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Abstract

Recent empirical studies often support the positive relationship between corporate environmental performance (CEP) in terms of carbon dioxide (CO_2) and greenhouse gas (GHG) emissions and corporate financial performance (CFP). However, this depends on the measurements of CEP (the absolute and relative CEP) and CFP (accounting-based and market-based CFP). To understand the relationship structurally, based on the literature, this study proposes identity models that integrate CO_2 and GHG emissions and financial factors. The models decompose CO_2 (GHG) emissions into carbon intensity (GHG intensity), energy intensity, the cost-to-sales ratio, the total-assets-turnover ratio (TATR), leverage, and equity. The model of supply-chain GHG emissions additionally adopts supply-chain GHG intensity. As a decomposition method, this study uses the log-mean Divisia index (LMDI). As an application example of the carbon dioxide model, this study targets Japanese manufacturing firms in 16 sectors from fiscal years (FY) 2011 to 2015. Results show that the change in CO_2 emissions as of 2015 (−802.1 kilotonnes [kt]) is decomposed into 2922.5 kt for carbon intensity, −26036.3 kt for energy intensity, −6350.5 kt for the cost-to-sales ratio, −8495.6 kt for the TATR, −7912.3 kt for leverage, and 45070.1 kt for equity. Average values of relative contribution ratios are 20.6% for carbon intensity, 19.1% for energy intensity, and the remaining approximately 60% for financial factors. Among the 16 sectors, as of 2015, the change in total CO_2 emission is statistically significantly positive for equity and significantly negative for the TATR and leverage, and it is not significantly correlated to the carbon intensity, the energy intensity, and the cost-to-sales ratio.

Keywords: Carbon dioxide and greenhouse gas emissions; Japanese manufacturing sectors; Kaya identity; index decomposition analysis; log-mean Divisia Index

JEL codes: M11, M20, Q54

1. Introduction

In the literature of corporate social responsibility (CSR), many studies have examined the relationship between corporate social performance (CSP) and corporate financial performance (CFP) (Aguinis and Glavas, 2012; Carroll and Shabana, 2010; Griffin and Mahon, 1997; Margolis and Walsh, 2003; Roman et al., 1999). In particular, CSP-CFP research has shifted to corporate environmental performance (CEP)-CFP research, focusing on carbon dioxide (CO_2) and greenhouse gas (GHG) emissions, because of an increasing awareness of climate change issues in recent years (Busch and Hoffmann, 2011). Recent empirical studies mainly support the positive relationship between corporate performance in terms of CO_2/GHG emissions (that is, their amount) and CFP, such as return on assets (ROA), return on equity (ROE), return on investment (ROI), return on sales (ROS), and Tobin's q (market value divided by replacement value) (Busch and Hoffmann, 2011; Fujii et al., 2013; Hatakeda et al., 2012; Wang et al., 2014a). In addition to improving CEP, the recent literature tends to support the view that CO_2/GHG emissions management enhances CFP in the manufacturing sectors (except for energy-intensive sectors) (Capece et al., 2017; Nishitani et al., 2014). These findings seem to indicate that while CO_2/GHG emissions are essential to corporate profits, improvement in environmental performance (and its management efforts) is directly linked to CFP.

Recently, Busch and Lewandowski (2017) reviewed CEP-CFP studies (published between 2010 and 2016) for a meta-analysis. Examining 68 individual estimates from 32 studies, they find that the relationship between CEP and CFP tends to be positive (for 46 of 68 estimates), as noted above, but depends on the measurements of CEP and CFP. Two measurements of carbon performance (CEP) are absolute emissions (e.g., emission reductions) and relative emissions (i.e., emissions divided by a certain variable) whereas two measurements of CFP are accounting-based (e.g., ROA) and market-based (e.g., Tobin's q). As a matter of convenience, this study calls these emissions absolute and relative CEP, respectively, and calls these measurements of CFP accounting-based and market-based CFP, respectively. Among the 68 estimates, relative CFP is predominant (53 estimates) whereas the CFP are almost equally divided (36 for accounting-based CFP and 32 for market-based CFP). Busch and Lewandowski (2017) find that market-based CFP is more likely to support the positive relationship between CEP and CFP (24 of 32 estimates) than accounting-based CFP (22 of 38 estimates).

Based on this background, we have the following three questions. First, why is it that the positive relationship of CEP and CFP is often supported in the first place? Second, why is it that relative CEP is adopted much more often in the literature than absolute CEP? Third, why is it that accounting-based CFP often has a less robust relationship with CEP than does market-based CFP? We believe that these questions are important in the CEP-CFP literature, potentially extending our knowledge. The motivation of this study is to answer these questions, focusing on CO_2/GHG emissions as CEP and accounting-based CFP in a simple framework.

Regarding the first question (the positive relationship of CEP and CFP in general), this study supposes that it is understandable by considering cash flow and material flow in a certain company. Material flow here refers to non-financial flow within a company, including CO_2/GHG emissions and energy use. Simply stated, this study assumes that if cash flow is smooth, material flow will also be smooth: smooth cash flow will make for better CFP whereas smooth material flow causes better CEP, leading to the positive relationship between CEP and CFP. Because this idea is just our intuition, however, this study aims to explain it in a somewhat more scientific manner, using the concepts of cash flow and material flow within a company. Related to the combination of cash flow and material flow, material flow cost accounting (MFCA) has in recent years been standardized as ISO 14051 and ISO 14052 by the International Organization for Standardization (ISO) (Asian Productivity Organization [APO], 2014; ISO, 2011, 2017). MFCA is a cost-accounting tool that simultaneously considers material flow and cash flow (APO, 2014). Considering the relationship between material flow (including CO_2/GHG emissions) and cash flow, based on the MFCA concept, it seems clear that CO_2/GHG emissions and CFP are closely tied together. Specifically, this is because manufacturing companies purchase raw materials from suppliers and process products, exhausting CO_2/GHG emissions, and sell those products to consumers. These economic activities are supported by funds from financial and stock markets.

Regarding the second question (why absolute CEP is not often popular), the two reasons are, intuitively, that absolute CEP and relative CEP are different from each other and that, compared to relative CEP, absolute CEP often has an uncertain relationship with CFP. Numerically, absolute and relative CEP are clearly different because absolute CEP takes a size value (e.g., the amount of CO_2 reduction) while relative CEP takes a ratio value (e.g., CO_2 emissions per sales). Meanwhile, CFP often takes a ratio value (e.g., ROA is equal to profit divided by total assets) rather than a size value (e.g., sales). Therefore, we expect CFP to more often be correlated to relative CEP than to absolute CEP because of numerical sense. Note, however, that this idea is just intuitive and has no scientific form. Thus, as research motivation, this study aims to integrate absolute and relative CEP as well as CFP in a simple framework because both absolute and relative CEP are important for sustainable development.

Regarding the third question (why accounting-based CFP is not robustly correlated with CEP), we suppose that one of the reasons is the measurement of accounting-based CFP. For example, ROA is the most widely represented CFP in the literature and is usually expressed as profit (return) divided by total assets. We here consider ROA to be potentially unstable for two reasons. First, profit (return, the numerator) is uncertain because it is the remaining factor that is calculated by sales minus all costs, which are affected by various factors. Thus, the profit often takes a negative value. Second, ROA itself is affected by several factors, leading to it being unstable. Because a given manufacturing sector usually puts much importance on the cost of goods sold (COGS) and sales, ROA can be divided into the following three factors: profit divided by COGS (as profitability), COGS divided by sales (as the proportion of operation), and sales divided by total assets (as the efficiency of the funds [or cash flow]). Because these changes (the profitability, the proportion of operation, and the efficiency of the funds) do not always match, ROA can be unstable (affected by various factors). In this way, accounting-based CFP is usually decomposed into different, smaller units. As motivation for this study, this kind of decomposition can lead to a structural understanding of the relationship between CEP and CFP because the literature does not much focus on this kind of decomposition in its empirical models.

Based on the above motivations, the contribution of this study to the literature is to propose a single model that integrates corporate CO_2/GHG emissions and financial factors (based on corporate accounting). Specifically, this study improves Kaya identity (Kaya and Yokoburi, 1998; Raupach et al., 2007) for corporate analysis. The model of this study decomposes CO_2, direct + indirect GHG (Scope 1+2), and supply-chain (or corporate value-chain) GHG emissions (Scope 1+2+3) into financial factors. The CO_2 model decomposes CO_2 emissions into CO_2 intensity (carbon intensity), energy intensity, the cost-to-sales ratio (or COGS-to-sales ratio [COGSR]), the total-assets-turnover ratio (TATR), leverage, and equity. The model of direct + indirect GHG emissions (Scope 1+2) uses GHG intensity instead of CO_2 intensity, and the model of supply-chain GHG emissions (Scope 1+2+3) additionally adopts supply-chain intensity. This study proposes to use the log-mean Divisia index (LMDI) as the model's decomposition method (Ang, 2004, 2015; Ang and Zhang, 2000; Cansino et al., 2015; Chapman et al., 2018; Chong et al., 2015; Fujii, 2016; Fujii and Managi, 2016; Fujii et al., 2016, 2017; Kwon et al., 2017; Wang et al., 2014b).

The specific research contribution is that this study integrates absolute and relative CEP and part of CFP. Previous studies often adopt ad-hoc regression models, where the dependent variable is absolute or relative CEP and the key independent variable is (accounting-based or market-based) CFP, controlling for other firm-specific effects. However, the ad-hoc regression models do not fully show the structure of the relationships among absolute and relative CEP and CFP. The model of this study is an identity equation of CO_2/GHG emissions as absolute CEP. Because the identity equation has no errors, the model can provide the detailed effects of all terms as the whole structure. In addition, the model considers the decomposition of relative CEP and CFP to understand the relationship between CEP and CFP structurally. It considers part of the relative CEP (carbon intensity and energy intensity), part of ROA (COGSR and TATR), and part of ROE (i.e., leverage, because ROE is equal to ROA times leverage). The model also includes the scale effect (equity) due to considering absolute CEP as a size value (i.e., as noted above, the size values of CEP-CFP tend to be correlated with each other numerically). This kind of model development using the identity equation (e.g., Kaya identity) is seldom conducted, as shown in our review and Busch and Lewandowski (2017). As to limitations, the model of this study does not consider profit (return) because it often takes zero or a negative value (i.e., zero or a negative value is not appropriate for the identity equation). Nevertheless, we believe that the model of this study is useful for understanding the relationship between CEP and CFP structurally.

Given data availability, this study targets 225 Japanese listed firms in 16 manufacturing sectors for the fiscal years (FY) 2011 to 2015 as an application example of a CO_2 decomposition model among the three models. Because FY2011 is the year after the Great East Japan Earthquake (GEJE) (March 2011), this study investigates how CO_2 emissions changed as the supply of electricity recovered in that period (Hayashi, 2012; Hayes et al., 2017; Managi and Guan, 2017).

Results of the entire sample show that the change in CO_2 emissions as of 2015 (−802.1 thousand tonnes [kilotonnes, kt]) is decomposed into 2922.5 kt for carbon intensity, −26036.3 kt for energy intensity, −6350.5 kt for the COGSR, −8495.6 kt for the TATR, −7912.3 kt for leverage, and 45070.1 kt for equity. Hence, the largest positive and negative factors at the aggregated level are equity and energy intensity, respectively. Average values of relative contribution ratios (or explained portions of relative variations in corporate CO_2 emissions) are 20.6% by CO_2 intensity, 19.1% by energy intensity, and the remaining approximately 60% by financial factors. Note that the relative contribution ratios refer to how a particular term (i.e., each of the six terms) changes between certain periods relative to the remaining (five) terms in the model.

Among the 16 sectors, as of 2015, the change in total CO_2 emissions is statistically significantly positive for equity and significantly negative for the TATR and leverage, and it is not significantly correlated to the carbon intensity, the energy intensity, or the COGSR. Regarding the first question above, this thus indicates that absolute CEP is not significantly correlated to relative CEP (carbon intensity and energy intensity). In addition, this study finds that the effects of carbon intensity and energy intensity are significantly negatively correlated with each other, indicating that relative CEP consists of the adverse factors. Similarly, it finds that the effects of the COGSR and the TATR (which are part of ROA as CFP) are significantly positively correlated with each other, indicating that ROA also consists of the adverse factors. Therefore, regarding the second and third questions above, these results imply that both relative CEP and ROA (as CFP) may be unstable indicators because they respectively have two contrasting effects on CO_2 emissions (as absolute CEP).

The structure of this study is organized as follows. As the background of this study, Section

2 examines the literature on the CSP-CFP relationship. Section 3 shows how this study treats CO_2/GHG (Scope1+2+3) emissions and financial factors, based on MFCA. Section 4 proposes the models that decompose CO_2, direct + indirect GHG (Scope 1+2), and supply-chain GHG emissions (Scope 1+2+3) into financial factors and the application method of LMDI. As an application example, Section 5 adopts the CO_2 decomposition model using data from Japanese manufacturing firms from FY2011 to FY2015. Finally, Section 6 concludes.

