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Analysis

From twin transition to twice the burden? Digitalisation, energy demand, and economic growth

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ABSTRACT

This paper evaluates the potential of digitalisation to drive structural transformations towards a sustainable economy. We apply an index decomposition analysis (IDA) to understand the factors influencing energy demand in a panel of 31 high-income countries (1971–2019). The IDA framework includes four factors related to the scale and sectoral composition of the economy and technical improvements, accounting for the quality of energy flows and actual work potential through useful exergy measures. We apply the model at the sector level across 16 productive industries to explore cross-sector heterogeneity in energy demand, and then compare results across digitial intensity categories. We find that value added growth is the primary driver of energy use. While digitalisation alone does not fully explain trends in energy demand, it is strongly associated with value added growth in high digital intensity sectors and amplifies the use of energy. Left ungoverned, digitalisation risks intensifying economic–ecological tensions, but if steered towards socio-ecological priorities—while addressing the environmental costs of growth—it holds potential to deliver real benefits. We discuss these findings in the context of recent policy actions promoting the "twin" green and digital transition.

1. Introduction

Climate change is one of the greatest challenges humanity has ever faced, carrying high risks of disruption to all life on Earth (Rockström et al., 2009; Steffen et al., 2015; Richardson et al., 2023; Lee et al., 2023). Public actions in the coming years will decide if we can meet the 1.5°C target of the Paris Agreement and the Sustainable Development Goals (SDGs; see Appendix A for a list of all abbreviations), particularly *SDG13: Take urgent action to combat climate change and its impacts* (UN General Assembly, 2015). Can technological change—here, the widespread adoption of digital technologies—drive structural shifts in energy use and support the transition to more sustainable economic models? This is the overarching question we address in this paper.

Since the 1970s, economists have increasingly questioned the sustainability of economic growth in the face of increasing environmental degradation and resource depletion. The 'Georgescu-Roegen/Daly vs. Solow/Stiglitz' controversy highlights two opposing perspectives on resource limits (Georgescu-Roegen, 1975; Daly, 1997; Solow, 1997; Stiglitz, 1997). On the one hand, Solow and Stiglitz recognise that unbounded resource productivity is a prerequsite for unbounded economic growth, but they tend to downplay the relevance of resource constraints in the short to medium term. On the other hand, Georgescu-Roegen and Daly argue that thermodynamic constraints impose fundamental limits on growth, even in the near term. Despite some potential areas of convergence, the debate has endured and evolved into a lasting academic divide (see, e.g., Germain, 2019; Couix, 2019; Polewsky et al., 2024).[1]

Yet optimistic assumptions regarding productivity gains and the compatibility of Gross Domestic Product (GDP) growth with environmental sustainability have shaped the (*smart*) *green growth* narrative of recent decades. Innovation has been placed at the cornerstone of the

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[1] As an anonymous referee reminded us, Couix (2019) concludes that "*neither side provided a definitive proof of its own claim because both face important conceptual issues*", thus leaving the discussion open.

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dominant climate change mitigation strategies in high-income countries, reflecting an enduring belief in the role of technological change in decoupling economic growth from environmental impacts.[2] Yet green growth requires absolute decoupling, and current evidence shows an emerging consensus that the growing observations of such decoupling remain insufficient to achieve mitigation targets (Savona and Ciarli, 2019; Le Quéré et al., 2019; Haberl et al., 2020; Hubacek et al., 2021; Lamb et al., 2022; Vogel and Hickel, 2023). Even so, the emphasis on innovation and efficiency continues to shape Europe's discourse on the *twin transition*, which promotes the integration of advanced digital technologies (ADTs) into environmental strategies (Perez, 2019; Lesher et al., 2019; Bianchini et al., 2023; Damioli et al., 2025).

The assumption that digital and green transitions can progress in tandem has faced growing criticism. Although empirical evidence remains limited, indications suggest that digitalisation may not automatically contribute to sustainability goals (Fouquet and Hippe, 2022). Information technologies (IT) and some ADTs—e.g., Artificial Intelligence—are considered by many as *General Purpose Technologies* (GPTs), and as such, they can unlock new opportunities and expand the range of possibilities (Bresnahan and Trajtenberg, 1995; Brynjolfsson and Yang, 1996; David and Wright, 1999; Lee and Lee, 2021). These include the development of new products, production processes, and services that offer environmental benefits (Montresor and Vezzani, 2023; Verendel, 2023; Damioli et al., 2025). However, digitalisation also incurs substantial direct demand for energy and material related to the production, use, and disposal of digital technologies (see Williams, 2011; Jones, 2018; Strubell et al., 2019; Freitag et al., 2021; OECD, 2022; Williams et al., 2022), all of which are expected to keep growing in the future. In addition, there are potential indirect, or structural, effects which are complex and difficult to quantify (Schulte et al., 2016; Yang and Shi, 2018; Zhang and Wei, 2022; Niebel et al., 2022; Ahmadova et al., 2022; Barteková and Börkey, 2022; Kunkel et al., 2023).

In a seminal article, Lange et al. (2020) propose an analytical framework to capture the interactions between digitalisation and energy consumption. They identify four channels through which digitalisation may affect the environment: (1) direct effects from the production, use, and disposal of ADTs; (2) digitally-induced gains in energy efficiency; (3) economic growth driven by productivity gains; and (4) shifts in sectoral composition. Channels (1) and (3) are expected to intensify energy use, while (2) and (4) should moderate demand through technical improvements and the expansion of less energy-intensive sectors. This framework informs our empirical analysis, which draws on data from a panel of 31 high-income countries over 1971–2019 to assess whether technological change can drive the structural changes needed for a green transition. We propose some extensions by combining concepts from ecological and exergy economics with insights from evolutionary economics (see Section 2), allowing us to account for both structural and technological changes as well as the physical processes underlying economic production. Specifically, we conduct an energy decomposition analysis across 16 productive sectors, comparing outcomes between digital-intensive sectors—as defined by the OECD taxonomy (Calvino et al., 2018)—to assess the structural effects of digitalisation. We find that digitalisation polarises the dynamics of energy demand through its boosting effect on sectoral growth, which remains the dominant driver of energy use. Efficiency gains following the adoption of ADTs are far lower than expected and, despite improvements in energy productivity, do not translate into reduced energy demand.

This study contributes to the literature on the environmental impacts of digitalisation in several ways. First, most studies focus on a single dimension of digitalisation—such as the number of machines or internet usage (Añón Higón et al., 2017; Haseeb et al., 2019; Chimbo, 2020; Oteng-Abayie et al., 2023), ICT capital (Bernstein and Madlener, 2010; Khayyat et al., 2016; Schulte et al., 2016; Niebel et al., 2022), ICT sectors (Zhou et al., 2018, 2019; Wang et al., 2022), or ICT patents (Yan et al., 2018); and even when multiple dimensions are considered (e.g., robots, skills, and digital capital), they are often treated as independent variables (Matthess et al., 2023). Here, we rely on a taxonomy that captures multiple facets of digital transformation, so that sectors vary in their development and adoption of ADTs, the human capital needed to integrate them into production, and the extent to which digital tools are used in interactions with clients and suppliers. Second, many existing studies overlook the (strong) sectoral heterogeneity of technological change, focusing instead on country-level digitalisation (Ahmadova et al., 2022; Zhang and Wei, 2022; Benedetti et al., 2023) or highly aggregated sectors (Oteng-Abayie et al., 2023). We propose a more granular, sector-level analysis that considers both the economic and energy impacts of digitalisation. Third, and perhaps most critically, many studies underestimate the role of energy and energy efficiency in economic production, due to inconsistent definitions, misconceptions, mismeasurements, and limited accounting of advances in ecological and exergy economics. In this work, we do our best to address these gaps.

The remainder of the paper is organised as follows: Section 2 lays out the analytical framework of our research; Section 3 presents the decomposition model and data; Section 4 reports the main results and discusses their implications; and Section 5 concludes with some remarks and implications for policy.

2. Background

In this study, we investigate the indirect effects of digitalisation on energy, focusing on the *structural* drivers of energy demand. Structural change is not limited to mere changes in economic composition—as usually understood in energy analysis (see details in Sections 2.1 and 2.3)—but is a multi-layered process with interconnection among its components, that accompanies economic growth through perpetual changes in technologies and products (Savona and Ciarli, 2019; Ciarli and Savona, 2019). Economic composition is only one dimension, together with growth dynamics, technical improvements, institutional evolution, and changes in the international division of labour. Accordingly, our analytical framework and empirical model build on recent advances in ecological and exergy economics—which stress the role of physical processes in production—as well as concepts from evolutionary economics, which highlight the multidimensional, heterogeneous, and dynamic nature of technological change. In what follows, we elaborate on these theoretical foundations (Sections 2.1 and 2.2), introduce the structural drivers of energy demand considered in our analysis (Section 2.3.1), and present the taxonomy of sectors based on their level of digitalisation used in this work (Section 2.3.2).

2.1. Metrics and modelling tools for energy analysis

Energy quality is central to economic production. Yet, most studies on the relationship between digitalisation and energy have overlooked the quality of energy flows and their actual work potential, known as *exergy* (see Brockway et al., 2018 for a detailed outline).[3] Exergy

[2] Decoupling refers to the "uncoupling" of resource use or environmental impacts from economic growth (Browne et al., 2011; María Regueiro-Ferreira and Alonso-Fernández, 2022). Decoupling can be *relative*, meaning that resource use or environmental impacts grow at a slower rate than GDP; or *absolute*, in which GDP growth is accompanied by a reduction in resource use or environmental impacts (Parrique et al., 2019).

