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ESG complementarities in the US economy

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ABSTRACT

This paper investigates ESG from the perspective of changes in input elasticities of substitution and complementarity. Rather than compute these elasticities from the cost function, we compute them from the Input Distance Function (IDF). Our data are from Refinitiv Eikon Datastream database. We focus on the US economy due to her global role in the world economy and hence spillover effects of uncertainties on the rest of the world. The data consist of 5,798 companies comprising 38 US industries that span for 12 years from 2009 to 2020 and include: (i) financial data on sales, capital and employees; (ii) two financial ratios and (iii) three main ESG indicators. We compute Antonelli Elasticity of Complementarity (AEC) and Allen-Uzawa Elasticity of Substitution (AES) from the translog of IDF function. We find that the standard inputs have positive AEC elasticities; however, ESG cross-elasticities exhibit negative signs, classifying them as q-substitutes. Therefore, an increase in one of the ESG values leads to a decrease in the marginal value of the other. On the other hand, AES elasticities have a negative sign only for the Governance-Environment "doublet'; the rest of the pairs are positive implying that they are p-complements.

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1. Introduction

World Commission on Economic Development (WCED) interprets sustainability as 'development that meets the needs of present without compromising the ability of future generations to meet their own needs.' However, their assertions are at odds with the assumption that sustainability initiatives and economic development are not compatible with each other (see Jain and Jain 2019). Nevertheless, the stance on economic development and sustainability is changing dramatically. Presently, there is growing public pressure on companies to adopt more socially responsible approaches, despite the high cost of environment, social and government (ESG) initiatives.

Academic interest and hence literature on sustainability and its impact on the economy are growing too. They range from the overall impact of ESG on the financial performance of firms (Chambers and Serra 2018) and cost of debt (Foneska, Rajapakse, and Richardson 2019) to the impact of green growth on employment (Bowen and Kuralbaeva 2015) and economic development (Bansal 2004) among others. While there are numerous reports and papers on sustainability (e.g. Aintablian, Mcgraw, and Roberts 2007; Kotsantoni and Bufalari 2019; La Rosa et al. 2018; see also section 2), to the best of our knowledge, there are only two studies that can be identified on the complementarity of ESG inputs. Cavaco and Crifo (2014) investigate the impact of interactions among Corporate Social Responsibility (CSR) indicators on financial performance. They define their findings of synergies and trade-offs as complementarity and substitutability. On the other hand, Zhang, Loh, and Wu (2020) examined the interactive effect of ESG indicators on innovation. However, both studies do not use q-complementarity/p-substitutability[1]. Our paper fills this gap in the literature.

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Investments in sustainable practices are expensive to businesses; therefore, identifying p-complementarity/q-substitution of inputs are important to firms for cost reduction purposes. Consequently, the motivation behind the paper is to find ways to decrease costs associated with sustainability. Therefore, our paper is the first empirical study that contributes to the literature investigating sustainability expenditure through the prism of input elasticities of substitution and complementarity. Moreover, following Glass, Kenjegaliev, and Kenjegalieva (2020) rather than compute elasticities of substitution and complementarity from a cost function, which is common in the operational research literature (e.g. Berndt and Wood 1975; Athanasios, Ray, and Miller 1990; Michaelides et al. 2015), we compute the elasticities from an input distance function (IDF). In contrast to the standard production function, the IDF technology is, in terms of multiple inputs, to produce outputs.

We obtain data on inputs and outputs from the Refinitiv Eikon Datastream ESG database (formerly Asset 4). This dataset is used, for example, by Chambers and Serra (2018), De Lucia, Pazienza, and Bartlett (2020) and Eliwa, Aboud, and Saleh (2019). We focus on the US economy due to its global role in the world economy and, hence, spillover effects of uncertainties on the rest of the world. In addition, there are rich ESG data on the US market, especially starting from 2009. Hence focusing on the US considerably increases our data sample. For example, our original data consist of 5798 companies comprising 38 U.S. industries that span from 2009 to 2020 and include (i) financial data on sales, capital and employees; (ii) two financial ratios – return on assets (ROA) and return on equity (ROE) and (iii) three main ESG indicators – ESG scores.

Although we have 69,576 observations in our original data, 78.5% of ESG observations are missing. As we remove companies with any missing ESG our sample drops to only 385 companies. Therefore, we have to choose between being restrictive in selecting firms and our desire to have a large sample. To keep more firms, we augment missing ESG data by applying multiple imputations (MI). However, we are more conservative than some MI literature works suggest, see, for example, Lan et al. (2021), Lin, Liu, and Lan (2021) and Madley-Dowd et al. (2019). They indicate that the missing observations should not exceed 50%. Instead, we eliminate an individual company if the percentage of missing ESGs, for that particular company, exceed 50%. Hence, we ensure that on an aggregate level our data only have approximately 20% of missing ESG observations. The final sample including imputed data has 962 companies.

We compute primal elasticities from a translog of an IDF function. These elasticities quantify complementarity and substitutability for two ESG inputs. The approach we use in this paper allows us to employ an IDF function without the need to rely on a dual-cost function. However, we obtain our IDF through the duality of an IDF and the cost function. Therefore, we analytically transformed the dual functions to get price and quantity complementarity and substitutability of ESG indicators. Whence, our dual elasticities are estimated from an IDF indirectly instead of a direct estimation from the cost function.

The first measure of complementarity that we use in the paper is Antonelli Elasticity of Complementarity (AEC) as in Blackorby and Russell (1981). This elasticity measures the response as a marginal value of an input to a change in the input quantity of the other and is defined as a true dual of the Allen-Uzawa Elasticity of Substitution (AES) under non-constant returns to scale. The AES was introduced by Allen (1934; 1938) and further developed by Uzawa (1962). The dual AES measures the response of the input quantity to a change in input price p. In this paper, we derive the dual AES from the cost function because of the duality between this function and the IDF.

Our findings show that standard inputs have positive AEC elasticities; however, ESG cross-elasticities exhibit negative signs, classifying them as q-substitutes. Therefore, an increase in one of the ESG values leads to a decrease in the marginal value of the other while keeping the overall output constant. On the other hand, AES elasticities have a negative sign only for the Governance-Environment 'doublet'; the rest of the pairs are positive implying that they are p-complements. Moreover, since each ESG indicator appears twice, the impact of these changes is spread simultaneously across the other ESG indicators. These findings suggest that investments in sustainability have multiplicative effects through complementarity/substitutability.

Our paper makes three distinctive contributions to the existing literature. First, unlike current studies that examine ESG and its impact on financial and other indicators, our paper is the first study that investigates the interaction exclusively among ESG initiatives. To the best of our knowledge, no previous research empirically focused on ESG cross-elasticities. Second, we empirically apply the existing theoretical approach in IDF and cross-elasticities of complementarity and substitution to ESG initiatives. Therefore, we provide a precedent and bring closer together two distinct sciences, namely operational research literature and ESG and sustainability literature. Finally, in line with the existing ESG studies, we highlight the severity of the issue caused by missing data and its statistical solution by using MI to augment missing observations.

The rest of the paper is as follows. In the next section, we provide a review of the literature on sustainability and a subsection with research hypotheses. In the third section, we describe the theoretical aspects of the paper. We also detail on how we obtain AEC and AES. The fourth and fifth sections are on data and results of the translog function, respectively. Section 6 is the main section on results, where we discuss the results of our estimation with a focus on q-complementarity/substitution and p-substitution/complementarity. The final section is the conclusion.

