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Is energy intensity a driver of structural change? Empirical evidence from the global economy

Jaime Nieto[1,2] | **Pedro B. Moyano**[1] | **Diego Moyano**[1,2] | **Luis Javier Miguel**[2]

[1]Department of Applied Economics, University of Valladolid, Valladolid, Spain

[2]Research Group on Energy, Economy and System Dynamics, University of Valladolid, Valladolid, Spain

Correspondence
Jaime Nieto, Facultad de CC. EE. y Empresariales Universidad de Valladolid Avda del Valle Esgueva 6 47011 - Valladolid (Spain)
Email: jaime.nieto@eco.uva.es

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Abstract

Input–output tables (IOTs) provide a relevant picture of economic structure as they represent the composition and interindustry relationships of an economy. The technical coefficients matrix (A matrix) is considered to capture the technological status of an economy; so, it is of special relevance for the evaluation of long-term, structural transformations, such as sustainability transitions in integrated assessment models (IAMs). The A matrix has typically been considered either static or exogenous. Endogenous structural change has rarely been applied to models. The objective of this paper is to analyze energy intensity, a widely used variable in IAMs, and its role as a driver of structural change. We therefore identify the most relevant technical coefficients in the IOTs time series and estimate an econometric model based on the energy intensity of five different final end-use energy sources. The results of this analysis show that energy intensity has a significant influence on the evolution of the A matrix and should therefore be taken into consideration when analyzing endogenous structural change in models.

KEYWORDS

energy efficiency, industrial ecology, industrial metabolism, input–output analysis (IOA), structural change, technical coefficients

1 | INTRODUCTION

The input–output analysis (IOA) framework consists both an accounting method based on the conventions of the System of National Accounts (SNA) and a modelling tool based on the principles stated by Leontief (Leontief, 1986; Miller & Blair, 2009). Inspired by Quesnay's *Tableau Economique*, IOA outlines the economy as the result of a system of economic flows between agents. Far from the conventional approach to the economy as an aggregated body, IOA pictures the economic system based on its interindustry relationships. Since Leontief first proposed his model, numerous important contributions have been made, and we can point out, just as examples, the pioneering work of Chenery and Watanabe (1958), Ghosh (1958), Hirschman (1958), or Rasmussen (1957) and the later nuances of Hazari (1970), Laumas (1975, 1976), or McGilvray (1977) and the critiques of Giarratani (1980) and Oosterhaven (1981).

In the IOA framework, the relationship between the inputs used and the output produced (supply side) is related to the final demand of goods and services, that is, consumption, investment, and changes in inventories (demand side). From the supply side, the production of each industry's output is presented as the sum of the purchases of intermediate goods and services plus gross value added (GVA).[1] The relevance of the information underlying the amount of input required to produce one unit of each sector's output is at the core of IOA. These ratios are known as "technical coefficients" and, applied to all industries, produce the "A matrix," also known as the technical coefficients matrix or technological matrix. Thus, knowing the technological state (as interindustry relationships) of the economy to satisfy the total final demand, we can turn IOA into a modeling tool whereby changes in final demand trigger direct and indirect (interindustry) spill-over effects of production. In addition, extensions to this model have flourished in order to estimate these effects on employment and use of resources or waste (Leontief, 1970; Miller & Blair, 2009; Suh, 2009). As a consequence, IOA has typically been a relevant tool for policy analysis.

However, a downside arises as the "A matrix" is set to represent the technological structure of the economy at a certain period "*t*," that is, it is static by definition. Because it is considered to be stable in the short term (Dietzenbacher, 2013), input–output tables (IOTs) were typically published with a considerable time lag. However, the gap between publications has been narrowing. In recent years, such projects as EORA (Lenzen et al., 2013), Exiobase (Merciai & Schmidt, 2018), or WIOD (Timmer et al., 2015) pioneered the production of relatively long-time series of global multi-regional IOTs with environmental and social extensions. As longer time series were made available, the focus shifted from updating to forecasting the technical coefficients matrix. Although still unresolved, the relevance of the debate on the drivers of the A matrix evolution has been stimulated by the increasing use of IOA in long-term models; in particular, its use in integrated assessment models (IAMs) that evaluate the energy–environment–economy relationships, especially focused on energy transitions to tackle climate change (Hardt & O'Neill, 2017). Moreover, a relevant body of literature highlights the existence of an energy-economy nexus (Ayres et al., 2019; Hall & Klitgaard, 2012; Kümmel & Lindenberger, 2020; Lindenberger & Kümmel, 2011; Sakai et al., 2018). According to these studies, economic history shows the tight connection between access to relatively abundant and cheap energy sources and development. In other words, the link between the energy metabolism of a society and economic growth is highlighted. A number of scholars provide evidence that such socioeconomic implications are driven by the structural change unleashed by energy transitions (Hardt et al., 2020; Jackson, 2019; Nieto et al., 2020, 2020). Moreover, Gaggl et al. (2021) carried out a historical analysis of the electrification process in the United States, finding that important structural changes took place in the sectoral distribution of the economy. Hence, the energy flows that an economy relies upon determine the sectoral composition, technological state, and even the institutions that shape the economic structure of a territory.

Therefore, the literature has observed a qualitative relationship between the energy metabolism of a society and structural change that still remains unquantified. In this article, we propose a method to advance in the understanding of this relationship. To represent the energy metabolism of society, we take sectoral energy intensities from different sources and estimate their explanatory power of the historical global A matrix, as a representation of the economic structure. We thus propose a methodology that allows us to quantify the influence of energy intensity (from different sources) in the change of technical coefficients. The results also have implications on policies aimed at the energy transition toward a low-carbon economy. By linking energy and industrial policy, important benefits could be derived for both the energy transition and structural change. Section 2 briefly reviews the literature on updating and forecasting the technical coefficients; Section 3 outlines the methodological approach followed; Section 4 collects the main results; Section 5 discusses the relevance of the main findings, and Section 6 sets out the main concluding remarks.

2 | UPDATING AND FORECASTING THE TECHNICAL COEFFICIENTS MATRIX

According to the European system of national and regional accounts, IOTs show "changes in the structure of the economy, e.g. changes in the importance of various industries, changes in the inputs used and outputs produced and changes in the composition of final consumption expenditure, gross capital formation, imports and exports. Such changes may reflect developments such as globalisation, outsourcing, innovation and changes in labour costs, taxes, oil prices and exchange rates" (Regulation EU n° 549/2013, 9.14, page. 322). Miller and Blair (2009) identify several processes that can guide the A matrix evolution: (i) technological change, typically industrialization and tertiarization, but also mechanization, robotization, and so on; (ii) economies of scale; (iii) new products or sectors; (iv) institutional factors, for example, industrial policy, banning of certain products, and so on; (v) changes in relative prices; and (vi) substitution of imports. Therefore, despite the consideration that the technical coefficients remain relatively stable in the short term, it does not hold true either when looking at the medium to long term or to rapidly transforming economies.

