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NEW PERSPECTIVES ON GROWTH AND SUSTAINABILITY. GLIMPSES INTO THE AI INDUSTRIAL REVOLUTION

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ABSTRACT. We introduce the *economic efficiency of the energy* defined as the ratio between GDP produced and energy used at country level. We study its behaviour over time both from historical data and recent detailed databases. We observe that at the start of the first industrial revolution such quantity decreases dramatically. The comparison of the efficiency between underdeveloped, developing and advanced countries shows that the first have the highest efficiency and the second led on the third until around the year 2000 when a switch occurred due to a constant growth in efficiency of the advanced economies in the time window 1980-2018. The current AI industrial revolution is forecasted to have a growth impact on GDP several times larger than the first postwar (WW2) decade in western society. We argue that, since AI is still an energy eager technology, the danger of a collapse of the efficiency now is real in analogy with the first industrial revolution. A central question revolves around whether, and if so in what time scale, the AI revolution will follow an efficiency growth strong enough to enhance the global one.

1. INTRODUCTION

Climate change and the sustainability of our lifestyles occupy nowadays the news in most countries worldwide and, by consequence, their governments agendas. On one side, our economies need large amounts of energy, hundreds of times higher than in the pre-industrial era, to keep the GDP growing or at least non-decreasing. On the other side, the intensive use of fossil resources is causing the depletion of non-renewable sources and an increase in CO_2. While waiting for the discovery of new clean energy sources, like nuclear fusion, we face the challenge of decreasing energy consumption by making our global economies more efficient. On that perspective, several studies [17, 34, 42, 24, 25, 41] have appeared about the relation between GDP and energy consumption. In particular, the one by Jancovici et al. [24, 25] finds a strong correlation between energy and GDP changes in the last 20 years in the Italian economy. The output show that, in average, the production of GDP, a crucial index albeit not the only one relating to the quality of life, grows linearly, roughly speaking, with the consumption of energy. Such ratio, that represents the *economic efficiency of energy* in society, has of course fluctuations depending on the country, the years etc, and carries very important information that we aim to display in this work. By disentangling the economic efficiency for different areas by averaging on three large groups of developed, developing and third world countries, we found that while developed countries have a very high total production of GDP they are in general less efficient with respect to simpler, pre-industrial economies.

We are currently in the era of AI, which is revolutionizing and already changing our economic and social paradigms. The modern machines that learn from huge databases with the deep learning

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techniques by synthetizing raw information into knowledge play the same role that heat engines had in the old industrial revolution where they produced work by extracting it from an energy source [16]. Historically, industrial revolutions have led to a decrease in the economic efficiency of energy in the early stages of the transition [29]. This is very likely because the technology is far from being optimized at the beginning, and also due to the fact the economic pressure to make profit out of it takes into account only the generation of GDP and disregards the amount of energy spent and its impact on the environment.

Following this preliminary studies of the evolution of economic efficiency of energy, we present a research problem that can be summarised as follows. Having established that traditionally technological revolutions come with non optimal performances, what is the future that we face with the AI revolution? In other terms: will the AI technology improve the global economic efficiency of our society? If so, in what time scale? The few data that we know as of today indicates that AI, as the 18^{th} century machines, is extremely eager for energy [19]. Moreover, since the forecasts of the AI impact largely agree on a GDP growth of the same order as of that in the postwar years for Western countries, it seems unthinkable to stop or slow down the race toward its adoption. Therefore the risk of going through the same path of the past, so following only GDP maximization without considering the economic efficiency of energy of the new technology, is very high.

On the other hand it is also true that the AI revolution is the only industrial revolution so far accompanied with a global concern on the danger of climate change due to the intensive use of non renewable energy sources. Furthermore, AI has the advantage to potentially solve a complex problem like the optimization of economic efficiency itself, even without the advent of new energy sources. We could tackle the efficiency problem through improving the AI technologies both by selecting the models with higher energy efficiency and by pushing towards the development of more energetically efficient models. In order to achieve that, we should devote large efforts and investments to fundamental research in AI.

