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Efficiency of Farms producing Sustainable Energy in Italy with DEA

Supervisor
Ch. Prof. Maria Bruna Zolin

Assistant supervisor
Ch. Prof. Antonella Basso

Graduand

Andrea Pistolato

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INTRODUCTION

The objective of this thesis is to understand whether **farms that produce renewable energy** are significantly **more economically efficient** than farms that do not produce renewable energy.

The reasons behind the research question are the **growing need for renewable energy** to respond to the problem of **pollution** and the resulting **global warming** on the one hand and the **energy price crisis** that erupted in Italy and beyond during 2022 on the other.

The results of this study are intended to pose as, possibly, a tool for Italian and European policies in the area of **agricultural support** on the one hand, and as a tool for farms to support, possibly, the argument that **producing renewable energy improves the overall efficiency of the farm's economic activity**. For example, by reducing energy costs or by providing a complementary cash flow from the sale of surplus energy.

This paper then begins by defining **energy as an economic good**, dissecting the energy market in its components: demand, supply and price.

As is well known, most energy is produced from **fossil fuels**, an energy source based on the combustion of organic substances that have undergone a transformation lasting millions of years. These fossil fuels bring with them **three main issues**: **pollution** from combustion as a negative externality, **scarcity of resources** that will run out in a relatively short time, and finally **geopolitical issues** related to the location of the raw material.

At the same time, the technological progress requires a great deal of energy that must necessarily be satisfied, and the price to be paid for this, in the event of a serious failure of demand, would be the socio-economic collapse of modern society.

So the imperative is to **provide**, on the production side, **substitutes for fossil fuels** that can meet demand while avoiding the unpleasant drawbacks of fossil fuels. This is **energy from renewable sources**. At the same time, it is necessary to limit energy waste and become more efficient in order to make the most of the energy produced.

The process of solving the above-mentioned problems is called **ecological transition** and is one of the priorities that states should pursue. Italy is a country that has a negative **'ecological balance'**, meaning that it produces more pollution than it can absorb in its own territory.

This is where **farms** get involved. As a first thought, it may seem strange that farms produce energy; in fact, they are normally associated with other types of production, related to the biological cycle of animal and plant life.

However, farms have two advantages that can be exploited: **open spaces**, generally large and exposed to the sun, and **biological production waste**, both animal and vegetable. Photovoltaic panels or even wind turbines can be installed in open spaces if the space is suitable. Production waste, on the other hand, can be treated to obtain clean energy, such as biogas or simply heat from combustion.

The energy produced by farms can therefore serve two main purposes: **energy self-sufficiency** and the **sale of energy** to providers as a business.

At this point, only one piece is missing to answer the fundamental question expressed at the beginning: **how can the economic efficiency of several farms be compared?**

Economic efficiency is the condition in which, with the available tools, the desired level of achievement cannot be improved. Economic efficiency is when the output values of the process cannot be increased by using or allocating the available inputs differently, i.e. when the difference between the gross benefits and the costs incurred is maximum (Franzini, 2012).

It must be emphasized that this definition refers to a concept of absolute efficiency, whereas for the purposes of comparison, a comparative **tool of relative efficiency** is more useful.

For this purpose, a methodology called **Data Envelopment Analysis (DEA**) was used, which associates an efficiency score between 0 and 1, where 1 means relative efficiency, with each unit considered in a population. Farms are then **compared according to their relative efficiency score**.

This methodology has **three main characteristics**: it is a **non-parametric method**, i.e. it does not need the a priori specification of a production function; it **handles multi-input and multi-output**, as companies often use different inputs to produce different outputs; finally, it **relies on the best performers** in the population to set the efficiency bar, thus, the score reflects relative and not necessarily absolute efficiency.

The study is based on **over 10,000 Italian companies** from an Italian database called RICA, which belongs to the Farm Accountancy Data Network, which is a European institution that monitors companies from a statistical economic perspective. This database contains, for each company, over a hundred quantitative and qualitative variables.

The **same input and output variables** were chosen for all companies, which, when put together in the DEA model, provided each company with an efficiency score. Then the companies were divided into those producing and those not producing renewable energy and the scores were compared.

Chapter 1 describes the **energy market**, starting from defining energy as a commodity and then it shows how does this market work in terms of supply, demand and price.

Chapter 2 summarizes the **three main issues** that come along with the **fossil fuels**: environmental issues, scarcity of resources and geopolitical issues.

Chapter 3 looks at the **Italian ecological situation** and presents the state of art of the **ecological transition**, in terms of policies. Then it highlights the link between agriculture and sustainability that Italian policies are pursuing.

Chapter 4 introduces how **farms can deal with sustainability** and then it briefly describes the energy production of two renewable sources that will be significant in the following analysis: solar and biogas. Finally it presents four works from the existing literature.

Chapter 5 describes the DEA methodology and its formal characterization. In particular, it presents the CCR and BCC models.

Chapter 6, finally, shows the analysis that has been done. It starts from data selection, followed by the model specifications and then it presents and discusses the results.

1. THE ENERGY MARKET

Section 1.1 introduces the topic of the energy market by discussing **energy as an economic good**. **Sections 1,2 and 1.3** show the **different energy sources** that can theoretically and limited to their own characteristics be **used alternatively to produce energy**. **Sections 1.4 through 1.8 describe the energy market**, starting with the context and continuing with demand, supply, equilibrium, and prices.

1.1. Preliminary Energy Concepts

What is energy?

Energy, in physics, is defined as the capacity for doing work. Moving an object is work, heating it is work. Work is defined as the transfer of energy to an object from another or viceversa. Work and energy are two concepts that are strictly connected and they define each other themselves.

For example, a man lifting a chest from the floor is putting some work that requires some quantity of energy: without the required energy the chest would not move.

Energy may exist in various forms: potential, kinetic, thermal, electrical, chemical, nuclear or others. All these forms of energy are associated with motion: any given body has kinetic energy if it is in motion. A tensioned device such as a bow contains the potential energy for creating motion. A heated body contains moving particles that determine its heat.

First principle of thermodynamics

Energy can be neither created nor destroyed but only converted from one form to another. This principle is known as the **conservation of energy or the first law of thermodynamics**. In the previous example, lifting that chest has required some energy from the man that has not been exhausted but instead has been converted into potential energy and heat.

In the International System of Units (SI), energy is measured in **joules**. A joule is defined to be equal to the kinetic energy of a kilogram mass moving at the speed of one meter per second. To give a practical example, a joule is the amount of energy needed to lift a medium tomato up one meter or, thanks to the first principle of thermodynamics, is the energy released when dropping that same tomato from a height of one meter.

Energy is An Economic Good

Economically speaking, energy is one of the most important **good** in the human society for its uncountable uses: movement, heating, lighting. Without energy vehicles wouldn't move, food couldn't be cooked, streets would be completely dark at night. Society must exploit energy for its own conservation.

How is it possible to "produce" energy?

The law of conservation of energy implies that **energy cannot be produced in a physical sense**. Instead, **in an economic sense, energy can be produced** and that does not break physics rules. Energy, as a good, is the realization of the effects from the energy transfer: the lightbulb that lights up, the vehicle that moves along the road.

Energy production is therefore a conversion process: from an "useless" form to a form that can be useful to mankind. Energy development is then obtaining sources of energy from natural resources. These natural energy resources may be classified as **primary resources**, when the resource is disposable and can be used in substantially its original form, or as **secondary resources**, when the energy source is not disposable and must be converted into a more conveniently usable form.

1.2. Non-Renewable Sources

Another classification is between **renewable and non-renewable source**. The former is produced by ongoing processes that can sustain virtually indefinite human exploitation and that are naturally replenished on a human timescale such as sunlight , wind, rain, tides, waves and geothermal heat, while the latter is limited, and in most cases, significantly depleted by human use. Nuclear power is a controversial one, for the purpose of this thesis it will be taken off from renewables discussion.

Hereafter there are listed the most common energy sources divided into fossil fuels, nuclear power and renewable sources.

Fossil Fuels

The most widely known non-renewable energy source is fossil fuel which implies burning coal or hydrocarbon fuels, which are the rests of the decomposition of living being. There are three main kinds of fossil fuels: coal, petroleum, and natural gas. Fossil fuels are part of the carbon cycle and allow the “biological energy” (that came from nutrition and solar power) stored in the fuel, in form of carbon chains, to be released through the burning process.

Coal

Coal is mostly carbon with variable amounts of other elements, that is formed when dead plant matter decays and is converted into coal by the heat and pressure of deep burial over millions of years. The energy density of coal is roughly 24 megajoules per kilogram.

Petroleum

Petroleum, also known as crude oil, or just oil, is a naturally occurring yellowish-black liquid mixture of hydrocarbons and other elements. Petroleum is formed when large quantities of dead organisms are buried underneath sedimentary rock and subjected to millions of years of heat and pressure. The energy density of oil is about 45 megajoules per kilogram.

Natural Gas

Natural gas is a naturally occurring mixture of gaseous hydrocarbons mainly consisting of methane. Natural gas is formed when layers of organic matter decompose underground in anaerobic conditions and are subjected to heat and pressure over millions of years. The energy density of natural gas is roughly 83 megajoules per kilogram.

Nuclear Power

Nuclear power is the exploit of nuclear fission to produce heat and electricity. Fission of uranium produces nearly all economically significant nuclear power. There is an ongoing debate about nuclear power: the WNA (World Nuclear Association), the IAEA (International Atomic Energy Association) and ENA (Environmentalists for Nuclear Energy) claim that nuclear power is a safe, sustainable energy source; while opponents contend that nuclear power introduces threats to people and the environment due to the radioactivity of nuclear waste.

1.3. Renewable Sources

Hydroelectric Power

Hydroelectricity is electric power generated by waterpower; the force coming from falling or flowing water. Remarkable is the energy storing part: lifting volumes of water during the night stores energy, in potential form, that can be exploited during the day whenever it is more convenient.

Wind power

Wind power, or Eolic, harnesses the power of the wind to propel the wind turbines that generates electricity.

Solar Energy

Solar energy is the energy coming directly from the sun in the form of radiant light and heat that are exploited to produce electricity (photovoltaic) and solar thermal energy that stores energy through a heating process.

Biofuels

A biofuel is a fuel that differs from the fossil ones because it contains energy from geologically recent carbon fixation that is produced from living organisms. These fuels are made by a biomass conversion (biomass refers to recently living organisms, most often plants or plant-derived materials that are cultivated for generating energy).

This biomass can be converted to convenient energy in three diverse ways: thermal conversion, chemical conversion, and biochemical conversion. The resulting biofuel can result in solid, liquid, or gas form. The most common biofuels are bioethanol and biodiesel.

Geothermal

Thermal energy is the energy that generically determines the temperature of matter. Geothermal energy is thus the thermal energy generated and stored in the Earth. The geothermal gradient, which is defined as the difference in temperature between the core of the planet and its surface, drives a continuous flows of thermal energy, in the form of heat, from the nucleus to the crust.

Marine power

Marine power refers to the energy carried by the movement of water in the oceans that creates a large store of kinetic energy. This energy can be exploited to generate electricity.

Recovery and reuse

Alongside with the energy production there is energy consumption: some of it is necessary for living and cannot be dismissed, but some other is not necessary and generates inefficiency. This issue can be fixed approaching more sustainable consumption that goes from avoiding squandering to recovery and reuse of energy that would otherwise been wasted. Energy awareness, conservation and efficiency measures reduce then the demand for energy development.

1.4. Energy Market Characterization

Energy sector is one of the most important worldwide: according to the European Commission nearly 58 million people worldwide were employed in the energy sector in 2018.

About half of these jobs are related to the fossil fuel industries, while employment in the renewable energy sector accounts for 11 million total jobs in 2018. Forecasting suggests that the employment in the broad energy sector is expected to be in the range of 87 to 100 million total jobs by 2050.

Specifically, European energy sector had 7.5 million total jobs in 2018, of which 1.5 million are related to the renewables sector.

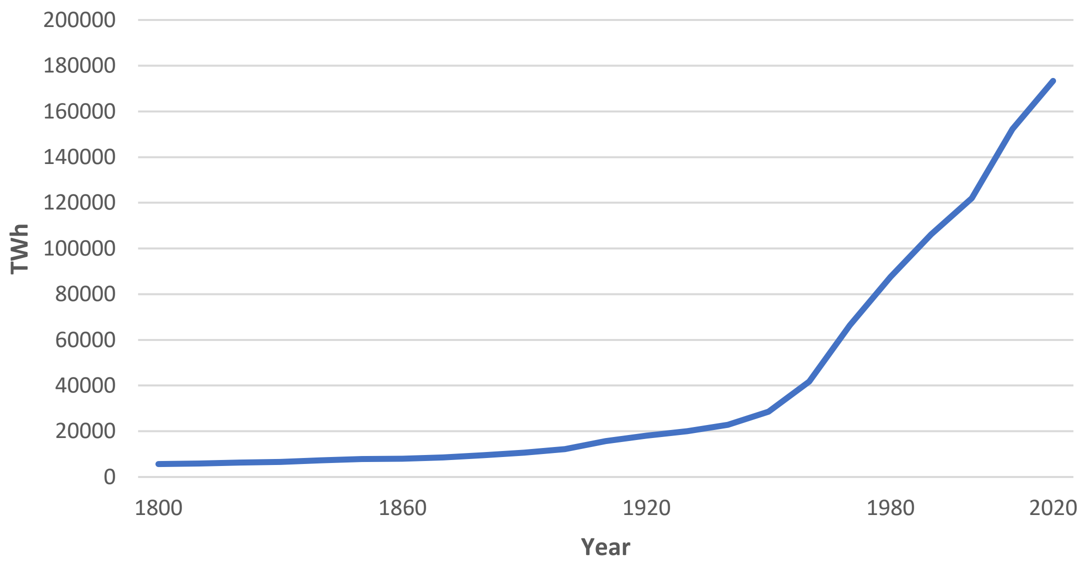
Despite the growing share of renewable energy, a downward trend in occupation took place from 2011 onwards, turning to stagnation in the following years. The reasons behind this uncertain development include the aftermath of the 2008 financial crisis, the relocation of some manufacturing capacities outside of Europe due to their lower costs, and changes in subsidy schemes for renewables within the EU.

The structure of energy markets has changed dramatically over the past two centuries: with technological transitions as new fuels have emerged and a vertiginous growth in global production and consumption. Although the demand for energy has long paired economic growth, its consumption accelerated drastically after WWII.

Fig. 1.4.1 shows the growth of the global energy market, from the First Industrial Revolution to our days, in terms of total energy supply. Table 1.1 reports the annual energy production by source during the years that are multiples of 10, during the aforementioned period.

In both Fig. 1.4.1 and Table 1.4.1 the unit of measurement is TWh, that stands for Terawatt per hour, which is equal to the energy that gives a power of 10^{12} Watt for one hour.

Fig. 1.4.1: Energy Market Growth (1800 – 2020)



Source: Our World in Data, 2022

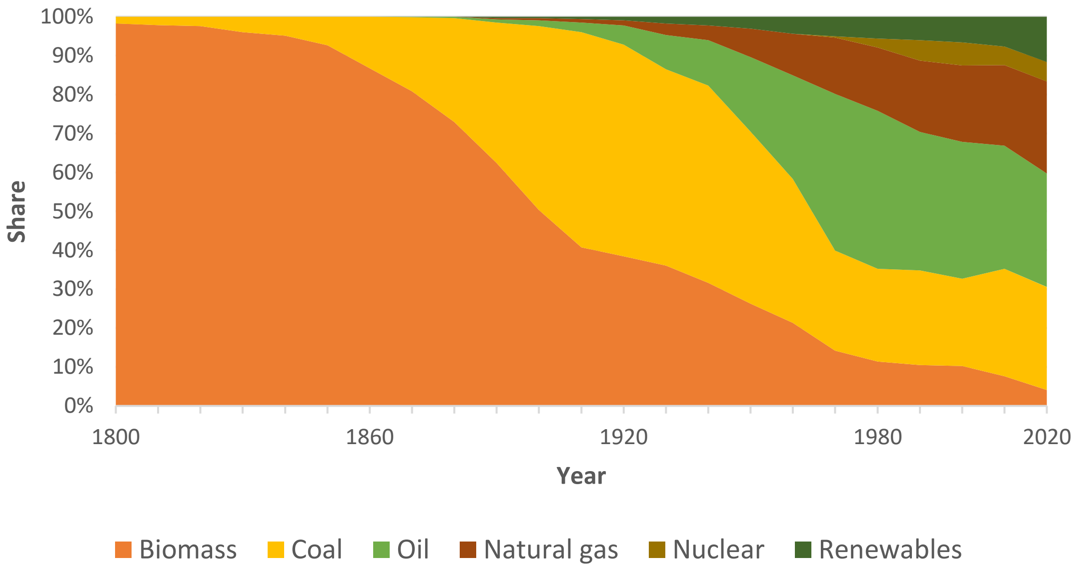
Table 1.4.1: Global Energy Production by Source (1800 – 2020)

Year	Coal	Oil	Natural gas	Nuclear	Biomass	Renewables
1800	97	0	0	0	5,556	0
1810	128	0	0	0	5,833	0
1820	153	0	0	0	6,111	0
1830	264	0	0	0	6,389	0
1840	356	0	0	0	6,944	0
1850	569	0	0	0	7,222	0
1860	1,061	0	0	0	6,944	0
1870	1,642	6	0	0	6,944	0
1880	2,542	33	0	0	6,944	0
1890	3,856	89	33	0	6,667	37
1900	5,728	181	64	0	6,111	44
1910	8,656	397	142	0	6,389	88
1920	9,833	889	233	0	6,944	168
1930	10,125	1,756	603	0	7,222	344
1940	11,586	2,653	875	0	7,222	504
1950	12,603	5,444	2,092	0	7,500	877
1960	15,442	11,097	4,472	0	8,889	1,813
1970	17,059	26,708	9,614	219	9,444	3,334
1980	20,858	35,577	14,239	1,978	10,000	4,947
1990	25,895	37,691	19,483	5,557	11,111	6,424
2000	27,417	42,897	24,000	7,169	12,500	8,090
2010	41,997	48,087	31,606	7,219	11,667	11,673
2020	43,849	53,620	39,292	6,923	11,111	18,545

Source: Our World in Data, 2022

In the following Fig. 1.4.2 is reported the market share of each sources throughout the period, showing how the production sources shifted from biomasses to coal and oil at the beginning of the 20th Century. In Table 1.4.2 are reported the percentages of each source for each considered year.