The first approach to estimate A matrices was driven by the necessity to update the lack of IOTs between releases by non-survey methods. Thus, projections of the latest available version were commonly estimated using different techniques. Tilanus (1966) proposed the linear extrapolation of matrices, only to conclude that maintaining the latest available one was more reliable. Additionally, Tilanus (1967) also applied marginal coefficients measuring the typical variation of intermediate consumption over one unit of output. Miernyk (1965), in turn, considered that all enterprises would eventually converge to the structure of a selected *Best Practice* firm. With time, these methods were dismissed for being too simplistic, and mathematical developments allowed for more sophisticated methods, the most accepted one being the RAS method[2] (Bacharach, 1970; Stone,

[1] Consisting of wages, the gross operating surplus and net taxes on production if presented at basic prices, plus net taxes on products if presented at market prices. It also includes margins, transport, etc.

[2] Also known as "biproportional" matrix balancing technique, it is named RAS after the notation of the matrices considered in the calculations.

1961; Stone & Brown, 1962) and especially the Generalized RAS (Gunluk-Senesen & Bates, 1988; Junius & Oosterhaven, 2003). More recently, a non-iterative method "Matrix Transformation Technique" or MTT (Wang et al., 2015; Zheng et al., 2018) has shown a great fitting capacity updating IOTs. Both RAS and MMT are theoretically suited to forecasting, which is further discussed later. However, their main purpose is not to capture structural change or their main drivers; rather, they are oriented to delivering mathematically consistent IOTs when not available, given certain assumptions, mainly related to the sectoral output evolution.

In the field of forecasting IOTs, it is worth mentioning that Leontief himself evaluated the effects on employment of automation by exogenously applying qualitatively assessed variations of the United States A matrix (Leontief & Duchin, 1986). This qualitative assessment to evaluate different scenarios of the A Matrix evolution has also been used in Briens (2015) and Nietoet al. (2020). Although a valid and useful approach to evaluate scenarios, it lacks an endogenous explanation of the drivers of structural change. From an endogenous point of view, Israilevich et al. (1997) applied econometric equations to estimate the evolution of technical coefficients in his model of the Chicago economy with a set of explanatory variables. Hughes (1987, 2015) selects the matrix of the less and the most developed countries as benchmarks and then, according to the Gross Domestic Product per capita (GDPpc) estimated in their model, interpolates an A matrix between them. Pan (2006), Pan and Köhler (2007), and Wiebe (2016) highlight the relevance of taking R&D expenditures into account in order to update technical coefficients, which is considered a suitable alternative to learning curves in models. However, little or no attention had typically been paid to the role of the energy systems in the technical coefficients change.

Nevertheless, recent contributions to the literature are introducing this dimension into the equation. Bergesen and Suh (2016) analyze supply chain learning curves capturing, among others, intermediate input learning, including materials and energy efficiency as drivers of the technical coefficients change. However, it is a partial, non–economy-wide analysis focused on the PV industry. D'Alessandro et al. (2020) include an innovation module to their IAM, where the evolution of the A matrix relies upon a variety of innovations that entail different combinations of labor productivity and energy efficiency. As a result of the innovation selection process, and based on costs, the technical coefficients evolve in one direction or another. Nonetheless, no direct quantification of the relationship between energy efficiency and technical coefficients is reported. From a different viewpoint, Chai et al. (2009) evaluate how the A matrix evolution influences the energy efficiency trends of China. Conversely, in this article, we analyze the opposite relationship and discuss it.

Hence, updating IOT methods have typically been employed in the construction of IOT time series or for analytical purposes. On the other hand, the ambition of forecasting has traditionally relied on both analytical and modelling objectives. The former approach is related to assessing how the A matrix could be influenced by the evolution of different explanatory variables. The latter implies evaluating the influence of a different future A matrix on the economy. Hereafter, we present a methodology to evaluate the influence of energy intensity by different sources on the A matrix evolution (analytical view) in order to improve the consistency of forecasted IOTs in long-term models (modelling view), with a particular focus on those assessing important structural changes, for example, energy transitions.

3 | METHODOLOGY

As mentioned before, the main purpose of the article is to estimate the technical coefficients of the A matrix as a function of energy intensities, to evaluate the explanatory power of this variable as a driver of structural change. Following a significant body of literature, we argue that the energy metabolism of an economy, both production and consumption patterns along with their composition, determines productive processes, as represented by the technical coefficients of the A matrix. Although this evolution may depend on a large number of socioeconomic and technological variables, the method aims to capture only those changes that can be derived from two types of combined factors: the historical inertial trend and changes due to technological changes in energy production and consumption.

With this purpose, we have used the world input–output tables (WIOTs) from WIOD (Dietzenbacher, Los, et al., 2013). The sectoral breakdown into 35 economy branches is shown in Table A10 of Supporting Information S2 and the time sample goes from 1995 to 2009 (15 years). To estimate the energy intensities, five end-use final energy sources ("final energy source" from now on) have been considered: liquids, solids, heat, gases, and electricity. This breakdown of energy intensity into 5 components is very relevant from the perspective of the energy transition toward a low-carbon society. One of the key processes in this transition is an important electrification of sectors, such as transportation. It is expected that this electrification implies an increase in the electrical component of energy intensity and a decrease in other components of energy intensity (solids, liquids, and gases) whose origin is mainly from nonrenewable sources. Energy intensity is measured as the energy required to produce one unit of output by the 5 final energy sources and the 35 sectors. The WIOD environmental extensions and IEA data were employed to produce the energy intensities time series (de Blas et al., 2019).

Hence, in order to achieve the article's objectives, 1225 econometric equations have been estimated, one for each technical coefficient (35×35 sectors). As there is a broad agreement among the academic community in relation to the relative stability of the technical coefficients in the short term, we considered that a first autoregressive model was justified prior to the addition of the energy intensities. In other words, we argue that the technical coefficients are path-dependant, that is, the value of a technical coefficient in year "t" is influenced by the values of the same technical coefficient in past years "$t-1$", "$t-2$," and so on. Given the relatively short size of the sample (see below), an autoregressive model of order 1 (AR1) was used. After that, the sectoral energy intensities by five different final sources were tested as explanatory variables: electricity, heat, liquids, gases, and solids (see Table A11 in Supporting Information S2 for additional details). This process is described in Section 3.2. To evaluate the validity of the method used in this article, the fit of the resulting estimated technical coefficients is compared to the real ones in Section 4. Therefore, the methodology could be summarized as follows:

1. Classification of the technical coefficients regarding their relevance.
2. Estimation of an AR1 model to determine the evolution of the technical coefficients.
3. Estimation of the residuals of the AR1 model with final energy intensities by 5 sources, selecting only the final energy source that shows a better explanatory power using their coefficient of determination (R^2).
4. Merging both models to obtain the final predictions on the evolution of the technical coefficients.
5. Assessment of goodness-of-fit and results analysis regarding the relevance classification.

