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The Relationship between Carbon Emissions and Wages: Evidence from Japanese manufacturing installations¹

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Abstract

The global transition toward a low-carbon economy is substantially transforming economic structures. In the European Union, where low-carbon policies are being actively promoted, policy measures have increasingly been introduced to address economic disparities arising from decarbonization. Nevertheless, there is still insufficient empirical evidence on the relationship between decarbonization and economic inequality. This study examines how progress in decarbonization at Japanese manufacturing installations, measured in changes in CO₂ emissions, is associated with employee wages. We first present a conceptual framework that organizes the mechanisms proposed in previous studies into six channels and states the conditions under which the correlation between emissions and wages becomes positive or negative. The estimated association is negative when installation productivity is not held constant, and positive once total factor productivity (TFP) is controlled for. The positive association is stronger at installations with a higher value-added share, and it is larger when estimated using persistent rather than year-to-year variation in emissions. These findings are consistent with mechanisms such as rent sharing and with differences in working conditions and production processes across installations, but are difficult to reconcile with the explanation of a dominant green skill premium over the sample period. These findings highlight a potentially important distributional dimension of decarbonization in the manufacturing sector.

Keywords: Decarbonization, Wage, Manufacturing, TFP

JEL classification: D22, J31, Q50

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1. Introduction

As climate change mitigation efforts advance worldwide, there is growing concern that rapid decarbonization may create labor market challenges. Decarbonization entails a transition from fossil fuels toward low-carbon energy sources, including renewable energy. Such a transition is expected to involve structural transformation on an exceptional scale, with few historical precedents. In the European Union, extensive discussions are underway regarding how a “just transition” should be designed to mitigate the labor market disruptions associated with decarbonization.

The concept of a just transition originated in response to labor problems in the United States in the 1990s. Workers in pollution-intensive industries experienced job losses and wage reductions due to more stringent environmental regulations. The current global transition toward a low-carbon economy may have substantially greater consequences for labor markets worldwide than earlier episodes of environmental regulatory tightening. From an academic perspective, concerns have been raised that a major shift in energy use could significantly affect regional economies and labor markets (Hanson, 2023). The European Union has therefore established funding mechanisms to support a just transition and has introduced policy measures amounting to approximately EUR 55 billion over the 2021–2027 period. These measures include assistance for displaced workers, vocational training, reskilling programs, and support for the economic transformation of affected regions.

Previous research has generated a substantial body of evidence on the effects of environmental regulation on labor market outcomes. However, it remains unclear whether decarbonization itself generates wage disparities. Although policy initiatives aimed at achieving a just transition have accelerated, empirical evidence on the extent to which decarbonization affects wage inequality remains limited. In recent years, several studies in Europe and the United States have examined the wage effects of employment in environmentally sustainable firms or of possessing skills related to the low-carbon transition (Godøy & Isaksen, 2025; Saussay et al. 2026). In Japan, however, the relationship between decarbonization and wages has not yet been systematically investigated.

Against this background, this study examines the relationship between progress toward decarbonization at Japanese manufacturing installations, as reflected in changes in CO₂ emissions, is associated with employee wages. The analysis uses a panel dataset of Japanese manufacturing installations constructed by linking government statistics containing detailed information on operational and financial characteristics with installation’s CO₂ emissions data.

The sign of the estimated association depends on whether installation productivity is held constant. When TFP is not controlled for, CO₂ intensity is negatively associated with wages, which is consistent with more productive installations paying higher wages while emitting less per unit of output. Once TFP is controlled for, the association becomes positive. As set out in Section 2, this reversal is what the framework predicts if productivity-linked rent sharing accounts for the negative association and compensating wage differentials, sorting on amenities, rent sharing in carbon-intensive production, and differences in production processes account for the positive one. The positive association is stronger at installations with a higher value-added share, and larger when estimated from persistent variation in emissions, which helps narrow down which of these channels are likely to be at work. Holding productivity constant, the within-installation relationship is positive: periods in which an installation emits more CO₂ are periods in which it pays higher average wages.

The remainder of this paper is organized as follows. Section 2 sets out the conceptual framework and the channels through which CO₂ emissions and wages may be related. Section 3 describes the data of this study. Section 4 explains the estimation of TFP and the empirical framework. Section 5 presents the main estimation

results, and Section 6 examines heterogeneity across installations and the sources of variation in emissions. Section 7 discusses the findings and concludes.

2. Conceptual Framework: Channels Linking CO₂ Emissions and Wages

2.1 What the Emissions-Wage Relationship Can and Cannot Tell Us

This study examines the relationship between CO₂ emissions and average wages across Japanese manufacturing installations. Before describing the data and the empirical specification, we set out the mechanisms that previous studies have proposed for the link between environmental performance and wages, and arrange them into a small number of channels, each with a predicted sign.

The parameter of interest is the coefficient on CO₂ emissions in a within-installation regression of average wages, conditional on output, labor, capital, and total factor productivity (TFP). It describes how average wages differ across periods in which an installation emits more or less CO₂, holding its output and measured inputs constant, and it is an association rather than a causal effect. In the decision problem that underlies the data, emissions and wages are not related as a cause and its consequence: an installation chooses its production technology, its energy and material inputs, its employment, and the wages it offers at the same time, subject to the same input prices, technological constraints, and product and labor market conditions. Both variables are therefore endogenous. A change in an underlying condition, such as the vintage of an installation's equipment, the rents it earns in its product market, or the type of workers it seeks to attract, moves both variables at the same time, and the direction in which each of them moves depends on which condition has changed. For this reason, the estimated coefficient reflects the relative strength of several mechanisms rather than the effect of any single one of them, and instrumenting emissions with their own past values would not by itself deliver a causal interpretation.

This shapes how we use the estimate. Rather than interpreting the coefficient as the effect of decarbonization on wages, we ask which combinations of mechanisms are consistent with the sign, the magnitude, and the pattern of heterogeneity that we observe, and which are not. Previous studies on environmental issues and wages provide the necessary building blocks, but they do not state the conditions under which the correlation between emissions and wages is positive or negative. This section supplies that statement. We group the mechanisms into six channels, four of which predict a positive relationship and two a negative one, and describe for each the sign it predicts, whether controlling for TFP removes it, and the observable dimensions along which its strength should vary.

2.2 Channels Predicting a Positive Relationship

Channel 1: Compensating wage differentials. Wage differentials may arise through the mechanism described by the compensating wage differential hypothesis. When installations employ workers who are exposed to adverse working conditions, such as environmental pollution, noise, heat, or occupational hazards, they may need to offer higher wages to compensate those workers for accepting less desirable or riskier jobs. Godøy and Isaksen (2025) find that wages may in fact be higher at brown firms than at green firms, and attribute this to the fact that brown firms tend to be energy intensive and that their workers are more likely to face occupational hazards and other job-related risks. Saussay et al. (2026) similarly show that the wage premium associated with jobs and occupations in carbon-intensive industries tends to exceed that associated with low-carbon-related

vacancies. This channel predicts a positive relationship between emissions and wages. Because it operates through working conditions rather than through installation performance, controlling for TFP does not remove it, and its strength should be greater in industries in which production involves more hazardous or physically demanding work.

Channel 2: Worker preferences and sorting on amenities. Workers' preferences for employment at environmentally responsible firms may also affect wages. If workers derive nonpecuniary benefits from working for such employers, these firms may be able to attract and employ them at lower wages than otherwise comparable firms. Krueger et al. (2023) report a sustainability wage gap of this kind for Swedish workers, and find that the gap is larger among high-skilled workers. Because this channel lowers wages at low-emission installations rather than raising them at high-emission installations, it also predicts a positive relationship, and it is likewise unaffected by controlling for TFP. Channels 1 and 2 therefore cannot be distinguished by the sign of the coefficient alone. They differ in where they should be strong: Channel 1 where working conditions are hazardous, Channel 2 at installations with relatively low emissions and among more highly skilled workers.

Channel 3: Rent sharing in carbon-intensive production. Rent sharing may be more pronounced in carbon-intensive industries, which are often characterized by substantial resource rents, high capital intensity, product-market barriers, and strong insider bargaining power (Godøy and Isaksen, 2025). If installations in these industries share part of these rents with their employees, the observed wage premium may reflect rent sharing rather than a relationship between carbon intensity itself and wages. Evidence from petroleum extraction and coal mining shows that changes in industry rents are partly passed through to workers' wages (Cho and Krueger, 2022), and differences in pay between employers, of which rent sharing is one of the main sources, account for a substantial share of overall wage inequality (Card et al., 2018). This channel predicts a positive relationship. Controlling for TFP does not remove it, because measured productivity does not fully capture economic rents arising from market power, product prices, barriers to entry, capacity constraints, or access to infrastructure. Its strength should be greater at installations whose value added accounts for a larger share of shipment values, and where a larger share of value added is paid to workers.

