both direct emissions, i.e., emissions resulting from energy generated or consumed directly at the installation, and indirect emissions associated with energy purchased from other firms and consumed at the reporting installation. Thus, the reported CO_2 emissions generally cover both Scope 1 and Scope 2 emissions. In 2019, the system covered 15,020 installations, including non-manufacturing installations. In 2019, Japan's mandatory greenhouse gas accounting, reporting, and disclosure system covered approximately 53% of Japan's total greenhouse gas emissions, based on a comparison between emissions reported by specified emitters and total national greenhouse gas emissions.

To measure energy consumption of installations, this study uses data from the "Current Survey of Energy Consumption in the Selected Industries" and the "Structural Survey of Energy Consumption." Current Survey of Energy Consumption in the Selected Industries, conducted by the METI, collects monthly data on energy consumption in industries selected for their energy-intensive nature and importance for obtaining a detailed understanding of energy-use trends in Japan. The coverage criteria differ across industries, with installations above an industry-specific size threshold included in the survey. This analysis aggregates monthly data from each installation covered by the statistics into annual totals for analysis.

By contrast, the Structural Survey of Energy Consumption cover manufacturing installations not included in the Current Survey of Energy Consumption in the Selected Industries, as well as installations in non-manufacturing industries. The survey started in 2007. Installations that satisfy the industry-specific coverage criteria are surveyed on a census basis, whereas installations below the relevant size thresholds are surveyed using random sampling. The survey reports each installation's total annual energy consumption as well as detailed consumption by energy source.

Using installation names, addresses, and other identifying information contained in the directories of the respective surveys, we linked installation-level records across datasets to construct panel data covering the period from 2007 to 2019.

The annual distribution of installations included in the dataset used in this study is reported in Table A-1 of Appendix A. Relative to the total number of installations covered by Form A of the 2019 Census of Manufacture, the number of installations included in our analytical dataset in 2019, i.e., installations for which complete information on TFP, CO_2 emissions, energy consumption, and shipment value is available, corresponds to 6.17% of the installations covered by the Census of Manufacture[1]. In addition, approximately 20% of the installations in our analytical sample are those for which energy consumption data are obtained from the Current Survey of Energy Consumption in the Selected Industries. When the comparison is based on the number of installations for which survey questionnaires were actually collected, installations covered by the Current Survey of Energy Consumption in the Selected Industries account for approximately 2.94% of Form A installations[2]. Because the Current Survey of Energy Consumption in the Selected Industries specifically targets installations in relatively energy-intensive industries, our analytical sample consequently tends to contain a relatively large proportion of installations operating in energy-intensive industries.

[1] Form A covered 45,636 installations in 2019. Assuming a response rate of 95.1%, the number of Form A installations actually covered by the Census of Manufacture is approximately 43,400. This figure is used as the denominator when calculating the 2019 coverage rate of the analytical sample reported in this paper.

[2] The number of installations covered by the Current Survey of Energy Consumption in the Selected Industries is reported to be approximately 1,300, with a response rate of 98% (METI, 2026). Accordingly, assuming that 1,300 installations were surveyed, the number of questionnaires actually collected is calculated as 1,274.

Using this panel, we examine how changes in the structure of energy use affect CO_2 intensity at the installation. Accordingly, the analytical sample consists of manufacturing installations sufficiently large to be covered by all the statistical surveys used in this study. The resulting unbalanced panel dataset contains 5,193 installations for which complete data on TFP, CO_2 emissions, and energy consumption are available.

3.3 Overall trends in the sample (CO_2 emissions, energy consumption and output)

Figure 1 presents the annual trends in the aggregate values of the sample used in this analysis. The figure indexes CO_2 emissions, energy consumption, and output (shipment value) to 100 in 2007 and shows how each aggregate measure changed relative to its 2007 level. Two notable characteristics of the sample can be identified from this figure.

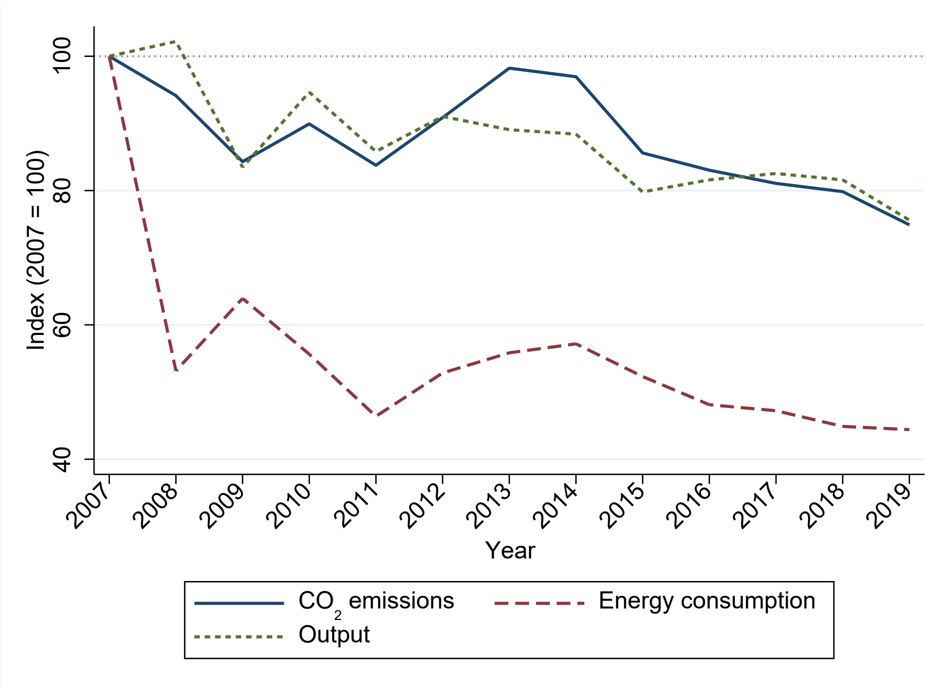

Figure 1: Overall trends of CO2 emissions, Energy consumption, and Output

First, energy consumption declined substantially between 2007 and 2008. This sharp decrease in energy consumption may largely reflect production cutbacks and temporary shutdowns associated with the Global Financial Crisis. In particular, production shutdowns were concentrated among relatively large installations, the effects are likely to have been especially pronounced in the installations covered by this study, because our sample consists primarily of relatively large installations. In addition, as discussed above, the dataset used in this study contains a relatively high proportion of installations operating in energy-intensive industries. Therefore, changes in the structure of energy consumption associated with major economic shocks such as the Global Financial Crisis may be more strongly reflected in our sample.