2. Background: literature on the CSP-CFP relationship

Looking at the literature on company analysis in the energy and environmental fields, activities exhausting CO_2/GHG emissions are often regarded as types of CSR activities (Busch and Hoffmann, 2011). One of the key themes in the CSR literature is to examine the relationship between CSP and CFP (Aguinis and Glavas, 2012; Carroll and Shabana, 2010). In particular, 127 empirical studies have been found from 1972 to 2002 (Griffin and Mahon, 1997; Margolis and Walsh, 2003; Roman et al., 1999). Some studies support the positive relationship between CSP and CFP (CSP enhances CFP or vice versa), whereas others show a negative or no relationship between the two. In recent years, it has been recognized that it is important to investigate not only the simple correlation between CSP and CFP but also the structure and mediating and moderating variables for the relationship (Aguinis and Glavas, 2012; Carroll and Shabana, 2010).

Following the growing awareness of climate-change issues, the discussion of CSP has been shifting to CEP, such as CO_2/GHG emissions performance, in recent years (for discussion, see Busch and Hoffmann, 2011). Recent empirical studies have examined the relationship between CEP of CO_2/GHG emissions (and its management efforts) and CFP, which often includes ROA, ROE, ROI, and ROS (as profitability), and Tobin's q (Busch and Hoffmann, 2011; Capece et al., 2017; Delmas et al., 2015; Fujii et al., 2013; Hatakeda et al., 2012; Nishitani et al., 2014; Wang et al., 2014a).

Busch and Hoffmann (2011) were the first in recent years to conduct a typical empirical study examining the relationship between CO_2/GHG emissions performance (as CEP) and ROA, ROE, and Tobin's q (as CFP), carefully reviewing the CSP-CFP literature. They analyze 174 firms in the Dow Jones Global Index in 2007, uniquely classifying CEP into outcome-based and process-based CEP. Their three hypotheses are: 1) outcome-based CEP is positively associated with CFP; 2) process-based CEP is negatively associated with CFP; and 3) process-based CEP moderates the effects of outcome-based CEP. The results indicate that outcome-based CEP is positively associated with Tobin's q and process-based CEP is negatively associated with ROE and Tobin's q. However, they have no evidence that process-based CEP moderates the effects of outcome-based CEP.

Wang et al. (2014a) examine whether an increase in CO_2 emissions affects Tobin's q using data of 69 listed firms in ASX200 (Australian Securities Exchange) in 2000. Estimated elasticity is significantly positive, ranging from 0.26 to 0.3. In addition, they find the carbon emissions can explain 6.2% of the variation in Tobin's q.

Hatakeda et al. (2012) investigate the relationship between GHG emissions performance (which is GHG emissions times 3,000 Japanese yen [JPY] divided by total assets) and profitability (ROA). Using data of 1,089 Japanese listed firms of manufacturing industries in FY2006, results show that GHG emissions performance is positively related to profitability.

Fujii et al. (2013) examine whether environmental efficiency (EE) affects CFP (ROA, ROS, and capital turnover). They use two proxy variables of EE, sales per CO_2 emissions using 758 observations from 2006 to 2008, and sales per toxic release using 2,498 observations between 2001 and 2008. Results show that EE of CO_2 emissions is positively related to ROA. Meanwhile, the EE of toxic release is positively related to ROS and has an inverted-U relationship for ROA and capital turnover.

While the above four studies (Busch and Hoffmann, 2011; Fujii et al., 2013; Hatakeda et al., 2012; Wang et al., 2014a) use common ad-hoc regression models, Nishitani et al. (2014) and Capece et al. (2017) derive regression models based on the Cobb-Douglas production function, examining whether corporate management of CO_2/GHG emissions affects CFP. Nishitani et al. (2014) examine whether the degree of GHG emissions management (CO_2 management score, CO_2 emissions score, and CO_2 reduction score) affects CFP (net sales over raw materials expense), using data of 423

Japanese manufacturing firms between 2007 and 2008. Results show that GHG emissions management enhances CFP through an increase in demand and improvement in productivity (except for energy-intensive firms). Meanwhile, Capece et al. (2017) empirically show that the adoption of an environmental management system and CO_2 emissions management enhance ROI, using data from 237 Italian companies from 2008 to 2013. However, this enhancing effect varies among sectors, and they find the positive effect in six sectors (paper, non-metal minerals, food, textiles, chemical, and other activities) and negative effect in two sectors (energy and metals).

These series of studies show that CO_2/GHG emissions performance and management efforts are likely to be positively related to CFP (except for energy-intensive sectors). Note, however, that some studies indicate that there is more likely to be a positive relationship between CEP and CFP for market-based CFP (e.g., Tobin's q) than accounting-based CFP (e.g., ROA). Delmas et al. (2015) examine the relationship between CEP and CFP using a dataset of 1,095 U.S. firms from 2004 to 2008. Their regression model adopts total GHG emissions (absolute emissions) as a negative CEP and ROA and Tobin's q as accounting-based and market-based CFP, respectively, adding to other control variables. The result shows that there is a positive relationship between CEP and Tobin's q and a negative relationship between CEP and ROA (i.e., total GHG emissions have a negative effect on Tobin's q and a positive effect on ROA).

Recently, Busch and Lewandowski (2017) have conducted a meta-analysis for the relationship between corporate carbon (as part of CEP) and CFP. This analysis reviewed 68 individual estimates from 32 studies (26 journal articles and 6 working papers examining firms in North America, Europe, and Asia) between 2010 and 2016. One of the most important characteristics of this review is the measurement perspective of carbon performance and CFP. Two measurements of carbon performance are relative emissions based on annual emissions (i.e., emission ratios or carbon efficiency) and absolute emissions (e.g., actual emission reductions between two or more years). Similarly, two measurements of CFP are accounting-based (e.g., ROA) and market-based (e.g., Tobin's q). The review uniquely categorizes the 68 estimates in terms of carbon performance measurement and CFP. The former characteristics are reporting scheme (mandatory [25 estimates] or voluntary [43 estimates]), emission scope (direct [31 estimates] or direct + indirect [37 estimates]), standardization (absolute [15 estimates] or emission ratio [53 estimates]), and perspective (current [60 estimates] or reduction [8 estimates]). The latter characteristic is whether measurements are accounting-based [36 estimates] or market-based [32 estimates].

Among the 68 estimates, the relationship between CEP and CFP can be divided into positive correlations for 46 estimates, negative correlations for 16 estimates, and no correlation for 6 estimates. Thus, the majority of estimates support a positive relationship. However, Busch and Lewandowski (2017) argue that this tendency is different due to the measurement characteristics. Regarding CFP measurement (accounting-based and market-based), the 36 estimates with accounting-based CFP show positive, negative, and no correlations for 22, 12, and 2 estimates, respectively, whereas the 32 estimations with market-based CFP indicate positive, negative, and no correlations for 24, 4, and 4 estimations, respectively. This indicates that market-based CFP is more likely to support a positive relationship between CEP and CFP than accounting-based CFP. Meanwhile, regarding the standardization of CEP (relative emissions [53 estimations] and absolute emissions [15 estimations]), the meta-analysis shows that relative CEP (relative emissions) is significantly positively related to CFP but absolute CEP (absolute emissions) is not significantly related to CFP. In summary, Busch and Lewandowski (2017) conclude “that climate change mitigation does not yet have the financial relevance it deserves” because their meta-analysis supports a positive relationship between CEP and CFP only for relative CEP improvements but not for absolute CEP.

3. Research perspective regarding CEP-CFP

3.1 The structural relationship between CEP and CFP based on material and cash flow

As shown above, the literature often supports a positive relationship between CEP and CFP. However, there are differences depending on the types of measurement. Regarding CFP, a positive relationship is more likely to be robust for market-based CFP than accounting-based CFP. Regarding CEP, a positive relationship is likely to be supported by using relative CEP (e.g., carbon efficiency) but not by using absolute CEP (e.g., carbon reductions).

Based on this background, this study aims to understand the structure of the CEP-CFP relationship from the viewpoint of accounting variables (including accounting-based CFP) rather than market-based variables. In other words, it aims to examine why the relationship of CEP-CFP is often positive but sometimes not robust. It investigates the relationships among absolute CEP, relative CEP, and accounting-based CFP in a simple framework. We propose that understating the relationships will be useful for corporate managers and industrial policymakers seeking to predict and mitigate corporate CO_2/GHG emissions with corporate activity.

In considering absolute and relative CEP and accounting-based CFP, this study focuses on a company's material flow and cash flow. This is because manufacturing companies purchase raw materials from suppliers and process products, exhausting CO_2/GHG emissions, and sell products to consumers; these economic activities are supported by funds from financial and stock markets. Therefore, the higher the energy efficiency (lower cost, lower emissions), the better the flow of cash and funds (and vice versa). Thus, rather than empirically examining the relationship between CO_2/GHG and CFP, the motivation of this study is to integrate CO_2/GHG emissions and financial factors in a single model.

In devising a model that integrates CO_2/GHG emissions and financial factors, Figure 1 explains how this study treats CO_2/GHG emissions in corporate accounting, based on material and cash flow. This study adopts as analogy the idea of MFCA, which considers both corporate material and cash flow, as an accounting tool. The reason this study adopts the idea of MFCA is that we consider CEP as related to material flow (including CO_2/GHG emissions) and CFP consists of cash flow, as in MFCA.

MFCA is an accounting method that combines cost accounting and material flow management and is an effective management tool for improving corporate material efficiency through material flow transparency (APO, 2014). Since MFCA is standardized by ISO as ISO 14051 and 14052 (ISO, 2011, 2017), it has become easier for firms to implement MFCA (for the history of MFCA, see Wagner, 2015; for a general explanation, see Bierer et al., 2015; Christ and Burritt, 2015; Guenther et al., 2015; Kokubu and Kitada, 2015; Rieckhof et al., 2015; Schaltegger and Zvezdov, 2015). MFCA divides COGS into the material cost (MC), energy cost (EC), system cost (SC, which consists of other costs, such as the labor cost), and waste management cost (WMC) (APO, 2014). These costs are further divided into positive products (usual products) and negative products (waste and/or recycled items) and are allocated in each quantity center.

This subsection discusses a series of basic corporate behaviors: purchasing, production, sales, and financing. Suppose a manufacturing firm emits CO_2/GHG and waste as two kinds of absolute emissions (as negative CEP), based on material and cash flow. We believe that it will be possible to structurally understand the relationships among absolute and relative CEP and accounting-based CFP by taking into account raw materials (as input factors); CO_2/GHG emissions, waste, and products (as outputs); and energy use (as intermediate inputs). Thus, the framework of this study is versatile, as it can be applied not only to CO_2/GHG emissions but also to waste analysis.

Figure 1 shows a simple model of material (a straight line) and cash (a dotted line) flows in a manufacturing firm, treating raw materials used, positive products, waste (negative product), and CO_2/Scope 1+2+3 for simplification purposes. Here CO_2 refers to direct + indirect CO_2 emissions. For simplification, EC is assumed to be incurred only in the manufacturing process, including all energy use in a firm. Note that Scope 1 is direct GHG emissions (in a narrow sense) by a company, and Scope 2 is indirect GHG emissions from purchased energy (see the GHG protocol, as in WRI and WBCSD, 2004). Therefore, Scope 1+2 comprises direct + indirect GHG emissions, which the previous studies refer to for CEP. In recent years, Scope 3 has been developed as supply-chain GHG emissions within a corporate value chain (i.e., GHG emissions from activities outside a company, such as resource harvesting, production, and transportation) (WRI and WBCSD, 2011). This consists of GHG emissions from 15 categories, both upstream and downstream of the corporate operations.

From the left in Figure 1, raw materials (for negative and positive products) are purchased from suppliers, causing MC. The purchased materials are then made into the negative and positive products, causing EC and SC (EC&SC). From here, the flows of negative (upper) and positive (lower) products are different from each other. The negative product is processed as waste and dealt with accordingly outside the firms, causing WMC. Note that the waste is assumed to be partially recycled into a MC process for simplicity. Meanwhile, the positive product does not cause WMC because it is not wasted; rather, it is managed for sales, causing selling, general, and administrative expenses (SGA), and sold to customers in the product markets, causing customers' payment (as sales). Conversely, waste (negative product) causes costs in order of WMC, EC&SC, and MC, whereas the positive product causes costs in order of SGA, EC&SC, and MC. In addition, the payment from customers is equal to sales, which consists of COGS, SGA, and (operation) profit. Therefore, customers incur not only profits and all costs of positive products, but also all costs of negative products. In other words, customers do not receive the negative product but indirectly buy it. As another feature, these corporate activities are supported by funds (debt plus equity) from financial and stock markets.