Figure 1.4.2: Energy Sources Shares (1800 – 2020)



Source: Our World in Data, 2022

Table 1.4.2: Energy Sources Shares (1800 – 2020)

Year	Coal	Oil	Natural gas	Nuclear	Biomass	Renewables
1800	1.7%	0	0	0	98.3%	0
1810	2.1%	0	0	0	97.9%	0
1820	2.4%	0	0	0	97.6%	0
1830	3.9%	0	0	0	96.1%	0
1840	4.8%	0	0	0	95.1%	0
1850	7.3%	0	0	0	92.6%	0
1860	13.2%	0	0	0	86.7%	0
1870	19.1%	0	0	0	80.8%	0
1880	26.7%	0.3%	0	0	72.9%	0
1890	36%	0.8%	0.3%	0	62.4%	0.3%
1900	47.2%	1.4%	0.5%	0	50.3%	0.3%
1910	55.2%	2.5%	0.9%	0	40.7%	0.5%
1920	54.4%	4.9%	1.2%	0	38.4%	0.9%
1930	50.4%	8.7%	3%	0	36.0%	1.7%
1940	50.7%	11.6%	3.8%	0	31.6%	2.2%

1950	44.1%	19%	7.3%	0	26.3%	3%
1960	37%	26.6%	10.7%	0	21.3%	4.3%
1970	25.6%	40.2%	14.4%	0.3%	14.2%	5%
1980	23.8%	40.6%	16.2%	2.2%	11.4%	5.6%
1990	24.3%	35.5%	18.3%	5.2%	10.4%	6%
2000	22.4%	35.1%	19.6%	5.8%	10.2%	6.6%
2010	27.5%	31.5%	20.7%	4.7%	7.6%	7.6%
2020	25.2%	30.9%	22.6%	3.9%	6.4%	10.6%

Source: Our World in Data, 2022

At the start of the 20th century, coal was the dominant fuel, but by 1920 oil was already increasing its market share: global crude oil production increased from 1 million barrels per day (mb/d) in 1920 to nearly 100 mb/d in 2019. Crude oil's share of global energy rose from less than 5% in 1920 to a peak of 43% in 1973, decreasing to 29% in 2019.

Consumption of natural gas began to rise in the 1900s, but initially at a much slower pace than crude oil. However, the increasing use of natural gas in electricity generation, in heating and cooking, resulted in natural gas share rising from 1% of global energy consumption in 1920 to 22% in 2019.

Since the demand for energy continuously expanded it is the case that new sources of energy have not replaced existing sources, even if they took a greater market share. Consumption of coal has risen in every decade, even though its share of total energy demand has fallen since 1920 in which its share was 54% to 2019 with a 26% share. Coal is mainly used for electricity generation, but also for smelting iron ore for steel production.

Among the non-fossil fuel sources of energy, nuclear power emerged as an important source of electricity in the 1970s, peaking in 2000 at around 6% of total energy consumption.

The share of broad renewable energy (comprehensive of hydro-electric, solar, wind, geothermal, wave, and tidal) gradually increased over the 20th century before accelerating in the 2010s, reaching 10% of energy consumption in 2019.

The economic system needs to have a continuous and generous access to energy sources, otherwise, without that essential input, the whole system would collapse. Generally speaking, countries are the major players in the energy sector, since they provide the infrastructure that permits the energy circulation. They generally control pipelines, cables, even plants and so on.

Countries have essentially two ways of collecting energy: by directly producing it, controlling internally each segment of the production chain, or by purchasing it from other countries.

The following sections treat the topics of energy production and consumption, showing the evolution over the 1990 – 2020 period of the energy supply and demand, separating the different energy sources, respectively for World, EU and Italy.

1.5. Energy Production

In this section, three pairs of graphs and tables will be shown: the first pair refers to world data, the second to European data and the last to Italian data. The line chart shows the development of energy production, divided by resource, from 1990 until 2019, while the corresponding table shows the data from which the graph was constructed.

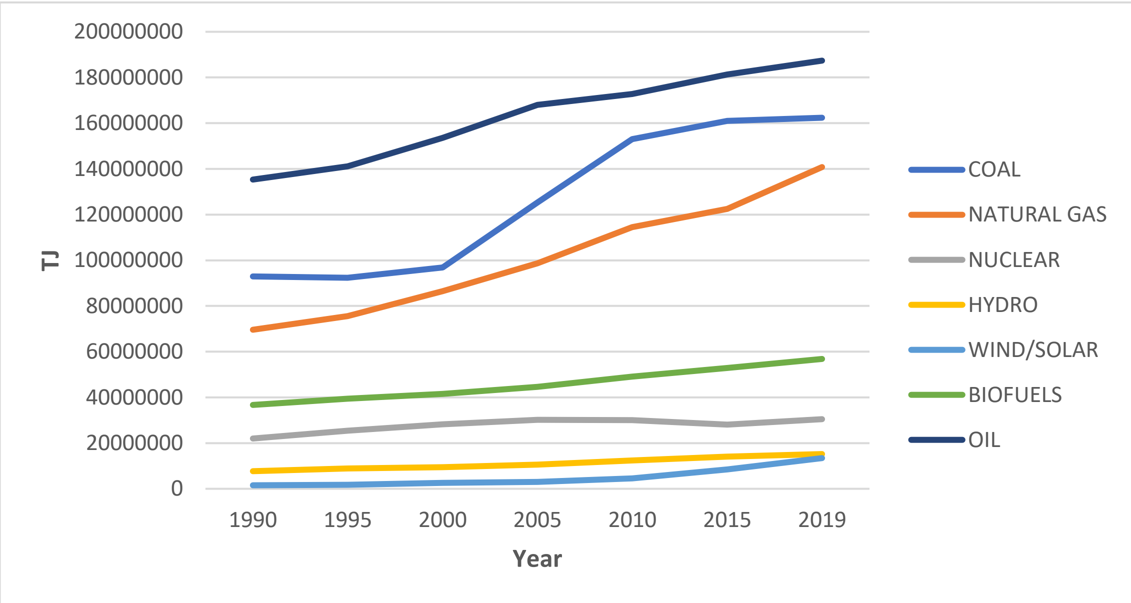
Global Energy Production

As the following figure 1.3 and table 1.3 show, energy production worldwide, in Europe and specifically in Italy, has been increasing over the years. The worldwide broad energy production in 1990 was 366 million TJ and it nearly doubled to 606 million TJ in 2019 (where TJ stands for *Terajoules*: the prefix *tera-* denotes a factor of a trillion, which means that there are 10^{12} joules in a *Terajoule*).

The choice of normalizing the unit of measurement of data in terajoule, which is a multiple measure of joule, that is the unit of energy in the International System of Units (SI)., has been made for the purpose of comparing different energy sources that have different unit measures: oil is counted in barrels, coal in mass, in kilograms, bio or natural gas in liters and so on.

Looking at the different energy sources is it possible to note that each one of them increased worldwide since 1990, but at different paces: the three combined fossil fuels (Coal, Natural Gas and Oil) increased over the 1990-2019 period from 297 million TJ to 490 million TJ by 64.67% while the combined renewables (Hydro, Wind/Solar and Biofuels, excluding Nuclear) increased along the same period from 46 million TJ to 85 million TJ by 86.01%. Considering only Wind/Solar sources the production increased by a notable 775.18%.

Fig. 1.5.1: Energy Supply, by Source, World (1990 – 2019)



Source: IEA – Data & Statistics

Table 1.5.1: Energy Supply, by Source, World (1990 – 2019)

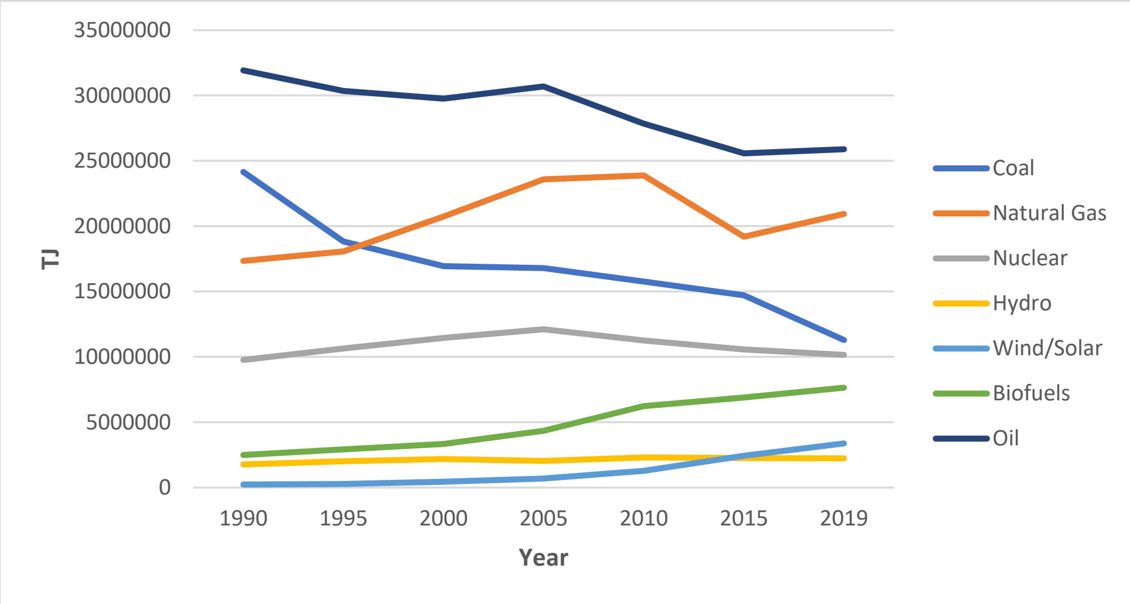
Year	Coal	Oil	Natural Gas	Nuclear	Biofuels	Hydro	Wind/ Solar
1990	92,962,604	135,326,568	69,597,508	22,002,473	36,688,520	7,703,880	1,533,085
1995	92,345,651	141,138,864	75,495,152	25,459,860	39,397,760	8,908,060	1,784,759
2000	96,876,327	153,594,988	86,550,367	28,280,459	41,490,083	9,406,153	2,529,177
2005	125,224,095	167,959,369	98,640,052	30,216,369	44,663,882	10,564,092	2,944,819
2010	152,992,480	172,740,070	114,447,753	30,091,065	49,123,321	12,414,905	4,616,284
2015	160,976,300	181,265,383	122,498,778	28,063,289	52,822,020	14,017,921	8,526,212
2019	162,375,732	187,364,800	140,784,380	30,461,171	56,813,210	15,194,639	13,417,236

Source: IEA – Data & Statistics 2022, measurement unit: TJ

European Energy Production

Looking at the European situation, instead, it is possible to see a different trend: fossil fuels sources are being progressively less produced within the Europe, in 1990 the aggregate production was 73 million TJ while in 2019 was 58 million TJ, stating a -20,84% total decrease; on the other hand, renewables has been boosted from a 4 million TJ production in 1990 to 13 million TJ in 2019 with a 194.59% increase.

Fig. 1.5.2: Energy Supply, by Source, EU (1990 – 2019)



Source: IEA – Data & Statistics 2022

Table 1.5.2: Energy Supply, by Source, EU (1990 – 2019)

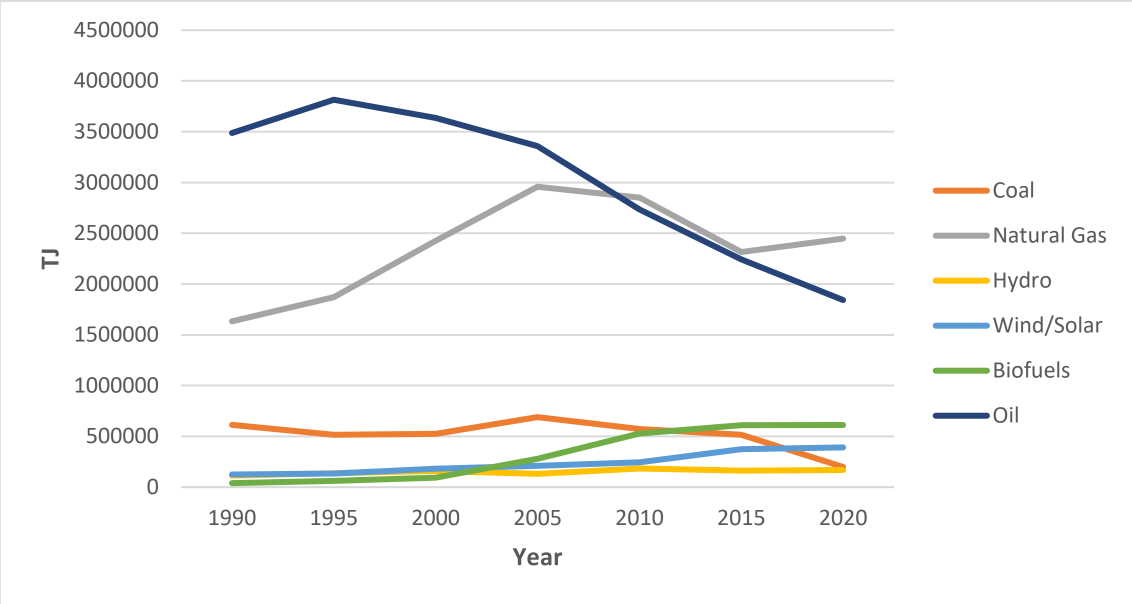
Year	Coal	Oil	Natural Gas	Nuclear	Hydro	Wind/Solar	Biofuels
1990	24,155,553	31,924,210	17,346,559	9,768,029	1,774,688	233,978	2,494,575
1995	18,834,809	30,353,204	18,063,280	10,654,667	2,006,501	269,667	2,919,827
2000	16,947,498	29,772,554	20,751,535	11,445,537	2,178,647	446,546	3,334,324
2005	16,793,044	30,690,604	23,587,524	12,114,495	2,036,969	696,431	4,354,915
2010	15,779,286	27,861,447	23,888,208	11,267,110	2,306,006	1,269,367	6,243,335
2015	14,705,949	25,576,068	19,194,880	10,564,594	2,266,540	2,438,786	6,895,024
2019	11,293,304	25,901,281	20,932,232	10,166,636	2,241,261	3,379,812	7,645,042

Source: IEA – Data & Statistics 2022, measurement unit: TJ

Italian Energy Production

In Italy fossil fuels broad production decreased from roughly 6 million TJ to roughly 5 million TJ by -21.70%. Although is remarkable that the natural gas supply increased by 49.94%. Renewables increased from 277,865 TJ to more than 1 million TJ by 321.50%. Biofuels themselves increased by an astonishing 1453.26%. Note that Italy does not produce nuclear energy and that is why it does not appear on the table.