Second, following the sharp decline in energy consumption in 2008, energy use by manufacturing installations did not return to its previous level and instead continued to exhibit a generally declining trend. For several years after the Great East Japan Earthquake in 2011, however, both energy consumption and CO_2 emissions increased. Following the shutdown of nuclear power plants after the earthquake, many sectors of the Japanese economy became more dependent on fossil fuels (Taghizadeh-Hesary, 2017). Together with reconstruction-related demand after the disaster, this shift may have contributed to a temporary increase in both energy consumption and CO_2 emissions. From 2014 onward, however, energy consumption began to decline again.

These long-term declines in energy consumption and CO_2 emissions may reflect not only improvements in energy efficiency and decarbonization within manufacturing installations, but also the exit of installations from the sample. As shown in Appendix A, the total number of installations included in the sample declined over time, which is broadly consistent with the overall trend observed in Japan's manufacturing sector. However, the number of installations captured in our sample decreased by approximately 30% between 2007 and 2019. By comparison, the number of installations covered by Form A of the Census of Manufacture declined by only about 4.8% over the same period[3]. Therefore, it cannot be ruled out that the decline in the number of observations in our sample reflects not only installations that ceased operations, but also installations that were no longer required to report CO_2 emissions because of reductions in energy consumption, as well as installations that fell outside the scope of the relevant surveys because of a contraction in the scale of their operations.

4 Empirical framework

4.1 Factor analysis of CO_2 emissions

The effect of TFP on CO_2 emissions is theoretically ambiguous because productivity improvements operate through competing channels[4]. Following the scale–composition–technique framework of

[3] The number of installations covered by Form A of the 2020 Census of Manufacture (The census covered installation's business activity at 2019) is reported to be 47,682.

[4] In estimating TFP, this study follows the conventional approach and uses capital, labor, and intermediate inputs as production inputs, and then examines the relationship between TFP and CO_2 intensity (CI). In the theoretical framework following Copeland and Taylor (1994), energy would ideally be included as an input factor; however, previous studies examining the relationship between TFP and CO_2 intensity have generally not incorporated energy consumption into the measurement of TFP. As a robustness check, we also estimated an alternative measure of TFP that includes energy consumption, measured on a heat-content basis, as an additional production input. The correlation coefficient between this energy-augmented TFP measure and the conventional TFP measure that excludes energy consumption is 0.9945. This very high correlation suggests that using conventional TFP as a proxy for energy-augmented TFP is unlikely to materially affect the interpretation of the analysis.

Copeland and Taylor (1994), effect of TFP can be decomposed into scale and technique effect. Total CO_2 emissions can first be written as the product of output and emissions per unit of output[5].

$$CO_2 = Y \times \frac{CO_2}{Y} \quad (1)$$

where Y denotes output and CO_2 denotes total CO_2 emissions of each installation. $\frac{CO_2}{Y}$ denotes CO_2 intensity. Taking logarithmic derivatives with respect to TFP gives the following two-part decomposition:

$$\frac{d\ ln\ CO_2}{d\ ln\ TFP} = \frac{d\ ln\ Y}{d\ ln\ TFP} + \frac{d\ ln\ (\frac{CO_2}{Y})}{d\ ln\ TFP} \quad (2)$$

The first term on the right-hand side is defined as the scale effect. Higher TFP lowers the effective marginal cost of production and increases the firm's optimal output. Holding CO_2 intensity constant, the resulting expansion in production raises energy use and total CO_2 emissions. The scale effect is therefore generally positive for total emissions. On the other hand, the second term on the right-hand side is defined as the technique effect. The technique effect captures changes in CO_2 emissions per unit of output while holding the scale of production constant. Productivity improvements may reduce CO_2 intensity through better production organization, improved utilization of capital and labor, the adoption of energy-saving technologies, fuel switching, electrification, or investment in abatement equipment. The technique effect is therefore expected to be negative when higher TFP is associated with cleaner production.

To identify the mechanisms underlying the technique effect, CO_2 intensity can be decomposed into energy use per unit of output and CO_2 emissions per unit of energy.

$$\frac{CO_2}{Y} = \frac{Energy}{Y} \times \frac{CO_2}{Energy} \quad (3)$$

Energy denotes the energy consumed by installation i, measured in megajoules (MJ). Substituting this identity into the general decomposition yields:

$$\frac{d\ ln\ CO_2}{d\ ln\ TFP} = \frac{d\ ln\ Y}{d\ ln\ TFP} + \frac{d\ ln\ (\frac{Energy}{Y})}{d\ ln\ TFP} + \frac{d\ ln\ (\frac{CO_2}{Energy})}{d\ ln\ TFP} \quad (4)$$

In this formulation, we define the second term on the right-hand side as energy efficiency effect of

TFP. This component captures the effect of TFP on the amount of energy required to produce one unit of output, $\frac{Energy}{Y}$. It is negative when productivity improvements reduce energy intensity through improved production management, more efficient use of existing inputs, reduced production losses, or the adoption of energy-efficient equipment and processes.

Additionally, in this formulation, we define the third term on the right-hand side as energy decarbonization effect of TFP. This component captures the effect of TFP on CO_2 emissions per unit of energy, $\frac{CO_2}{Energy}$. It is negative when more productive firms shift toward less carbon-intensive fuels, electrify production processes, increase their use of low-carbon electricity, or adopt technologies that reduce emissions without necessarily reducing total energy use. The conventional technique effect is therefore the sum of these two components.