While the above flows are based on the MFCA concept, this study extends the idea to CO_2/GHG emissions. In the process of EC&SC, a firm pays EC, causing CO_2/Scope 1+2. Thus, conversely, CO_2/Scope 1+2 emissions cause costs in order of EC&SC and MC for both of the negative and positive products. Customers do not receive but indeed indirectly buy CO_2/GHG emissions. Thus, CO_2/GHG emissions are directly linked to financial factors.

In summary, absolute emissions seem closely related to relative CEP and CFP. As shown in Figure 1, absolute emissions (CO_2/GHG) are caused primarily by energy use (or EC), indicating that carbon/GHG intensity is important for absolute emissions. Meanwhile, EC relies largely on COGS (the manufacturing process) and sales; hence, for smaller EC, COGS and sales are more advantageous in reducing the absolute emissions. Similarly, sales activity is supported by funds and higher leverage (more efficient funds) and more equity (more scale) tend to cause greater absolute emissions.

3.2 Decomposition of the relative CEP and CFP

Based on the background of the relationship between CEP and CFP, we need to understand CEP and CFP in a more detailed way. This may explain why the relationship between CEP and accounting-based CFP is occasionally not robust.

Regarding CEP, absolute CEP refers to just the absolute emissions (CO_2/GHG) or their reduction and has little room for misunderstanding. On the other hand, in the literature, relative CEP usually refers to the emissions amount divided by an accounting variable (e.g., sales and total assets). We suppose that relative CEP can be unstable because it includes two different factors: carbon intensity and energy intensity. For example, suppose CO_2 emissions (CO2) divided by sales as a representative relative CEP is decomposed:

$$\frac{CO2}{Sales} = \frac{CO2}{Energy} \cdot \frac{Energy}{Sales} \tag{1}$$

where Energy stands for energy use. To improve carbon intensity, the choice of energy source is usually important. To improve energy intensity, meanwhile, general energy conservation is important.

As with the relative CEP, CFP also consists of several factors. For example, we can decompose ROA (profit divided by total assets), the most representative CFP, as follows:

$$\begin{aligned} ROA &= \frac{Profit}{COGS} \cdot \frac{COGS}{Sales} \cdot \frac{Sales}{Assets} \\ &\left(= \frac{Profit}{Margin} \cdot \frac{Margin}{Sales} \cdot \frac{Sales}{Assets} \right) \end{aligned} \tag{2}$$

where COGS is equal to sales minus gross margin (denoted by Margin). Because COGS and gross margin are inextricably linked based on the sales, equation 2 has two versions (upper for COGS and lower for the gross margin). The first term is profitability in a narrow sense, meaning the amount of profit generated by the operation process (or gross margin). The second term is the COGSR, which means the proportion of the operating process. The third term is the TATR, which is the efficiency of the company's funds (assets). Thus, ROA may be somewhat unstable due to consisting of three different factors. ROA is also unstable because the profit (the numerator of CFP) often changes easily. This is because profit is the remainder from sales minus all costs and hence often takes a negative value.

For the same reason, other CFP may be also unstable. For example, ROE, as another representative CFP, is equal to ROA times leverage (i.e., total assets divided by total equity). Therefore, because of the leverage, ROE is expected to be more unstable than ROA.

In summary, we first argue that the positive relationship in the literature between CEP and accounting-based CFP is natural because CO_2/GHG emissions are generated by corporate funds (cash flow). In other words, a better CFP (more fluent cash flow) tends to lead to a better CEP (more fluent material flow) (and vice versa). Second, we suppose that the reason why the relationship of CEP and accounting-based CFP is occasionally not robust is probably because they each consist of several different factors. Relative CEP usually consists of carbon intensity and energy intensity, while ROA, as the representative CFP, is decomposed into profitability, operational proportion, and TATR. Based on these discussions, it is necessary as the motivation of this study to not only verify whether the relationship between CEP and CFP is positive or negative but also understand the structure of that relationship.

4. Model

4.1 Identity equations of CO_2/GHG emissions

The contribution of this study to the literature is to propose a single model that integrates each of corporate CO_2/GHG emissions and financial factors. Specifically, this study improves the Kaya identity for corporate analysis. The Kaya identity is one of the most popular models that decomposes CO_2/GHG emissions (Kaya and Yokoburi, 1998; Raupach et al., 2007). This study finds 94 articles (including 64 journal articles) published by 2017 in the academic literature by using "kaya identity" as keywords in the topic search of Web of Science (Thomson Reuters' journal database). It is usually expressed by the following formula for CO_2 (or GHG):

$$CO2 = \frac{CO2}{Energy} \cdot \frac{Energy}{GDP} \cdot \frac{GDP}{Pop} \cdot Pop \tag{3}$$

The amount of CO_2 emissions is decomposed by the product of the following four terms. The first term is carbon intensity (CO_2 intensity), which is CO_2 per unit of energy use [Energy]). The second term is energy intensity (energy use per unit gross domestic product [GDP]). The third term is GDP per capita, which is a proxy for the degree of economic activity. The fourth term is the national population, indicating the magnitude of the scale.

The Kaya identity is useful for macro analysis but not especially suited for corporate analysis because GDP (value added) and population, in particular, are rarely considered in corporate accounting. Therefore, based on the Kaya identity, this study proposes simple new models that decompose CO_2/GHG emissions into financial factors. The CO_2 model is expressed as follows:

$$\begin{aligned} CO2 &= \frac{CO2}{Energy} \cdot \frac{Energy}{COGS} \cdot \frac{COGS}{Sales} \cdot \frac{Sales}{Assets} \cdot \frac{Assets}{Equity} \cdot Equity \\ &= CO2Int \cdot EneInt \cdot COGSR \cdot TATR \cdot AtER \cdot Equity \end{aligned} \tag{4}$$

Equation 4 decomposes CO_2 emissions on the left-hand side (LHS) into the following six terms. The first term is CO_2 intensity (COInt; carbon intensity), or CO_2 divided by energy consumption. This is the same as in the Kaya identity. The second term is (corporate) energy intensity (EneInt), which is energy use divided by COGS. This indicates how much energy is consumed compared to the production cost (energy pressure over production cost). The third to sixth terms are common financial factors. The third term is the COGSR, which is COGS divided by sales (the cost ratio). The fourth term is the TATR, which is sales divided by total assets. The fifth term is the total-assets-to-equity ratio (AtER), indicating the degree of leverage. The sixth term is total equity (Equity), which is proxy for firm size.

Although basic interpretations of the third to sixth terms are provided, this study performs an additional interpretation from a management (or stakeholder) perspective. The COGSR is considered an indicator of operation pressure because relatively higher COGS (numerator) values mean that firms depend on a higher proportion of value creation than other financial factors (gross margin). The TATR is interpreted as market pressure because a higher sales (numerator) value means that the firm will face a larger market (more money in the market). The AtER is an internal firm decision but is considered as financial market pressure because debt (part of the numerator) is brought from the financial market. In addition, equity is considered stock market pressure simply because of the funds coming from the stock market.

We note that each decomposed factor in the model, as well as the Kaya identity, does not always have the positive relationship with CO_2 emissions (for example, Raupach et al. (2007) show that some terms in the Kaya identity have changed negatively from 1980 to 2004 although the total CO_2 emissions have increased during the period). We also note that if researchers cannot obtain certain financial variables, because the third to sixth terms in Equation 4 are canceled out, Equation 4 can be further simplified. An example equation is

$$CO2 = \frac{CO2}{Energy} \cdot \frac{Energy}{Sales} \cdot Sales \tag{5}$$

Energy use per sales (the second term) denotes another energy intensity and sales denotes another size variable.

This study further proposes models that decompose each of Scope 1+2 (direct + indirect GHG emissions) and Scope 1+2+3 (supply-chain GHG emissions) as follows. Equation 6 decomposes Scope 1+2 (denoted by S12) as follows:

$$\begin{aligned} S12 &= \frac{S12}{Energy} \cdot \frac{Energy}{COGS} \cdot \frac{COGS}{Sales} \cdot \frac{Sales}{Assets} \cdot \frac{Assets}{Equity} \cdot Equity \\ &= GHGInt \cdot EneInt \cdot COGSR \cdot TATR \cdot AtER \cdot Equity \end{aligned} \tag{6}$$

The first term is GHG intensity, which is Scope 1+2 divided by energy use, instead of CO_2 intensity in equation 4. Meanwhile, equation 7 decomposes Scope 1+2+3 (denoted by S123) as follows:

$$\begin{aligned} S123 &= \frac{S123}{S12} \cdot \frac{S12}{Energy} \cdot \frac{Energy}{COGS} \cdot \frac{COGS}{Sales} \cdot \frac{Sales}{Assets} \cdot \frac{Assets}{Equity} \cdot Equity \\ &= SCInt \cdot GHGInt \cdot EneInt \cdot COGSR \cdot TATR \cdot AtER \cdot Equity \end{aligned} \tag{7}$$

The first term is supply chain intensity (SCInt). It is more greatly increased to the extent that other companies in the supply chain exhaust more GHG emissions (Scope 1+2+3) compared to a certain firm's direct + indirect GHG emissions (Scope 1+2).

4.2 LMDI

Because equations 4, 6, and 7 are just identity equations, this study uses index decomposition analysis (IDA) to identify the degrees of contribution in each term. Two approaches are popular in the literature of the decomposition analysis: structural decomposition analysis (SDA) (Su and Ang, 2012), and IDA (Ang, 2004; Ang and Zhang, 2000; Cansino et al., 2015). Typically, IDA is easier to adopt than SDA because it requires only the aggregated data (Ang, 2015). In IDA, LMDI is a popular method for the analysis of energy and CO_2 emissions usually based on the IPAT equation and Kaya identity (for recent studies, see Cansino et al., 2015; Chapman et al., 2018; Chong et al., 2015; Fujii, 2016; Fujii and Managi, 2016; Fujii et al., 2016; Fujii et al., 2017; Kwon et al., 2017; Wang et al., 2014b).

Because equations 4, 6, and 7 are similar to each other, this study shows LMDI for equation 4 (see Appendix for LMDI of equations 6 and 7). For identity equations, LMDI decomposes the change between two periods on LHS into each of the change rates on the right-hand side (RHS). The two periods usually refer to the base (beginning) and other years. Suppose there are i firms in j sectors from the base year 0 to a certain year t, and summation of the change in CO_2 emissions (ΔCO2) of j-th sector from years 0 to t is expressed as follows:

$$\begin{aligned}\sum_i \Delta CO2_{ij}^t &= \sum_i \left(CO2_{ij}^t - CO2_{ij}^0 \right) \\ &= \sum_i \Delta CO2Int_{ij}^t + \sum_i \Delta EneInt_{ij}^t + \sum_i \Delta COGSR_{ij}^t + \sum_i \Delta TATR_{ij}^t \\ &\quad + \sum_i \Delta AtER_{ij}^t + \sum_i \Delta Equity_{ij}^t\end{aligned} \tag{8}$$

where

$$\Delta CO2Int_{ij}^t = \begin{cases} 0, & \text{if } CO2_{ij}^t - CO2_{ij}^0 = 0 \\ L\left(CO2_{ij}^t, CO2_{ij}^0\right) \ln\left(CO2Int_{ij}^t / CO2Int_{ij}^0\right), & \text{if } CO2_{ij}^t - CO2_{ij}^0 \neq 0 \end{cases} \tag{9}$$

$$\Delta EneInt_{ij}^t = \begin{cases} 0, & \text{if } CO2_{ij}^t - CO2_{ij}^0 = 0 \\ L\left(CO2_{ij}^t, CO2_{ij}^0\right) \ln\left(EneInt_{ij}^t / EneInt_{ij}^0\right), & \text{if } CO2_{ij}^t - CO2_{ij}^0 \neq 0 \end{cases} \tag{10}$$

$$\Delta COGSR_{ij}^t = \begin{cases} 0, & \text{if } CO2_{ij}^t - CO2_{ij}^0 = 0 \\ L\left(CO2_{ij}^t, CO2_{ij}^0\right) \ln\left(COGSR_{ij}^t / COGSR_{ij}^0\right), & \text{if } CO2_{ij}^t - CO2_{ij}^0 \neq 0 \end{cases} \tag{11}$$

$$\Delta TATR_{ij}^t = \begin{cases} 0, & \text{if } CO2_{ij}^t - CO2_{ij}^0 = 0 \\ L\left(CO2_{ij}^t, CO2_{ij}^0\right) \ln\left(TATR_{ij}^t / TATR_{ij}^0\right), & \text{if } CO2_{ij}^t - CO2_{ij}^0 \neq 0 \end{cases} \tag{12}$$

$$\Delta AtER_{ij}^t = \begin{cases} 0, & \text{if } CO2_{ij}^t - CO2_{ij}^0 = 0 \\ L\left(CO2_{ij}^t, CO2_{ij}^0\right) \ln\left(AtER_{ij}^t / AtER_{ij}^0\right), & \text{if } CO2_{ij}^t - CO2_{ij}^0 \neq 0 \end{cases} \tag{13}$$

$$\Delta Equity_{ij}^{t} = \begin{cases} 0, & if\ CO2_{ij}^{t} - CO2_{ij}^{0} = 0 \\ L\left(CO2_{ij}^{t}, CO2_{ij}^{0}\right) \ln\left(Equity_{ij}^{t} / Equity_{ij}^{0}\right), & if\ CO2_{ij}^{t} - CO2_{ij}^{0} \neq 0 \end{cases} \tag{14}$$

$$L\left(CO2_{ij}^{t}, CO2_{ij}^{0}\right) = \frac{CO2_{ij}^{t} - CO2_{ij}^{0}}{\ln CO2_{ij}^{t} - \ln CO2_{ij}^{0}} \tag{15}$$