Fig 1.5.3: Energy Supply, by Source, ITA (1990 – 2019)



Source: IEA – Data & Statistics 2022

Table 1.5.3: Energy Supply, by Source, ITA (1990 – 2019)

Year	Coal	Natural Gas	Hydro	Wind/Solar	Biofuels	Oil
1990	61,258	163,290	11,385	12,461	3,939	348,835
1995	51,407	186,950	13,601	13,298	6,097	381,462
2000	52,583	242,584	15,911	18,084	9,426	363,636
2005	68,952	295,802	12,984	21,029	27,865	335,981
2010	57,249	284,939	18,402	24,528	52,969	273,415
2015	51,495	231,536	16,393	37,298	61,101	224,229
2020	19,898	244,840	16,799	39,129	61,190	184,230

Source: IEA – Data & Statistics 2022, measurement unit: TJ

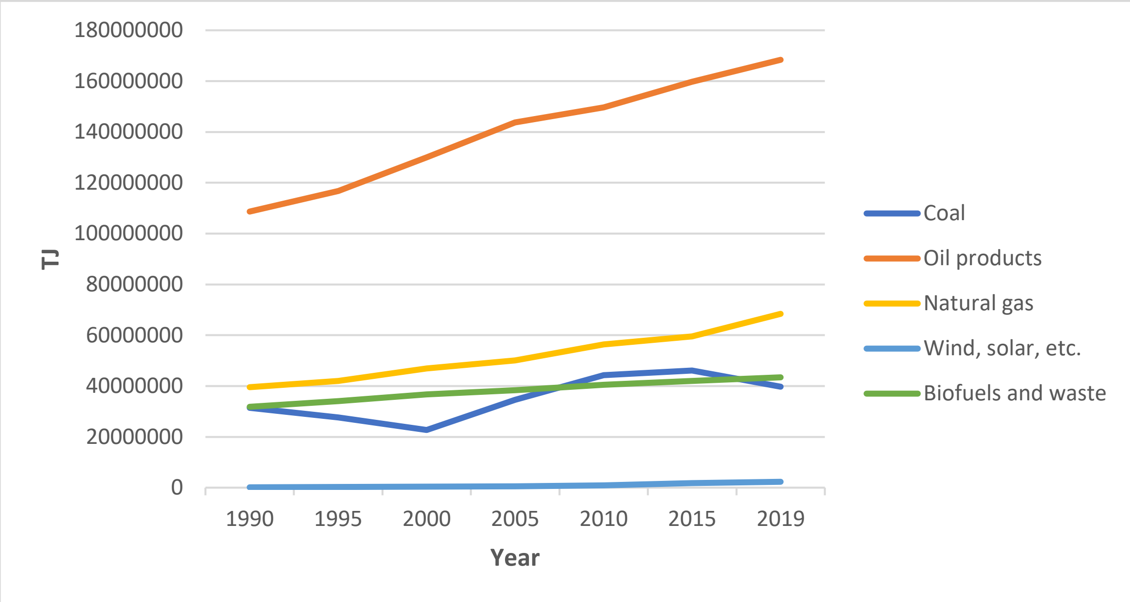
1.6. Energy Consumption

As in the previous section, this one will show three pairs of graphs and tables that refer to energy consumption at the global, European and Italian levels.

Global Energy Consumption

Worldwide demand for energy, in the 1990-2019 period has significantly risen from 261 million TJ to 418 million TJ with a percentage increase of 60.08%. In particular, fossil fuel consumption remained stable starting from 140 million TJ in 1990 and ending with 144 million TJ in 2019 with a slight growth of 3.06%, renewables resources instead grew 59.61% from 71 million TJ in 1990 to 114 million TJ in 2019; showing that the composition of the demand changed in favor of renewables share.

Fig. 1.6.1: Final Energy Consumption, by Source, World (1990 – 2019)



Source: IEA – Data & Statistics 2022

Table 1.6.1: Final Energy Consumption, by Source, World (1990 – 2019)

Year	Coal	Oil Products	Natural gas	Wind, solar, etc.	Biofuels and Waste
1990	31,470,482	108,656,537	39,543,757	143,516	31,824,701
1995	27,648,926	116,771,810	42,003,303	224,410	34,030,361
2000	22,689,352	129,979,163	46,864,239	361,948	36,680,293
2005	34,522,696	143,682,184	50,049,872	503,348	38,341,923

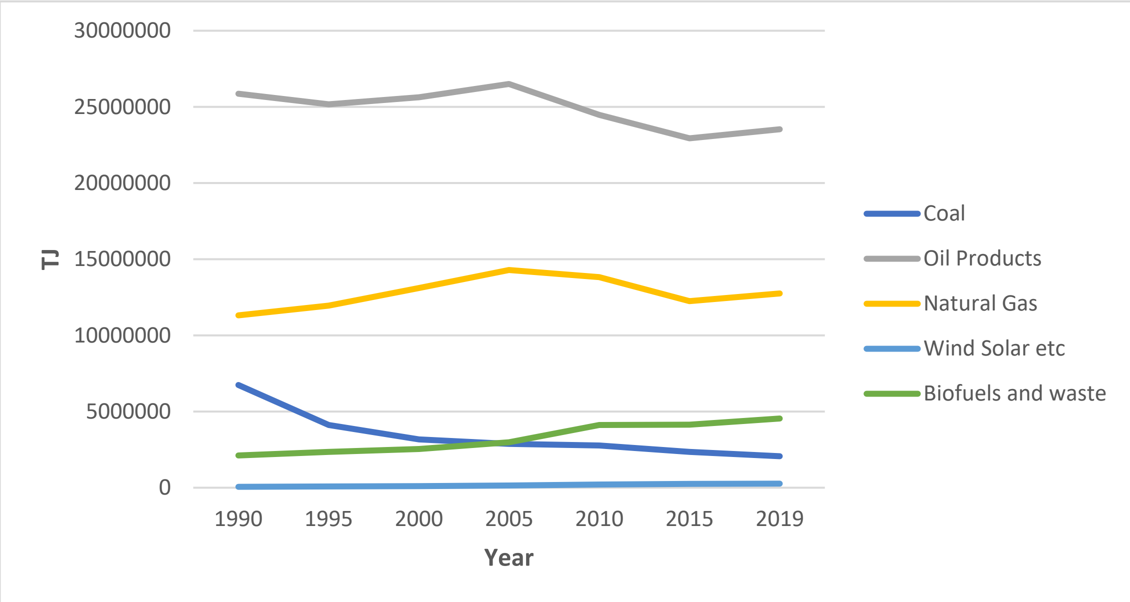
2010	44,257,171	149,660,971	56,341,398	895,700	40,536,083
2015	46,098,834	159,773,622	59,521,976	1,732,437	41,945,250
2019	39,786,218	168,375,005	68,404,947	2,318,093	43,414,906

Source: IEA – Data & Statistics 2022, measurement unit: TJ

European Energy Consumption

Total energy consumption rose dramatically in Europe over the period: from 261,096,296 TJ demanded in 1990, demands rose to 417 million TJ marking a 60.08% increase.

Fig. 1.6.1: Final Energy Consumption, by Source, EU (1990 – 2019)



Source: IEA – Data & Statistics 2022

Although worldwide fossil fuels consumption remained stable over the period, in Europe significantly rose from 180 million TJ in 1990 to 277 million TJ in 2019 by 53.87%. Renewables rose as well by 43.06%, from 32 million TJ in 1990 to 46 million TJ in 2019. The quota of fossil fuels consumption over the broad consumption was 68.69% in 1990 and decreased to 66.31% in 2019. The quota of renewables, instead, rose from 12.24% to 14.16%.

Table 1.6.2: Final Energy Consumption, by Source, EU (1990 – 2019)

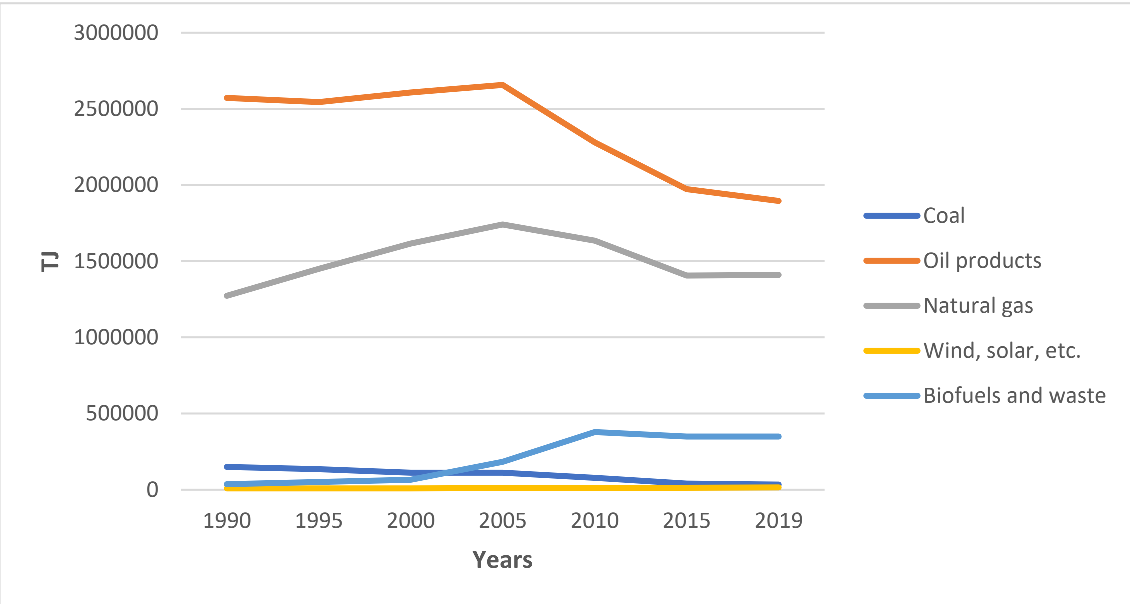
Year	Coal	Oil Products	Natural Gas	Wind, Solar, etc	Biofuels and Waste
1990	6,743,182	25,872,230	11,314,717	5,8131	2,118,140
1995	4,123,733	25,165,165	11,953,217	7,7697	2,352,370
2000	3,171,965	25,638,068	13,112,459	10,5426	2,543,426
2005	2,868,816	26,502,378	14,291,419	14,1156	2,985,110
2010	2,773,183	24,476,734	13,823,192	21,2527	4,121,543
2015	2,354,057	22,935,945	12,257,291	24,6351	4,138,594
2019	2,067,157	23,535,993	12,752,657	26,5876	4,541,949

Source: IEA – Data & Statistics 2022, measurement unit: TJ

Italian Energy Consumption

In Italy total consumption stayed stable over the period: with a 2.41% increase from 1990 to 2019. Fossil fuels consumption decreased from 4 million TJ in 1990 to 3,3 million in 2019 marking a -16.21% decrease. Demand for renewables on the other hand, rose significantly from 0,8 million TJ in 1990 to 1,4 million TJ in 2019 by 73.1%.

Fig 1.6.3: Final Energy Consumption, by Source, ITA (1990 – 2019)



Source: IEA – Data & Statistics 2022

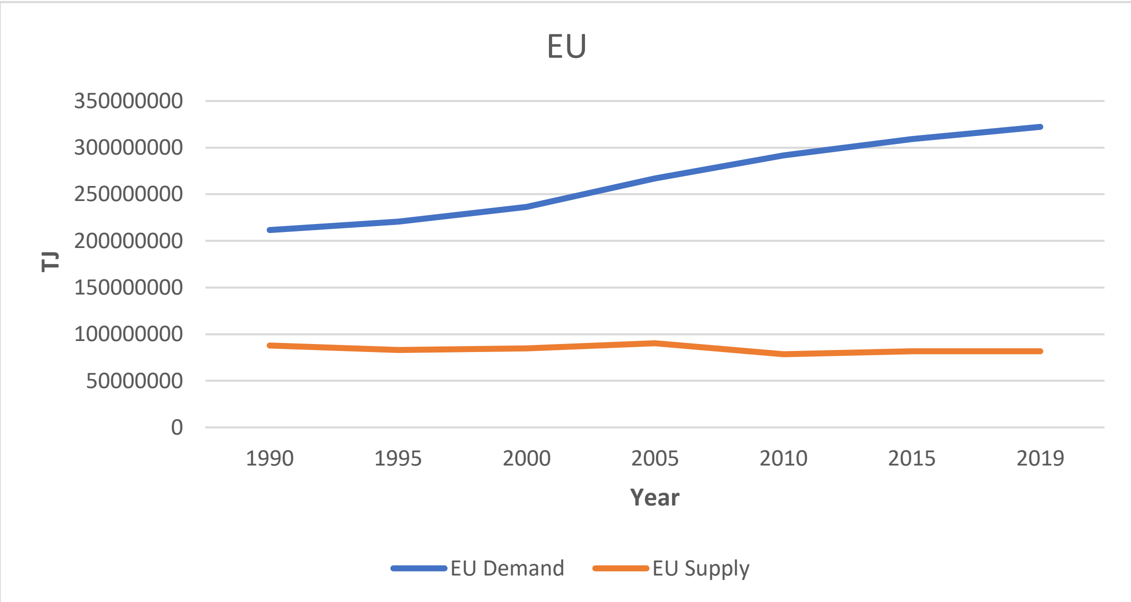
Table 1.6.3: Final Energy Consumption, by Source, ITA (1990 – 2019)

Year	Coal	Oil products	Natural gas	Wind, solar, etc.	Biofuels and Waste
1990	149,464	2,572,800	1,272,905	8,602	36,148
1995	133,691	2,544,434	1,449,389	9,209	51,291
2000	112,260	2,608,225	1,615,620	9,372	66,063
2005	112,339	2,657,032	1,740,996	10,060	182,761
2010	78,966	2,278,874	1,635,585	10,859	378,333
2015	39,634	1,973,578	1,404,937	12,731	348,727
2019	33,593	1,895,606	1,410,345	15,021	349,121

Source: IEA – Data & Statistics 2022, measurement unit: TJ

1.7. Supply and Demand

Figure 1.7.1: Aggregate Energy Supply and Demand, EU (1990 – 2019)



Source: IEA – Data & Statistics 2022

This section shows the trends, over the period from 1990 to 2019, of supply and demand, divided into Europe and Italy. The data are presented through three line charts and then shown in two tables. Both EU and Italy are not self-sufficient and in both cases the demand curve grew while the supply curve has generally flattered.

Table 1.7.1: Aggregate Energy Consumption

Year	**1990**	**1995**	**2000**	**2005**	**2010**	**2015**	**2019**
EU	**211,638,993**	**220,678,810**	**236,574,995**	**267,100,023**	**291,691,323**	**309,072,119**	**322,299,169**
Italy	**2,239,776**	**2,501,359**	**2,786,025**	**3,129,324**	**3,181,270**	**2,840,968**	**2,859,038**

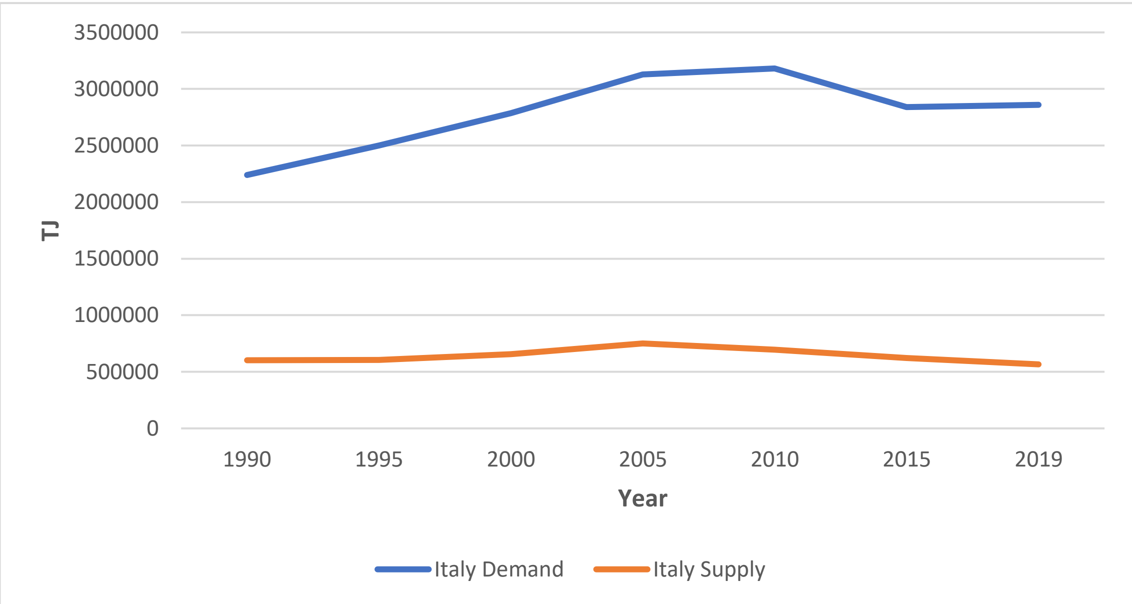
Source: IEA – Data & Statistics 2022, measurement unit: TJ

Table 1.7.2: Aggregate Energy Production (1990 – 2019)

Year	**1990**	**1995**	**2000**	**2005**	**2010**	**2015**	**2019**
EU	87,697,592	83,101,955	84,876,641	90,273,982	78,474,360	816,418,41	81,559,568
Italy	6,011,711	6,065,515	6,549,023	7,509,290	6,949,428	6,220,547	5,660,890

Source: IEA – Data & Statistics 2022, measurement unit: TJ

Figure 1.7.2: Aggregate Energy Supply and Demand, ITA (1990 – 2019)



Source: IEA – Data & Statistics 2022

1.8. Energy Prices

The last section discusses the prices that, together with supply and demand, define the energy market.

The prices for energy evolve over time depending on many different factors like the prices of inputs, market conditions, regulatory and policy-related costs, taxation as well as demand's needs and behavioral patterns.

The global energy sector strongly relies on bilateral and multilateral agreements between countries, that can vary a lot, depending on the geopolitical situation and often is hard to access the specifications of these pacts. Additionally, there is a secondary energy market which is financially regulated. For the above-mentioned reason, energy market prices considered in this paragraph are only the European ones.