This nested interpretation preserves the conventional scale–technique decomposition while allowing the analysis to distinguish whether lower CO_2 intensity is attributable to reduced energy requirements or to a cleaner energy mix. The two channels are conceptually distinct: an installation may lower energy intensity without changing its fuel mix, or it may reduce the carbon intensity of energy through fuel switching while leaving total energy consumption largely unchanged. If we consider only changes in carbon intensity, Equation (4) can be further formulated as follows.

$$\frac{d\ ln\ (\frac{CO_2}{Y})}{d\ ln\ TFP} = \frac{d\ ln\ (\frac{Energy}{Y})}{d\ ln\ TFP} + \frac{d\ ln\ (\frac{CO_2}{Energy})}{d\ ln\ TFP} \quad (5)$$

Based on the theoretical formulation, we examine how TFP is associated with CO_2 intensity through the energy-efficiency and energy-decarbonization channels using panel data of Japanese manufacturing installations between 2007 and 2019. The index to capture the energy efficiency is defined as energy intensity (EI) in line with the formulation (5). Additionally, the index to capture the energy decarbonization effect is defined as CO_2 intensity of energy (CIE) in line with the formulation (5). To reveal each effect using each index, we analyze the TFP impact for each index by fixed effect regression model. The estimation formulations are as follows.

$$\ln(CI_{i,t}) = \beta_1 TFP_{i,t} + \mu_i + \varepsilon \quad (6)$$
$$\ln(EI_{i,t}) = \beta_2 TFP_{i,t} + \mu_i + \varepsilon \quad (7)$$
$$\ln(CIE_{i,t}) = \beta_3 TFP_{i,t} + \mu_i + \varepsilon \quad (8)$$

i mean manufacturing installations, and t show years. TFP is estimated TFP of each installation using the Wooldridge (2009) estimation way. The term μ_i represents manufacturing-installation fixed effects, while ε_{it} denotes the error term.

In these specifications, β_1 captures the effect of an improvement in TFP on CO_2 intensity (CI), while β_2 and β_3 capture its effects on energy intensity (EI) and the carbon intensity of energy (CIE), respectively. Given the logarithmic identity $\ln CI = \ln EI + \ln CIE$, when the three equations are estimated using the same sample and an identical set of control variables and fixed effects, $\beta_1$equals the sum of β_2 and β_3. The results from these three specifications therefore allow us to assess the extent to which an improvement in TFP affects EI and CIE, and how these effects jointly translate into a change in CI.

Equation (5) allows us to examine how changes in energy use affect CI. However, previous empirical studies have shown that the scale effect associated with higher TFP may increase firms' CO_2 emissions. To better understand the determinants of CO_2 emissions in the Japanese manufacturing sector, following the theoretical formulation presented in equation (4), we examine the scale effect of TFP by estimating specifications in which total CO_2 emissions and output (Shipment value), measured by the value of shipments, are used as the dependent variables.

In addition, the main specifications presented in Section 4.1 include regressions that control for the electrification share (*Electricity*) in manufacturing, defined as the share of electricity in total energy consumption. Following the Great East Japan Earthquake in 2011, operations at many of Japan's nuclear power plants were suspended, and fossil fuels, including coal and natural gas, were increasingly used as substitutes in electricity generation. Consequently, the CO_2 emission factor of electricity increased during the sample period. Changes in the share of electrification may therefore have affected the estimated relationship between TFP and CO_2 emissions.

4.2 TFP Estimation

Methodologies for estimating TFP have been extensively explored, including by Olley and Pakes (1992), Blundell and Bond (1998), Levinsohn and Petrin (2003), Jefferson et al. (2008), and Wooldridge (2009). Ackerberg et al. (2015) posit that the Olley–Pakes methodology may face issues related to functional dependence, potentially leading to identification challenges. Guo and Zhang (2023) suggest that the methodologies of Jefferson et al. (2008) and Blundell and Bond (1998) may be susceptible to endogeneity and a lack of comprehensive information. To address potential biases in the estimation of production function parameters, Wooldridge (2009) recommends employing proxy variables within a generalized method of moments framework to control for unobserved productivity shocks impacting the production function. Consequently, we adopt the Wooldridge methodology to estimate the production functions for installation TFP. Installation-level TFP is estimated as

$$log(TFP_{it}) = log(Y_{it}) - \hat{\alpha}_L log(L_{it}) - \hat{\alpha}_K log(K_{it}) - \hat{\alpha}_m log(M_{it}) \quad (9)$$

where TFP_{it} is TFP for installation i in year t. Y is the installation output. L and K are the labor and capital inputs, respectively. *M* is the intermediate input (Intermediate material costs: ten thousand JP yen). $\hat{\alpha}_L$, $\hat{\alpha}_K$, and $\hat{\alpha}_m$ are elasticities estimated using the one-step generalized method of moments estimator of Wooldridge (2009). Also, the estimation also includes year fixed effects to control for common macroeconomic shocks. This study uses shipment value (ten thousand JP yen) as output, the number of employees as labor input, fixed assets (ten thousand JP yen) as the capital input, and expenditure on raw materials as the intermediate inputs (ten thousand JP yen).

In this study, TFP is estimated using a panel of installations that can be tracked in the Census of Manufacture and the Economic Census for Business Activity over the period from 2000 to 2019. TFP is estimated using data extending further back than the period used in the analysis of the determinants of CO_2 intensity to mitigate measurement bias arising from the price adjustment of capital stock.

When capital stock is estimated, the accumulation history of capital prior to an installation's first year in the sample is generally unobservable. Initial capital stock must therefore be approximated by treating the observed nominal capital stock in the first year as if it had been acquired in that year and deflating it using the corresponding year's capital-goods deflator. Capital stock in subsequent years is then constructed using the perpetual inventory method: net fixed capital stock[6] from the preceding year is combined with new investment deflated into real terms. As real investment is accumulated over time, the influence of measurement error associated with the price adjustment of initial capital stock gradually diminishes.