Each term (ΔCO2Int, ΔEneInt, ΔCOGSR, ΔTATR, ΔAtER, and ΔEquity) represents a contribution to the change in waste (ΔCO2), which denotes how much each term explains changes in CO_2 emissions (ΔCO2). From the above equations, ΔCO2 is expressed as the sum of equations 9 to 14:

$$\begin{aligned} \Delta CO2_{ij}^{t} &= \Delta CO2Int_{ij}^{t} + \Delta EneInt_{ij}^{t} + \Delta COGSR_{ij}^{t} + \Delta TATR_{ij}^{t} + \Delta AtER_{ij}^{t} + \Delta Equity_{ij}^{t} \\ &= \Big\{ \ln\left(CO2Int_{ij}^{t} / CO2Int_{ij}^{0}\right) + \ln\left(EneInt_{ij}^{t} / EneInt_{ij}^{0}\right) + \ln\left(COGSR_{ij}^{t} / COGSR_{ij}^{0}\right) \\ &\quad + \ln\left(TATR_{ij}^{t} / TATR_{ij}^{0}\right) + \ln\left(AtER_{ij}^{t} / AtER_{ij}^{0}\right) + \ln\left(Equity_{ij}^{t} / Equity_{ij}^{0}\right) \Big\} \\ &\quad \times \Delta CO2_{ij}^{t} \Big/ \ln\left(CO2_{ij}^{t} / CO2_{ij}^{0}\right) \end{aligned} \tag{16}$$

When ΔCO2 is not equal to zero, based on the index number, the contribution ratios sum up to 100% as follows:

$$100\% = \frac{\Delta CO2Int_{j}^{t}}{\Delta CO2_{j}^{t}} + \frac{\Delta EneInt_{j}^{t}}{\Delta CO2_{j}^{t}} + \frac{\Delta COGSR_{j}^{t}}{\Delta CO2_{j}^{t}} + \frac{\Delta TATR_{j}^{t}}{\Delta CO2_{j}^{t}} + \frac{\Delta AtER_{j}^{t}}{\Delta CO2_{j}^{t}} + \frac{\Delta Equity_{j}^{t}}{\Delta CO2_{j}^{t}} \tag{17}$$

Note that because the numerators of each term in equation 17 are the product terms of ΔCO2 (see equations 9 to 15), the ΔCO2 of numerators and denominators can be canceled out. Thus, the sum of the change ratios of each term in log form divided by the change rate of CO_2 in log form ($\ln(CO2^t/CO2^0)$) is 100%:

$$\begin{aligned} 100\% &= \Big\{ \ln\left(CO2Int_{ij}^{t} / CO2Int_{ij}^{0}\right) + \ln\left(EneInt_{ij}^{t} / EneInt_{ij}^{0}\right) + \ln\left(COGSR_{ij}^{t} / COGSR_{ij}^{0}\right) \\ &\quad + \ln\left(TATR_{ij}^{t} / TATR_{ij}^{0}\right) + \ln\left(AtER_{ij}^{t} / AtER_{ij}^{0}\right) \\ &\quad + \ln\left(Equity_{ij}^{t} / Equity_{ij}^{0}\right) \Big\} \Big/ \ln\left(CO2_{ij}^{t} / CO2_{ij}^{0}\right) \end{aligned} \tag{18}$$

In addition, each contribution ratio (equation 17) is equal to each change ratio divided by

($\ln(CO2^t/CO2^0)$) (equation 18), as follows:

$$\frac{\Delta CO2Int_{ij}^t}{\Delta CO2_{ij}^t}=\frac{\ln\left(CO2Int_{ij}^t / CO2Int_{ij}^0\right)}{\ln\left(CO2_{ij}^t / CO2_{ij}^0\right)};\frac{\Delta EneInt_{ij}^t}{\Delta CO2_{ij}^t}=\frac{\ln\left(EneInt_{ij}^t / EneInt_{ij}^0\right)}{\ln\left(CO2_{ij}^t / CO2_{ij}^0\right)}$$
$$\frac{\Delta COGSR_{ij}^t}{\Delta CO2_{ij}^t}=\frac{\ln\left(COGSR_{ij}^t / COGSR_{ij}^0\right)}{\ln\left(CO2_{ij}^t / CO2_{ij}^0\right)};\frac{\Delta TATR_{ij}^t}{\Delta CO2_{ij}^t}=\frac{\ln\left(TATR_{ij}^t / TATR_{ij}^0\right)}{\ln\left(CO2_{ij}^t / CO2_{ij}^0\right)}; \tag{19}$$
$$\frac{\Delta AtER_{ij}^t}{\Delta CO2_{ij}^t}=\frac{\ln\left(AtER_{ij}^t / AtER_{ij}^0\right)}{\ln\left(CO2_{ij}^t / CO2_{ij}^0\right)};\frac{\Delta Equity_{ij}^t}{\Delta CO2_{ij}^t}=\frac{\ln\left(Equity_{ij}^t / Equity_{ij}^0\right)}{\ln\left(CO2_{ij}^t / CO2_{ij}^0\right)}$$

Each of the change rates (equations 17 and 18) is helpful for understanding each contribution to the change in CO_2 emissions. However, each term (ratio) may often be sensitive to outliers because of the lack of an error term. Therefore, to examine the relative degrees of contribution in each term, this study proposes to calculate the relative contribution ratios of each term by taking absolute values as follows:

$$\begin{aligned}100\% = &\frac{\left|\Delta CO2Int_{ij}^t\right|}{Denom_{ij}^t}+\frac{\left|\Delta EneInt_{ij}^t\right|}{Denom_{ij}^t}+\frac{\left|\Delta COGSR_{ij}^t\right|}{Denom_{ij}^t}+\frac{\left|\Delta TATR_{ij}^t\right|}{Denom_{ij}^t}\\ &+\frac{\left|\Delta AtER_{ij}^t\right|}{Denom_{ij}^t}+\frac{\left|\Delta Equity_{ij}^t\right|}{Denom_{ij}^t}\end{aligned} \tag{20}$$

where

$$\begin{aligned}Denom_{ij}^t = &\left|\Delta CO2Int_{ij}^t\right|+\left|\Delta EneInt_{ij}^t\right|+\left|\Delta COGSR_{ij}^t\right|+\left|\Delta TATR_{ij}^t\right|\\ &+\left|\Delta AtER_{ij}^t\right|+\left|\Delta Equity_{ij}^t\right|\end{aligned} \tag{21}$$

Denom denotes a denominator in equation 20. No ratio (term) takes a negative value because they take absolute values. The relative contribution ratios of each term describe how a given term (i.e., each of the six terms) changes between certain periods, relative to the remaining (five) terms in the model. Note that this study does not calculate the relative contribution ratio when Denom = 0.

As another way of thinking, note that equations 22 and 23 have the same meaning as the relative ratios of changes in each term, as in equations 20 and 21:

$$100\% = \frac{\left|\ln\left(CO2Int_{ij}^{t} / CO2Int_{ij}^{0}\right)\right|}{Denom_{ij}^{t}} + \frac{\left|\ln\left(EneInt_{ij}^{t} / EneInt_{ij}^{0}\right)\right|}{Denom_{ij}^{t}} + \frac{\left|\ln\left(COGSR_{ij}^{t} / COGSR_{ij}^{0}\right)\right|}{Denom_{ij}^{t}}$$
$$+ \frac{\left|\ln\left(TATR_{ij}^{t} / TATR_{ij}^{0}\right)\right|}{Denom_{ij}^{t}} + \frac{\left|\ln\left(AtER_{ij}^{t} / AtER_{ij}^{0}\right)\right|}{Denom_{ij}^{t}} + \frac{\left|\ln\left(Equity_{ij}^{t} / Equity_{ij}^{0}\right)\right|}{Denom_{ij}^{t}} \quad (22)$$

where

$$\begin{aligned} Denom_{ij}^{t} = & \left|\ln\left(CO2Int_{ij}^{t} / CO2Int_{ij}^{0}\right)\right| + \left|\ln\left(EneInt_{ij}^{t} / EneInt_{ij}^{0}\right)\right| \\ & + \left|\ln\left(COGSR_{ij}^{t} / COGSR_{ij}^{0}\right)\right| + \left|\ln\left(TATR_{ij}^{t} / TATR_{ij}^{0}\right)\right| \\ & + \left|\ln\left(AtER_{ij}^{t} / AtER_{ij}^{0}\right)\right| + \left|\ln\left(Equity_{ij}^{t} / Equity_{ij}^{0}\right)\right| \end{aligned} \quad (23)$$

5. Example application to Japanese manufacturing sectors

5.1 Data

As an application example of the three proposed models considering data availability, this study demonstrates LMDI for equation 4, using data of 225 Japanese listed firms in 16 manufacturing sectors from FY2011 to FY2015. It obtains data on CO_2 emissions and energy consumption from Bloomberg Professional Service (provided by Bloomberg L.P., the U.S.), and financial data from Nikkei NEEDS-FinancialQUEST (provided by Nikkei Inc., Japan). One of the reasons it chooses Japanese manufacturing sectors is because data are relatively easy to access among countries. Among 33 sector indices of Tokyo Stock Exchanges, this study selects 16 manufacturing sectors: foods (#4, Foods), textiles and apparels (#5, Textiles), pulp and paper (#6, Pulp), chemicals (#7, Chem), pharmaceutical (#8, Pharma), oil and coal products (#9, OilCoal), rubber products (#10, Rubber), glass and ceramics products (#11, Glass), iron and steel (#12, Iron), nonferrous metals (#13, Nonferrous), metal products (#14, MetalProd), machinery (#15, Machinery), electric appliances (#16, ElecApp), transportation equipment (#17, Transport), precision instruments (#18, PrecInst), and other products (#19, Other).

This study finds 1,506 Japanese listed firms in the 16 manufacturing sectors for the period (Table 1). Table 2 indicates descriptive statistics. This study selects firms where data on financial factors (COGS, sales, assets, and equity), CO_2 emissions, and energy consumption are available for the five years. Note that data on CO_2 emissions and energy consumptions are relatively difficult to access. Also, because there often seem to be outliers of CO_2 emissions and energy consumption, probably because of record errors, this study excludes firms that have more than five-time fluctuations in CO_2 emissions or energy consumption for the period. As a result, this study selects 225 firms (225 uncensored firms), whereas there are 1,281 censored firms (see Supplementary material for the raw dataset [a comma-separated values file of the 225 firms] of this study, including information on sector, firm [identification numbers without names], year, CO_2 [co2], energy use [energy], COGS [cogs], sales, assets, and equity).

This study also notes that the fiscal year in this study refers to account-closing date from April 1 to March 31 because Japanese firms tend to adopt December or March as account-closing months. Account-closing year of FY2011 (the base year) includes the year of GEJE (March 11, 2011) (Hayes et al., 2017), and/or the next year. GEJE generated triple disasters: the biggest earthquake (magnitude 9.0) on record, tsunami, and the nuclear problem of Fukushima (Managi and Guan, 2017). According to the Fire and Disaster Management Agency, Japan (2018) (of March 1, 2018), the death toll are 19,630 people and there are 2,569 missing persons. The damage to residences is 121,781 complete destruction, and 280,962 half-destruction. Economic damage is estimated as 6% of GDP (Hayashi, 2012). Also, coastal areas were washed away, logistics and supply chains were stopped, and there were various problems such as electric power and medical problems (Managi and Guan, 2017). Therefore, this study investigates how CO_2 emissions have changed over the four years immediately after GEJE when the supply of electricity was severely disrupted.

There may be sample selection bias, because this study selects a higher number of firms that disclose more information on CO_2 emissions and energy consumption. Therefore, this study conducts t-tests to determine whether there is a difference in the average values of the two groups, censored and uncensored observations, in terms of financial items (COGS, sales, assets, and equity; unit is million JPY). In Table 3, the average values of COGS, sales, assets, and equity are 117018.3, 151272.3, 159975.8, and 69220.6 million JPY, respectively, for the censored firms (non-selected firms) and 340939.6, 448159.0, 480685.5, and 198773.9 million JPY, respectively, for the uncensored firms (the sample firms of this study). Thus, average values for the uncensored firms (the sample of this study) are higher than those for the censored firms (non-selected firms). T-values are −10.7, −11.7, −12.1, and −12.7, respectively, indicating a statistically significant difference at the 1% level. This indicates that these average values differ in a statistically significant way between the censored firms (non-selected firms) and the uncensored firms (the sample of this study). Thus, this study selects relatively large firms among the Japanese manufacturing sectors.

