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Post-Growth Economics Network

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Abstract

In this paper, we evaluate the potential of digitalisation to drive structural transformations toward 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 from 1971 to 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 first apply the model at the sector level across 16 productive industries to explore cross-sector heterogeneity in the structure of energy demand. Industries are then classified by digital intensity categories, allowing us to compare results across different levels of digitalisation. 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 associated with substantial value added growth in high digital intensity sectors and amplifies the use of energy. This suggests that digitalisation, if unchecked, may in fact exacerbate economic-ecological tensions rather than alleviate them. We discuss the implications of these findings in the context of recent policy actions aimed at accelerating the green and digital— "twin"—transition.

Keywords: Structural Change, Energy, Energy Efficiency, Digitalisation, Technological Change
JEL: Q43, Q55, L16, O44, O13

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Highlights:

- Economic factors drive energy demand changes more than technical factors.
- Cross-sector heterogeneity shapes trends in energy demand.
- High digital intensity substantially amplifies sectoral growth and energy demand.
- Future efficiency gains must target energy demand reductions, addressing rebound.
- Greener technological trajectories require addressing economic-ecological tensions.

1 Introduction

Climate change is one of the greatest challenges humanity has ever faced, with 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 taken in the coming years will be decisive in determining whether we can achieve a future aligned with the 1.5° target set by the Paris Agreement and meet 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 light of increasing environmental degradation and resource depletion. The 'Georgescu-Roegen/Daly vs. Solow/Stiglitz' controversy highlights contrasting views on resource limits (Georgescu-Roegen 1975, Daly 1997, Solow 1997, Stiglitz 1997). Solow and Stiglitz implicitly assume unbounded resource productivity through technology and substitution, downplaying resource constraints, while Georgescu-Roegen and Daly argue that thermodynamic limits fundamentally restrict growth. Despite potential common ground, this debate has persisted, evolving into a lasting academic divide (see, e.g., Germain 2019, Couix 2019, Polewsky et al. 2024). 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 been placed at the cornerstone of the dominant climate change mitigation strategy in high-income countries, reflecting an enduring belief in the role of technological change in decoupling economic growth from environmental impacts.[1] As a matter of fact, while green growth requires absolute decoupling, there is an emerging consensus that the growing observations of such decoupling remain insufficient to achieve mitigation targets (Savona & Ciarli 2019, Le Quéré et al. 2019, Haberl et al. 2020, Hubacek et al. 2021, Lamb et al. 2022, Vogel & Hickel 2023). Regardless, the focus on innovation and efficiency has also been rooted in the current discourse on the *twin transition* in Europe, which emphasises the integration of advanced digital technologies (ADTs) into environmental strategies (Perez 2019, Lesher et al. 2019, Bianchini et al. 2023, 2024).

The assumption that digital and green transitions can progress in tandem has attracted growing criticism. While empirical evidence remains limited, there are in fact indications that digitalisation may not automatically align with sustainability goals (Fouquet & 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

[1] Decoupling refers to the "uncoupling" of resource use or environmental impacts from economic growth (Browne et al. 2011, Regueiro-Ferreira & 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).

range of possibilities (Bresnahan & Trajtenberg 1995, Brynjolfsson & Yang 1996, David & Wright 1999, Lee & Lee 2021), including the development of new products, production processes and services that offer environmental benefits (Montresor & Vezzani 2023, Verendel 2023, Damioli et al. 2024). 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 for examples), all of which are expected to keep growing in the future. Besides, there are potential indirect, or structural, effects which are complex and difficult to quantify (Schulte et al. 2016, Yang & Shi 2018, Zhang & Wei 2022, Niebel et al. 2022, Ahmadova et al. 2022, Barteková & Börkey 2022, Kunkel et al. 2023).

In a seminal article, Lange et al. (2020) propose an analytical framework to capture interactions between digitalisation and energy consumption. They identify four channels through which digitalisation may affect the environment: (1) direct effects related to the production, use and disposal of ADTs; (2) digitally-induced gains in energy efficiency; (3) economic growth following 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 sectors with lower energy requirements. This framework informs our empirical analysis, which uses 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 complementing concepts from ecological and exergy economics with a flavour of 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 the results between digital-intensive sectors—as defined by the OECD (Calvino et al. 2018)—to understand 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 strongest driver of energy use. The observed efficiency gains following the adoption of ADTs are much lower than expected and, despite improvements in energy productivity, do not lead to a reduction in energy demand. Our work highlights the existing economic-ecological tensions that must be addressed for greener technological trajectories.

Our work 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 (Higón et al. 2017, Haseeb et al. 2019, Chimbo 2020, Oteng-Abayie et al. 2023), ICT capital (Bernstein & 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 when multiple dimensions are considered (e.g., robots, skills, and digital capital), they are often examined 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, often focusing on country-level digitalisation (Ahmadova et al. 2022, Zhang & Wei 2022, Benedetti et al. 2023) or highly aggregated sectors (Oteng-Abayie et al. 2023). In contrast, 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 study, 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 Section 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 & Ciarli 2019, Ciarli & Savona 2019). Economic composition is but one part of structural change, alongside growth dynamics, technical improvements, the evolution of institutions or changes in the international division of labour. Our analytical framework and empirical model draw on recent advances in ecological and exergy economics—which emphasize the role of physical processes in economic production—as well as on some concepts inspired from evolutionary economics—which highlight the multidimensional, heterogeneous, and dynamic nature of technological change. In the following section, we first elaborate on these theoretical foundations (Section 2.1 and 2.2), then introduce the structural drivers of energy demand considered in our analysis (Section 2.3.1), and finally 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, surprisingly, 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).[2] Exergy eco-

[2]As a reminder: *energy* represents the total (heat) quantity of energy in a system, which is conserved (first law of thermodynamics); while *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

nomics brings thermodynamic principles into economic analysis, considering energy across the three stages of the *energy conversion chain* (ECC): primary, final, and useful—along which energy/exergy quantities can be measured (see Aramendia et al. 2021, Fig. 1 and Section 1.2 for details). The *primary* stage represents raw energy resources extracted from nature; the *final* stage captures the energy/exergy purchased by end-users; and the *useful* stage measures energy/exergy 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).[3] 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 the progress in exergy economics, however, many studies frequently conflate energy intensity with thermodynamics-based (second-law) efficiency, neglecting the work potential, or exergy, of energy flows (Guevara 2014, Proskuryakova & 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 & Kovalev 2015, Saunders et al. 2021). Moreover, as shown in Equation (1), energy intensity depends on economic metrics that are frequently reported with insufficient detail or lack precise definitions, all of which affect its accuracy (Semieniuk 2024).

Here, we explicitly accounts 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) is fundamental in explaining total factor productivity and, hence, economic growth (Santos et al. 2018, Sakai et al. 2018, Santos et al. 2021). Second, these efficiency improvements appear much less substantial when the quality of energy flows is factored in (Aramendia et al. 2021, Brockway et al. 2024).

With this in mind, our empirical analysis relies on *Index Decomposition Analysis* (IDA), a method particularly suited for investigating the evolution of energy use (or emissions).[4] 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

of the system.

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

[4] 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 & Yang 2023).

factors driving its variation. Few studies only have recently also integrated useful energy or work potential within 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 & Domingos 2024).

Different IDA models vary in their methodological basis, but the core idea is to decompose an aggregate indicator into three factors: *production* (or *scale*), *structure* (economic composition), and *technology* (Hoekstra & 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 activities using energy; 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.[5] Due to its simplicity, 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. And to this end, we believe it is useful to consider (at least) three main caveats inspired from evolutionary economics.

First, most studies on the environmental impact of digitalisation focus on a single dimension: the number of machines or internet usage (Higón et al. 2017, Haseeb et al. 2019, Chimbo 2020, Oteng-Abayie et al. 2023), ICT capital (Bernstein & Madlener 2010, Khayyat et al. 2016, Schulte et al. 2016, Niebel et al. 2022), specific ICT sectors (Zhou et al. 2018, 2019, Wang et al. 2022), or ICT patents (Yan et al. 2018). We believe that digitalisation should instead be understood and measured as a multidimensional transformation, encompassing ICT alongside other key ADTs.[6] At a minimum, these should 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 teaches us that heterogeneity matters (see, e.g., Dosi 2023, Ch.3 and 9). In a recent review, Zhang & Wei (2022) confirms that sector-level studies that address both the economic and environmental impacts of ICT remain scarce. Moreover, a substantial body of literature shows that production technologies vary

[5]The structure effect in decomposition methods is estimated considering only economic composition as part of structure, and thus leads to a narrow definition of structural change in interpreting this effect.

[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 & Lee 2021).

significantly by sector, with distinct patterns of diffusion and use across industries (Fierro et al. 2022, McElheran et al. 2024); and recent research aiming 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 do not capture the path-dependent, long-term patterns of adoption and use of (advanced) digital technologies, nor do they 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 been suggested as a reason why the productivity effects of information technology were initially difficult to observe; timing, therefore, matters too (David & Wright 1999, Brynjolfsson & Hitt 2000). Cumulative effects over time are particularly important; for instance, it has been shown that "computer-enabled" organizational changes show much larger impacts over longer periods (Brynjolfsson & Hitt 2000, p. 33). Thus, as further discussed in Section 3.2.1, we apply decomposition analysis on a long time series spanning almost 50 years (1971–2019) to capture the cumulative effects of technological and structural changes.

2.3 The analytical framework

We combine the elements discussed above into a single analytical framework. Conceptually, we first consider that digitalisation affects various energy-related structural components across different sectors; and second, these components shape and define the dynamics of energy demand. Our empirical approach is reversely structured: we begin with a decomposition model (briefly introduced in Section 2.1) that disaggregates energy demand into structural drivers—technical details in Section 3.1. Second, we examine the heterogeneous effects of digitalisation across sectors based on the methodology from the OECD (Calvino et al. 2018) (outlined in Section 1), 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 & 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 & Brockway 2019). Many studies, however, focus only on relative changes in sectoral composition—a narrow view of structural change (see Henriques & Kander 2010, Mulder & De Groot 2012 for example). 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 using the *scale* effect. Second, the *technical components* are split between physical measures regarding the exergy-to-energy conversion ratio (*conversion* effect) and the second-law efficiency (*efficiency* effect), and a hybrid physical-monetary measure for energy productivity (*productivity* effect).[8] Table 1 lists the driving factors used to understand structural changes in energy demand and their formula.

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.

Some concrete examples of causes for 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) that have 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 for converting final to 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 result 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 products.

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 that

[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 & De Groot (2012) also consider cross-sector heterogeneity and confirm diverging trends across sectors, particularly between manufacturing and services.

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

value added growth will be a strong driver of energy demand, as observed at the economy-wide level, with digitalisation potentially amplifying this effect (Hajko 2012, Zhang & Wei 2022). Second, we expect digitally intensive sectors to display stronger technical improvements, particularly in terms of efficiency, as implied by the *smart green growth* narrative (Perez 2019, Lesher et al. 2019). The previous expectation is the necessary condition for digitalisation to contribute to decoupling, where technical gains should be stronger than value added growth to reflect absolute decoupling. 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 & De Groot 2012). Historically, 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). The framework identifies three components that affect the degree of digitalisation of a sector: a *technological* component, a *human capital* component, and a *market* component.[9]

The *technological component* consists of five sub-indicators: intensity of investment in ICT tangibles (1) and intangibles (2), intensity of intermediate expenditure in ICT goods (3) and services (4), and robots density (5). 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. The seven sub-components are eventually aggregated to build an indicator for digital intensive sectors. For each sub-component, all sectors are ranked based on their quartile position across four categories: low, medium-low, medium-high, and high digital intensity. The global indicator is an average of the sector's posi-

[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 limit to a broad overview of the indicators.

tion across the different 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 instance, low digital intensive sector *Food products, beverages, and tobacco* (ISIC divisions 10-12) is poorly ranked for ICT investments, expenditures, and specialists, despite important 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 sector *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 Equation (2). E^f is final energy, VA is value added, X^f is final exergy, and X^u is useful exergy; S is the *scale* effect, IC is the *conversion* effect, IE is the *efficiency* effect and IP is the *productivity* effect. Subscripts i and j account for the i-th country and j-th sector.

$$E_{ij}^f = VA_{ij} \times \frac{E_{ij}^f}{X_{ij}^f} \times \frac{X_{ij}^f}{X_{ij}^u} \times \frac{X_{ij}^u}{VA_{ij}} = S_{ij} \times IC_{ij} \times IE_{ij} \times IP_{ij} \tag{2}$$

The choice between multiplicative and additive models does not affect decomposition results, and results can be converted straightforwardly from one form to another (Ang 2015, Section 3.2, p.236-237). We choose the multiplicative version as the 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 & Domingos (2024), inverse values of the formulas presented in Table 1 are taken for the *conversion*, *efficiency*, and *productivity* effects to fit the accounting equality of Equation (2). Inverse values for the three technical components reflect that improvements in these metrics will translate into decreasing factors, thus contributing to *reduce* 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 Equation (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 Equation (4). $L(x, y) = (x - y)/log(x/y)$ is the logarithmic mean function, T refers to the subsequent period, and 0 to the previous period. At the country-level, the results are first weighted by ω_{ij}, the ratio of the logarithmic mean function applied to the j-th sector and to the entire country, then summed across all j sectors in country i.