Although the technical coefficients' matrix can be considered longitudinal—or panel data—the possibility of running panel data regressions was ruled out. Preliminary tests were conducted, obtaining very low determination coefficients (R^2), a vast majority of nonsignificant coefficients—individually and joint—and a poor prediction fit to the real ones. Moreover, panel data are better suited to assessing the explanatory variable when considering the cross-sectional category—sectors in this case. However, we considered that, in order to estimate a certain technical coefficient, the only relevant energy intensity (the explanatory variable) is that of the producing sector. Therefore, the ordinary least squares (OLS) method was used to estimate the equations. Although OLS estimations are typically inefficient because the 1225 may not be independent of each other—as they are bounded by the balance conditions of the IOTs—the estimated parameters are still consistent, and it would have been impractical to run seemingly unrelated regressions (SUR) for so many equations. Moreover, concerns about endogeneity due to omitted variables or simultaneity—that is, the explanatory variable (energy intensity) and the endogenous variable (technical coefficients) simultaneously causing each other—may arise. It is highly likely that there are omitted variables in the equations because structural change is a complex process that depends on multiple factors. In addition, we acknowledge the potential contribution of industrial policy to modify energy intensity—see the discussion section. However, the purpose of this article is to explore the capacity of one variable (energy intensity) to explain structural change, and to what extent, through 1225 equations. Given the general approach adopted and the size of the analysis, the results ought to be analyzed and discussed considering the fact that more accurate estimators could be obtained.

Finally, it is important to note that WIOD used the SUT-RAS method to update—when IOTs are nonavailable—the national supply–use tables (SUTs) that were used to build their global IOTs time series. RAS consists of an iterative process of algebraic adjustments that estimates the new A matrix required to produce a new volume of production, given a total intermediate consumption. This method is based on mathematical adjustments, that is, not necessarily capturing the structural change drivers. However, this should have a relatively low impact on our results; first, because RAS was applied to SUTs, not to the A matrices; second, because there are enough available long time series for the majority of the most important (in terms of GDP) countries (Erumban et al., 2012)[3] to assert that the potential effect on the results should be limited; third, because when long time series are not possible, available matrices are separated by sufficient time to reflect the real changes in the tables. Therefore, if the construction of the data being analyzed is having an effect on the results, not only should it be relatively low, but it may also be interpreted as a caveat on their possible undervaluation.

3.1 | Identification of relevant coefficients

A six-stage procedure is used to determine the extent to which variations in any of the five types of energy intensity in sector j explain the variations in the elements of the technical coefficients of matrix A on the basis of an autoregressive model. We define the A Matrix (**A**) as the n x n matrix of technical coefficients, defined in turn as the proportion of inputs from each industry required to produce 1 unit of output of every sector, according to Equation (1):

$$\mathbf{A} = \begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & a_{ij} & \vdots \\ a_{n1} & \cdots & a_{nn} \end{pmatrix}; \quad a_{ij} = \frac{x_{ij}}{X_j} \tag{1}$$

With $i = 1,\ldots,n$ and $j = 1,\ldots,n$ being the number of rows and columns, respectively; a_{ij} the technical coefficient, and x_{ij} the value of the intermediate products purchased to produce the output of sector j (X_j). According to the IO framework, this matrix represents the technological structure of an economy at a certain period, as it reflects what products are necessary in the productive process of each sector.

[3] An exception could be made with Russia and Mexico, with only two SUTs and Australia, China, and India, with three.

First, the relevance of the a_{ij} technical coefficients has been estimated, considering the effect of their variation on the overall changes in the sectoral total output. As the technical coefficients are defined in relation to their respective sectoral output, there could be a situation where a certain $a_{ij} > a_{ij^*}$ but, if the output of sector $j^* > j$, then, a_{ij^*} may be more relevant economy-wide than the first one, despite being smaller (Hernández, 2012). Therefore, relatively smaller changes in a_{ij^*} could potentially trigger more sensitive changes across the supply chain than changes in a_{ij}, despite being greater than a_{ij^*}. This is consistent with the IO theoretical framework, which relies on the assumption of complementarity between productive factors, that is, every input is crucial to the productive process. Consequently, the importance of a certain input—or technical coefficient—is not only related to its volume, but also its capacity to produce effects along the supply chain, for example, microchips for the automotive sector or critical raw materials used in renewable technologies. Hence, identifying the more relevant coefficients is key to capturing the drivers of the A matrix evolution.

With this objective in mind, we have followed the method put forward by Schintke and Stäglin (1988). Inverse coefficients could also be used for this analysis (Chenery & Watanabe, 1958), but this method is the most commonly used among scholars due to its practical utility and its adequate theoretical and practical behavior. For example, it allows the aggregation restrictions posed by other methodologies based on multipliers and chaining to be overcome (Pino & Barriga, 2015).The starting point is to consider that a minimum alteration entails in-depth changes in the output of the branches. To do so, this method evaluates the effect produced in the economy after specifically altering one of the productive stages by a certain percentage, typically 1%. First, w_{ij} measures how much a technical coefficient a_{ij} has to vary in order to change the sectoral output by 1%:

$$w_{ij}(p) = a_{ij}\left(m_{ji}p + m_{ii}\frac{X_j}{X_i}\right) \tag{2}$$

m_{ji} and m_{ii} being the components of the Leontief Matrix,[4] p the percentage change (1%), and X_j and X_i the output of sectors j and I, respectively. Then, the relative relevance quantifies the sensitivity of a_{ij} to 1%. Hence, c_{ij} represents the maximum variation of a_{ij} that does not imply a more than 1% change in the total output of sector i. As a consequence, the more relevant the technical coefficient is, the lower the value of c_{ij} will be.

$$c_{ij} = \frac{p}{w_{ij}(p)} = \frac{p}{a_{ij}\left(m_{ji}p + m_{ii}\frac{X_j}{X_i}\right)} \tag{3}$$

According to this methodology, the coefficients are classified into four intervals (Hernández, 2012; Iraizoz & Garate, 1999): very relevant coefficients ($c_{ij} < 0.1$), relevant coefficients ($0.1 \le c_{ij} < 0.5$), slightly relevant ($0.5 \le c_{ij} < 1.0$), and less relevant ($c_{ij} \ge 1$). The sensitivity analysis is performed for the 18,375 technical coefficients of the 15 WIOTs, taking as reference the arithmetic average of the 15 years.

