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Substitution between Energy and Capital: Evidence from a Four-Factor Translog Production Function Disentangling Tangible and Intangible Capital*

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Abstract

The substitution/complementarity relationship between production factors has received substantial interest in economic literature. Since the oil crisis period of 1970s, this stream of literature has particularly focused on the substitutability of energy with other factors of production. This paper assesses the substitution between energy and capital using a four-factor translog production approach separating capital into tangible and intangible forms. Using a panel data set of 14 OECD countries from 1995-2020, we estimated substitution elasticities for 11 manufacturing subsectors using Ridge Regression. Empirical results suggest a substitution between energy and both capital inputs for all manufacturing subsectors. The substitution elasticity between energy and intangible capital is found to be higher than that between energy and tangible capital. Moreover, substitution elasticity between energy and intangible capital is found to be highest in energy-intensive industries while the highest substitution elasticities between energy and tangible capital are recorded in high- and medium-high technology manufacturing subsectors.

JEL Classification: D24, C33, Q41

Keywords: substitution between energy and capital, tangible and intangible capital, translog production function, panel data, ridge regression

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Enerji ve Sermaye Arasındaki İkame: Maddi ve Maddi Olmayan Sermayenin Ayrıştırıldığı Dört Faktörlü Translog Üretim Fonksiyonundan Bulgular

Öz

Üretim faktörleri arasındaki ikame/tamamlayıcılık ilişkisi, ekonomik literatürde ilgi gören bir konudur. 1970'lerin petrol krizleri döneminden bu yana, literatür özellikle enerjinin diğer üretim faktörleriyle ikame edilebilirliği üzerine yoğunlaşmıştır. Bu makale, enerjinin sermaye ile ikamesini değerlendirmek için, sermayeyi maddi ve maddi olmayan sermaye olarak ayıran dört faktörlü bir translog üretim yaklaşımı kullanmaktadır. 14 OECD ülkesine ait, 1995-2020 dönemini kapsayan panel veri seti kullanılarak, Ridge Regresyon yöntemiyle 11 imalat sanayii alt sektörü için ikame esneklikleri tahmin edilmiştir. Ampirik sonuçlar, tüm imalat sanayii alt sektörlerinde enerji ile her iki sermaye girdisi arasında ikame ilişkisinin bulunduğunu göstermektedir. Enerji ile maddi olmayan sermaye arasındaki ikame esnekliğinin, enerji ile maddi sermaye arasındaki ikame esnekliğinden daha yüksek olduğu bulunmuştur. Ayrıca enerji ile maddi olmayan sermaye arasındaki ikame esnekliği enerji yoğun sektörlerde en yüksek seviyede bulunurken, enerji ile maddi sermaye arasındaki en yüksek ikame esneklikleri yüksek ve orta-yüksek teknoloji imalat sanayii alt sektörlerinde kaydedilmiştir.

JEL Kodları: D24, C33, Q41

Anahtar Kelimeler: enerji ve sermaye arasındaki ikame, maddi ve maddi olmayan sermaye, translog üretim fonksiyonu, panel veri, ridge regresyonu

1. Introduction

As suggested by Medlock III (2009), the demand for energy is rather a derived demand, as it is used to provide certain services for both households and industry. Particularly, when energy as a factor of production is concerned, there are two ways through which energy is utilized in the production function: (1) energy consumed as a final product, such as energy carriers to provide for district heating and transportation, and (2) energy as a value-creating production factor, which Pokrovski (2003) identifies as "productive energy".

The interplay between productive energy, as an essential input in the production function (Kümmel et al., 1985), and other factors of production, especially capital, has received significant attention from scientific literature particularly since 1970's oil crises, until when most of the studies focused on capital-labor substitution/complementarity relationship (Arrow et al., 1961; Bell, 1964; Marcus, 1964; Weitzman, 1970; Revankar, 1971; Behrman, 1972). Although the translog cost function, which allows for the derivation of own and cross-price elasticities, is widely used in the literature to examine the energy-capital relationship (Berndt and Wood, 1975; Griffin and Gregory, 1976; Field and Grebenstein, 1980; Garofalo and Malhotra, 1988; Arnberg and Bjørner, 2007; Özatalay et al., 1979; Pindyck, 1979; Iqbal, 1986; Dahl and Erdoğan, 2000; Woodland, 1993; Nguyen and Streitwieser, 1999; Bardazzi et al., 2015), there are also studies using the translog production function. Smyth et al. (2011), for instance, examined the substitution/complementarity relationship between labor, energy and capital in the Chinese steel industry and revealed that capital-energy, as well as energy-labor are substitutes. Lin and Ahmad (2016), moreover, constructed a three-factor translog production function for the transportation sector of Pakistan, incorporating energy, capital and labor as input factors. Each factor's output elasticities and input factors' elasticity of substitution were examined during the years 1980 to 2013. The findings show that all factor pairs are substitutable. In addition, Lin and Liu (2017a) established a translog production function model for China's heavy industry, incorporating energy, capital and labor. In the analysis using the ridge regression method, it was found that all input factors are substitutes for each other. According to the findings, the substitution elasticity between labor and energy is the highest. While the substitution elasticity between energy and labor shows a declining trend, the substitution elasticity between capital and both labor and energy are rising.