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

In our situation, the decomposition model is estimated for each country-sector (i, j) pair separately, and there is no need for aggregation across sectors. Equation (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 Equation (5). The weight parameter ω_{ij} cancels out from Equation (4) to Equation (5) due to our focus on country-sector pairs, but our model remains structured to reflect the influence of the usual LMDI procedure.[10]

$$D_{V_{ij}} = \exp\left(\frac{L(E_{ij}^T, E_{ij}^0)}{L(E_{ij}^T, E_{ij}^0)} \cdot \ln\frac{V_{ij}^T}{V_{ij}^0}\right) = \exp\left(1 \cdot \ln\frac{V_{ij}^T}{V_{ij}^0}\right) = \frac{V_{ij}^T}{V_{ij}^0} \tag{5}$$

We obtain chained times series of $D_{V_{ij}}$ for each (i, j) pair from estimating Equation (5).[11] Decomposition results in their multiplicative version are strictly positive: results in the interval $[0; 1]$ imply *downward* effects for $D_{V_{ij}}$, while results 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 & Brockway 2019, Fig. 7, p.9 for a graphical visualisation of index decomposition results). Chained series refer to series computed dynamically, where each year t is compared directly to its preceding year $t - 1$, instead of a base year. Cumulative results are 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 allows us to account for the long-term dynamics of energy demand, by observing the contributions of each factor aggregated over time. The size of the sample under consideration (433 (i, j) pairs in total) and the focus on sectoral dynamics make the analysis of individual series tedious. For this reason, we analyse the distribution of the results and compare the differences across groups: sectors, digital intensity categories, and periods.

Our main interest lies in the differences across the group-specific distribution 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 they are central to our analysis.[12] Non-parametric tests are appropriate given the presence of outliers, strong dispersion,

[10] Although our adaptation of the model 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 are observed for the first time in a given year. Based on these observations, we make the conjecture that these substantial yearly changes are due to statistical errors in early years of accounting for new sectors. By filtering any instance where $D_{V_{ij}}$ exceeds a tenfold increase, we only remove 17 observations, which constitutes less than 0.01% of our total sample.

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

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. Bonferroni 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. 2018, Marshall et al. 2024). These are available across 158 IEA countries, between periods from 1960-2020 (OECD countries) or 1971-2000 (non-OECD), and available for sectors based on IEA classes (see United Nations 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 join the energy and economic data, 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 exists as such in the CL-PFU database (as do 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. Having multiple currencies for the monetary and physical-monetary measures used here does not pose a problem 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

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(1)
TRANSPEQ	Transport equipment	29-30	H-DI
OTIND*	Other industries	22, 31-32	MH-DI(2)
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(3)

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 Table 3.2 (p.18) in Horvát & Webb (2020) for the original classification.
(1) MACHIN: 25% ML-DI (ISIC division 25) and 75% MH-DI (ISIC divisions 26-28).
(2) OTIND: 33% ML-DI (ISIC division 22) and 66% MH-DI (ISIC divisions 31 and 32).
(3) 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).

The full time series for the digital-intensive sector classification developed by Calvino et al. (2018) is not publicly available; however, we have obtained the most recent classification from Horvát & Webb (2020). Consistent with the rest of the STAN database, the classification of sectors is based on the ISIC Rev.4 industry classification and thus requires to be matched with IEA sector (United Nations 2008). Three of the productive sectors selected for this work cannot be exactly matched, namely: *Other industries*; *Machinery, electrical & electronic equipment*; and *Commercial and public services*. Taking *Other industries* as an example, it is composed of *Manufacture of rubber and plastic products* (ISIC division 22), *Manufacture of furniture* (ISIC division 31), and *Other manufacturing* (ISIC division 32); respectively classified as medium-low digital intensity,

[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*.

medium-high digital intensity and medium-high digital intensity. In this situation there is no perfect matching strategy that could allow to assign one single digital intensity (DI) category to *Other industries*. Hence, each ISIC division within our selection of 16 industries is given an equal weight in determining the DI classification. Consequently, the assignment of a sector to a specific DI category is guided by the predominant classification among its constituent ISIC divisions. In the example above, *Other industries* has 66% of its composing ISIC divisions classified as medium-high digital intensity; therefore, we assign this category to the sector.

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

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 provide the main set of results, with summary statistics calculated as unweighted mean and median values for each sector and digital intensity categories (detailed results with summary statistics calculated for each decade are available in SI Tables S.1.1–S.1.4).[14] Figures 1 and 2 display the cumulative results for a selection of sectors and the distribution of cumulative results across digital intensity categories, respectively. Figure 3 summarises the relative contributions of technical and composition components across all sectors and DI-4 categories. Additional results have been moved to the Supplementary Information Sections S.1–S.3 for readability, including those for the *Conversion* effect (SI Section S.3), who show no significant effect to discuss.

4.1 Aggregate and sectoral energy demand

4.1.1 Economic dynamics matter more than physical processes

Across the entire 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 moderate 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, as well as absolute decoupling on a few occasions: while the growth rate of value added

[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.

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

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

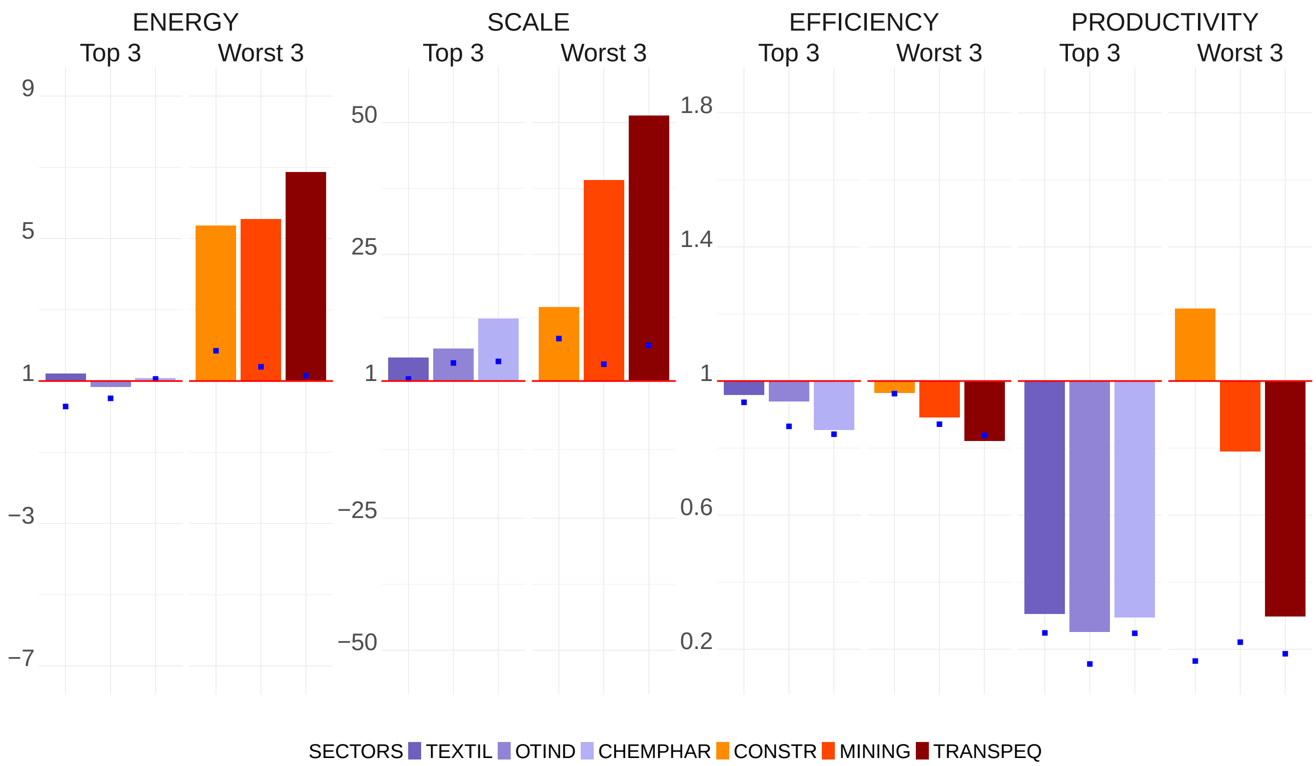
Note: Summary statistics for the full sample (Tot.) correspond to the unweighted cross-country and cross-sector mean (Avg.) and median (Med.) values of the cumulative decomposition results, where cumulative series are aggregated over the total period. Results by digital intensity category (L-, ML-, MH-, 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.

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

Figure 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.

and across time: the growth rate in value added is the most striking difference between sectors with strong growth in energy demand and those with low growth or reductions in energy demand (Figure 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 growth or reductions in energy demand are those with scale effects that are below the full 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 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 amplify the impact of sectoral growth on energy use (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 understood 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, we find that strong scale effects with no gains in efficiency result in strong growth in energy demand, even when the productivity effect is strong. Without significant efficiency improvements, even the strongest improvements in productivity are not enough to effectively achieve reductions in energy demand (e.g., *COMSER*). In some 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 with low value added growth (e.g., *WOOD* or *PAP*). While we mentioned above that economic dynamics, and more particularly economic growth, may be more conductive 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 notable differences, confirming the importance of cross-sector heterogeneity for the dynamics of energy demand (Table 3, see also SI Figures S.1 and S.2). Only 4 sectors display either mean or median values below 1, indicating an average or median 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, with up to a 22-fold increase for *MACHIN*, and 7 other sectors with 2-fold to 7-fold increases.[16] The median values for increases in energy demand 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 effects of value added, with the few exceptions cited above.

Heterogeneity across sectors is stronger for economic dynamics (*scale* and *productivity* effects) than it is 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, the 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 considering 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. In contrast, *FOOD*,

[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 (5,347-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).

METAL, *COKE*, and *COMSER* perform poorly in terms of efficiency with no improvements or deteriorations; *CONSTR* and *WOOD* perform poorly for 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 (SI Tables S.1.1–S.1.4). The scale effect was strongest in these periods, which confirms the strong connection between the size of economic activities and energy use.

Even during economic slowdowns and periods of recession, this connection is confirmed by the associated slowdowns or reductions in energy demand. Although energy demand has increased in most decades, its rate of increase has been declining over time, occasionally resulting in absolute decreases. The reduced magnitude of the scale effect is observed in recent decades for all sectors but four: *AGRI*, *METAL*, *COKE* and *CONSTR*. We find the same reduction in magnitude for the productivity effects, with a stable convergence towards of effects 1, with some exceptions again. For the few sectors for which economic growth has not slowed down over the decades, it may be the reason for which productivity has remained stable or kept improving (e.g., *AGRI*, *METAL*). The efficiency effect displays more variation across time and no clear trend.

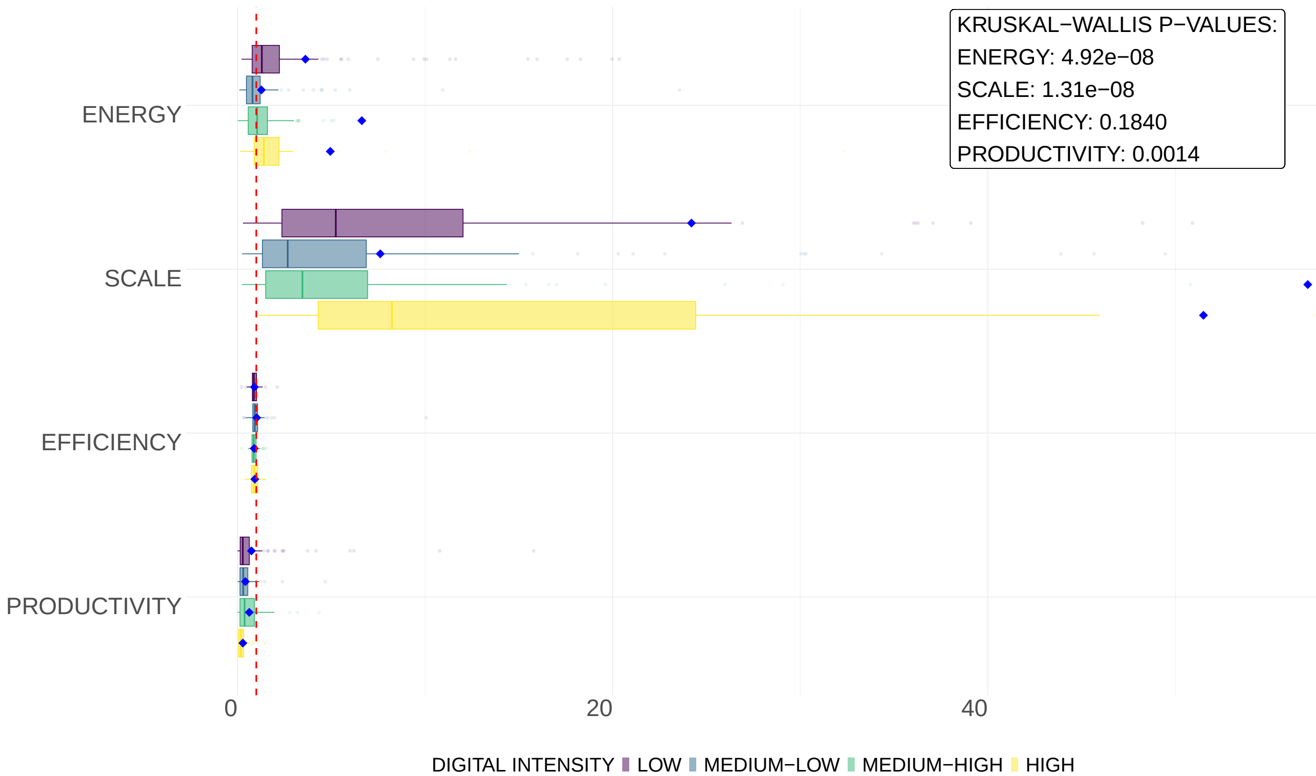
Overall, this generalised reduction in the magnitude of most effects (both upward and downward) over the decades, as seen with a convergence towards 1, may explain why reductions in energy demand in the latest decades have seemed to spread to more sectors. This again underlines the facilitating role of lower economic growth to achieve energy demand reductions through productivity gains. Even with productivity gains converging towards 1, we still find more reductions in energy demand in the final decades of the sample. If, however, productivity deteriorates in the final periods (i.e., $D_{\mathrm{IP}} > 1$), energy demand may strongly increase, even with lower sectoral growth (e.g., *CONSTR* or *MACHIN*). Once again, variations in economic factors—value added growth and energy productivity—are more strongly associated to variations in energy demand that those related to physical processes.