[3] As a reminder: *energy* represents the total (heat) quantity of energy in a system, which is conserved (first law of thermodynamics); *exergy* measures the work potential or available energy in a system, reflecting its quality (second law of thermodynamics). Exergy accounts for irreversibilities and is essential when assessing the efficiency of the system.

economics brings thermodynamic principles into economic analysis, considering energy across the three stages of the *energy conversion chain* (ECC): primary, final, and useful—each of which can be measured in energy/exergy terms (see Aramendia et al., 2021, Fig. 1 and Section 1.2 for details). The *primary* stage refers to raw energy resources extracted from nature; the *final* stage to the energy/exergy purchased by end-users; and the *useful* stage to the energy/exergy actually available at the point of use in the production of energy services—such as heating, cooling, mechanical drive, lighting, electronics, and muscle work (see Guevara, 2014, Section 2.1.4; or Brockway et al., 2018, Table 8.1 for details).[4] The provision of energy services accounts for end-use device efficiencies, so assessing energy/exergy at the useful stage captures improvements in second-law efficiency from advances in energy technologies.

Despite progress in exergy economics, many studies still conflate energy intensity with thermodynamics-based (second-law) efficiency, neglecting the work potential—or exergy—of energy flows (Guevara, 2014; Proskuryakova and Kovalev, 2015). In other words, they rely on energy intensity as a (poor) proxy for energy efficiency. Energy intensity (I) is typically calculated by dividing energy quantities (E) by the monetary value of GDP, gross output, or value added (Y), or by physical quantities (Q) for specific goods or services:

$$I = E/Y \quad \text{or} \quad I = E/Q \tag{1}$$

Yet this approach has clear limitations. For instance, energy intensity primarily captures changes in first-law (energy) efficiency, which measures only the quantity of energy input versus output, often with significant delays (Stern, 2004; Proskuryakova and Kovalev, 2015; Saunders et al., 2021). Moreover, as shown in Eq. (1), energy intensity depends on economic metrics that are frequently reported with insufficient detail or imprecise definitions, all of which affect its accuracy (Semieniuk, 2024).

Here, we explicitly account for the quality and work potential of energy flows. Two main empirical findings further underscore the importance of an exergy-based analysis. First, qualitative improvements in energy conversion technologies (i.e., second-law efficiency) are fundamental in explaining total factor productivity and, consequently, economic growth (Santos et al., 2018; Sakai et al., 2018; Santos et al., 2021). Second, energy efficiency appears much less substantial—in absolute terms—when the quality of energy flows is factored in (Aramendia et al., 2021; Brockway et al., 2024).

With this in mind, our empirical approach relies on *Index Decomposition Analysis* (IDA), a method particularly suited to studying the evolution of energy use (or emissions).[5] Technical details are provided in Section 3.1; for now, it is sufficient to note that IDA models decompose an aggregate variable—i.e., energy use—into multiple components, offering insights into the underlying factors driving its variation. Only a few recent studies, however, have integrated useful energy or work potential into energy decomposition analyses (see, e.g., Guevara, 2014; Brockway et al., 2015; Silverio, 2015; Guevara et al., 2016; Hardt et al., 2018; Aramendia et al., 2021; Ecclesia and Domingos, 2024).

Different IDA models vary in their methodological basis, but all share the core idea of decomposing an aggregate indicator into three factors: *production* (or *scale*), *structure* (economic composition), and *technology* (Hoekstra and van den Bergh, 2003). For example, in analysing national energy consumption, changes in consumption can be decomposed into: the production effect, which captures the scale of overall energy-using activities; the structure effect, which reflects shifts in the composition of these activities and thus the sectoral structure of energy demand; and the technology effect, which indicates the impact of energy-converting technologies. IDA can be flexibly adapted to various dimensions (e.g., temporal and spatial) and scales (e.g., economies, sectors, firms), and is therefore well suited to our aims.

2.2. Multidimensionality, heterogeneity, and temporality of changes

In studying energy dynamics, it is important to account for the multidimensionality, heterogeneity and temporality of technological and structural changes. To this end, we highlight three caveats drawn from evolutionary economics.

First, most studies on the environmental impact of digitalisation focus on a single dimension—for example, the number of machines, internet usage, or ICT capital. By contrast, we argue that digitalisation digitalisation should be understood and measured as a multidimensional transformation, encompassing ICT as well as other key ADTs.[6] At a minimum, these include artificial intelligence (AI), big data, IT infrastructure, and robotics (see Bianchini et al., 2023 for a comprehensive classification). In addition to technological change, shifts in skills, markets, and business strategies also evolve and should be included in the analysis (Calvino et al., 2018; Benedetti et al., 2023).

Second, there is a tendency to overlook the sectoral heterogeneity of technological change by focusing on country-level digitalisation (Ahmadova et al., 2022; Benedetti et al., 2023) or using highly aggregated sectoral data (Oteng-Abayie et al., 2023). Yet evolutionary economics reminds us that such heterogeneity matters (see, e.g., Dosi, 2023, Ch.3 and 9). A recent review by Zhang and Wei (2022) confirms that sector-level studies on the economic and environmental impacts of ICT remain scarce. Moreover, a substantial body of literature shows that production technologies vary significantly across sector, with distinct patterns of diffusion and use (Fierro et al., 2022; McElheran et al., 2024); and recent attempts to classify sectors by levels of digitalisation confirms this strong heterogeneity (Calvino et al., 2018; Matthess et al., 2023). To account for all this, as discussed further below, we conduct a sector-level analysis that captures multiple dimensions of digital transformation.

Finally, most studies fail to capture the path-dependent, long-term patterns of adoption and use of advanced digital technologies, or to consider potential structural breaks in their environmental impacts. The limited temporal scope of many analyses—understandable given the challenges of accessing reliable long-term data—reflects a general tendency to treat technical change as exogenous. This limitation has also been cited as a reason why the productivity effects of information technology were initially hard to detect; timing, therefore, matters (David and Wright, 1999; Brynjolfsson and Hitt, 2000). Cumulative effects over time are particularly important: for instance, studies show that computer-enabled organisational changes have much larger impacts in the long run (Brynjolfsson and Hitt, 2000, p. 33). For this reason, as discussed in Section 3.2.1, we apply decomposition analysis to a long time series spanning almost 50 years (1971–2019) to capture the cumulative effects of technological and structural change.

2.3. The analytical framework

We combine the elements discussed above into a single analytical framework. Conceptually, we assume that digitalisation affects various energy-related structural components across different sectors, which in turn shape and define the dynamics of energy demand. Empirically, our approach is structured in reverse. First, we apply a decomposition model (briefly introduced in Section 2.1) that disaggregates energy

[4] In the remainder of this paper, *exergy* and *work potential* or *work* are used interchangeably, as well as *useful exergy* and *useful work*.

[5] Since their development in the 1970s for energy balance analysis, decomposition methods (IDA, SDA, etc.) have been continually refined, with over 10,000 publications recorded as of 2023 (Wang and Yang, 2023).

[6] In this analysis, we do not draw a strict distinction between ADTs and ICT. Instead, we consider ICT the historical foundation for the emergence of ADTs and, therefore, a subset of them (Lee and Lee, 2021).

Table 1
List of driving factors for the decomposition model.

Structural component	Decomposition factor	Formula
Composition	*Scale* effect: S	VA
Technical	Exergy-to-energy *conversion* effect: IC	X^f/E^f
	Thermodynamic *efficiency* effect: IE	X^u/X^f
	Energy *productivity* effect: IP	VA/X^u

Note: VA is value added, X^f is final exergy, E^f is final energy, X^u is useful exergy.

demand into structural drivers—technical details in Section 3.1. Second, we examine the heterogeneous effects of digitalisation across sectors based on the OECD methodology (Calvino et al., 2018), comparing results across levels of digital intensity—technical details in Section 2.3.2.

Our preference for sector-level decomposition over country-level analysis is motivated by three main reasons. First, as discussed in previous sections, sectors exhibit distinct patterns of digital penetration that cannot be captured at the country level. While firm-level studies may be best suited to identify these changes, data limitations and the inability to aggregate results for country-wide effects make sector-level models better suited to our research question. Second, estimating decomposition models directly at the sector level allows us to avoid the aggregation issues common in country-level analysis (Weber, 2009; Mulder and De Groot, 2012; Guevara, 2014). Indeed, as we directly estimate separate models for each sector, we sidestep issues that may arise from different aggregation strategies. Third, sector-level decomposition often shows that the scale of production (or *activity* effect) plays a significant role in energy use (Hajko, 2012; Brockway et al., 2015; Heun and Brockway, 2019). Many studies, however, focus only on relative changes in sectoral composition—a narrow view of structural change (see Henriques and Kander, 2010; Mulder and De Groot, 2012). When these changes are aggregated at the country level, some important sector-specific patterns may be hidden, potentially underestimating structural shifts and overestimating the role play by the scale of production.[7]

2.3.1. Structural drivers of energy demand

We distinguish two components of structural change, which materialise through four driving factors. First, the *composition component* captures sectoral growth dynamics as drivers of economic composition, and is measured through the *scale* effect. Second, the *technical component* is divided into three factors: the exergy-to-energy conversion ratio (*conversion* effect), second-law efficiency (*efficiency* effect), and a hybrid physical-monetary measure of energy productivity (*productivity* effect).[8] Table 1 lists the driving factors used to analyse structural changes in energy demand.

Some concrete examples of changes in the decomposition factors from Table 1 include the following. The *scale* effect may be influenced by changes in total sales volume, market share, or markups. The *conversion* effect can result from shifts between final energy carriers (e.g., from heat to electricity) with different exergy-to-energy coefficients (for more details, see Table 1 in Brockway et al., 2024). The *efficiency* effect reflects changes in production processes, such as the adoption of more or less efficient machines to convert final into useful energy, or shifts across categories and subcategories of useful exergy (e.g., from medium-temperature heat, MTH 200°C, to MTH 300°C). Finally, the *productivity* effect may stem from changes in the quality of products without altering the requirements for useful exergy, or from shifts in the product structure of an industry towards less (or more) exergy-intensive goods.