5.2 Results of LMDI

Table 4 shows a summation of each financial item from FY2011 to FY2015. Data in FY2011 are 289,672 kt for CO_2 emissions, 1,043,980 MWh for energy consumption, 71,061,331 million JPY for COGS, 92,833,893 million JPY for sales, 97,018,265 million JPY for total assets, and 40,385,463 million JPY for total equity. As of 2015, relative percentages (2010 = 100%) are 99.7%, 99.1%, 111.6%, 113.5%, 115.9%, and 118.8%, respectively, for CO_2 emissions, energy consumption, COGS, sales, assets, and equity. Thus, the sample firms have expanded their economic activities but decreased environmental burdens, indicating CEP has improved at the aggregated level.

Table 5 and Figure 2 (for the entire sample) show the results of LMDI. They show the results not only in FY2015 but also for other years FY2012 to FY2014, because this makes it easy to confirm the robustness of the results over years (from FY2011). Regarding the entire sample, the changes in CO_2 emissions (△CO2) are −5465.1, 4536.6, 9380.0, and −802.1 kt in FY2012 to FY2015, respectively. This indicates that the changes in CO_2 emissions do not fluctuate much at the aggregated level. The change in CO_2 emissions as of 2015 (−802.1 kt) is decomposed into 2922.5 kt for △CO2Int, −26036.3 kt for △EneInt, −6350.5 kt for △COGSR, −8495.6 kt for △TATR, −7912.3 kt for △AtER, and 45070.1 kt for △Equity. Thus, the largest positive and negative factors are △Equity (firm size) and △EneInt (energy intensity), respectively.

Regarding each sector, as of 2015, the largest positive factors of the change in CO_2 emissions are △CO2Int in 1 sector (#4), △EneInt in 1 sector (#9), △COGSR and △TATR in no sectors, △AtER in 2 sectors (#7, #16), △Equity in 12 sectors (#5, #6, #8, #10, #11, #12, #13, #14, #15, #17, #18, #19).

On the other hand, the largest negative factors are △CO2Int in no sectors, △EneInt in 9 sectors (#4, #5, #7, #10, #13, #14, #15, #17, #19), △COGSR in 1 sector (#8), △TATR in 1 sector (#11), △AtER in 3 sectors (#6, #12, #18), and △Equity in 1 sector (#9, #16).

Table 6 and Figure 3 show average values of the relative contribution ratios in each sector. Average values for the entire sample are 0.206 for △CO2Int, 0.191 for △EneInt, 0.255 for △COGSR, 0.055 for △TATR, 0.138 for △AtER, and 0.155 for △Equity. Thus, approximately 40% of the variations in the changes in CO_2 emissions are explained by carbon intensity and energy intensity (39.7% = 20.6%+19.1%), whereas the remaining approximate 60% are explained by financial factors (60.3% = 25.5%+5.5%+13.8%+15.5%). Therefore, COGSR (operation pressure) and TATR (consumer pressure) have the most and least contributions to variations in CO_2 emissions, respectively, on average.

The largest ratios in each sector are △CO2Int for two sectors (#4, #18), △EneInt for no sectors, △COGSR for 13 sectors (#5, #6, #7, #8, #9, #10, #11, #13, #14, #15, #16, #17, #19), △TATR for no sectors, △AtER for 1 sector (#12), and △Equity for no sectors. Similarly, the smallest ratios are △CO2Int, △EneInt, and △COGSR for no sectors, △TATR for 14 sectors (#4, #5, #6, #7, #9, #10, #11, #12, #13, #14, #15, #16, #17, #19), △AtER for 1 sector (#18), and △Equity for 1 sector (#8).

5.3 Discussion of the results

We confirm the relationship between CEP and CFP from the results of LMDI (as of 2015). Table 7 shows the correlation matrix of each term as of 2015 in the 16 sectors (i.e., 16 observations). △CO2 (change in total CO_2) is statistically significantly positive for △Equity (0.662) and significantly negative for △TATR (−0.431) and △AtER (−0.846). This indicates that absolute CEP (△CO2) is not significantly related to relative CEP (0.226 for △CO2Int and −0.011 for △EneInt) and the operation factor (−0.344 for △COGSR) whereas it is significantly related to TATR (△TATR), leverage (△AtER), and firm size (△Equity).

As to each term on the RHS in equation 4, △CO2Int is correlated significantly positively to △Equity (0.489) and significantly negatively to △EneInt (−0.734), △COGSR (−0.561), and △TATR

(−0.712). Similarly, △EneInt is correlated significantly positively to △COGSR (0.885) and △TATR (0.782) and significantly negatively to △CO2Int and △Equity (−0.680). △COGSR is correlated significantly positively to △EneInt, △TATR (0.891), and △AtER (0.696) and significantly negatively to △CO2Int and △Equity (−0.923). △TATR is correlated significantly positively to △EneInt, △COGSR, and △AtER (0.708) and significantly negatively to △CO2Int and △Equity (−0.887). △AtER is correlated significantly positively to △COGSR and △TATR and significantly negatively to △Equity (−0.911). Accordingly, △Equity is correlated significantly positively to △CO2Int and significantly negatively to △EneInt, △COGSR, △TATR, and △AtER.

Regarding the relationship between CEP and CFP in this study, △CO2Int and △EneInt are part of CEP and △COGSR, △TATR, and △AtER are part of ROE (whereas △COGSR and △TATR are part of ROA), as noted above. Accordingly, Figures 4 and 5 show scatter plots among them, based on the results of LMDI as of 2015 for the 16 sectors (where the horizontal axes are △CO2Int for Figure 4 and △EneInt for Figure 5). #6 (Pulp), #7 (Chem), #9 (OilCoal), #12 (Iron), and #16 (ElecApp) denote characteristic sectorial numbers.

Regarding relative CEP, △CO2Int (carbon intensity) and △EneInt (energy intensity) are correlated negatively with each other (the correlation coefficient $r = -0.734$) (Figures 4 and 5). This negative relationship is probably because energy use is both the denominator of ΔCO2Int and the numerator of ΔEneInt, suggesting that greater energy use tends to decrease ΔCO2Int and increase ΔEneInt. Therefore, relative CEP consists of two adverse factors, leading to an unstable relationship with absolute CEP. As characteristically opposite sectors, #6 (Pulp) has the lowest △CO2Int and the highest △EneInt, while #12 (Iron) has the highest △CO2Int and the lowest △EneInt.

Regarding the relationship between △CO2Int and parts of CFP (Figure 4), △CO2Int (carbon intensity) is correlated significantly negatively to △COGSR (the COGSR) and △TATR (the TATR) and not significantly to △AtER (leverage). On the other hand, regarding the relationship between △EneInt and parts of CFP (Figure 5), △EneInt (energy intensity) is correlated significantly positively to △COGSR and △TATR and not significantly to △AtER.

This relationship provides an insight somewhat new to the literature: a greater carbon intensity (worse CEP) is related to a smaller COGSR (better CFP) and smaller TATR (worse CFP) and not related to AtER. Similarly, a greater energy intensity (worse CEP) is related to a larger COGSR (worse CFP) and larger TATR (better CFP) and not related to AtER. This implies that ROA (as CFP) seems unstable because the COGSR (the worse CFP) is related significantly positively to the TATR (the better CFP), canceling out the effects on CEP.

As contrasting examples (Figures 4 and 5), #9 (OilCoal) and #6 (Pulp) have the highest △COGSR and △TATR, respectively, as well as the smallest △CO2Int (and the highest △EneInt). Meanwhile, #12 (Iron) has the smallest △COGSR and △TATR as well as the highest △CO2Int (and the smallest △EneInt).

Note that ROE is expected to have a less stable relationship with CEP than ROA. This is because ROE is equal to ROA times leverage, and leverage (△AtER) is not significantly correlated to carbon intensity and energy intensity (△CO2Int and △EneInt) as part of CEP in this study.

In addition, firm size (scale factor) plays an important role in the model across the board because △Equity is correlated significantly with all factors in the model. △Equity is correlated significantly positively to △CO2. This is intuitive because we often find that larger firms tend to have higher CO_2/GHG emissions. Regarding each term, the larger sectors (△Equity) tend to have higher carbon intensity (△CO2Int), lower energy intensity (△EneInt), lower COGSR (△COGSR), lower TATR (△TATR), and lower leverage (△AtER).

6. Conclusions

This study proposes new models that decompose corporate CO_2/GHG emissions (CO_2, direct + indirect GHG [Scope 1+2], and supply-chain GHG [Scope 1+2+3]) into financial factors using a decomposition method of LMDI. The model of CO_2 consists of CO_2 intensity, energy intensity, COGSR, TATR, leverage, and equity. The model of Scope 1+2 adopts GHG intensity instead of CO_2 intensity, whereas the model of Scope 1+2+3 additionally uses supply-chain GHG intensity. As an application example of the CO_2 model, this study targets 225 Japanese listed firms in 16 manufacturing sectors. Results show that the change in CO_2 emissions as of 2015 (−802.1 kt) is decomposed into 2922.5 kt for carbon intensity, −26036.3 kt for energy intensity, −6350.5 kt for the COGSR, −8495.6 kt for the TATR, −7912.3 kt for leverage, and 45070.1 kt for equity. In the entire sample, therefore, the largest positive and negative factors for the change in CO_2 emissions as of FY2015 are equity (firm size) and energy intensity, respectively. Average values of relative contribution ratios are 20.6% for CO_2 intensity, 19.1% for energy intensity, and the remaining approximately 60% for financial factors (25.5% for COGSR, 5.5% for TATR, 13.8% for leverage, and 15.5% for equity).

The results imply that, in order to reduce CO_2/GHG emissions, we should focus on financial factors as well as carbon intensity and energy intensity, as suggested in previous empirical studies. Companies often tend to pay attention to carbon intensity and energy intensity when seeking to reduce CO_2/GHG emissions, but the financial factors can explain the majority of CO_2 emissions, on average, in the sample used in this study. In particular, at the aggregated level, the CO_2 decrease by energy intensity is almost canceled out by the CO_2 increase by firm size (equity). What should be noted here is the cost ratio (COGSR), which on average has the largest relative contribution (25.5%), indicating that reduction (improvement) of the cost ratio (hence, operation pressure) is directly linked to CO_2/GHG emissions reduction. Thus, the models of this study are helpful for identifying which part of corporate activities contributes to CO_2/GHG emissions.

As implications for the literature, we first find that our sample has the following important tendencies in terms of the relationship between CEP and CFP. First, absolute CEP (△CO2) is not significantly related to relative CEP (the carbon intensity and energy intensity) and the operation factor (the COGSR), whereas it is significantly related to TATR, leverage, and firm size. This provides evidence that absolute CEP can be different from relative CEP, suggesting that the choice of CEP type is important when examining the relationship between CEP and CFP.

Second, we suppose that relative CEP and CFP are themselves unstable indicators because they contain adverse factors that are related to absolute CEP in opposite ways over years. Relative CEP can be divided into carbon intensity and energy intensity, which are correlated negatively with each other. Meanwhile, ROA, as the representative CFP, consists of operational profitability, the

COGSR (worse CFP), and the TATR (better CFP), whereas the COGSR and the TATR in the sample are correlated positively with each other.

This study thus supports the view that there is a significant relationship between CEP and CFP because the carbon intensity, the energy intensity, the COGSR, and the TATR are significantly correlated with each other among the 16 sectors (as of 2015). Thus, it supposes that the reason the relationship between CEP and CFP is occasionally not robust in the literature is that the relative CEP and CFP are themselves unstable indicators, as noted above.

As to limitations, the findings of this study may be unique to the Japanese manufacturing sectors and therefore future studies should investigate other examples (e.g., different sectors, countries, and times) to make the findings more robust. Also, regarding an issue of CFP, the model of this study does not include profit (return) because it often takes a negative value. However, model development may be able to include profit in some way. In addition, the model of this study only focuses on CO_2/GHG emissions and energy use as non-financial variables. Potentially, however, the identity model can consider other materials, such as raw materials and waste. These issues with the sample and model development remain to be addressed in future study.