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 (Figure 2; see also Table S.2 and Figure S.3 in the Supplementary Information). 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%, whereas for the other categories, increases range from 3.62-fold (262%) to 6.62-fold (562%). Over time, the growth rates of energy demand generally decline across all categories, though with distinct patterns. Energy

Figure 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 SI 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.

demand slows and begins declining in the ML-DI category starting in the 1990s, while similar declines appear in the other categories 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 patterns observed for energy demand: L-DI and, especially, H-DI show 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 (SI 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 (Figure 2, see also SI Figure S.3). Table 4 reinforces this conclusion: sectors with high or low 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 (Figure 1) respectively fall in ML-DI/MH-DI and L-DI/H-DI categories. Although polarisation is less clear for the technical components (SI Table S.2), improved efficiency and productivity, combined with lower scale effects, result in ML-DI and MH-DI sectors experiencing lower growth—or even reductions—in energy demand.

Further validation of polarisation if found through Wilcoxon-Mann-Whitney and Dunn pairwise tests (for detailed results, see SI Figures S.4–S.5). Energy dynamics significantly differ across groups, displaying a 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 & MH-DI are also significantly different, their distributions remain closer to each other. This holds across all tests, except for the Wilcoxon-Mann-Whitney test with Bonferroni correction (SI Figure S.4), where MH-DI and H-DI are not found to be significantly different. The differences in energy dynamics are primarily driven by variations in the scale effect: all groups display significantly different dynamics, except between ML- & MH-DI. In this case, L-DI & H-DI also display significant differences, but 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.

Overall, our results suggest that digital intensity does not impact energy demand in a straightforward, "linear" way. One might expect that moving from low to high digital intensity would linearly result in both higher growth rates for value added and greater technical improvements (Niebel et al. 2022, Zhang & Wei 2022).[17] In contrast, our results indicate that energy demand dynamics are polarised across levels of digital intensity, and that the primary driver is the disparity in value added growth. 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 (Figure 3; see SI Figure S.6 for the same figure corrected from two outliers). This finding is consistent with the pairwise statistical tests in SI 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 Figure 3) shift in parallel to the bisection line. This suggests

[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.

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

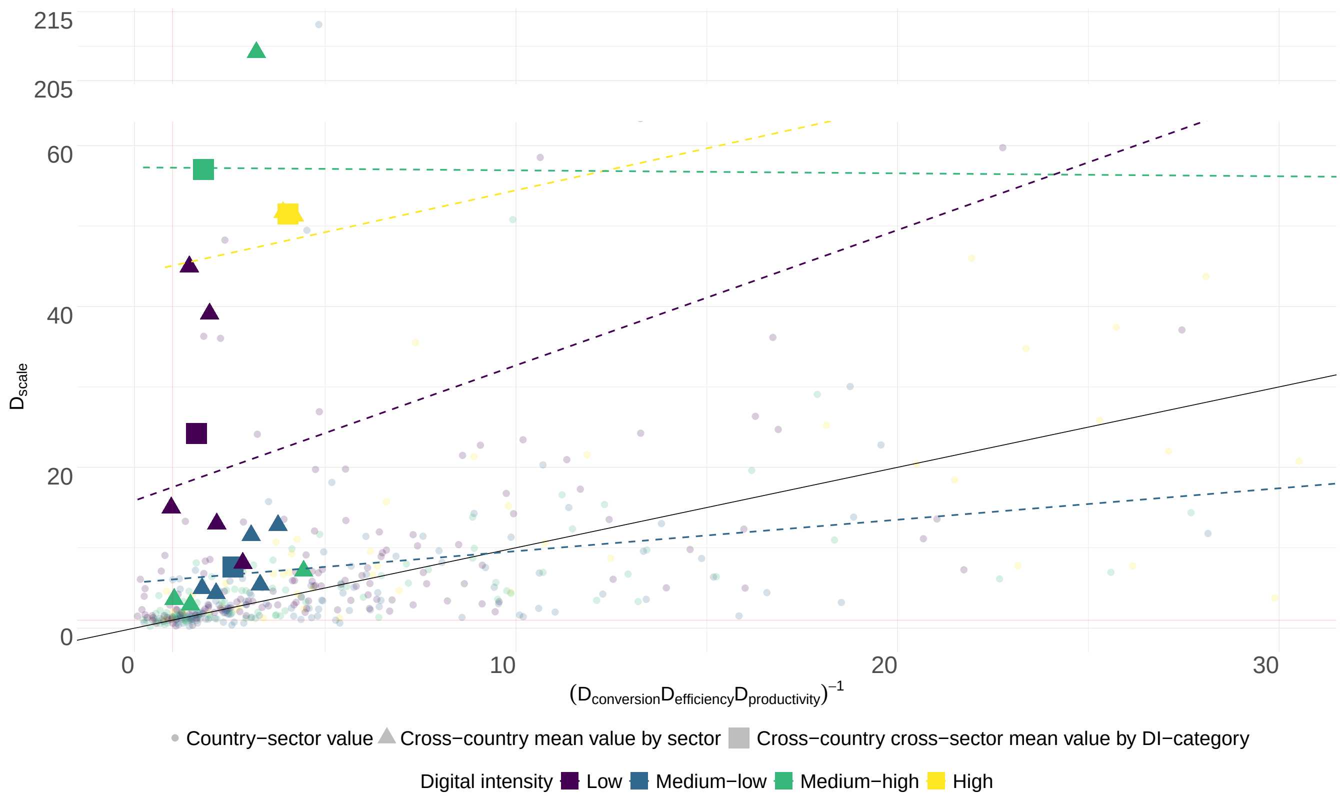
While scale effects remain the strongest driver of energy use for both L-DI and H-DI, H-DI sectors experience substantially and significantly stronger sectoral growth than L-DI, along with greater productivity improvements. In fact, the H-DI category shows a stronger correlation between combined technical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

This may indicate the occurrence of a digitally-induced energy rebound—a largely under-researched empirical question (Coroamă & Mattern 2019, Kunkel & Tyfield 2021, Kunkel et al. 2023)—or alternatively, that strong technical improvements are facilitated by strong economic growth.[19] The second hypotheses is less plausible, however, as other sectors achieve strong technical improvements even without a boost 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 & Wei 2022). While it is also associated with stronger productivity gains, these do not translate into reductions in energy demand. Strong scale effects systematically translate into higher energy demand, whether technical improvements are strong (e.g., *TRANSPEQ*) or

[18] Figure 3 also displays the correlation between technical improvements and changes in composition, but the correlation for the L-DI category is strongly influenced by an outlier: the *AGRI* sector in Iceland displays a substantial (1,143-fold) value added growth rate, and we remove this outlier in SI 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.

Figure 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. SI Figure S.6 displays the same plot with two outliers removed.

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, with the exception of *ELECGAS*, struggle with technical gains, mostly efficiency. In these sectors, efficiency remains a critical challenge and future gains might be fostered by digitalisation. However, strong value added growth should also be addressed to ensure technical improvements translate to reductions in energy demand, as they do in some occasion in ML-DI and MH-DI sectors. With respect to H-DI sectors, our work finds that irrespective of their productivity improvements, the overall scale of economic activity must be questioned in order to achieve targeted reductions. Digitalisation still falls short on the promises made 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 strong efficiency gains, but also shows little potential to drive the economic transformations needed—here, the decline of energy-hungry sectors—to achieve energy demand reductions. While strategies to manage energy use should be tailored to the specific context of each sector, it is fundamental that the risk of digitally-induced rebound in the future is addressed, particularly for sectors already strongly benefiting from ADTs in which efficiency gains are already visible. For sectors lagging in digital adoption, promoting digital technologies and practices in the future may yield environmental benefits without neglecting economic advances. As mentioned above, however, this would still not prevent from the need to address 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. While methods like regression analysis or Granger causality could help identify causal relationships, 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. Second, the classification of digital intensive industries suffers its own limitations (Calvino et al. 2018), and may benefit from improvements to capture the dynamics of digitalisation with other emerging technologies such as AI (or generative AI, *GenAI*), or the cross-country differences in such developments. Third, our focus on advanced economies omits the effects of outsourcing and globalisation, which likely explain some of the reductions in energy use that we observe (Hardt et al. 2018, Niebel et al. 2022). Fourth, the high aggregation of the *Commercial and public services* sector in energy accounting only allows a limited understanding of the changes in sectoral composition occurring in this aggregate sector. 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 allow to observe general trends in the data, further 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 more detailed level.

5 Conclusion

Our model inspired by ecological and exergy economics, to which we added a flavour of evolutionary economics, provides a fruitful theoretical background for our empirical analysis, aimed at reconciling a broader definition of structural change with the physical groundings of production processes. Our analysis highlights clear cross-sector structural differences in both the dynamics of energy demand and its driving factors. We also observe structural effects from digitalisation, though these effects are more complex than anticipated. Indeed, we find that the dynamics of energy demand are polarised across 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 displaying high-growth and high-energy-demand. Statistical tests confirm these two key findings: (i) significant differences exist between digital intensity categories, in terms of overall energy dynamics and its economic drivers (*scale* and *productivity* effects), and (ii) the polarisation that emerges between high-growth, high-energy-demand groups and low-growth, low-energy-demand groups, is robust. Rather than driving energy demand itself, digital intensity appears more as a booster to sector-specific dynamics of energy demand, as it is associated with much higher value added growth.

Strong growth in value added thus remains the primary driver of final energy demand, and significant reductions in demand are only achieved when both efficiency and energy productivity improvements are combined to lower growth. Over time, the magnitude of scale and productivity effects reduces and converge 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 changes in economic factors (value added and energy productivity) are more conductive to energy demand than changes in 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. In contrast, energy productivity improvements play a stronger role in mitigating scale effect in periods of modest value-added growth. Notably, energy demand reductions are observed primarily during economic slowdowns, confirming earlier findings (Le Quéré et al. 2019). However, caution is needed in interpreting these reductions as absolute decoupling, as they often occur during periods of economic decline, reflecting recessions rather than true decoupling. These may also result from the relocation of specific sectors to other countries outside of 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 hopes are high about potential efficiency gains. Instead, our analysis seems to point to the *double burden* related to an intensive digitalisation: in addition to its direct energy requirements, it is associated to an increase in output, but contrary to expectations does not lead to sufficient technical improvements. If digitalisation were kept at moderate levels, with a less pronounced boost to value added growth, our findings suggest it could yield the expected environmental benefits. With the pursuit of innovation and efficiency gains dominating the public discourse and policy proposals for sustainability, technological change should be considered with respect to its broader economic, social, and ecological implications. This emphasises the need to critically 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 perspective, 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 be tailored to sectors' technological capabilities (Bianchini et al. 2023). Yet these agendas should not underestimate the transformational 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 public policies only targeting technical improvements through digitalisation, as 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 anticipating the development of digital technologies regardless of available knowledge on their environmental—e.g., digitally-induced energy rebound effects—or social implications—e.g., labour displacements or risks of monopoly—and to face the long-term consequences of technological lock-in (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, with broader societal involvement being essential to ensure that the direction of digitalisation aligns with ecological and social priorities. Whether it may 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.

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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.

CRediT authorship contribution statement

Author contributions for this paper are shown in Table 5.

Table 5: Author contributions following CRediT (contributor roles taxonomy) (NISO 2023)

CRediT Role	JHV	SB	PEB	EA	MKH	ZM
Conceptualisation	•	•				
Data curation	•		•	•	•	•
Formal analysis	•					
Funding acquisition	•	•	•			
Investigation	•	•	•	•	•	•
Methodology	•		•	•		
Project administration	•	•				
Software	•			•	•	•
Supervision	•	•				
Validation	•	•	•	•	•	•
Visualisation	•					
Writing – original draft	•	•				
Writing – review & editing	•	•	•	•		

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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

Acronym/Term	Definition/Description
Y	Production in monetary quantities
Φ	Exergy-to-energy coefficient
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

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 & 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 2$^{\text{nd}}$, 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 & 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 & 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.

Supplementary Information for:

From Twin Transition to Twice the Burden? Digitalisation, Energy Demand, and Economic Growth

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Introduction

This document provides supplementary information and results to support the findings reported in the main article titled "From Twin Transition to Twice the Burden? Digitalisation, Energy Demand, and Economic Growth."

Contents

S.1 Complementary Tables and Figure for main decomposition results

This Appendix section presents the following additional results. Appendix Tables S.1.1–S.1.4 display the complementary results to Table 3 by providing the summary statistics by sector and time period, for each digital intensity category. Figures S.1 and S.2 present the distributions of results by sector for the total cumulative and decadal results. Table S.2 and Figure S.3 display the results by digital intensity category, with results cumulatively aggregated for each decade. Figures S.4 and S.5 contain the results from the pairwise tests for statistical significance outlined in Section 3.1.

Table S.1.1: Decomposition results by sector and decade for H-DI sectors, 1971-2019

Sector	Period	Energy		Scale		Efficiency		Productivity	
		Avg.	Med.	Avg.	Med.	Avg.	Med.	Avg.	Med.
Tot.	**Tot.**	**3.82**	**1.07**	**30.73**	**4.24**	**0.935**	**0.880**	**0.560**	**0.280**
H-DI	**Tot.**	**4.95**	**1.40**	**51.50**	**8.23**	**0.923**	**0.881**	**0.284**	**0.180**
TRANSPEQ	**Tot.**	**6.86**	**1.15**	**51.29**	**7.78**	**0.821**	**0.838**	**0.298**	**0.187**
TRANSPEQ	1971-80	1.47	1.38	3.14	2.60	0.973	0.976	0.712	0.484
TRANSPEQ	1980-90	0.953	0.985	4.52	3.06	1.06	1.02	0.342	0.297
TRANSPEQ	1990-00	4.53	1.12	2.99	1.85	0.971	0.929	1.54	0.619
TRANSPEQ	2000-10	1.08	0.993	1.73	1.19	0.942	0.968	0.733	0.711
TRANSPEQ	2010-19	0.987	0.970	1.37	1.40	0.900	0.876	0.868	0.823
COMSER	**Tot.**	**3.27**	**1.59**	**51.68**	**9.26**	**1.01**	**1.00**	**0.272**	**0.173**
COMSER	1971-80	1.69	1.27	3.35	3.09	0.894	0.920	0.914	0.591
COMSER	1980-90	1.34	1.13	3.22	2.86	1.06	1.12	0.415	0.381
COMSER	1990-00	1.31	1.21	2.54	1.77	0.994	0.999	0.709	0.625
COMSER	2000-10	1.32	1.25	2.15	1.88	1.06	1.07	0.639	0.609
COMSER	2010-19	1.00	0.954	1.37	1.31	0.961	0.932	0.814	0.804

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. Results by sector and period correspond to the unweighted cross-country average and median values across sectors for each decade, where cumulative results by decade are obtained by multiplying the results for all periods in the same decade. For cross-sector comparison, the two minimum and maximum values for each factor (across all Tables S.1.1–S.1.4) have been highlighted.