Our analysis is primarily descriptive rather than causal, and we do not test specific hypotheses with respect to each factor. However, we outline some expected patterns. First, we expect value added growth to be a strong driver of energy demand, as observed at the economy-wide level, with digitalisation potentially amplifying this effect (Hajko, 2012; Zhang and Wei, 2022). Second, we expect digitally intensive sectors to display stronger technical improvements, particularly in terms of efficiency, as suggested by the *smart green growth* narrative (Perez, 2019; Lesher et al., 2019). This expectation is also the necessary condition for digitalisation to contribute to absolute decoupling, where technical gains must outweigh value added growth. Third, the overall impact on energy demand will depend on the relative magnitude of composition and technical effects, which we do expect to vary across sectors depending on their level of digital intensity (Mulder and De Groot, 2012). Historically, however, at the economy-wide level, growth has typically exceeded efficiency improvements, leading us to anticipate an absolute increase in energy demand in high-growth sectors (Brockway et al., 2021).

2.3.2. Measuring sectoral digitalisation

To account for the heterogeneous diffusion and use of digital technologies, skills, and business models, we adopt the multidimensional framework proposed by the OECD (Calvino et al., 2018). This framework identifies three components that affect the degree of sectoral digitalisation: a *technological* component, a *human capital* component, and a *market* component.[9]

The *technological component* consists of five sub-indicators: (1) intensity of investment in ICT tangibles and (2) intangibles, (3) intensity of intermediate expenditure in ICT goods and (4) services, and (5) robots density. Investment intensities are computed with total capital investment as the denominator, and investment in computer hardware and telecommunications equipment (for tangibles) or in software and databases (for intangibles) as numerators. Intermediate expenditure intensities use input–output data to identify purchases made to ICT goods and ICT services sectors, as a share of total output. Expenditure of ICT goods are characterised as purchases to the sector *Manufacture of computer, electronic and optical products* (ISIC division 26), which mostly concerns microchips and intermediate electronic components. Expenditure of ICT services are characterised as purchases to the sector *IT and other information services* (ISIC divisions 62–63), which includes hardware & software consultancy, computing equipment maintenance, and data processing. Finally, robots density is computed by dividing the stock of industrial robots in a sector by the number of employees.

The *human capital* component focuses on skills and is measured as the intensity of ICT specialists, computed as the percentage of ICT specialists over total employment. Finally, the *market component* is measured as the share of turnover from online sales. Together with the five technological indicators, these form seven sub-components, which are aggregated into an indicator of sectoral digital intensity. For each sub-component, sectors are ranked into quartiles—low, medium-low, medium-high, and high digital intensity. The global indicator is the average quartile position across all sub-components. This implies a sector may be classified in the low digital intensity category while being ranked at the top of one sub-component. For example, low digital intensive sector *Food products, beverages, and tobacco* (ISIC divisions

[7] Forin et al. (2018) is one example of decomposition analysis adopting a sectoral perspective, but sectors are aggregated across countries to capture potential effects of industry offshoring. Although this is an interesting and original perspective, it differs from the aim of our study. Mulder and De Groot (2012) also consider cross-sector heterogeneity and confirm diverging trends across sectors, particularly between manufacturing and services.

[8] While energy intensity is computed as $I = E/Y$, energy productivity (its inverse) is defined as $P = I^{-1} = Y/E$.

[9] Data sources and specific metrics used to compute each indicator can be found in the Methodological Appendix of Calvino et al. (2018); here we provide only an overview.

10–12) scores poorly on ICT investments, expenditure, and specialists, but relatively high on online sales. Opposing examples for high digital intensity sectors are *Transport equipment* (ISIC divisions 29–30) with its high stock of robots per employee, its online sales, and its ICT specialists; or *Scientific research and development* (ISIC division 72) with its hardware and communications infrastructures, and its expenditures in ICT goods and services, but no online sales.

3. Methods and data

3.1. The sector-level decomposition model

Using the factors introduced in Section 2.3.1 (see Table 1), our decomposition model is based on Eq. (2). Here, E^f denotes final energy, VA value added, X^f final exergy, and X^u useful exergy. S represents the *scale* effect, IC the *conversion* effect, IE the *efficiency* effect, and IP the *productivity* effect. Subscripts i and j refers to the ith country and jth sector.

$$E^f_{ij} = VA_{ij} \times \frac{E^f_{ij}}{X^f_{ij}} \times \frac{X^f_{ij}}{X^u_{ij}} \times \frac{X^u_{ij}}{VA_{ij}} = S_{ij} \times IC_{ij} \times IE_{ij} \times IP_{ij} \tag{2}$$

The choice between multiplicative and additive models does not affect decomposition results, as one form can be converted into the other (Ang, 2015, Section 3.2, p. 236–237). We choose the multiplicative version because results are normalised around 1, which allows to smoothly visualises the dynamics of change and to make direct cross-sector comparisons regardless of differences in aggregation levels.

Following Ecclesia and Domingos (2024), we take the inverse values of the formulas in Table 1 for the *conversion*, *efficiency*, and *productivity* effects to fit the accounting equality of Eq. (2). Using inverse values for these three technical components reflects the fact that improvements in these metrics translate into decreasing factors, thus contributing to reduced energy demand. Indeed, improvements in the exergy-to-energy *conversion* ratio, the final-to-useful exergy *efficiency*, and the useful work *productivity* will lead to reductions in the *conversion*, *efficiency*, and *productivity* effects. Taking the rates of change in Eq. (2), we get the following multiplicative relationship.

$$D_{\text{energy}} = \frac{E^T}{E^0} = D_{\text{S}} \times D_{\text{IC}} \times D_{\text{IE}} \times D_{\text{IP}} \tag{3}$$

Our model is based on the multiplicative LMDI model with type-I weights (details about the mathematical properties for the LMDI-I model, and its difference with respect to LMDI-II, can be found in Ang, 2015). The general country-level estimation procedure for any driving factor D_V in country i is reproduced in Eq. (4). Here, $L(x, y) = (x - y)/log(x/y)$ is the logarithmic mean function, T refers to the subsequent period, and 0 to the previous period. At the country level, results are first weighted by ω_{ij}, the ratio of the logarithmic mean function applied to the jth sector and to the entire country, and then summed across all j sectors in country i.

$$D_{V_i} = \sum_j \exp\left(\frac{L(E^T_{ij}, E^0_{ij})}{L(E^T{}_i, E^0{}_i)} \cdot \ln \frac{V^T_{ij}}{V^0_{ij}} \right) = \exp\left(\omega_{ij} \cdot \ln \frac{V^T_{ij}}{V^0_{ij}} \right) \tag{4}$$

In our situation, the decomposition model is estimated separately for each country-sector (i, j) pair, so that aggregation across sectors is unnecessary. Eq. (4) is thus transformed to focus directly on the changes at the subgroup (sector) level. Our estimation procedure for each factor $V = \{$*scale*, *conversion*, *efficiency*, and *productivity*$\}$ is reported in Eq. (5). The weight parameter ω_{ij} cancels out from Eq. (4) to Eq. (5) due to our focus on country-sector pairs, but the model remains structured to reflect the influence of the standard LMDI procedure.[10]

$$D_{V_{ij}} = \exp\left(\frac{L(E^T_{ij}, E^0_{ij})}{L(E^T_{ij}, E^0_{ij})} \cdot \ln \frac{V^T_{ij}}{V^0_{ij}} \right) = \exp\left(1 \cdot \ln \frac{V^T_{ij}}{V^0_{ij}} \right) = \frac{V^T_{ij}}{V^0_{ij}} \tag{5}$$

We obtain chained times series of $D_{V_{ij}}$ for each (i, j) pair by estimating Equation (5).[11] Decomposition results in their multiplicative version are strictly positive and asymmetric: values in the interval $[0; 1]$ imply *downward* effects for $D_{V_{ij}}$, while values in the interval $[1; +\infty[$ imply *upward* effects (see Ang, 2015, Model 2 and 4, Table 3, p. 237 for an numerical example; and Heun and Brockway, 2019, Fig. 7, p.9 for a graphical illustration of index decomposition results).

Chained series are computed dynamically, comparing each year t directly with the preceding year $t - 1$, rather than with a fixed base year. Cumulative results are then aggregated either over the entire period—by taking the cumulative product of the whole time series—or by decade, by taking the cumulative product of sub-series grouped by decade. This approach allows us to account for the long-term dynamics of energy demand by observing the contributions of each factor aggregated over time. Given the size of our sample (433 (i, j) pairs) and our focus on sectoral dynamics, analysing individual series is impractical. We therefore examine the distribution of the results and compare differences across groups: sectors, digital intensity categories, and periods.

Our main interest lies in the differences across group-specific distributions of decomposition results. To assess whether the differences are statistically significant, we use three sets of non-parametric tests, focusing only on the digital intensity categories, as these are central to our analysis.[12] Non-parametric tests are appropriate given the presence of outliers, strong dispersion, and the absence of normality assumptions. First, we apply the Kruskal–Wallis test, a rank-based test that assesses whether multiple samples originate from the same distribution. A significant result indicates that at least one category differs from another. To further explore these differences, we conduct pairwise comparisons using two additional tests: (i) the Wilcoxon–Mann–Whitney test, which compares ranks between two independent samples, and (ii) the Dunn test, a pairwise extension of the Kruskal–Wallis test using the same rankings. Since multiple comparisons increase the risk of Type I error, we apply Bonferroni and Holm corrections to control the family-wise error rate. The Bonferroni correction is more conservative, but increases the risk of Type II error, while Holm provides a less restrictive alternative.

3.2. Data

3.2.1. Energy and economic data

Energy and exergy data at the final and useful stage are derived from the International Energy Agency IEA 2023 Extended World Energy Balances (International Energy Agency, 2023) and accessed through the country-level primary-final-useful (CL-PFU) energy and exergy database (Heun et al., 2024; Brockway et al., 2024; Marshall et al., 2024). These data are available across 158 IEA countries, between periods from 1960–2020 (OECD countries) or 1971–2020 (non-OECD), and are available for sectors based on IEA classes (see United Nations

[10] Although our adaptation omits the *Log Mean* component to which it owes its name, the simplification to mere rates of change does not compromise the effectiveness of our approach or the validity of our conclusions.