2. Literature review and research hypotheses

2.1. Literature review

ESG implementation can have a significant impact on companies and their financial performance. Whence, many researchers justify investment in sustainability based on economic and financial reasons. For instance, Chambers and Serra (2018) investigate the CSR and financial performance. They conclude that ESG initiatives are incorporated into firm performance and are treated as part of the firm's production process. As an alternative, awareness of climate change on financial earnings is the main reason for De Lucia, Pazienza, and Bartlett (2020) research. The authors use two measures of financial performance: ROE and ROA. They find a positive relationship between ROE and ROA and ESG practices.

Typically, stock market returns can be seen as direct indicators of financial performance. Hence, despite investigating green initiatives**,** Fang, Su, and Yin (2021) take a different approach to the impact on the firm performance. They develop a green factor to measure the risk and investigate whether this risk factor can explain stock returns. They find out that stocks of green companies can outperform traditional companies through two channels: economic fundamentals and investor attention. They conclude that indeed excess returns can be explained by the presence of a green factor; moreover, the impact of this factor on stocks is accelerating particularly after 2008.

Similar to Fang, Su, and Yin (2021), Eichholtz, Kok, and Yonder (2012) investigate stock returns. However, the focus of their paper is on the role of energy efficiency and sustainability of commercial properties on the stocks and performance of real estate investment trusts (REIT) in the US. They argue that there are two channels through which sustainability can affect REITs: (a) the direct effect of green buildings or (b) through better reputation. The latter channel is also raised by Miras-Rodriguez, Carrasco-Gallego, and Escobar-Perez (2015). They research if the energy companies committed to CSR because of the firm performance, legal issues or reputation motives. According to them, the main driver behind CSR in these companies is financial performance. Nonetheless, if CSR is environmentally focused then, they conclude, such CSR actions are driven by reputational motives.

There are other papers that focus on different aspects of CSR and ESG. For example, Iguchi, Katayama, and Yamanoi (2021) suggest that management's religious beliefs affect corporate green initiatives. On the other hand, Umar and Gubareva (2021) researched ESG leaders. They find a high correlation between ESG scores and the news proxied by the Media Coverage Index (MCI). Transparency of S&P companies is the focus of the paper by Tamimi and Sebastianelli (2017). These authors find that the highest disclosure can be found on governance and the lowest on environmental indicators. Additionally, their results show that large companies have higher ESG scores compared to medium companies.

Several studies discuss the 'complementarity' of sustainability initiatives. For example, the impact of interactions between CSR indicators and financial performance is investigated by Cavaco and Crifo (2014). They find a positive synergy (they defined it as a complementarity) between a responsible attitude towards customers and workers and financial performance. At the same time, there is a trade-off (substitution) effect between an attitude towards customers and the environment. Zhang, Loh, and Wu (2020) research – though not explicitly complementarily – an interactive effect of corporate sustainability initiatives in the context of innovation in the corporate operating process. According to them, ESG initiatives are positively correlated with innovations.

However, to the best of our knowledge, there are no studies that investigate ESG elasticities of q-substitutability and p-complementarity. Moreover, we compute our elasticities of substitution and complementarity from an IDF. In contrast to other models of production functions; the methodology we employ allows us to use multiple inputs.

2.2. Research hypothesis

In the paper, we use the IDF function given by Glass, Kenjegaliev, and Kenjegalieva (2020). They develop the function and primal elasticity measures to research complementarity in the banking sector. We, on the other hand, expand the application of the approach further by using them to investigate the complementarity of green initiatives. There are papers that investigate green economy and the substitutability of inputs in particular (see, for example, Papageorgiou, Saam, and Schulte 2017; Malikov, Sun, and Kumbhakar 2018). However, they mostly focus on clean and dirty inputs while the focal point of our paper is the interactive effect of ESG inputs among them. As far as we know, there are only two papers that investigate related, to some extent, questions: Cavaco and Crifo (2014) and Zhang, Loh, and Wu (2020). Nonetheless, they examine interactions between CSR and financial performance and ESG and investment.

The nucleus of our research is quantity- and price-complementarity and substitutability among ESG initiatives and has practical implications. For example, two ESG inputs are q-complements suggesting that both ESG inputs move in the same direction while for ESGs classified as q-substitutes move in opposite directions. Knowledge of this interaction allows firms to make better choices between investment into ESG investments. Accordingly, these choices can be extended on p-complementarity and p-substitutability with input price acting on the input quantity of the other ESG. Therefore, q- and p-complementarity and substitutability assist companies in their decisions on green initiatives by providing a selection method for an optimal level of ESG inputs. Consequently, two independent research hypotheses are formulated to capture input quantity and input price impacts on ESGs. These research hypotheses are given as

H*a*: There is q-complementarity between ESG inputs (measured by AEC)

H*b*: Increase in the price of ESG input raises the quantity of the other ESG input (i.e. they are p-substitutes according to AES)

3. Methodology

Our methodology uses the production function with a set of multiple inputs and outputs as in Glass, Kenjegaliev, and Kenjegalieva (2020). We denote these inputs as $x \in \mathbb{R}^+$ with a vector of $x = x_1, \ldots, x_K$ and K indicates the number of inputs in the production function. Analogous to inputs, we assume that outputs are represented by a vector of $y \in \mathbb{R}^+$ with $y = y_1, \ldots, y_M$ and M is the number of outputs. The vector of inputs $x \in \mathbb{R}^+$ is used to produce the vector of outputs $\in \mathbb{R}^+$; this process can be represented as

$$L(y) = \{x \in \mathbb{R}^+ : y \in \mathbb{R}^+ \text{ is produced by } x\} \tag{1}$$

Using production technology in Equation (1), we define an IDF as

$$D_I(y, x) = \sup\{\lambda \geq 1 : (x/\lambda) \in L(y) \geq 1\} \tag{2}$$

where $D_I(y, x) \geq 1$ is the IDF that shows the radial contraction of x towards the production isoquant $L(y)$ and λ is a scalar such that $1 - \lambda \leq 0$. We assume that IDF is convex and points on the IDF boundary have $\lambda = 1$ and, therefore, the distance $D_I(y, x)$ is unity, while, $D_I(y, x) \geq 1$ indicates the free disposability of inputs and whence $x \in L(y)$. Because $D_I(y, x) \geq 1$ and $x \in L(y)$ McFadden (1978; see Glass, Kenjegaliev, and Kenjegalieva 2020) gives five properties of the IDF:

(i) non-decreasing in x, $\partial \ln D_I(y, x)/\partial \ln x_k \equiv ex_k \geq 0$, where ex_k is the kth input elasticity;
(ii) non-increasing in y, $\partial \ln D_I(y, x)/\partial \ln y_m \equiv ey_m \leq 0$, where ey_m is the mth output elasticity;
(iii) homogeneity of degree one in x, $D_I(y, x/x_k) = D_I(y, x)/x_k$;

(iv) (iv) concave and continuous in x;
(v) $E_I = -\left(\sum_{m=1}^{M} \frac{\partial \ln D_I(y,x)}{\partial \ln y_m}\right)^{-1} \equiv -\left(\sum_{m=1}^{M} ey_m\right)^{-1}$ is the scale elasticity of the IDF representation of the production technology.