Table S.1.2: Decomposition results by sector and decade for MH-DI sectors, 1971-2019

Sector	Period	Energy		Scale		Efficiency		Productivity	
		Avg.	Med.	Avg.	Med.	Avg.	Med.	Avg.	Med.
Tot.	**Tot.**	**3.82**	**1.07**	**30.73**	**4.24**	**0.935**	**0.880**	**0.560**	**0.280**
MH-DI	**Tot.**	**6.62**	**1.04**	**57.06**	**3.46**	**0.888**	**0.865**	**0.626**	**0.376**
WOOD	**Tot.**	**2.02**	**1.70**	**3.61**	**2.34**	**0.874**	**0.888**	**1.05**	**0.541**
WOOD	1971-80	3.04	1.41	2.40	2.46	1.14	1.14	1.10	0.492
WOOD	1980-90	1.20	0.886	1.66	1.61	1.08	1.04	0.685	0.604
WOOD	1990-00	1.31	1.20	1.67	1.40	0.897	0.907	0.987	0.884
WOOD	2000-10	1.30	1.06	1.31	1.20	1.01	1.01	1.07	0.854
WOOD	2010-19	1.09	1.01	1.26	1.27	0.931	0.963	1.07	0.881
PAP	**Tot.**	**1.20**	**1.02**	**2.91**	**1.61**	**0.831**	**0.825**	**0.829**	**0.842**
PAP	1971-80	1.50	1.28	1.96	2.05	1.05	1.02	0.799	0.874
PAP	1980-90	1.29	1.19	2.49	2.40	1.03	1.03	0.516	0.518
PAP	1990-00	1.22	1.17	1.55	1.37	0.938	0.924	0.924	0.944
PAP	2000-10	1.02	0.924	1.22	1.01	0.916	0.939	1.04	0.884
PAP	2010-19	0.913	0.896	1.04	0.995	0.961	0.947	0.942	0.940
MACHIN*	**Tot.**	**21.83**	**1.25**	**209.1**	**7.00**	**0.915**	**0.890**	**0.344**	**0.151**
MACHIN	1971-80	2.61	1.17	5.02	2.54	1.08	1.06	0.568	0.513
MACHIN	1980-90	1.84	0.962	3.19	2.69	0.958	0.985	0.546	0.421
MACHIN	1990-00	0.976	0.890	2.29	1.70	0.996	0.998	0.571	0.541
MACHIN	2000-10	1.15	1.06	1.61	1.36	0.983	0.962	0.874	0.910
MACHIN	2010-19	1.17	0.946	1.30	1.25	0.931	0.929	1.10	0.881
OTIND	**Tot.**	**0.844**	**0.513**	**7.11**	**4.42**	**0.939**	**0.865**	**0.253**	**0.156**
OTIND	1971-80	0.122	0.060	2.10	1.94	1.00	0.991	0.112	0.019
OTIND	1980-90	2.18	2.30	2.36	2.47	1.26	1.33	0.992	0.824
OTIND	1990-00	1.12	0.860	2.33	1.71	1.09	0.968	0.612	0.451
OTIND	2000-10	0.984	0.887	1.56	1.19	0.983	0.938	0.805	0.602
OTIND	2010-19	0.924	0.797	1.31	1.24	0.973	0.944	0.741	0.646

* 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.

Note: See bottom of Table S.1.1 above.

Table S.1.3: Decomposition results by sector and decade for ML-DI sectors, 1971-2019

Sector	**Period**	**Energy**		**Scale**		**Efficiency**		**Productivity**	
		Avg.	**Med.**	**Avg.**	**Med.**	**Avg.**	**Med.**	**Avg.**	**Med.**
Tot.	**Tot.**	**3.82**	**1.07**	**30.73**	**4.24**	**0.935**	**0.880**	**0.560**	**0.280**
ML-DI	**Tot.**	**1.27**	**0.798**	**7.61**	**2.67**	**1.02**	**0.920**	**0.418**	**0.301**
TEXTIL	**Tot.**	**1.20**	**0.285**	**5.37**	**1.39**	**0.959**	**0.936**	**0.305**	**0.249**
TEXTIL	1971-80	1.58	1.11	2.70	1.62	0.991	0.993	0.873	0.794
TEXTIL	1980-90	1.36	0.852	1.78	1.53	1.11	1.06	0.618	0.502
TEXTIL	1990-00	0.965	0.931	1.27	1.10	0.964	0.953	0.884	0.897
TEXTIL	2000-10	0.486	0.494	0.853	0.801	1.01	0.960	0.637	0.599
TEXTIL	2010-19	0.804	0.782	1.10	1.12	0.962	0.934	0.779	0.769
CHEMPHAR	**Tot.**	**1.08**	**1.06**	**12.78**	**4.71**	**0.854**	**0.841**	**0.295**	**0.248**
CHEMPHAR	1971-80	0.971	0.991	2.65	2.55	0.918	0.922	0.493	0.429
CHEMPHAR	1980-90	1.09	1.03	2.37	2.42	0.956	0.907	0.524	0.493
CHEMPHAR	1990-00	1.10	1.00	1.85	1.41	0.991	0.939	0.748	0.673
CHEMPHAR	2000-10	1.00	0.923	1.75	1.48	0.941	0.948	0.697	0.636
CHEMPHAR	2010-19	1.05	0.961	1.34	1.29	1.00	0.986	0.856	0.760
MINERAL	**Tot.**	**1.12**	**0.885**	**4.31**	**2.71**	**0.960**	**0.906**	**0.504**	**0.432**
MINERAL	1971-80	2.26	1.54	1.79	1.74	1.03	1.03	1.20	0.867
MINERAL	1980-90	0.755	0.624	2.07	1.95	1.01	1.01	0.349	0.335
MINERAL	1990-00	1.03	0.996	1.64	1.42	0.969	0.974	0.733	0.786
MINERAL	2000-10	0.957	0.877	1.41	1.07	1.02	1.02	0.798	0.789
MINERAL	2010-19	1.08	0.991	1.28	1.20	0.960	0.955	0.901	0.908
METAL	**Tot.**	**1.20**	**0.822**	**4.93**	**1.94**	**1.31**	**0.906**	**0.605**	**0.466**
METAL	1971-80	1.40	1.38	2.43	2.49	0.940	0.920	0.643	0.625
METAL	1980-90	0.890	1.01	2.46	2.50	0.963	0.940	0.370	0.419
METAL	1990-00	1.18	1.06	1.48	1.26	0.945	0.940	0.983	0.974
METAL	2000-10	1.09	0.848	1.59	1.18	1.07	0.967	0.728	0.774
METAL	2010-19	0.951	0.935	1.29	1.17	1.20	0.993	0.774	0.811
COKE	**Tot.**	**1.86**	**1.16**	**11.53**	**6.84**	**1.00**	**0.996**	**0.376**	**0.202**
COKE	1971-80	1.62	1.13	5.18	4.39	0.816	0.876	0.624	0.557
COKE	1980-90	1.18	1.06	1.28	1.08	1.18	1.06	0.842	0.791
COKE	1990-00	1.02	0.973	1.96	1.38	0.948	0.958	0.929	0.805
COKE	2000-10	1.28	1.08	3.04	1.58	1.01	0.966	0.805	0.848
COKE	2010-19	0.955	0.953	1.59	1.37	1.05	1.03	0.809	0.736

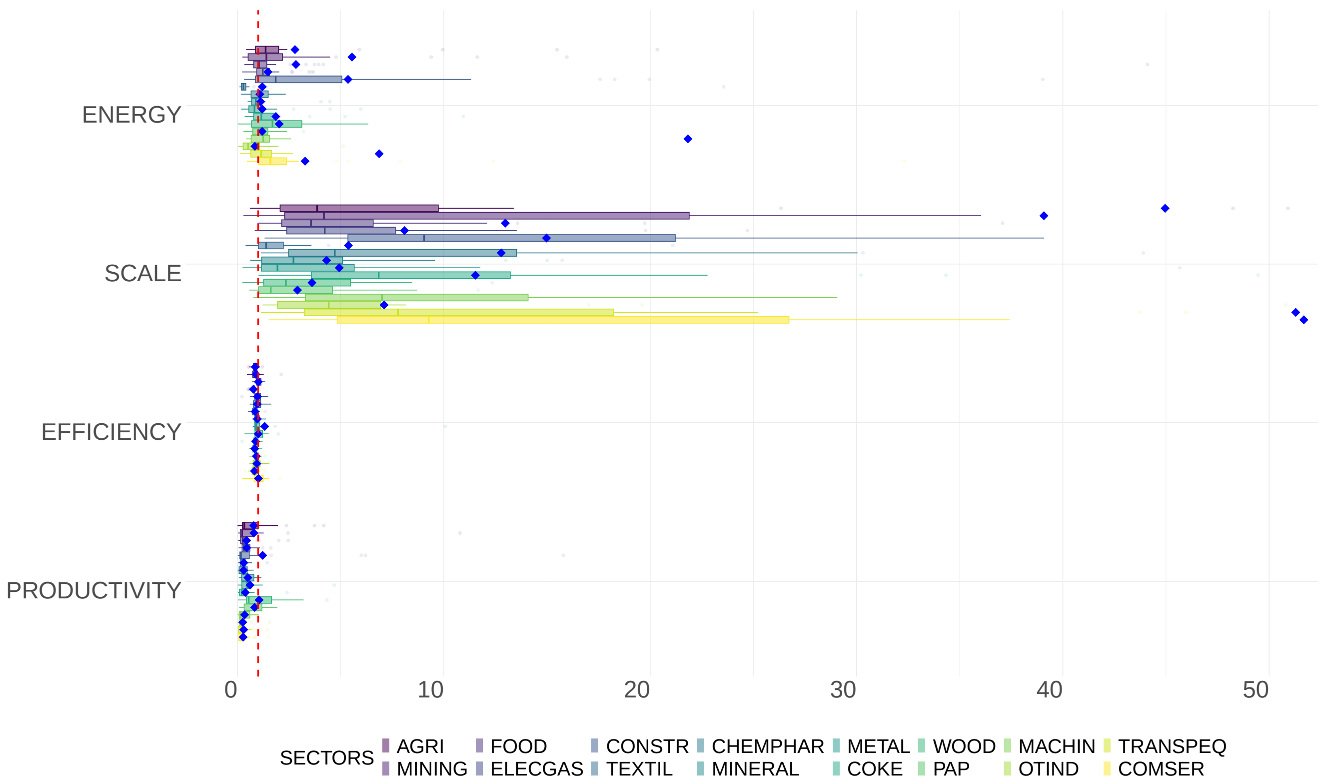
Note: See bottom of Table S.1.1 above.

Table S.1.4: Decomposition results by sector and decade for L-DI sectors, 1971-2019

Sector	Period	Energy		Scale		Efficiency		Productivity	
		Avg.	Med.	Avg.	Med.	Avg.	Med.	Avg.	Med.
Tot.	**Tot.**	**3.82**	**1.07**	**30.73**	**4.24**	**0.935**	**0.880**	**0.560**	**0.280**
L-DI	**Tot.**	**3.62**	**1.30**	**24.20**	**5.24**	**0.900**	**0.872**	**0.741**	**0.280**
AGRI	**Tot.**	**2.79**	**1.36**	**44.96**	**3.86**	**0.859**	**0.876**	**0.786**	**0.327**
AGRI	1971-80	2.17	1.38	3.12	2.14	0.929	0.941	1.31	0.692
AGRI	1980-90	1.72	1.38	3.50	2.06	1.13	0.988	0.707	0.575
AGRI	1990-00	1.05	1.02	1.22	1.11	0.982	0.926	1.02	1.07
AGRI	2000-10	1.10	0.906	1.28	0.962	0.936	0.968	1.50	0.977
AGRI	2010-19	1.07	0.997	1.59	1.46	0.946	0.947	0.749	0.748
MINING	**Tot.**	**5.55**	**1.40**	**39.08**	**4.18**	**0.892**	**0.871**	**0.791**	**0.221**
MINING	1971-80	2.29	1.10	6.89	2.94	0.978	0.971	0.469	0.408
MINING	1980-90	2.14	1.16	2.83	2.19	0.958	0.955	1.95	0.814
MINING	1990-00	1.20	1.07	1.31	1.19	0.956	0.926	1.07	1.05
MINING	2000-10	1.12	1.05	2.46	1.58	1.05	0.977	0.765	0.468
MINING	2010-19	1.23	0.955	1.25	1.10	0.957	0.943	1.17	1.07
FOOD	**Tot.**	**2.83**	**1.04**	**12.98**	**3.56**	**1.01**	**1.02**	**0.437**	**0.251**
FOOD	1971-80	1.61	1.24	2.83	2.26	1.01	0.997	0.720	0.579
FOOD	1980-90	1.78	0.950	2.41	2.29	1.01	1.04	0.719	0.428
FOOD	1990-00	1.24	1.05	1.49	1.34	0.972	0.964	0.941	0.760
FOOD	2000-10	0.985	0.893	1.45	1.33	1.04	1.03	0.690	0.665
FOOD	2010-19	1.05	1.02	1.20	1.16	0.989	0.986	0.894	0.876
ELECGAS	**Tot.**	**1.48**	**1.22**	**8.09**	**4.22**	**0.770**	**0.793**	**0.447**	**0.306**
ELECGAS	1971-80	1.39	1.41	2.48	2.50	0.919	0.911	0.691	0.649
ELECGAS	1980-90	1.40	1.35	2.18	2.07	0.890	0.933	0.794	0.729
ELECGAS	1990-00	1.07	1.07	1.55	1.30	0.976	0.968	0.829	0.834
ELECGAS	2000-10	1.14	1.07	2.23	1.83	0.977	0.975	0.692	0.599
ELECGAS	2010-19	0.947	0.897	1.20	1.08	0.858	0.857	0.966	0.967
CONSTR	**Tot.**	**5.36**	**1.85**	**14.97**	**9.04**	**0.965**	**0.962**	**1.22**	**0.165**
CONSTR	1971-80	3.26	1.19	2.31	2.37	1.02	0.983	1.72	0.589
CONSTR	1980-90	1.68	0.956	2.93	2.31	0.948	0.960	0.935	0.350
CONSTR	1990-00	1.74	1.17	1.81	1.69	0.945	0.915	1.20	0.827
CONSTR	2000-10	1.27	1.05	1.98	1.68	1.04	1.02	0.740	0.631
CONSTR	2010-19	1.36	1.06	1.53	1.36	1.01	0.990	1.10	0.749