The paper is organized as follows: in Section 2, we introduce the main quantity of interest, called the economic efficiency of energy; Section 3 discusses the efficiency trends from historical to recent data; AI and its associated economic growth and energetic impact are discussed respectively in Sections 4 and 5; Section 6 gives a general conclusion and perspective on the topic; and Appendix A contains supplementary figures of efficiency trends.

2. Energy and GDP

Several studies have evidenced that energy consumption and GDP exhibit a clear positive correlation [24, 34, 41]. In other words, energy use per capita increases with GDP per capita, leading to the observation that wealthier countries tend to use more energy per person than their less affluent counterparts. However, empirical investigations into whether energy drives economic growth or vice versa have yielded inconclusive results, often applicable only in specific case studies [24, 33, 34].

In this context, we define the *economic efficiency of energy*, referred from now on simply as *efficiency*, as the GDP, measured in US$, produced per unit of energy E, measured in kWh (Kilowatt-hour). For an entity, which can be e.g. a country or a set of countries, fixing a time interval, the *efficiency* measure is thus given by the total GDP produced over the total energy consumed

$$E_{ff} := \frac{GDP}{Energy}. \tag{1}$$

Thus, efficiency is a numerical value that indicates how well an economy converts energy into monetary output. An economy is considered to be more efficient when smaller amount of energy is used to generate more goods and services. On the other hand, an economy is less efficient if it needs to use more energy for generating income.

Drawing an analogy with the thermal efficiency of a heat engine (work/heat) in thermodynamics seems reasonable, and similar ideas have already been explored by studies aiming to transfer thermodynamic concepts into economics [10, 14, 5]. Yet, it is essential to note that efficiency in the economic sense is not a pure, dimensionless, number: rather, it is an empirical measure of dollars per Kilowatt-hour (US\$/kWh).

In the economic literature, the term *energy intensity* is more commonly used for studying the correlation between energy and GDP. We emphasize that our definition of efficiency corresponds to the reciprocal of the energy intensity. It is worth highlighting that efficiency plays a crucial role in considerations of global warming and enters in the well-known Kaya identity [25, 27], which measures the global CO_2 emissions from human sources.

3. Efficiency trends

3.1. **Historical trends.** Studies conducted on European aggregate data report that historically (16th-21th century) energy consumption per capita experiences an almost permanent growth over time [21, 26]. Such growth is particularly consistent in the period after the outbreak of a technological revolution, with some latency time: the different revolutions coincide with the introduction and diffusion of respectively coal-steam, electricity-oil, and information and communication technologies (ICT).

The work in [29] focuses on per capita energy and per capita GDP trends in the time period 1560-1900 in Central and Northern Italy and in England and Wales. By analyzing the data in the study, we observed that the efficiency values were substantially lower (around $0.1 - 0.3$ \$/kWh) than the current ones in both areas. Moreover, the efficiency consistently decreased in England and Wales at the time of the first industrial revolution: it nearly halved, passing from a pre-industrial efficiency of around 0.21 \$/kWh to 0.11 \$/kWh during the early stages of the revolution and 0.13 in the successive period. On the other hand, in Italy, where the industrial revolution arrived much later, the efficiency stayed steady. This suggests that efficiency significantly decreases at the start of a technological revolution, when the adoption of the innovative technology is profitable regardless of its energetic impact. At the beginning, indeed, the new technology is still unregulated and its use is lead by the private sector which is naturally driven by profit maximization. On the other hand, efficiency starts to grow when the revolution is more mature and the energy consumption of the new technology plays a more important role.

In the second half of the 20th century, in general both total energy use and efficiency have increased over time, globally [17, 41, 42]. In these years, citing [41], "although efficiency has increased, per capita energy use has increased over time, and when we also take population growth into account total energy use has risen strongly, though at a slower pace than total world economic output".