There are also studies in the literature that specifically investigate substitution relationships by disaggregating the energy input. Wesseh et al. (2013), for instance, explored the potential substitution among capital, labor, oil and electricity by using both the translog production and translog cost approaches in Liberia. According to the results obtained by using the ridge regression method, all inputs are substitutes. Xie and Hawkes (2015), moreover, examined the substitution potential among electricity, natural gas, coal and oil in the transportation sector of China between 1980 and 2010 to estimate the potential of China to reduce its oil dependency and reduce carbon dioxide emissions. Using log-linear translog production and cost function and applying the ridge regression method, the model parameters are estimated. The findings demonstrate that although all energy inputs are substitutes for each other, the highest substitution potential among energy input pairs is observed between oil and natural gas. Lin et al. (2016) employed the translog production and cost function approach to investigate the substitution relationship among capital, labor, oil and electricity. The findings reveal that all inputs are substitutable for each other and their technological advances tend to converge over time. Lin and Atsagli (2017) examined the energy substitution potential between electricity, oil and coal by employing the translog production function during the years from 1980 to 2012. The findings show that all energy inputs are substitutable. Khalid et al. (2021) explored the substitution potential between energy and non-energy inputs employing the translog production model. For parameter estimation, the ridge regression method was used to derive the elasticity of substitution between labor, capital, oil, coal, natural gas and hydroelectric energy pairs. The analysis using time series data during the years 1980-2017 shows that energy-labor and energy-capital factors are substitutable with each other. These results highlight the need to focus more on technological improvement and creating qualified employment to save energy and reduce carbon dioxide emissions. Raza and Lin (2024) investigated the substitution potential between energy and non-energy inputs within the industrial sector using the translog production function. To address the issue of multicollinearity, they employed the ridge regression technique. According to the findings, the elasticity of substitution for labor-oil, capital-coal, capital-gas and capital-oil are 1.404, 1.045, 1.088 and 1.231, respectively, whereas those for oil-gas and gas-coal are 0.953 and 0.901, respectively. This indicates that dedicating more resources to labor and capital in the industrial sector of Pakistan will have a positive impact on sustainable development. Additionally, some studies incorporate both the translog production function and other functional forms to analyze substitution dynamics. Başeğmez (2022), aims to analyze the impact of input factors (capital, energy and labor) on economic growth for 22 developing countries in the period 1980-2016 with capital, labor and energy consumption, applies both the translog production function and Constant Elasticity of Substitution (CES) production function. According to the findings, it is concluded that using external debt to compensate for inadequate capital accumulation would not be an advisable solution in developing countries.

This paper aims to assess the substitution/complementarity relationship between energy and capital inputs in different manufacturing industry sub-sectors. The debate over whether energy and capital are substitutes or complements requires further investigation for two reasons. Firstly, there is still no consensus in the literature regarding whether capital and energy are substitutes. Although most of the studies have reported a significant substitution relationship between capital and energy, some found a complementarity relationship. The main gap in this stream of literature is that capital is generally recognized as physical (tangible) in nature. Secondly, given the international initiatives on climate change mitigation policies and since the industrial sectors still rely on exhaustible fossil fuels contributing significantly to greenhouse gas emissions, increasing energy efficiency/decreasing energy intensity in manufacturing subsectors remains a significant target for national climate change policies (Lagomarsino and Turner, 2017).

To this end, we utilize panel data comprising tangible and intangible capital stock, energy, labor and output levels from 11 manufacturing industry sub-sectors classified according to NACE Rev.2 in 14 OECD countries over the period between 1995 and 2020. The substitution/complementarity relationship is examined using ridge regression analysis with a four-factor (energy, tangible capital, intangible capital, labor) translog production function approach.

The main contribution of this paper to the related literature is that by separating capital into tangible and intangible forms, it provides a deeper analysis of the output elasticity and substitution relationships between tangible and intangible capital inputs and energy offering valuable insights for informing future energy efficiency policies in the manufacturing industry.

According to the findings, the highest output elasticity among the inputs is attributed to tangible capital followed by intangible capital and energy. The variation in output elasticities across manufacturing sub-sectors indicates that the role of inputs in the production process varies depending on the sector. Additionally, the higher elasticity of substitution between intangible capital and energy relative to the elasticity of substitution between tangible capital and energy suggests that investments in technology and knowledge provide more efficient and sustainable production processes compared to investments in tangible capital.

The remaining of the paper is structured as follows. In section 2, the identification strategy and data used for empirical analysis are introduced. Section 3 provides empirical findings. Finally, Section 4 concludes with policy implications.

2. Methodology and Data

2.1. Identification Strategy

In studies examining the substitution/complementarity relationship between capital and energy, CES or flexible functions such as translog function are generally used. The translog production function, introduced by Christensen et al. (1973), quickly became popular after being introduced as an extension of the CES production function. The translog form is preferred over the CES because it does not impose restrictive assumptions such as constant elasticity of substitution across factors (Arnberg and

Bjørner, 2007). Moreover, the translog form can be estimated using simpler linear modeling techniques. Output elasticity and substitution elasticity parameters are directly derived based on the data, making it a flexible tool for analyzing substitution effects between production factors (Lin and Liu, 2017b).

In literature, studies have either used the translog production function (Smyth et al., 2011; Lin and Wesseh, 2013; Wesseh et al., 2013) or the translog cost function (Woodland, 1993; Nguyen and Streitwieser, 1999; Haller and Hyland, 2014; Bardazzi et al., 2015; Deininger et al., 2018). Duality theory[1] allows for the extraction of all the relevant information about the solution to the primal function from its associated dual function (Lin and Ahmad, 2016). Similarly, according to Debertin and Pagoulatos (1985), all the information derived from the translog cost function can also be derived from the translog production function. The translog cost function is widely utilized in literature because it contains information about input prices and cross-price or own-price elasticities can be simply derived from it. However, in many cases, especially for larger samples, data on input prices is often not available. In these cases, the translog production function approach enables a more flexible estimation method for revealing the elasticities of substitution. In this study, the translog production function is used because data on input prices for the manufacturing sub-sectors could not be obtained.