Now let's look at the general form of the cost function corresponding to IDF

$$C(y,p) \equiv \inf\{px : x \in L(y)\} \tag{3}$$

Unlike Equation (2), a cost function includes a set of K input prices represented as $p \in \mathbb{R}^{+}$ and the expenditure on inputs, $C = \sum_{k=1}^{K} p_k x_k$. This cost function can be rewritten using Equation (2) which gives an equivalent cost function but with an $D_I(y,x)$ as a predicate:

$$C(y,p) \equiv \inf\{px : D_I(y,x) \geq 1\} \tag{4}$$

whence the properties of IDF have a bijective mapping onto properties of $C(y,p)$:

(i) non-decreasing in y, $\partial \ln C(y,p)/\partial \ln y_m \equiv ey_m \geq 0$;
(ii) non-decreasing in p, $\partial \ln C(y,p)/\partial \ln p_k \equiv ep_k \geq 0$, where ep_k is the kth input price elasticity;
(iii) homogeneity of degree one in p, $C(y,p/p_k) = C(y,p)/p_k$;
(iv) (iv) concave and continuous in p;
(v) $E_C = \left(\sum_{m=1}^{M} \partial \ln C(y,p)/\partial \ln y_m\right)^{-1} \equiv \left(\sum_{m=1}^{M} ey_m\right)^{-1}$ is the scale elasticity of the cost function representation of the production technology.

Because functions $C(y,p)$ and $D_I(y,x)$ are dual and also are isomorphic and hence for a given $y \in \mathbb{R}^{+}$ there is a bijective mapping between input quantities and prices (Shephard 1970). This property allows us to formulate IDF from Equation (4), in terms of input prices:

$$D_I(y,x) \equiv \inf\{px : C(y,p) \geq 1\} \tag{5}$$

Now we can utilise Shephard's lemma (Shephard 1970) to function $C(y,p)$ to obtain X_k that is the input demand function for the k^{th} input:

$$X_K = \frac{\partial \ln C(y,p)}{\partial \ln p_k} = \frac{\partial C(y,p)}{\partial p_k} \frac{C(y,p)}{p_k} \tag{6}$$

Finally, the cost share equation associated with the k^{th} input, S_k, is given as

$$S_K = \frac{\partial \ln C(y,p)}{\partial \ln p_k} \tag{7}$$

In this paper, we use the general form of the translog of IDF given as

$$\begin{aligned} -x_{Kit} &= \alpha_i + \rho_i t + \zeta_i t^2 + \kappa'_i \tilde{x}_{it} + \eta'_i y_{it} + \frac{1}{2}\tilde{x}'_{it}\Theta\tilde{x}_{it} + \\ &+ \frac{1}{2} y'_{it}\Gamma y_{it} + \tilde{x}'_{it}\Phi y_{it} + \delta'_i \tilde{x}'_{it} t + \psi'_{it} y_{it} t + \gamma'_i z_{it} + \varepsilon_{it} \end{aligned} \tag{8}$$

To compute Equation (8), we use panel data where there are N units, indexed $i = 1, \ldots, N$, that operate over T periods, indexed $t = 1, \ldots, T$. We normalise logs of inputs with $-x_{Kit}$ so $\tilde{x}_{it} = x_{it} - x_{Kit}$. Logged outputs are given by y_{it} and t is a time trend that can also interact with itself and corresponding regression coefficients are

ρ_i and ζ_i. The variables that shift the IDF are contained in z_{it} while ε_{it} is the error term. Finally, regression coefficients are κ'_{it}, η'_{it}, δ'_{it}, ψ'_i and γ'_i and matrices containing the regression coefficients are Θ_i, Γ_i and Φ_i.

We compute elasticities of complementarity and substitution from the IDF. The first measure of complementarity we use in the paper is AEC. This elasticity measures the response as a marginal value of x° to a change in the input quantity x_*. It was introduced by Blackorby and Russell (1981) who defined it as a true dual of the AES under non-constant returns to scale. To find AEC, we use the following equation.

$$\mathrm{AEC}_{*^{\circ}} = D_I(y,x)\frac{\partial^2 D_I(y,x)}{\partial x_* \partial x^{\circ}}\left(\frac{\partial D_I(y,x)}{\partial x_*}\frac{\partial D_I(y,x)}{\partial x^{\circ}}\right)^{-1} = S_*^{-1} \times \frac{\partial \ln P^{\circ}(y,x)}{\partial \ln x_*} \tag{9}$$

The above equation shows the shadow price of the input $^{\circ}$, $P^{\circ}(y,x) = \partial D_I(y,x)/\partial x^{\circ}$. The shadow price is derived by utilising Shephard's lemma on the IDF to get the inverse input demand function. Additionally, from the same IDF we get the cost share equation for input $*$, $S_* = \partial \ln D_I(y,x)/\partial \ln x_*$.

The above equation provides a theoretical base for the derivation of AEC. To get empirical results for $\mathrm{AEC}_{*^{\circ}}$ we employ estimates of a translog IDF function in Equation (7) using the following formula.

$$\mathrm{AEC}_{*^{\circ}} = (\theta_{i,*^{\circ}} + S_{i,*}S_{i,^{\circ}}) \times (S_{i,*}S_{i,^{\circ}})^{-1} \tag{10}$$

And for the AEC_{**}, we adapt Stern (2011) which is given as

$$\mathrm{AEC}_{**} = (\theta_{i,**} + {S_{i,*}}^2 - S_{i,*}) \times {S_{i,*}}^{-2} \tag{11}$$

where $S_{i,*} = \kappa_{i,*}$ and $S_{i,^{\circ}} = \kappa_{i,^{\circ}}$ and $\theta_{i,*^{\circ}}$, $\theta_{i,**}$, $\kappa_{i,*}$ and $\kappa_{i,^{\circ}}$ are the parameters from the coefficient matrix Θ_i and κ'_i in the translog IDF function, respectively.

To compute the elasticities of substitution, we use symmetric AES. The AES was introduced by Allen (1934, 1938) and further developed by Uzawa (1962). The AES measures the response of the input quantity to a change in input price p. There are two approaches to finding the AES. The first approach is to derive the AES from a production function; hence it is also called the primal AES. In the second approach, the AES is computed from a cost function, in this instance, it is called the dual AES. In this paper, we derive the dual AES from the cost function because of the duality between this function and the IDF.

$$\mathrm{AES}_{*^{\circ}} = C(y,p)\frac{\partial^2 C(y,p)}{\partial p_* \partial p^{\circ}}\left(\frac{\partial C(y,p)}{\partial p_*}\frac{\partial C(y,p)}{\partial p^{\circ}}\right)^{-1} = S_*^{-1} \times \frac{\partial \ln X^{\circ}(y,p)}{\partial \ln p_*} \tag{12}$$

This formula specifies how the dual AEC can be obtained from the IDF. To get numerical estimates of $\mathrm{AES}_{*^{\circ}}$, we employ a matrix of the AECs – drawing on Stern (2011) – and define them as

$$\begin{bmatrix} \mathrm{AES}_{*^{\circ}} & \iota \\ \iota' & 0 \end{bmatrix}^{-1} = \left[\mathrm{diag}(S_1, \cdots, S_K, 1)\begin{bmatrix} AEC_{*^{\circ}} & \iota \\ \iota' & 0 \end{bmatrix}\mathrm{diag}(S_1, \cdots, S_K, 1)\right] \tag{13}$$

Our preference for AEC and AES measures stems from the fact that our models include more than two inputs. They are symmetrical and, hence, can be used when a model has more than one input (see Stern 2011).