Starting in 2014 and for every 2 year since, the European Commission publishes a report on energy prices and costs, which considers the latest trends for gas, electricity and oil prices, in Europe and internationally.

The 2020 report shows that wholesale prices rose up in recent years, before starting to fall in 2019 due to economic slowdown and exceeding supply. The prices then collapsed in 2020, due to the economic crisis and restrictions triggered by the COVID-19 pandemic.

The report also points out the high reliance on fossil fuel imports for EU and their related costs. In fact, the EU's energy net import/export balance reached in 2018 the negative value of -€331 billion, after three years of consecutive import rises.

Finally, the report shows that energy taxes is a crucial and stable source of revenues for EU governments, amounting to 4.6% of their total tax revenues in 2018.

Oil Prices

Oil prices are mainly determined by the biggest players in oil supply: OPEC, Russia and United States.

The Organization of Petroleum Exporting Countries (OPEC) consists of Algeria, Angola, Congo, Equatorial Guinea, Gabon, Iran, Iraq, Kuwait, Libya, Nigeria, Saudi Arabia, the United Arab Emirates and Venezuela. Founded in 1960, OPEC reports oil production by member country and collectively manages the amount of oil produced. This ensures that their supply does not exceed demand. Russia and the United States which have become large energy producers in recent decades, are not part of this group and compete with OPEC for market share.

Oil prices are often taken as reference prices for other commodities in the energy sector and therefore they can be an efficient indicator on the status of the whole energy market.

Crude oil prices have been very volatile in the recent years. They fell in 2014-2016 and rose from mid-2017 to 2018. In 2020, again prices collapsed due to demand decreases as an effect from the COVID-19 pandemic.

Uncertainty and variability in crude oil prices affect the whole energy system prices, increasing risks and costs for suppliers and consumers. This suggests that switching to renewable energy sources would reduce the volatility linked to crude oil prices.

Gas and Coal Prices

Traditionally, Natural Gas and Oil prices have moved with positive correlation, but since 2006, new drilling techniques have led to Natural Gas being an independent commodity.

Europe strongly relies on crude oil and oil products, whose hold 52% of total consumption, while gas and coal accounts for only 33%.

European wholesale gas prices fluctuated between 10 and 40 €/MWh over the 2015-2019 period. In late 2018 liquefied natural gas imports started to ramp up, resulting in a significant price fall in 2019. In 2020, wholesale gas prices fell further, reaching historical minimums in May 2020, which was the result of falling gas demand due to the COVID-19 pandemic.

On the other hand there has not been a similar drop in coal prices, making gas relatively more convenient. The current high carbon price and low gas prices pushed to rely more on gas in power generation, helping to cut the energy environmental impact, since natural gas has significantly lower emissions than coal.

Generally, the overall variability of gas prices reflects oil prices, but there are some significant seasonal dummies for gas: price spikes usually appear in winter, when demand grows for heating.

Electricity Prices

In the electricity market, in 2016, began the trend of rising wholesale prices and culminated towards the end of 2018, with wholesale prices falling drastically in 2019 due to the falling fuel costs and the expanding renewable energy sector.

The decrease in prices across the continent was uneven and that resulted in growing price divergence among different regions. In the first half of 2020, prices fell between 30% in some southern European regional markets and up to 70% in some northern regions.

The differences in prices could be explained by local infrastructures, uneven renewable generation across markets and a strengthened CO_2 price, that particularly affected Member States with a greater presence of fossil fuels in the energy mix.

In addition, COVID-19's negative impact on broad economic activity caused a further significant drop in the electricity demand that has pushed wholesale electricity prices to very low levels.

Moreover, electricity producers may have not the full ability to dispose of their production. Insufficient interconnections, some generators lack in technical flexibility, the difficulties in efficiently storing energy and/or the absence of sufficient economic incentive to reduce production, together provoke a much steeper decrease in prices, since supply still needs to match demand.

Compared internationally, Europe's position has been relatively stable over the last years. Wholesale electricity prices in the EU have been higher than in the US, Canada and Russia, but lower than those in Japan, Australia and Brazil.

2. FOSSIL FUELS ISSUES

Along the human history many sources and forms of energy have been used by mankind: from solar beams for cooking to nuclear power. Nowadays electricity is largely identified with the concept itself of energy: electricity can be transmitted and distributed easily with small losses.

The electric power industry is dominated by electromechanical generators that convert the chemical energy of fuels first into heat, then through turbines into kinetic energy and finally into electricity. Unfortunately, big amount of electricity is produced by **burning fossil fuels**, such as coal, oil and natural gas, which brings about several issues:

1) The burning process produces negative externalities, such as: smog, CO2 and other greenhouse gases that provoke climate change and reduce the quality of life.
2) Fossil fuels are a limited source on earth.
3) Fossil fuels location and control give rise to Geopolitical Issues.

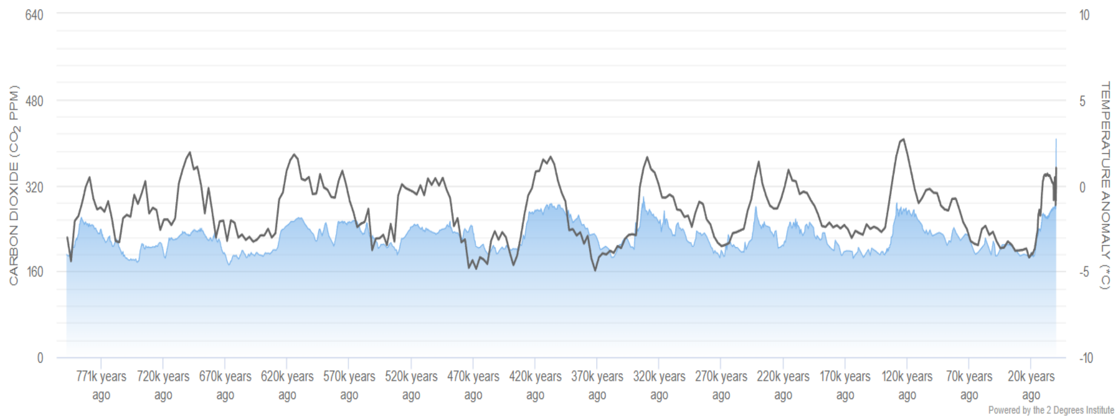
Section 2.1 covers the negative externalities, section 2.2 the scarcity of the resources and section2.3 the geopolitical issues.

2.1. Negative Externalities

Figure 2.1 depicts the **history**, starting more than 700.000 years ago, **of the carbon dioxide** ($C0_2$), in blue, **paired with temperature anomalies**, the black line, throughout the period.

Looking at the picture there is evidence of **positive correlation between carbon dioxide level** (on the left) **and temperature anomaly** (on the right). The more CO_2 is putted in the atmosphere the more the temperature would rise.

Fig. 2.1.1: Relation between CO_2 PPM and anomalous temperature changes (800.000 B.C – Today)



Source: 2DegreesInstitute, 2022

While there is some understanding of CO_2 levels throughout 4.5 billion years of existence of the planet, the most reliable data covers only the last 800,000 years.

Levels from long time ago about atmospheric carbon dioxide concentrations can be determined by measuring the composition of air bubbles trapped in ice from Antarctica. Drilling and extracting ice cores up to three kilometres has provided detailed information about the “recent” composition of the atmosphere. The data from 20,000 years ago to 2000 years ago was instead reconstructed using marine sediments. Finally, most of the past 2000 years’ records were found using lake sediments and tree rings, while the last 35 years of CO_2 fluctuations have been precisely measured thanks to scientists at Mauna Loa observatory. (Inglis and Gordon, 2015)

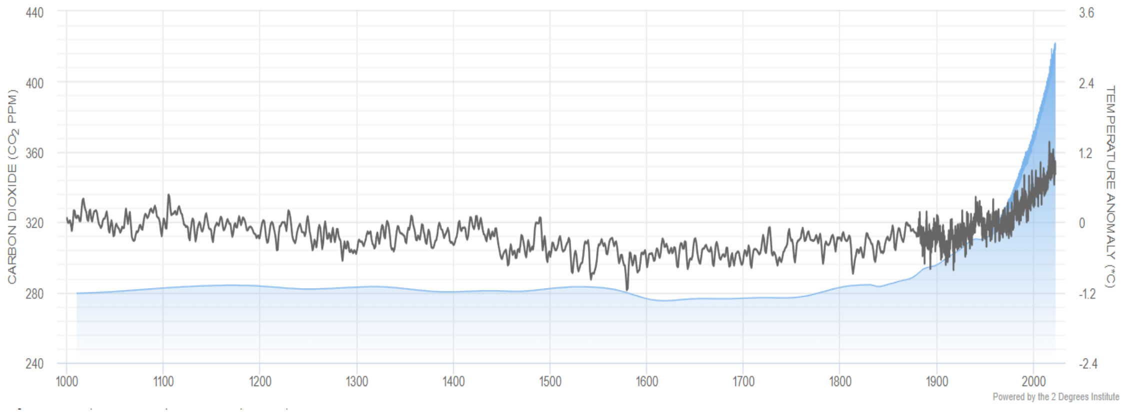
At this moment (July 2022), CO_2 PPM (parts per million) is at 418 and the global temperature rise is 1.1 degrees Celsius compared to pre-industrial levels and the last time carbon dioxide levels on our planet were as high as today was more than 4 million years ago. (Snyder, 2016)

Increased emissions of greenhouse gases have led to a rapid and steady increase in global temperatures since the 19^{th} Century Industrial Revolution, which in turn is causing catastrophic events all over the world: from Australia and the US experiencing some of the most devastating bushfire seasons ever recorded, locusts swarming across parts of

Africa, the Middle East and Asia, decimating crops, desertification pace speeding 30 to 35 times faster than ever according UN, sea levels rising threatening seaside land and a heatwave in Antarctica that saw temperatures rise above 20 degrees for the first time.

It must be noted that the time lag between CO_2 emission and their pollution and warming effect is around 50 years, and whatever changes is observable now is just the tip of the iceberg. (Snyder, 2016)

Fig. 2.1.2: Relation between CO_2 PPM and anomalous temperature changes (1000 A.C – Today)



Source: 2DegreesInstitute, 2022

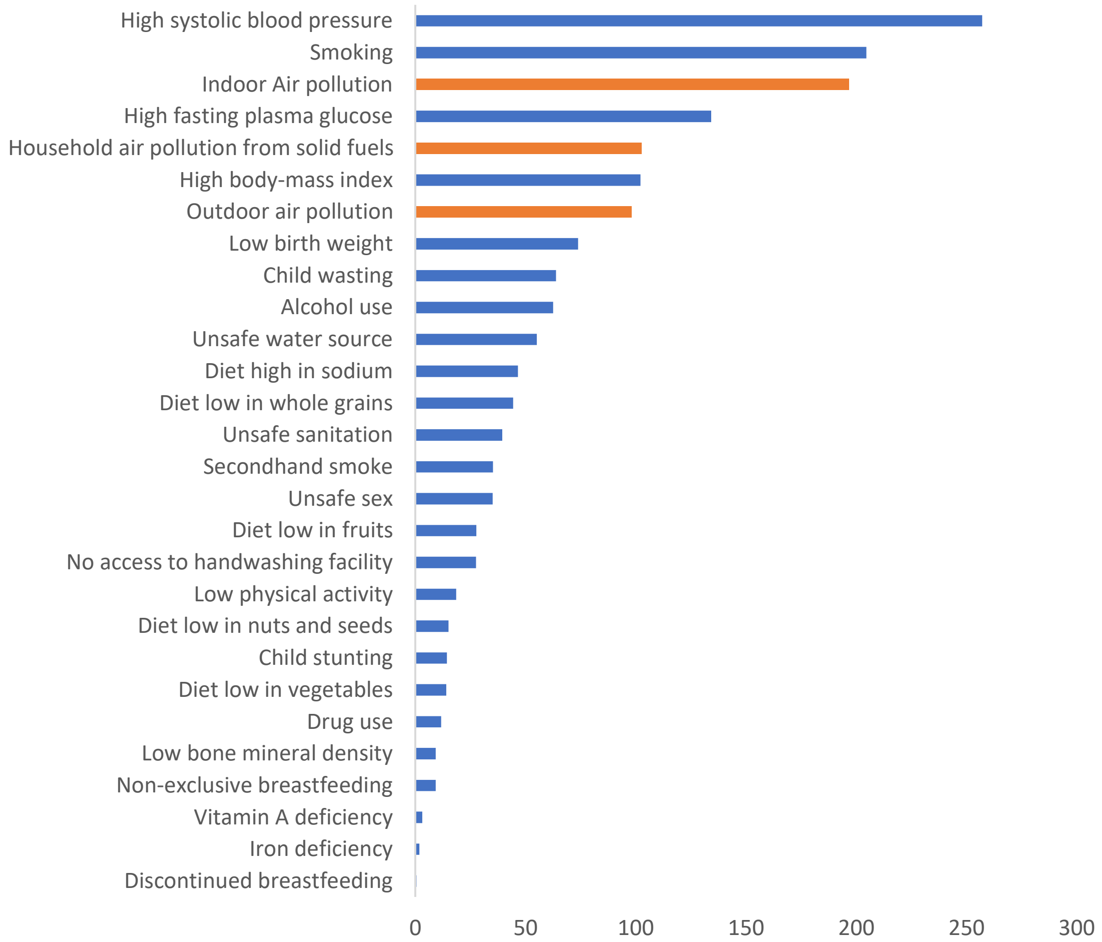
Even if all greenhouse gas emissions were halted immediately, global temperatures would continue to rise in the coming years. That is why it is imperative starting now to drastically reduce greenhouse gas emissions, invest in renewable energy sources, and phase out fossil fuels as fast as possible.

Fossil fuels are also a major contributor to **local air pollution**, which is estimated to be linked to millions of premature deaths each year and a **factor that lower life quality overall**.

Air pollution is one of the world's leading **risk factors for death**, attributed to millions of deaths each year that are estimated to be 11.65% of deaths globally.

It is also one of the leading risk factors for disease burden. Air pollution is a risk factor for many of the principal causes of death, including heart disease, stroke, lower respiratory infections, lung cancer, diabetes and chronic obstructive pulmonary disease.

Fig. 2.1.3: Deaths by source (1990 – 2019)



Source: Our World in Data, 2022

As fig. 2.3 depicts, three out of the top 10 causes of death in the last thirty years are linked to air pollution. Note that death rates from air pollution are highest in low-to-middle income countries.

2.2. A Limited Source on Earth

Fossil fuels have a limited availability due to the **Carbon Cycle duration**.

The Carbon Cycle is the biogeochemical cycle by which carbon is exchanged among various forms crossing the biosphere, the pedosphere, the geosphere, the hydrosphere, and the atmosphere of the Earth.

Fossil fuels consist of deposits of once living organisms. Coal is a solid fossil fuel formed over millions of years by decay of land vegetation. When layers are compacted and heated over time, deposits are turned into coal that is usually extracted in mines.

Oil is a liquid fossil fuel that is formed from the remains of marine microorganisms deposited on the sea floor. After millions of years the deposits end up in rock and sediment where oil is trapped in small spaces. It can be extracted by large drilling platforms.

Natural gas is a gaseous fossil fuel that is versatile, abundant and relatively clean compared to coal and oil. Like oil, it is formed from the remains of marine microorganisms. It is highly compressed in small volumes at large depths in the earth. Like oil, it is brought to the surface by drilling.

Given that, it is not an option to “farm” fossil fuels due to their enormous time required for generation and reserves are slowly being emptied. According to the MET group, **fossil fuels will eventually phase out**. It is predicted that we will run out of fossil fuels in this century. **Oil** can last up to **50 years**, **coal** up to **114 years** and **natural gas** up to **53 years** (IEA, 2022).

2.3. Geopolitical Issues

The location of fossil resources is not evenly distributed around the globe and **few countries dominate the fossil fuels production** side of the market. Controlling some specific areas and their reserves to grant the access to the energy sources, has become crucial in the geopolitical framework. In the last decades there have been several conflicts denominated “Oil Wars”, such as the Gulf War and the Iraq war. Among the causes that generated those conflicts, oil control in the Middle East was probably the most determinant one.

In the next sections there will be a look over the **major extracting countries** of the three fossil fuel resources.