The consistent variation of the quantities in the game, both energy consumption and economic growth, during every technological revolution in the past justifies our spotlight on the efficiency trends during the current technological revolution, driven by Artificial Intelligence machines.

3.2. **Recent trends.** The data used for this study is obtained from the database "Our World in Data"[39]. There, GDP measures are adjusted for inflation and differences in the cost of living

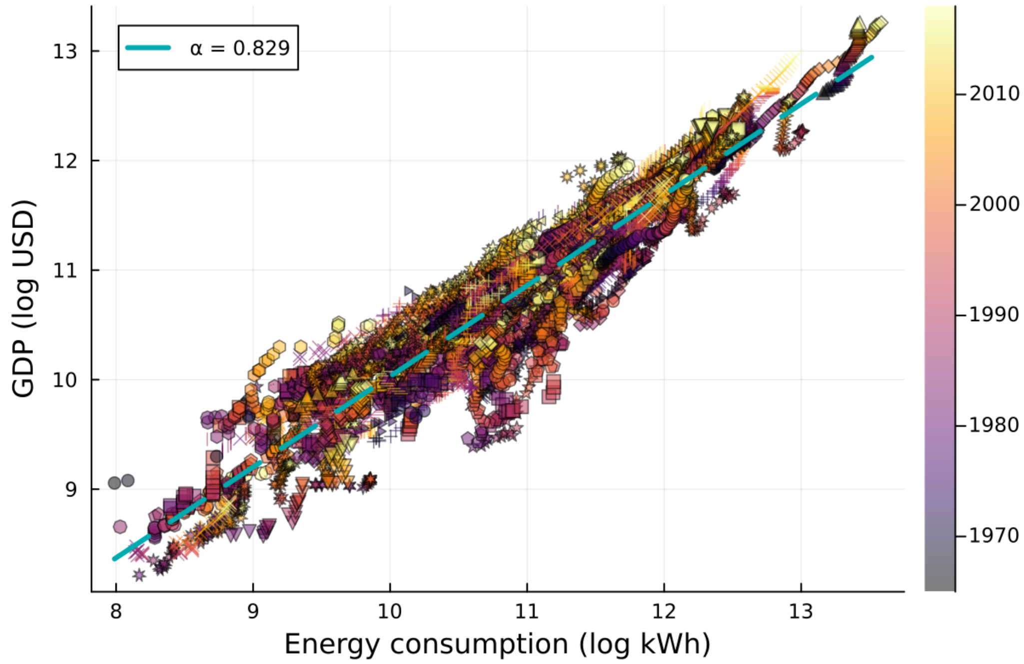


FIGURE 1. **Countries' GDP vs Energy consumption, over time.** Different years are represented by different colors as in the legend. Different countries have different markers. The measured Spearman coefficient value is 0.94.

between countries (*Purchasing Power Parity*). Energy use refers to the use of primary energy before transformation to other end-use fuels, which is equal to indigenous production plus imports and stock changes, minus exports and fuels supplied to ships and aircraft engaged in international transport. Figure 1 displays the log-log relationship between total energy consumption in kWh and total GDP in USD from 1965 to 2018. An almost linear relation between GDP and energy consumption is found. Furthermore, a very high Spearman correlation [40] indicates that the two variables are strongly monotonically related.

Now, we are interested in analyzing the efficiency trends depending on the wealth of a country. To do so, we consider three groups of representative countries for respectively Advanced economies, Developing and Emerging economies and Underdeveloped economies. The division is performed following [23]. The countries in the groups are listed in the caption of Figure 2. We consider two aggregate measures of the efficiency: one considers the total GDP of the countries in the cluster over the total energy

$$E_{ff_c} = \frac{\sum_{i \in C} GDP_i}{\sum_{i \in C} E_i} \tag{2}$$

while the other considers the weighted average by country's population:

$$E_{ff_c}^{(Pop)} = \frac{\sum_{i \in C} \frac{GDP_i}{E_i} Pop_i}{\sum_{i \in C} Pop_i} \tag{3}$$

where GDP_i, Pop_i, E_i are respectively the gross domestic product, the population and the energy consumption of country i, belonging to the cluster C. The two measures can be in general different: for example, highly populated countries with relatively low values of GDP and energy are more influential in $E_{ff_c}^{(Pop)}$ than in E_{ff_c}. If their efficiency is high with respect to the other countries in the cluster, then we would have $E_{ff_c}^{(Pop)} > E_{ff_c}$.