Appendix. LMDI for Scope 1+2 and Scope 1+2+3

Regarding equation 6, suppose there are i firms in j sectors from the base year 0 to a certain year t, and summation of the change in Scope 1+2 emissions (ΔS12) of j-th sector from years 0 to t is expressed as follows:

$$\begin{aligned}\sum_i \Delta S12_{ij}^t &= \sum_i \left(S12_{ij}^t - S12_{ij}^0\right) \\ &= \sum_i \Delta GHGInt_{ij}^t + \sum_i \Delta EneInt_{ij}^t + \sum_i \Delta COGSR_{ij}^t + \sum_i \Delta TATR_{ij}^t \\ &\quad + \sum_i \Delta AtER_{ij}^t + \sum_i \Delta Equity_{ij}^t\end{aligned} \tag{A1}$$

where

$$\Delta GHGInt_{ij}^t = \begin{cases} 0, & if\ S12_{ij}^t - S12_{ij}^0 = 0 \\ L\left(S12_{ij}^t, S12_{ij}^0\right)\ln\left(GHGInt_{ij}^t / GHGInt_{ij}^0\right), & if\ S12_{ij}^t - S12_{ij}^0 \neq 0 \end{cases} \tag{A2}$$

$$\Delta EneInt_{ij}^t = \begin{cases} 0, & if\ S12_{ij}^t - S12_{ij}^0 = 0 \\ L\left(S12_{ij}^t, S12_{ij}^0\right)\ln\left(EneInt_{ij}^t / EneInt_{ij}^0\right), & if\ S12_{ij}^t - S12_{ij}^0 \neq 0 \end{cases} \tag{A3}$$

$$\Delta COGSR_{ij}^t = \begin{cases} 0, & if\ S12_{ij}^t - S12_{ij}^0 = 0 \\ L\left(S12_{ij}^t, S12_{ij}^0\right)\ln\left(COGSR_{ij}^t / COGSR_{ij}^0\right), & if\ S12_{ij}^t - S12_{ij}^0 \neq 0 \end{cases} \tag{A4}$$

$$\Delta TATR_{ij}^t = \begin{cases} 0, & if\ S12_{ij}^t - S12_{ij}^0 = 0 \\ L\left(S12_{ij}^t, S12_{ij}^0\right)\ln\left(TATR_{ij}^t / TATR_{ij}^0\right), & if\ S12_{ij}^t - S12_{ij}^0 \neq 0 \end{cases} \tag{A5}$$

$$\Delta AtER_{ij}^t = \begin{cases} 0, & if\ S12_{ij}^t - S12_{ij}^0 = 0 \\ L\left(S12_{ij}^t, S12_{ij}^0\right)\ln\left(AtER_{ij}^t / AtER_{ij}^0\right), & if\ S12_{ij}^t - S12_{ij}^0 \neq 0 \end{cases} \tag{A6}$$

$$\Delta Equity_{ij}^t = \begin{cases} 0, & if\ S12_{ij}^t - S12_{ij}^0 = 0 \\ L\left(S12_{ij}^t, S12_{ij}^0\right)\ln\left(Equity_{ij}^t / Equity_{ij}^0\right), & if\ S12_{ij}^t - S12_{ij}^0 \neq 0 \end{cases} \tag{A7}$$

$$L\left(S12_{ij}^t, S12_{ij}^0\right) = \frac{S12_{ij}^t - S12_{ij}^0}{\ln S12_{ij}^t - \ln S12_{ij}^0} \tag{A8}$$

Similarly, regarding equation 7, summation of the change in Scope 1+2+3 emissions (ΔS123) of j-th sector from years 0 to t is expressed as follows:

$$\sum_i \Delta S123_{ij}^t = \sum_i \left(S123_{ij}^t - S123_{ij}^0 \right)$$
$$= \sum_i \Delta SCInt_{ij}^t + \sum_i \Delta GHGInt_{ij}^t + \sum_i \Delta EneInt_{ij}^t + \sum_i \Delta COGSR_{ij}^t \tag{A9}$$
$$+ \sum_i \Delta TATR_{ij}^t + \sum_i \Delta AtER_{ij}^t + \sum_i \Delta Equity_{ij}^t$$

where

$$\Delta SCInt_{ij}^t = \begin{cases} 0, & if\ S123_{ij}^t - S123_{ij}^0 = 0 \\ L\left(S123_{ij}^t, S123_{ij}^0\right) \ln\left(SCInt_{ij}^t / SCInt_{ij}^0\right), & if\ S123_{ij}^t - S123_{ij}^0 \neq 0 \end{cases} \tag{A10}$$

$$\Delta GHGInt_{ij}^t = \begin{cases} 0, & if\ S123_{ij}^t - S123_{ij}^0 = 0 \\ L\left(S123_{ij}^t, S123_{ij}^0\right) \ln\left(GHGInt_{ij}^t / GHGInt_{ij}^0\right), & if\ S123_{ij}^t - S123_{ij}^0 \neq 0 \end{cases} \tag{A11}$$

$$\Delta EneInt_{ij}^t = \begin{cases} 0, & if\ S123_{ij}^t - S123_{ij}^0 = 0 \\ L\left(S123_{ij}^t, S123_{ij}^0\right) \ln\left(EneInt_{ij}^t / EneInt_{ij}^0\right), & if\ S123_{ij}^t - S123_{ij}^0 \neq 0 \end{cases} \tag{A12}$$

$$\Delta COGSR_{ij}^t = \begin{cases} 0, & if\ S123_{ij}^t - S123_{ij}^0 = 0 \\ L\left(S123_{ij}^t, S123_{ij}^0\right) \ln\left(COGSR_{ij}^t / COGSR_{ij}^0\right), & if\ S123_{ij}^t - S123_{ij}^0 \neq 0 \end{cases} \tag{A13}$$

$$\Delta TATR_{ij}^t = \begin{cases} 0, & if\ S123_{ij}^t - S123_{ij}^0 = 0 \\ L\left(S123_{ij}^t, S123_{ij}^0\right) \ln\left(TATR_{ij}^t / TATR_{ij}^0\right), & if\ S123_{ij}^t - S123_{ij}^0 \neq 0 \end{cases} \tag{A14}$$

$$\Delta AtER_{ij}^t = \begin{cases} 0, & if\ S123_{ij}^t - S123_{ij}^0 = 0 \\ L\left(S123_{ij}^t, S123_{ij}^0\right) \ln\left(AtER_{ij}^t / AtER_{ij}^0\right), & if\ S123_{ij}^t - S123_{ij}^0 \neq 0 \end{cases} \tag{A15}$$

$$\Delta Equity_{ij}^t = \begin{cases} 0, & if\ S123_{ij}^t - S123_{ij}^0 = 0 \\ L\left(S123_{ij}^t, S123_{ij}^0\right) \ln\left(Equity_{ij}^t / Equity_{ij}^0\right), & if\ S123_{ij}^t - S123_{ij}^0 \neq 0 \end{cases} \tag{A16}$$

$$L\left(S123_{ij}^t, S123_{ij}^0\right) = \frac{S123_{ij}^t - S123_{ij}^0}{\ln S123_{ij}^t - \ln S123_{ij}^0} \tag{A17}$$

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Table 1. The number of entire, censored, and uncensored firms

#	Sector	Entire firms	Censored firms	Uncensored firms
#4	Foods (Foods)	130	106	24
#5	Textiles and Apparels (Textiles)	55	47	8
#6	Pulp and Paper (Pulp)	26	20	6
#7	Chemicals (Chem)	215	169	46
#8	Pharmaceutical (Pharma)	66	56	10
#9	Oil & Coal Products (OilCoal)	12	10	2
#10	Rubber Products (Rubber)	19	17	2
#11	Glass and Ceramics Products (Glass)	58	50	8
#12	Iron and Steel (Iron)	47	38	9
#13	Nonferrous Metals (Nonferrous)	36	26	10
#14	Metal Products (MetalProd)	91	83	8
#15	Machinery (Machinery)	233	209	24
#16	Electric Appliances (ElecApp)	261	216	45
#17	Transportation Equipment (Transport)	96	88	8
#18	Precision Instruments (PrecInst)	52	49	3
#19	Other Products (Other)	109	97	12
Total		1506	1281	225

Table 2. Descriptive statistics for uncensored observations

Variables	Average	SD	Median	Min	Max
Total CO_2 emission (kt)	1294.2	7565.4	77.2	0.9	96965.0
Total energy consumption (MWh)	4652.0	24384.7	310.2	2.1	309722.0
COGS (million JPY)	340939.6	665566.7	118428.0	2443.0	4865787.0
Sales (million JPY)	448159.0	812546.5	170685.0	4789.0	6489702.0
Assets (million JPY)	480685.5	861736.4	180729.0	7517.0	7157929.0
Equity (million JPY)	198773.9	322173.9	91057.0	2887.0	2552512.0

Note: SD stands for standard deviation.

Table 3. T-test for censored and uncensored observations

	Censored obs (1281 firms)			Uncensored obs (225 firms)					
	obs	Average	(SD)	obs	Average	SD	Difference	t-value	Probability
COGS (million JPY)	6219	117018.3	(519084.9)	1125	340939.6	(665566.7)	−223921.3	−10.7	0.000
Sales (million JPY)	6248	151272.3	(595497.7)	1125	448159.0	(812546.5)	−296886.7	−11.7	0.000
Assets (million JPY)	6245	159975.8	(544955.2)	1125	480685.5	(861736.4)	−320709.7	−12.1	0.000
Equity (million JPY)	6101	69220.6	(260676.1)	1125	198773.9	(322173.9)	−129553.3	−12.7	0.000

Table 4. Summation of data from FY2011 to FY2015

Year	CO_2 (kt)	Energy (Mhw)	COGS (million JPY)	Sales (million JPY)	Assets (million JPY)	Equity (million JPY)
2011	289,672	1,043,980	71,061,331	92,833,893	97,018,265	40,385,463
2012	284,207	1,018,408	71,804,964	93,349,160	103,482,411	41,855,892
2013	294,208	1,065,570	79,377,191	104,558,703	110,525,822	45,462,230
2014	299,052	1,070,509	81,998,402	108,026,283	117,311,371	47,949,518
2015	288,870	1,035,047	79,315,176	105,410,839	112,433,350	47,967,521
2011	(100.0%)	(100.0%)	(100.0%)	(100.0%)	(100.0%)	(100.0%)
2012	98.1%	97.6%	101.0%	100.6%	106.7%	103.6%
2013	101.6%	102.1%	111.7%	112.6%	113.9%	112.6%
2014	103.2%	102.5%	115.4%	116.4%	120.9%	118.7%
2015	99.7%	99.1%	111.6%	113.5%	115.9%	118.8%

Table 5. Results of LMDI (unit: kt)

Sector	Year	△CO2	△CO2Int	△EneInt	△COGSR	△TATR	△AtER	△Equity
#4 (Foods)	2012	309.1	80.4	102.4	−20.1	−70.9	82.0	135.3
#4 (Foods)	2013	605.1	36.5	130.1	−16.0	70.8	31.8	351.9
#4 (Foods)	2014	518.6	454.4	−488.8	32.8	−149.2	167.6	501.7
#4 (Foods)	2015	624.1	455.8	−454.5	−28.3	132.8	188.0	330.3
#5 (Textiles)	2012	−271.1	150.1	−88.6	32.7	−374.6	377.9	−368.6
#5 (Textiles)	2013	−319.7	67.8	−251.4	50.1	−196.2	374.9	−364.8
#5 (Textiles)	2014	−555.8	248.4	−595.5	−39.9	−378.8	328.3	−118.2
#5 (Textiles)	2015	−665.8	121.3	−400.4	−193.4	−320.8	−47.1	174.6
#6 (Pulp)	2012	110.8	−74.2	15.1	−41.4	−254.3	−910.0	1375.6
#6 (Pulp)	2013	1172.5	−4540.6	3851.8	−236.0	1332.4	−2874.2	3639.0
#6 (Pulp)	2014	1186.3	−4545.5	3869.7	−246.3	1209.6	−3864.8	4763.6
#6 (Pulp)	2015	1182.7	−4563.7	3956.6	−234.9	1665.3	−4588.7	4947.9
#7 (Chem)	2012	−6977.4	−1331.1	−5592.9	578.5	−3691.9	4076.1	−1016.1
#7 (Chem)	2013	−4994.4	2985.4	−12409.0	400.2	−2673.2	5058.3	1643.9
#7 (Chem)	2014	−4960.4	1767.9	−12804.1	207.7	−2745.4	6742.7	1870.7
#7 (Chem)	2015	−6929.2	665.5	−10912.3	−1517.5	−811.1	8627.7	−2981.5
#8 (Pharma)	2012	23.2	25.3	44.6	−45.0	−37.1	13.1	22.2
#8 (Pharma)	2013	39.2	42.9	29.8	−51.6	−42.8	20.1	40.7
#8 (Pharma)	2014	15.1	3.4	32.7	−29.5	−76.8	34.6	50.7
#8 (Pharma)	2015	25.6	8.4	10.0	−53.2	−36.4	18.7	78.2
#9 (OilCoal)	2012	−1380.0	−48.6	−1320.1	166.9	−479.5	−441.9	743.1
#9 (OilCoal)	2013	−924.7	−480.6	−2689.4	235.9	426.6	−891.3	2474.1
#9 (OilCoal)	2014	−1511.8	−735.3	−2740.1	749.2	1198.3	1351.2	−1335.2
#9 (OilCoal)	2015	−738.0	−224.7	2615.5	370.1	−862.5	1148.6	−3785.0
#10 (Rubber)	2012	1.9	5.2	−3.7	0.3	−1.6	0.3	1.3
#10 (Rubber)	2013	6.1	7.5	−7.1	0.5	0.5	0.2	4.4
#10 (Rubber)	2014	7.9	7.7	−6.7	−0.1	−1.3	−0.2	8.5
#10 (Rubber)	2015	6.9	7.2	−7.2	−0.4	−1.3	−1.9	10.4
#11 (Glass)	2012	386.6	16.6	384.9	206.8	−292.0	−146.4	216.7
#11 (Glass)	2013	86.1	−232.9	284.5	324.7	−549.7	−210.2	469.8
#11 (Glass)	2014	−223.6	−188.4	124.5	344.6	−1021.0	−259.1	775.7
#11 (Glass)	2015	−262.1	−19.0	42.8	172.4	−875.2	−588.3	1005.3