Channel 4: Production processes and capacity utilization. Installations within the same industry differ in the range of production processes they carry out and in the intensity with which they operate their facilities, and these processes differ substantially in their energy requirements. In the textile industry, for example, wet-processing activities such as scouring, bleaching, dyeing, drying, and finishing are substantially more energy intensive than sewing and other relatively simple assembly operations (Hasanbeigi and Zuberi, 2022). Installations that undertake a broader range of technically demanding processes may also employ a more skill-intensive workforce and pay higher wages. In addition, higher emissions in a given year may reflect higher capacity utilization and greater production activity, which may be accompanied by higher overtime payments and bonuses. Both mechanisms predict a positive relationship. This channel is not a behavioral relationship between emissions and wages but a difference in the composition of production that is jointly associated with both variables, and it is therefore the main alternative interpretation of a positive coefficient. We return to it in Sections 5.2 and 6.1.

2.3 Channels Predicting a Negative Relationship

Channel 5: Productivity-linked rent sharing. Installations with better environmental performance tend to exhibit better financial and operational performance than other installations (Konar and Cohen, 2001; Endrikat et al., 2014). Firms that export more, which tend to be more productive, have also been found to be cleaner (Forslid et al., 2018), and recent work reports a systematic relationship between measured productivity and emissions (Belloc et al., 2025). Konishi and Tarui (2015) provide a theoretical basis for this pattern, showing that when firms differ in productivity and minimize costs, more productive firms emit less per unit of output. Because installations with stronger economic performance also tend to pay higher wages (Chan et al., 2023), and because productivity gains are partly passed through to workers' wages (Kline et al., 2019), higher-productivity installations may pay higher wages while emitting less per unit of output. This channel predicts a negative relationship. Unlike Channels 1 to 4, it is removed when TFP is controlled for, since it operates through the productivity differences that TFP is intended to measure. The same data may therefore yield a negative coefficient when TFP is not controlled for and a positive coefficient when it is.

Channel 6: Green skill premium. The adoption of new technologies may generate a skill premium in green jobs, that is, in jobs addressing environmental issues. Workers with more advanced or highly demanded skills are generally expected to earn higher wages (Katz and Murphy, 1992), so that workers who can operate, maintain, or develop low-carbon technologies may command higher wages. Consistent with this argument, Consoli et al. (2016) show that workers in environmentally related occupations exhibit higher levels of educational attainment, work experience, and job training than workers in non-green jobs, and that green jobs require greater use of cognitive and interpersonal skills. Kuai et al. (2025) report that Japanese workers with skills related to green technologies earn approximately 7 percent higher wages than workers without such skills, and Saussay et al. (2026) find a wage premium for low-carbon technological skills in the U.S. labor market, although its magnitude is relatively small. To the extent that installations with lower emissions employ more of these workers, this channel predicts a negative relationship. It may be weak over our sample period, since the premium documented for Japan is based on survey data from 2021, whereas our sample covers 2006 to 2019, a period in which ambitious decarbonization policies were not yet widespread. It should nevertheless be more visible in knowledge-intensive industries, in which value creation has increasingly extended beyond physical production toward design, control systems, software, and lifecycle support (Chávez et al., 2023).

2.4 The Role of Conditioning on Output, Inputs, and TFP

The interpretation of the estimated coefficient depends on what is held constant, and two points deserve attention. First, controlling for TFP is what separates Channel 5 from the remaining channels. A substantial body of research has documented a relationship between productivity and wages (Carlsson et al., 2016; Morikawa, 2025), and installations with better environmental performance also tend to be more productive (Forslid et al., 2018). If TFP were approximately constant over time within an installation, installation fixed effects would absorb these differences. Our sample spans 14 years, however, leaving substantial scope for within-installation changes in TFP that fixed effects alone cannot capture. Including TFP as an explanatory variable therefore removes the part of the emissions–wage relationship that operates through productivity, so that the coefficients estimated with and without TFP differ in interpretation rather than in accuracy.

Second, the specification that includes output and inputs together with TFP requires care. TFP is constructed as the part of output that is not explained by labor, capital, and intermediate inputs. Once output, labor, and capital per worker are included as separate regressors, the remaining variation in TFP therefore reflects mainly the use of intermediate inputs, including energy and raw materials, which is in turn closely related to CO₂ emissions. In this specification, the coefficient on emissions is thus close to a coefficient on emissions per unit of input, that is, on the emission factor of the energy and materials used at the installation, rather than on the scale of production. This is consistent with the high variance inflation factors reported for output and TFP as reported in footnote 4 of Section 4.2, and it also accounts for the conditional sign of the TFP coefficient. We report specifications with and without TFP and output so that the estimates can be read under both interpretations.

2.5 What Determines the Sign of the Relationship

Let β denote the estimated coefficient on CO₂ emissions and let β_k denote the contribution of channel k . The sign of the estimated relationship can then be written as

$$\beta = \underbrace{\beta_1 + \beta_2 + \beta_3 + \beta_4}_{\text{positive contributions}} - \underbrace{(\beta_5 \cdot 1[\text{TFP not controlled}] + \beta_6)}_{\text{negative contributions}}$$

The relationship is positive when compensating wage differentials, sorting on amenities, rent sharing in carbon-intensive production, and differences in production processes together outweigh the green skill premium. When TFP is not controlled for, productivity-linked rent sharing enters as an additional negative contribution, and the relationship may be negative even though the same channels operate. The sign of the coefficient is therefore not a property of the data alone but also of the set of variables held constant, and a change of sign across specifications is itself informative about the relative strength of the channels.

The channels also differ in the dimensions along which their strength should vary, which allows some of them to be distinguished. The empirical analysis is organized around these predictions. Section 5.1 compares specifications with and without TFP and output, which separates Channel 5 from the remaining channels, and Section 5.2 examines industry heterogeneity, which speaks to Channels 1, 4, and 6. Section 6.1 compares estimates based on persistent and short-run variation in emissions, which bears on Channel 4, while Sections 6.2 and 6.3 examine heterogeneity across TFP quintiles and across indirect proxies for rents, which bear on Channels 5 and 3. These comparisons indicate which channels are consistent with the observed patterns and which are not. They do not identify the contribution of each channel separately, and we do not interpret them as doing so.

2.6 Contribution and Related Evidence for Japan

This study makes two contributions to the existing literature. First, it examines the relationship between wages and a continuous measure of decarbonization, CO₂ emissions, at the manufacturing installation, and interprets the estimated relationship within the framework set out above. Saussay et al. (2026) use online job vacancy data, which capture recent labor market developments through wages offered in newly posted vacancies but not changes in the wages of incumbent workers. This limitation is particularly important in Japan, where wage determination is influenced not only by external labor market conditions but also by firm-internal employment practices such as long-term employment relationships and internal labor markets, although these features have evolved in recent years (Kato, 2016; Kambayashi and Kato, 2026). Our installation-level data therefore

complement vacancy-based evidence by capturing wage outcomes for incumbent workers.

Second, this study explicitly accounts for the relationship between an installation's TFP and wages. Previous studies often control for firm performance by including firm fixed effects. As discussed in Section 2.4, however, fixed effects cannot absorb within-installation changes in productivity over a period as long as ours, and controlling for TFP is what allows Channel 5 to be separated from the other channels. Estimating TFP at the installation level is therefore not merely the addition of a control variable; it is what makes the comparison of specifications informative about the channels.

To the best of our knowledge, empirical evidence on decarbonization, low-carbon policies, and wages in Japan remains very limited. Kuai et al. (2025) use individual-level questionnaire data to examine the presence of a green wage premium, and provide detailed evidence on the relationship between workers' employment characteristics, green skills, and wages. Their analysis, however, does not account for the characteristics of the installations in which workers are employed or for changes in installations' CO₂ emissions.

Mortha and Arimura (2026) examine the Saitama Emissions Trading System (SETS), a cap-and-trade scheme introduced in 2011 under which targeted plants must reduce their emissions relative to a baseline but face no penalty for non-compliance, so that the scheme is essentially voluntary. Using the Census of Manufacture for 2004 to 2019 and comparing targeted with non-targeted plants by means of two-way fixed effects and propensity score matching, they find that the scheme increased value added, labor productivity, and average wages, with the wage increase estimated at 3.66%. Their wage variable, like ours, is the plant's total wage expenditure divided by its number of employees. Lu et al. (2025) provide related evidence on the effects of the Tokyo and Saitama ETs on installation-level productivity.

Our study differs from these studies in what is measured and in what is estimated. Their analysis is based on the Census of Manufacture, in which plant-level CO₂ emissions are not observed: coverage by the SETS is determined by whether a plant's annual energy consumption exceeds 1,500 kiloliters of crude oil equivalent, and the explanatory variable of interest is an indicator for being targeted by the scheme. Their estimates therefore describe how outcomes differ between covered and uncovered plants, rather than how wages vary with the level of emissions. By linking the Census of Manufacture to emissions reported under the SHK system, we observe CO₂ emissions for each installation in each year, and can describe the relationship between wages and emissions across the distribution of emissions rather than across a regulatory threshold.

The two studies also estimate different objects, and their results are complementary rather than contradictory. Mortha and Arimura (2026) estimate the average treatment effect of a policy that raised energy and electricity costs and, in their interpretation, encouraged investment in newer equipment and in research and development, leading to higher productivity and higher wages. In the framework set out above, that mechanism is Channel 5, which in our analysis is separated out by controlling for TFP. Their estimates are thus informative about how wages respond when a policy changes productivity, whereas ours describe how wages and emissions are related when productivity differences are held constant, for the manufacturing sector as a whole.