We find (see Figure 2) that the advanced economies have increased their aggregate efficiency almost monotonically in the last 40 years, and in the 2000s they surpassed the developing economies whose aggregate efficiency stayed almost steady in the last decades. Globally, the world efficiency grew monotonically in the last 40 years, and the growth was driven by the improvement of the efficiency of the advanced economies. Furthermore, we find that Underdeveloped economies have the highest values of efficiency. Since their GDP is produced mainly by human work, the data suggests that, in general, organized human work at a societal level requires less energy for generating the same amount of income than industrial machines. In order to account for the energy consumed by human labour, we modify the measure of energy consumption of a country by adding a term proportional to the country's population. Considering a daily use for each individual of 2500 kcal/day $= 2.9\ kWh$ [38], we modify the measure of the energy as follows

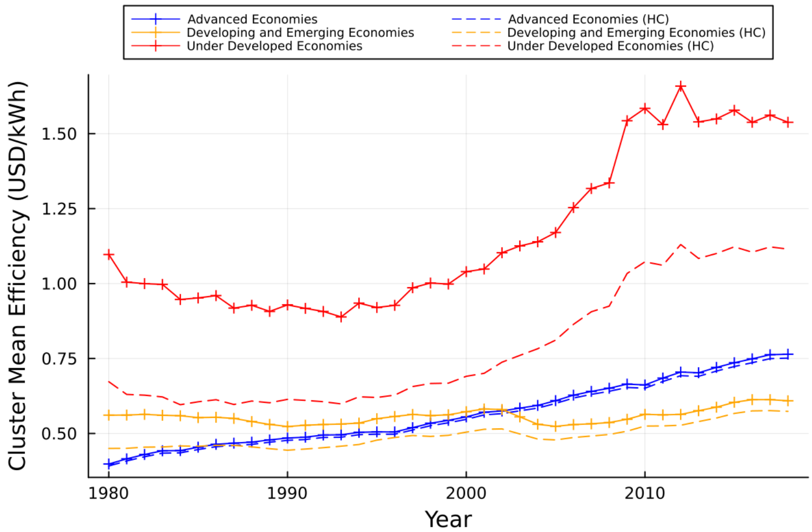
$$E_i' = E_i + 2.9 \cdot 365 \cdot Pop_i, \tag{4}$$

where E_i' denotes the total energy accounting for human consumption and E_i is the energy consumed by machines. The efficiency with human energy consumption are illustrated through the dashed lines in Figure 2. The perturbation is obviously more effective for underdeveloped and developing economies, whose values of GDP and Energy consumption are lower, while the efficiency of advanced economies remains almost unaltered. Taking into account the human energy consumption we find that the efficiency of the three clusters have generally a smaller dispersion, proving that (4) provides a robust definition of energy consumption. Last, we point out that these results do not depend much on the measure of average efficiency that we choose.