3.2 | Model estimation

Once all the technical coefficients have been classified according to their sensitivity, the starting point is an autoregressive model of order one (AR1) (Equation 4), where the relative variation (Equation 5) of the technical coefficients of matrix A is taken as a dependent variable.

$$\Delta a_{ij}^{t} = \beta_0 + \beta_1 \Delta a_{ij}^{t-1} + \varepsilon_{ij}^{t} \tag{4}$$

$$\Delta a_{ij}^{t} = \frac{a_{ij}^{t} - a_{ij}^{t-1}}{a_{ij}^{t-1}} \quad \begin{cases} i,j = \{1, \ldots, 35\} \\ t = \{1996, \ldots, 2009\} \end{cases} \tag{5}$$

The relative variation is equivalent to the first difference, which also allows problems of the non-stationarity of the variables to be avoided. At this stage, 1225 simple linear regressions are performed, one for each technical coefficient a_{ij} of the A matrix (35 sectors x 35 sectors), taking their relative year-on-year (y-o-y) variations. The determination coefficient R^2 has been estimated to evaluate whether there is a significant linear relationship or not. The R^2 is a measure of the goodness-of-fit (see Equation 12) in relative terms (Wooldridge, 2018) resulting from dividing the explained sum of squares (ESS) by the total sum of squares (SST). The R^2 results fall between 0 and 1 and can be understood as how much the explanatory variables explain the dependent. Thus, if the values are closer to zero, most of the variation would be explained by the residuals ε_{ij} (Equation 6).

$$\varepsilon_{ij}^{t} = \Delta a_{ij}^{t} - \Delta \hat{a}_{ij}^{t} = \Delta a_{ij}^{t} - \beta_0 - \beta_1 \Delta a_{ij}^{t-1} \tag{6}$$

[4] The Leontif matrix $L = (I - A)^{-1}$, with I being the identity matrix, quantifies the sensitivity of the sectoral production to the final demand.

The residuals term ε_{ij} summarizes the differences between the observed and estimated values, that is, it is the error (Equation 6). As all those factors explaining the dependent variable other than their lagged value would be included in the error term, we estimate the residuals as a function of the energy intensities in Equation (7) by the different final energy sources (Equation 8). A total of 5625 residuals are estimated (35 sectors x 35 sectors x 5 energy intensities), as well as their determination coefficients (R^2).

$$\varepsilon_{ij}^{t} = \delta_0 + \delta_1 \Delta EI_{kj}^{t} + \Delta_{ij} \tag{7}$$

$$\Delta EI_{kj}^{t} = \frac{EI_{kj}^{t} - EI_{kj}^{t-1}}{EI_{kj}^{t-1}} \begin{cases} \text{j} = \{1, \; \ldots, \; 35\} \\ \text{t} = \{1996, \; \ldots, \; 2009\} \\ \text{k} = \{\text{electricity, heat, liquids, gases, solids}\} \end{cases} \tag{8}$$

$$\hat{\varepsilon}_{ij}^{t} = \delta_0 + \delta_1 \Delta EI_{kj}^{t} \tag{9}$$

Then, we replace Equation (7)'s estimation (Equation 9) in Equation (4) to estimate 17,150 technical coefficients $\hat{a}_{ij}^{t}$ (35 sectors x 35 sectors x 14 years) according to the following equations:

$$\Delta\hat{a}_{ij}^{t} = \beta_0 + \beta_1 \Delta a_{ij}^{t-1} + \delta_0 + \delta_1 \Delta EI_{(k\_m\hat{a}x)j}^{t} \tag{10}$$

$$\hat{a}_{ij}^{t} = \Delta\hat{a}_{ij}^{t} * \hat{a}_{ij}^{t-1} + \hat{a}_{ij}^{t-1} = \hat{a}_{ij}^{t-1} * \left(\Delta\hat{a}_{ij}^{t} + 1\right) \tag{11}$$

where $EI_{(k\_m\hat{a}x)j}^{t}$ is the final energy source intensity that produced the highest R^2 estimation in Equation (9). Equation (10) is the regression of the first difference of the technical coefficients, that is, the yearly variation of each technical coefficient. On the other hand, Equation (11) represents the final prediction of the technical coefficient, using the predicted variables ($\Delta\hat{a}_{ij}^{t}$ and $\hat{a}_{ij}^{t-1}$) instead of the actuals. This means that a dynamic model was used instead of a static one. The dynamic model uses the estimated ($\hat{a}_{ij}^{t-1}$) instead of the actual (a_{ij}^{t-1}) value of the lagged technical coefficient, so the prediction is more sensitive to the previous period's estimate. Using a static model would have resulted in a better fit of the results, but achieving a good fit for a dynamic model enhances the validity of the method employed.

Although the R^2 is a widely accepted measure of goodness-of-fit, it very often obtains relatively low results in social sciences, given the frequent existence of unobserved explanatory variables. The equation to estimate this is the following:

$$R^2 = \frac{\sum_{96}^{09} (\hat{y}_t - \bar{y})^2}{\sum_{96}^{09} (y_t - \bar{y})^2} = \frac{\sum_{96}^{09} \left(\Delta\hat{a}_{ij}^{t} - \overline{\Delta a_{ij}}\right)^2}{\sum_{96}^{09} \left(\Delta a_{ij}^{t} - \overline{\Delta a_{ij}}\right)^2} \tag{12}$$

where y_t, $\hat{y}_t$ and $\bar{y}$ are the dependent variable's actuals, predictions, and averages, respectively. Anlogously, Δa_{ij}^{t}, $\Delta\hat{a}_{ij}^{t}$ and $\overline{\Delta a_{ij}}$ are the actuals, predictions, and averages of the variations of the technical coefficients. R^2 has been estimated for the AR1 model (Equation 4), the energy intensities model (Equation 9), and the complete model (Equation 10). Although the adjusted R^2 is sometimes reported together with or instead of the R^2; here it has been considered a sufficient measure of the goodness of fit. This is due to the fact that the main purpose of the adjusted R^2 is to impose a penalty on additional independent variables—Equations (4) and (9) account for only one—and it has been proven not to be a better estimator than R^2 (Wooldridge, 2018). The results are collected in the data repository, the Supporting Information, and summarized in Table 2.