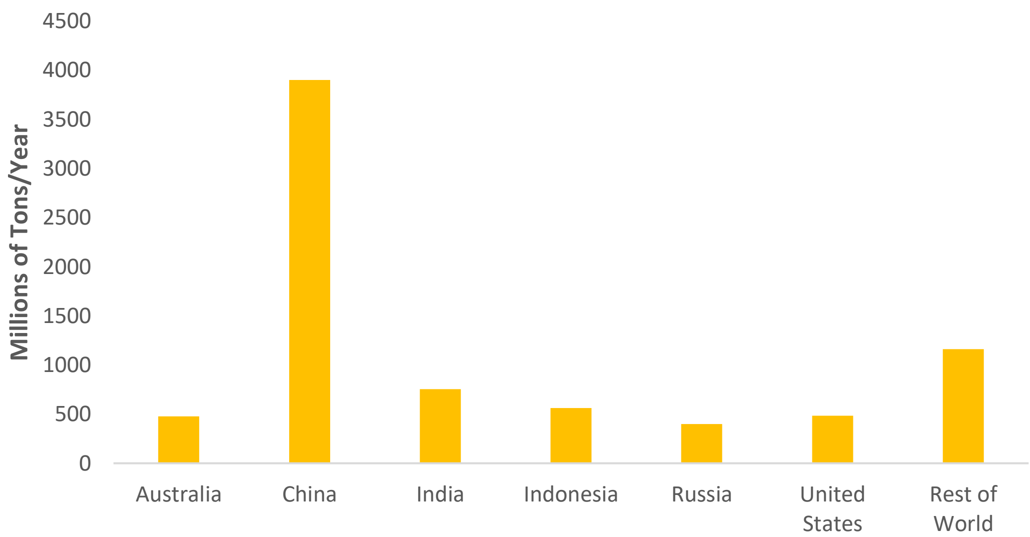
Coal

Since the year 2000 China has been steadily the leader country in coal production, marking a continuous increment in production that created an even larger spread between China and the other producing countries.

According to British Petroleum, China increased the coal extraction from 1.384 million of tons in 2000 to 3.902 million of tons in 2020 by a factor of 181%. In 2020, China accounted for over 50% of the worldwide coal production. In comparison, the second largest player, India, had a global share of roughly ten percent.

In Fig. 2.4 and in Table 2.4 are reported the annual coal extraction in 2020 in terms of millions of tons and their relative share of the market, by the countries that exceeds 300 million of tons of annual extracted coal.

Fig. 2.3.1: Coal Production by Country (2020)



Source: BP Statistical Review, 2022

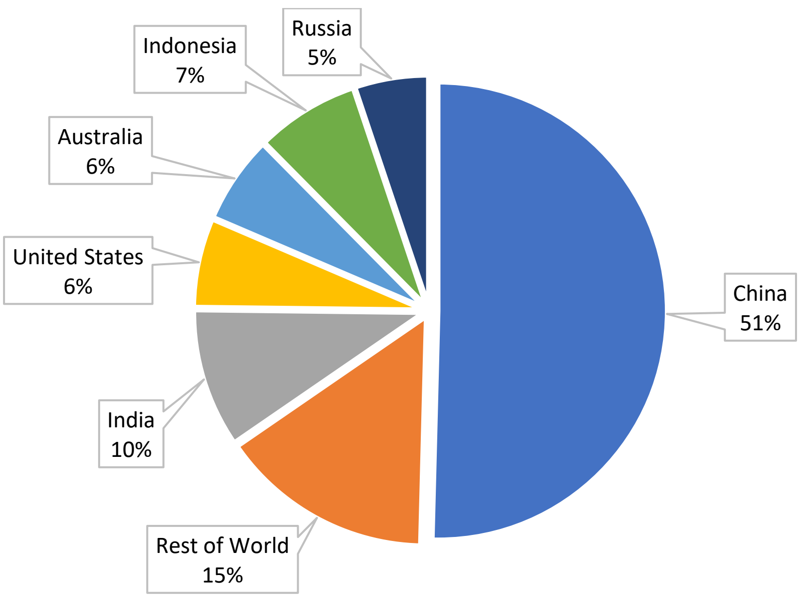
Table 2.3.1: Coal Production by Country (2020)

Country	Millions of Tons/year
Australia	476
China	3,902
India	756
Indonesia	562
Russia	399
United States	484
Rest of World	1,162
World Total	7,741

Source: BP Statistical Review, 2022

Then, in Fig. 2.5 and in Table 2.5 is reported the evolution of the market share held by each country during the 2000 – 2020 period. China, Indonesia and India consistently expanded their market share while on the other hand, the US notably reduced its piece of the pie.

Fig. 2.3.2: Coal Production Share by Country (2020)



Source: BP Statistical Review, 2022

Table 2.3.2: Coal Production Share by Country (2020)

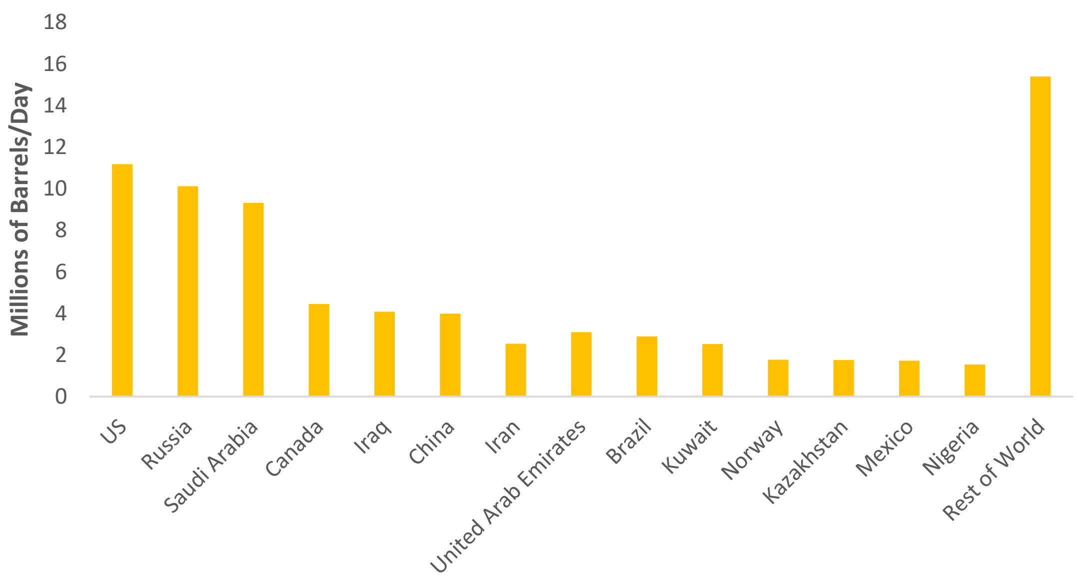
Country	2020
Australia	6.15%
China	50.41%
India	9.77%
Indonesia	7.26%
Russia	5.15%
United States	6.25%
Rest of World	15.011%

Source: BP Statistical Review, 2022

Oil

Differently from coal production, oil extraction is a matter of many countries. In the year 2000, top ten oil producer countries covered only around 50% of the total share of the market, while in 2020 they covered more than 75% of the total share. Global production has increased from 41.846 TWh to 45.508 TWh.

Fig. 2.3.3: Oil Production by Country (2020)



Source: Our World In Data, 2022

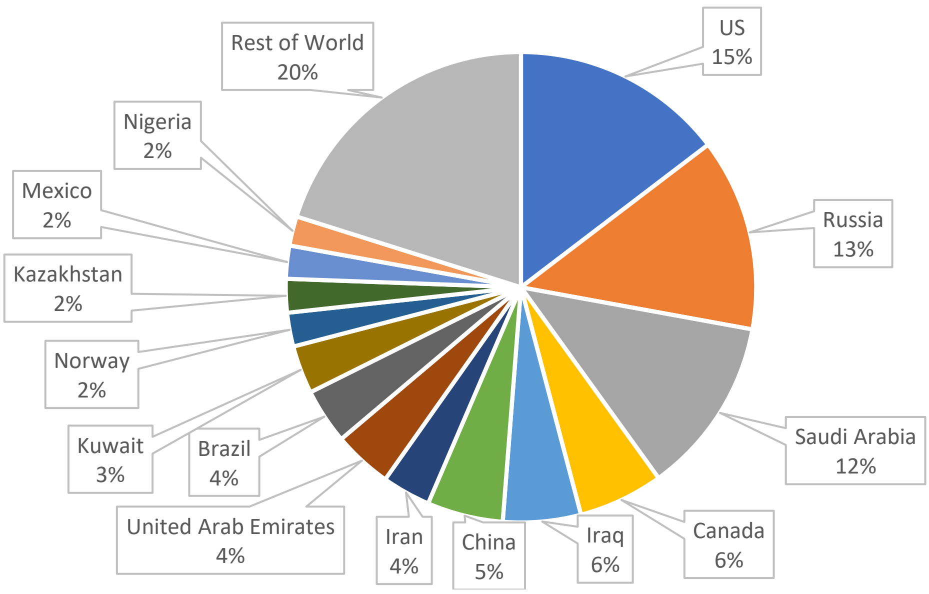
Table 2.3.3: Oil Production by Country (2020)

Country	Millions of Barrels/Day
US	11.18487
Russia	10.11183
Saudi Arabia	9.313145
Canada	4.459455
Iraq	4.084822
China	3.987677
Iran	2.546336
United Arab Emirates	3.091481
Brazil	2.905121
Kuwait	2.527106
Norway	1.775813
Kazakhstan	1.764463
Mexico	1.734495
Nigeria	1.540991
Rest of World	15.387601
Total	76.415206

Source: Our World In Data, 2022

Russia, United States and Saudi Arabia dominates the market in 2020 with an aggregate share of roughly 45%.

Fig. 2.3.4: Oil Production Share by Country (2020)



Source: Our World In Data, 2022

Table 2.3.4: Oil Production Share by Country (2020)

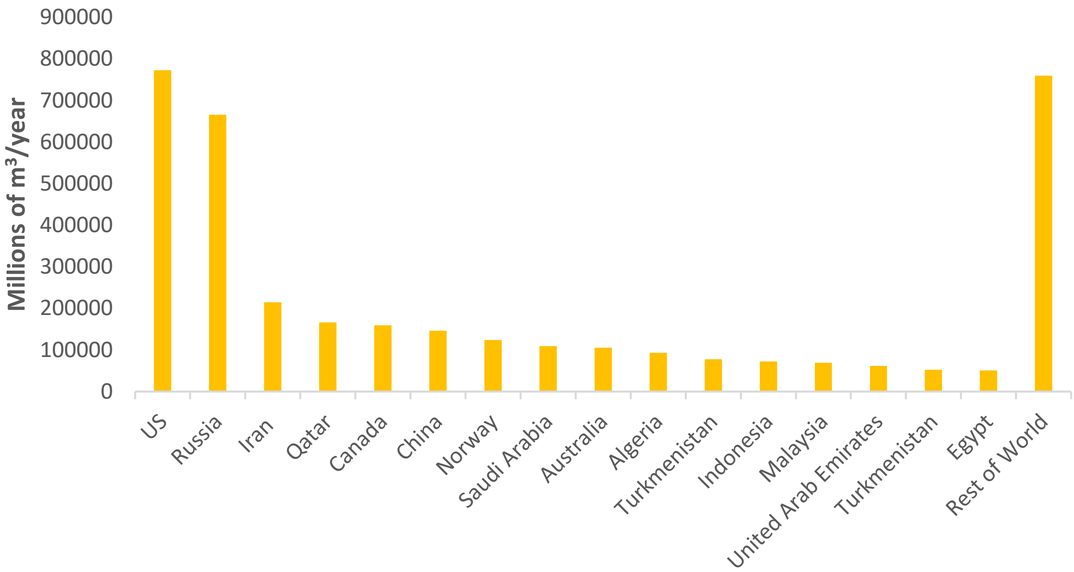
Country	Share
US	14.64%
Russia	13.23%
Saudi Arabia	12.19%
Canada	5.84%
Iraq	5.35%
China	5.22%
Iran	3.33%
United Arab Emirates	4.05%
Brazil	3.80%
Kuwait	3.31%
Norway	2.32%
Kazakhstan	2.31%
Mexico	2.27%
Nigeria	2.02%
Rest of World	20.14%

Source: Our World In Data, 2022

Natural Gas

Natural gas production is currently dominated by US and Russia that cover respectively the 21% and the 18% share of the worldwide market. The third power in the natural gas is Iran, with only 6% share.

Fig. 2.3.5: Natural Gas Production by Country (2020)



Source: Indexmundi, 2022

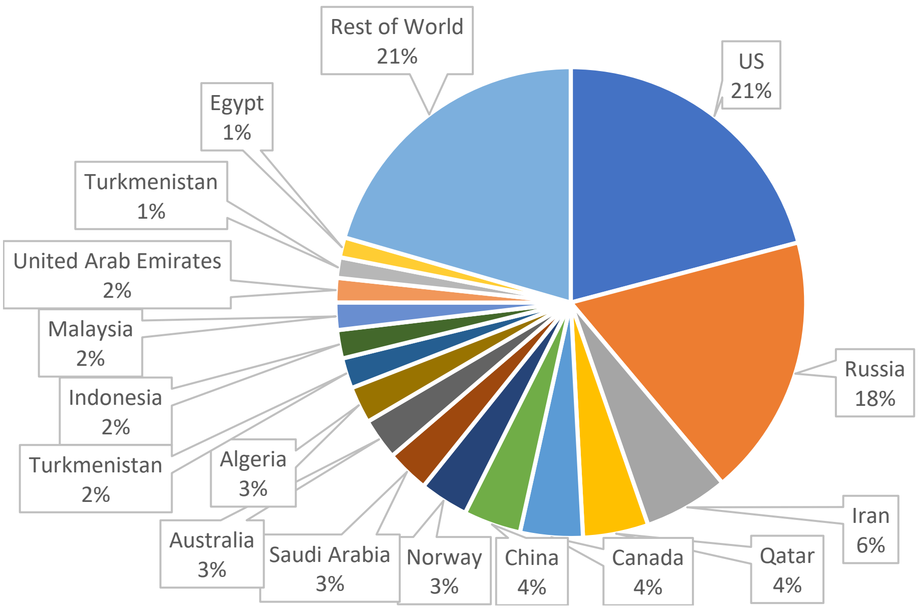
Table 2.3.5: Natural Gas Production by Country (2020)

Country	Millions of m^3/year
US	772,799
Russia	665,600
Iran	214,499
Qatar	166,400
Canada	159,099
China	145,899
Norway	123,900
Saudi Arabia	109,299
Australia	105,200
Algeria	93,499

Turkmenistan	77,450
Indonesia	72,090
Malaysia	69,489
United Arab Emirates	62,009
Turkmenistan	52,100
Egypt	50,859
Rest of World	759,823
Total	3,700,023

Source: Indexmundi, 2022

Fig. 2.3.6: Natural Gas Production Share by Country (2020)



Source: Indexmundi, 2022

Fig. 2.3.6: Natural Gas Production Share by Country (2020)

Country	Share
US	20.89%
Russia	17.99%
Iran	5.80%
Qatar	4.50%
Canada	4.30%
China	3.94%

Norway	3.35%
Saudi Arabia	2.95%
Australia	2.84%
Algeria	2.53%
Turkmenistan	2.09%
Indonesia	1.95%
Malaysia	1.88%
United Arab Emirates	1.68%
Turkmenistan	1.41%
Egypt	1.37%
Rest of World	20.54%

Source: Indexmundi, 2022

US, China and Russia

Given that, fossil fuels production is a sector that is highly polarized towards the few countries that possess these natural resources. It is, then, possible to identify three countries that dominates the sector: **US, Russia and China**. These countries are globally recognized as three of the **main geopolitical forces** that drive world policies since they are leaders in economic and military fields. Moreover, they have the **power to affect politics** outside of their national borders due to their enormous influence, in particular China and US.

According to the International Monetary Fund, the **United States** with a gross domestic product of 25,346 billion of US$ is placed at the **first place in terms of nominal GDP**. **China** follows in **second place**, with a GDP of 19,911 billion US$. **Russia** is only in **11th place** with a GDP of 1,829 billion US$.

According to "Global Firepower", the **United States** are the **first military power**, with a power index of 0.0453, **Russia** is right behind in **second place**, with a power index of 0.0501, **China** is then the **third power** with a power index of 0.0511.

Global Firepower utilizes a ranking system, that considers over 50 individual factors to determine a given country military score with categories ranging from military might and financials to logistical capability and geography. The closer the score is to zero, the greater is the theoretical military power of the given nation (nuclear power is excluded from their calculations).

In terms of the energy sector (including only fossil fuels) these three countries are close to an **oligopoly situation**.

US detains 6% of the global coal supply, 15% of the global oil supply and 21% of the global natural gas supply. Russia holds 5% in coal production, 13% in oil production and 18% in natural gas production. China currently detains 51% of the global coal production, 5% of the global oil production and 4% of the global natural gas production.

Comprehensively these three countries control: **62%** of **coal supply**, **33%** of **oil supply** and **43%** of **natural gas supply**.

It is straightforward, then, that these countries exercise a great power on the energy market. Then political issues, like the recent conflict in Ukraine, can affect the whole energy sector destabilizing the supply – demand fragile equilibrium.

Transition towards Renewable Energy Sources

Therefore, significant efforts are made to **replace conventional power plants**. With doubts on the safety of nuclear energy and a limited number of places where dams can be built to develop hydro-electric power plants, **new renewable energy sources** are of paramount importance in this path toward decarbonization.

Transition to renewable energy sources (RES) and reducing greenhouse gas (GHG) emissions is at the center of attention in recent years in the public and in the research community. While there are several other sectors that contributes to greenhouse gases emission, such as meat and textile industry, deployment of renewable resources in electricity and heat production can strongly mitigate the GHG emission from the **energy secto**r which accounts for **35% of overall GHG emissions**. (Jafari et al. 2019)

The green transition would take **long time to be implemented**, since it requires the entire economy to be reshaped: vehicles and machineries that are powered directly by fossil fuels need to be substituted with other ones that can exploit electricity produced in sustainable plants, or directly renewable sources, like solar power.