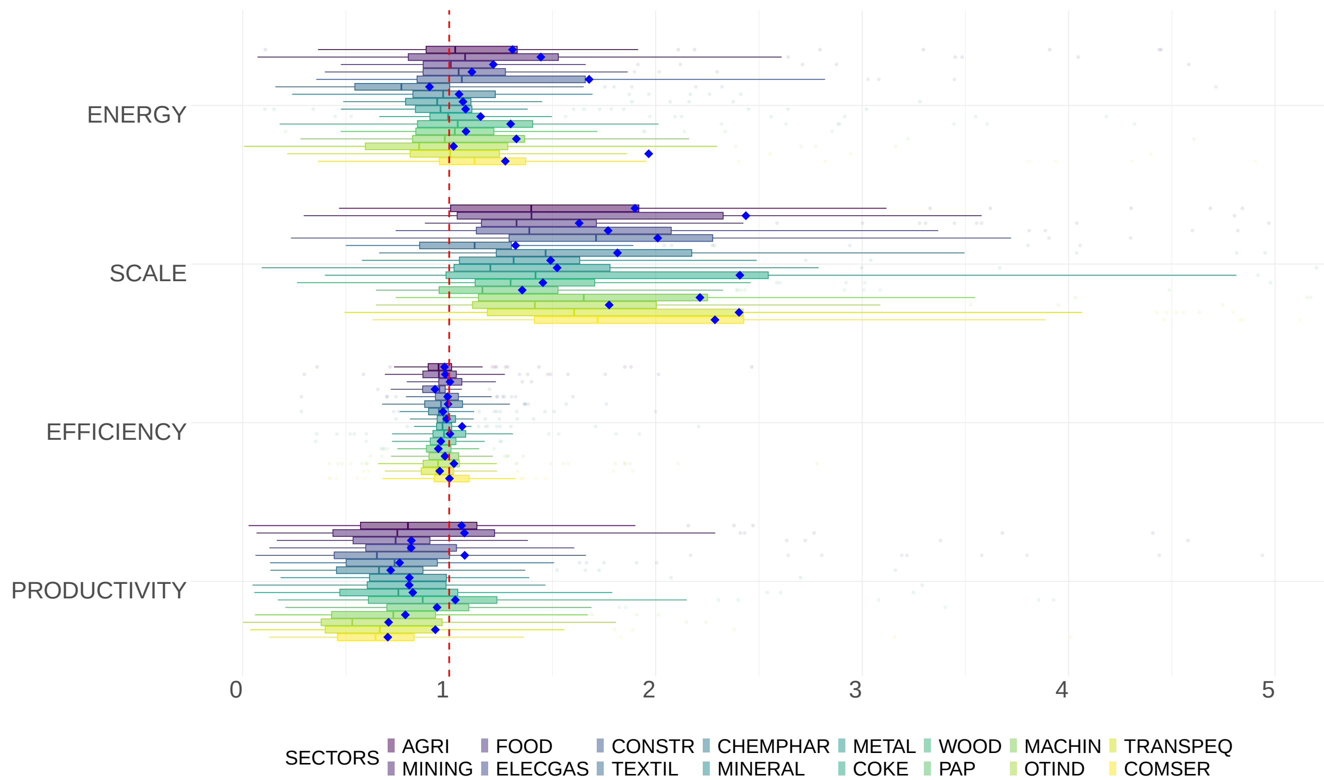
Note: See bottom of Table S.1.1 above.

Figure S.1: Boxplots of cumulative (total) decomposition results by sector



Note: The decomposition results in this Figure are cumulative and have been aggregated over the entire period. All sectors are distincted by their colour and are ordered by digital intensity (DI-4) groups, going from L-DI (purple) to H-DI (yellow). 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, Conversion, Efficiency, and Productivity.

Figure S.2: Boxplots of cumulative (decadal) decomposition results by sector



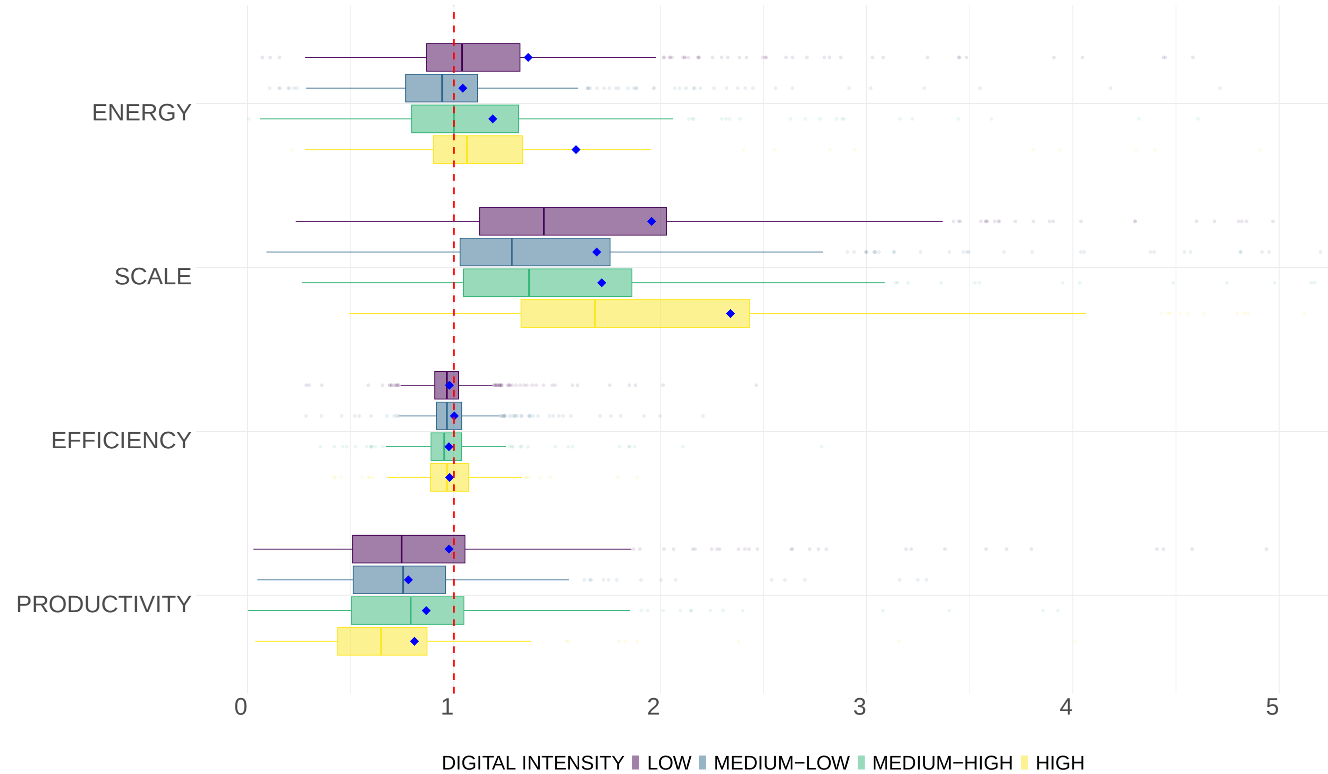
Note: The decomposition results in this Figure are cumulative and have been aggregated by decade. All sectors are distincted by their colour and are ordered by digital intensity (DI-4) groups, going from L-DI (purple) to H-DI (yellow). Central boxplot lines corresponds to the median values, and the blue 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, Conversion, Efficiency, and Productivity.

Table S.2: Decomposition results by DI-4 category and decade, 1971-2019

Sector	Period	Energy		Scale		Efficiency		Productivity	
		Avg.	Med.	Avg.	Med.	Avg.	Med.	Avg.	Med.
Tot.	**Tot.**	**3.82**	**1.07**	**30.73**	**4.24**	**0.935**	**0.880**	**0.560**	**0.280**
L	**Tot.**	**3.62**	**1.30**	**24.20**	**5.24**	**0.900**	**0.872**	**0.741**	**0.280**
L	1971-80	2.23	1.26	3.66	2.34	0.973	0.957	1.02	0.582
L	1980-90	1.77	1.09	2.88	2.17	0.999	0.960	1.05	0.534
L	1990-00	1.26	1.07	1.48	1.31	0.966	0.955	1.01	0.891
L	2000-10	1.12	0.993	1.88	1.48	1.01	0.992	0.881	0.662
L	2010-19	1.13	1.00	1.36	1.23	0.953	0.955	0.976	0.854
ML	**Tot.**	**1.27**	**0.798**	**7.61**	**2.67**	**1.02**	**0.920**	**0.418**	**0.301**
ML	1971-80	1.50	1.10	3.18	2.28	0.930	0.950	0.733	0.587
ML	1980-90	1.15	0.967	1.88	1.74	1.07	0.977	0.605	0.535
ML	1990-00	1.06	0.999	1.63	1.31	0.964	0.954	0.854	0.817
ML	2000-10	0.943	0.846	1.66	1.15	1.01	0.966	0.729	0.715
ML	2010-19	0.965	0.935	1.31	1.18	1.03	0.973	0.823	0.795
MH	**Tot.**	**6.62**	**1.04**	**57.06**	**3.46**	**0.888**	**0.865**	**0.626**	**0.376**
MH	1971-80	2.08	1.12	3.58	2.33	1.07	1.06	0.626	0.490
MH	1980-90	1.69	1.07	2.72	2.40	1.03	1.00	0.624	0.506
MH	1990-00	1.16	1.13	1.95	1.51	0.977	0.947	0.776	0.729
MH	2000-10	1.11	0.986	1.42	1.17	0.973	0.962	0.950	0.831
MH	2010-19	1.03	0.938	1.22	1.17	0.949	0.944	0.967	0.891
H	**Tot.**	**4.95**	**1.40**	**51.50**	**8.23**	**0.923**	**0.881**	**0.284**	**0.180**
H	1971-80	1.59	1.38	3.25	2.92	0.932	0.968	0.818	0.580
H	1980-90	1.17	0.989	3.79	2.87	1.06	1.04	0.383	0.375
H	1990-00	2.78	1.14	2.75	1.77	0.984	0.974	1.09	0.623
H	2000-10	1.21	1.10	1.96	1.63	1.01	0.995	0.682	0.680
H	2010-19	0.994	0.963	1.37	1.35	0.933	0.922	0.839	0.823

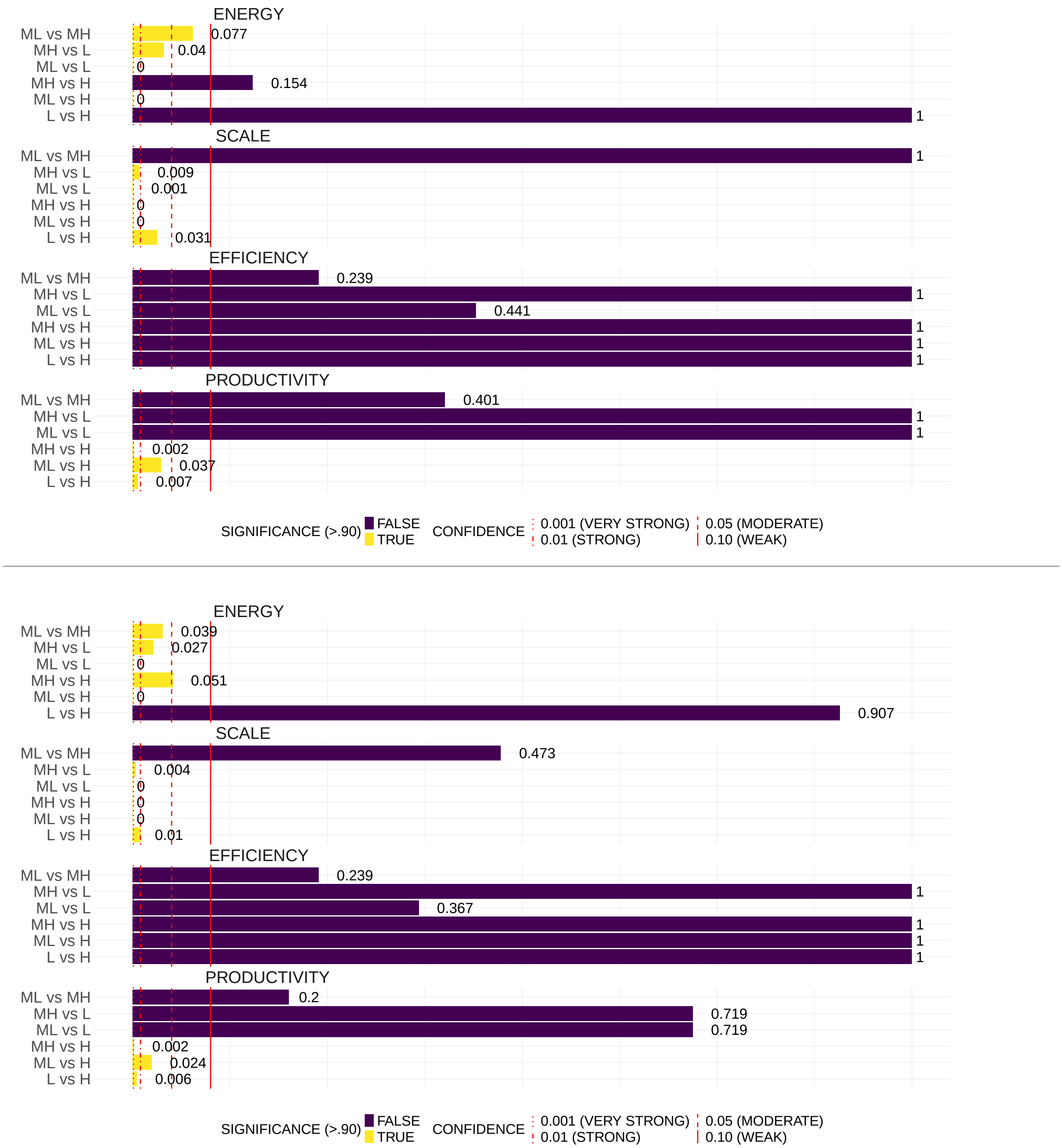
Note: Summary statistics for the full sample (Tot.) correspond to the unweighted cross-country and cross-sector mean (Avg.) and median (Med.) values of the cumulative decomposition results derived, where cumulative series are aggregated over the total period. Results by digital intensity category (L-, 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 DI-4 category and period correspond to the unweighted cross-country average and median values across sectors for each decade, where cumulative results by decade are obtained by multiplying the results for all periods in the same decade. For cross-sector comparison, the minimum and maximum values for each factor have been highlighted.