[11] The results presented in Section 4 exclude outliers where the annual rate of change exceeds a tenfold increase. This methodological choice only concerns sectors that are newly included in the database and observed for the first time in a given year. We conjecture that these extreme yearly changes are due to statistical errors in the early years of sectoral accounting. By filtering any case where $D_{V_{ij}}$ exceeds a tenfold increase, we only remove 17 observations—less than 0.01% of the total sample.

[12] We thank an anonymous referee for suggesting this improvement.

Table 2
List of sectors classified by ISIC division and level of digital intensity.

Sector	Full name	ISIC div. rev.4	DI-4
AGRI	Agriculture, forestry, fishing	01–03	L-DI
MINING	Mining, quarrying	05–09	L-DI
FOOD	Food products, beverages, tobacco	10–12	L-DI
TEXTIL	Textiles, wearing apparel, leather	13–15	ML-DI
WOOD	Wood, wood products	16	MH-DI
PAP	Paper, pulp, printing	17–18	MH-DI
CHEMPHAR	Chemicals, chemical products, pharmaceutical products	20–21	ML-DI
MINERAL	Non-metallic minerals	23	ML-DI
METAL	Metals, metal products	24	ML-DI
MACHIN*	Machinery, electrical and electronic products	25–28	MH-DI[a]
TRANSPEQ	Transport equipment	29–30	H-DI
OTIND*	Other industries	22, 31–32	MH-DI[b]
COKE	Coke & refined petroleum products	19	ML-DI
ELECGAS	Electricity, gas, steam, air conditioning	35	L-DI
CONSTR	Construction	41–43	L-DI
COMSER*	Commercial & public services	33, 36–39, 45–96	H-DI[c]

Note: L-DI is low digital intensity, ML-DI is medium-low digital intensity, MH-DI is medium-high digital intensity, H-DI is high digital intensity.
* Sectors among the 16 selected for which a perfect matching with the DI classification was not possible (see details in footnotes a, b, and c below). See Table 3.2 (p.18) in Horvát and Webb (2020) for the original classification.
[a] MACHIN: 25% ML-DI (ISIC division 25) and 75% MH-DI (ISIC divisions 26-28).
[b] OTIND: 33% ML-DI (ISIC division 22) and 66% MH-DI (ISIC divisions 31 and 32).
[c] COMSER: 19% L-DI (ISIC divisions 36–39, 49–53, 55–56, 68), 8.5% ML-DI (ISIC divisions 85-88), 25.5% MH-DI (ISIC divisions 33, 45–47, 58–60, 84, 90–93) and 46.8% H-DI (ISIC divisions 61–66, 69–82, 94–96).

Statistical Division, 2018, for information about the IEA classification of sectors). Sector-level value added data comes from the STructural ANalysis (STAN) OECD database, spanning 38 countries over the 1971–2019 period. To merge the energy and economic datasets, we must match sectors across the data sources: we aggregate IEA sectors to match ISIC (Rev.4) 2-digit divisions of sectors. After matching the data sources, we are able to build a large panel of 31 high-income countries (see Appendix B), mostly OECD or EU countries, across 16 sectors that represent the entire productive economy from 1971 to 2019 (see Appendix C for details about the data collection and aggregation mapping).

Final energy is our variable of interest and is directly available in the CL-PFU database (as well as final exergy, useful energy and useful exergy), and is measured in terajoules (TJ). The data used in the analysis accounts for gross energy, which includes energy producing sectors' own energy use (i.e., *energy industry own energy use*) but excludes non-energy uses and muscle work (see Appendix C for details). The *scale* effect is measured with *value added* data from the STAN database, concerning gross value added and expressed in millions of national currency, with chained prices (previous year base). The *conversion*, *efficiency*, and *productivity* effects are computed using final energy and value added, to which *final exergy* and *useful exergy* data from the CL-PFU database—also measured in TJ—are added. The use of different currencies for monetary and hybrid measures poses no issue for our analysis; although this prevents direct comparison of value added and energy productivity levels across countries with different currencies, decomposition analysis relies on rates of change in factors, and thus allows us to compare results across all countries regardless of their currency.[13]

3.2.2. Sectoral digitalisation

The full time series for the OECD digital-intensive sector classification (Calvino et al., 2018) is not publicly available; however, we rely on the most recent version reported in Horvát and Webb (2020). Consistent with the rest of the STAN database, this classification is based on the ISIC Rev.4 industries and thus requires to be matched with IEA sectors (United Nations, 2008). Three productive sectors selected for this work cannot be exactly matched, namely: *Other industries*; *Machinery, electrical & electronic equipment*; and *Commercial and public services*. Take *Other industries* as an example: it is composed of *Manufacture of rubber and plastic products* (ISIC division 22, medium-low digital intensity), *Manufacture of furniture* (ISIC division 31, medium-high), and *Other manufacturing* (ISIC division 32, medium-high). Since no perfect matching strategy exists to assign a single digital intensity (DI) category to such aggregated sectors, each ISIC division within our 16 industries is given equal weight. The sector is then assigned to the DI category that predominates among its constituent divisions. In the example above, two-thirds of the ISIC divisions fall into medium-high digital intensity, so *Other industries* is classified accordingly.

Table 2 lists the 16 sectors included in our analysis along with their digital intensity (DI) classifications. Our main analysis relies on four digital intensity categories (DI-4); however, for robustness, we also conduct a comparative analysis that consolidates digital intensity into just two categories: low and high (see Supplementary Material).

4. Results

This section is organised as follows. We first present general results for the entire sample and across sectors; next, we compare the results across categories of digital intensity. Table 3 provides the main set of results, with summary statistics calculated as unweighted mean and median values for each sector and digital intensity category (detailed results with summary statistics calculated for each decade are available in SM Tables S.1.1–S.1.4).[14] Figs. 1 and 2 display the cumulative results for a selection of sectors and the distribution of cumulative results across digital intensity categories, respectively. Fig. 3 summarises the relative contributions of technical and composition components across all sectors and DI-4 categories. Additional results are reported in the

[13] Note that it would be appropriate to use the expression *exergy productivity*, *useful exergy productivity*, or *useful work productivity* instead of *energy productivity*. For simplicity of writing and to refer to the common concept of *energy productivity*, we use the term energy as a generic term encompassing all stages of the energy conversion chain (ECC), and the qualitative measure of exergy. Thus in the remainder of the paper, the term *energy productivity* may be used, but will always refer to our metric of productivity based on *useful work*.

[14] The unweighted statistics should not be interpreted as aggregate effects. Instead, they represent the effects for the average country-sector pair, or the average country when results are grouped by sector, digital intensity category, or time. The production of average statistics also prevents aggregation of the values in the tables directly from disaggregated values (e.g., multiplying all effects to find the effect for energy), which is a common practice in LMDI decomposition analysis.

Table 3
Decomposition results by sector and digital intensity category, 1971–2019.

Sector	Energy		Scale		Efficiency		Productivity	
	Avg.	Med.	Avg.	Med.	Avg.	Med.	Avg.	Med.
Tot.	**3.82**	**1.07**	**30.73**	**4.24**	**0.935**	**0.880**	**0.560**	**0.280**
L–DI	**3.62**	**1.30**	**24.20**	**5.24**	**0.900**	**0.872**	**0.741**	**0.280**
AGRI	2.79	1.36	44.96	3.86	0.859	0.876	0.786	0.327
MINING	5.55	1.40	39.08	4.18	0.892	0.871	0.791	0.221
FOOD	2.83	1.04	12.98	3.56	1.01	1.02	0.437	0.251
ELECGAS	1.48	1.22	8.09	4.22	0.770	0.793	0.447	0.306
CONSTR	5.36	1.85	14.97	9.04	0.965	0.962	1.22	0.165
ML–DI	**1.27**	**0.798**	**7.61**	**2.67**	**1.02**	**0.920**	**0.418**	**0.301**
TEXTIL	1.20	0.285	5.37	1.39	0.959	0.936	0.305	0.249
CHEMPHAR	1.08	1.06	12.78	4.71	0.854	0.841	0.295	0.248
MINERAL	1.12	0.885	4.31	2.71	0.960	0.906	0.504	0.432
METAL	1.20	0.822	4.93	1.94	1.31	0.906	0.605	0.466
COKE	1.86	1.16	11.53	6.84	1.00	0.996	0.376	0.202
MH–DI	**6.62**	**1.04**	**57.06**	**3.46**	**0.888**	**0.865**	**0.626**	**0.376**
WOOD	2.02	1.70	3.61	2.34	0.874	0.888	1.05	0.541
PAP	1.20	1.02	2.91	1.61	0.831	0.825	0.829	0.842
MACHIN*	21.83	1.25	209.1	7.00	0.915	0.890	0.344	0.151
OTIND	0.844	0.513	7.11	4.42	0.939	0.865	0.253	0.156
H–DI	**4.95**	**1.40**	**51.50**	**8.23**	**0.923**	**0.881**	**0.284**	**0.180**
TRANSPEQ	6.86	1.15	51.29	7.78	0.821	0.838	0.298	0.187
COMSER	3.27	1.59	51.68	9.26	1.01	1.00	0.272	0.173

Note: Summary statistics for the full sample (Tot.) correspond to the unweighted cross-country and cross-sector mean (Avg.) and median (Med.) values of the cumulative decomposition results, where cumulative series are aggregated over the total period. Results by digital intensity category (L-, ML-, MH-, H-DI) correspond to the unweighted cross-country average and median values of the (total) cumulative decomposition results. For each DI-4 category, the summary statistics are derived for the (total) cumulative decomposition results across all the sectors composing the DI-4 category. Results by sector correspond to the unweighted cross-country average and median values of the (total) cumulative decomposition results. For cross-sector comparison, the two minimum and maximum values for each factor have been highlighted.
* The value of *MACHIN* for *energy* and *scale* is surprisingly high, driven by the substantial value added growth of this sector in South Korea, with a 5,347-fold increase between 1971 and 2018. When South Korea is removed from the sample, the mean total cumulative change in energy demand drops to 1.2, compared to 21.83. While all countries are kept in our results to avoid arbitrary outlier exclusions, it is worth noting that *MACHIN* is no longer among the sectors with the strongest growth in energy demand once South Korea is excluded.