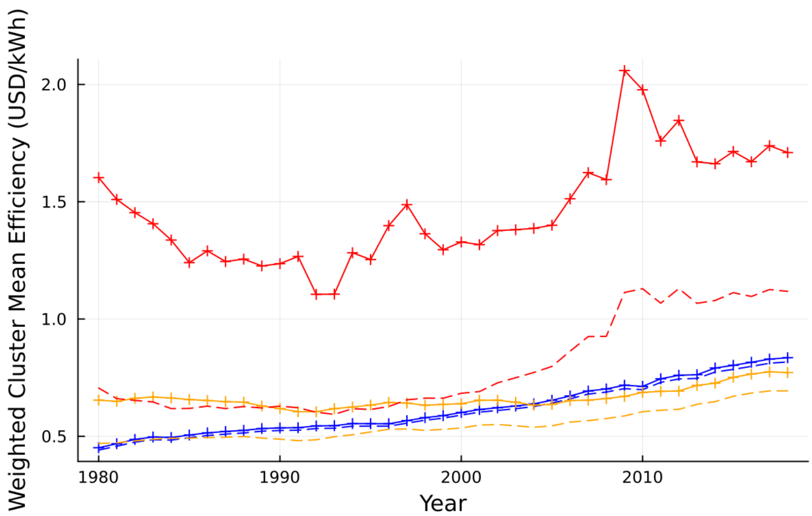
4. AI AND ECONOMIC GROWTH

Several reports from business consulting companies such as the McKinsey Global Institute 2018 [30], 2019 [31] and 2023 [15], the Goldman Sachs Economics Research report 2023 [22] and PWC [37] have made predictions of the overall impact of AI on the economy globally. These consulting firms make use of expert surveys (i.e., experts in AI, economics, and other fields to provide insights into the different ways that AI is likely to impact the economy), or econometric models to estimate the impact of AI on GDP by simulating the effects of AI on productivity, economic growth, and job creation. Additionally, they use case studies of specific industries and companies to see how AI is being used to improve productivity, reduce costs, and create new products and services.

It was estimated in [22] that the annual US labor productivity due to generative AI could grow by about 1.5 percentage point over a 10-year period following a widespread adoption. This leads to double the recent 1.5% average growth pace, roughly the same-sized boost that followed the emergence of prior transformative technologies like the electric motor and personal computer. Additionally, at the global level, there will be an economically significant boost to labor productivity, and estimated that AI could eventually increase annual global GDP by 7%. A 2-3 percentage point increase in labor productivity growth on the average following AI adoption was found in [7, 9, 18, 11, 12, 15]. However, it is important to note that the growth attributed to AI can exhibit highly non-linear patterns, heavily influenced by the rate of adoption [13, 31], akin to the delayed effects observed with personal computers on labor productivity growth. While personal computers were invented in 1981, their impact on productivity only became significant in the late 1990s [22].



(a) Mean of the cluster (eq. (2))



(b) Mean of the cluster weighted by population (eq. (3))

FIGURE 2. **Mean efficiency for different clusters of countries over time, without (solid lines) and with (dashed lines) human energy consumption.** Advanced economies (blue): Australia, France, Germany, Italy, Japan, UK, Canada and the United States of America; Developing and Emerging economies (red): China, India, Brazil, South Africa, Iran, United Arab Emirate, Indonesia; Underdeveloped economies (orange): Pakistan, Ghana, Ethiopia, Nigeria, Kenya, Sudan, Eritrea, Niger, Zimbabwe, Senegal.

According to [22], AI will boost GDP by increasing productivity directly by increasing labor quality and indirectly by increasing labor automation and, thus, through worker re-employment in other sectors. AI will impact different sectors differently [22]. Nevertheless, the predictive analysis generally do not take into account in their estimation the potential of AI creating new sectors. On the other hand, among the several limitations of such predictions, survey answers depend on the knowledge and perceptions of respondents and the sample of customers of the business consulting firms may be biased towards early movers, thus overestimating the impact of AI [15, 22, 30, 31].

Importantly, the studies predict a gap between developed and developing countries in terms of AI-driven growth and labour productivity [30], highlighting how AI boosts mainly the economies of developed countries. Indeed, adoption in developed countries is enforced by the need to increase productivity. As wages are high, there is an incentive to substitute a human workforce. Nevertheless, countries like China established national strategies to become global leaders in the field [20]. AI may also widen the gaps between companies (gap between front-runners on one side and slow adopters and non-adopters on the other) and workers (ones with digital skills and ones doing repetitive labors) [30]. PWC report [37] predicts a boost to the GDP due to AI by 2030 of (% of the current GDP): 26.1% for China, 14.5% for North America, $9.9\%, 11.5\%,$ and 10.4% respectively for Northern Europe, Southern Europe and developed Asia, 5.4% for Latin America, and 5.6% for the rest of the world.