To derive the translog production function, the general production function representing the relationship between inputs and output is as follows:

$$Y = f(x_1, \dots, x_n) = \beta_0 \prod_{i=1}^{n} x_i^{\beta_i} \prod_{i=1}^{n} x_i^{1/2\left[\sum_{j=1}^{n} \beta_{ij} \, lnx_j\right]} \tag{1}$$

Equation (1) can also be expressed in natural logarithm form as follows:

$$\ln Y = \ln \beta_0 + \sum_{i=1}^{n} \beta_i \ln x_i + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \beta_{ij} \ln x_i \cdot \ln x_j \tag{2}$$

where, Y represents the level of output, β_0 is the efficiency parameter and x_i and x_j represent the inputs i and j, respectively.

In this paper we utilized translog production function approach in equation (2), in a four-factor setting as follows:

$$\begin{aligned} lnY_t = {} & \beta_0 + \beta_{K^N} lnK_t^N + \beta_{K^T} lnK_t^T + \beta_L lnL_t + \beta_E lnE_t + \beta_{K^N K^N}(lnK_t^N)^2 + \\ & \beta_{K^T K^T}(lnK_t^T)^2 + \beta_{LL}(lnL_t)^2 + \beta_{EE}(lnE_t)^2 + \beta_{K^N K^T}(lnK_t^N)(lnK_t^T) + \\ & \beta_{K^N L}(K_t^N)(lnL_t) + \beta_{K^N E}(lnK_t^N)(lnE_t) + \beta_{K^T L}(lnK_t^T)(lnL_t) + \beta_{K^T E}(lnK_t^T)(lnE_t) + \\ & \beta_{LE}(lnL_t)(lnE_t) \end{aligned} \tag{3}$$

where, K^N and K^T represent two types of capital, i.e., intangible and tangible, respectively, and L and E are labor and energy inputs, respectively. As proposed by

[1] For the foundations of duality theory, seminal works of Shephard (1953) and McFadden (1978) can be consulted.

Christensen et al. (1973), using equation (3) output elasticities of all four factors can be derived as follows:

$$\varepsilon_{K^T} = \frac{dY/Y}{dK^T/K^T} = \frac{d\ln Y}{d\ln K^T} = \beta_{K^T} + 2\beta_{K^TK^T}\ln K_t^T + \beta_{K^NK^T}\ln K_t^N + \beta_{K^TL}\ln L_t + \beta_{K^TE}\ln E_t \quad (4a)$$

$$\varepsilon_{K^N} = \frac{dY/Y}{dK^N/K^N} = \frac{d\ln Y}{d\ln K^N} = \beta_{K^N} + 2\beta_{K^NK^N}\ln K_t^N + \beta_{K^NK^T}\ln K_t^T + \beta_{K^NL}\ln L_t + \beta_{K^NE}\ln E_t \quad (4b)$$

$$\varepsilon_E = \frac{dY/Y}{dE/E} = \frac{d\ln Y}{d\ln E} = \beta_E + 2\beta_{EE}\ln E_t + \beta_{K^NE}\ln K_t^N + \beta_{K^TE}\ln K_t^T + \beta_{LE}\ln L_t \quad (4c)$$

$$\varepsilon_L = \frac{dY/Y}{dL/L} = \frac{d\ln Y}{d\ln L} = \beta_L + 2\beta_{LL}\ln L_t + \beta_{K^NL}\ln K_t^N + \beta_{K^TL}\ln K_t^T + \beta_{LE}\ln E_t \quad (4d)$$

Moreover, substitution elasticities are calculated using output elasticities in (4a) - (4d) as follows:

$$\sigma_{K^NE} = \left[1 + \left[-\beta_{K^NE} + \left(\frac{\varepsilon_{K^N}}{\varepsilon_E}\right)\beta_{EE}\right](-\varepsilon_{K^N} + \varepsilon_E)^{-1}\right]^{-1} \quad (5a)$$

$$\sigma_{K^TE} = \left[1 + \left[-\beta_{K^TE} + \left(\frac{\varepsilon_{K^T}}{\varepsilon_E}\right)\beta_{EE}\right](-\varepsilon_{K^T} + \varepsilon_E)^{-1}\right]^{-1} \quad (5b)$$

$$\sigma_{K^NK^T} = \left[1 + \left[-\beta_{K^NK^T} + \left(\frac{\varepsilon_{K^N}}{\varepsilon_{K^T}}\right)\beta_{K^TK^T}\right](-\varepsilon_{K^N} + \varepsilon_{K^T})^{-1}\right]^{-1} \quad (5c)$$

$$\sigma_{K^NL} = \left[1 + \left[-\beta_{K^NL} + \left(\frac{\varepsilon_{K^N}}{\varepsilon_L}\right)\beta_{LL}\right](-\varepsilon_{K^N} + \varepsilon_L)^{-1}\right]^{-1} \quad (5d)$$

$$\sigma_{K^TL} = \left[1 + \left[-\beta_{K^TL} + \left(\frac{\varepsilon_{K^T}}{\varepsilon_L}\right)\beta_{LL}\right](-\varepsilon_{K^T} + \varepsilon_L)^{-1}\right]^{-1} \quad (5e)$$

$$\sigma_{LE} = \left[1 + \left[-\beta_{LE} + \left(\frac{\varepsilon_L}{\varepsilon_E}\right)\beta_{EE}\right](-\varepsilon_L + \varepsilon_E)^{-1}\right]^{-1} \quad (5f)$$

The translog production function model in equation (3) includes the second-order and cross terms of all explanatory variables. This can lead to multicollinearity problems among the independent variables, resulting in high variance and covariance values for the coefficients obtained from the Ordinary Least Squares (OLS) estimator (Songur, 2019). This situation leads to inefficient estimates. To address this issue, the ridge regression method, proposed by Hoerl and Kennard (1970), is employed by introducing bias into the regression coefficients.