4. Data

There is a large amount of ESG data on the US market particularly starting from 2009 and, hence, concentrating on the US considerably increases the sample size. Additionally, we focus on the US due to its global role in the world economy and hence spillover effects of uncertainties on the rest of the world. Our data are from the Refinitiv Eikon Datastream ESG database (formerly Asset 4). This database is used for example by Chambers and Serra (2018), De Lucia, Pazienza, and Bartlett (2020) and Eliwa, Aboud, and Saleh (2019). The original data consist of 5798 companies comprising 38 US industries (see Table 1) that span 12 years from 2009 to 2020 and include (i) financial data on sales, capital and employees; (ii) two financial ratios – ROA and ROE and (iii)

Table 1. The number of observations and companies.

	Industry	Initial number of		Final number of	
		Observations	Companies	Observations	Companies
1	Aerospace and Defence	960	80	264	22
2	Alternative Energy	1212	101	24	2
3	Automobiles and Parts	756	63	180	15
4	Banks	6336	528	1056	88
5	Beverages	564	47	120	10
6	Chemicals	1116	93	276	23
7	Construction and materials	924	77	240	20
8	Electricity	660	55	324	27
9	Electronic and Electrical Equipment	600	50	168	14
10	Equity and Investment Instruments	2592	216	12	1
11	Fixed Line telecommunications	612	51	132	11
12	Food and Drug Retailers	540	45	120	10
13	Food Producers	2052	171	252	21
14	Forestry and Paper	192	16	60	5
15	Gas, Water and Multiutilities	552	46	228	19
16	General Industrials	660	55	288	24
17	General Retailers	3540	295	744	62
18	Health Care Equipment and Services	3612	301	600	50
19	Household Goods and Home Construction	1068	89	240	20
20	Industrial Engineering	1092	91	132	11
21	Industrial Metals and Mining	564	47	108	9
22	Industrial Transportation	1308	109	276	23
23	Leisure Goods	912	76	96	8
24	Life insurance	336	28	120	10
25	Media	1764	147	216	18
26	Mining	1884	157	96	8
27	Nonlife Insurance	1176	98	480	40
28	Oil and Gas Producers	2376	198	324	27
29	Oil Equipment and Services	1368	114	300	25
30	Personal Goods	1008	84	216	18
31	Pharmaceuticals and Biotechnology	10,056	838	744	62
32	Real Estate Investment and Services	1188	99	84	7
33	Real Estate Investment Trusts	1548	129	636	53
34	Software and Computer Services	7200	600	852	71
35	Support Services	1500	125	276	23
36	Technology Hardware and Equipment	2772	231	600	50
37	Tobacco	228	19	36	3
38	Travel and Leisure	2748	229	624	52
	Total	**69,576**	**5798**	**11,544**	**962**

three main ESG indicators – ESG scores. All variables are in logs and, except for financial ratios, are centred and standardised; additionally, inputs are normalised by a dependent variable. Similar to Kotsantonis and Serafeim (2019), our initial ESG data exhibit a large proportion of missing observations. There are ESG 'data gaps' across all dimensions – missing observations on companies, across years and also across variables. In such an instance, Kotsantonis and Serafeim (2019) suggest using a MI approach to provide more variability and improve the accuracy of augmented data.

Despite our original data having 69,576 observations, 78.5% of observations on ESG indicators are missing. The current literature does not have a clear consensus on the maximum proportion of missing observations for MI. Some research studies indicate that the cut-off is at most 50%, see for example Lan et al. (2021), Lin, Liu, and Lan (2021) and Madley-Dowd et al. (2019). Hence, we face a trade-off between being restrictive in selecting companies and a desideratum for a larger sample size. Therefore, before applying MI, we ensure that on an aggregate level, our data have approximately 80% of ESG observations by eliminating individual firms with missing ESG above 50%. This selection gives us 962 companies. Descriptive statistics are provided in Tables 2 and 3.

Table 2. Descriptive statistics of the initial data.

	Employees (thousands)	Capital (mil.)	Sales (mill.)	RoE (thousands)	RoA (mil.)	Environment Score	Governance Score	Social Score
Mean	10.43	3.18	2.81	−0.22	−0.03	22.77	47.25	41.18
Std. Dev.	54.44	18.60	15.00	16.33	4.41	27.44	22.65	20.67
Min	0.00	−5.96	−2.31	−2245.00	−746.00	0.00	0.17	0.45
Max	2300.00	587.00	559.00	60.90	51.80	98.55	99.41	98.12
Avail. Obs.	34,396.00	48,981.00	49,435.00	37,234.00	45,042.00	14,963.00	14,963.00	14,963.00
Missing	35,180.00	20,595.00	20,141.00	32,342.00	24,534.00	54,613.00	54,613.00	54,613.00
Percent missing	50.56	29.60	28.95	46.48	35.26	78.49	78.49	78.49
Total	69,576.00	69,576.00	69,576.00	69,576.00	69,576.00	69,576.00	69,576.00	69,576.00

Table 3. Descriptive statistics of the final data.

	Employees (thousands)	Capital (mil.)	Sales (mill.)	RoE (thousands)	RoA	Environment Score	Governance Score	Social Score
Mean	28.98	11.60	10.40	0.01	3.74	32.48	52.20	47.34
Std. Dev.	92.97	36.20	28.90	0.45	22.11	29.28	22.41	21.32
Min	0.00	−5.96	−2.31	−24.85	−976.60	0.00	0.25	0.53
Max	2300.00	587.00	559.00	31.56	161.43	98.55	99.41	98.12
Avail. Obs.	10,875	11,347	11,415	10,701	11,137	9138	9138	9138
Missing	669	197	129	843	407	2406	2406	2406
Percent Missing	5.80	1.71	1.12	7.30	3.53	20.84	20.84	20.84
Total	11,544	11,544	11,544	11,544	11,544	11,544	11,544	11,544

Table 4. Little's MCAR test.

Number of observations		11,417
Number of patterns		32
Observations per pattern:	Minimum	1
	Average	356.783
	Maximum	7149
Chi-square distance		4731.179
Degrees of freedom		130
Prob $>$ chi-square		0.000
Log-likelihood		−31,246.07

Notes: 127 observations omitted from EM estimation because of all imputation variables missing. Prior: uniform. Expectation-maximisation estimation.

Essentially, there are three types of missing data mechanisms: (1) missing completely at random (MCAR) – the missing observations are completely independent of observed variables. Rubin (1976) and more recently Horton and Kleinman (2007) show this as $\Pr(\mathrm{R}{:}y_{obs}, x_{obs}, y_{mis}, x_{mis}) = \Pr(\mathrm{R})$ where R is a missingness value indicator. In such an instance, both MI and listwise deletion of data provide unbiased results; (2) missing at random (MAR) – the missing observations depend on the observed variables, i.e. they are conditional on covariates. Sometimes MAR is called a covariate-dependent missingness. It can be shown as $\Pr(\mathrm{R}{:}y_{obs}, x_{obs}, y_{mis}, x_{mis}) = \Pr(\mathrm{R}{:}y_{obs}, x_{obs})$. MI requires MAR assumption; and (3) missing not at random (MNAR) which arises when neither MCAR nor MAR holds. In such an instance, a process, that generates missing values, is called non-ignorable. In practice, MNAR models are not identifiable (see Eddings and Marchenko 2012).