SM Sections S.1–S.3 for readability, including those for the *Conversion* effect (SM Section S.3), which shows no significant effects worth discussing.

4.1. Aggregate and sectoral energy demand

4.1.1. Economic dynamics matter more than physical processes

Across the full sample, we observe a significant mean increase in energy demand, with a 3.82-fold rise from 1971 to 2019, while the median increase is more modest at 1.07-fold (Table 3). The strongest driver of energy demand over this period is growth in value added, reflected in the scale effect (30.73; 4.24).[15] We find evidence of relative decoupling between energy use and sectoral growth, and of absolute decoupling in a few cases: while the growth rate of value added generally exceeds that of energy demand, we also observe periods with reductions in energy demand. Nevertheless, sectoral growth mostly offsets technical gains, despite progress towards more efficient (0.935; 0.880) and more productive (0.560; 0.280) processes. The magnitude of value added growth is 16.1 (mean) or 1.04 (median) times stronger than the combined downward effects of efficiency and productivity.

The pivotal role of economic dynamics in driving energy demand remains observed across sectors and across time: differences in value added growth largely explain why some sectors experience strong increases in energy use while others show low growth or even declines (Fig. 1). Indeed, sectors with high growth in energy use are those with the strongest scale effects (e.g., *TRANSPEQ*, *MINING*, *CONSTR*, or *COMSER*). On the contrary, sectors with low or negative growth in energy demand are those with scale effects that are below the sample mean or median, or that decrease over time (e.g., *TEXTIL*, *OTIND*, *CHEMPHAR*, or *PAP*). This suggests that absolute or strong relative decoupling is facilitated when growth is low, which is consistent with other empirical evidence (Le Quéré et al., 2019). Furthermore, we find that strong productivity gains help moderate growth in energy demand (e.g., *TRANSPEQ*), while productivity declines exacerbate the impact of sectoral growth (e.g., *CONSTR*). Overall, productivity plays a stronger role than efficiency in offsetting energy demand growth associated with low economic growth. Taken together, these results confirm that economic factors (*scale* and *productivity* effects) are stronger drivers of energy demand compared to factors associated with physical processes (*conversion* and *efficiency* effects).

However, this should not be taken to mean that efficiency gains play no role in moderating energy demand. While efficiency gains display lower variation, the absence of improvements for this factors may results in strong growth in energy demand. Indeed, when scale effects are strong and efficiency gains are absent, energy demand rises sharply, even when productivity gains are significant. Without substantial improvements in efficiency, even the strongest productivity gains are insufficient to reduce energy demand (e.g., *COMSER*). In other cases, efficiency gains also compensate for weak productivity improvements, which on their own are not enough to significantly reduce the growth in energy demand, even under low value added growth (e.g., *WOOD* or *PAP*). While we have shown that economic dynamics, and particularly economic growth, may be more conductive

[15] Values in parentheses correspond to (mean; median). This notation applies throughout the remainder of this section.

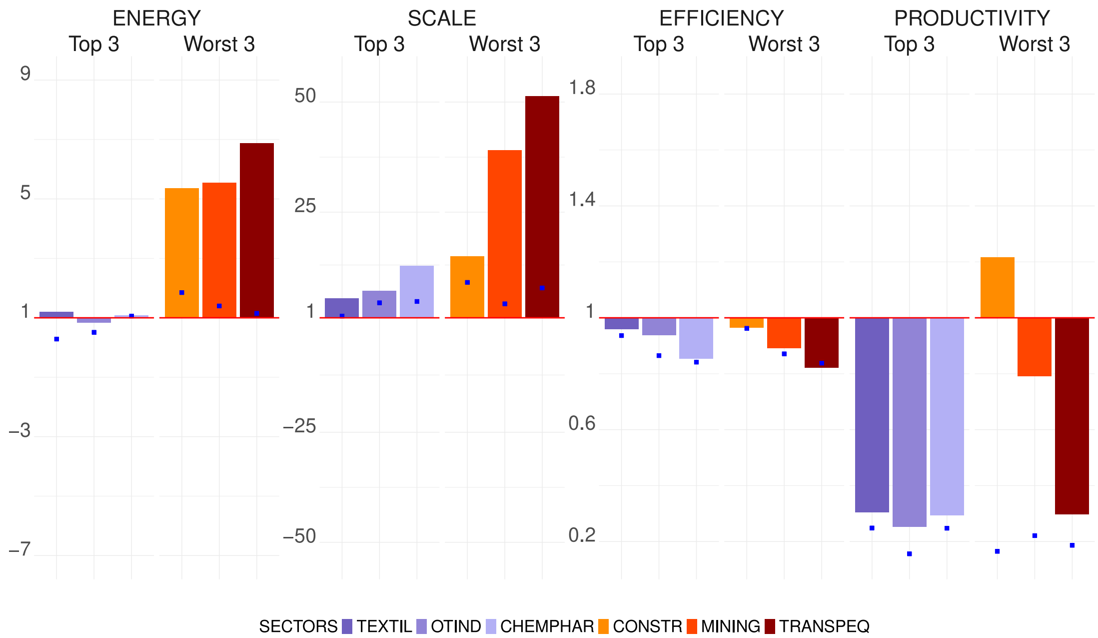

Fig. 1. Bar charts of decomposition results for selected sectors.
Note: The bar chart displays the cumulative decomposition results aggregated over the full period for the Top 3 and Worst 3 sectors. Top 3 sectors—*TEXTIL*, *OTIND*, and *CHEMPHAR*—display either reductions or low growth in energy demand, while Worst 3 sectors—*CONSTR*, *MINING*, and *TRANSPEQ*—display the strongest increases. The bars in the chart represent the mean value, while the blue square represents the median value. The horizontal red line sets the threshold between upward and downward effects. From left to right, the factors appear in the following order: Energy, Scale, Efficiency, and Productivity. The scale of the *y*-axis is the same for Efficiency and Productivity.

to energy demand, it remains that improving the efficiency of physical processes is fundamental to achieving the targeted reductions.

4.1.2. Heterogeneity across sectors is strong

The above results are confirmed in most sectors, but do however conceal some differences, confirming the importance of cross-sector heterogeneity for the dynamics of energy demand (Table 3, see also SM Figures S.1 and S.2). Only 4 sectors display either mean or median values below 1, indicating a reduction in energy demand in 2019 relative to 1971: *OTIND*, *TEXTIL*, *MINERAL*, and *METAL*. In contrast, all other 12 sectors display moderate to high increases in energy use, including a 22-fold increase in *MACHIN*, and 7 other sectors with 2-fold to 7-fold increases.[16] Median values are much lower and indicate, as might be expected, that outliers are driving the mean values upward. Despite observable improvements in efficiency and productivity across most sectors, these gains are insufficient to counter the upward pressure of value added growth, apart from the the few exceptions cited above.

Heterogeneity across sectors is stronger for economic dynamics (*scale* and *productivity* effects) than for thermodynamics-based measures of efficiency (*conversion* and *efficiency* effects). Mean scale and productivity values respectively range from 2.91 (*PAP*) to 51.68 (*COMSER*, if we disregard the extreme mean value of *MACHIN*) and from 0.253 (*OTIND*) to 1.22 (*CONSTR*). Their median values range from 1.37 (*TEXTIL*) to 9.26 (*COMSER*) and from 0.150 (*MACHIN*) to 0.842 (*PAP*). In contrast, mean efficiency effects range from 0.770 (*ELECGAS*) to 1.31 (*METAL*), and its median values from 0.793 (*ELECGAS*) to 1.02 (*FOOD*). *CONSTR*, *MACHIN*, *TRANSPEQ*, and *COMSER* are the sectors with the strongest value added growth, while *TEXTIL*, *METAL*, *WOOD*, and *PAP* have the lowest. When turning to technical components, there is no clear sector outperforming for both factors: *ELECGAS*, *PAP*, and *TRANSPEQ* have the strongest efficiency improvements; *OTIND*, *MACHIN*, and *COMSER* perform best in terms of productivity. Conversely, *FOOD*, *METAL*, *COKE*, and *COMSER* perform poorly in terms of efficiency with no improvements or deteriorations; *CONSTR* and *WOOD* underperform in productivity.

4.1.3. The magnitude of effects reduces over time

Over time, we first notice that the periods of economic expansion in the 1970s–1980s and early 2000s are characterised by the strongest increases in energy demand (SM Tables S.1.1–S.1.4). In these phases, the scale effect dominates, confirming the close connection between the size of economic activities and energy use. Even during economic slowdowns and periods of recession, this relationship holds, as energy demand tends to stagnate or fall.

Although energy demand has increased in most decades, its rate of increase has been declining over time, occasionally resulting in absolute decreases. The weakening of the scale effect is visible in recent decades for all sectors but four: *AGRI*, *METAL*, *COKE* and *CONSTR*. A similar decline is found for productivity effects, which converge steadily towards 1, with a few exceptions. In sectors where economic growth has remained strong (*AGRI*, *METAL*), productivity has also been stable or improving. The efficiency effect displays more variation across time without a clear trend.

This overall weakening of most effects over time—moving closer to 1—may explain why energy demand reductions have become more common across sectors in recent decades. It also highlights how slower economic growth can make it easier to achieve such reductions through productivity gains. Even as productivity effects converge towards 1, we still find more reductions in energy demand in the last decades of the sample. If, however, productivity deteriorates in these later periods (i.e., $D_{IP} > 1$), energy demand may rise sharply despite weaker sectoral growth (e.g., *CONSTR* or *MACHIN*). Once again, changes in economic factors—value added growth and energy productivity—are more strongly associated to variations in energy demand that those related to physical processes.