To provide an extended measure of the fit, we calculated (Equation 13), an Index of Adjustment (IA) from the arithmetic mean of the percentages of deviation between the actual (a_{ij}^{t}) and the estimated ($\hat{a}_{ij}^{t}$) values. As using the y-o-y variation to estimate an AR1 model reduces two periods of the sample, only the 13 technical coefficients from 1997 to 2009 are taken into account. Moreover, a graphic measure of the goodness-of-fit is provided in Section 4, with the results shown in Figures 1 and 2.

$$IA_{ij} = \left(1 - \frac{1}{13} \sum_{1997}^{2009} \frac{\left|a_{ij}^{t} - \hat{a}_{ij}^{t}\right|}{a_{ij}^{t}}\right) \times 100 \tag{13}$$

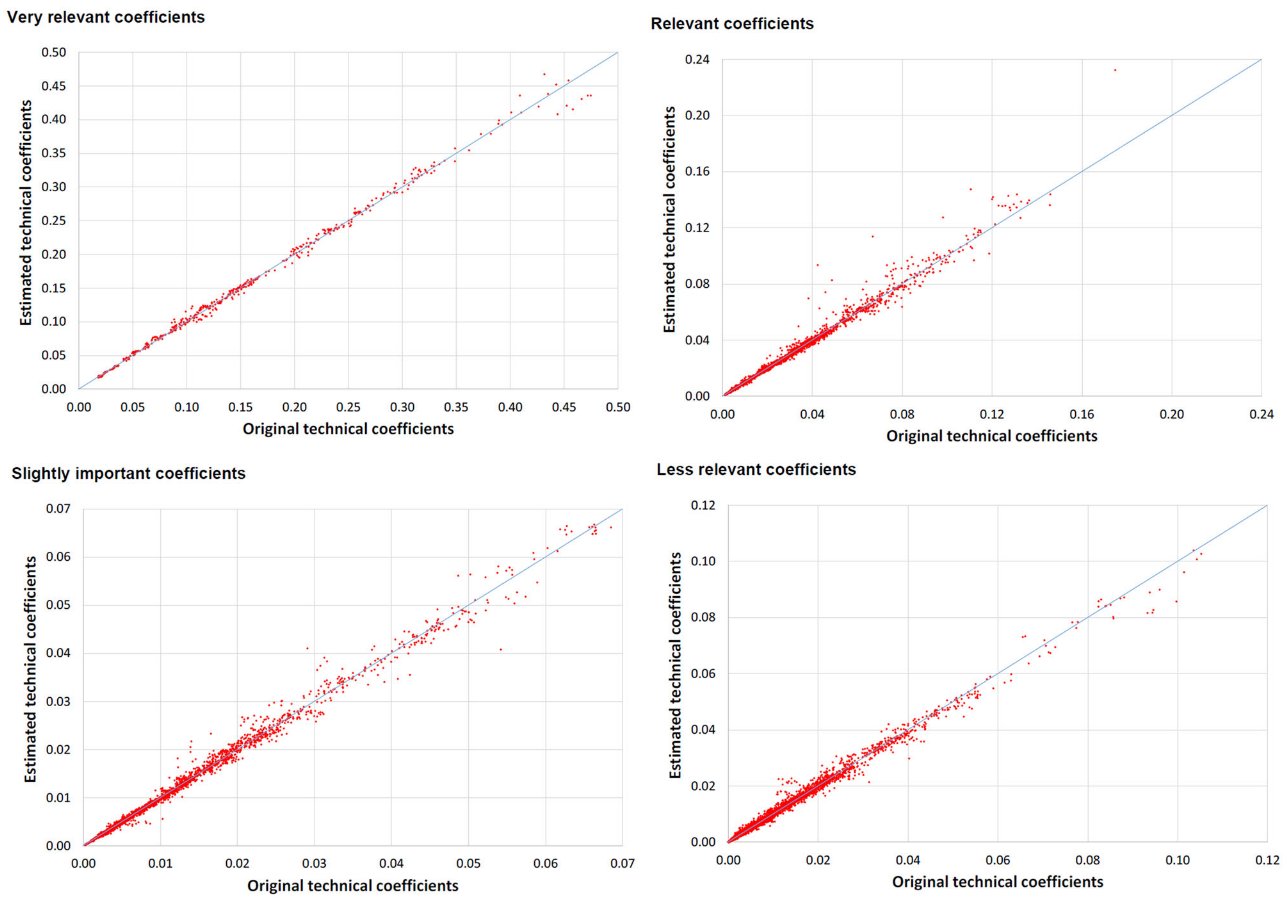

FIGURE 1 Estimated vs. actual technical coefficients by relevance. Underlying data for this figure are available in the data repository.

TABLE 1 Number of technical coefficients according to their importance. Underlying data are available in Table A1 of Supporting Information S2

Rank of the technical coefficients	Criterion	Number	Percentage
Very relevant coefficients	$c_{ij} < 0.1$	38	3.1%
Relevant coefficients	$0.1 \leq c_{ij} < 0.5$	205	16.7%
Slightly relevant coefficients	$0.5 \leq c_{ij} < 1.0$	214	17.5%
Not relevant coefficients	$c_{ij} \geq 1$	768	62.7%

Source: Own elaboration.

4 | RELEVANT TECHNICAL COEFFICIENTS AND ESTIMATION

The relative stability of the technical coefficients and the importance of intra-industry consumption lead to a low (3.1%) number of "very relevant" coefficients (Table 1). On the other hand, 62.7% of the technical coefficients were classified as "not relevant," that is, they require more than a 100% change to produce a 1% impact on production. This implies that a very significant part of the structural change can be captured by just covering a reduced selection of the technical coefficients (19.8% if "relevant coefficients" are included).

Table A1 in Supporting Information S2 shows that, on the one hand, half of the 38 most important technical coefficients cover the intra-industry demand of the different branches, for example, the primary sector (agriculture, hunting, forestry, and fishing: sector 1) purchasing goods from other primary sector firms. This would reveal that the intra-industry trade is not only important in terms of volume, but also regarding the economy-wide direct and indirect effects on other sector's output triggered by changes in their technical coefficients. The analysis by sectors can be viewed by rows (sales) or columns (purchases). If a sector has a great number of "very relevant" or "relevant" coefficients in a row or column, it reveals how important the sector is as a demanding (columns) sector or as a supplier (rows) sector.