Since the effectiveness of the MI depends on the type of missing data – data ought to be MAR – we use Little's test on our dataset to detect the type of process generating missing observations (see Li 2013 and Little, 1988). Even though this test allows the use of auxiliary data, the eight variables we employ are sufficient to run the test. The results of this test are given in Table 4. According to this test, the Chi-square distance is 4731.17 with probability zero; hence, the null that data are MCAR can be rejected in favour of MAR. Consequently, in line with Kotsantonis and Serafeim (2019) we use an MI. The MI approach we employ is based on the posterior predictive distribution with the multivariate normal regression.

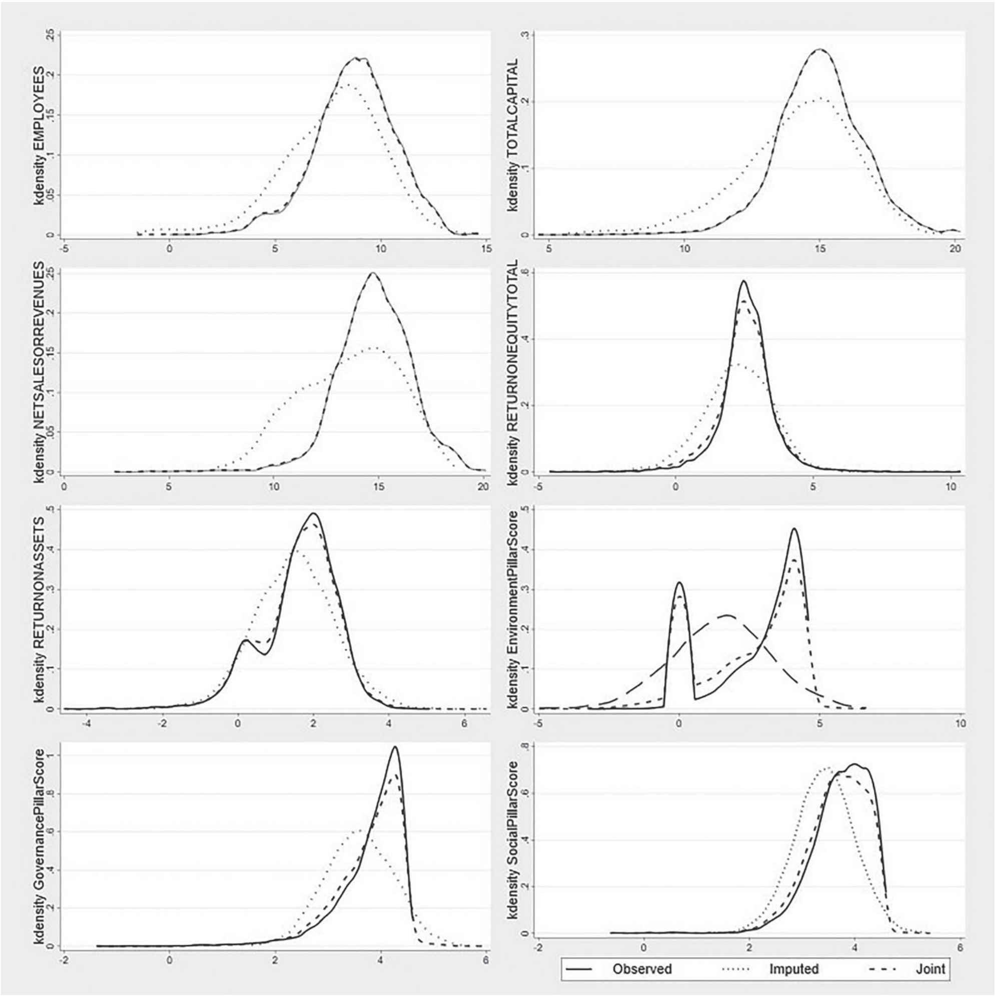

Figure 1. Joint distribution of observed and imputed data.

The distribution of the joint densities of the observed and imputed data is provided in Figure 1. According to this figure, most of the variables exhibit unimodal distribution with the exceptions of an 'Environment Score' and somewhat 'Return on assets. Figure 1 indicates the bimodal distribution for these two variables. Although we augment the missing data with imputed observations, the joint density of the variables closely follows and supplements the distribution of the observed data.

5. Estimates of the translog function

Results of the translog function are provided in Tables 5–8. These tables focus on ESG indicators, and each of them includes one ESG pair - Environment and Social pair (ES, specification 1, Table 5), Environment and Governance pair (EG, specification 2, Table 6) and Governance and Social pair (GS, specification 3, Table 7) – and Table 8 includes all three indicators (ESG, specification 4, Table 8). These indicators are used as inputs in the translog regression function, in addition to the standard inputs. In all specifications the dependent variable is employed and due to the third property of the distance function it has to be less than zero. As anticipated, we have a negative coefficient for the output variable (*Sales*) and positive coefficients for input variables. This is in

Table 5. Random effects regression: environment and Social Scores (specification 1).

	Coefficient		Coefficient
Sales	−0.771***	Time∗Sales	−0.006***
	(0.015)		(0.001)
Capital	0.445***	Sales∗Capital	0.051***
	(0.013)		(0.007)
Return on Equity	0.007	Time∗Capital	0.004***
	(0.004)		(0.001)
Return on Assets	0.040***	Time∗(Environment	−0.003***
	(0.005)	Score)	(0.001)
Time	0.019***	Time∗(Social Score)	0.000
	(0.002)		(0.001)
Environment Score	0.053***	(Environment Score)	0.002
	(0.007)	∗Capital	(0.009)
Social Score	0.031***	(Social Score) ∗Capital	−0.009
	(0.007)		(0.006)
Sales^2	−0.112***	(Environment Score)	−0.014***
	(0.005)	∗(Social Score)	(0.004)
Capital^2	0.120***	Constant	−0.159***
	(0.013)		(0.009)
Time^2	−0.001***	Sigma_u	0.266
	(0.000)		
$(\text{Environment Score})^2$	0.017*	Sigma_e	0.161
	(0.010)	Rho	0.731
$(\text{Social Score})^2$	0.018***	Hausman test: chi2(22)	1676.64
	(0.004)	Prob > chi2(22)	0.000
Sales∗(Environment Score)	−0.040***	Number of imputations	10
	(0.007)	Number of observations	11,544
Sales∗(Social Score)	0.008	Number of groups	962
	(0.006)	Specification	re

Notes: ***, **, * significant at 1%, 5% and 10% levels, respectively.
Standard errors are in parentheses. Dependent variable: - Employees.

line with the literature where negative output and positive input coefficients, at the sample mean, indicate the monotonicity of the distance function.

The returns to scale indicate the response of output to factor changes in inputs of production. Homogeneity of degree one can be observed when the production function exhibits constant returns to scale. In such an instance, the output increases proportionally to the increase in inputs. However, in the case of homogeneity greater or less than one, the process belongs to increasing or decreasing returns to scale, accordingly. Our results indicate that during the analysed period, US companies exhibit a significant increase in returns to scale. The returns to scale for our models are approximately equal to 1.32 with a statistically significant level at 1% according to the Wald test.

Firms within the analysed period are educed with substantial development in disruptive technologies: both hardware and software applications. To confirm this proposition, we apply the student t-test on the time variable. As we expect, the time trend has a statistically significant and positive impact over an analysed period – hence, indeed it implicitly indicates the presence of technological innovation. Due to this factor, the average shift in the production function is in the range of 0.018–0.019 or about 2% annually. Nonetheless, estimates of the partial derivative for the translog with respect to the time trend indicate that these shifts are nonlinear. Moreover, the ESG values have a soothing impact on the global extremum of this derivative function.