[16] *MACHIN* has a surprisingly strong mean scale effect, 209.1, which leads to the strongest growth in energy demand. This is due to the strong economic growth observed in this sector in South Korea over the entire period (5347-fold). If South Korea is excluded from the analysis, the mean growth in energy for *MACHIN* falls to 1.20, but its mean scale effect remains among the strongest (11.48).

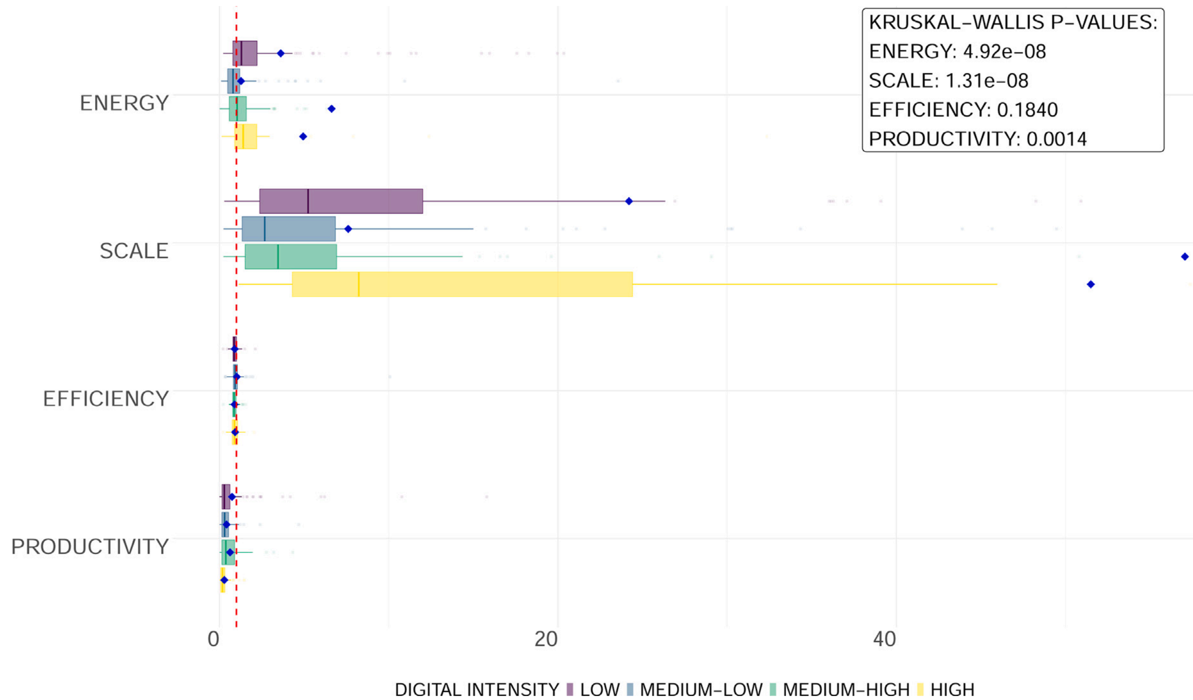

Fig. 2. Cumulative decomposition results by digital intensity category.
Note: The decomposition results in this Figure are cumulative and have been aggregated over the total period (the same box plots with cumulative results aggregated by decade are available in SM Figure S.3). The yellow, green, blue and purple correspond respectively to H-DI, MH-DI, ML-DI and L-DI sectors. Central boxplot lines corresponds to the median values, and the blue diamonds to the mean values. The vertical red dashed line sets the threshold between upward and downward effects. From top to bottom, the factors appear in the following order: Energy, Scale, Efficiency, and Productivity. The box in the upper-right corner contains p-values computed from the Kruskal–Wallis non-parametric test, described in Section 3.1. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

4.2. Energy demand by digital intensity categories

4.2.1. Structural drivers of energy demand vary with levels of digitalisation

The dynamics of energy demand differ across digital intensity categories (Fig. 2; see also Table S.2 and Figure S.3 in the Supplementary Material). Mean and median values are consistently above 1 for L-DI and H-DI, while ML-DI and MH-DI show overall lower effects. For instance, the mean increase in energy demand for ML-DI from 1971 to 2019 is only 27%, compared to increases ranging from 3.62-fold (262%) to 6.62-fold (562%) in the other categories. Over time, the growth rates of energy demand generally decline across all categories, though with distinct patterns. Energy demand in ML-DI sectors slows and begins to fall in the 1990s, whereas similar declines in the other categories appear only from the 2000s or 2010s.

Interestingly, the structure of energy demand differs across categories, particularly for the economic factors (*scale* and *productivity* effects). The distribution of value added growth across digital categories mirrors the overall patterns observed for energy demand: L-DI and, especially, H-DI record higher values than ML-DI and MH-DI. Differences in productivity effects across categories are less clear-cut, though H-DI consistently shows lower values than other groups (SM Table S.2). Finally, variation in the efficiency effect is minor, with weak cross-category differences. The Kruskal–Wallis test confirms these findings: statistically significant differences are observed across groups for energy, the scale effect, and the productivity effect, but not for the efficiency effect.

4.2.2. Digitalisation reveals polarised dynamics of energy demand

The differences across categories reveal that digitalisation creates some polarisation of energy demand dynamics, where disparities are mainly driven by value added growth rather than by efficiency or productivity gains (Fig. 2, see also SM Figure S.3). Table 4 reinforces this conclusion: sectors with low or high digital intensity (L-DI and H-DI) tend to have both high value added growth and high energy demand, while sectors with medium digital intensity (ML-DI and MH-DI) have lower growth and lower energy demand. One can also note that the sectors identified as best and worse in terms of energy demand growth rate (Fig. 1) respectively fall in ML-DI/MH-DI and L-DI/H-DI categories. Although polarisation is less pronounced for the technical components (SM Table S.2), improvements in efficiency and productivity, combined with lower scale effects, enable ML-DI and MH-DI sectors to achieve lower growth—or even reductions—in energy demand.

Further validation of polarisation comes from the Wilcoxon–Mann–Whitney and Dunn pairwise tests (for detailed results, see SM Figures S.4–S.5). Energy dynamics differ significantly across groups, displaying a clear pattern of polarisation: L-DI and H-DI do not significantly differ from each other, but both are significantly different from ML-DI and MH-DI. While ML-DI and MH-DI are also significantly different, their distributions are much closer. The differences in energy dynamics are primarily driven by variations in the scale effect: all groups display significantly different dynamics, except ML-DI and MH-DI. In this case, L-DI and H-DI also display significant differences, but effects remain stronger than for the intermediate categories. Differences in productivity also contribute, but they do so to a lesser extent, with only H-DI showing significant differences from all other categories.

In short, our results suggest that digital intensity does not affect energy demand in a simple, “linear” way. One might expect that moving from low to high digital intensity would linearly result in higher growth rates for value added and greater technical improvements (Zhang and Wei, 2022; Niebel et al., 2022).[17] Instead, our findings indicate that energy demand dynamics are polarised across levels of digital intensity, and that the primary driver is the disparity in value added growth.

[17] By linear increase we do not mean an increase from a factor α from one DI category to another, but that the direction of variation from one category to the next one remains the same such that effects for each DI-4 categories were always ordered as follows: L-DI, ML-DI, MH-DI, H-DI.

Table 4
Average rankings by digital intensity and factor.

DI-4	Energy		Scale		Efficiency		Productivity	
	Avg.	Med.	Avg.	Med.	Avg.	Med.	Avg.	Med.
L	11	11.4	10.6	9	7.8	8.6	11.6	8.6
ML	4.8	4.8	5.8	6.4	10.8	10.2	7.2	10
MH	7.5	8.25	6.25	7.25	6.5	6	9	8.5
H	13.5	11	14.5	15	8.5	9	3	4.5

Note: The table provides the average rankings of sectors according to their digital intensity (DI-4) category. The rankings were calculated using both the cross-country (unweighted) mean and median values of cumulative decomposition results, where cumulative results were aggregated over the entire period. For each factor (*Energy*, *Scale*, *Efficiency* and *Productivity*), sectors were ranked from 1 to 16, where 1 corresponds to the lowest and 16 to the highest. Once the sectors were ranked across the mean and median values for each factor, the rankings were averaged across the sectors within each DI-4 category, resulting in an overall average rank for each category. Higher averages indicate stronger effects for the underlying factors, while lower average indicate weaker effects.