The ridge regression estimator can be derived by solving the following equation:

$$\hat{\beta}_{ridge} = (\boldsymbol{X'X} + k\boldsymbol{I})^{-1}\boldsymbol{X'Y} \quad (6)$$

where k represents the ridge parameter and I denotes the identity matrix (Hoerl and Kennard, 1970). The addition of kI into the equation serves to introduce bias into the regression estimates. When the multicollinearity present, to reduce the variance of the ridge estimates, this bias is intentionally added. With a decreasing value of k, there is a reduction in the variance of the ridge estimates and in the mean squared error (MSE) estimates which helps in stabilizing the coefficient estimates, making the model more efficient. Each problem has its own optimal value of k. Although several methods have been proposed to identify the optimal value of k, this study preferred the ridge trace plot, recommended by McDonald (2009) and widely used in the literature (see for instance Lin et al., 2016; Lin and Atsagli, 2017; Songur, 2019; Başeğmez, 2022; Raza and Lin, 2024). According to this method, the optimal k value is selected when the estimated coefficients stabilize for values of k within the 0-1 range (Lin and Ahmad, 2016).

2.2. Data

The 11 manufacturing sub-sectors (C10-C12, C13-C15, C16-C18, C19, C22-C23, C24-C25, C26, C27, C28, C29-C30, C31-C33) classified according to NACE Rev. 2 in 14 OECD countries (Austria, Belgium, Czechia, Denmark, Finland, France, Italy, Latvia, Netherlands, Slovakia, Spain, Sweden, US and Germany) selected to investigate the substitution/complementarity relationship between energy and two types of capital. These countries and sectors were selected based on their high data availability, ensuring a balanced dataset which enhances the reliability of the results. The use of aggregated panel data at the sectoral level instead of firm-level data was driven by limited access to firm-level datasets. Table 1 presents the manufacturing sub-sectors included in the sample.

Table 1. Manufacturing sub-sectors included in estimation

Nace Rev.2	Sector
C10-C12	Manufacture of food products; beverages and tobacco products
C13-C15	Manufacture of textiles, wearing apparel, leather and related products
C16-C18	Manufacture of wood, paper, printing and reproduction
C19	Manufacture of coke and refined petroleum products
C22-C23	Manufacture of rubber and plastic products and other non-metallic mineral products
C24-C25	Manufacture of basic metals and fabricated metal products, except machinery and equipment
C26	Manufacture of computer, electronic and optical products
C27	Manufacture of electrical equipment
C28	Manufacture of machinery and equipment n.e.c.
C29-C30	Manufacture of motor vehicles, trailers, semi-trailers and of other transport equipment
C31-C33	Manufacture of furniture; jewelry, musical instruments, toys; repair and installation of machinery and equipment

World Input-Output Table (WIOT) from Timmer et al. (2015) is used as the primary source for gross energy data in this study. World Input-Output Database (WIOD) contains environmental accounts with detailed information on energy use. Both the environmental accounts from the WIOD 2013 release (as documented in Genty, 2012) and the WIOD 2016 release (as documented in Corsatea et al., 2019) are incorporated into the analysis. The 2013 and 2016 releases of the WIOD environmental accounts use different sector classification systems (NACE Rev. 1.1 and NACE Rev. 2, respectively); to harmonize these, data from the 2013 version were converted to NACE Rev. 2 using the Correspondence Table (Instituto Nacional de Estadística [INE], 2009). Additionally, after verifying data consistency, the OECD (2022) was also utilized. These different data sources are used to expand the scope of the analysis.

In this study, tangible capital encompasses physical assets utilized in production, such as dwellings, other buildings and structures, transport equipment, other machinery and equipment, cultivated biological resources, computer hardware, and telecommunications equipment. Conversely, intangible capital comprises research and development (R&D), computer software and databases and other intellectual property products (Stehrer, 2024). Data on both tangible and intangible capital, spanning from 1995 to 2020, were sourced from the EU KLEMS INTANprod database and are measured in millions of national currencies at 2015 constant prices. The 2023 release was preferred as it includes the necessary data on tangible and intangible capital for the analysis.

Table 2. Variables and Data sources

Variable	Source	Unit	Years
Gross Output	EU KLEMS National Accounts	Millions of national currencies (2015=100)	1995-2020
Energy	WIOD EU files and OECD Database	terajoules	1995-2020
Labor	EU KLEMS National Accounts	Thousand person	1995-2020
Tangible-Intangible Capital	EU KLEMS INTANprod database	Millions of national currencies (2015=100)	1995-2020

The gross output data from 1995 to 2020 were obtained from the EU KLEMS National Accounts (2023 release) and measured in millions of national currencies at 2015 prices. Similarly, labor data covering the same period were also sourced from the EU KLEMS National Accounts (2023 release) and expressed in thousand persons.

Descriptive statistics of the variables for the four-factor translog model are presented in Table 3. The descriptive statistics in the table reveal significant variations in both the mean values and distributions of output, tangible/intangible capital, labor, and energy variables. These statistics highlight tangible/intangible capital, energy and labor diversity among countries and manufacturing sectors.

Table 3. Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Gross output	3472	96701.55	161921.6	51.81	1473156
Intangible Capital	3472	8625.02	21377.6	0.07	255730.1
Tangible Capital	3472	43404.73	69971.58	24.63	566250.2
Labor	3472	82206.94	342989.6	1	2381000
Energy	3472	538005.4	3321847	18.28	44600000

3. Results

Since the input factors in the translog production function have interaction and square terms (see Eq. 3), the model may suffer from a multicollinearity problem. In this case, spurious relationships may occur in regression analyses. To address the spurious regression problems, Fisher-Type Augmented Dickey-Fuller (ADF) unit root test was applied and results are presented in Table A1 in Appendix A.1. According to the findings, all variables are stationary at level once the trend is controlled for. Hence, trend components were incorporated into the model to account for trend stationarity.