This study constructs capital stock using the same procedure. Specifically, capital stock is accumulated from years preceding the sample period used in the CO_2 intensity regressions, and TFP is estimated using this longer time series. This approach helps mitigate potential bias in the TFP estimates arising from the price adjustment of initial capital stock. Using the JIP Database 2023, we construct industry-specific deflators corresponding to the value of shipments, capital stock, and expenditure on raw materials. TFP is then estimated after converting each nominal variable into real terms using the corresponding deflator.

5 Results

5.1 Main results

Table 1 presents summary statistics for the variables used in the analysis[7]. Table 2 reports the results of the fixed-effects models based on equations (6), (7), and (8). It also presents estimates from the same model specifications examining the relationships between TFP and CO_2 emissions and between TFP and the value of shipments.

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[6] This study employs rate of consumption of fixed capital as 10 percent.

[7] Most of the main analyses use an unbalanced panel covering the period from 2007 to 2019. To examine whether sample attrition associated with the use of an unbalanced panel affects the results, Appendix B reports estimates based on a balanced panel using both the fixed-effects and fixed effects 2SLS specifications.

Table 1 Summary statistics

Variable	Obs	Mean	Std. dev.	Min	Max
CI	44,415	0.031657	0.111267	4.99E-06	4.347829
EI	44,415	937.1336	26195.26	0.038131	3723497
CIE	44,415	0.000129	0.001533	8.48E-09	0.195429
Electricity	44,415	0.468209	0.298099	0	1
TFP	44,415	10.48692	0.960494	4.223785	14.68831
Shipment	44,415	3022039	8633402	2409.939	2.45E+08
CO_2	44,415	76451.44	602481.7	3	2.04E+07

Table 2-1 reports the results of specifications in which TFP is the only explanatory variable, whereas Table 2-2 presents the results obtained after adding the electrification share (*Electricity*) as a control variable.

The estimation results are qualitatively similar regardless of whether the electrification share is included as a control variable. TFP is negatively associated with all three dependent variables: CI, EI, and CIE. However, the estimated relationship between TFP and CIE is small in magnitude and statistically significant only at the 10% significant level. By contrast, EI exhibits a strong negative relationship with TFP. The estimated coefficient indicates that a 1% increase in TFP is associated with a 0.821% decrease in EI. Given that a 1% increase in TFP is associated with a 0.834% decrease in CI, the improvement in CI associated with higher TFP can be attributed almost entirely to the improvement in EI, that is, the energy-efficiency channel by TFP advancement. Taken together, these findings suggest that, in the Japanese manufacturing sector during the period from 2007 to 2019, the improvement in CO_2 intensity associated with higher TFP was driven primarily by improvements in energy efficiency.

Table 2-1: Factor analysis of CI, EI and CIE (Without controlling for electrification)

Dependent variable	CI	EI	CIE	Output	CO_2
TFP	-0.834***	-0.821***	-0.013	1.004***	0.171***
	(0.004)	(0.009)	(0.009)	(0.001)	(0.004)
Within R-squared	0.5379	0.2199	0.0408	0.9374	0.1098
Observations	44,415	44,415	44,415	44,415	44,415
Number of installations	5,186	5,186	5,186	5,186	5,186

Note: The analysis does not control for fuel switching. Values in parentheses are standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2-2: Factor analysis of CI, EI and CIE (Controlling for electrification)

Dependent variable	CI	EI	CIE	Output	CO_2
TFP	-0.834*** (0.004)	-0.822*** (0.008)	-0.011 (0.008)	1.004*** (0.001)	0.171*** (0.004)
Electricity	-0.085*** (0.012)	-2.098*** (0.023)	2.013*** (0.024)	-0.014*** (0.004)	-0.099*** (0.012)
Within R-squared	0.5385	0.3552	0.1875	0.9375	0.1113
Observations	44,415	44,415	44,415	44,415	44,415
Number of installations	5,186	5,186	5,186	5,186	5,186

Note: Values in parentheses are standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

The results also show that a 1% increase in TFP is associated with a 1.004% increase in output (Shipment value). This output expansion generates a scale effect that exceeds the reductions in CO_2 emissions attributable to the energy-efficiency and energy-decarbonization effects. Consequently, despite the reduction in CO_2 intensity, total CO_2 emissions increase as TFP rises. Consistent with this interpretation, the estimated relationship between TFP and CO_2 emissions is positive and statistically significant.

5.2 Sector analysis

Table 3 reports the estimated TFP coefficients from regressions conducted separately by industry. The industry specific estimates are broadly consistent with the main results. In most industries, higher TFP is associated with lower EI, which in turn contributes to a reduction in CI. By contrast, the relationship between TFP and CIE is statistically insignificant in many industries.

A closer examination of the industry-specific estimates shows that the reduction in CI associated with a 1% increase in TFP ranges from 1.014% in business-oriented machinery, where the estimated effect is largest, to 0.688% in fabricated metal products, where it is smallest. These results indicate that the substantial improvement in EI associated with higher TFP is broadly observed across all industries. Admittedly, because the number of observations varies considerably across industries, the robustness of each industry-specific estimate cannot be conclusively established. Nevertheless, these industry-level findings provide further evidence supporting the robustness of the main results.