The translog regression includes two related variables that shift the production function: ROE and ROA. These variables signal the profitability of the US firms against their shareholder's equity and assets. There is also an interesting observation about the firms' performance. Despite that the returns on assets have no statistical impact on inputs, this is not the case with the null of the returns on equity. Strangely, by decomposing the returns on equity into two components (i.e. the returns on assets and financial leverage), you can deduce that there is no considerable association between the firms' inputs and the level of debt. Moreover, DuPont's relation suggests

Table 6. Random effects regression: Environment and Governance Scores (specification 2).

	Coefficient		Coefficient
Sales	−0.760***	Time∗Sales	−0.007***
	(0.010)		(0.001)
Capital	0.421***	Sales∗Capital	0.049***
	(0.010)		(0.005)
Return on equity	0.005	Time∗Capital	0.004***
	(0.004)		(0.001)
Return on Assets	0.043***	Time∗(Governance	−0.001
	(0.005)	Score)	(0.001)
Time	0.018***	Time∗(Environment	−0.003***
	(0.002)	Score)	(0.001)
Governance Score	0.051***	(Governance	−0.004
	(0.006)	Score)∗Capital	(0.005)
Environment Score	0.061***	(Environment	0.001
	(0.006)	Score)∗Capital	(0.008)
Sales^2	−0.116***	(Governance Score)∗	−0.017***
	(0.005)	(Environment Score)	(0.003)
Capital^2	0.111***	Constant	−0.165***
	(0.013)		(0.011)
Time^2	−0.001***		
	(0.000)	sigma_u	0.216
(Governance Score)^2	0.020***	sigma_e	0.158
	(0.003)	rho	0.650
(Environment Score)^2	0.021**	Hausman test: chi2(22)	31.91
	(0.008)	Prob > chi2(22)	0.0789
Sales∗(Governance Score)	−0.007**	Number of imputations	10
	(0.003)	Number of observations	11,544
Sales∗(Environment Score)	−0.033***	Number of groups	962
	(0.007)	Specification	re

Notes: ***, **, * significant at 1%, 5% and 10% levels, respectively.
Standard errors are in parentheses. Dependent variable: '- Employees'.

that the major contributors are profit margin and asset turnover; as a consequence, these are the firms' market power and assets' efficiency in producing sales.

Lastly, since the main focus of this paper is elasticities of complementarity, we concentrate our discussion on ESG coefficients only. According to these tables, the coefficients are positive and statistically significant at the 1% level. Tables 5–7 (with specs 1–3) indicate that at the sample mean, the values for ESG indicators range from 0.042 for Social Score in the GS table to 0.061 for Environment Score in the EG table. In Table 8, the coefficients are 0.014, 0.063 and 0.126 for Social, Environment and Governance indicators, respectively. As it is expected, the squared values of ESG indicators are all positive and statistically significant.

We use the Hausman test to identify the random effects in Tables 7 and 8. We reject the null for ES (spec. 1) and ESG (spec. 4) and vice versa for GS (spec. 3). At the same time, the Hausman test for the EG model (spec. 2) could be rejected only at 10% level. Moreover, Tables 5–8 exhibit a company-specific variance that is larger than the overall variance of the model. This is an expected result since we are using a large dataset with heterogeneous companies from different sectors of the US economy. There are important factors that belong to individual companies and do not change over time. In specifications 1–3, we use 10 imputations to run regressions. Within each imputation, we use 1000 iterations with 100 burn-in periods. Finally, specification 4 is based on all available data without imputing missing observations.

6. Combined AEC and AES, estimation results and discussion

6.1. Combined Antonelli elasticity of complementarity (AEC^C) and AES (AES^C)

We estimated both AEC and AES elasticities directly from IDF. Therefore, positive values of AEC are positive primal elasticities that suggest that two inputs are q-complements. In such a case, an increase in the quantity of one input leads to an increase in the quantity of the other; hence, both inputs increase. The opposite is true

Table 7. Fixed effects regression: Governance and Social Scores (specification 3).

	Coefficient		Coefficient
Sales	−0.757***	Time∗Sales	−0.007***
	(0.010)		(0.001)
Capital	0.433***	Sales∗Capital	0.034***
	(0.011)		(0.005)
Return on Equity	0.001	Time∗Capital	0.003***
	(0.004)		(0.001)
Return on Assets	0.050***	Time∗(Governance	−0.001*
	(0.005)	Score)	(0.001)
Time	0.018***	Time∗(Social Score)	−0.001
	(0.002)		(0.001)
Governance Score	0.057***	(Governance Score)∗	−0.004
	(0.006)	Capital	(0.004)
Social Score	0.042***	(Social Score)∗Capital	−0.014**
	(0.006)		(0.005)
Sales^2	−0.107***	(Governance	−0.010***
	(0.005)	Score)∗(Social Score)	(0.003)
Capital^2	0.124***	Constant	−0.168***
	(0.013)		(0.012)
Time^2	−0.001***		
	(0.000)	Sigma_u	0.21742
(Governance Score)^2	0.018***	Sigma_e	0.160784
	(0.004)	rho	0.646464
(Social Score)^2	0.024***	Hausman test: chi2(22)	0.44
	(0.004)	Prob > chi2(22)	1.000
Sales∗(Governance Score)	−0.016***	Number of imputations	10
	(0.003)	Number of observations	11,544
Sales∗(Social Score)	0.010*	Number of groups	962
	(0.005)	Specification	fe

Notes: ***, **, * significant at 1%, 5% and 10% levels, respectively.
Standard errors are in parentheses. Dependent variable: '- Employees'.

for negative AEC values. They are negative primal elasticities that indicate q-substitution and an increase in the number of one input leads to a decrease in the marginal product of the other.

Our AES elasticities are dual because we estimate them indirectly from the IDF. Positive estimates of AES suggest that two inputs are price substitutes. Whence, the price increases lead to increases in the quantity of the other input. On the other hand, negative estimates of AES indicate price complementarity between two inputs and consequently increase in the price of one input decreases the quantity of the other input, i.e. they are p-complements.

Before proceeding with estimation results, we note that we have four different models; therefore, we have up to four estimates of elasticities for some pairs (see Table 9). We test them for mean differences using an independent samples test. The results of this test indicate that elasticities obtained using different specifications are statistically different from each other. Whence, instead of relying on one model, we aggregate them into a combined complementarity measure by adapting the approach provided by Gibson, Hall, and Tavlas (2020). Combined measures for complementarity/substitution ought to provide more accurate results compared to individual ones.

The combined estimate of AEC (AEC^C) in our paper is given by

$$\mathrm{AEC}^C = \sum_{\mathcal{M}=1}^{N} \varpi_{\mathcal{M}} \mathrm{AEC}_{\mathcal{M}} \tag{14}$$

And the square root of its variance is

$$\sigma_{\mathrm{AEC}}^C = \sqrt{\sum_{\mathcal{M}=1}^{N} \varpi_{\mathcal{M}}^2 \sigma_{\mathcal{M}}^2} \tag{15}$$

Table 8. Random effects regression: Environment, Social and Governance Scores (specification 4).