#12 (Iron)	2012	2320.8	1131.7	−4996.7	845.7	−30749.7	18973.7	17116.0
#12 (Iron)	2013	9120.6	3733.1	−24630.3	−6619.2	−2235.1	4174.6	34697.5
#12 (Iron)	2014	12629.4	3127.6	−23914.8	−8605.8	−3381.9	1093.5	44310.8
#12 (Iron)	2015	5153.8	3823.6	−14793.9	−4794.0	−7001.7	−16578.8	44498.7
#13 (Nonferrous)	2012	354.0	391.0	131.5	−56.7	−790.7	374.0	305.0
#13 (Nonferrous)	2013	463.5	555.7	−755.2	−33.6	−1194.5	866.0	1025.1
#13 (Nonferrous)	2014	1408.8	930.3	−801.4	−160.0	−1261.5	1113.9	1587.5
#13 (Nonferrous)	2015	995.5	733.1	−988.7	56.5	−951.1	764.8	1380.9
#14 (MetalProd)	2012	98.9	114.0	−83.4	−10.4	18.7	1.0	59.0
#14 (MetalProd)	2013	−533.0	−1246.1	568.8	−23.3	3.6	55.8	108.3
#14 (MetalProd)	2014	279.7	355.0	−295.3	−2.4	−105.9	167.4	160.9
#14 (MetalProd)	2015	−727.2	104.8	−999.6	−31.0	−54.6	91.0	162.1
#15 (Machinery)	2012	−343.5	401.4	−701.7	34.2	−425.6	90.1	258.1
#15 (Machinery)	2013	−95.0	103.3	−404.0	−18.5	−400.1	−5.8	630.1
#15 (Machinery)	2014	−142.1	−46.9	−435.7	−58.5	−482.3	33.4	848.0
#15 (Machinery)	2015	−189.1	−13.4	−661.0	−66.8	−309.7	−82.7	944.4
#16 (ElecApp)	2012	128.0	577.6	−534.7	136.6	−225.2	1076.6	−903.0
#16 (ElecApp)	2013	22.1	1199.7	−2417.1	−175.5	658.8	−269.2	1025.4
#16 (ElecApp)	2014	836.6	1669.2	−2528.7	−149.5	405.8	822.8	617.0
#16 (ElecApp)	2015	994.9	1839.2	−2620.3	129.5	913.2	3378.5	−2645.1
#17 (Transport)	2012	−204.7	−51.3	−231.5	−29.8	73.0	−20.6	55.4
#17 (Transport)	2013	−50.3	−20.1	−313.2	−75.3	121.0	−115.1	352.4
#17 (Transport)	2014	−18.7	−5.0	−445.2	−72.6	114.4	−165.6	555.2
#17 (Transport)	2015	−11.0	−11.6	−573.3	−63.7	222.7	−264.9	679.8
#18 (PrecInst)	2012	8.2	6.5	21.0	−9.4	−13.9	−30.9	34.8
#18 (PrecInst)	2013	6.4	9.4	37.2	−32.8	−24.9	−62.9	80.4
#18 (PrecInst)	2014	34.6	11.8	66.2	−45.1	−25.3	−64.1	91.0
#18 (PrecInst)	2015	50.7	22.4	69.3	−51.7	−8.3	−90.3	109.3
#19 (Other)	2012	−29.8	21.0	−67.2	−7.5	−38.4	46.3	16.0
#19 (Other)	2013	−68.0	1.3	−153.7	−15.8	−32.1	75.8	56.6
#19 (Other)	2014	−124.5	4.4	−210.4	−22.8	−222.5	224.0	102.7
#19 (Other)	2015	−313.8	−26.4	−319.3	−44.1	−196.8	113.1	159.7
Total	2012	−5465.1	1415.7	−12920.9	1781.4	−37353.8	23561.5	18051.0
Total	2013	4536.6	2222.5	−39128.2	−6286.2	−4734.8	6228.8	46234.6

Total	2014	9380.0	3059.1	−41173.6	−8098.1	−6923.8	7725.7	54790.8
Total	2015	−802.1	2922.5	−26036.3	−6350.5	−8495.6	−7912.3	45070.1

Table 6. Average values of relative contribution ratios

Sector	$\frac{\lvert\triangle CO2Int\rvert}{Denom}$	$\frac{\lvert\triangle EneInt\rvert}{Denom}$	$\frac{\lvert\triangle COGSR\rvert}{Denom}$	$\frac{\lvert\triangle TATR\rvert}{Denom}$	$\frac{\lvert\triangle AtER\rvert}{Denom}$	$\frac{\lvert\triangle Equity\rvert}{Denom}$
#4 (Foods)	0.241 (0.141)	0.223 (0.127)	0.231 (0.147)	0.043 (0.035)	0.135 (0.107)	0.126 (0.096)
#5 (Textiles)	0.202 (0.116)	0.175 (0.157)	0.260 (0.137)	0.031 (0.027)	0.161 (0.132)	0.170 (0.144)
#6 (Pulp)	0.202 (0.132)	0.201 (0.164)	0.214 (0.131)	0.039 (0.034)	0.155 (0.139)	0.189 (0.158)
#7 (Chem)	0.178 (0.133)	0.200 (0.131)	0.279 (0.146)	0.052 (0.047)	0.144 (0.126)	0.147 (0.135)
#8 (Pharma)	0.184 (0.120)	0.156 (0.111)	0.246 (0.136)	0.137 (0.091)	0.148 (0.095)	0.128 (0.111)
#9 (OilCoal)	0.186 (0.149)	0.076 (0.062)	0.336 (0.096)	0.053 (0.033)	0.096 (0.069)	0.254 (0.153)
#10 (Rubber)	0.260 (0.108)	0.209 (0.148)	0.292 (0.085)	0.044 (0.036)	0.093 (0.051)	0.101 (0.141)
#11 (Glass)	0.206 (0.139)	0.199 (0.133)	0.213 (0.138)	0.092 (0.082)	0.154 (0.120)	0.135 (0.097)
#12 (Iron)	0.197 (0.154)	0.150 (0.158)	0.205 (0.150)	0.060 (0.050)	0.211 (0.139)	0.177 (0.160)
#13 (Nonferrous)	0.222 (0.095)	0.181 (0.133)	0.244 (0.154)	0.020 (0.024)	0.146 (0.130)	0.187 (0.126)
#14 (MetalProd)	0.212 (0.138)	0.192 (0.147)	0.239 (0.172)	0.047 (0.064)	0.141 (0.142)	0.168 (0.174)
#15 (Machinery)	0.204 (0.139)	0.198 (0.146)	0.274 (0.174)	0.054 (0.044)	0.143 (0.115)	0.127 (0.121)
#16 (ElecApp)	0.208 (0.150)	0.186 (0.129)	0.250 (0.153)	0.056 (0.075)	0.125 (0.108)	0.175 (0.160)
#17 (Transport)	0.186 (0.100)	0.219 (0.153)	0.266 (0.128)	0.037 (0.032)	0.105 (0.079)	0.188 (0.148)
#18 (PrecInst)	0.307 (0.210)	0.107 (0.099)	0.168 (0.102)	0.105 (0.068)	0.090 (0.053)	0.224 (0.137)

#19 (Other)	0.235	0.183	0.289	0.049	0.115	0.129
	(0.118)	(0.161)	(0.192)	(0.067)	(0.089)	(0.120)
Total	0.206	0.191	0.255	0.055	0.138	0.155
	(0.137)	(0.138)	(0.153)	(0.060)	(0.116)	(0.138)

Notes: Values with and without parentheses are average values and standard deviations, respectively. See Figure 3.

Table 7. Correlation matrix of results of LMDI, as of 2015 (16 sectors)

Variables (Results of LMDI)	△CO2 (−802.1 kt)	△CO2Int (2922.5 kt)	△EneInt (−26036.3 kt)	△COGSR (−6350.5 kt)	△TATR (−8495.6 kt)	△AtER (−7912.3 kt)	△Equity (45070.1 kt)
△CO2 (−802.1 kt)	(1.000)	--	--	--	--	--	--
△CO2Int (2922.5 kt)	0.226	(1.000)	--	--	--	--	--
△EneInt (−26036.3 kt)	−0.011	−0.734***	(1.000)	--	--	--	--
△COGSR (−6350.5 kt)	−0.344	−0.561**	0.885***	(1.000)	--	--	--
△TATR (−8495.6 kt)	−0.431*	−0.712***	0.782***	0.891***	(1.000)	--	--
△AtER (−7912.3 kt)	−0.846***	−0.234	0.321	0.696***	0.708***	(1.000)	--
△Equity (45070.1 kt)	0.662***	0.489**	−0.680***	−0.923***	−0.887***	−0.911***	(1.000)

Notes: This table shows a correlation matrix of the results of LMDI for the 16 sectors, as of 2015. ***, **, and * show statistically significant levels of 1%, 5%, and 10%, respectively.

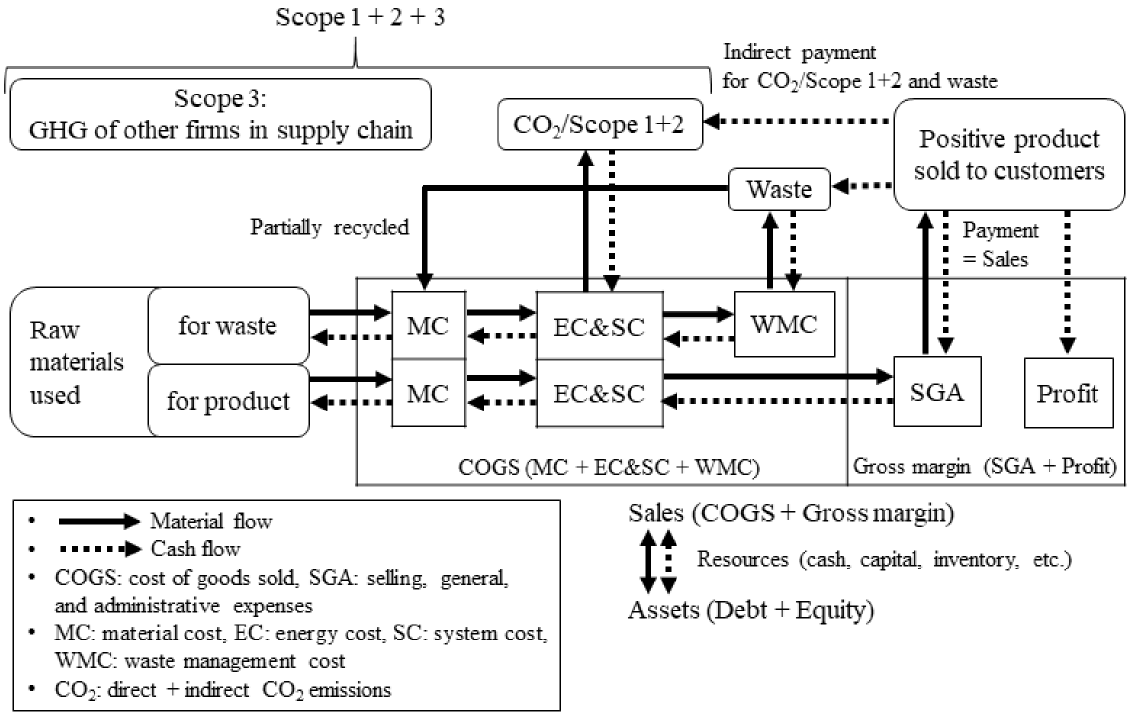

Figure 1. The flow of material and cash in a firm

Notes: This figure shows a simple model of material (a straight line) and cash (a dotted line) flows in a manufacturing firm. From the left, raw materials are purchased from suppliers, causing MC, and they are then made into waste and product, causing EC&SC. Waste (upper) is processed, causing WMC. Meanwhile, the positive product (lower) is then managed for SGA and sold to customers in the markets, causing sales. CO_2/Scope 1+2 emissions are generated by energy use, which causes EC in the manufacturing costs (EC&SC).