Therefore, due to the limited availability of fossil fuels resources, it is mandatory switching as soon as possible to renewable energy sources.

Moreover, the recent unstable political situation has accelerated the need to switch from fossil fuels to renewable sources. The sudden cut in fossil fuel supply (especially Natural Gas) from Russia, has strongly increased energy prices over the European market, threatening all the European economy by a horizontal, unexpected rise of costs. Switching to a RES economy imply for EU a much more stable equilibrium in the energy market than before, since external factor such US, China and Russia would have a significantly less impact.

It is clear that RES transition would improve the environment and the society that we live in. Reducing emissions would mean improvement in population health, arresting global warming and safeguard the environment, reducing issues like desertification and bushfires.

On the other hand, one can say that the carbon industry is granting a lot of jobs and economic prosperity but, stated that RES transition would bring **social issues** such as job losses and **private investments** to pollute less (like buying new sustainable cars or renovate house heating/cooling systems), several studies and reports claim that **RES transition could enhance the economic system overall**.

The “Economic Report of The President” reported in fact that GHG emission reductions coincided with economic growth in the United States in 2008 to 2015 period. Moreover, renewable energy consumption has a significant positive impact on the economic output for 57% of the top thirty-eight renewable energy consuming countries. (Bhattacharya et al., 2016).

It must be noted that, from an economic point of view, Renewable Energy Sources becomes relatively more convenient as the traditional fossil fuels sources become more expensive or RES become cheaper.

Since fossil fuels are a limited source on earth that is slowly falling down, it is straightforward that ceteris paribus the price will increase due to the expected shortage of supply. Moreover, the negative externalities of fossil fuels (GHG emissions) push the policies to disincentive exploiting such sources and that contributes to make fossil fuels relatively less convenient compared to RES.

Given that, renewable electricity costs have fallen significantly in recent years, leading to increased interest in a large-scale RES expansion in power systems. From 2008 to 2015, the cost of electricity fell 41% for wind, 54% for rooftop solar photovoltaic (PV) installations, and 64% for utility-scale PV (Donohoo-Vallett, 2016).

3. ITALIAN ECOLOGICAL SITUATION

Section 3.1 describes the concept of **ecological balance** and shows the Italian situation in this term. **Section 3.2** brings together the **main policies** in place in Italy **toward ecological transition**. Finally, **section 3.3** deepens into the topic of **agriculture 4.0** among the various policies that promote ecological transition.

3.1. Ecological Balance

The **environment**, through plants photosynthesis, can **reduce the greenhouse gases** distribution over the atmosphere. Unfortunately, this purification requires more plants and green areas the more the GHG are spread into the atmosphere. Basically, there are **two effects** that an area can produce: a **positive one**, depending on how "green" that area is, that reduces GHG density; and a **negative one**, depending on how much that area emits GHG. There is then a **balance** between those effects.

In some uncontaminated natural areas, the positive effect is so big that they can even cover for other territories emissions. In some high-density areas, on the other hand, the soil is not even nearly sufficient for covering all the emissions in that area; therefore, these areas are, in some way, borrowing the beneficial effects that the uncontaminated ones are granting.

The next paragraphs present a more detailed view over the Italian ecological impact.

The following assessment (Franco, S. et al. 2021), performed for all the 8.092 Italian municipalities, is based on the evaluation of the **Ecological Balance** (EB), obtained as the difference between **Biocapacity** (BC), which is the "positive effect", and **Ecological Footprint** (EF), that is the "negative one".

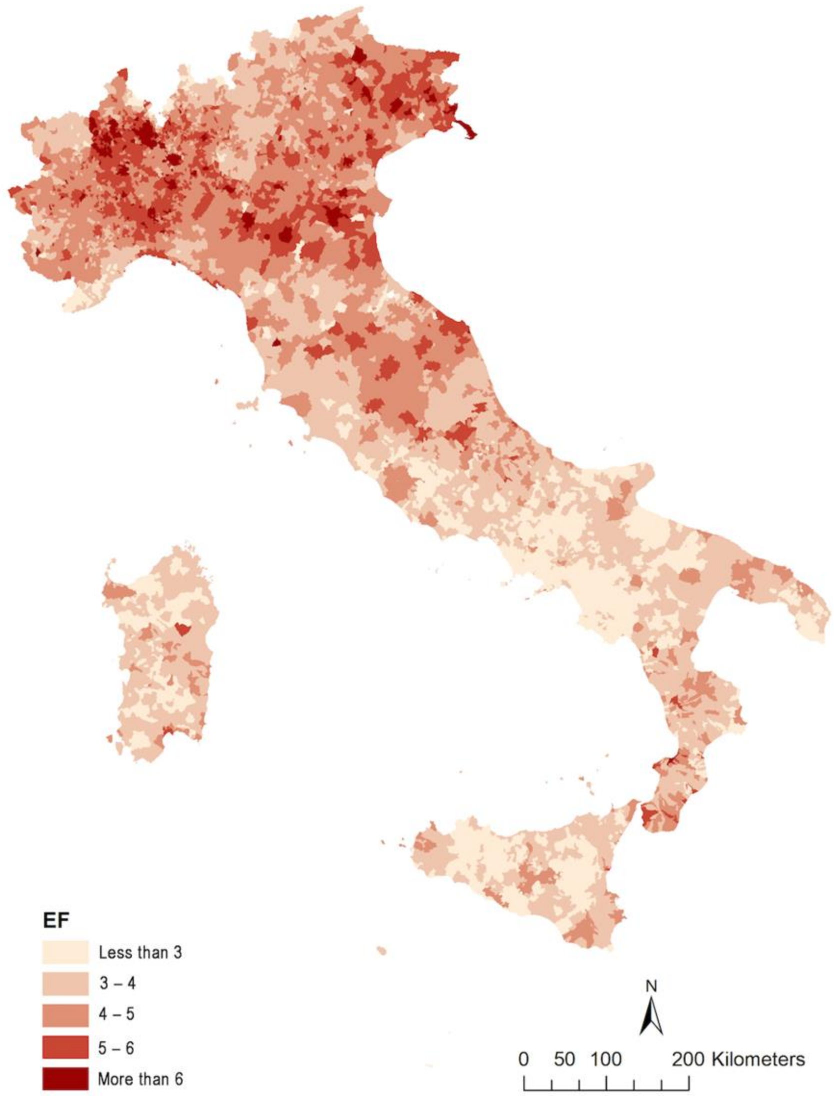
$$EB = BC - EF \qquad (1)$$

The following maps show respectively the ecological footprint (EF), Biocapacity (BC) and the Ecological Balance (EB) in each Italian municipality.

The estimation of the **Ecological Footprint** has been performed by estimating EF per capita at the municipal level, that was carried out considering the most updated value of Italian per capita ecological footprint and the relative level of consumption per capita with respect to the national one. This value has then been multiplied for the living population in the municipality to obtain the EF of the given municipality.

Regarding the estimation of **Biocapacity**, each area was converted into a bioproductive surface, measured in global hectares (gha), adjusted for a yield factor. Equivalent factors convert one of the five land types (Built-up land, Cropland, Grazing land, Forest land, Water) into a standard unit of biologically productive area, represented by one gha. The yield factor accounts for the level of productivity of a given land type in a specific country with respect to the average world productivity.

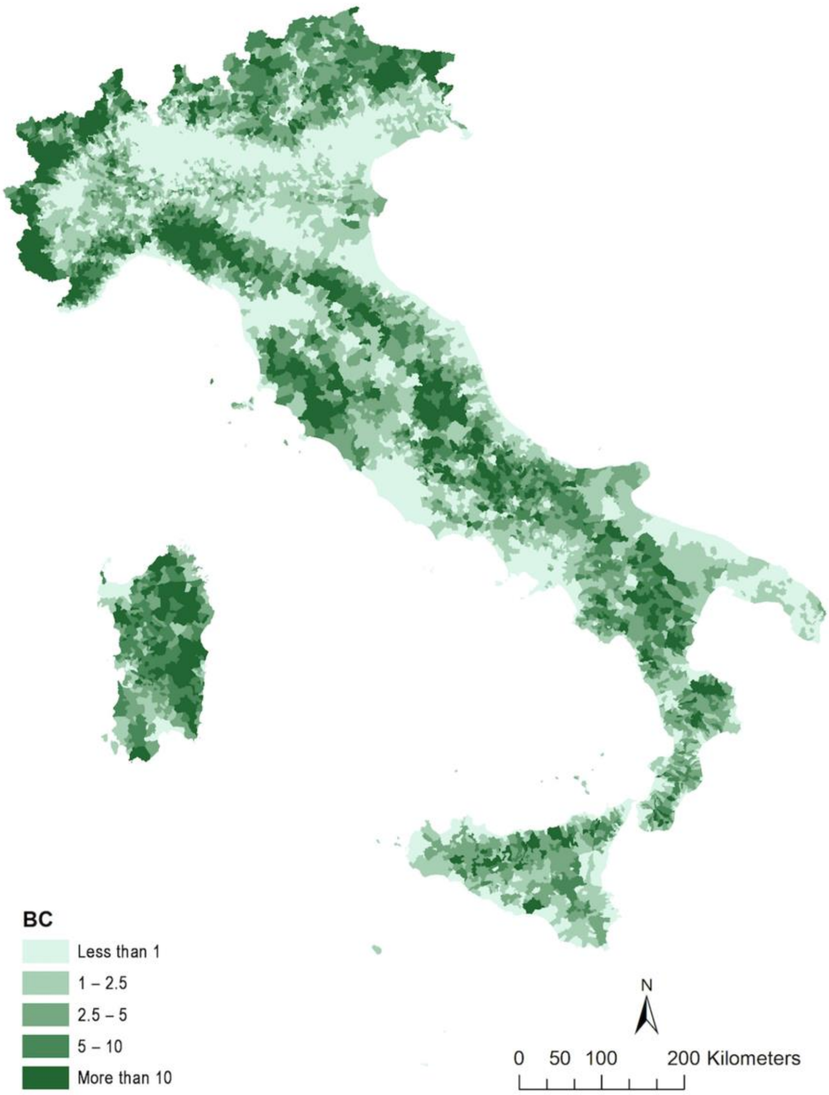
Map 3.1.1: Italian Ecological Footprint (2021)



Source: Franco S. et al. 2021

Looking at Map 3.1.1 is clear that Northern Italy has a relatively higher Ecological Footprint than Southern Italy. That difference is partially explained by the different density of population, but the main reason behind is the difference in EF per capita. Which means that northern regions are producing more emission than the southern ones.

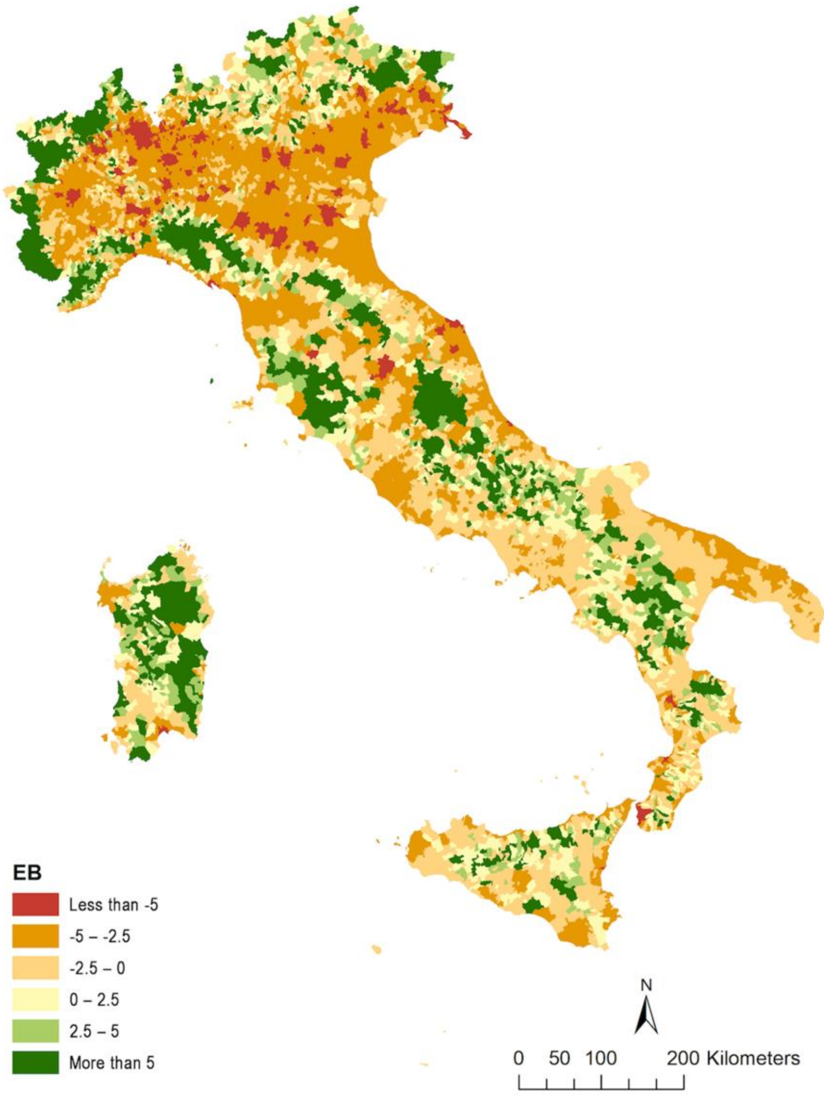
Map 3.1.2: Italian Biocapacity (2021)



Source: Franco S. et al. 2021

Performing then equation (1), 71.4% of the Italian municipalities appears to have a negative Ecological Balance and thus to be not sustainable. On the other hand, 38.6% of the Italian territories are sustainable municipalities, showing a positive value of EB. As far as the Italian population is concerned, the vast majority, almost 95%, live in municipalities characterized by unsustainable conditions, which implies that the quality of life could be threatened by problems like bad air quality, increased probability of flood and bushfire and so on. (Franco, S. 2021)

Map 3.1.3: Italian Ecological Balance (2021)



Source: Franco S. et al. 2021

Table 3.1.1: Sustainable and unsustainable municipalities (2021)

Condition	Number of Municipalities	%	Aggregate Area (Km^2)	%	Aggregate Population	%
Sustainable	2,314	28.6%	118,654	39.3%	3.159 M	5.2%
Unsustainable	5,778	71.4%	183.419	60.7%	57.638 M	94.8%
Total	8,092	100%	302.073	100%	60.797 M	100%

Source: Franco S. et al. 2021

Overshoot Day for Italy

Individual ecological footprint for Italy is 4.4 gha (global hectare) while **global biocapacity is 1.6 gha per person**. One global hectare is the world's annual amount of biological production for human use and human waste assimilation, per hectare of biologically productive land and fisheries.

Given that, and considering a 365-day year, one can calculate the **"Overshoot Day"** for Italy, that is the day in which Italy ecological footprint meets its biocapacity. The Overshoot Day for Italy in 2022 has been on the 135th day of the year, that is May 15th. From that day, Italy is making a sort of a debt with the planet, exploiting the resources that other areas are giving, and that allows Italian people to live over their possibilities. In comparison, the global Overshoot Day for 2022 have been estimated to be on July 28th (Global Footprint Network, 2022).

If all global population would live like Italy, one planet wouldn't be enough to fulfil everyone lifestyle. In fact, more than two and a half planets would be necessary, according to the Global Footprint Network.

3.2. Italy Transition to Renewables

Italy, on its own, accounts for **0.97% of global CO_2 emissions** with 361,176 tonnes released in 2021 (Our World in Data, 2022). It is therefore clear that is mandatory reducing Italian ecological footprint improving **Italian sustainability**.

First, it must be defined what does **sustainability** means. Literature has defined two concepts of sustainability: a **weak** one and a **strong** one.

For neoclassical economists, sustainability is a **condition wherein the capital is maintained at least at a constant level**. To this end, natural capital can be substituted with man-made capital. When the income of an economic activity is reinvested in manufactured or human capital, and its value is greater than the value of the natural capital lost in such an activity, a weak sustainability condition is established. Weak sustainability therefore implies that there is no loss of capital (Ayres, R. U. 2001).

On the other hand, the **strong sustainability paradigm** is based on the idea that **natural capital is not an input that can be freely replaced**, since it accomplishes many functions that man-made capital cannot. The functions of natural capital associated with production and consumption processes, such as raw material provision and waste assimilation, can be partially substituted by man-made capital. However, the basic life support function cannot be substituted. This implies that "the global environmental and ecological system that provides us with the basic functions of food, water, breathable air and a stable climate should be subject to a strong sustainability rule" (Ekins, P. 2003).

The 2020 GSE ("Gestore Servizi Energetici", that stands for "Italian Energy Provider") report shows that in Italy 20.4% of total energy consumption comes from Renewable Energy Sources, below the European average of 22.1%. Looking at the Electric sector Italy electricity production from RES accounts for 38.1%, above the European average of 37.5%. Regarding the heating sector RES account for 19.9%, below the average 23.1%. Finally, in the transport sector RES are used in 10.7% of the cases, above the average of 10.2%.