Table3: Estimated coefficients in each industry

Industry	CI	EI	CIE	Output	CO_2	Installations
Food products	-0.827***	-0.861***	0.034	0.972***	0.145***	6125
Beverages, tobacco, and feed	-0.894***	-0.905***	0.012	0.975***	0.081***	1286
Textiles	-0.811***	-0.796***	-0.015	1.008***	0.198***	1750
Wood products	-0.791***	-1.103***	0.312**	1.033***	0.242***	249
Furniture and fixtures	-0.691***	-0.747***	0.057	0.962***	0.271**	147
Pulp, paper, and paper products	-0.753***	-0.644***	-0.109**	0.993***	0.241***	2495
Printing	-0.884***	-0.882***	-0.002	1.003***	0.118***	466
Chemicals	-0.802***	-0.768***	-0.033	0.960***	0.158***	5155
Petroleum and coal products	-0.686***	-0.794***	0.107***	1.008***	0.321***	353
Plastic products	-0.839***	-0.795***	-0.044	1.011***	0.173***	3413
Rubber products	-0.825***	-0.739***	-0.086	1.010***	0.185***	917
Ceramic, stone, and clay products	-0.717***	-0.698***	-0.019	0.995***	0.278***	2687
Iron and steel	-0.739***	-0.700***	-0.038	0.996***	0.258***	3163
Non-ferrous metals	-0.820***	-0.780***	-0.039	0.968***	0.148***	1618
Fabricated metal products	-0.688***	-0.939***	0.250***	0.991***	0.302***	2317
General-purpose machinery	-0.880***	-0.691***	-0.189***	1.017***	0.138***	1293
Production machinery	-0.893***	-0.829***	-0.064**	1.002***	0.109***	1133
Business-oriented machinery	-1.014***	-1.043***	0.029	1.019***	0.005	508
Electronic parts and devices	-0.836***	-0.861***	0.025	1.018***	0.182***	2512
Electrical machinery	-0.811***	-0.761***	-0.050	1.034***	0.223***	1201
Information and communication equipment	-0.889***	-0.895***	0.006	1.004***	0.115***	476
Transportation equipment	-0.916***	-0.895***	-0.021	1.056***	0.140***	4749
Miscellaneous manufacturing	-0.828***	-0.633***	-0.195	0.977***	0.149**	381

Note: Values in parentheses are standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. In this table, the estimation results for “Leather, leather products, and fur products” are excluded because the industry's sample size is too small (only 21 installations in this sample) to produce valid estimates.

6 Robustness check

The preceding estimates show that the relationships between TFP and CI, EI, and CIE do not differ substantially from the main results even after accounting for industrial heterogeneity. Nevertheless, the estimates may still be affected by endogeneity or sample-selection issues that have not yet been adequately addressed.

First, endogeneity remains a potential concern. For example, an installation's TFP and CO_2 emissions may both respond to common production or technology shocks. Moreover, TFP and CO_2 emissions may be simultaneously determined through the firm's production decisions. Second, some installations may perform specific functions that are strongly associated with both TFP and CO_2 emissions. In particular, previous studies have shown that exporting firms tend to exhibit better environmental performance and higher TFP (Forslid et al., 2018; Cui et al., 2016). In the case of Japanese firm, exporting firms tend to show higher TFP performance (Okubo & Tomiura, 2019). Failure to account for such installation characteristics may therefore bias the estimated TFP coefficients.

The following subsections assess the robustness of the main results by addressing each of these potential econometric concerns.

6.1 Endogeneity problem between TFP and CO_2 intensity

Table 4-1. and 4-2 report the results of specifications using lagged TFP as the explanatory variable. Table 4-1 uses TFP lagged by one period (one year), while Table 4-2 uses TFP lagged by two periods (two years) as independent variable. The estimated relationships between lagged TFP (TFP_{t-1} and TFP_{t-2}) and the respective dependent variables in period t are qualitatively consistent with the main results. Although the relationship between TFP_{t-2} and EI_t is weaker, the estimated negative association of TFP_{t-2} with EI_t remains stronger than that with CIE_t.

Table4-1: Estimated relationship between the dependent variables and TFP_{t-1}

Variable	CI	EI	CIE	Output	CO_2
TFP_{t-1}	-0.352*** (0.006)	-0.337*** (0.009)	-0.015* (0.009)	0.460*** (0.005)	0.108*** (0.004)
Within R-squared	0.125	0.066	0.040	0.211	0.087
Observations	45,128	45,128	45,128	45,128	45,128
Installations	5,215	5,215	5,215	5,215	5,215

Note: Values in parentheses are standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table4-2: Estimated relationship between the dependent variables and TFP_{t-2}

Variable	CI	EI	CIE	Output	CO_2
TFP_{t-2}	-0.198*** (0.006)	-0.166*** (0.009)	-0.032*** (0.008)	0.277*** (0.005)	0.079*** (0.004)
Within R-squared	0.067	0.043	0.041	0.095	0.079
Observations	46,640	46,640	46,640	46,640	46,640
Installations	5,553	5,553	5,553	5,553	5,553

Note: Values in parentheses are standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

These findings indicate that the direction of the relationships between TFP and the respective outcome variables remains stable across different lag structures. They therefore provide some reassurance that the main results are not driven primarily by simultaneity between TFP and CO_2 emissions.

Table 5: Estimated relationship between the dependent variables and TFP by fixed effect 2SLS

	CI	EI	CIE	Output	CO_2
TFP	-0.760*** (0.026)	-0.629*** (0.056)	-0.130** (0.055)	1.052*** (0.012)	0.292*** (0.028)
First-stage F	285.11	285.11	285.11	285.11	285.11
Kleibergen–Paap rk Wald F	285.110	285.110	285.110	285.110	285.110
Kleibergen–Paap rk LM (p-value)	<0.001	<0.001	<0.001	<0.001	<0.001
Observations	44168	44168	44168	44168	44168
Installations	4979	4979	4979	4979	4979
Centered R2	0.5344	0.2101	0.0363	0.9360	0.0895

Note: Values in parentheses are standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Cluster-robust standard errors at the installation level. TFP is treated as endogenous and instrumented using its second lag.

To further address the potential endogeneity between TFP and CO_2 intensity, this study employs a fixed-effects two-stage least squares (2SLS) model using TFP lagged by two periods (TFP_{t-2}) as an instrumental variable. The estimation results are reported in Table 5. Based on the Kleibergen–Paap rk Wald F-statistic and the Kleibergen–Paap rk LM statistic, TFP_{t-2} can be considered a relevant and sufficiently strong instrument in the present analysis. The 2SLS estimates indicate that a 1% increase in TFP is associated with a 0.76% reduction in CI. Compared with the estimates from the standard fixed-effects model that does not explicitly account for endogeneity, the estimated effect of TFP improvement on reducing CI becomes smaller.