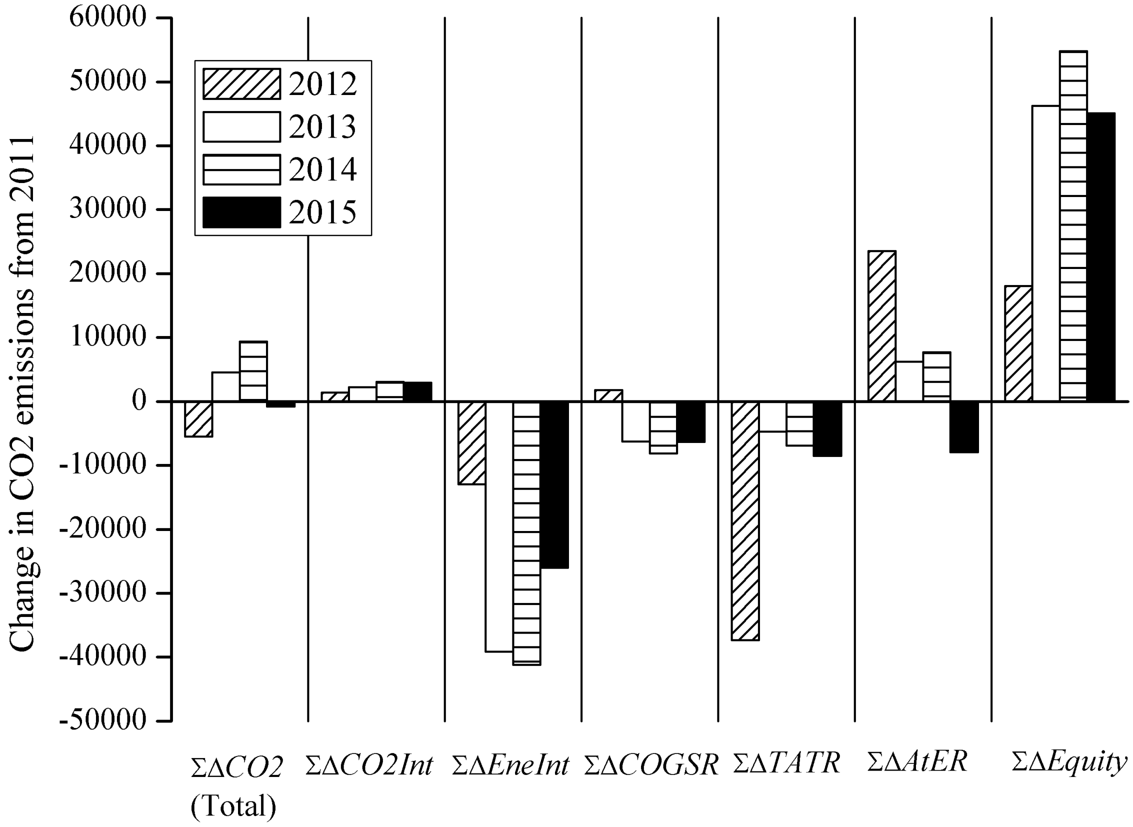

Figure 2. Results of LMDI in the entire sample

Note: See Table 5.

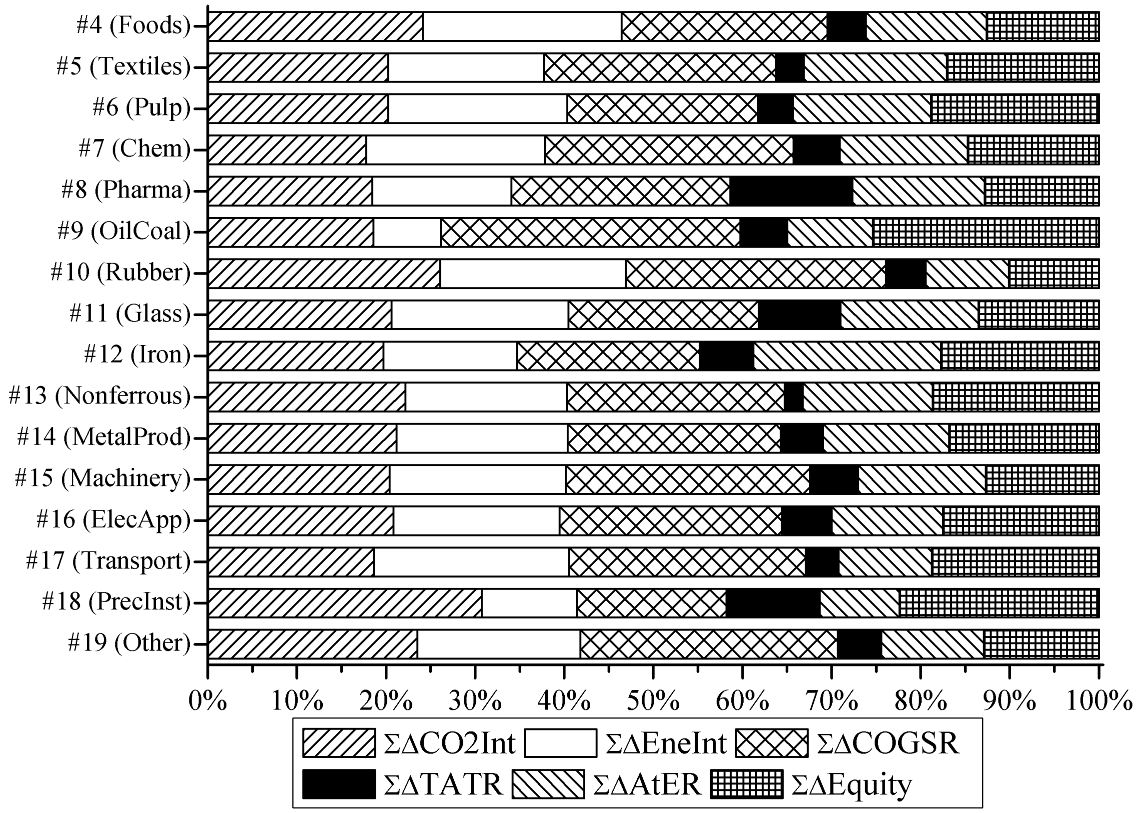

Figure 3. Average values of relative contribution ratios in each sector

Note: See Table 6.

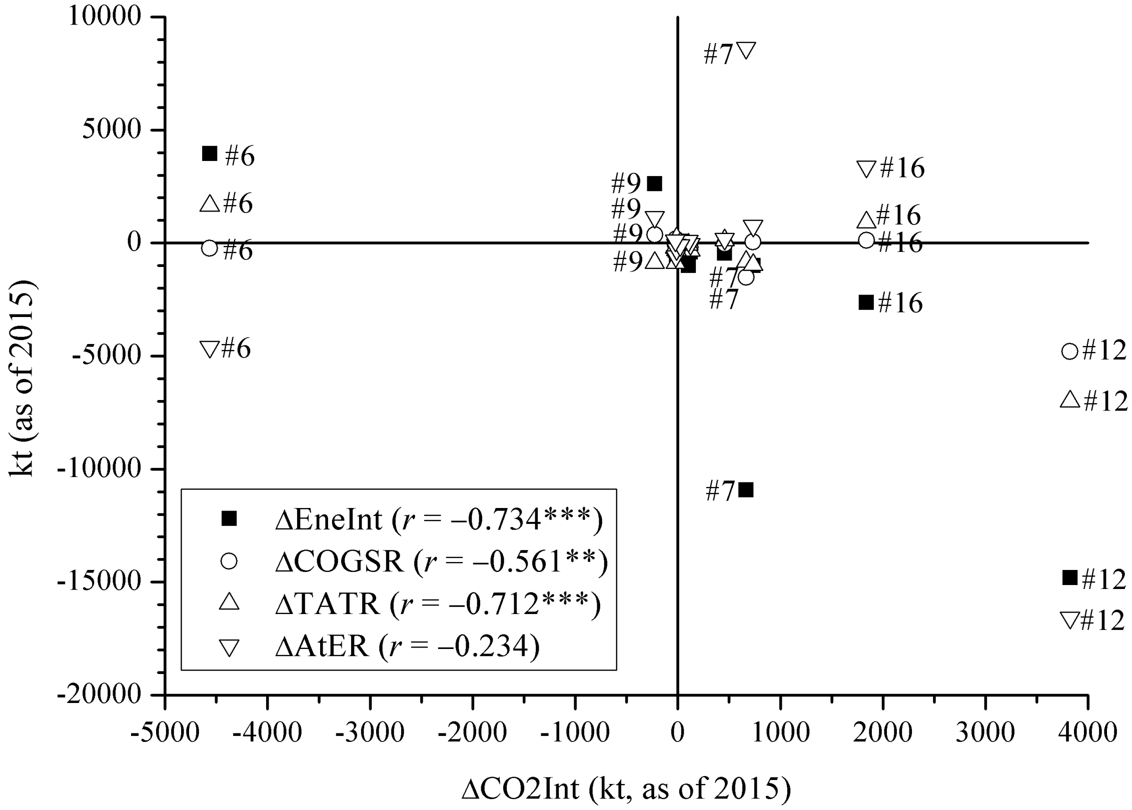

Figure 4. △CO2Int vs. △EneInt, △COGSR, △TATR, and △AtER

Notes: This figure shows scatter plots between △CO2Int on the horizontal axis and △EneInt, △COGSR, △TATR, and △AtER on the vertical axis, using the results of LMDI as of 2015 for the 16 sectors. *r* denotes the correlation coefficient and *** and ** show statistically significant levels of 1% and 5%, respectively (see Table 7). #6 (Pulp), #7 (Chem), #9 (OilCoal), #12 (Iron), and #16 (ElecApp) denote characteristic sectorial numbers (see Table 1).

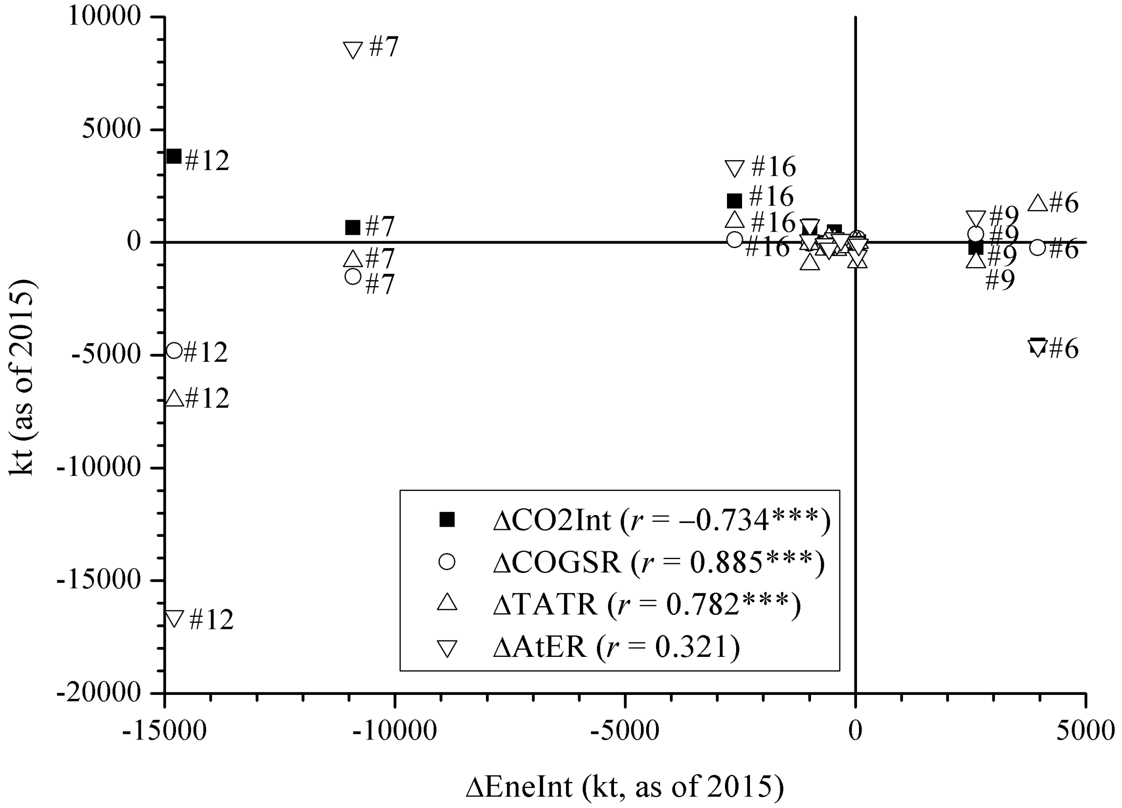

Figure 5. △EneInt vs. △CO2Int, △COGSR, △TATR, and △AtER

Notes: This figure shows scatter plots between △EneInt on the horizontal axis and △CO2Int, △COGSR, △TATR, and △AtER on the vertical axis, using the results of LMDI as of 2015 for the 16 sectors. r denotes the correlation coefficient and *** shows a statistically significant level of 1% (see Table 7). #6 (Pulp), #7 (Chem), #9 (OilCoal), #12 (Iron), and #16 (ElecApp) denote characteristic sectorial numbers (see Table 1).