In the figures 3.1 and 3.2 below, there are the **comparisons** between the first four energy consumers EU countries (Deutschland, Spain, France and Italy) and Union average in terms of:

- Aggregate energetic consumption that comes from renewable sources.
- Renewable sources usage in the electricity production sector.
- Renewable sources usage in the heating sector.
- Renewable sources usage in the transport sector.

In absolute terms Italy consumes 107.3 mtoe and 21.9 mtoe comes from renewable sources.

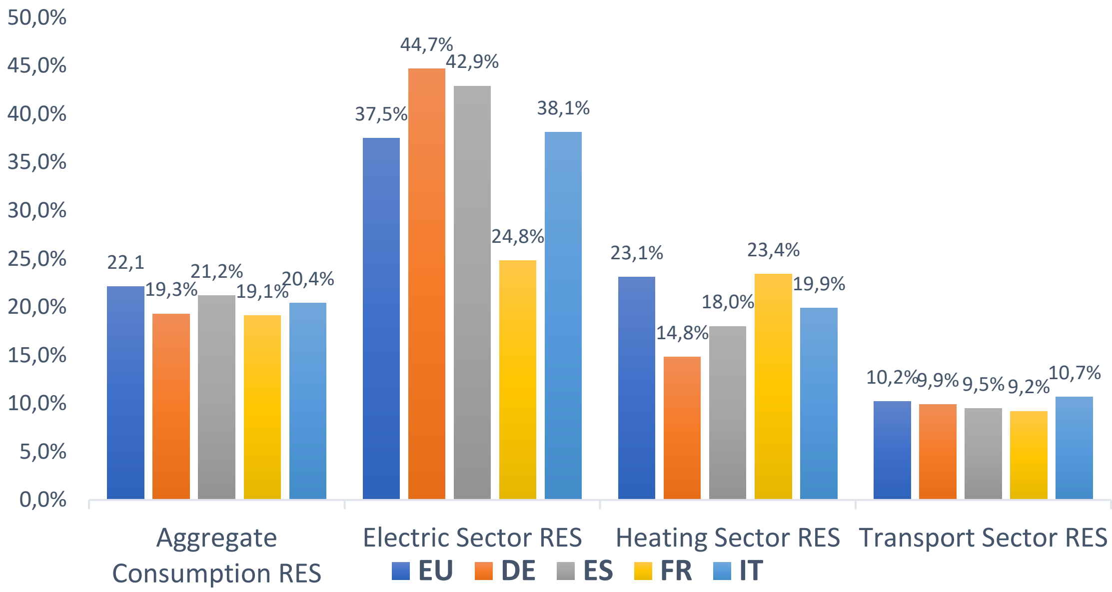
Mtoe stands for millions of tonnes oil equivalent, which is a unit of energy used to describe the energy content of all fuels, typically on a very large scale. It is equal to 4.1868×10^{16} Joules, or 41.868 petajoules which is a tremendous amount of energy. A tonne of oil equivalent (toe) is a unit of energy, defined as the amount of energy released by burning one tonne (1000 Kilograms) of crude oil.

The composition of renewable energy consumption in Italy is thus the following: 9.9 mtoe for the electric sector, 10.4 mtoe for the heating sector and 1.6 mtoe for the transport sector (biofuel and renewable electric vehicles are considered).

Italy has slightly less aggregate consumption of renewable energy sources, with respect to the EU average. In the heating sector RES accounts only for 19.9%, while the European average is at 23.1%.

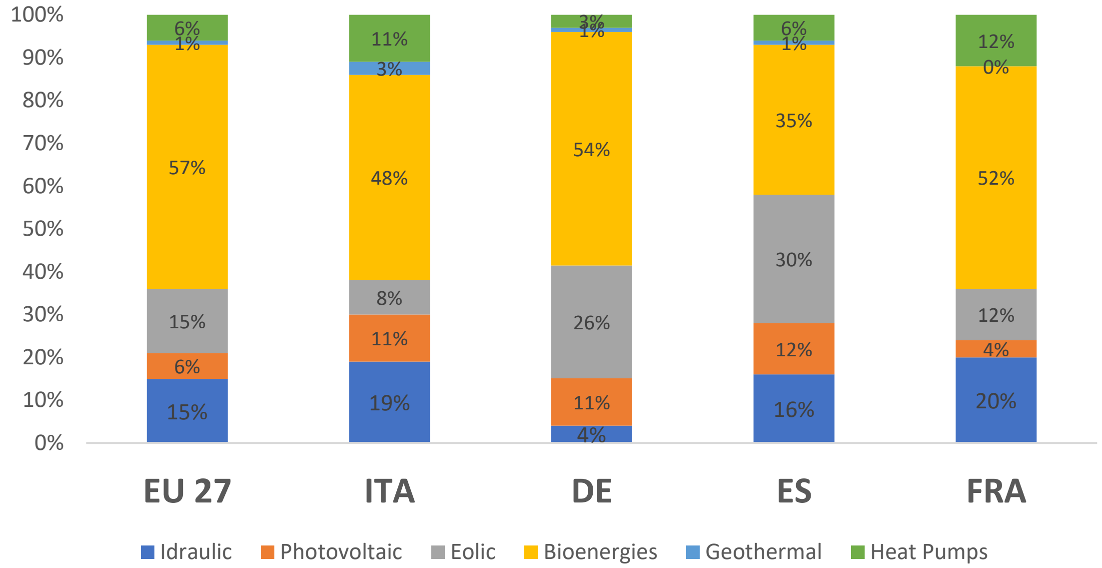
On the other hand, Italy performs better than the average in the electric sector, where the renewables quota is 0.6% better than other EU members, and in the transport sector, where 10.7% of energy consumption comes from RES.

Fig. 3.2.1: Renewables Consumption Shares (2019)



Source: GSE report, 2020

Fig. 3.2.2 Renewable Energy Composition (2019)



Source: GSE report, 2020

In fig. 3.2, there are shown the different compositions of sources of RES in the top4 Eu countries and the average of the Union. Bioenergies could be divided into derived electricity, thermal energy and biofuels.

For all the European country Bioenergies represent the predominant source for renewable energy, but the other sources may vary a lot depending on the country. In Italy the Eolic sector is not as developed as in the other countries, but the Hydraulic sector has a relative predominance in the Italian composition.

Italian Policies towards the Green Transition

In the next section are listed some of the major Italian and European policies, purposes and objectives for the ecological transition.

Regulation (EU) 2018/1999 establish that as an objective for 2030 that the RES aggregate consumption quota should be at least equal to 32%, that the quota in the transport sector should be at least 14% and that the energy consumption for heating and cooling systems should have a + 1.3% annual growth.

While the **2020 PNIEC** ("Piano Nazionale Integrato per l'Energia e il Clima", that stands for "Integrated National Energy and Climate Plan") sets the goal at 30% for the aggregate RES quota, at 22% for the transport sector and it is aligned with the +1.3% growth in the heating and cooling systems.

Currently, the most important policy in place is the **2021 NRRP** ("National Recovery and Resilience Plan").

The National Recovery and Resilience Plan is part of the Next Generation EU (NGEU) program, the €750 billion package allocated by the European Union in response to the pandemic crisis. The main component of the NGEU program is the Recovery and Resilience Facility (RRF), which has a duration of six years, from 2021 to 2026, and a total size of €672.5 billion.

Total funds provided by the NRRP presented by Italy amount to 222.1 billion. Moreover, an additional 26 billion has been earmarked by 2032 for the implementation of specific works and for the replenishment of resources from the Development and Cohesion Fund. In addition to these resources, there are those made available by the REACT-EU program, which, as stipulated by EU regulations, are meant to be spent in the years 2021-2023. These funds amount to an additional €13 billion.

Overall, total funds amount to €261 billion.

The NRRP is divided into 6 Missions that are further subdivided into 16 Components, functional to achieve the economic and social objectives defined in the government's strategy. The Components, in turn, are divided into 43 areas of intervention for homogeneous and coherent projects.

The 6 Missions are:

1) Digitalization, Innovation, Competitiveness and Culture

2) Green Revolution and Ecological Transition

3) Infrastructure for Sustainable Mobility

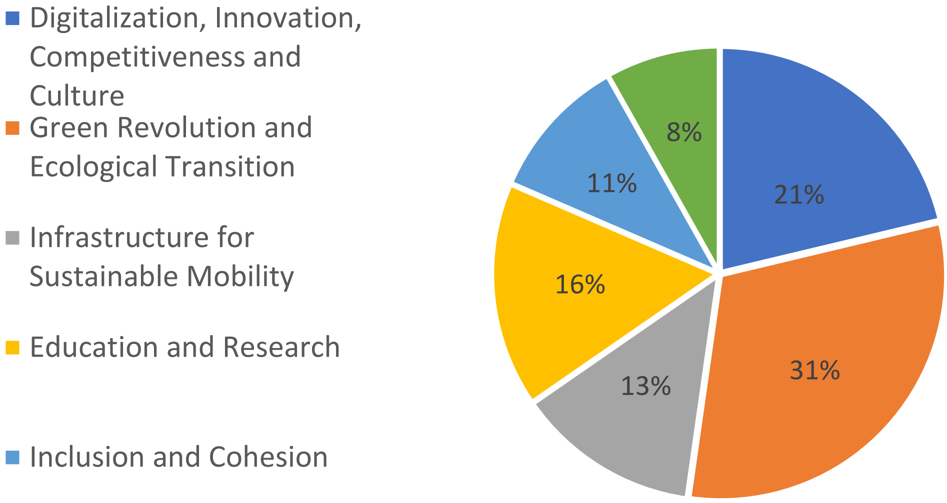
4) Education and Research

5) Inclusion and Cohesion

6) Healthcare

In fig. 3.3 are depicted the 6 Missions and their relative share of fundings.

Fig. 3.2.3: Allocation of NRRP Funds (2021)



Source: European Commission, 2021

The NRRP among its missions includes the key point of the **"Green Revolution and Ecological Transition"** that allocates a total of € 68.6 billion (€59.3 billion from NRRP and 9.3 from a complementary fund) with the **main goals** of **improving the sustainability and resilience of the economic system and ensuring a fair and inclusive environmental transition**. The NRRP is the Italian purpose within the Next Generation EU program that the European Union negotiated in response to the pandemic crisis. The PNRR comprehends several points: waste recycling enhancement (increases of 55% electric material, 85% paper, 65% plastic materials, 100% textile material); reduction in drinking water leakage on water networks; an additional 50,000 more efficient private and public buildings; support for research on the use of hydrogen in industry and transport.

3.3. Agriculture 4.0

Among the measures in the NRRP, within the 2nd Mission, €5.2 billion are allocated for the **agricultural sector** to support technological innovation. First, modernization in the agricultural mechanics sector, a driver for the so called **"Agriculture 4.0"** market, is planned. Added to this are measures for **technological innovation** in the sector, a transformation that could make a difference for all players involved in the agrifood supply chain.

The areas of interest are **logistics**, **agrisolar**, **supply chain contracts** and the **modernization of agricultural machinery**.

And this is where "**Agriculture 4.0**" comes in, which provides significant innovation on the agricultural activities such as: driver assistance or autonomous driving systems, satellite systems installed on the means for tracking the operations carried out in the field and even sensors for monitoring the quality and quantity of crops.

Through this measure, the NRRP thus seems to want to give a boost to the process of upgrading agricultural machinery in use, to encourage overall innovation in the sector with undoubted benefits on **environmental sustainability**.

As of today, the **agricultural mechanics sector** is actually driving the Agriculture 4.0 market: in 2020, Agriculture 4.0 generated a turnover of about €540 million in Italy (Italiadomani.gov.it, 2022). About 73% was generated by manufacturers of agricultural machinery and auxiliaries. The solutions driving the market growth are those associated with monitoring and control of agricultural vehicles and equipment (36% of the market), followed by related machinery, accounting for 30% of the market (Smart Agrifood Observatory, 2022).

Despite the fact that market data therefore indicate an already relevant attention of agricultural companies with respect to digital solutions applied to agricultural equipment, Italy is one of the countries with the **highest number of registered agricultural equipment**, despite the average size of companies being smaller than those of all other European countries, and the **active fleet of machines is still quite dated** (Smart Agrifood Observatory, 2022).

Agriculture 4.0 has become in recent years one of the factors recognized as a **lever for the competitiveness and resilience of the primary sector**. In fact, over time it has been the subject of national and European funding, aimed at supporting companies in the sector in the transition and innovation process in order to respond to the major challenges they face. From the CAP (Common Agricultural Policy) 2014-2020, to the Horizon 2020 program, to the NRRP, funds have been dedicated to support investments by agricultural enterprises in, among others, technological and digital innovation for the benefit of different objectives such as: improving water resource management, upgrading the machinery fleet, improving supply chain traceability.

Thanks to the market entry of innovative technologies, such as the Internet of Things, data analytics and drones, it is now possible to transfer the approach of **agricultural data valorization** to the entire farm dimension and, more broadly, to the entire supply chain, generating benefits in terms of **process efficiency**, **sustainability** and **transparency**. The potential of Agriculture 4.0 is therefore not only for primary production actors to generate efficiency and sustainability within their own realities, but also for upstream and downstream actors in the agrifood supply chain.

It is certainly positive, then, that in measures such as those defined by the NRRP there is a **focus on innovation**, including technological innovation in the sector. For the future, however, it will be desirable to consider the potential of such solutions as a whole. Potentialities that are not in opposition to the perceived needs of businesses in the sector. Traceability of agricultural products along the supply chain, for example, is among the top needs expressed by agricultural enterprises. Moreover, if we look more broadly at the European Community's strategic objectives for the agrifood sector, it becomes clear that, with a long-term view, it will be important in the coming years to support investments in Agriculture 4.0 by directing them toward solutions that can actually affect agricultural enterprises as a whole and their supply chains.

To summarize, **Agriculture 4.0** and technologic innovation in the agricultural sector can **improve the overall efficiency of farms** and help **making them more sustainable**.

4. A NEW ROLE FOR FARMING

Section 4.1 introduces the topic of sustainable farms within a circular economy. **Sections 4.2 and 4.3** briefly describe **solar energy and biogas production on farms**. Finally, **section 4.4** collects four papers from the **literature related to efficiency issues in renewable energy production in agriculture**.

4.1. Sustainable Farms

Farming has always been a part of human history from its very first origin, in fact the discover of agriculture is considered one of the crucial steps that caused the transition from the “homo abilis” to the more developed “homo sapiens”.

Nowadays, agriculture still plays a **fundamental role** in the human society but due to the technological progress the number of workers employed in the sector has diminished drastically. Nevertheless, agriculture remains a **major sector for employment** in the EU, employing approximately 9.7 million workers and accounting for almost 4% of total employment in the EU in 2016.

Farming provides, as its core feature, some of the fundamental human needs, such as nutrition and clothing, but recently there have been some **new perspectives** on the role of farms in an economic system that should not still be linear, but that should aim to be **circular**.

Circular economy is defined as “a model of production and consumption, which involves sharing, leasing, reusing, repairing, refurbishing and recycling existing materials and products as long as possible” (European Commission, 2022). In this way, the **life cycle** of products is **extended** and, in practice, it implies **reducing waste** to a minimum. When a product reaches the end of its life, wherever possible, its components are reinserted inside the economy. This is a departure from the traditional, linear economic model, which is based on a production chain that starts with raw materials that subsequently are being processed then purchased, consumed and thrown away by final consumers. Also, part of this model is planned obsolescence, that is when a product has been designed to have a limited lifespan to encourage consumers to buy it again and again, producing piles of waste.

The world's population is growing and alongside the demand for raw materials. However, the supply of crucial raw materials is naturally finite. Limited supplies also means that some countries are dependent on other countries for their raw materials. In addition, extracting and using raw materials has a major impact on the environment. It also increases energy consumption and CO_2 emissions. However, a smarter, sustainable use of raw materials can drastically lower CO_2 emissions. Measures such as waste prevention, eco-design and re-use could make companies more efficient in terms of costs, while also reducing total annual greenhouse gas emissions.

Specifically, 2022 geopolitical situation has caused a limited supply of natural gas for EU states that was mainly coming from Russia. A more sustainable production and utilization of energy is, therefore, crucial to overcome economical-political issues and environmental ones.

It appears then mandatory, to the extent of **safeguard the environment**, reconsider both the energy production/consumption and the idea of a linear economy.

Farms are one of the **protagonists** of the **circular economy**: farms provide food and clothing starting from the very raw materials and in doing so they could protect the environment, drive innovation and help the industry stay competitive.

Energy has always been a struggle for agriculture: it is a sector that has always been input-intensive in energy, whether in the past it came from human or animal labour or more recently from fuels that move machineries (fossil fuels most of all).

Moreover, farms can produce themselves energy in a sustainable way: through bio-energies, solar, wind, geothermal and even hydraulic power. In the next sections are briefly described the solar and biogas production, that will be significant subjects of the analysis within the following chapters.

4.2. Solar Production

Solar energy production on farms can basically take place in two ways: **separately from agricultural activities** or by **merging with them**.