Figure S.3: Boxplots of cumulative (decadal) decomposition results by digital intensity category



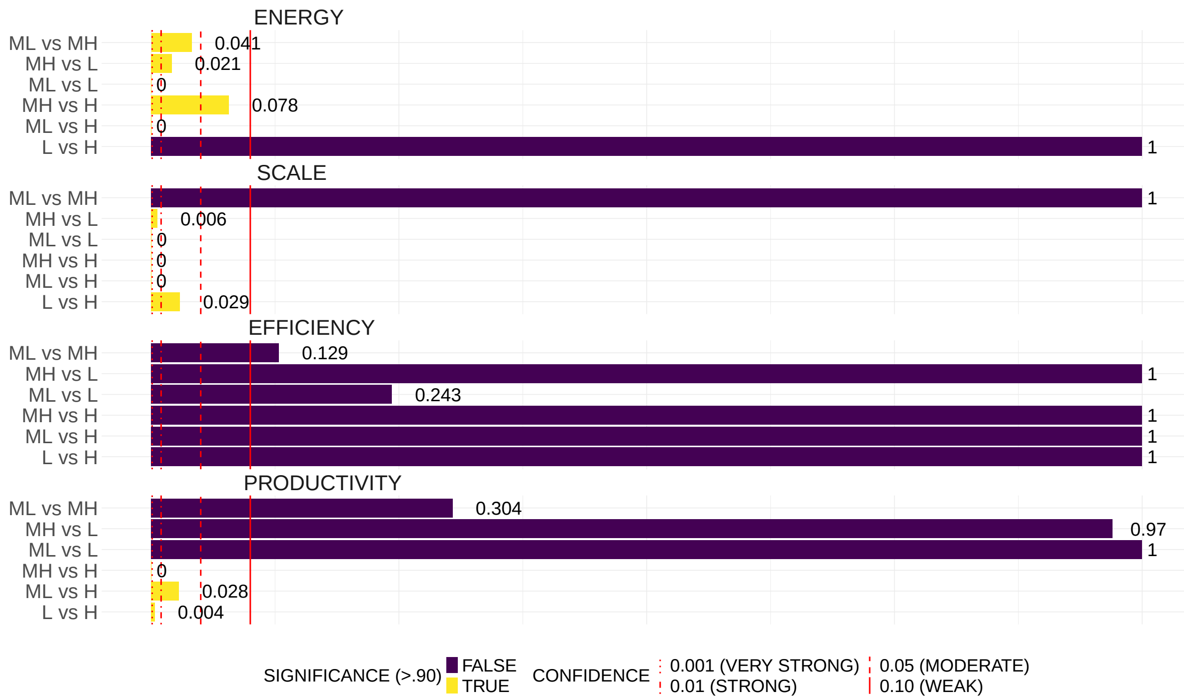
Note: The decomposition results in this figure are cumulative and have been aggregated by decade. The yellow, green, blue and purple correspond respectively to H-DI, MH-DI, ML-DI and L-DI sectors. Central box plot lines correspond to the median values, and the blue diamonds to the mean values. The vertical 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.

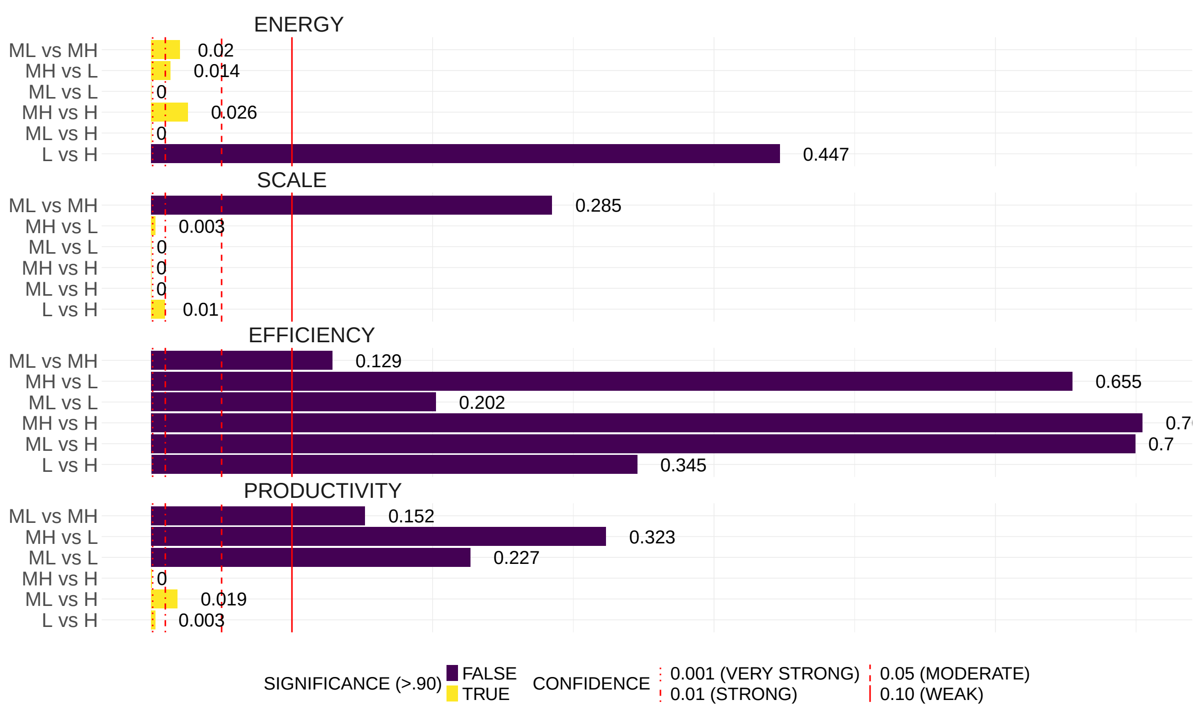
Figure S.4: Wilcoxon-Mann-Withney pairwise tests with Bonferroni and Holm corrections



Note: The Figure above the line corresponds to the Bonferroni correction, the one below to the Holm correction. The horizontal bars in this Figure correspond to the p-values corrected for multiple testing, represented for each factor and for each pairwise combination of DI-4 categories. Vertical red lines represent the different confidence thresholds. Purple bars correspond to non-significant corrected p-values, and yellow bars correspond to significant (<0.10) corrected p-values.

Figure S.5: Dunn pairwise tests with Bonferroni and Holm corrections

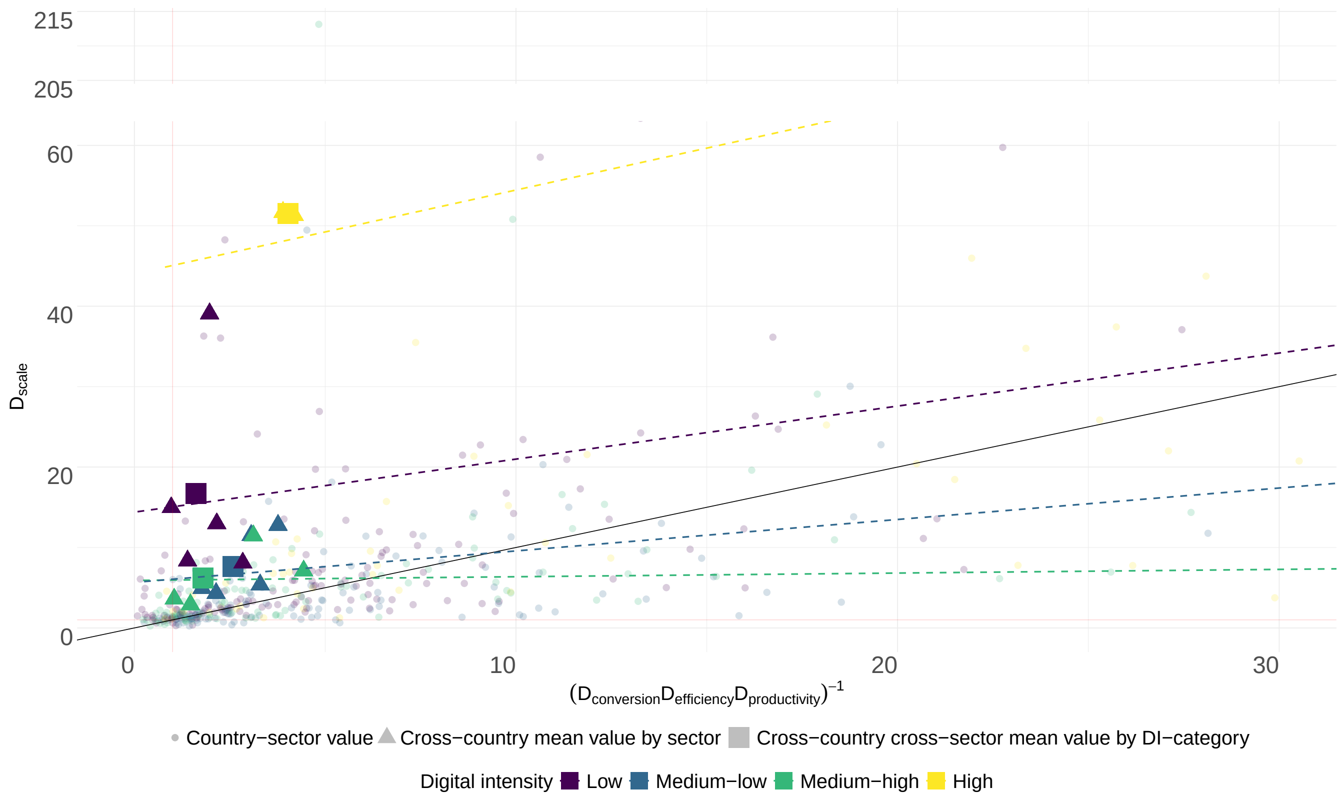




Note: The Figure above the line corresponds to the Bonferroni correction, the one below to the Holm correction. The horizontal bars in this Figure correspond to the p-values corrected for multiple testing, represented for each factor and for each pairwise combination of DI-4 categories. Vertical red lines represent the different confidence thresholds. Purple bars correspond to non-significant corrected p-values, and yellow bars correspond to significant (<0.10) corrected p-values.

S.2 Scatterplot of cumulative changes in composition versus technical improvements, without outliers

Figure S.6: Figure 3 without the *MACHIN* sector from South Korea and the *AGRI* sector from Iceland



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.