When the Variance Inflation Factor (VIF) values for the independent variables are checked, it is found that they are significantly greater than 10. These VIF values (provided in Table A2 in Appendix A.2) indicate the presence of a multicollinearity problem which must be solved before establishing the regression equation.

While making parameter estimates, the ridge regression method which takes into account the multicollinearity problem, was used instead of the Ordinary Least Square (OLS) method. In the ridge regression method, parameter estimates are made by adding the k ridge parameter. In the analysis conducted using the NCSS 2024 software, it is observed that the VIF values for all independent variables (provided in Table A3 in

Appendix A.2) fall below 10 after k=0.02. Additionally, when the ridge trace plot and ridge VIF plot (provided in Figure A1 and Figure A2 Appendix A.2, respectively) are examined together, it is seen that all parameters stabilize at k=0.02. In Table 4 created using the coefficient estimates obtained according to the ridge regression method for the translog production function, the independent variables have VIF values of less than 10. In addition, the model's performance is assessed through ANOVA[2] for k=0.02 (provided in Table A4 in Appendix A.2).

Table 4. Ridge Regression Results for k = 0.02

Independent Variable	Ridge Regression (R^2=0.9570)		
	Coefficients	**Standard Deviation**	**VIF**
Constant	2.8130		
lnK^N	0.1701	0.0066	6.279
lnK^T	0.3548	0.0079	4.806
lnL	0.0534	0.0057	6.086
lnE	0.0640	0.0066	5.611
lnK^NlnK^N	0.0005	0.0005	7.392
lnK^TlnK^T	0.0124	0.0003	2.706
lnLlnL	0.0006	0.0003	7.267
lnElnE	0.0041	0.0002	4.858
lnK^NlnK^T	0.0063	0.0003	2.694
lnK^NlnL	-0.0046	0.0004	5.599
lnK^NlnE	0.0004	0.0004	6.178
lnK^TlnL	-0.0001	0.0002	2.091
lnK^TlnE	0.0025	0.0003	3.599
lnLlnE	-0.0041	0.0004	6.624
t	-0.0012	0.0027	8.370
tt	0.00004	0.00009	7.268
$tlnK^N$	0.0016	0.0002	8.367
$tlnK^T$	0.0011	0.0002	6.859
tlnL	-0.0003	0.0003	5.972
tlnE	-0.0024	0.0002	8.623

The four-factor translog production function obtained using ridge regression coefficients is as follows:

[2] According to the ANOVA table obtained with the bias parameter k = 0.02 in the ridge regression method, the model explains the dependent variable quite well (0.95) and is statistically significant (0.000). Additionally, low error terms indicate that the model has a strong ability to predict the dependent variable.

$$lnY = 2.8130 + 0.1701\, lnK^N + 0.3548\, lnK^T + 0.0534\, lnL + 0.0640\, lnE + 0.0005\, lnK^N lnK^N + 0.0124\, lnK^T lnK^T + 0.0006\, lnLlnL + 0.0041\, lnElnE + 0.0063\, lnK^N lnK^T - 0.0046\, lnK^N lnL + 0.0004\, lnK^N lnE - 0.0001\, lnK^T lnL + 0.0025\, lnK^T lnE - 0.0041\, lnLlnE + 0.00004\, tt + 0.0016\, tlnK^N + 0.0011\, tlnK^T - 0.0003\, tlnL - 0.0024\, tlnE - 0.0012\, t \quad (7)$$

After obtaining the ridge regression estimates, the output elasticities of energy and two types of capital inputs are calculated using equations 4a-4c (Table 5). As seen in Table 5, the output elasticities of these three inputs take the value between 0 and 1. This indicates that the average physical products of energy and capital inputs are greater than the marginal physical products. Therefore, all of these inputs are in the region of diminishing returns. In addition, bootstrap standard deviations are quite low and confidence intervals are narrow for all sectors and all factors. These results indicate that the estimates are consistent and reliable.

According to Table 5, moreover, the output elasticity of tangible capital is the highest pointing to the largest responsiveness relative to other inputs in all manufacturing sub-sectors. The output elasticity of tangible capital varies between 0.629 (C27-Manufacture of electrical equipment) and 0.684 (C24-C25-Manufacture of basic metals and fabricated metal products, except machinery and equipment), indicating that output growth is highly sensitive to increased tangible capital (machinery, production facilities, etc.), especially for C24-C25 sector. Intangible capital output elasticity values are generally between 0.215 (C13-C15-Manufacture of textiles, wearing apparel, leather and related products) and 0.229 (C19-Manufacture of coke and refined petroleum products). The lowest output elasticity is associated with energy input. Energy output elasticity varies depending on the sector and is between 0.137 (C26-Manufacture of computer, electronic and optical products) and 0.196 (C19-Manufacture of coke and refined petroleum products).

Finally, using the output elasticities reported in Table 5, substitution elasticities for energy and capital inputs are calculated using equations 5a-5c (Table 6). According to Table 6, the highest substitution elasticity for the whole manufacturing sector is observed between energy and intangible capital, followed by those between energy and tangible capital and between intangible and tangible capital inputs. Particularly, when the substitution between tangible and intangible capital inputs is concerned, the results suggest a weak substitution. Furthermore, the low bootstrap standard deviations and narrow confidence intervals across all sectors and factors suggest that the estimates are both consistent and reliable.