The scope of the evidence also differs. The SETS targets roughly 600 facilities in a single prefecture, of which about 80% are manufacturing plants, and plants located in Tokyo are excluded from their analysis because they were covered by a different scheme (Mortha and Arimura, 2026). Our sample covers 6,611 installations located throughout Japan and accounts for between 36% and 64% of the CO₂ emissions reported by manufacturing installations under the SHK system, depending on the year. Evidence from a single regional scheme is difficult to generalize to Japanese manufacturing as a whole, particularly because the sector underwent substantial

restructuring after the 2008 global financial crisis, accompanied by significant changes in energy use (Aoki et al., 2023). Both studies, however, are limited to relatively large plants, as we discuss in Section 3.3.

Against this background, this study does not seek to identify the effect of a specific regional carbon regulation, nor the causal effect of emissions on wages. It documents the relationship between CO₂ emissions and wages across Japanese manufacturing and asks which of the channels described above are consistent with that relationship. Because nationwide low-carbon policies and direct CO₂ regulations were still relatively limited during the sample period, the estimates provide a benchmark description under that policy environment, and they should not be interpreted as estimates of the wage effects of future decarbonization policies.

3. Data

3.1 Data for TFP Estimation

This study uses data on manufacturing installations 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 191,339 installations in 2019. The Census of Manufacture requires the manufacturing installations covered by the survey to complete and submit the relevant form to the government. This study restricts the analysis to installations with 30 or more employees, which are required to complete Form A. Installations below the Form A employment threshold complete Form B. Form A contains variables necessary for estimating TFP, including fixed assets, whereas Form B does not include this information. The analysis therefore focuses on installations that completed Form A (approximately 34,000 installations in 2019).

For 2011 and 2015, the study uses data from the Economic Census for Business Activity, jointly conducted by METI and the Ministry of Internal Affairs and Communications (MIC). This census has been conducted every five years since 2012. It covers business establishment in both manufacturing and non-manufacturing sectors throughout Japan. In years in which the Economic Census for Business Activity is conducted, the Census of Manufacture is not administered. However, during the years in which the Economic Census for Business Activity was conducted, a survey comparable to the Census of Manufacture was carried out using the manufacturing questionnaire. By integrating data from these two censuses, this study compiles a panel dataset covering 2000-2019 for the estimation of each installation's TFP.

3.2 CO₂ Emissions Data

This study uses manufacturing installation data on CO₂ emissions to examine the relationship between CO₂ emissions and average wages of each installation. The CO₂ emissions data are obtained from the Greenhouse Gas Emissions Calculation, Reporting and Publication System (SHK system), administered by the Ministry of the Environment (MOE), Japan. The system was introduced 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 CO₂ 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 CO₂ 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 CO₂ emissions generally cover both Scope 1 and Scope 2 emissions. In 2019, the system covered 15,020 manufacturing installations and non-manufacturing entities. 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.

3.3 Panel data and Sample Characteristics

For the empirical analysis, we constructed an unbalanced panel dataset of Japanese manufacturing installation by matching data from the Census of Manufacture, the Economic Census for Business Activity, and CO₂ emissions data reported under the SHK System, as described above. The resulting dataset includes installation-year observations for which installation-level TFP, variables used as wage controls, CO₂ emissions, shipment values, and average wages are all available. The final estimation sample consists of 59,316 installation-year observations covering 6,611 installations².

Table 1 compares the annual number of installations included in our panel dataset with the number of installations covered by Form A of the Census of Manufacture. Our sample covers approximately 7.1–11.9% of the installations covered by Form A. The coverage rate declines over time, suggesting that sample attrition and the loss of observations arising from matching multiple statistical datasets become more pronounced in later years.

Table 1: Sample Coverage of Manufacturing Installations' Economic Activity

Year	Installation		Average wage		Sample coverage rate				
	Sample	Census	Sample	Census	Labor	Wage	Shipment value	Value added	Installation
2006	5,522	46366	539.6985	485.2483	0.209	0.259	0.325	0.315	0.119
2007	5,676	47682	536.7144	484.3874	0.208	0.259	0.327	0.313	0.119
2008	5,614	46455	539.1443	490.5034	0.212	0.263	0.326	0.310	0.121
2009	5,015	44006	513.4031	463.2093	0.217	0.264	0.326	0.313	0.114
2010	5,105	43628	513.7391	467.564	0.219	0.269	0.325	0.320	0.117
2011	3,143	44708	518.346	482.0108	0.162	0.194	0.220	0.210	0.070
2012	4,229	43756	527.3493	478.1979	0.207	0.253	0.304	0.293	0.097
2013	4,207	43459	524.1396	474.7481	0.205	0.252	0.306	0.292	0.097
2014	4,166	43461	528.396	480.5037	0.205	0.252	0.308	0.294	0.096
2015	3,472	45346	539.1277	489.1476	0.185	0.227	0.279	0.266	0.077
2016	3,362	44595	586.5295	479.7331	0.179	0.232	0.283	0.274	0.075
2017	3,316	45430	619.9459	479.1131	0.175	0.229	0.280	0.271	0.073

² The balanced panel consists of 2,855 establishments with complete information on all variables used in the estimation, including average wages, CO₂ emissions, TFP, shipment values, and the control variables, for every year in the sample period.

2018	3,259	45997	609.4689	487.973	0.174	0.228	0.279	0.269	0.071
2019	3,230	45636	615.9683	490.8599	0.174	0.228	0.275	0.261	0.071

Note: “Sample” indicates the number of installations included in the analysis, while “Census” indicates the number of installations covered by the Census of Manufacture and the Economic Census for Business Activity.

Average wages, the main outcome variable in this study, are higher in our estimation sample than among installations in the Census of Manufacture as a whole. This difference is consistent with the fact that our sample disproportionately represents relatively large installations. The Census of Manufacture also shows that, among manufacturing installations with 30 or more employees, average wages tend to increase with installation size. For example, according to the 2019 Census of Manufacture, the average annual wage was JPY 3.866 million at installations with 30–49 employees, compared with JPY 4.332 million at installations with 100–199 employees and JPY 6.503 million at installations with 1,000 or more employees. Table 1 also shows that sample coverage rates in terms of wages, shipment values, and value added are generally higher than the coverage rate measured by the number of installations. This pattern is consistent with the relatively large size of the installations included in our sample. Accordingly, the higher average wage in the estimation sample is also consistent with differences in the size distribution of installations between the two samples.

Table 2: Sample Coverage of Manufacturing Installations’ CO₂ Emissions

Year	Installation			Total CO ₂ emissions (tonnes)		
	Sample	SHK	Sample coverage rate	Sample	SHK	Sample coverage rate
2006	5,522	8,824	0.626	273,982,376	519,487,957	0.527
2007	5,676	9,140	0.621	335,052,861	524,763,911	0.638
2008	5,614	9,206	0.610	309,989,910	490,411,932	0.632
2009	5,015	8,310	0.603	276,873,415	438,470,156	0.631
2010	5,105	8,575	0.595	298,246,849	475,305,749	0.627
2011	3,143	8,682	0.362	180,917,163	463,542,431	0.390
2012	4,229	8,860	0.477	283,924,825	467,342,616	0.608
2013	4,207	8,907	0.472	307,279,236	493,463,785	0.623
2014	4,166	8,955	0.465	302,768,374	493,982,173	0.613
2015	3,472	8,907	0.390	268,564,635	476,789,028	0.563
2016	3,362	9,046	0.372	257,653,231	467,097,143	0.552
2017	3,316	9,069	0.366	251,469,654	476,004,998	0.528
2018	3,259	9,013	0.362	249,057,976	466,578,713	0.534
2019	3,230	9,049	0.357	236,892,484	442,207,669	0.536

Table 2 presents annual trends in total CO₂ emissions and the number of installations in our study sample (Sample), together with the corresponding figures for manufacturing installations reported under the SHK system (SHK). The sample coverage rate in terms of total CO₂ emissions ranges from 0.390 to 0.638 over the study period. Although the coverage rate fluctuates from year to year, there is no clear increasing or decreasing trend between 2007 and 2019.

In contrast, the sample coverage rate in terms of the number of installations declines over time after 2006. While the coverage rate was relatively high at 0.626 in 2006, it had fallen to 0.357 by 2019. Taken together, the coverage patterns for the number of installations and total CO₂ emissions suggest that our sample may disproportionately capture larger installations with relatively high CO₂ emissions.

4 TFP Estimation and Empirical Specification for wages

4.1 Estimation of TFP

In this study, we apply the Wooldridge (2009) methodology to estimate the installation's TFP. Wooldridge (2009) recommends using proxy variables within a generalized method of moments framework to account for unobserved productivity shocks affecting the production function. We therefore use this methodology to estimate the production function and recover each installation's TFP as follows:

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

where TFP_{it} is TFP for installation i in year t . and 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). This study employs the installation output as the shipment value (ten thousand JP yen), the number of employees as the labor input, fixed assets (ten thousand JP yen) as the capital input, and expenditure on raw materials as the intermediate input (ten thousand JP yen). We include year fixed effects in the production function to control for year-specific shocks common to all installations, such as macroeconomic fluctuations and economy-wide changes in production conditions.