With respect to CIE, TFP is also found to have a statistically significant negative relationship with CIE. Compared with the normal fixed-effects estimates, the effect of TFP improvement on reducing CIE is estimated to be larger and statistically significant in the 2SLS model. Nevertheless, consistent with the findings from the preceding analyses, the 2SLS results suggest that improvements in TFP at manufacturing installations lead primarily to substantial improvements in EI, and that this energy-efficiency channel remains the main mechanism through which higher TFP contributes to lower CI.

6.2 Sample bias by exporting installations

To account for potential selection bias arising from the tendency of installations with greater export activity to exhibit both higher TFP and better environmental performance, we assess the robustness of the main results by controlling for the share of exports in each installation's total shipment value. Table 6-1 reports the results obtained after adding the export share as a control variable. Although the estimated improvement in CI associated with higher TFP is slightly smaller than in the main results, the overall findings remain largely unchanged. Specifically, the main results indicate that a 1% increase in TFP is associated with a 0.834% decrease in CI, whereas the corresponding decrease is approximately 0.806% after controlling for the export share. The estimated relationships of TFP with $EI$and CIE are also consistent with the main results: higher TFP is associated with a substantial improvement in EI, and most of the improvement in CI associated with higher TFP occurs through improvements in EI.

Table 6-1: Factor analysis of CI, EI and CIE (Controlling export rate of shipment)

Dependent variable	CI	EI	CIE	Output	CO_2
TFP	-0.8061*** (0.0046)	-0.8002*** (0.0098)	-0.0059 (0.0100)	0.9995*** (0.0015)	0.1934*** (0.0047)
Export	0.0003** (0.0002)	0.0008** (0.0004)	-0.0005 (0.0004)	0.0001*** (0.0001)	0.0005*** (0.0002)
Within R-squared	0.4952	0.1969	0.0392	0.9328	0.1103
Observations	39,611	39,611	39,611	39,611	39,611
Groups	5,172	5,172	5,172	5,172	5,172

Note: Values in parentheses are standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table6-2: Factor analysis of indexes (Controlling export rate of shipment and cross effect between export and TFP)

Dependent variable	CI	EI	CIE	Output	CO2
TFP	-0.8020*** (0.0048)	-0.8041*** (0.0102)	0.0021 (0.0104)	0.9961*** (0.0015)	0.1941*** (0.0049)
Export	0.0047*** (0.0015)	-0.0034 (0.0031)	0.0080** (0.003152)	-0.0035*** (0.0005)	0.0012 (0.0015)
Export×TFP	-0.0004*** (0.0001)	0.0004 (0.0003)	-0.0008*** (0.0003)	0.0003*** (0.0000)	-0.0001 (0.0001)
Within R-squared	0.4954	0.1970	0.0394	0.9330	0.1103
Observations	39,611	39,611	39,611	39,611	39,611
Installations	5,172	5,172	5,172	5,172	5,172

Note: Values in parentheses are standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 6-2 reports the results obtained after adding both the export share and its interaction with TFP to the explanatory variables. The overall findings are broadly similar to those reported in Table 6-1. There are, however, some differences in the coefficients related to export activity. In Table 6-1, the export share is positively and significantly associated with both CI and EI. In Table 6-2, the coefficient on the export share itself is positive for CI and CIE, whereas the interaction between the export share and TFP is negative for these two outcomes. Consistent with previous studies, these results suggest that exporting installations with higher TFP tend to achieve greater improvements in CI. At the same time, the expansion of output associated with export activity may generate a scale effect that increases the installations' total CO_2 emissions.

6.3 Time trend analysis

As discussed in relation to Figure 1, a number of major economic events occurred during the study period. In particular, not only the Global Financial Crisis and the Great East Japan Earthquake, but also the worldwide advancement of low-carbon policies following the adoption of the Paris Agreement may have affected the estimation results. To examine whether dynamic changes in the economic environment may have influenced the estimated relationships, we divide the sample into several subperiods and conduct separate analyses for each period.

Table 7-1 examines the relationships between TFP and the respective outcome variables using the sample from 2007 to 2010. Table 7-2 presents the results for the 2011–2014 period, which captures the years immediately following the Great East Japan Earthquake. Table 7-3 reports the results for the 2015–2019 period, during which global attention to decarbonization increased following the adoption of the Paris Agreement. For each subperiod, as in Table 2-1, we employ fixed-effects models that control for time-invariant establishment-specific effects.

Table 7-1: Estimated relationship between the dependent variables and TFP between 2007 and 2010

	CI	EI	CIE	Output	CO_2
TFP	-0.8443***	-0.8495***	0.0053	0.9905***	0.1463***
	(0.0092)	(0.0250)	(0.0258)	(0.0020)	(0.0093)
Within R-squared	0.4402	0.1035	0.0049	0.9631	0.1128
Observations	15,452	15,452	15,452	15,452	15,452
Installations	4,485	4,485	4,485	4,485	4,485

Note: Values in parentheses are standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 7-2: Estimated relationship between the dependent variables and TFP between 2011 and 2014

	CI	EI	CIE	Shipment	CO_2
TFP	-0.8913***	-0.8435***	-0.0478***	0.9860***	0.0947***
	(0.0062)	(0.0143)	(0.0146)	(0.0019)	(0.0062)
Within R-squared	0.6999	0.2560	0.0759	0.9620	0.2293
Observations	14,238	14,238	14,238	14,238	14,238
Installations	3,998	3,998	3,998	3,998	3,998

Note: Values in parentheses are standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 7-3: Estimated relationship between the dependent variables and TFP between 2015 and 2019

	CI	EI	CIE	Shipment	CO_2
TFP	-0.9117***	-0.9312***	0.0195	1.0107***	0.0989***
	(0.0083)	(0.0127)	(0.0139)	(0.0024)	(0.0082)
Within R-squared	0.5448	0.3372	0.0142	0.9416	0.0934
Observations	14,725	14,725	14,725	14,725	14,725
Installations	3,416	3,416	3,416	3,416	3,416

Note: Values in parentheses are standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

The results show that, across all subperiods, improvements in TFP are consistently associated with improvements in EI, which in turn contribute substantially to reductions in CI. With respect to CIE, however, the results for the 2011–2014 sample suggest that higher TFP may contribute to an improvement in CIE. In the other subperiods, no statistically significant relationship between TFP and CIE is observed.