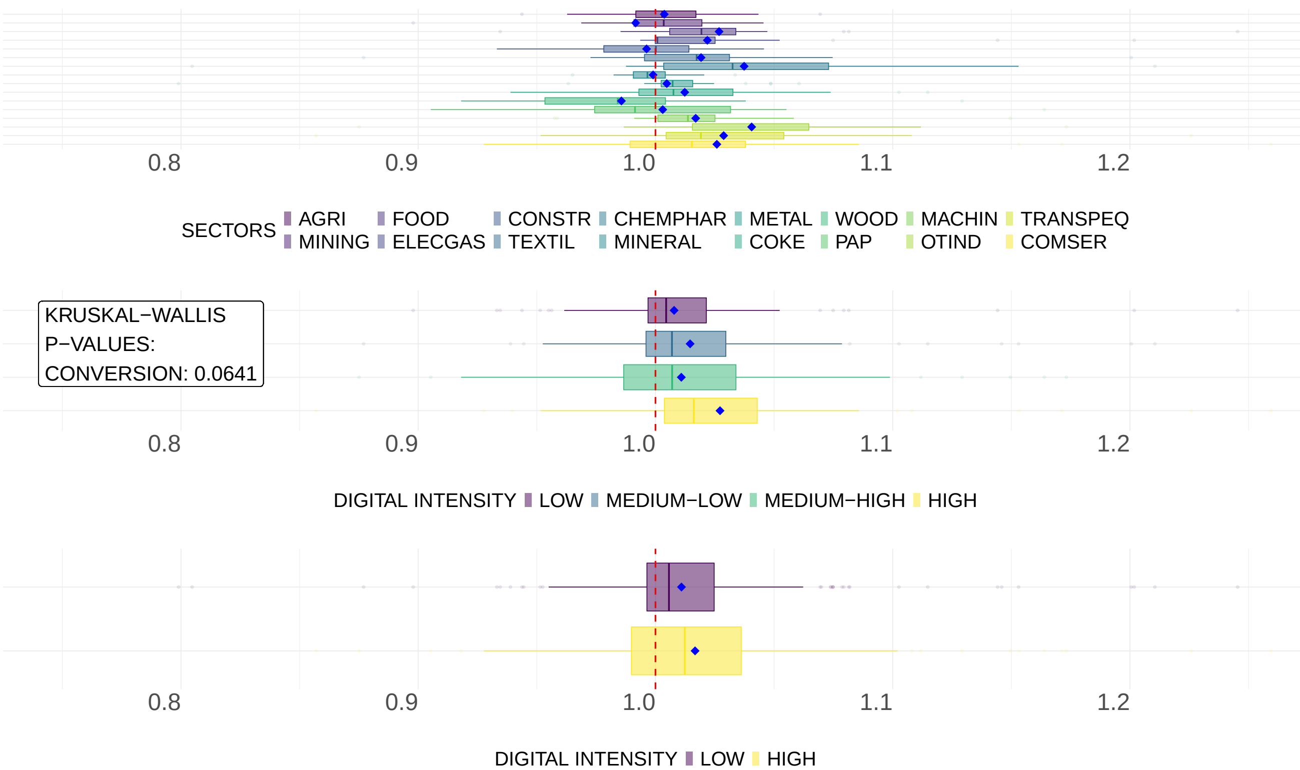
S.3 Results for the *Conversion* effect

Table S.3: Decomposition results for the *Conversion* effect for full sample, by sector, by DI categories, and across time, 1971-2019

Sector	**Period**											
	Tot.		***1971-80***		***1980-90***		***1990-00***		***2000-10***		***2010-19***	
	Avg.	**Med.**	***Avg.***	***Med.***	***Avg.***	***Med.***	***Avg.***	***Med.***	***Avg.***	***Med.***	***Avg.***	***Med.***
Tot.	**1.01**	**1.01**										
Sectors												
AGRI^{L}	**1.00**	**1.00**	0.997	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
MINING^{L}	**0.992**	**1.00**	1.00	1.00	1.01	1.00	1.01	1.00	1.00	1.00	0.981	0.997
FOOD^{L}	**1.03**	**1.02**	1.00	1.00	1.01	1.01	1.01	1.00	1.01	1.00	1.01	1.00
ELECGAS^{L}	**1.02**	**1.00**	1.00	1.00	1.01	1.00	1.00	1.00	1.01	1.00	1.01	1.00
CONSTR^{L}	**0.996**	**1.00**	0.989	1.00	1.00	1.00	0.999	1.00	1.00	1.00	0.998	0.998
TEXTIL^{ML}	**1.02**	**1.02**	0.949	0.999	1.09	1.00	1.01	1.00	0.988	1.00	1.04	1.00
CHEMPHA^{ML}	**1.04**	**1.03**	1.01	1.00	1.00	1.00	1.02	1.01	1.02	1.01	0.996	1.00
MINERAL^{ML}	**0.999**	**0.997**	0.991	0.997	1.01	1.01	1.00	1.00	0.997	0.996	1.00	0.998
METAL^{ML}	**1.00**	**1.01**	0.998	0.995	1.02	1.01	1.01	1.00	1.00	1.00	0.995	1.00
COKE^{ML}	**1.01**	**1.01**	0.998	0.999	1.00	1.00	1.00	1.00	1.01	1.00	0.996	1.00
WOOD^{MH}	**0.986**	**0.984**	0.972	0.994	0.973	0.989	0.996	0.992	0.999	0.998	0.998	0.995
PAP^{MH}	**1.00**	**0.991**	0.991	1.00	0.997	0.999	1.00	1.00	1.00	1.00	0.999	0.999
MACHIN^{MH}	**1.02**	**1.01**	1.00	1.00	1.01	1.01	1.01	1.00	1.01	0.999	1.00	1.00
OTIND^{MH}	**1.04**	**1.04**	1.14	1.18	0.947	0.840	1.03	1.01	1.00	1.00	1.01	1.01
TRANSPEQ^{H}	**1.03**	**1.02**	0.998	1.00	1.01	1.01	1.00	1.00	1.02	1.00	1.00	1.00
COMSER^{H}	**1.03**	**1.01**	1.01	1.00	1.03	1.01	1.00	1.01	1.01	1.00	0.998	1.00
DI-4												
L-DI	**1.01**	**1.00**	0.997	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.999	1.00
ML-DI	**1.01**	**1.01**	0.985	1.00	1.03	1.00	1.01	1.00	1.00	1.00	1.00	1.00
MH-DI	**1.01**	**1.01**	1.02	1.00	0.992	1.00	1.01	1.00	1.00	0.999	1.00	1.00
H-DI	**1.03**	**1.02**	1.01	1.00	1.02	1.01	1.00	1.00	1.01	1.00	0.999	1.00
DI-2												
L-DI	**1.01**	**1.01**	0.993	1.00	1.01	1.00	1.01	1.00	1.00	1.00	1.00	1.00
H-DI	**1.02**	**1.01**	1.01	1.00	1.01	1.01	1.01	1.00	1.01	1.00	1.00	1.00

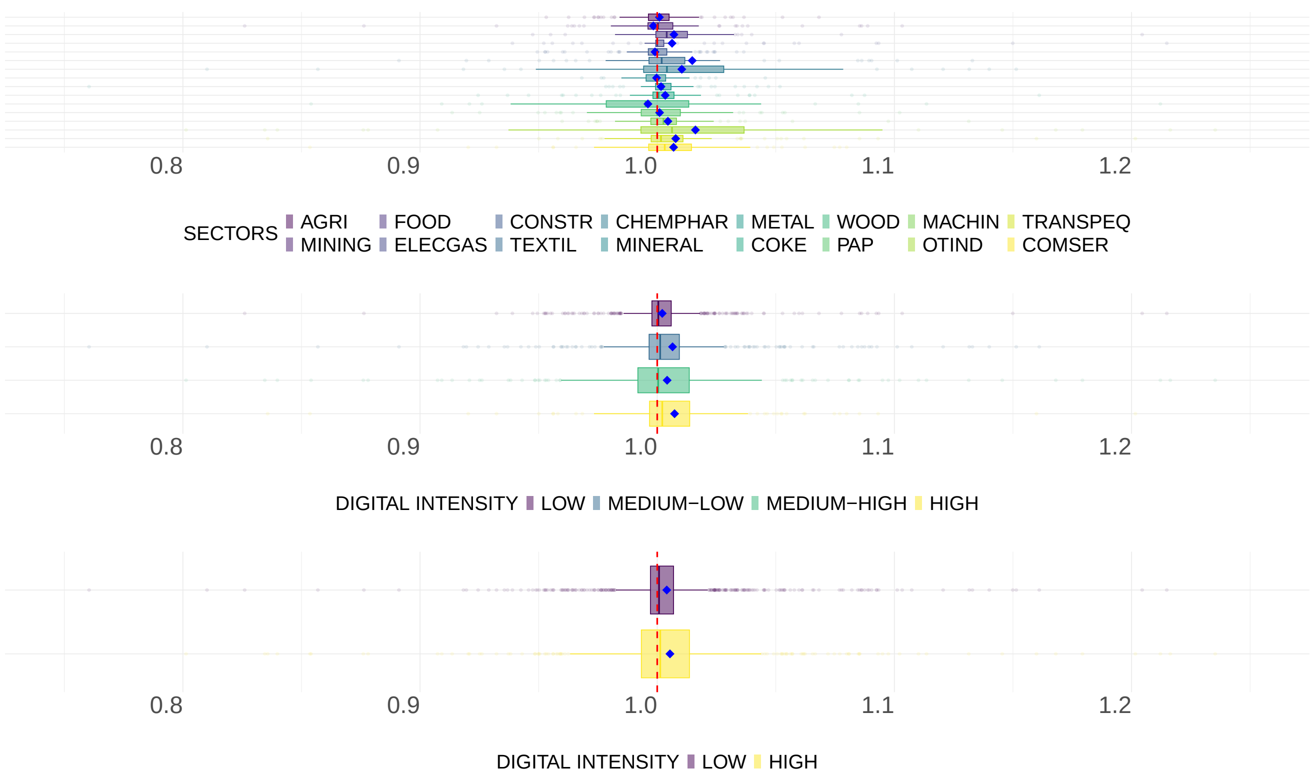
Note: Summary statistics for the full sample (Tot.) correspond to the unweighted cross-country and cross-sector mean (Avg.) and median (Med.) values of the cumulative decomposition results derived, where cumulative series are aggregated over the entire period. Results by sector correspond to the unweighted cross-country average and median values of the (total) cumulative decomposition results. Results by sector and period correspond to the unweighted cross-country average and median values across sectors for each decade, where cumulative results by decade are obtained by multiplying the results for all periods in the same decade. Results by digital intensity categories (DI-4, DI-2) correspond to the unweighted cross-country average and median values of the (total) cumulative decomposition results. For each DI category, the summary statistics are derived for the cumulative decomposition results across all the sectors composing the DI category. Sectors have been ordered by their digital intensity categories, as found in Table 2.

Figure S.7: Boxplots of cumulative (total) decomposition results for the *Conversion* effect by sector and by DI categories, 1971-2019



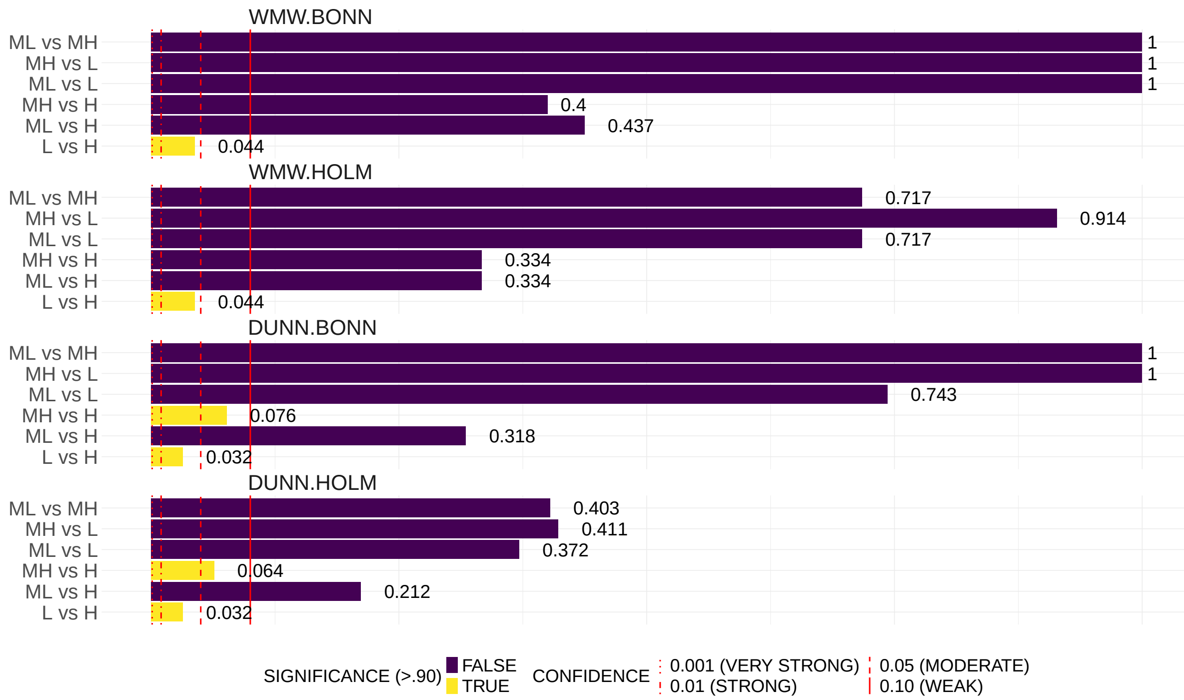
Note: The decomposition results in this Figure are cumulative and have been aggregated over the total period. The yellow and purple on the lower plot correspond respectively to H-DI and L-DI sectors. The yellow, green, blue and purple on the middle plot correspond respectively to H-DI, MH-DI, ML-DI and L-DI sectors. All sectors in the upper plot are distincted by their colour and are ordered by digital intensity (DI-4) groups, going from L-DI (purple) to H-DI (yellow). The central boxplot line corresponds to the median value, and the blue diamond to the mean value. The vertical red dashed line sets the threshold between upward and downward effects.
Note that the Kruskal-Wallis p-value computed for the differences across DI-4 categories is (weakly) significant.

Figure S.8: Boxplots of cumulative (decadal) decomposition results for the *Conversion* effect by sector and by DI categories, 1971-2019



Note: The decomposition results in this Figure are cumulative and have been aggregated by decade. The yellow and purple on the lower plot correspond respectively to H-DI and L-DI sectors. The yellow, green, blue and purple on the middle plot correspond respectively to H-DI, MH-DI, ML-DI and L-DI sectors. All sectors in the upper plot are distincted by their colour and are ordered by digital intensity (DI-4) groups, going from L-DI (purple) to H-DI (yellow). The central boxplot line corresponds to the median value, and the blue diamond to the mean value. The vertical red dashed line sets the threshold between upward and downward effects.

Figure S.9: Wilcoxon-Mann-Whitney and Dunn pairwise tests with Bonferroni and Holm correction for the *Conversion* effect



Note: The horizontal bars in this Figure correspond to the p-values corrected for multiple testing, represented for each test and for each pairwise combination of DI-4 categories. WMW.BONN stands for the Wilcoxon-Mann-Whitney test with Bonferroni correction, WMW.HOLM stands for the Wilcoxon-Mann-Whitney test with Holm correction, DUNN.BONN stands for the Dunn test with Bonferroni correction, and DUNN.HOLM stands for the Dunn test with Holm correction. Vertical red lines represent the different confidence thresholds. Purple bars correspond to non-significant corrected p-values, and yellow bars correspond to significant (<0.10) corrected p-values.
These test results confirm a robust difference between L-DI & H-DI, with lower conversion decomposition factors for L-DI. With less robustness, MH-DI and H-DI are also found significant using the Dunn tests.