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 estimation sample extends further back than the period used in the main wage regressions analysis in order to mitigate measurement error associated with 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 stock³ 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 main wage analysis, 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 for shipment values, capital stock, and expenditure on raw materials. TFP is then estimated after converting each nominal variable

³ This study assumes a 10 percent rate of fixed-capital consumption per a year.

into real terms using the corresponding deflator.

4.2 Empirical Specification for Average Wages

we estimate following model (Equation(1)), primarily using fixed-effect specification.

$$\ln(Wage_{i,t}) = \beta \ln(CO2_{i,t}) + \gamma TFP_{i,t} + \delta \ln Y_{i,t} + x'_{i,t} \theta + \mu_i + \varepsilon_{i,t} \quad (1)$$

i and t denote installations and years, respectively. μ_i represents installation i 's fixed effects, while ε denotes the error term. The coefficient β is the parameter defined in Section 2.5. $Wage$ is the average wage at installation i in year t . TFP denotes installation-level total factor productivity estimated following Wooldridge (2009), and x is a vector of control variables. Production output may be correlated with both CO₂ emissions and TFP. We therefore include shipment values (Y), our measure of output, as an additional explanatory variable⁴.

Following the literatures on wage determination, the control variables include the total number of employees, the share of regular or permanent employees, the share of female employees, and the stock of tangible fixed assets per employee. Year fixed effects are also included to account for shocks and other factors common to all installations in a given year.

In this study, we estimate two sets of specifications: one using CO₂ intensity, defined as CO₂ emissions divided by shipment values, and another using the level of CO₂ emissions. Kronmal (1993) argues that the use of ratios as dependent or explanatory variables may impose inappropriate restrictions on the effects of the numerator and the denominator. In the present context, the CO₂ intensity specification constrains the coefficients on emissions and on output to be equal in absolute value and opposite in sign. Once output is included as a separate regressor, this restriction is relaxed, and the specification becomes an exact reparameterization of the one using the level of emissions, since $\ln(CO_2/Y) = \ln CO_2 - \ln Y$ (see Appendix A). The two specifications therefore yield identical coefficients on emissions once output is controlled for, and they should not be read as independent evidence. We report both because the specifications without output differ, and we use the level of emissions in the remainder of the analysis because its coefficient is easier to interpret. Summary statistics for the variables used in the estimations are reported in Appendix B.

5. Results

5.1 Baseline Relationship between CO₂ Emissions and Average Wages

Based on the data and estimation methodology described above, we estimate a fixed-effects model to examine the relationship between CO₂ emissions and average wages at individual manufacturing installations. Table 3 reports the fixed-effects estimates of the relationship between average wages and CO₂ intensity using the unbalanced panel data⁵.

⁴ The strong correlations among CO₂ emissions, CO₂ intensity, TFP, and output, measured by the value of shipments, raise concerns about multicollinearity. After estimating a pooled OLS model that included CO₂ emissions, CO₂ intensity, TFP, and output simultaneously as explanatory variables, we calculated the variance inflation factors (VIFs). The VIF values for output and TFP exceeded 10, indicating potentially serious multicollinearity between these variables. To address this concern, we estimate several alternative specifications that include different combinations of TFP and output and compare the results across these models.

⁵ Estimation results based on balanced panel data are shown in Appendix C.

Table 3 Relationship between CO₂ Intensity and Average Wages at Manufacturing Installations

Variables	(1)	(2)	(3)	(4)
ln(CO ₂ intensity)	-0.0589*** (0.0021)	0.0325*** (0.0029)	0.0358*** (0.0029)	0.0345*** (0.0029)
TFP	—	0.1540*** (0.0035)	—	-0.0862*** (0.0179)
ln(Shipment values)	—	—	0.1632*** (0.0035)	0.2496*** (0.0182)
ln(Labor)	-0.2345*** (0.0039)	-0.2531*** (0.0038)	-0.3078*** (0.0041)	-0.3353*** (0.0071)
Regular employee share	0.2091*** (0.0106)	0.2035*** (0.0104)	0.2004*** (0.0104)	0.1988*** (0.0104)
Male employee share	0.2380*** (0.0136)	0.1960*** (0.0134)	0.1913*** (0.0134)	0.1893*** (0.0134)
Capital per labor	5.45e-06*** (1.33e-07)	4.85e-06*** (1.32e-07)	4.64e-06*** (1.32e-07)	4.55e-06*** (1.33e-07)
Constant	6.9233*** (0.0255)	5.8651*** (0.0345)	5.5442*** (0.0389)	5.4026*** (0.0483)
Within R-squared	0.2508	0.2777	0.2800	0.2803
Observations	59,572	59,316	59,572	59,316

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

The letter "e" denotes scientific notation, representing a power of 10.

The results in Table 3 show that CO₂ intensity is negatively associated with average wages when TFP is not controlled for, and positively associated with wages once TFP is included. This reversal is the pattern anticipated in Section 2.5. When productivity is not held constant, the association combines the negative contribution of productivity-linked rent sharing (Channel 5) with the positive contributions of the remaining channels, and the estimates in column (1) indicate that the former dominates: installations that are more productive tend both to emit less per unit of output and to pay higher wages. Column (2) holds productivity constant, which removes Channel 5, and the coefficient becomes positive. Under the framework of Section 2, the positive coefficient in column (2) therefore reflects the net contribution of compensating wage differentials (Channel 1), sorting on amenities (Channel 2), rent sharing in carbon-intensive production (Channel 3), and differences in production processes and capacity utilization (Channel 4), less the green skill premium (Channel 6).

The reversal is not a consequence of using a ratio variable. As shown in Section 4.2 and Appendix A, once output is included as a separate regressor the intensity and level specifications are the same regression, and the coefficients on emissions in columns (4) and (8) are identical. What changes the sign of the coefficient is the inclusion of TFP, not the choice between intensity and levels.

TFP is negatively and significantly associated with wages in column (4). As discussed in Section 2.4, this is what the construction of the TFP measure implies: once output, labor, and capital per worker are held constant,

the remaining variation in TFP reflects mainly the use of intermediate inputs, so that the coefficient on TFP in this specification should not be read as the wage return to productivity. The specification in column (2), which does not include output, is the appropriate one for that purpose, and there TFP is positively associated with wages. For the same reason, the coefficient on emissions in columns (4) and (8) is closer to a coefficient on emissions per unit of input than on the scale of emissions.

Table 4 Relationship between CO₂ Emissions and Average Wages at Manufacturing Installations

Variables	(5)	(6)	(7)	(8)
ln(CO ₂ emissions)	0.0629*** (0.0029)	0.0384*** (0.0029)	0.0358*** (0.0029)	0.0345*** (0.0029)
TFP	—	0.1216*** (0.0025)	—	-0.0862*** (0.0179)
ln(Shipment values)	—	—	0.1274*** (0.0026)	0.2151*** (0.0183)
ln(Labor)	-0.2381*** (0.0040)	-0.2655*** (0.0039)	-0.3078*** (0.0041)	-0.3353*** (0.0071)
Regular employee share	0.2195*** (0.0106)	0.2030*** (0.0104)	0.2004*** (0.0104)	0.1988*** (0.0104)
Male employee share	0.2244*** (0.0137)	0.1939*** (0.0134)	0.1913*** (0.0134)	0.1893*** (0.0134)
Capital per labor	5.25e-06*** (1.34e-07)	4.79e-06*** (1.32e-07)	4.64e-06*** (1.32e-07)	4.55e-06*** (1.33e-07)
Constant	6.6364*** (0.0327)	5.7710*** (0.0367)	5.5442*** (0.0389)	5.4026*** (0.0483)
Within R-squared	0.2466	0.2784	0.2800	0.2803
Observations	59,572	59,316	59,572	59,316

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

The letter "e" denotes scientific notation, representing a power of 10.

As discussed above, we also report specifications that use the level of CO₂ emissions in place of CO₂ intensity. The results are presented in Table 4, and the coefficient on emissions is positive in all four specifications. Comparing column (1) of Table 3 with column (5) of Table 4 shows that the difference in sign between the two measures arises from what is held constant, not from the measure itself. In the intensity specification without output, emissions and output are constrained to enter with coefficients of equal absolute value and opposite sign, so that the estimated coefficient is dominated by the positive association between output and wages, which enters negatively through the ratio. The level specification without output leaves that association in the coefficient on emissions, since larger installations both emit more and pay higher wages. Once TFP is included, the two measures give similar estimates, and once output is also held constant they coincide, as columns (4) and (8) show.

5.2 Relationship between CO₂ Emissions and Wages by Manufacturing Industry

Industry heterogeneity bears on three of the channels described in Section 2. Compensating wage differentials (Channel 1) should be concentrated in industries in which production involves hazardous or physically demanding work; rent sharing in carbon-intensive production (Channel 3) in industries with substantial product-market rents; and the green skill premium (Channel 6) in knowledge-intensive industries, where it would push the coefficient in the opposite direction.

As shown in Section 4.2, the two measures coincide once output is held constant. In the remainder of the analysis, we therefore use the level of CO₂ emissions, together with output as a separate regressor, because the coefficients of this specification are easier to interpret. Table 5 presents the results of industry-specific estimates of the relationship between CO₂ emissions and average wages.