The results reported in Tables 7-1, 7-2, and 7-3 also indicate that the effect of TFP improvements on EI becomes stronger in the more recent subperiods. However, while the increase in CO_2 emissions associated with higher TFP becomes smaller in the 2011–2014 sample, this tendency appears to reverse in the 2015–2019 sample, with the increase in CO_2 emissions associated with TFP growth becoming larger again.

6.4 Heterogeneity by Installation Characteristics

In the preceding analyses, we conducted several additional estimations to control for factors that may affect the main results, including potential endogeneity, dynamic change of economic structures, and installations' export behavior. Nevertheless, this study has limitations in identifying a clear causal relationship between TFP and CO_2 emissions. To partially mitigate concerns regarding potential estimation bias, we further conducted analyses that take into account heterogeneity in installation characteristics.

Specifically, we constructed quintile groups based on four major installation characteristics that are likely to affect both CO_2 emissions and TFP: installation size (number of employees), TFP, shipments, and value added[8]. We then re-estimated the relationship between TFP and CO_2 emissions and related outcomes within each quintile group using the same empirical specifications as in the main analysis. If patterns similar to the main estimation results are observed even within groups of installations that are relatively homogeneous with respect to these characteristics, this would provide additional support for the robustness of the main findings. The estimation results are reported in Appendix C.

Overall, the results across the quintile groups defined by installation size, TFP, shipments, and Value add share for output show patterns broadly consistent with the main findings. In particular, improvements in TFP are associated with substantial reductions in EI, which in turn contribute to improvements in CI across most groups.

7 Discussion and conclusion

The empirical analysis provides detailed evidence on changes in CO_2 intensity among Japanese manufacturing installations. The first main finding is that improvements in energy efficiency, as measured by reductions in energy intensity, were the principal driver of lower CO_2 intensity among

[8] For each installation, we calculated the average value of each variable over the entire sample period and constructed quintile groups based on these installation-level averages.

Japanese manufacturing installations between 2007 and 2019. In the environmental and energy economics literature, the technique effect through which higher TFP reduces CO_2 emissions has generally been treated as a single mechanism, leaving its underlying components insufficiently understood. This study provides a more detailed account of how TFP affects CO_2 intensity by decomposing this effect into an energy-efficiency effect and an energy decarbonization effect. The results show that, in Japanese manufacturing, the energy-efficiency effect accounts for most of the reduction in CO_2 intensity associated with higher TFP. These results suggest that productivity improvements alone may not be sufficient to induce the energy transition required to reduce total CO_2 emissions. Although this pattern is consistent with findings from macro-level decomposition analyses of the Japanese economy, there has been limited empirical evidence showing that the same pattern holds at the micro level. For example, Aoki et al. (2023) suggest that, following the 2008 financial crisis, Japan's industrial sector, including manufacturing, may have undergone a structural shift toward producing more energy-efficient and higher-value-added products. The findings therefore offer useful policy implications for the design of support measures and regulations targeting Japan's manufacturing sector.

The estimated energy-efficiency effect is substantial, even relative to those reported in previous studies. However, when the scale effect is also considered, the increase in output associated with higher TFP more than offsets the reduction in CO_2 intensity resulting from improved energy efficiency. Consequently, among installations above the relevant size thresholds that remained in operation during the sample period, total CO_2 emissions may have increased despite improvements in CO_2 intensity. This finding is broadly consistent with Belloc et al. (2025), which examines the European Union, where CO_2 emissions are subject to comparatively stringent regulation. Taken together, these results suggest that, even under different regulatory conditions, firms may not undertake sufficient energy transition to reduce their total CO_2 emissions.

However, our study has several limitations. One of this study's limitations is that it does not consider a structural change in output, such as changes in products. Rottner & von Graevenitz (2024) found that the production composition in German manufacturing shifted towards less CO_2-intensive goods, while production emission intensities increased. This evidence implies that the energy-efficiency effect we estimated may rely on changes in the products of each installation. Further policy discussion is therefore needed on how improvements in TFP can be more closely linked to energy transition, thereby enabling firms to reduce CO_2 emissions further while maintaining or improving their economic performance and achieving sustainable growth.

Second, this study estimates revenue-based TFP. Revenue-based TFP may reflect not only physical productivity but also the process through which installations generate higher value added from their products. This feature complicates the interpretation of the relationship between TFP and CO_2 emissions examined in this study. If physical-quantity-based TFP could be estimated, it would allow for a more precise analysis of how the energy-efficiency and decarbonization effects identified in this study are related to the process of value creation within industries.

Finally, the findings of this study are based on data covering the period from 2007 to 2019 and therefore do not capture the progress in decarbonization after the COVID-19 pandemic. This limitation should be taken into consideration, particularly because global efforts to accelerate decarbonization policies have intensified substantially since the pandemic. Nevertheless, evidence from Japan during a period when regulations on CO_2 emissions were relatively limited provides a useful benchmark for comparison with previous studies from the EU, where such regulations had already become more stringent during the same period.

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Appendix A: The time trend of samples

Table A-1: The number of samples on each year

year	Selected Industries	All
2007	843	3,819
2008	828	4,154
2009	780	3,826
2010	789	3,655
2011	705	3,472
2012	699	3,581
2013	674	3,583
2014	654	3,603
2015	567	3,028
2016	542	3,084
2017	539	3,026
2018	527	2,909
2019	523	2,678

Note) "Selected Industries" indicates the number of installations for which data from the Current Survey of Energy Consumption (METI) in the Selected Industries are used. "All" indicates the total number of installations included in the analytical sample.