S.4 Robustness analysis: two categories of digital intensity (DI-2)

In this section, we perform a robustness analysis to verify whether the previous results hold when going from four categories of digital intensive industries (DI-4) to only two (DI-2). In particular, this allows to address the issue raised in Section 3.2.2 of the main article, namely that perfect matching is not possible for three of the macro-sectors analysed: *Other industries*; *Machinery, electrical & electronic equipment*; and *Commercial and public services*. As a robustness, we simply include both ML-DI and L-DI in a single category (L-DI), and both MH-DI and H-DI in another (H-DI). Table S.4 presents the final 16 sectors under scrutiny with their DI-4 and DI-2 classification.

Table S.4: List of industries classified by ISIC division and level of digital intensity.

Sector	**Full Name**	**ISIC Div. Rev.4**	**DI-2**	**DI-4**
AGRI	Agriculture, forestry, fishing	01-03	L-DI	L-DI
MINING	Mining, quarrying	05-09	L-DI	L-DI
FOOD	Food products, beverages, tobacco	10-12	L-DI	L-DI
TEXTIL	Textiles, wearing apparel, leather	13-15	L-DI	ML-DI
WOOD	Wood, wood products	16	H-DI	MH-DI
PAP	Paper, pulp, printing	17-18	H-DI	MH-DI
CHEMPHA	Chemicals, chemical products, pharmaceutical products	20-21	L-DI	ML-DI
MINERAL	Non-metallic minerals	23	L-DI	ML-DI
METAL	Metals, metal products	24	L-DI	ML-DI
MACHIN*	Machinery, electrical and electronic products	25-28	H-DI(1)	MH-DI(1)
TRANSPEQ	Transport equipment	29-30	H-DI	H-DI
OTIND*	Other industries	22, 31-32	H-DI(2)	MH-DI(2)
COKE	Coke & refined petroleum products	19	L-DI	ML-DI
ELECGAS	Electricity, gas, steam, air conditioning	35	L-DI	L-DI
CONSTR	Construction	41-43	L-DI	L-DI
COMSER*	Commercial & public services	33, 36-39, 45-96	H-DI(3)	H-DI(3)

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 Table 3.2 (p. 18) in Horvát & Webb (2020) for the original classification.

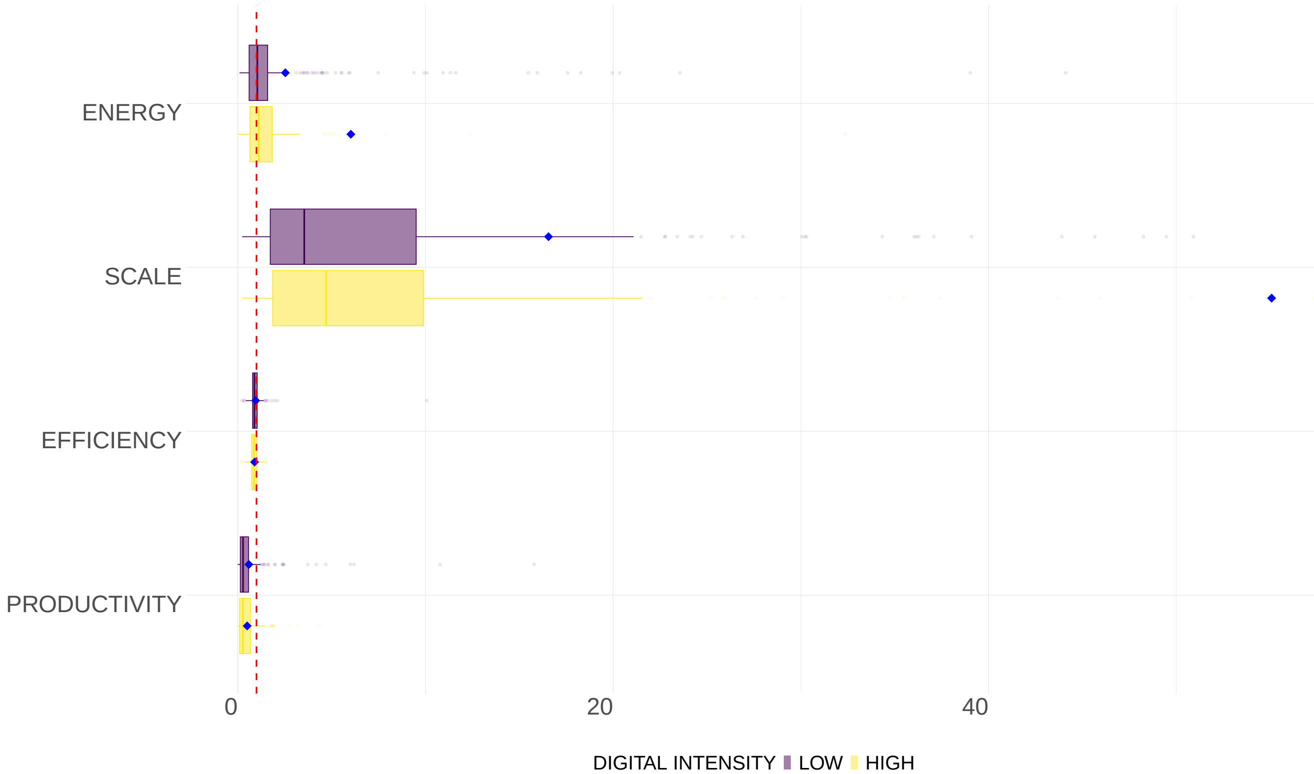
(1) MACHIN: 25% ML-DI (ISIC division 25) and 75% MH-DI (ISIC divisions 26-28).

(2) OTIND: 33% ML-DI (ISIC division 22) and 66% MH-DI (ISIC divisions 31 and 32).

(3) 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).

The results for this robustness analysis are presented and commented below. Note that the results for the *Conversion* effect, as in the main analysis, have been removed and placed in SI Section S.3 below.

Figure S.10: Boxplots of cumulative (total) decomposition results by sector



Note: The decomposition results in this Figure are cumulative and have been aggregated over the total period. The yellow and purple correspond respectively to H-DI and L-DI sectors. The central boxplot line corresponds to the median value, and the blue diamond to the mean value. 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.

Energy demand does not substantially differ when comparing low and high digital intensity (L- & H-DI) categories (DI-2), despite a very slightly lower mean value for L-DI. This apparent similarity conceals more pronounced differences among driving factors and periods. As may be expected, the average effects are stronger for H-DI for all factors: H-DI sectors have a stronger upward scale effect and slightly stronger downward efficiency and productivity effects. The role played by digitalisation may thus not be visible directly in the dynamics of energy demand, but rather through its effect on value added growth.

Looking into differences across periods, we find similar dynamics across both categories, with subtle differences. Despite a higher mean values for the entire period, H-DI display reductions in energy use in the final period, alongside a progressive reduction of the scale effect and a slowdown in the rate of productivity improvements. Efficiency improvements however keep accelerating from 2000 onwards. With decelerating value added growth, reductions in energy demand may be achieved through combined technical improvements, even with productivity gains slowing down. The same trends can be observed for L-DI, but with overall lower magnitude. Productivity gains were weaker for L-DI relative to H-DI in the 1970s and 1980s. While both groups converge to similar rates of improvements in the 2010s, the initial difference in productivity, combined with reduced value added growth, explains the weaker reductions in energy for L-DI.

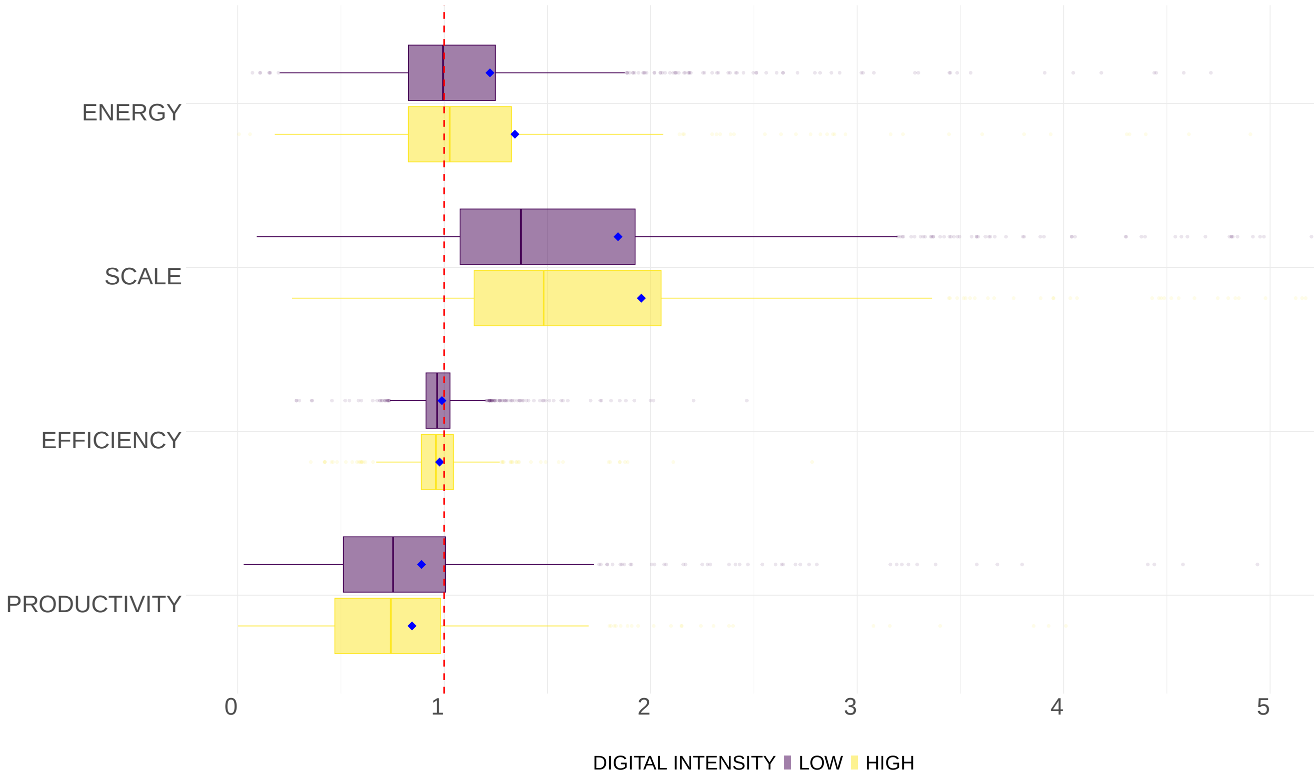
Overall, the mixed understanding of energy dynamics looking at DI-2 groups masks the polarisation of the effects observed with DI-4, as presented in Section 4.2.2 in the main article. H-DI and L-DI have stronger growth in energy demand, and this is associated with stronger scale effects (when considering the median, which moderates the effect of the South Korean *MACHIN* sector that drives the mean values up for MH-DI). The intermediate DI-4 categories combine lower scale effect with either the strongest efficiency gains (MH-DI) or strong productivity improvements (ML-DI), and this results in the lowest growth (or reductions) in energy demand. Considering only two categories of digital intensive industries does not allow to observe this polarisation, and justifies the choice of the original DI-4 classification, despite its limitations.

Table S.5: Decomposition results by DI-2 category and decade, 1971-2019

Sector	**Period**	**Energy**		**Scale**		**Efficiency**		**Productivity**	
		Avg.	**Med.**	**Avg.**	**Med.**	**Avg.**	**Med.**	**Avg.**	**Med.**
Tot.	**Tot.**	**3.82**	**1.07**	**30.73**	**4.24**	**0.935**	**0.880**	**0.560**	**0.280**
L	**Tot.**	**2.54**	**1.04**	**16.56**	**3.54**	**0.955**	**0.890**	**0.592**	**0.283**
L	1971-80	1.96	1.21	3.49	2.31	0.957	0.952	0.915	0.582
L	1980-90	1.56	1.05	2.54	2.06	1.02	0.965	0.902	0.535
L	1990-00	1.17	1.03	1.54	1.31	0.965	0.954	0.940	0.856
L	2000-10	1.04	0.913	1.78	1.32	1.01	0.982	0.811	0.681
L	2010-19	1.06	0.964	1.33	1.21	0.990	0.965	0.906	0.817
H	**Tot.**	**6.03**	**1.12**	**55.08**	**4.71**	**0.901**	**0.870**	**0.504**	**0.269**
H	1971-80	1.83	1.21	3.41	2.39	1.00	1.02	0.724	0.492
H	1980-90	1.41	1.05	3.30	2.69	1.05	1.03	0.493	0.406
H	1990-00	1.73	1.13	2.23	1.63	0.980	0.956	0.887	0.644
H	2000-10	1.15	1.02	1.61	1.34	0.985	0.973	0.855	0.738
H	2010-19	1.01	0.949	1.28	1.23	0.943	0.935	0.921	0.843

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 derived, where cumulative series are aggregated over the total period. Results by digital intensity category (L-, H-DI) correspond to the unweighted cross-country average and median values of the (total) cumulative decomposition results. For each DI-2 category, the summary statistics are derived for the (total) cumulative decomposition results across all the sectors composing the DI-2 category. Results by DI-2 category and period correspond to the unweighted cross-country average and median values across sectors for each decade, where cumulative results by decade are obtained by multiplying the results for all periods in the same decade. For cross-sector comparison, the minimum and maximum values for each factor have been highlighted.

Figure S.11: Boxplots of cumulative (decadal) decomposition results by digital intensity (DI-2)



Note: The decomposition results in this Figure are cumulative and have been aggregated by decade. The yellow and purple correspond respectively to H-DI and L-DI sectors. The central boxplot line corresponds to the median value, and the blue diamond to the mean value. 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.

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