	Coefficient		Coefficient
Sales	−0.756***	Time∗Capital	0.005***
	(0.008)		(0.001)
Capital	0.273***	(Governance Score)^2	0.018***
	(0.007)		(0.002)
Return on Equity	0.014***	(Social Score)^2	0.013***
	(0.003)		(0.003)
Return on Assets	0.020***	(Environment Score)	0.045***
	(0.004)	2	(0.005)
Time	0.013***	Sales∗Capital	0.010
	(0.001)		(0.006)
Governance Score	0.037***	(Governance Score)∗	0.007***
	(0.004)	Capital	(0.003)
Social Score	0.018***	(Social Score)∗Capital	0.009***
	(0.005)		(0.003)
Environment Score	0.042***	(Environment	−0.010
	(0.005)	Score)∗Capital	(0.004)
Sales^2	−0.032***	(Governance	−0.006***
	(0.008)	Score)∗(Social Score)	(0.002)
Capital^2	0.147***	(Governance Score)∗	−0.005**
	(0.007)	(Environment Score)	(0.002)
Time^2	0.000***	(Environment Score)	−0.010***
	(0.000)	∗(Social Score)	(0.003)
Sales∗(Governance Score)	0.008***	Constant	−0.166***
	(0.003)		(0.011)
Sales∗(Social Score)	−0.006*		
	(0.003)	Sigma_u	0.237
Sales∗(Environment Score)	−0.032***	Sigma_e	0.073
	(0.006)	rho	0.912
Time∗Sales	−0.002***	Hausman test: chi2(28)	622.78
	(0.001)	Prob > chi2(28)	0.000
Time∗(Governance Score)	−0.001*	Number of imputations	n/a
	(0.000)	Number of observations	7,149
Time∗(Social Score)	−0.001	Number of groups	906
	(0.001)	Specification	re
Time∗(Environment Score)	0.000		
	(0.001)		

Notes: ***, **, * significant at 1%, 5% and 10% levels, respectively.
Standard errors are in parentheses. Dependent variable: '- Employees'.
The model is based on all available data without imputing missing observations.

where ϖ is the weight associated with each model that sums to unity and N is the number of models to be combined. Since we do not have a strict preference for any model, weights ϖ are equally allocated across the individual AECs.

An equivalent equation is obtained for the combined estimate of AES (AES^C):

$$\mathrm{AES}^C = \sum_{\mathcal{M}=1}^{N} \varpi_{\mathcal{M}} \mathrm{AES}_{\mathcal{M}} \tag{16}$$

6.2. Estimation results

Numerical elasticity estimates of complementarity and substitution are presented in Tables 9 and 10, respectively. The results presented in columns 2–4 of these tables are for AECs and AESs computed from four models, while the last column shows the combined estimates.

According to estimates in Table 9, most of individual (specs 1–4 in columns 2–5) and combined (column 6) AEC estimates for input pairs are statistically different from zero. There are exceptions for two input pairs. First, a Social and Capital inputs pair (Soc.-Cap.) with two AEC estimates (specs 1 and 3 in columns 2 and 4) having

Table 9. Estimates of Antonelli elasticities of complementarity (AEC).

	Model based on the regression with				Combined
Input Pairs	Environment and Social Scores (spec. 1)	Environment and Governance Scores (spec. 2)	Governance and Social Scores (spec. 3)	Environment, Social and Governance Scores (spec. 4)	
1	2	3	4	5	6
Gov.-Gov.	-	−10.798***	−11.029***	−12.645***	−11.491***
		(1.470)	(1.642)	(1.442)	(0.878)
		[0.000]	[0.000]	[0.000]	[0.000]
Envir.-Envir.	−10.666***	−9.770***	-	2.604	−5.944***
	(3.375)	(2.350)		(3.218)	(1.741)
	[0.002]	[0.000]		[0.418]	[0.001]
Gov.-Envir.	-	−4.321***	-	−2.095	−3.208***
		(0.982)		(1.319)	(0.822)
		[0.000]		[0.112]	[0.000]
Soc.-Soc.	−10.316***	-	−8.999***	−15.079	−11.465***
	(4.060)		(2.664)	(10.888)	(3.974)
	[0.011]		[0.001]	[0.166]	[0.004]
Gov.-Soc.	-	-	−3.052**	−7.468**	−3.507**
			(1.343)	(3.320)	(1.791)
			[0.023]	[0.024]	[0.050]
Envir.-Soc.	−7.813***	-	-	−12.552***	−10.183***
	(2.842)			(4.313)	(2.582)
	[0.006]			[0.004]	[0.000]
Cap.-Cap.	−0.673***	−0.752***	−0.649***	−0.685***	−0.690***
	(0.065)	(0.076)	(0.072)	(0.098)	(0.039)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Gov.-Cap.	—	0.814***	0.821***	1.648***	1.094***
		(0.213)	(0.169)	(0.266)	(0.127)
		[0.000]	[0.000]	[0.000]	[0.000]
Envir.-Cap.	1.085***	1.029***	-	0.116	0.743***
	(0.363)	(0.325)		(0.289)	(0.189)
	[0.003]	[0.002]		[0.688]	[0.000]
Soc.-Cap.	0.365	-	0.248	2.924***	1.179***
	(0.424)		(0.295)	(0.922)	(0.352)
	[0.389]		[0.401]	[0.002]	[0.001]
Emp.-Emp.	−0.602***	−0.627***	−0.626***	−0.099***	−0.489***
	(0.061)	(0.057)	(0.073)	(0.022)	(0.028)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Emp.-Gov.	-	1.013***	0.843***	0.375***	0.744***
		(0.176)	(0.137)	(0.125)	(0.085)
		[0.000]	[0.000]	[0.003]	[0.000]
Emp.-Envir.	0.755***	0.829***	-	0.258***	0.614***
	(0.228)	(0.189)		(0.148)	(0.110)
	[0.001]	[0.000]		[0.081]	[0.000]
Emp.-Soc.	1.257***	-	0.937***	0.433	0.875***
	(0.362)		(0.262)	(0.336)	(0.186)
	[0.001]		[0.000]	[0.198]	[0.000]
Emp.-Cap.	0.462***	0.456***	0.467***	0.110**	0.374***
	(0.056)	(0.056)	(0.055)	(0.044)	(0.027)
	[0.000]	[0.000]	[0.000]	[0.012]	[0.000]

Notes: ***, **, * significant at 1%, 5% and 10% levels, respectively.
Standard errors are in parentheses. *p*-values in brackets.

insignificant coefficients. Nevertheless, the third AEC (spec 4, column 3) for the same pair is significant and it drives up the statistical significance of the combined AEC. The opposite results are for the second exception. Estimates obtained for self-elasticity of Environment (Envir.-Envir.) for specs 1 and 2 (columns 2 and 3) are negative and statistically different from zero, while the estimates of AEC for spec 4 (column 5) are positive and insignificant; however, the combined AEC for Envir.-Envir. is negative and significantly different from zero.