To examine whether the relationship differs across industries, we conduct industry-specific estimations using different combinations of TFP and output (shipment values), as explanatory variables, following the specifications reported in Table 5. In Table 5, “TFP, Shipment values” refers to the specification that includes both TFP and shipment values as explanatory variables. “TFP” and “Shipment values” refer to specifications that include TFP or shipment values, respectively. Finally, “CO₂ only” refers to the specification that includes neither TFP nor shipment values as an explanatory variable.

The estimated coefficients on CO₂ emissions are very similar in the “TFP, Shipment values” and “TFP” specifications. By contrast, the “CO₂ only” specification produces substantially different estimates in several industries, suggesting that the estimated relationship is sensitive to TFP or shipment values are included. We therefore focus primarily on the “TFP, Shipment values” specification in the following discussion.

Table 5 Relationship between CO₂ Emissions and Average wages by Manufacturing Industry

Name of industry	TFP, Shipment values	TFP	CO ₂ only	The number of installations
Food products	0.0583***	0.0625***	0.0878***	961
Beverages, tobacco, and animal feed	0.0070	0.0163	0.0268	202
Textile products	0.0713***	0.0747***	0.1124***	284
Wood and wood products, except furniture	-0.0151	-0.0185	0.0180	58
Furniture and fixtures	0.0844	0.0880	0.1304**	38
Pulp, paper, and paper products	0.0403***	0.0436***	0.0513***	325
Printing and related activities	0.0326	0.0305	0.0352	137
Chemical products	0.0206***	0.0235***	0.0372***	732
Petroleum and coal products	0.0755**	0.0873***	0.0743**	58
Plastic products	0.0144	0.0159	0.0370***	621
Rubber products	0.0150	0.0141	0.0252	148
Ceramic, stone, and clay products	0.0211*	0.0223*	0.0533***	413
Iron and steel	0.0102	0.0113	0.0339***	411
Non-ferrous metals	0.0092	0.0186	0.0318***	292
Fabricated metal products	0.0439***	0.0454***	0.0862***	382
General-purpose machinery	-0.0478**	-0.0498**	-0.0031	235
Production machinery	0.0812***	0.0938***	0.1120***	234
Business-oriented machinery	0.0304	0.0308	0.0375	123
Electronic parts, devices, and electronic circuits	0.0555***	0.0580***	0.0713***	502
Electrical machinery, equipment, and supplies	-0.0007	0.0092	0.0403**	278
Information and communication electronics equipment	-0.0063	0.0072	0.0255	134
Transportation equipment	0.0541***	0.0637***	0.0838***	717
Miscellaneous manufacturing industries	0.0708*	0.0753**	0.0871**	76

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 10 installations in this sample) to produce valid estimates.

Based on the “TFP, Shipment values” specification, the estimated coefficient on CO₂ emissions is positive in many industries. Among the 23 industries examined, eight exhibit a positive and statistically significant relationship between CO₂ emissions and wages at the 1 percent level. Specifically, this positive relationship is observed in food products, Textile products, Pulp, paper, and paper products, Chemical products, Fabricated metal products, Production machinery, Electronic parts, devices, and electronic circuits, and Transportation

equipment. These results suggest that, within these industries, higher CO₂ emissions are associated with higher wages.

In general, industries such as Iron and steel, Chemicals, Cement manufacturing, and Pulp and paper are commonly regarded as representative energy-intensive industries. In our analysis, higher CO₂ emissions are also positively associated with wages in the Chemical, Cement, and Pulp and paper industries. However, in the Iron and Steel industry, we do not find a statistically significant relationship between CO₂ emissions and wages.

Table 5 also shows that the positive relationship between CO₂ emissions and wages is relatively strong in several industries, including Textile products, Petroleum and coal products, and Production machinery. The Petroleum and coal products industry directly handles fossil-fuel-related products and is inherently carbon-intensive. Within this industry, higher CO₂ emissions may reflect higher capacity utilization and greater production activity at the installation. For petroleum and coal products, the positive relationship between CO₂ emissions and wages is unlikely to be explained solely by differences in installation size, because the regressions control for both employment and capital per worker. Nevertheless, these controls may not fully capture differences in production throughput, capacity utilization, or the composition and complexity of refining processes. CO₂ emissions may therefore partly reflect the intensity with which large-scale refining facilities are operated rather than their physical size alone.

More importantly, this is the pattern predicted by Channel 3 (rent sharing). Petroleum refining is characterized by large sunk costs, substantial barriers to entry, location-specific advantages, and potentially significant product-market rents. Part of these rents may be shared with workers through higher wages. Although the regressions control for TFP, measured productivity does not fully capture economic rents arising from market power, product prices, barriers to entry, capacity constraints, or access to infrastructure. Accordingly, the positive coefficient on CO₂ emissions may partly reflect unobserved differences in profitability or economic rents across installations, rather than a direct effect of emissions on wages.

By contrast, in industries such as Textile products and Production machinery, the connection between carbon intensity and wages is less straightforward. Even within the Textile industry, production processes differ substantially in their energy requirements. Wet-processing activities such as scouring, bleaching, dyeing, drying, and finishing are substantially more energy intensive than sewing and other relatively simple assembly operations because they require considerable process heat and steam (Hasanbeigi & Zuberi, 2022). Higher emissions may therefore partly capture differences in the scope and vertical integration of production, with some installations undertaking energy-intensive wet-processing and finishing activities in addition to basic textile production. These interpretations correspond to Channel 4.

Similarly, in the production machinery industry, installations that manufacture high-value-added products using advanced manufacturing processes may also have higher CO₂ emissions. Higher emissions may proxy for the scale and breadth of in-house production, including machining, heat treatment, surface treatment, testing, and assembly. Installations undertaking a broader range of technically demanding processes may also employ a more skill-intensive workforce and pay higher wages. These interpretations are suggestive rather than causal and cannot be distinguished directly with the available data.

Among the sectors examined, General-purpose machinery is the only industry sector in which the relationship between CO₂ emissions and wages found to be negative and statistically significant. Recent studies on the machinery and machine-tool industries suggest that value creation has increasingly extended beyond the physical production of machinery toward service- and knowledge-intensive activities, including product design, control

systems, software, digital services, maintenance, and lifecycle support (Chávez et al., 2023). This is the direction predicted by Channel 6.

Accordingly, installations that engage more intensively in these non-manufacturing and high-value added activities may employ a larger share of engineers and other highly skilled workers with expertise in advanced technologies. Such installations may therefore pay relatively higher wages while generating lower CO₂ emissions than installations that are more heavily engaged in physical production. This structural difference within the industry is one possible interpretation of the negative relationship between CO₂ emissions and wages observed in the estimation results.

6. Heterogeneity and Sources of Variation

The analyses in this section examine whether the estimated relationship varies in the ways that the channels of Section 2 imply. Section 6.1 compares estimates based on persistent and on year-to-year variation in emissions, Section 6.2 examines heterogeneity across TFP quintiles, and Section 6.3 uses indirect proxies for rents.

6.1 Persistent and Year-to-Year Variation in Emissions

As discussed in Section 2.1, emissions and wages are jointly determined, and instrumenting emissions with their own past values does not by itself deliver a causal interpretation. We nevertheless report fixed-effects two-stage least squares estimates in which the second lag of log CO₂ emissions is used as an instrument, because they isolate a different source of variation. The predicted component corresponds to the persistent level of emissions at an installation, whereas the residual variation reflects year-to-year changes in operating conditions. Comparing the two therefore indicates which kind of variation in emissions is associated with wages. The estimation results from the fixed-effects two-stage least squares (2SLS) model are presented in Table 6.

The first-stage results indicate that the instrument is strongly correlated with the endogenous regressor. Across the four specifications, the first-stage F-statistics range from 90.39 to 98.60, indicating a strong first-stage relationship. The Kleibergen–Paap rk LM statistics range from 185.45 to 208.88 and are statistically significant at the 1% level in all specifications, allowing us to reject the null hypothesis of underidentification. The Kleibergen–Paap rk Wald F-statistics range from 90.39 to 98.60, suggesting that weak-instrument concerns are limited. Taken together, these diagnostics indicate that the second lag of CO₂ emissions is strong first -stage predictor of current CO₂ emissions. They do not, however, establish the validity of the exclusion restriction.

Table 6: Fixed-effects 2SLS Estimates of the Relationship between CO₂ Emissions and Wages

Variable / Statistic	(9)	(10)	(11)	(12)
ln(CO ₂ emissions)	0.2046*** (0.0264)	0.1566*** (0.0262)	0.1471*** (0.0262)	0.1446*** (0.0266)
TFP	—	0.1148*** (0.0113)	—	-0.0412 (0.0398)
ln(Shipment values)	—	—	0.1205*** (0.0117)	0.1627*** (0.0428)

ln(Labor)	-0.3067*** (0.0256)	-0.3250*** (0.0241)	-0.3620*** (0.0248)	-0.3744*** (0.0302)
Regular employee share	0.1985*** (0.0282)	0.1856*** (0.0272)	0.1848*** (0.0271)	0.1840*** (0.0272)
Male employee share	0.2189*** (0.0462)	0.1967*** (0.0440)	0.1940*** (0.0437)	0.1935*** (0.0440)
Capital per labor	4.26E-6*** (1.19e-6)	3.94E-6*** (1.09e-6)	3.86E-6*** (1.08e-6)	3.84E-6*** (1.09e-6)
First-stage F	98.600	95.250	94.300	90.390
Kleibergen–Paap rk LM	208.878	201.303	197.941	185.454
KP Wald F	98.596	95.246	94.305	90.387
Centered R-squared	0.2402	0.2803	0.2841	0.2844
Installations	5,484	5,453	5,484	5,453
Observations	45,107	44,962	45,107	44,962

Notes) Cluster-robust standard errors at the installation level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All specifications include installation and year fixed effects. In CO₂ emissions is instrumented by its second lag. The letter "e" denotes scientific notation, representing a power of 10.