The AI revolution is not in its infancy, but the majority of the economic impact is yet to come (step-change improvements in computing power and capacity, explosion of data, progress in algorithms). Indeed, after the advent of Large Language Models (e.g., ChatGPT) and in general generative AI, the estimations of AI's impact on GDP and productivity have been revised to a further addition of 0.1-0.6 percentage point to the annual growth of productivity from 2023 to 2040, according to the McKinsey Global Institute [15].

5. The energetic impact of AI

Artificial intelligence (AI) is poised to revolutionize various domains, rivaling the impact of the internet's emergence. However, this breakthrough in AI comes with a significant drawback: the substantial energy consumption and associated carbon footprint, for which there is an increasing concern (see [2]). For instance, research by the University of Washington [32] and others [19] has shown that AI models like OpenAI's ChatGPT can consume enormous amounts of energy, equivalent to that used by tens of thousands of households.

These AI models, such as ChatGPT, rely on extensive computational resources, comprising large networks of processing units housed in data centers. Unlike conventional cloud computing workloads, which are less computationally intensive, AI models require massive amounts of computation during training and inference phases. This computing demand necessitates data center infrastructure, leading to substantial electricity consumption.

Training a single large language model, like ChatGPT-3, can consume up to 10 gigawatt-hours (GWh) of power, equivalent to the yearly electricity consumption of over 1,000 U.S. households [19]. Moreover, a significant portion of AI-related energy consumption stems from inference, with Google reporting that 60% of energy usage from 2019 to 2021 was during the inference phase. The training phase for ChatGPT uses approximately 1,287 MWh in total, and 564 MWh per day for its inference phase (1 MWh = energy provided by an electric power of 1 Watt for 1 hour). Other models of generative AI have different energetic impact than ChatGPT, which nowadays has the largest market.

Today there are hundreds of millions of daily queries on ChatGPT, Google's Brad, Bloom and others [6]. This many queries can cost around 1 GWh each day, which is the equivalent of the daily energy consumption for about 33,000 U.S. households. Alphabet's chairman indicated in February 2023 that interacting with an LLM could "likely cost 10 times more than a standard keyword search (see Figure 1 of [19] for data on energy per query for Google without AI, ChatGPT, Bloom and estimations for Google search with AI).

Despite the increasing energy consumption driven by AI, efforts are underway to mitigate its environmental impact. Tech companies, such as Google, Microsoft, and Amazon, are striving to achieve sustainability goals, including carbon neutrality and reliance on renewable energy sources [4, 3, 1, 35, 8].

Arijit Sengupta, CEO of Aible, an enterprise AI solution company, warns that AI adoption is only at 1% of its potential, highlighting the looming energy crisis if corrective measures are not implemented [32]. Suggestions include optimizing AI models and machines to minimize carbon footprint and incorporating emissions considerations into machine learning papers to incentivize environmental responsibility [36]. In any case, the rapid adoption and development of AI models underscore the urgent need for energy-efficient solutions to prevent an impending energy crisis.

6. Conclusions and perspectives

In this work, we provide a new perspective on the potential impacts of the AI revolution, combining economic growth and environmental sustainability through the defined measure of *economic efficiency of the energy*. The latter measures the income generated by a unit of energy used. We are interested in its historical and recent trends; specifically, we investigate the behaviour of the efficiency for different clusters of countries divided according to their degree of economic development. We find that the advanced economies have monotonically increased their aggregate efficiency in the last 30 years (see Figure 2) and they are currently more efficient than developing economies. Nevertheless, the economies that generate more income for a unit of energy are the ones of underdeveloped countries. Furthermore, by interpreting historical data during the first industrial revolution in England and Wales and in Italy [29], we deduce that at the start of the revolution the efficiency drastically lowers and it starts growing only when the revolution is more mature.