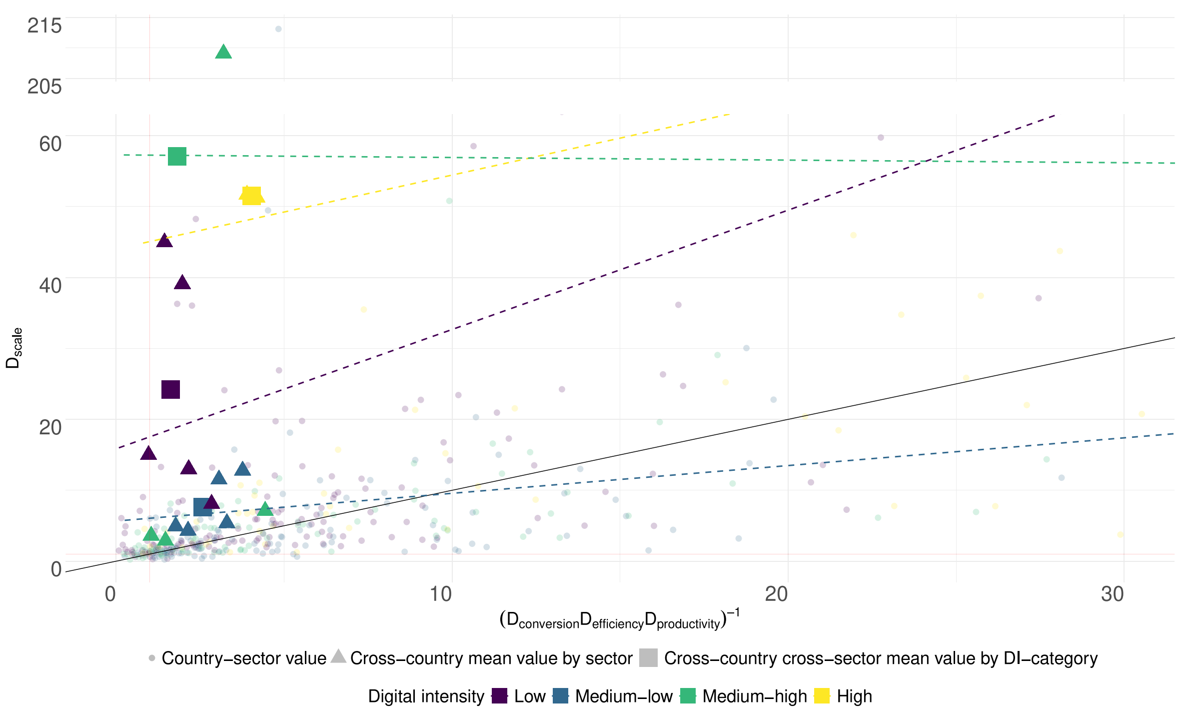

Fig. 3. Total cumulative changes in composition components vs. technical components, by sector and digital intensity category.
Note: The *y*-axis corresponds to changes in the composition component and is equivalent to the *scale* effect. The *x*-axis corresponds to (inverse) changes in the technical components and is equivalent to the (inverse) product of the *conversion*, *efficiency*, and *productivity* effects. Moving from the bottom to the top implies growth in value added cumulative over the entire period, while moving from the left to the right implies stronger combined gains in technical components. The red vertical and horizontal lines separate between upward and downward changes. Beneath the horizontal line value added has decreased, while it has increased above. On the left of the vertical line deterioration of technical components is observed, while technical gains are found on the right side of the vertical line. Dashed coloured lines correspond to the linear regression line showing the correlation between the composition component and the technical components. Observations resulting in increased energy demand over the entire period fall above the black bisection line, while observations resulting in reduced demand fall below. SM Figure S.6 displays the same plot with two outliers removed.

This means that increasing digital intensity from low to intermediate levels may reduce growth and energy demand, whereas moving from intermediate to high levels may offset technical gains and trigger a surge in growth and energy demand.

A few details on the dynamics specific to high digital intensity sectors are noteworthy. These sectors form a distinct cluster, with value added growth substantially higher than in any other sector or category, and coupled with stronger productivity improvements (Fig. 3; see SM Figure S.6 for the same figure corrected from two outliers). This finding is consistent with the pairwise statistical tests in SM Figures S.4–S.5, and highlights the specificity of high digital intensity sectors. In contrast, sectors in the other categories display stronger within-category dispersion. ML-DI and MH-DI sectors vary both across technical and composition components, and their mean values (represented by the triangles in Fig. 3) shift in parallel to the bisection line. This suggests that for the sectors within these categories, even when value added growth is stronger, technical improvements help to somewhat moderate the growth in energy demand. L-DI sectors are generally characterised by lower variation for technical improvements, but vary widely across rates of sectoral growth. This suggests that these disparities cannot be related directly to variations in technical components.

4.2.3. Value added growth intensifies energy demand in digital intensive sectors

While scale effects remain the strongest driver of energy use in both L-DI and H-DI, H-DI sectors experience substantially, and significantly, stronger sectoral growth than L-DI, along with greater productivity improvements. In fact, the H-DI category shows a stronger correlation between combined technical improvements and growth in value added, as illustrated by the dashed yellow line in SM Figure S.6.[18]

This may point to the occurrence of a digitally-induced energy rebound—a largely under-researched empirical question (Coroama and Mattern, 2019; Kunkel and Tyfield, 2021; Kunkel et al., 2023)—or alternatively, to the possibility that strong technical improvements are themselves facilitated by strong economic growth.[19] The second hypotheses is less plausible, however, since other sectors achieve strong technical improvements even without corresponding surges in sectoral growth (e.g., *PAP*). Our analysis thus confirms that high digital intensity is associated with substantially stronger value added growth, which is consistent with previous evidence (Zhang and Wei, 2022). While it is also associated with stronger productivity gains, these do not translate into reductions in energy demand. Strong scale effects systematically drive higher energy demand, whether technical improvements are strong (e.g., *TRANSPEQ*) or low (e.g., *CONSTR*). The degree to which lower scale effects translate into reductions in energy demand varies significantly, and depends on the relative magnitude of technical improvements.

Finally, it remains true that L-DI sectors—except *ELECGAS*—struggle with technical gains, particularly efficiency. In these sectors, efficiency remains a critical challenge and future gains might be fostered by digitalisation. However, strong value added growth must also be addressed to ensure technical improvements translate into actual reductions in energy demand, as occasionally observed in ML-DI and MH-DI sectors. With respect to H-DI sectors, our findings show that irrespective of productivity improvements, the overall scale of economic activity must be questioned if targeted reductions are to be achieved.

Digitalisation therefore falls short on the promises embedded in the *twin transition* or *smart green growth* narratives, instead carrying *twice the burden*: at high levels of digital intensity, it not only fails to deliver the expected efficiency gains, but also shows little potential to drive the economic transformations needed—here, the decline of energy-hungry sectors—to reduce energy demand. Strategies to manage energy use should thus be tailored to the specific context of each sector, while also addressing the risk of digitally-induced rebound, particularly in sectors already benefiting from ADTs where efficiency gains are visible. For sectors lagging in digital adoption, promoting digital technologies and practices may yield environmental benefits without neglecting economic advances—but this does not remove the need to confront the role of strong value-added growth.

Before concluding, it is important to acknowledge some limitations of our analysis as a cautionary note and to suggest directions for future research. First, our analysis is descriptive rather than causal. Methods such as regression analysis or Granger causality could help identify causal relationships, but our data and empirical setting do not support such approaches. A complete time series, rather than a fixed classification for digital-intensive industries, would be better suited for this purpose. Second, the classification of digital intensive industries has its own limitations (Calvino et al., 2018) and could be refined to better capture the dynamics of digitalisation with other emerging technologies such as AI and GenAI—see a recent attempt in Calvino et al. (2024)—as well as the cross-country differences in their adoption. Third, our focus on advanced economies omits the effects of outsourcing and globalisation, which likely explain part of the reductions in energy use that we observe (Hardt et al., 2018; Niebel et al., 2022). Fourth, the high level of aggregation in the *Commercial and public services* sector in energy accounting only allows a limited understanding of the changes in sectoral composition occurring within this broad category. Improving the disaggregation in data collection would allow to better understand which of its constituent sectors are responsible for the growth in energy demand. Finally, while large-sample studies like ours help reveal general trends, future research could benefit from focusing on specific sectors to better understand the mechanisms and impacts of ADTs on economic growth and energy demand at a finer level of detail.

5. Conclusion

Our model combines economic structure—how industries and sectors evolve, grow, or decline—with physical constraints, recognising that production ultimately depends on energy and materials and that thermodynamics sets limits to efficiency. Enriched with insights from evolutionary economics, this framework helps explain how uneven, path-dependent technological change shapes energy demand across sectors.

Empirically, our analysis shows clear cross-sector structural differences in both the dynamics of energy demand and their driving factors. We also observe structural effects of digitalisation, though these prove more complex than anticipated. Indeed, we find a polarisation between high-growth, high-energy-demand sectors and low-growth, low-energy-demand sectors, with both low and high digital intensity (L-DI and H-DI) sectors falling into the high-demand group. Statistical tests confirm two main points: (i) significant differences exist between digital intensity categories in terms of overall energy dynamics and their economic drivers (*scale* and *productivity* effects); and (ii) this polarisation between high- and low-energy-demand groups is robust. Digital intensity does not directly determine energy demand; instead, it amplifies sector-specific trajectories, mainly through its association with stronger value added growth, which drives higher energy demand.

Strong growth in value added thus remains the primary driver of final energy demand, and substantial reductions in demand occur only when efficiency and energy productivity improvements are combined with lower value added growth. Over time, the magnitude of scale and productivity effects have declined and converged to lower levels, which is consistent with the economic slowdown observed in advanced economies in recent decades. At the same time, changes in physical processes measured by the conversion and efficiency effects display less variation and distinct patterns across sectors. This confirms that economic drivers (value added and energy productivity) weigh more heavily on energy demand than physico-technical factors (exergy-to-energy conversion and thermodynamic efficiency). Thermodynamic efficiency gains alone are insufficient to trigger energy savings during periods of strong economic growth, whereas energy productivity improvements play a stronger role in mitigating scale effect in periods of modest growth. Energy demand reductions are observed primarily during economic slowdowns, confirming earlier findings (Le Quéré et al., 2019). Yet caution is needed in interpreting these reductions as absolute decoupling, as they often occur during periods of economic recessions or result from the relocation of energy-intensive sectors to countries outside our sample (Hardt et al., 2018; Bogmans et al., 2020).

The fact that energy demand reductions mainly occur during periods of low growth or recession highlights the challenge of reducing ecological impacts in a growing economy. This is particularly true in the context of the *twin transition*, where high hopes are placed on efficiency gains. Our analysis instead points to a *double burden* of intensive digitalisation: in addition to its direct energy requirements, it boosts output while failing to deliver sufficient technical improvements for energy savings. If digitalisation were kept at moderate levels, with a less pronounced stimulus to value added growth, our findings suggest it might yield the expected environmental benefits. With the pursuit of innovation and efficiency gains dominating the public discourse

[18] Fig. 3 also plots the correlation between technical improvements and changes in composition, but the result for the L-DI category is strongly influenced by an outlier: the *AGRI* sector in Iceland, which shows an exceptional 1143-fold increase in value added. This outlier is removed in SM Figure S.6.

[19] It should be noted that rigorously assessing the potential digitally-induced energy rebound would require further investigation and a formal analysis to ensure that energy efficiency precedes boosts in economic growth. This is out of the scope of our work.

and policy proposals for sustainability, technological change should be considered with respect to its broader economic, social, and ecological implications. This calls into question the relevance of sustained economic growth in relation to societal and environmental needs. Technological change is neither neutral nor purely driven by economic rationality; it is strongly connected to rent-seeking and accumulation, and thus serves as a primary engine of economic growth in the first place (Schmelzer et al., 2022).