Tablo 5. Output Elasticity

	K^N	K^T	E
C10-C12	0.223	0.681	0.158
	(0.010)	(0.051)	(0.009)
	[0.199, 0.240]	[0.569, 0.762]	[0.137, 0.169]
C13-C15	0.215	0.629	0.143
	(0.012)	0.058	(0.010)
	[0.191, 0.235]	[0.501, 0.719]	[0.119, 0.161]
C16-C18	0.223	0.674	0.164
	(0.010)	(0.047)	(0.010)
	[0.198, 0.243]	[0.568, 0.755]	[0.139, 0.184]
C19	0.229	0.650	0.196
	(0.007)	(0.040)	(0.006)
	[0.208, 0.243]	[0.596, 0.761]	[0.183, 0.206]
C22-C23	0.222	0.673	0.162
	(0.010)	(0.054)	(0.009)
	[0.198, 0.242]	[0.532, 0.754]	[0.139, 0.174]
C24-C25	0.222	0.684	0.167
	(0.010)	(0.058)	(0.012)
	[0.199, 0.241]	[0.523, 0.765]	[0.131, 0.180]
C26	0.220	0.649	0.137
	(0.011)	(0.072)	(0.014)
	[0.197, 0.242]	[0.473, 0.775]	[0.098, 0.155]
C27	0.217	0.637	0.138
	(0.011)	(0.064)	(0.012)
	[0.194, 0.237]	[0.473, 0.727]	[0.104, 0.156]
C28	0.219	0.661	0.145
	(0.011)	(0.067)	(0.011)
	[0.195, 0.240]	[0.486, 0.750]	[0.114, 0.161]
C29-C30	0.222	0.668	0.148
	(0.012)	(0.073)	(0.011)
	[0.194, 0.244]	[0.475, 0.772]	[0.118, 0.166]
C31-C33	0.217	0.652	0.142
	(0.011)	(0.056)	(0.009)
	[0.193, 0.236]	[0.513, 0.733]	[0.121, 0.157]
Manufacturing Sector	0.221	0.661	0.155
Total	(0.011)	(0.061)	(0.019)
	[0.195, 0.241]	[0.501, 0.762]	[0.118, 0.201]

Note: Values in parentheses represent bootstrap standard deviations, while those in square brackets denote bootstrap confidence intervals.

Table 6. Substitution Elasticity

	$\sigma_{K^N E}$	$\sigma_{K^T E}$	$\sigma_{K^N K^T}$
C10-C12	1.0940	1.0306	1.0048
	(0.0105)	(0.0019)	(0.00020)
	[1.0794, 1.1252]	[1.0286, 1.0354]	[1.0045, 1.0054]
C13-C15	1.0900	1.0338	1.0049
	(0.0095)	(0.0028)	(0.00027)
	[1.0762, 1.1161]	[1.0300, 1.0410]	[1.0044, 1.0056]
C16-C18	1.1007	1.0297	1.0048
	(0.0143)	(0.0018)	(0.00021)
	[1.0802, 1.1450]	[1.0263, 1.0351]	[1.0045, 1.0054]
C19	1.1723	1.0257	1.0045
	(0.0577)	(0.0008)	(0.00024)
	[1.1065, 1.3466]	[1.0245, 1.0274]	[1.0041, 1.0052]
C22-C23	1.0980	1.0301	1.0048
	(0.0120)	(0.0018)	(0.00022)
	[1.0815, 1.1323]	[1.0278, 1.0355]	[1.0045, 1.0055]
C24-C25	1.1043	1.0293	1.0048
	(0.0135)	(0.0025)	(0.00019)
	[1.0802, 1.1364]	[1.0270, 1.0372]	[1.0045, 1.0054]
C26	1.0833	1.0353	1.0047
	(0.0065)	(0.0046)	(0.00026)
	[1.0732, 1.1007]	[1.0308, 1.0494]	[1.0040, 1.0053]
C27	1.0856	1.0351	1.0048
	(0.0073)	(0.0039)	(0.00027)
	[1.0756, 1.1068]	[1.0309, 1.0466]	[1.0042, 1.0056]
C28	1.0880	1.0333	1.0048
	(0.0086)	(0.0032)	(0.00023)
	[1.0763, 1.1135]	[1.0298, 1.0428]	[1.0044, 1.0055]
C29-C30	1.0869	1.0328	1.0048
	(0.0081)	(0.0030)	(0.00023)
	[1.0757, 1.1122]	[1.0288, 1.0415]	[1.0043, 1.0054]
C31-C33	1.0877	1.0338	1.0049
	(0.0084)	(0.0025)	(0.00023)
	[1.0749, 1.1130]	[1.0305, 1.0402]	[1.0046, 1.0056]
Manufacturing Sector	1.0988	1.0317	1.0048
Total	(0.0299)	(0.0038)	(0.00025)
	[1.0758, 1.1833]	[1.0251, 1.0416]	[1.0043, 1.0055]

Note: Values in parentheses represent bootstrap standard deviations, while those in square brackets denote bootstrap confidence intervals.

The substitution elasticities between energy and intangible capital are generally above 1 and range from 1.0833 to 1.1723. This indicates a high degree of substitutability between energy and intangible capital. The highest value is observed in sector C19 (Manufacture of coke and refined petroleum products) with a substitution elasticity of 1.1723, followed by C24-C25 (Manufacture of basic metals and fabricated metal products) and C16-C18 (Manufacture of wood, paper, printing and reproduction) with values of 1.1043 and 1.1007, respectively. These sectors represent the most energy-intensive manufacturing industries[3], showing the potential of intangible capital in increasing energy efficiency in these sectors.

Moreover, the elasticity of substitution between tangible capital and energy varies across the sectors ranging from 1.0257 to 1.0353. Highest substitution elasticities are observed in C26 (Manufacture of computer, electronic and optical products) and C27 (Manufacture of electrical equipment). These two sectors are classified as high-tech and medium-high-tech manufacturing industries.[4]

Previous studies generally treat capital as a unified factor and evaluate energy-capital substitution within this framework. Similar to studies conducted on China's heavy industry sector (Lin and Liu, 2017a), Pakistan's transportation sector (Lin and Ahmad, 2016) and China's steel sector (Smyth et al., 2011), this study also confirms that energy and capital are substitutes. However, unlike previous studies, when capital is divided into tangible and intangible components, the elasticity of substitution between energy and intangible capital is found to be higher. This finding allows for the development of differentiated policy approaches that take sector-specific dynamics into account to enhance energy efficiency and reduce energy intensity.