This is very much of interest if we notice that the AI revolution, like the first industrial revolution guided by heat/steam engines, is *pre-scientific*, in the sense that the technological development arrives before a deep scientific understanding. For the first industrial revolution the building of the steam engine came decades before the discovery of the second law of thermodynamics. For the AI revolution, while large language models are already at work, the scientific community is currently deeply involved in understanding the new thermodynamic of learning [28]. A different path has been followed by other industrial revolutions where technology has followed science. For example, the second industrial revolution guided by electricity in the late 19th century is post-scientific: the technologies developed at the time are applications of the consolidated Maxwell's theory of electromagnetism. Another example of a post-scientific revolution is the one based on quantum mechanics which lead to the construction of micro-electronic devices, the building blocks of modern computer science.

This would lead to the diffusion of suboptimal technologies, even from an energy perspective. Thus, if the analogy to the first industrial revolution holds also in terms of the economic efficiency of the energy (the AI is extremely energy-consuming, see section 5), we may face a period of unsustainable growth when the AI adoption is profitable at any energetic cost, the energetic impact is disregarded, and the efficiency lowers.

However, the good news is *(a)* that AI can help in optimizing industrial processes and economic and societal organization, and *(b)* that nowadays there is a strong pressure from the public opinion towards a more sustainable economy, especially in developed countries. Those countries will experience the largest AI-driven boosts (see section 4) and are also the ones with the largest influence on global efficiency. Will it be enough to keep or even improve the current positive trend of efficiency in every stage of the actual or upcoming AI era? Future data analysis of efficiency trends, when AI adoption becomes significant, will provide valuable insights to evaluate the direction in which we are heading.

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Appendix A. Supplementary figures