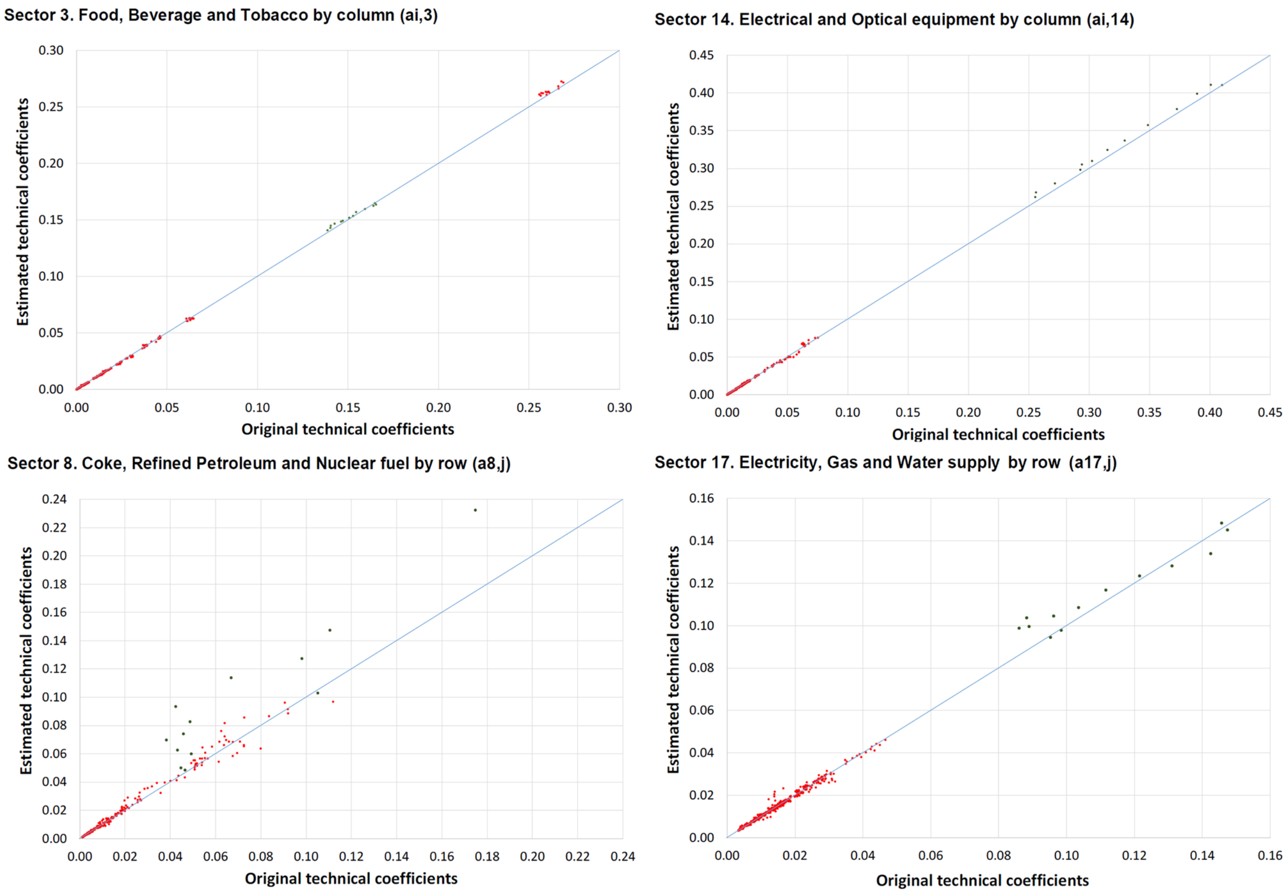

FIGURE 2 Estimated vs. actual technical coefficients: Selected sectors. Underlying data for this figure are available in the data repository. Green dots represent the intra-sector coefficients.

(a) The analysis by columns reveals that 57% of the 243 significant coefficients (very relevant and relevant coefficients) are concentrated in 10 sectors (see Table A10 in Supporting Information S2 with the list of industries for details): Food, beverages, and tobacco (3), chemicals (9), basic metals (12), electrical and optical equipment (14), transport equipment (15), construction (18), wholesale trade except vehicles (20), renting of machinery and equipment (30), public administration (31), and health and social work (33). These sectors would be more important as being relatively more demanding. For instance, sector 3 (food, beverages, and tobacco) is very relevant for the primary sector and intra-industry consumption; in addition, they are also relevant to packaging sectors such as the pulp and paper sector (7), distribution and transport sectors such as the sale, maintenance, and repair of vehicles sector (19), inland (23) and water transport (24), and other supporting transport activities (26).

(b) Focusing on the rows, 52% of the significant coefficients are also linked to 10 sectors: pulp and paper (7), coke and refineries (8), chemicals (9), rubber and plastics (10), electricity, gas and water supply (17), wholesale trade except vehicles (20), inland (23) and water transport (24), other supporting transport activities (26) and renting of machinery and equipment (30). These sectors are important for their main role as suppliers, and their activities are related to transformation industries, electricity and gas supply, and transport. For instance, the coke and refined petroleum sector (8) is a very relevant supplier for the inland transport (23) sector; whereas it is also relevant for the primary sector (fertilizers, fuels, etc.), intra-industry, chemicals, metals, electricity and gas supply, construction, other transport sectors, and the public administration.

Regarding the estimation of the technical coefficients, Table 2 summarizes the results obtained for all the models, including the initial AR(1) (see Table A2 in Supporting Information S2 for detailed results). Table 2 collects the total number of technical coefficients that were estimated; the R^2 of the estimation and the number of significant parameters obtained in rows and relates in columns to the AR1 model, using each final energy source as an explanatory variable. The determination coefficients R^2 and the levels of global significance obtained reveal that the AR1 model is insufficient to explain the variation in the technical coefficients. Specifically, this adjustment is only significant in 4.6% of cases; although, among the very relevant coefficients, the percentage rises to 13.2%. On average, the independent variable (Δa_{ij}^{t-1}) barely explains 8.3% of the dependent variable (Δa_{ij}^{t}), reaching 9.8% in the case of the very relevant coefficients.

TABLE 2 Estimation of the technical coefficients by type of final energy intensity. Underlying data are available in Tables A3–A7 of Supporting Information S2.

		AR(1)	Electricity	Heat	Liquids	Gases	Solids	Total	R^2 (Equation 10)
Very relevant coefficients	Technical coefficients	38	8	5	14	4	7	38	
	R^2 mean	0.0979	0.4651	0.2284	0.3566	0.1958	0.2996	0.3351	0.34278
	Significant	5 (13.2%)	6 (75.0%)	1 (20.0%)	8 (57.1%)	1 (25.0%)	2 (28.6%)	18 (47.4%)	
Relevant coefficients	Technical coefficients	204	42	27	54	45	37	205	
	R^2 mean	0.0819	0.3592	0.2866	0.3256	0.2606	0.3316	0.3142	0.31178
	Significant	11 (5.4%)	25 (59.5%)	11 (40.7%)	26 (48.1%)	14 (31.1%)	17 (45.9%)	93 (45.4%)	
Slightly relevant coefficients	Technical coefficients	213	45	32	62	41	34	214	
	R^2 mean	0.0831	0.3527	0.2607	0.3256	0.3509	0.3467	0.3298	0.33496
	Significant	10 (4.7%)	23 (51.1%)	12 (37.5%)	32 (51.6%)	23 (56.1%)	18 (52.9%)	108 (50.5%)	
Not relevant coefficients	Technical coefficients	730	151	103	187	156	136	733	
	R^2 mean	0.0851	0.3158	0.3073	0.3123	0.3224	0.2743	0.3074	0.31219
	Significant	29 (4.0%)	79 (52.3%)	44 (42.7%)	88 (47.1%)	76 (48.7%)	50 (36.8%)	337 (46.0%)	
Total number of regressions	1185	246	167	317	246	214	1190		
R^2 total average	0.0846	0.3348	0.2926	0.3191	0.3138	0.2965	0.3135	0.31715	
Total significant	55 (4.6%)	133 (54.1%)	68 (40.7%)	154 (48.6%)	114 (46.3%)	87 (40.7%)	556 (46.7%)		

Source: Own elaboration.