4. Conclusions and Policy Implications

This article investigates the substitution relationship between energy and capital using panel data from 11 manufacturing sub-sectors in 14 OECD countries for the period between 1995 and 2020. To deepen the analysis, capital is separated into tangible and intangible capital and the relationship between energy and these two types of capital is examined using a four-input translog production function, estimated via the ridge regression methodology.

The highest output elasticity among the inputs is attributed to tangible capital, followed by intangible capital and energy. The presence of sectoral differences in output elasticities implies that the role of inputs varies across sectors in the production process.

Based on the results captured from the four-factor (tangible capital, intangible capital, energy and labor) translog production function, the elasticity of substitution

[3] Please refer to: https://www.eia.gov/outlooks/ieo/pdf/industrial.pdf. Accessed on 02.01.2025.
[4] Please refer to: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:High-tech_classification_of_manufacturing_industries. Accessed on 02.01.2025.

between tangible capital and intangible capital is between 1.0045 and 1.0049, which indicates a weak substitution relationship. This means that production processes in sectors generally require the existence of both types of capital and one cannot be an alternative to the other.

Moreover, the elasticities of substitution between energy and intangible capital are above 1, ranging from 1.083 (C26-Manufacture of computer, electronic and optical products) to 1.172 (C19-Manufacture of coke and refined petroleum products). This indicates a high degree of substitutability between energy and intangible capital. Additionally, the elasticities of substitution between energy and tangible capital are slightly above 1, generally ranging from 1.025 (C19-Manufacture of coke and refined petroleum products) to 1.035 (C26-Manufacture of computer, electronic and optical products). These values indicate that there is also substitutability between energy and tangible capital.

These results demonstrate the importance of sectoral differences in the relationship between energy and tangible/intangible capital. The higher elasticity of substitution between intangible capital and energy compared to that between tangible capital and energy suggests that investing in knowledge and technology is more efficient than investing in tangible capital and provides a long-term solution for sustainability. This finding highlights the importance of technological innovation, especially for sectors aiming to develop high-value-added and energy-efficient production processes.

In addition, in energy-intensive sectors, increasing the use of intangible capital -thereby encouraging technological progress- can reduce energy consumption, which in turn increases energy efficiency and reduces energy intensity. On the other hand, in high-technology sectors, increasing tangible capital through investments in more efficient physical assets could contribute to reducing energy intensity. This highlights the critical role of technological progress in improving energy efficiency, both through intangible capital and through the modernization of tangible capital.

One of the main limitations of this study is the lack of firm-level data. Although country-level data utilized in this study provides insight for sectoral analyses, using firm-level data would further extend to assess firm behavior in different sectors. Additionally, the dataset used in this study covers only OECD countries and does not include the dynamics of developing countries. Hence, for further research, the following recommendations can be made. Firstly, utilizing micro-level data on energy and capital would allow for a detailed firm-level examination of the energy-capital substitution relationship. Secondly, expanding the study to include developing countries would provide an opportunity to test the validity of the findings across a broader geographical scope. In particular, understanding how the energy-capital substitution relationship evolves in energy-intensive industries within developing countries would be of significant interest to policy-makers for climate-neutrality targets.

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Appendices

Appendix A.1 Unit Root Test Results

Table A1. Fisher (ADF based) Unit Root Test

	Fisher (ADF based)		Fisher (ADF based)-with trend	
	Level	FirstΔ	Level	FirstΔ
lnY	4.02***	61.61***	9.65***	42.67***
lnK^N	1.53*	20.96***	6.25***	14.44***
lnK^T	6.93***	15.69***	5.96***	10.88***
lnL	0.65	36.12***	3.05***	24.34***
lnE	0.18	53.39***	2.14**	38.85***
lnK^NlnK^N	-0.97	20.70***	5.27***	14.08***
lnK^TlnK^T	6.63***	15.81***	5.88***	10.92***
lnLlnL	2.22**	35.86***	3.53***	24.78***
lnElnE	0.41	53.38***	2.22**	39.00***
lnK^NlnK^T	2.18**	19.52***	6.28***	13.59***
lnK^NlnL	7.26***	36.98***	12.88***	20.74***
lnK^NlnE	0.34	39.99***	5.79***	27.16***
lnK^TlnL	2.75***	36.07***	6.94***	21.80***
lnK^TlnE	1.59*	47.45***	4.20***	32.58***
lnLlnE	0.38	39.09***	1.88**	27.98***

**, **, * correspond to significance levels at 1%, 5% and 10%, respectively

Appendix A.2 Supplementary Tables and Figures

Table A2. OLS Regression Results

Variable	Coefficients	Standard Deviation	VIF	1/VIF
Constant	1.4573***	0.3296		
lnK^N	0.3475***	0.0449	181.38	0.0055
lnK^T	-0.0191	0.0859	315.78	0.0031
lnL	0.7818***	0.0667	340.46	0.0029
lnE	0.2199***	0.0473	182.70	0.0054
lnK^NlnK^N	0.0092***	0.0023	147.47	0.0067
lnK^TlnK^T	0.0491***	0.0084	1124.89	0.0008
lnLlnL	-0.0150***	0.0031	97.06	0.0103
lnElnE	0.0292***	0.0027	164.06	0.0060
lnK^NlnK^T	-0.0069	0.0081	1336.26	0.0007
lnK^NlnL	-0.0508***	0.0055	315.60	0.0031
lnK^NlnE	-0.0127***	0.0036	299.93	0.0033
lnK^TlnL	0.0419***	0.0092	1265.87	0.0007
lnK^TlnE	-0.0467***	0.0067	572.59	0.0017
lnLlnE	-0.0294***	0.0041	282.38	0.0035
t	0.0566***	0.0040	72.77	0.0137
tt	-0.0002***	0.00005	19.18	0.0521
$tlnK^N$	-0.0007**	0.0003	51.43	0.0194
$tlnK^T$	-0.0013**	0.0005	148.41	0.0067
tlnL	0.0005*	0.0003	13.97	0.0715
tlnE	-0.0022***	0.0002	40.46	0.0247
Mean VIF			348.63	