Appendix B: Balanced panel analysis

Table B-1: Factor analysis of CI, EI and CIE based on full panel data (Fixed effect model)

	CI	EI	CIE	Output	CO_2
TFP	-0.8479***	-0.8012***	-0.0467***	1.0011***	0.1532***
	(0.0064)	(0.0117)	(0.0120)	(0.0021)	(0.0065)
Observations	17,953	17,953	17,953	17,953	17,953
Installations	1,381	1,381	1,381	1,381	1,381
Within R^2	0.5379	0.2580	0.0513	0.9352	0.1069

Note: Values in parentheses are standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table B-2: Factor analysis of CI, EI and CIE based on full panel data (Fixed effects 2SLS)

	CI	EI	CIE	Output	CO_2
TFP	-0.7925*** (0.0376)	-0.6883*** (0.0763)	-0.1042 (0.0764)	1.0246*** (0.0175)	0.2321*** (0.0416)
Observations	17,952	17,952	17,952	17,952	17,952
Installations	1,381	1,381	1,381	1,381	1,381
Centered R^2	0.5357	0.2539	0.0500	0.9347	0.0990

Note) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. TFP is instrumented by L2_tfp; standard errors are cluster-robust at the installation level. First-stage excluded-instrument F = 132.60 for all five specifications.

Appendix C: Heterogeneity analysis of installation characteristics

Table C-1: Heterogeneity analysis by TFP quintile

Dependent variable	>20%	>40%	>60%	>80%	~100%
CO_2 intensity (CI)	-0.8399*** (0.0087)	-0.8008*** (0.0105)	-0.8019*** (0.0090)	-0.8464*** (0.0090)	- 0.8593*** (0.0084)
Energy intensity (EI)	-0.8326*** (0.0221)	-0.7714*** (0.0233)	-0.8268*** (0.0198)	-0.8202*** (0.0201)	- 0.8365*** (0.0134)
CO_2 intensity of energy (CIE)	-0.0073 (0.0221)	-0.0294 (0.0237)	0.0249 (0.0205)	-0.0262 (0.0200)	-0.0227 (0.0144)
Output (Shipment value)	1.0110*** (0.0030)	1.0014*** (0.0033)	1.0056*** (0.0028)	0.9973*** (0.0031)	1.0038*** (0.0027)
CO_2 emissions	0.1711*** (0.0089)	0.2006*** (0.0108)	0.2037*** (0.0091)	0.1509*** (0.0091)	0.1445*** (0.0086)
Observation	6,816	8,230	8,927	9,913	10,529
Installations	887	1,012	1,047	1,112	1,128

Note: Values in parentheses are standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table C-2: Heterogeneity analysis by installation scale (The number of employees) quintile

Dependent variable	>20%	>40%	>60%	>80%	~100%
CI	-0.7617*** (0.0113)	-0.8093*** (0.0097)	-0.8445*** (0.0098)	-0.7973*** (0.0095)	-0.8841*** (0.0069)
EI	-0.8186*** (0.0266)	-0.8097*** (0.0222)	-0.7870*** (0.0199)	-0.8613*** (0.0197)	-0.8274*** (0.0134)
CIE	0.0569** (0.0266)	0.0004 (0.0224)	-0.0575*** (0.0203)	0.0640*** (0.0206)	-0.0567*** (0.0137)
Output	0.9493*** (0.0036)	0.9979*** (0.0031)	1.0021*** (0.0030)	1.0062*** (0.0033)	1.0265*** (0.0023)
CO_2 emissions	0.1876 (0.0113)	0.1886 (0.0101)	0.1577 (0.0099)	0.2089 (0.0098)	0.1425 (0.0071)
Observation	7,663	8,339	8,643	9,294	10,476
Installations	944	1,007	1,013	1,087	1135

Note: Values in parentheses are standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table C-3: Heterogeneity Analysis by output (Shipment value) quintile

Dependent variable	>20%	>40%	>60%	>80%	~100%
CI	-0.785*** (0.011)	-0.833*** (0.010)	-0.791*** (0.010)	-0.828*** (0.009)	-0.871*** (0.007)
EI	-0.780*** (0.028)	-0.859*** (0.024)	-0.823*** (0.021)	-0.782*** (0.020)	-0.839*** (0.012)
CIE	-0.005 (0.028)	0.026 (0.024)	0.032 (0.022)	-0.046** (0.020)	-0.031** (0.013)
Output	0.990*** (0.004)	0.999*** (0.003)	1.003*** (0.003)	0.995*** (0.003)	1.016*** (0.002)
CO2 emissions	0.205*** (0.011)	0.166*** (0.010)	0.212*** (0.010)	0.167*** (0.009)	0.145*** (0.008)
Observations	6694	8034	9165	9667	10855
Installations	872	1003	1077	1078	1156

Note: Values in parentheses are standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table C-4: Heterogeneity analysis by value-added-to-shipment ratio quintile

Dependent variables	>20%	>40%	>60%	>80%	~100%
CI	-0.8654*** (0.0076)	-0.8284*** (0.0104)	-0.7977*** (0.0098)	-0.8413*** (0.0085)	-0.8074*** (0.0100)
EI	-0.8544*** (0.0155)	-0.8254*** (0.0188)	-0.7527*** (0.0219)	-0.8088*** (0.0193)	-0.8366*** (0.0227)
CIE	-0.0110 (0.0157)	-0.0030 (0.0198)	-0.0450** (0.0219)	-0.0326* (0.0198)	0.0292 (0.0233)
Output	1.0029*** (0.0026)	1.0085*** (0.0030)	1.0145*** (0.0032)	0.9995*** (0.0030)	0.9955*** (0.0035)
CO_2 emissions	0.1375*** (0.0077)	0.1801*** (0.0106)	0.2168*** (0.0099)	0.1582*** (0.0089)	0.1881*** (0.0101)
Observations	8,709	9,320	9,080	9,200	8,106
Installations	1,029	1,055	1,043	1,059	1,000

Note: Values in parentheses are standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.