The data obtained with this first model allows us to anticipate that most of the relevant factors to explain the variations in the technical coefficients would be accumulated within the residuals, ε_{ij}. Hence, we estimate the second model according to Equation (10). Due to the lack of data for the energy intensity of sector 35, it has been excluded from the equations. Tables A3–A7 in Supporting Information S2 show each coefficient's R^2 to estimate the residuals by final energy source; whereas Table A8 collects the R^2 of the energy intensity applied to each coefficient.

The results can be analyzed from three different perspectives:

1. Overall: the energy intensity significantly adds information to the explanation of the evolution of the technical coefficients, as the R^2 more than tripled compared to the AR1 model (see Table A2 and Table A12 in Supporting In). Given the relatively low share of relevant and very relevant coefficients (19.8% of the total), the number of significant regressions certainly seems promising.
2. By the relevance of the technical coefficients: in fact, the very relevant coefficients were the ones accounting for the greatest explanatory capacity (0.3351) and the second highest rate of significant values (47.4), above the average in any case. This would reinforce the method's validity to assess the overall evolution of the technical coefficients matrix. Despite there being a tendency of significance and explanatory capacity to decrease in line with the coefficients' relevance, an exception has to be made with the slightly relevant coefficients (50.5% and 0.3298, respectively). However, the difference is not too big compared to the other groups of coefficients.
3. By energy intensity: Liquids more often had the greater R^2 (317), followed by electricity and gases (both 246), solids (214), and heat (167). However, electricity proved to be the final energy source with the highest explanatory capacity (0.3348) when applied, especially for the "very relevant coefficients" (0.4651 R^2 and 75% significant values). Conversely, heat was the final energy source with the poorest performance. In addition, most of the δ_1 (see Equation 10), that is, the direct effect of energy intensities on the technical coefficients are positive (58%), as can be seen in the data repository. This means that, in the majority of cases, a reduction in energy intensity leads to a reduction in the technical coefficient. This is especially valid for energy-related sectors such as mining or refining (2 and 8), or such manufacturing sectors as machinery, electrical equipment, transport equipment (13, 14, and 15) and inland and water transport (23 and 24). Conversely, the existence of a negative δ_1 could be subject to further discussion. There are two possibilities:
   (a) An increase in energy intensity leads to lower technical coefficients: the substitution of certain material inputs by mechanized or digital, energy-intensive processes might be revealing. This may be the case of the primary sector (1), the food and paper industries (3 and 4), chemicals (9), processing of other non-metallic minerals and basic metals (11 and 12), and so on.

TABLE 3 Index of adjustment (IA) of the technical coefficients. Underlying data are available in Table A9 of Supporting Information S2.

	Total		IA ≥ 95%		90% ≤ IA < 95%		IA < 90%	
Technical coefficients	**N° coef.**	**IA (%)**	**N° coef.**	**IA (%)**	**N° coef.**	**IA (%)**	**N° coef.**	**IA (%)**
Very relevant coefficients	38	97.11	37	97.80	1	94.08	0	-
Relevant coefficients	205	95.42	178	97.15	25	92.71	2	84.74
Slightly relevant coefficients	213	95.45	192	96.96	18	93.27	3	84.37
Not relevant coefficients	700	92.30	502	96.71	157	93.04	41	82.09
Total	1,156	93.59	909	96.92	201	93.05	46	82.48

Source: Own elaboration.

(b) A reduction in energy intensity leads to higher technical coefficients: this may be the case of service sectors with growing capital concentration and overhead costs and/or a relatively higher dependence on human labor. Some examples could be the financial and telecommunications sector (28 and 19), or health and social work and other community, social and personal services (33 and 34).

In any case, the common belief that energy efficiency unequivocally leads to de-materialization (measured by the amount of inputs required for production) could be called into question in the light of these results.

We therefore assess the fit of the 1190 regressions graphically and with an index of adjustment statistic. Given the large amount of estimations, these results are presented as a scatter plot with the estimated coefficients in the vertical axis and the actuals in the horizontal axis. The more concentrated along the bisector line the coefficients are, the better the fit is. Figure 1 shows the estimated vs. the actual technical coefficients. Each dot represents the original (actual) value of one coefficient a_{ij} in a certain year (X-axis) and the value of the estimate for the same coefficient a_{ij} and the same year (Y-axis). Therefore, the closer the dots are to the bisector line, the better the fit is. The same graphic analysis has been applied to several important sectors shown in Figure 2, either by columns or by rows, as mentioned above in this section. The green dots represent the intra-industry technical coefficients, normally the more relevant ones. A different performance can be observed among the sectors, with some showing a relatively more disperse fit. Despite these particular differences in dispersion in some sectors, and for some of the higher technical coefficients, the Index of Adjustment (Equation 13) allows the fit to be evaluated in relative terms. Of the 1156 coefficients considered at this stage, the average adjustment index (I_a) is 96.2% (see Table 3). The greatest adjustment was found in the very relevant coefficients (98.04%).

5 | DISCUSSION

In this section, we discuss the relevance of this analysis from different angles, including its policy implications.

First, the results could contribute to the debate on the causality between energy intensity and structural change. We argue that it is the capability to switch from a certain energy mix to another that is more likely to trigger structural change than the opposite. For example, the decision to ban coal would lead to changes in the mining, electricity generation, and iron and steel sectors. The transition to renewables, in turn, would potentially produce a shift from the mining and refining (of fossil fuels) sectors to those processing the critical raw materials required to deploy the renewable infrastructures. Moreover, the electrification of the economy would lead to changes in all transport-related sectors, the electrical equipment sector, and even to the retail trade of petrol products. Sectoral structure is likely to reorganize when there are changes in energy demand. In fact, Voigt et al. (2014) analyzed 40 major intensities and found that the change in energy intensity was mostly driven by technological change and less by structural change. Therefore, there are qualitative and quantitative reasons to justify the analysis conducted in this article despite the caveats of potential simultaneity.