Post-growth and degrowth may offer alternative paths for future research and policy strategies that explicitly address these risks (Creutzig et al., 2018; Hardt et al., 2021). From this angle, a mix of hard—e.g., caps on energy use or environmental conditions for public R&D funding—and soft—e.g., promotion of digital sufficiency or support for technologies that prioritise collective well-being—policy instruments could help align digital innovation with sufficiency and sustainability goals. Crucially, such measures should avoid "one-size-fits-all" approaches and instead be tailored to sectors' technological capabilities (Bianchini et al., 2023). Yet these agendas should not underestimate the transformative potential of technological change, which, as we argued earlier, is a dynamic, multidimensional, and heterogeneous process.

We therefore conclude by suggesting to exercise caution with respect to policies only targeting technical improvements through digitalisation, since the empirical evidence for this connection remains weak. Our analysis finds that digitalisation has not yet been able to produce absolute and sufficient rates of decoupling, and while this may change in the future, refusing to address the role played by economic growth seems unwise. The risk lies in promoting digital technologies without adequate consideration of their environmental implications—e.g., digitally-induced energy rebound effects—or social consequences—e.g., labour displacements or risks of monopoly—thereby locking economies into long-term technological paths with uncertain outcomes (Matthess et al., 2023).

Digitalisation itself is no longer an option. But guiding its trajectory is a matter of choice, and must rely on sound evidence. This choice is not only about public policy design but also about democratic governance, where societal involvement is essential to ensure that the direction of digitalisation reflects ecological and social priorities. Whether it will trigger sustainable structural transformations in the future—be they technical, institutional, behavioural, organisational, compositional, or related to the scale of overall economic activities—will likely remain a debated question. It is our hope that the considerations presented here will inform economic research.

CRediT authorship contribution statement

Jérôme Hambye-Verbrugghen: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Stefano Bianchini:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Investigation, Funding acquisition, Conceptualization. **Paul E. Brockway:** Writing – review & editing, Validation, Methodology, Investigation, Funding acquisition, Data curation. **Emmanuel Aramendia:** Writing – review & editing, Validation, Software, Methodology, Investigation, Funding acquisition, Data curation. **Matthew K. Heun:** Validation, Software, Investigation, Data curation. **Zeke Marshall:** Validation, Software, Investigation, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. List of abbreviations

Acronym/Term	Definition/Description
General Terms:	
ADTs	Advanced digital technologies
DI	Digital intensive/intensity L-DI = low ML-DI = medium-low MH-DI = medium-high H-DI = high
ECC	Energy/exergy conversion chain
GDP	Gross domestic product
GPTs	General purpose technologies
ICT	Information and communication technologies
MTH	Medium-temperature heat
SDGs	Sustainable development goals
Methods:	
IDA	Index decomposition analysis
LMDI	Logarithmic Mean Divisia Index
SDA	Structural decomposition analysis
Data:	
CL-PFU	Country-level primary, final, useful (*database*)
IEA	International Energy Agency
ISIC	International standard industrial classification
STAN	STructural ANalysis (*database*)
TJ	Terajoules
Equations:	
I	Energy intensity
E	Energy
E^f	Final energy
Q	Production in physical quantities
VA	Value added
X^f	Final exergy
X^u	Useful exergy
Y	Production in monetary quantities
Driving factors:	
D_V	The rate of change of V with V = {final energy, S, IC, IE, IP} S = Scale IC = Inverse conversion IE = Inverse efficiency IP = Inverse productivity

Appendix B. List of countries and time span with available data

See Table B.1.

Table B.1
List of countries and time span with available data.

Country	Time span	Country	Time span
AUS — Australia	1990–2018	ITA — Italy	1971–2019
AUT — Austria	1977–2018	JPN — Japan	1971–2019
BEL — Belgium	1971–2019	KOR — South Korea	1971–2018
CHE — Switzerland	1991–2018	LTU — Lithuania	1996–2018
CZE — Czech Republic	1971–2019	LUX — Luxembourg	1986–2018
DEU — Germany	1992–2019	LVA — Latvia	1996–2018
DNK — Denmark	1971–2018	NLD — Netherlands	1971–2018
ESP — Spain	1981–2018	NOR — Norway	1971–2018
EST — Estonia	1996–2018	NZL — New Zealand	1978–2018
FIN — Finland	1971–2018	POL — Poland	1996–2018
FRA — France	1971–2019	PRT — Portugal	1978–2018
GBR — Great Britain	1971–2019	SVK — Slovakia	1994–2019
GRC — Greece	1971–2019	SVN — Slovenia	1996–2018
HUN — Hungary	1992–2018	SWE — Sweden	1981–2019
IRL — Ireland	1996–2018	TUR — Turkey	1999–2019
ISL — Iceland	1974–2019		

Note: The time span accounts for the first year for which some industry data is available, but these time spans do not account for perfectly balanced data. This means for the early periods, only some sectors may appear while data for other sectors only start in the 1990s or early 2000s. Additional countries were available in both the CL-PFU and the STAN databases but were excluded due to substantial missing values.

Appendix C. Description of data collection and selection from the CL-PFU and STAN OECD databases

More information on the CL-PFU database and access to the data can be found on the following GitHub repository and link:

https://github.com/EnergyEconomyDecoupling/CLPFUDatabase
https://doi.org/10.5518/1199.

More information about the STAN OECD database can be found in Horvát and Webb (2020) or on the following link:

https://www.oecd.org/en/data/datasets/structural-analysis-database.html

The exact version of the CL-PFU database used in this paper is not publicly available. It was accessed last on May 2nd, 2024, through Dropbox. This unique data version was updated on January 30, 2024, and has for unique identifier `pin_hash: da7862fab18aa2c7`. The STAN database was accessed directly through its official website on May 2, 2024.

C.1. Merging IEA products with ISIC rev.4 2-digits divisions of sectors

The CL-PFU database includes data across 7 aggregate sectors, 46 detailed sub-sectors, and 68 final energy products. It also accounts for non-energy uses of energy across 16 sub-sectors, which track energy resources used for purposes other than generating heat, electricity, or power, such as chemical or plastic production. The CL-PFU aggregation mapping is available in the *Data Availability Statement* in Brockway et al. (2024). This paper uses the sectoral level data from the CL-PFU database, covering 34 IEA products. The data include *energy industry own use* (EIOU), which is of interest for capturing potential structural transformations within energy industries. There is no double accounting: energy industries are treated as final energy consumers, similar to other sectors. Non-energy uses of energy are not included. This approach helps explore the effects of digitalisation on the use of energy resources, focusing only on energy purposes. Our analysis excludes muscle work (including feedstock inputs and human or animal labour) as it focuses on the structural impact of technological change on resource use, not on human or animal labour.

The 34 IEA products correspond to sectors, sub-sectors, or final energy products and are mapped to their respective ISIC Rev.4 classes or divisions, based on Table 5.1 (p. 59) and Table 5.3 (p. 66) from United Nations Statistical Division (2018). This mapping links the 34 IEA products in the CL-PFU database to 18 ISIC Rev.4 2-digit divisions (or groups of divisions, *e.g.*, the *Commercial and public services* sector is composed of multiple ISIC divisions). The 16 productive sectors used in this paper's decomposition model are listed in Table 2, along with 2 non-productive sectors: *Residential* and *Transport*. The final mapping file and R code are available upon request.

C.1.1. The nuclear industry

The CL-PFU database relies on the *International Energy Agency* (IEA) Extended World Energy Balances (EWEB) data, which presents aggregation challenges in some cases, notably the nuclear industry. It is the only IEA *energy industry* that cannot be perfectly mapped with specific ISIC divisions. The IEA nuclear energy industry covers both the *extraction* and *processing* of nuclear fuels in combination, making it impossible to separate between these processes. Extraction corresponds to ISIC class 0721 (*Mining of uranium and thorium ores*), while processing aligns with ISIC class 2011 (*Manufacture of basic chemicals*), placing the nuclear industry between ISIC divisions 05–09 (*Mining & quarrying*) and 20–21 (*Manufacture of chemicals and chemical products*). To the best of our knowledge, there is no empirical basis for preferring one ISIC division over the other for aggregating the nuclear industry's own use of energy. In this analysis, we arbitrarily include its energy use in the *Mining & quarrying* sector. Upon review, we find this choice has a negligible effect on the aggregate results. However, in specific countries where the nuclear industry is important, such as France, Slovakia, or Belgium, decomposition results may vary considerably between the two sectors involved in nuclear energy production.

C.2. Exclusion of non-productive sectors

The two non-productive sectors from the CL-PFU data, *Residential* and *Transport*, account for a large share of total energy use (Brockway et al., 2024, Figure 6, p.13). While decomposition analyses have been adapted to account for non-productive sectors (see Ecclesia and Domingos, 2024), conducting such analyses on a large panel is challenging for two main reasons. First, alternative measures of energy intensity or productivity are required due to the absence of monetary metrics (value added, gross output) for these sectors. One option is to approximate energy intensity by the ratio of energy use to total value added or gross output. Another approach is to use physical measures, such as energy intensity per floor area or per kilometers travelled, which requires additional data.

The second issue concerns how the IEA accounts for transport energy use. The *Transport* sector can be divided into six sub-categories (road, rail, domestic aviation, domestic navigation, pipeline transport, and not elsewhere specified), but commercial and private transport data are combined and cannot be differentiated. As a result, it is impossible to separate productive (commercial) from non-productive (private) uses of energy for transport. The method in Ecclesia and Domingos (2024) to split productive and non-productive transport energy use is not applicable to the large sample in our analysis. Therefore, both non-productive sectors are excluded.

Appendix D. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ecolecon.2025.108747.

Data availability

The IEA EWEB data are not publicly available; the user needs to access IEA data through a valid license.

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