Because the model is exactly identified, with one endogenous regressor and one excluded instrument, the exclusion restriction cannot be assessed using an overidentification test such as the Hansen J test.

A causal interpretation would therefore require the additional assumption that the second lag of CO₂ emissions affects current wages only through current CO₂ emissions, conditional on installation fixed effects, year fixed effects, and the included controls. This assumption is not directly testable in the present setting.

As in Table 4, workforce characteristics commonly associated with wage determination, including the regular-employee share, male-employee share, and capital per worker, are positively associated with average wages. The estimated coefficients on TFP and shipment values also show patterns consistent with those reported in Table 4. CO₂ emissions are likewise positively and statistically significantly associated with average wages.

The estimated coefficient is substantially larger than in the baseline fixed-effects models, at 0.1446 compared with 0.0345 in the corresponding specification. Because the two estimators use different variation, this difference should not be read as evidence of a larger causal effect, nor as confirmation that the baseline estimate is robust. It indicates that wages are more closely associated with the persistent level of an installation's emissions than with year-to-year fluctuations in emissions. This is consistent with channels that operate through installation characteristics, namely Channels 1, 2, and 3, and less consistent with the capacity-utilization component of Channel 4, under which short-run increases in emissions would be accompanied by higher overtime payments and bonuses.

6.2 Heterogeneity in the Relationship between CO₂ Emissions and Wages across TFP Quintiles

Previous studies have shown that firms with higher TFP tend to have lower CO₂ intensity and better environmental performance (Forslid et al., 2018; Belloc et al., 2025). It has also been documented that firms with higher TFP tend to pay higher wages (Chan et al., 2023). In the preceding analyses, we control for TFP directly as an explanatory variable to account for these relationships. However, if TFP is associated with both CO₂ emissions and wages, heterogeneity across installations with different TFP levels may still be related to the estimated relationship between CO₂ emissions and wages.

To examine this concern, we divide the sample into groups of installations with relatively similar TFP levels and assess whether the relationship between CO₂ emissions and wages is broadly consistent across groups. Specifically, we first calculate the average TFP of each installation over the sample period and rank all installations according to their period-average TFP. We then divide the installations into five equally sized groups, or quintiles, each containing approximately 20 percent of the sample. The fifth quintile consists of installations in the top 20 percent of the distribution of period-average TFP over the sample period, while the first quintile consists of installations in the bottom 20 percent.

Table 7 presents estimates of the relationship between CO₂ emissions and wages separately for each TFP quintile. For each quintile, we estimate the same specification as in the preceding analyses, including CO₂ emissions, TFP, shipment values, and the other control variables.

The estimation results show that, among the five TFP groups, CO₂ emissions are positively and statistically significantly associated with wages in all groups except the group of installations with the highest TFP (“Highest TFP”). For the “Highest TFP” group, the estimated association between CO₂ emissions and wages is smaller than that observed in the other groups and is also less statistically significant.

In terms of the framework of Section 2, this pattern suggests that the positive channels are weaker, or the green skill premium (Channel 6) stronger, among the most productive installations. Highly productive installations are more likely to employ workers whose skills are not tied to carbon-intensive production, which would offset the positive channels and flatten the relationship, as observed. By contrast, for most installations outside the “Highest TFP” group, the results indicate a positive relationship between CO₂ emissions and wages.

Table 7 Relationship between CO₂ Emissions and Wages across TFP Quintiles

Variables	Lowest TFP (>20%)	Second quintile (>40%)	Middle quintile (>60%)	Fourth quintile (>80%)	Highest TFP
ln(CO ₂ emissions)	0.0345*** (0.0079)	0.0435*** (0.0062)	0.0466*** (0.0071)	0.0472*** (0.0064)	0.0103* (0.0058)
TFP	-0.1514*** (0.0417)	0.0459 (0.0400)	-0.2365*** (0.0453)	-0.0543 (0.0372)	-0.1003** (0.0433)
ln(Shipment values)	0.2658*** (0.0429)	0.1006** (0.0413)	0.3684*** (0.0465)	0.1872*** (0.0380)	0.2188*** (0.0443)
ln(Labor)	-0.2997*** (0.0171)	-0.2966*** (0.0172)	-0.3924*** (0.0199)	-0.3340*** (0.0147)	-0.3390*** (0.0168)

Regular employee share	0.2513*** (0.0236)	0.1863*** (0.0226)	0.1627*** (0.0222)	0.1595*** (0.0225)	0.2717*** (0.0254)
Male employee share	0.1561*** (0.0331)	0.1388*** (0.0285)	0.2647*** (0.0291)	0.3188*** (0.0288)	0.0888*** (0.0314)
Capital per labor	-3.38e-06*** (1.16e-06)	2.22e-05*** (1.09e-06)	-1.03e-05*** (1.88e-06)	3.73e-06*** (1.84e-07)	5.59e-06*** (2.46e-07)
Within R-squared	0.2082	0.3043	0.2422	0.3526	0.3107
Observations	9,984	11,345	12,142	12,758	13,087

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

The letter "e" denotes scientific notation, representing a power of 10.

6.3 Heterogeneity in the Relationship between CO₂ Emissions and Wages: The Role of Rent Sharing

The preceding analyses show a positive association between CO₂ emissions and average wages. Although these specifications account for installation size, TFP, and industry heterogeneity, they do not directly measure rent sharing, whereby part of economic rents generated at the installation or firm level may be distributed to workers through higher wages. Because the extent of rent sharing is difficult to measure accurately at either the firm or installation level, we examine whether the positive relationship between CO₂ emissions and wages may partly reflect rent-sharing mechanisms by taking into account differences in the value-added share of shipment values, defined as value added divided by the shipment values. This ratio is used as an indirect proxy for economic rents rather than as a direct measure of rent sharing.

Table 8 Relationship between CO₂ Emissions and Wages across Quintiles of Value-Added Share of Shipment values

Variables	Lowest Value added/ Shipment value (>20%)	Second quintile (>40%)	Middle quintile (>60%)	Fourth quintile (>80%)	Highest Value added/ Shipment value
ln(CO ₂ emissions)	0.0214*** (0.0074)	0.0216*** (0.0056)	0.0379*** (0.0067)	0.0432*** (0.0069)	0.0462*** (0.0065)
TFP	0.1077** (0.0418)	-0.1179*** (0.0429)	-0.0641 (0.0406)	-0.0934** (0.0403)	-0.0780** (0.0378)
ln(Shipment values)	-0.0003 (0.0428)	0.2866*** (0.0444)	0.1893*** (0.0418)	0.2359*** (0.0413)	0.1814*** (0.0387)
ln(Labor)	-0.2352*** (0.0160)	-0.3498*** (0.0180)	-0.2994*** (0.0159)	-0.3723*** (0.0177)	-0.3216*** (0.0163)

Regular employee share	0.2842*** (0.0237)	0.1696*** (0.0221)	0.1500*** (0.0239)	0.1691*** (0.0223)	0.2387*** (0.0245)
Male employee share	0.1548*** (0.0307)	0.1733*** (0.0288)	0.2807*** (0.0295)	0.1513*** (0.0286)	0.1938*** (0.0331)
Capital per labor	6.02e-06*** (2.43e-07)	1.16e-05*** (9.53e-07)	4.42e-06*** (2.04e-07)	1.31e-05*** (1.05e-06)	1.60e-06*** (3.52e-07)
Constant	5.8620*** (0.1123)	4.9512*** (0.1121)	5.2706*** (0.1083)	5.3489*** (0.1023)	5.6119*** (0.1096)
Within R-squared	0.3272	0.2665	0.2908	0.2983	0.2420
Mean value add per shipment value	0.0594	0.2433	0.3330	0.4094	0.5515
Observations	11,672	12,203	12,367	12,238	10,836

Note: Values in parentheses are standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The letter "e" denotes scientific notation, representing a power of 10.

Table 8 presents estimates for five quintile groups based on the installation's value-added share of shipment values, using an approach similar to that in Section 6.2. The estimated coefficient on CO₂ emissions increases monotonically with the value-added share, from 0.0214 in the lowest quintile to 0.0462 in the highest. Section 2 predicts this gradient under Channel 3: where rents are larger, a larger part of them may be shared with workers, and the association between emissions and wages should be correspondingly stronger. Among the analyses reported in this paper, this is the most direct evidence on a single channel. The value-added share is an indirect proxy for rents, however, and the analysis does not measure the magnitude of rents or the extent of rent sharing.

Table 9 presents estimates results for five quintile groups constructed according to the wage share of value added. This ration indicates the share of value added paid to workers as wages and may therefore serve as an indirect indicator of labor-income distribution and rent sharing.