Table 10. Estimates of Allen-Uzawa elasticities of substitution (AES)

	Model based on the regression with				
Input Pairs	Environment and Social Scores (spec. 1)	Environment and Governance Scores (spec. 2)	Governance and Social Scores (spec. 3)	Environment, Social and Governance Scores (spec. 4)	Combined
1	2	3	4	5	6
Gov.-Gov.	–	−41.183	−29.135	−21.329	−30.549
Envir.-Envir.	−76.460	−30.850	–	17.670	−29.880
Gov.-Envir.	–	18.374	–	−32.610	−7.118
Soc.-Soc.	−240.070	–	−68.705	−361.869	−223.548
Gov.-Soc.	–	–	17.986	53.706	23.897
Envir.-Soc.	109.384	–	–	20.247	64.816
Cap.-Cap.	−2.932	−2.614	−2.772	−15.213	−5.883
Gov.-Cap.	–	1.759	0.531	18.632	6.974
Envir.-Cap.	−3.920	0.490	–	−8.981	−4.137
Soc.-Cap.	11.048	–	4.132	−55.121	−13.314
Emp.-Emp.	−2.346	−2.154	−2.146	−4.130	−2.694
Emp.-Gov.	–	0.495	1.433	−6.064	−1.379
Emp.-Envir.	5.046	1.608	–	3.964	3.539
Emp.-Soc.	−6.600	–	0.101	29.704	7.735
Emp.-Cap.	2.403	2.097	2.128	7.728	3.589

Table 9 also indicates that AEC's self-elasticities of each input, both standard and ESG, are negative implying that there is increasing pressure to reduce input demand. Similarly, estimates involving only ESG cross-elasticities are negative, while all estimates of cross-elasticities with standard inputs – capital and labour – are positive. The positive sign of these pairs implies that they are compensated complements to ESG indicators and to each other. Therefore, as one of the standard factors of production increases, it leads to an increase in the price of the other.

Table 10 presents estimates for AESs. Frondel and Schmidt (2002; see in Stern 2011) note that when elasticities of substitutions are erroneously calculated, they tend to classify all inputs as p-substitutes due to the large own-price elasticities compared to cross-price elasticities. Nonetheless, we believe our approach is resistant to such errors. Indeed, we find that ESGs' own-price elasticities are large in absolute values. For example, self-AES for Social indicator (Soc.-Soc.) provided by the combined AES^C estimate is -223.55. However, all cross-AESs involving the 'Social' indicator are positive, both for standard inputs and for ESG inputs. This is despite the self-AES^C for the Social score being greater than a factor of 80 compared to standard inputs' self-AES^Cs, e.g. own-elasticity of Employment (emp.-emp.) with $AES^C = -2.69$. Moreover, for the other three cross-elasticity pairs the AES^C signs are positive, classifying them as p-complements too and only for a 'Gov.-Envir.' pair the sign is negative indicating that it is a p-substitute.

6.3. Discussion on ESG elasticities of complementarity and substitution

This research is motivated by the high costs of sustainable practices on firms; therefore, identifying p-complementarity/q-substitution of inputs is important for cost reduction purposes. For instance, considering that ESG-only AEC cross-elasticities exhibit negative signs they are classified as q-substitutes (see Table 9 column 6). This suggests that an increase in the quantity of one ESG input leads to a decrease in the marginal quantity of the other. At the same time, overall output is expected to stay constant. However, the cross-elasticity of mixed input pairs (i.e. ESG and standard inputs) is predominantly positive. This is an indication that they are compensated complements to each other; hence, both standard and ESG inputs are concomitants.

As we have seen, AEC estimates are important because they show relations in terms of input quantities. AES, on the other hand, is useful when the focus is on price and quantity interaction. In this respect, our results indicate that only one ESG pair out of three is a p-complement (this is a pair involving government and environment initiatives), while the other two 'doublets' are p-substitutes. Moreover, both of them involve a social initiative indicator hence as the price of a social initiative increases, it increases the input quantity of two other ESG counterparts as well. These results are in line with McWilliams and Siegel (2000), and Cavaco and Crifo

(2014) who note that socially responsible firms commit to improvements in governance and environmental practices too. Expectedly, AES's self-elasticities – both for ESG and standard inputs – are negative that display a negative relationship between prices and demand for ESG reflecting the inverse law of demand, as stated by Kim (2000).

Finally, since we have three ESG indicators and each one appears in two cross-elasticities, the impact of the changes is felt across the other ESG indicators simultaneously. Albeit, the magnitude of the impact may differ across each input. Therefore, our findings suggest that investments in sustainability have a multiplicative effect through the complementarity of the other ESG initiatives.

7. Conclusion

In this paper we investigate the relationship between ESG indicators through elasticity concepts; specifically, we employ two elasticity types: AEC and AES. They are symmetrical and, more importantly, can be used when a model uses more than one input. Empirically, we find these elasticity measures through the translog of IDF following Glass, Kenjegaliev, and Kenjegalieva (2020).

Current literature, such as Kotsantonis and Serafeim (2019), report that data on ESG have many missing observations. We experience similar issues with our data. There are two practical ways to overcome such issues. The first approach is to remove observations with missing data. However, removing all missing observations considerably reduces the dataset. In our initial data, we have 69,576 unit-year observations; at the same time, the proportion of missing data for ESG indicators is close to 80%. Whence, instead of removing all missing data, we lacerate them to an acceptable level – total missing observations for ESG in the final data are roughly 20%. Subsequently, the missing data in the lacerated data are imputed using multiple imputations using an iterative Markov chain Monte Carlo method.

We find that own AEC elasticities are negative, implying that there is increasing pressure to reduce input demand. On the other hand, standard inputs – capital and labour – are compensated complements to ESG indicators and to each other. Hence, as one of these factors of production increases, the price of the other increases too. As opposed to the interaction of standard inputs, ESG-only cross-elasticities exhibit negative signs, classifying them as q-substitutes. Therefore, an increase in one of the ESG leads to a decrease in the marginal value of the other while output is kept constant. On the other hand, AES elasticities have a negative sign only for the Governance-Environment 'doublet"; the rest of the pairs are positive suggesting that they are p-complements. Moreover, since each ESG indicator appears twice, the impact of this change is felt simultaneously across the other ESG indicators. The implication of these findings suggests that investment in sustainability has a multiplicative effect through complementarity on the other ESG factors.

Accordingly, there is a practical implication of our results that enables firms to have much-needed methodical support for their decisions in green investment by providing the ability for appropriate selection of the ESG inputs that maximise benefits without compromising their ability to generate required output. Our work is important given that there are only two comparable studies on the complementarity of ESG initiatives – by Cavaco and Crifo (2014) and by Zhang, Loh, and Wu (2020). Focusing in-depth on quantity- and price- complementarity and substitutability of the green investments and sustainability activities, allows stakeholders to design tools and actions that capitalise on the benefits of ESG inputs in terms of green practices and from the production perspective.

Increasing public pressure to undertake green initiatives forces firms to carry out practices that are not always compatible with their financial performance (see Gillan, Koch, and Starks 2021). Therefore, ESG initiatives should be economically viable. In this sense, we believe our research is particularly timely. Although our study is empirical in nature, there are clear directions for future research in terms of not only empirics but also econometric dimensions. For example, given that we compute AEC duals using the inverse matrix, AEC's inverse variance matrix may yield negative values. To remedy negative variance, one may estimate Bayesian inference with posterior approximations with assigned probability near unity for values greater than zero in the inverse of the variance matrix (see, for example, Lancaster 2004 for Bayesian inference).

To conclude, there is a growing importance of sustainability and its impact on the financial standing of companies. Hence, our empirical results have a practical contribution to companies. Specifically, since sustainability initiatives are costly to firms, our paper can assist them in identifying the magnitude and type of ESG cross-impact. Based on this insight, companies can develop appropriate sustainability strategies, which will ultimately drive their overall expenditure down.

Note

1. Two inputs are q-complements/substitutes if an increase in the quantity of one of the inputs leads to an increase/decrease in the marginal product of the other. However, if the price increases/decreases and quantity of the other increase/decrease then the inputs are said to be p-substitutes/complements.

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No potential conflict of interest was reported by the author(s).

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