However, this does not imply that industrial policy could not play an important role in the socioecological transition. Rather, the results of this article highlight the necessity to link energy and industrial policy. A first insight could be the fact that this analysis found evidence that reducing the energy intensity tends to reduce the technical coefficient in most cases. Hence, industrial policy should be oriented toward reducing the energy intensity in these sectors first: energy-related sectors such as mining or refining (2 and 8), or manufacturing sectors such as machinery, electrical equipment, transport equipment (13, 14 and 15) and inland and water transport (23 and 24). Other sectors that should be prioritized would be those with a significant number of relevant and very relevant technical coefficients, as they are the sectors with the higher capacity to influence overall consumption. In this regard, there would be at least two policy options to explore. From the supply side, technological change aimed at improving efficiency at the device level. However, there is evidence that technical limits are being reached from this perspective (Paoli & Cullen, 2020). To overcome them, they could be accompanied by an avoid–shift–improve (ASI) framework for demand management policies: urban planning, a shift to collective transport, public and non-emission modes, building retrofit, behavioral change, meat-reduced diets, and so on (Creutzig et al., 2016, 2018; Owen et al., 2018). The electrification of these sectors could also be prioritized, as they are sectors that greatly rely on fossil fuels and in which electricity intensity proved to be the variable with the highest explanatory capacity to drive structural change.

A virtuous circle would be operated by following this path, at least in a first stage. When the technical coefficients of a certain sector are reduced, its intermediate goods and services' demand decreases. This means that fewer inputs are required to produce the same output, contributing to alleviating the pressure of the economy on the environment. However, a caveat should be made to this if this policy orientation is to be effective. There is a secondary expansive effect after the reduction of the technical coefficients, as the sector's added value is increased if prices are kept constant. This increases disposable income and eventually final consumption. The alternative is a reduction in prices, which ends up having the same effect on final consumption, both of them potentially leading to a rebound effect. As a consequence, policy makers should consider compensating mechanisms to avoid the rebound effect that offsets the initial benefits, such as the above-mentioned ASI policies. Moreover, this potentially harmful—for the socioecological transition–side effect could be brought back to the virtuous circle by re-orienting the additional value added toward the necessary investments in the energy sector and for the ASI framework. This could be operated via taxation or the implementation of incentives.

On the other hand, it should be taken into consideration that a significant amount of technical coefficients showed an inversely proportional relationship with energy intensity. An increase in energy efficiency could lead to a reduction of technical coefficients in the primary sector (1) and in many industry sectors, such as the food (3) and paper (4) industry, chemicals (9), or the processing of other non-metallic minerals and basic metals (11 and 12). This should not be done so as to seek an intensification of energy consumption in these sectors. Rather, it could be indicating that the substitution of final energy sources, mainly electrification, has a higher priority for these sectors. Moreover, it could be considered as a warning call that mechanization in these sectors may be reducing the intermediate inputs consumption, but at the expense of an increase in energy demand. Therefore, the electrification of these sectors may be accompanied by the ASI measures to avoid additional rebound effects. Moreover, it has also been found that some services sectors (e.g., telecommunications, financial, health, social work, and personal services) could increase the technical coefficients when energy intensity is reduced. In this case, it is important to evaluate whether the reduction in energy consumption is not offset by the increase in intermediate inputs demand. Nevertheless, these sectors are relatively more intensive in and easier to shift to electricity, which makes the previous condition more likely to be met.

However, some precautions should be taken into consideration. The historic sample shows an increase in the total proportion of inputs to produce 1 unit of output, that is, reducing the capacity to produce value added. Therefore, the past trends go in the opposite direction, as required to downsize the energy demand. This has to do with the increasing biophysical difficulties to further reduce energy intensity (Alcott et al., 2012; Blake, 2005), or with the process of rematerialization that is currently ongoing in the world, despite the declared commitment with sustainability of the international community (Fischer-Kowalski & Haberl, 2007; Krausmann et al., 2008, 2018). Thus, given the ineffectiveness of current policies and the scepticism about the stated ones (Nieto et al., 2018; Parrique et al., 2019; Spash, 2016), the combination of energy and industrial policy objectives could contribute to overcoming these difficulties and meeting climate goals.

6 | CONCLUSIONS

This analysis shows that the amount and types of energy consumed are significant drivers of structural change. Economy models are increasingly aiming toward relying on granular economic structures, rather than considering an aggregate point of view. This tendency is influenced by the improvement of input–output databases and by the increasing adoption of non-conventional growth models instead of the conventional aggregate production function approach. Moreover, there is a growing interest in energy–environment–economy relationships that has fostered the use of IAMs. Thus, both economy models and IAMs have traditionally relied upon aggregated and/or static economic structures. When a dynamic structure has been taken into consideration, energy has often been disregarded. Conversely, when considered, empirical evidence on the energy–economic structure was typically lacking. Moreover, energy transition plans typically only consider aggregated energy intensity despite the fact that it would entail the increase in electricity intensity and the reduction in fossil fuel intensity. Thus, it is important to take into consideration disaggregated energy intensities.

The results show the relevance of linking energy and industrial policy to meet climate goals. Reducing the amount of inputs required to produce one unit of output (i.e., the technical coefficients of the A Matrix) contributes to reducing intermediate demand, but could also increase sectoral value added. The growth of value added in the economy may need to be re-oriented toward financing the socioecological transition. Otherwise, an increase in final demand could offset the initial reduction, producing rebound effects. Although the more frequent consequence of a reduction in energy intensity leads to a reduction in the technical coefficients, the reality may be more complex than just that. Mechanization and digitalization processes may entail a reduction in the share of inputs required for production, but only by increasing energy use. Conversely, the tendency of certain sectors toward capital concentration (and therefore, increasing overhead costs) such as financial or telecommunications, or labor-intensive sectors, such as health and social work, could lead to an increase in the technical coefficients, despite energy being used more efficiently. Therefore, models should take into consideration this diverse reality when simulating structural change. For this purpose, demand-side management policies in an avoid–shift–improve (ASI) framework could become a necessary policy tool to combine with energy-industrial policy.

Finally, the analysis has found that a small share of the technical coefficients has the potential to explain the A matrix evolution. This would suggest that focusing solely on those coefficients may be sufficient to deliver insightful results. Therefore, it would be worth identifying the relevance of the different coefficients before starting to project A matrices to the future or simply analyzing their determinants. Another factor to consider when selecting relevant coefficients/sectors is related to the purpose and objectives of the analysis the researcher is to undertake. The method used in this article could be improved in future developments by applying a principal component analysis (PCA) approach. In addition, the relatively low R^2 results would reveal the necessity to consider additional dimensions to energy intensity. The introduction of R&D expenditure, as proposed by Pan (2006), or unit labour costs as in D'Alessandro et al. (2020) shall be studied as potentially omitted variables in the model estimated in this article.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in Data repository.xlsm at https://doi.org/10.35376/10324/55621.

ORCID

Jaime Nieto https://orcid.org/0000-0002-8925-4319
Pedro B. Moyano https://orcid.org/0000-0002-4767-573X
Luis Javier Miguel https://orcid.org/0000-0002-8243-8596

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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