Table 9 Relationship between CO₂ Emissions and Wages across Quintiles of the Wage Share of Value Added

Variables	Lowest Wage / Value added (>20%)	Second quintile (>40%)	Middle quintile (>60%)	Fourth quintile (>80%)	Highest Wage / Value add
ln(CO ₂ emissions)	0.0204*** (0.0059)	0.0326*** (0.0064)	0.0494*** (0.0072)	0.0355*** (0.0058)	0.0269*** (0.0082)
TFP	-0.1358*** (0.0429)	-0.0009 (0.0346)	0.0220 (0.0372)	-0.2442*** (0.0439)	-0.0588 (0.0493)
ln(Shipment values)	0.2043*** (0.0438)	0.1390*** (0.0355)	0.1452*** (0.0381)	0.4341*** (0.0452)	0.1868*** (0.0505)
ln(Labor)	-0.2869*** (0.0171)	-0.2718*** (0.0148)	-0.3322*** (0.0157)	-0.4592*** (0.0198)	-0.3315*** (0.0178)

Regular employee share	0.1615*** (0.0242)	0.2703*** (0.0224)	0.1769*** (0.0214)	0.2023*** (0.0214)	0.1942*** (0.0267)
Male employee share	0.3320*** (0.0312)	0.1956*** (0.0288)	0.2209*** (0.0280)	0.1197*** (0.0276)	0.1243*** (0.0338)
Capital per labor	4.94e-06*** (3.13e-07)	7.01e-06*** (2.69e-07)	1.22e-05*** (5.00e-07)	-9.49e-06*** (3.00e-06)	2.90e-06*** (2.16e-07)
Constant	5.8468*** (0.1109)	5.1238*** (0.1024)	5.0518*** (0.1060)	4.8028*** (0.1043)	5.7143*** (0.1235)
Within R-squared	0.2573	0.3127	0.3726	0.2711	0.2646
Observations	11,834	12,308	11,940	11,990	11,244

Note: Values in parentheses are standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The letter "e" denotes scientific notation, representing a power of 10.

The estimation results show a positive relationship between CO₂ emissions and average wages regardless of the share of wage payments in value added. The relationship is positive in all five groups, and is strongest in the middle quintile rather than increasing monotonically with the wage share of value added. This pattern does not line up with Channel 3 as closely as the results based on the value-added share, which is one reason we treat the wage share as the weaker of the two proxies.

Taken together, the quintile analyses based on the value-added share of shipment values and the wage share of value added show a positive relationship between CO₂ emissions and wages across groups with different levels of these ratios. The positive association tends to be stronger among installations with higher value-added shares. At the same time, because a positive association is observed across groups with different value-added and wage shares, these two proxies alone do not account for the entire emissions-wage pattern. The results do not directly identify the magnitude of rents or the extent of rent sharing.

7. Discussion and Conclusion

This study documents the relationship between average wages and CO₂ emissions at Japanese manufacturing installations. Using installation-level panel data over the study period, we find a positive association between CO₂ emissions and average wages within installations. Industry-specific analyses similarly show a positive relationship between CO₂ emissions and wages in a broad range of industries. The positive relationship is observed across most, though not all, of the groups examined in the heterogeneity analyses⁶.

The results allow some of the channels described in Section 2 to be assessed, although they do not identify the contribution of each of them separately. Productivity-linked rent sharing (Channel 5) is clearly present. The

⁶ Another potential concern is selection arising from differences in installation characteristics. For example, previous studies have shown that exporting firms tend to exhibit better environmental performance and that exporters also tend to have higher TFP and wages (Forslid et al., 2018). Regional differences in low-carbon regulation may also be associated with differences in the estimated emissions-wage relationship. We therefore conduct additional analyses that account for export activity and regional regulatory differences. These results are reported in Appendix D.

association between emissions and wages is negative when productivity is not held constant and positive once it is, which is the pattern that this channel implies. Rent sharing in carbon-intensive production (Channel 3) is supported by the gradient in the coefficient across quintiles of the value-added share, and by the large coefficient estimated for petroleum and coal products, an industry characterized by substantial sunk costs, barriers to entry, and location-specific advantages. Compensating wage differentials (Channel 1) are unlikely to account for the association on their own. The positive relationship appears in a broad range of manufacturing industries rather than only in those characterized by hazardous work. This does not rule the channel out, since we do not observe working conditions directly, but it limits the weight that can be placed on it. The green skill premium (Channel 6) does not appear to dominate over our sample period. It would imply a negative association, which we observe only in general-purpose machinery and, in attenuated form, among the most productive installations. This is consistent with the timing of the evidence for Japan, which is based on survey data collected in 2021, after our sample period ends (Kuai et al., 2025). Differences in production processes and capacity utilization (Channel 4) cannot be ruled out, and remain the main alternative interpretation of the positive association. The comparison in Section 6.1 speaks against its capacity-utilization component, since wages are more closely associated with persistent than with year-to-year variation in emissions, but not against differences in the scope of production processes across installations, which our data do not measure. Finally, compensating wage differentials (Channel 1) and sorting on environmental amenities (Channel 2) predict the same sign and cannot be separated with installation-level data. Distinguishing them requires information on individual workers. Linking our data to the Basic Survey on Wage Structure would allow worker composition to be held constant and is left for future research.

These findings have a potentially important policy implication. Over the period examined in this study, CO₂ emissions are positively associated with average wages within installations. This finding does not imply that reducing an installation's CO₂ emissions would cause its worker's wages to fall. Whether future decarbonization changes wages, and through which mechanisms, is a causal question that lies beyond the identification strategy used here. Nevertheless, the observed association suggests the distributional consequences of the low-carbon transition warrant further investigation, particularly for workers and regions that remain closely tied to carbon-intensive production.

This study has several limitations. First, the empirical design does not identify a causal effect of changes in installation-level CO₂ emissions on average wages. The emissions-wage relationship may be subject to endogeneity, including reverse causality and time-varying unobserved factors. Our analysis relies on installation fixed effects and a set of controls, and the fixed-effects 2SLS estimates reported in Section 6.1 are used to compare sources of variation rather than to establish causality. As discussed in Section 2.1, emissions and wages are jointly determined, and no specification reported here identifies the effect of emissions on wages.

Second, concerns about sample selection cannot be fully ruled out. As explained in Section 3, our sample consists primarily of relatively large manufacturing installations, raising questions about its representativeness for the Japanese manufacturing sector as a whole. In addition, some installations are inevitably lost when multiple government statistical datasets are matched, and we cannot exclude the possibility that this selection is related to the estimated results. The main findings are qualitatively stable across several heterogeneity analyses, but these excises do not eliminate concerns about sample representativeness.

Finally, the period covered by our analysis is limited to 2006–2019. Since the outbreak of the COVID-19 pandemic, many countries have introduced more ambitious policies to accelerate industrial decarbonization. In

Japan, the GX Promotion Act was enacted in 2023, and policies aimed at encouraging firms to pursue further decarbonization have subsequently been strengthened. These recent and substantial changes in the policy environment are not captured in our analysis. Given the recent progress in domestic and international decarbonization policies, it is therefore possible that workers possessing occupations or skills related to the low-carbon transition may increasingly receive a skill premium, such that their wages rise even as firms reduce CO₂ emissions. Indeed, Kuai et al. (2025), who document evidence of a green wage premium, use survey data from 2021.

Nevertheless, our findings provide a useful descriptive benchmark for the relationship between CO₂ emissions and wages during a period in which ambitious carbon-pricing and decarbonization policies were not yet widespread in Japan. As the economic and policy environment surrounding decarbonization continues to change substantially, further empirical research is needed to examine whether and how the relationship between CO₂ emissions and wages at firms and installations changes under these evolving conditions.

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Appendix A: Ratios variable problem in this study

The following equation presents a simplified version of the empirical model used in this study to examine the relationship between installation's average wages and carbon intensity

$$\ln w_{i,t} = \alpha + \beta' \ln CI_{i,t} + X'_{i,t} \gamma + \varepsilon \quad (1)$$

Here, w denotes the average wage at installation i in year t . Carbon intensity (CI) is defined as CO₂ emissions (CO_2) divided by shipment values (Y , output). Therefore, CI can be rewritten in terms of CO_2 and Y as follows.

$$CI_{i,t} = \frac{CO2_{i,t}}{Y_{i,t}} \quad (2)$$

Substituting this expression for CI into Equation (2) yields the following specification.

$$\ln w_{i,t} = \alpha + \beta' \ln \left(\frac{CO2_{i,t}}{Y_{i,t}} \right) + X'_{i,t} \gamma + \varepsilon \quad (3)$$

Finally, Equation (3) can be rewritten as Equation (4).

$$\ln w_{i,t} = \alpha + \beta' \ln CO2_{i,t} - \beta' \ln Y_{i,t} + X'_{i,t} \gamma + \varepsilon \quad (4)$$

In this specification, CO_2 and Y are constrained to have coefficients of equal absolute value but opposite signs. Thus, estimating Equation (3) implicitly imposes a restrictive functional form in which the association of CO_2 and Y cannot vary independently.