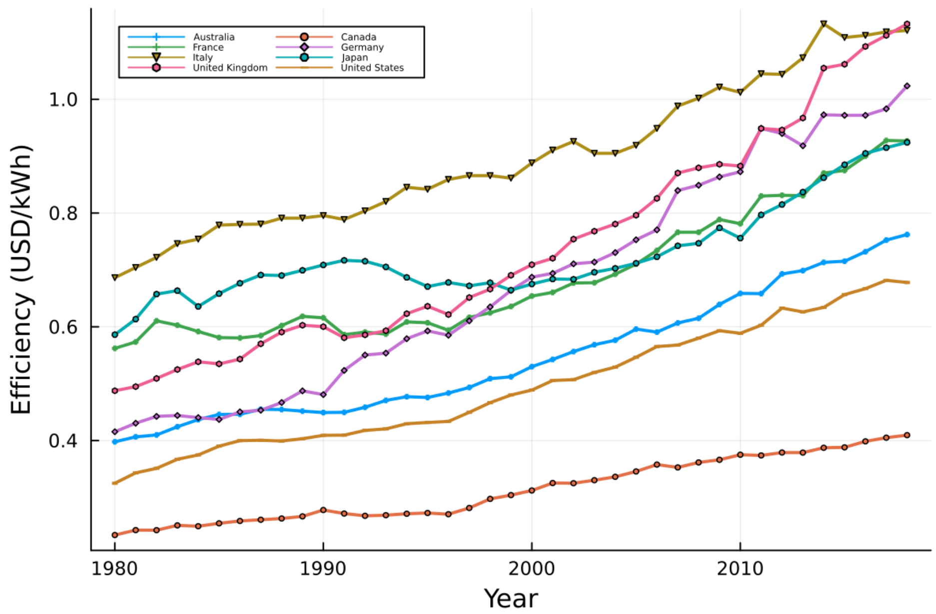

Figure 3. **Efficiency trends of advanced economies.**

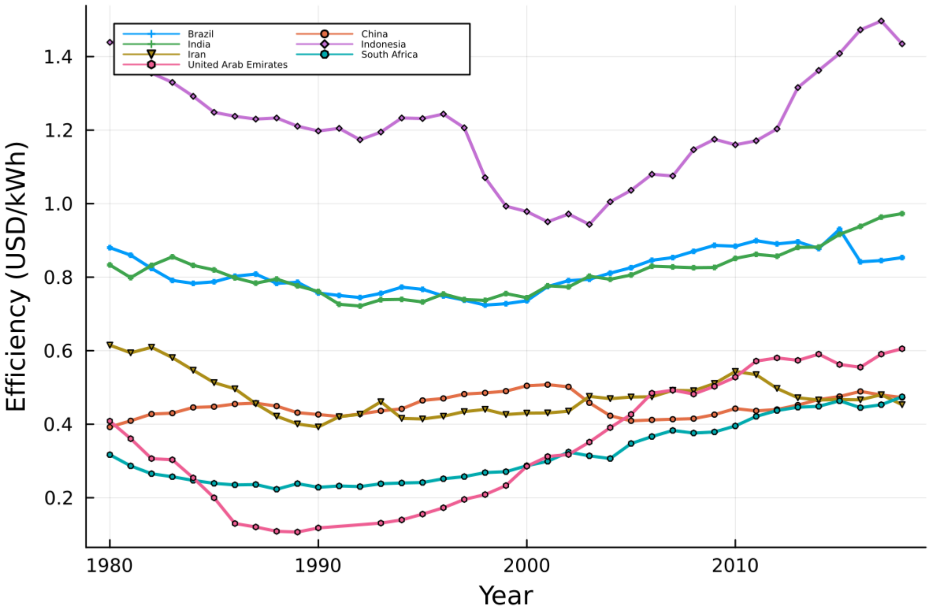

FIGURE 4. **Efficiency trends of developing economies.**

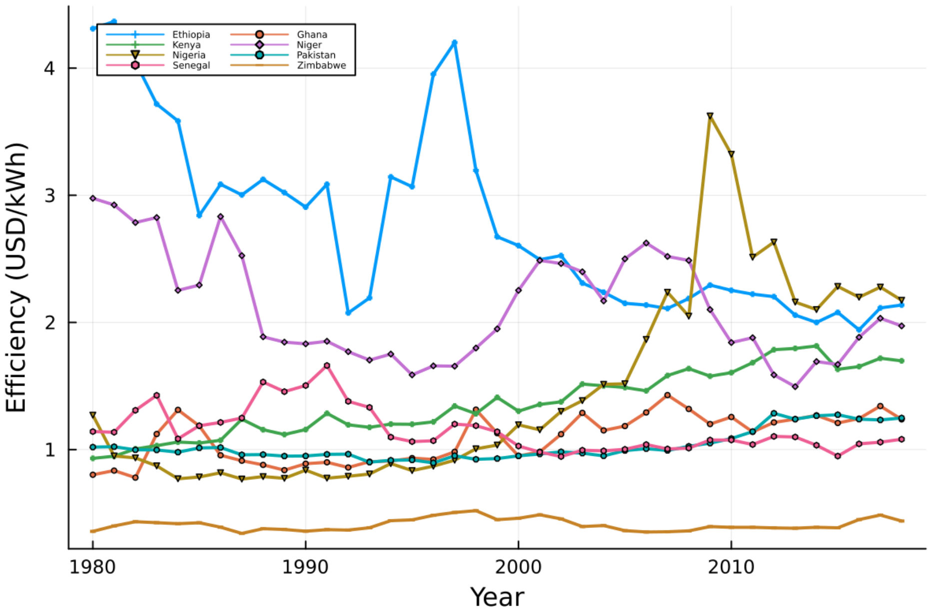

FIGURE 5. **Efficiency trends of underdeveloped economies.**

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