**, **, * correspond to significance levels at 1%, 5% and 10%, respectively

Table A3. VIF values

k	lnK^N	lnK^T	lnL	lnE	lnK^NlnK^N	lnK^TlnK^T	lnLlnL	lnElnE	lnK^NlnK^T	lnK^NlnL
0.0	181.380	315.777	340.462	182.704	147.470	1124.894	97.061	164.064	1336.260	315.596
0.005	18.130	22.924	25.106	24.398	19.899	13.511	20.896	26.080	20.065	35.639
0.01	10.762	10.687	12.485	12.231	12.831	5.871	12.737	11.793	7.464	15.123
0.02	**6.279**	**4.806**	**6.086**	**5.611**	**7.392**	**2.706**	**7.267**	**4.858**	**2.694**	**5.599**
0.03	4.413	3.013	3.866	3.402	5.029	1.801	4.974	2.835	1.490	3.009
0.04	3.350	2.175	2.738	2.343	3.717	1.382	3.696	1.932	0.984	1.920
0.05	2.664	1.699	2.066	1.742	2.894	1.142	2.888	1.440	0.716	1.352
0.1	1.214	0.826	0.803	0.697	1.242	0.670	1.237	0.610	0.277	0.464
0.5	0.177	0.173	0.093	0.141	0.167	0.174	0.152	0.148	0.056	0.061
1.0	0.080	0.078	0.045	0.081	0.074	0.079	0.069	0.086	0.034	0.032
k	**lnK^NlnE**	**lnK^TlnL**	**lnK^TlnE**	**lnLlnE**	**tt**	**$tlnK^N$**	**$tlnK^T$**	**tlnL**	**tlnE**	**t**
0.0	299.930	1265.871	572.585	282.378	19.175	51.429	148.414	13.970	40.461	72.768
0.005	29.614	18.981	28.239	29.989	13.416	20.545	34.808	9.988	21.487	28.088
0.01	14.049	6.407	10.409	14.776	10.502	13.830	16.784	8.109	14.688	16.710
0.02	**6.178**	**2.091**	**3.599**	**6.624**	**7.268**	**8.367**	**6.859**	**5.972**	**8.623**	**8.370**
0.03	3.699	1.090	1.921	3.947	5.473	5.838	3.860	4.739	5.837	5.175
0.04	2.537	0.696	1.237	2.673	4.330	4.366	2.532	3.923	4.266	3.573
0.05	1.883	0.498	0.884	1.951	3.541	3.413	1.816	3.338	3.277	2.643
0.1	0.738	0.198	0.335	0.698	1.710	1.424	0.642	1.847	1.302	0.981
0.5	0.096	0.049	0.069	0.078	0.199	0.139	0.078	0.267	0.131	0.103
1.0	0.041	0.030	0.040	0.039	0.078	0.057	0.040	0.101	0.060	0.049

Table A4. Analysis of Variance Section for k = 0.02

Source	DF	Sum of Squares	Mean Square
Intercept	1	364545.7	364545.7
Model	20	11591.3	579.5651
Error	3451	521.0387	0.1509819
Total (Adjusted)	3471	12112.34	3.489582
F-Ratio	3838.6380 (0.000)		
Mean of Dependent	10.24675		
Root Mean Square Error	0.388		
R-Squared	0.957		
Coefficient of Variation	0.037		

Figure A1. Ridge Trace Plot

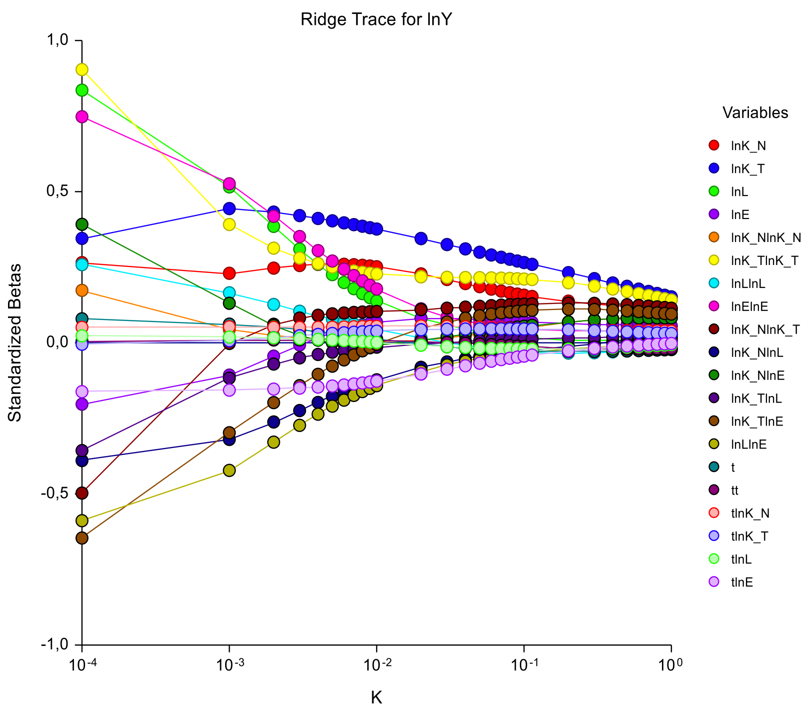

Figure A2. Ridge VIF Plot