By contrast, when CO₂ emissions are used instead of CI and Y is included separately as an additional control, the specification can be written as Equation (5). This specification is closely related to the one using CI , but it allows CO_2 and Y to enter the regression independently.

$$\ln w_{i,t} = \alpha + \ln \beta'_1 CO2_{i,t} + \ln \beta'_2 Y_{i,t} + X'_{i,t} \gamma + \varepsilon \quad (5)$$

In Equation (5), it is therefore unnecessary to impose the restrictive functional form described above. Kronmal (1993) presents several empirical examples comparing specifications that use a ratio variable as an explanatory variable with specifications that include the numerator and denominator of the ratio separately. Although these examples do not generally show changes large enough to reverse the signs of the estimated coefficients, they demonstrate that the use of ratio variables can materially affect coefficient magnitudes. Similar concerns have also been documented in other empirical applications (Musumeci & Peterson, 2011; Lien et al., 2017).

Appendix B: Summary statistics

Table B1: Summary statistics of variables used in the analysis

	Variable	Obs	Mean	Std. dev.	Min	Max
Variables for main analysis	Wage	59,316	546.0876	482.4748	29.0882	58598
	CI	55,844	0.0308	0.1130	2.50e-06	7.0218
	CO ₂ emissions	59,316	64614.49	526943.8	3	2.04e+07
	TFP	59,316	10.4333	0.9585	4.2238	14.6883
	Shipment values	59,316	2746553	7966250	2409.939	2.45e+08
	Labor	59,316	393.9877	708.6837	1	14471
	Regular employee share	59,316	0.8042	0.204232	0	3.5319
	Male employee share	59,316	0.7494	0.1795	0	3.4113
	Capital per labor	59,316	2566.038	6725.373	0.0320	811210.7
Variables for additional analysis	Value-added share of shipment values	59,316	0.3139	1.874	-447.792	2.3592
	The share of wage payments in value added	59,316	0.3860	20.5058	-3095.91	2272.548
	Export	54,354	7.0413	17.2939	0	100

Note: The summary statistics reported in this table are based on a panel dataset constructed from installation-level microdata from the Census of Manufacture (METI), the Economic Census for Business Activity (METI and MIC), and the SHK System (MOE).

Appendix C: Balanced panel data analysis

Table C-1: Fixed-effect model

	(1)	(2)	(3)	(4)
ln CO ₂ emissions	0.0607*** (0.0036)	0.0392*** (0.0036)	0.0363*** (0.0036)	0.0353*** (0.0036)
TFP	—	0.1182*** (0.0032)	—	-0.0809*** (0.0219)
ln Shipment values	—	—	0.1243*** (0.0032)	0.2065*** (0.0224)
ln Labor	-0.2258*** (0.0050)	-0.2535*** (0.0050)	-0.2945*** (0.0052)	-0.3219*** (0.0089)
Regular employee rate	0.1763*** (0.0129)	0.1596*** (0.0126)	0.1571*** (0.0126)	0.1558*** (0.0126)
Male employee rate	0.3167*** (0.0168)	0.2847*** (0.0165)	0.2818*** (0.0164)	0.2798*** (0.0164)
Capital per labor	4.84e-6*** (1.38e-7)	4.44e-6*** (1.36e-7)	4.32e-6*** (1.36e-7)	4.24e-6*** (1.37e-7)
Within R ²	0.2682	0.2982	0.2996	0.3000
Installations	2,855	2,855	2,855	2,855
Observations	35,630	35,592	35,630	35,592

Note: Values in parentheses are standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels. The letter "e" denotes scientific notation, representing a power of 10.

Table C-2: Fixed-Effect 2SLS Model

Variable / Statistic	(5)	(6)	(7)	(8)
ln(CO ₂ emissions)	0.1693*** (0.0267)	0.1327*** (0.0263)	0.1235*** (0.0263)	0.1223*** (0.0263)
TFP	—	0.1144*** (0.0138)	—	-0.0272 (0.0463)
ln Shipment values	—	—	0.1199*** (0.0143)	0.1477*** (0.0482)
ln Labor	-0.2866*** (0.0300)	-0.3077*** (0.0280)	-0.3446*** (0.0288)	-0.3534*** (0.0346)
Regular employee rate	0.1545*** (0.0289)	0.1400*** (0.0279)	0.1391*** (0.0279)	0.1384*** (0.0280)
Male employee rate	0.3076*** (0.0585)	0.2824*** (0.0557)	0.2802*** (0.0556)	0.2795*** (0.0558)
Capital per labor	4.05e-6*** (1.14e-6)	3.74e-6*** (1.04e-6)	3.67e-6*** (1.04e-6)	3.65e-6*** (1.04e-6)
First-stage F	84.140	82.520	81.540	77.900
Kleibergen–Paap rk LM	172.874	166.123	162.574	150.664
KP Wald F	84.141	82.524	81.535	77.899
Centered R ²	0.2702	0.3056	0.3085	0.3087
Installations	2,855	2,854	2,855	2,854
Observations	29,920	29,894	29,920	29,894

Notes) Cluster-robust standard errors at the installation level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All specifications include installation and year fixed effects. ln(CO₂) is instrumented by its second lag. The letter "e" denotes scientific notation, representing a power of 10.

Appendix D: Additional Analyses Accounting for Installation Characteristics: Exporting Activity and Regulatory Intensity

Previous studies have shown that exporting firms tend to exhibit better environmental performance and higher TFP (Forslid et al., 2018). This raises the possibility that differences in export activity across installations may affect be related to the estimated relationship between CO₂ emissions and average wages. To examine this concern, we conduct an additional analysis that controls for each installation's export share of each installation, defined as export value divided by shipment values. Given the potentially complex relationship between TFP and export activity, we also estimate a specification that includes an interaction term between TFP and the export share. The results are reported in Table D-1. Controlling for export dependence does not materially change the estimated coefficient on CO₂ emissions.

Table D-1: Relationship between CO₂ Emissions and Wages Accounting for Export Activity

Variables	Export share	Export share and Interaction term with TFP
ln(CO ₂ emissions)	0.0372*** (0.0029)	0.0370*** (0.0029)
TFP	-0.1102*** (0.0180)	-0.1094*** (0.0180)
ln(Shipment values)	0.2324*** (0.0184)	0.2337*** (0.0184)
ln(Labor)	-0.3545*** (0.0073)	-0.3547*** (0.0073)
Export share	0.0003*** (9.40e-05)	0.0027*** (0.0008)
Export share × TFP	—	-0.0002*** (7.47e-05)
Regular employee share	0.2030*** (0.0110)	0.2028*** (0.0110)
Male employee share	0.1624*** (0.0142)	0.1626*** (0.0142)
Capital per labor	5.07e-06*** (1.36e-07)	5.06e-06*** (1.36e-07)
Constant	5.5125*** (0.0490)	5.4868*** (0.0498)
Within R-squared	0.3023	0.3024
Observations	54,354	54,354

Note: Values in parentheses are standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels. The letter "e" denotes scientific notation, representing a power of 10.

Japan has a nationwide carbon tax, but its tax rate is relatively low and the overall stringency of CO₂-emission

regulation is not particularly high by international standards. According to the OECD (2025), Japan's effective carbon rate remains relatively low among advanced economies. At the same time, emissions trading systems (ETSs) were introduced in Tokyo in 2010 and Saitama Prefecture in 2011, creating regional differences in the stringency of CO₂-emission regulation. Lu et al. (2025), for example, provide evidence suggesting that the Tokyo–Saitama ETS may have affected installation-level TFP. These regional differences motivate an additional comparison of the estimated emissions-wage relationship across regulatory environments.

Table D-2: Relationship between CO₂ Emissions and Wages by Region

Variables	Tokyo & Saitama	Other prefectures
ln(CO ₂ emissions)	0.0203 (0.0140)	0.0339*** (0.0030)
TFP	0.0153 (0.0819)	-0.1019*** (0.0184)
ln(Shipment values)	0.0256 (0.0839)	0.2377*** (0.0189)
ln(Labor)	-0.2396*** (0.0450)	-0.3459*** (0.0073)
Regular employee share	0.4748*** (0.0495)	0.1879*** (0.0107)
Male employee share	0.1903*** (0.0636)	0.1881*** (0.0138)
Capital per labor	-4.29e-06* (2.35e-06)	4.57e-06*** (1.34e-07)
Constant	6.4263*** (0.2139)	5.3234*** (0.0496)
Within R-squared	0.2613	0.2850
Observations	3,073	56,243

Note: Values in parentheses are standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels. The letter "e" denotes scientific notation, representing a power of 10.

To examine this possibility, we divide the sample into manufacturing installations located in Tokyo and Saitama and those located in the rest of Japan, and estimate the relationship between CO₂ emissions and average wages separately for the two groups. The estimation results are reported in Table D-2.

The results show no statistically significant relationship between CO₂ emissions and average wages among installations located in Tokyo and Saitama, where CO₂-emission regulation is considered relatively stringent. By contrast, a positive and statistically significant relationship is observed among installations located outside Tokyo and Saitama. Thus, the estimated emissions-wage relationship differs across the two regional groups. This comparison is descriptive and does not identify the effect of differences in regulatory stringency.

This analysis does not fully account for differences in installation characteristics or potential sample selection between Tokyo and Saitama and the rest of Japan. The results should therefore not be interpreted as identifying

a causal effect of CO₂-emission regulation on the relationship between emissions and wages. Nevertheless, the positive and statistically significant relationship observed outside Tokyo and Saitama is consistent with the main estimation results.