In the former case, this involves, for example, placing solar panels on the roofs of buildings within the boundaries of the farm, while in the latter case it is precisely a matter of merging agricultural activity with solar energy production, and this practice is called **agrivoltaics**.

It is a system that combines agricultural production with photovoltaics, accommodating the two terms in the same plot. In fact, it is a combination of solar panels and food crops on the same unit of land that maximizes land use (Dupraz et al. 2011).

Agrivoltaics coexists mainly with vegetable crops, but even with farm animals. In fact, solar panels create shaded areas that promote crops but can also provide shelter for animals.

More specifically, sustainable agrivoltaics would function to:

Preserving land for food agricultural use

In fact, with the elevation of solar panels, the land retains its fertility and can switch from arable agricultural use to higher value types of crops such as horticulture, fruit growing or viticulture. Moreover, maintaining plant cover and plant mass counteracts the decarbonization of soils Shading also makes it possible to decrease solar radiation and increase the available water potential in the soil.

Reducing the water requirements of crops

Especially in particularly dry and hot seasons and places, agrivoltaics allows to minimize the water stress of crops. Their water requirements are reduced, even in comparison with their placement in the sun.

Supporting agricultural crops

Some types of cultivation require supportive conditions, such as shade or even mechanical supports to promote growth. Solar panels, in addition to producing energy, can act as supports to meet these demands.

Regulating rainwater and protecting against violent weathering

The raised photovoltaic panel forms a generally impermeable surface over which water flows by gravity. Water harvesting systems make it possible to reduce the amount of precipitation on the ground, reducing stormwater formation, and to conserve water for reuse according to crop needs.

Moreover, an agrivoltaics system can act as a protective cover in case of heavy rain, snow, hail or wind; these are potentially harmful factors to crops.

4.3. Biogas Production

Biogas is generally produced starting from agricultural by-products (biomass and livestock waste) that are subject to a process called **anaerobic fermentation**, that is the fermentation in the absence of oxygen of organic substrates (Insidewaste.com, 2022).

The most efficient biomass that can be fermented is corn, but sorghum and barley with lower yields are also used. The most efficient wastewater is cattle, but pigs’ manure is also used. Biomasses can either come from dedicated crops or can also be production waste.

Traditionally wastewater is used as natural fertilizers but can cause environmental problems such as air and water pollution (dispersion of methane and carbon dioxide). In addition, incorrect use of manure could lead to pathogens that are harmful to human health.

The process of anaerobic digestion of organic matter produces biogas. It mainly consists of methane (50-70%), carbon dioxide and a mix of other gases. It is a renewable gas that can be used in two ways:

1) Power an engine that, via an alternator, **converts thermal energy into electrical energy** that is sold to energy providers.

2) **Purify the gas**. This is known as biogas upgrading and the resulting gas is called biomethane (91% pure methane) which has multiple valuable uses. Thereafter, it can be injected into the gas grid or used as transportation fuel.

Currently the second option seems to be better from an energy point of view since it has less energy dispersion (in the form of heat) and there are Italian and European incentives to go in this direction. Even the first option, however, could have interesting implications from a circular economy point of view: energy waste (heat) could be used for crops and farms that require large amounts of heat and humidity, for example for the poultry sector or, with an eye to the future, insect farms and algae crops.

Anaerobic digestion is an **environmentally friendly**, **cost-effective solution** to process virtually all types of organic waste. These include food waste, food and drink production waste, farm waste (manures, slurries, etc.), garden waste and more. Furthermore, many farmers grow energy crops, such as energy maize and hybrid rye, specifically for anaerobic digestion. Some of them are meant to be "break crops" which grow in-between standard food crop cycles and this enables farmers to utilise their land during void periods, produce valuable crops which earn them income, improve soil condition and at the same time contribute to renewable development.

Currently most organic waste worldwide ends up in landfill sites that **threaten the environment** since they subsequently decompose and produce methane which escapes into the atmosphere. Methane is an extremely potent gas which causes up to 30 times more pollution than an equivalent amount of carbon dioxide (CO_2). In addition, organic waste at landfills also generates leachate (wastewater) which presents many challenges. In many parts of the world landfills have no leachate containment measures. As a result, leachate drains freely into natural rivers and lakes causing severe water pollution.

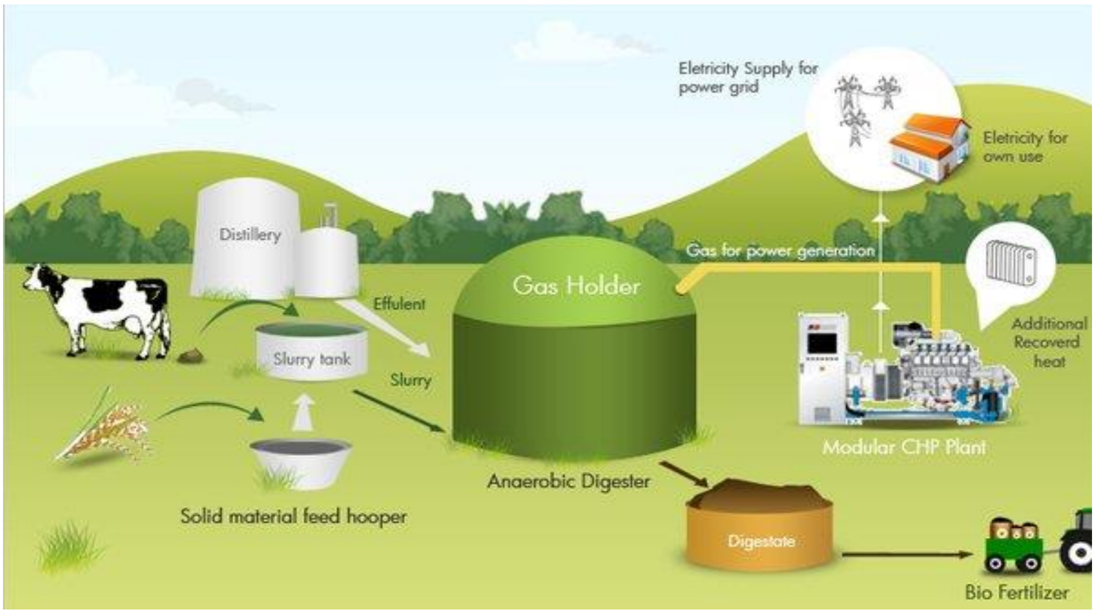
More recently, mixed municipal solid waste, which includes organic waste, has been sent to incineration plants (the most common type of energy from waste plants). Incineration can recover some of the waste by producing electricity and heat. Though is unquestionably a better solution than landfill, it is not a particularly efficient and environmentally friendly method of processing organic waste.

When organic waste is relatively pure or can be separated from mixed waste, anaerobic digestion is regarded as the best processing method. Biogas plants extract the energy content by converting it to useful biogas. Unlike other renewable technologies, such as wind and solar, **biogas production** is **very efficient**, it is **not uncertain** and also **allows energy storage**.

Combined heat and power engines (CHP plant) can burn it to produce renewable electricity and heat whenever it is needed, granting a **stable flow of energy**. Alternatively, upgrading it to biomethane (that is very close to pure methane) also allows **energy storage**, **transportation and usage where and when necessary**. Biomethane is useful in both gaseous and liquid form. It has similar properties to natural gas but it is a clean renewable biofuel. It has numerous benefits and plays an important part in making both gas grids and the transportation sector more sustainable.

Moreover, in addition to generating renewable energy, there is a **by-product** of the biogas production process, known as **digestate**, which is a **natural fertiliser** with numerous proven benefits for farming. Digestate **replaces traditional chemical fertilisers**, thus it saves costs to farmers and reduces pollution.

Fig. 4.1.1: Biogas Production Scheme



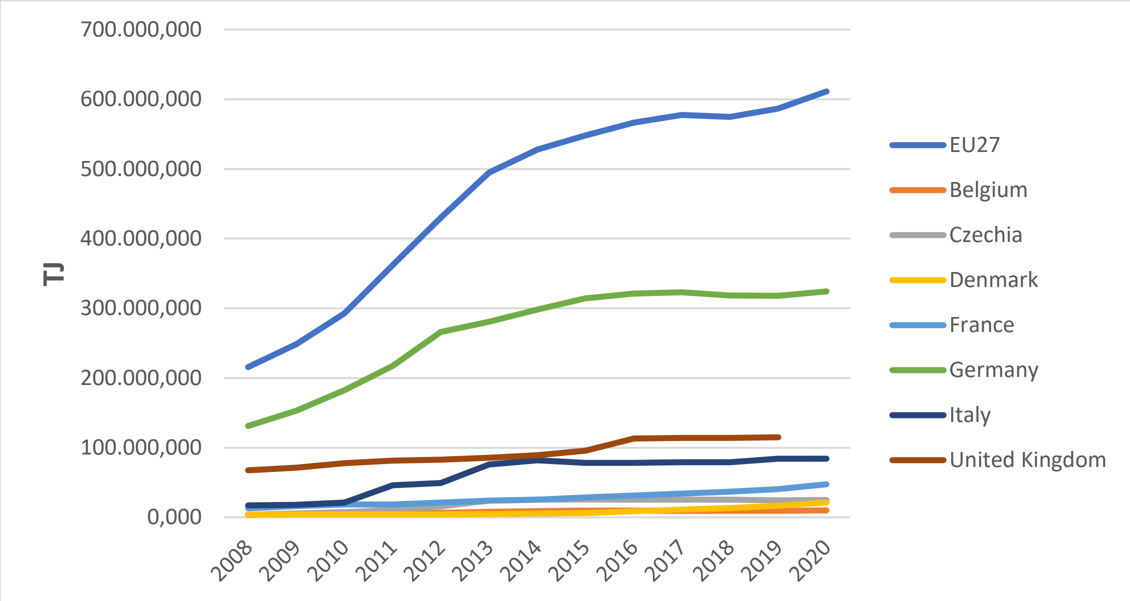
Source: InsideWaste.com, 2022

Fig. 4.1.1 portraits the production scheme for the electricity and heat production through a Combined Heat and Power Engine that burns the biogas from the anaerobic digestion of biomasses and wastewater. Alternatively, the biogas can be purified to obtain biomethane.

Fig. 4.1.2 depicts the growth in biogas production in EU from 2008 to 2020. It has significantly increased over the years, especially in Germany that have more than doubled its domestic production. Italy has witnessed a quick growth during the 2010-2013 period, then the curve has flattened.

Biogas is already seen as a reliable alternative to the common energy sources and the latest trends suggest that biogas production can keep increasing in the following years.

Fig. 4.1.2: Biogas Production Trends in Europe (2008 – 2020)



Source: Our World in Data, 2022

4.4. Works from Literature

The purpose of this thesis is to clarify the efficiency issue about the energy production within the agricultural sector using the Data Envelopment Analysis method. In other words, farms can produce energy (output) in several ways, using different inputs in several ways and through this input-output process some can be more efficient than others. The DEA method helps in identifying efficient and inefficient farms, in understanding the sources of inefficiencies and, moreover, in suggesting how inefficient farms can improve and being optimally efficient.

A large part of the literature of economic efficiency owes something to the early work by **Farrell (1957)**: "**The Measurement of Productive Efficiency**". After that a whole body of literature has been developed around the concept of **frontier methodology**.

The original frontier function model uses the **efficient unit isoquant** to measure economic efficiency, and to decompose this measure into **technical** and **allocative efficiency**. In this model, technical efficiency (TE) is defined as the **firm's ability to**

produce maximum output given a set of inputs and technology, while allocative efficiency (AE) measures the **firm's success in choosing the optimal input proportions**, that is where the ratio of marginal products for each pair of inputs is equal to the ratio of their respective market prices.

The large number of frontier models that have been developed based on Farrell's work can be classified into two basic types: **parametric** and **non-parametric**. Parametric frontiers rely on a specific functional form while non-parametric frontiers do not. Data Envelopment Analysis is a non-parametric model.

In addition, another important distinction can be made between **deterministic** and **stochastic frontiers**. The deterministic model assumes that any deviation from the frontier is due to inefficiency, while the stochastic approach allows for some statistical noise. DEA can be classified as a deterministic frontier model.

The deterministic parametric approach was initiated by the work of **Aigner and Chu (1968)**, who estimated a Cobb-Douglas production frontier through linear and quadratic programming techniques and it has been further developed by the work of **Timmer (1971)** that introduced the probabilistic frontier production model.

Then, another class of deterministic parametric models is the one proposed by Afriat (1972), in which technical efficiency (TE) is measured by a one-sided disturbance term. This class of models relies on a **statistical production frontier**.

If the distribution of the disturbance term is determined by explicit assumptions, the frontier is estimated by the **maximum likelihood estimation (MLE) method**. When no assumptions are made concerning the distribution of the error term, the frontier can be otherwise estimated by the **corrected ordinary least squares method (COLS)** which consists of simply and neutrally shifting the frontier upwards until no positive error term are left behind.

Further developments in frontier methodology exploited an **"econometric approach"** (Bauer, 1990) with the purpose of estimating frontiers using a **parametric**

representation of technology along with a **two-part composed error term**. This approach was first proposed by Aigner et al. (1977), Meeusen and Van den Broeck (1977), and Battese and Corra (1977). The first part of the composed error term represents statistical noise and is generally assumed to follow a normal distribution; it reflects all the casualties that are not under the firm's control, like luck or weather. The second part represents **inefficiency** and instead is assumed to follow a particular **one-sided distribution**.

Several authors have revolved around the definition and explication of the distribution that represents the inefficiency. The following one-sided distributions have been then employed: the half-normal and exponential distributions proposed by, among others, Aigner et al. (1977), the truncated normal proposed by Stevenson (1980), and the two-parameter Gamma distribution Proposed by Greene (1990).

The **"econometric approach"** recalls a recurring theme in frontier methodology and broadly in statistic modelization, that is the **conflict between structure and flexibility**. The more structure we impose on a model the better the estimates, provided the structure we impose is correct, and the econometric approach relies on the definition of a structure. Nevertheless, one must keep in mind that assuming a structured model bear the burden of being precisely correct about all the specifications.

Ideally, either the correct structure is known to be imposed a priori otherwise it has to be estimated a sufficiently flexible model so that possible restrictions can be tested.

In short, stronger assumptions generate stronger results, but they strain one's conscience more (Bauer, 1990). The appropriate structure to impose can only be determined by a careful consideration of the data and the characteristics of the sector under study. Unfortunately, there are not always statistical tests to guide the way.

Data Envelopment Analysis, originally proposed by Charnes, Cooper and Rhodes (1978), is on the other side with respect to the previous stated "econometric approach" since it is a **non-parametric method** that provide a **deterministic frontier** in which deviations from the frontier are paradigmatically considered inefficiencies. In that article they proposed the **CCR model**, named after authors initials.

Then Banker, Charnes and Cooper (1984) further developed the DEA methods, proposing the **BCC model**, named as well after the initials of the authors. Starting from that, many extensions to DEA have been proposed in the literature.

The textbook “Introduction to Data Envelopment Analysis and its uses” by Cooper (one of the original authors), Seiford and Tone (2006) reports a bibliography of over 2800 works that develop, rearrange, change perspective and open new possibilities for the DEA method. These developments range from adapting and changing implicit model assumptions such as **input and output orientation**, distinguishing **technical and allocative efficiency**, adding **limited disposability of inputs/outputs** or **varying returns-to-scale** to even develop new techniques that utilize DEA results and extend them for more sophisticated analyses, such as **stochastic DEA** or **cross-efficiency analysis**.

Given that, in the following paragraphs are presented some works that come close to this thesis topic and deserve to be acknowledged.

1. **First paper**

The first one is the work of Dogan and Tugcu (2015) “**Energy efficiency in electricity production: a data envelopment analysis (DEA) approach for the G-20 countries”**, which is about a DEA efficiency analysis in the **energy production field**. The study adopts the **DEA techniques** to compare the energy efficiency performances of G-20 countries in electricity production for the periods 1990, 1995, 2000, 2005 and 2011.

They considered **five different inputs**: Coal Sources (CS), Hydroelectric Sources (HS), Natural Gas Sources (NGS), Oil Sources (OS), and Renewable energy Sources (RS), excluding hydroelectric. On the other hand **one output** is taken into consideration, which is the Electricity Produced.

Data for this study have been obtained from the World Development Indicators Database of World Bank. Data Envelopment Analysis was used because of its **ability of handling multiple inputs and multiple outputs simultaneously without the need of specifying a cost or a production function.**

Efficiency measurement is made using **CCR model** and **Super Efficiency Model**. Two values have then been found: ES, "efficiency score", and SES, "super-efficiency score" and their values are given for each period (1990 – 2011) and country (G-20 members). ES and SES are derived from solving CCR and Super Efficiency Models, respectively.

DEA assigns the efficiency value of one (normalized to 100 in this case) to the DMUs which are efficient. All the DMUs lying on the efficiency frontier are therefore considered efficient, anyway there might be several units with an efficiency value of unity. Each one of them is efficient in their way, but **which one is the "more efficient"**?

Super Efficiency is perhaps the most well-known answer to this question. The idea of Super Efficiency is that the best practice frontier is created first without evaluating DMU_0, and then with its inclusion. With this procedure, DMU_0 may even be attributed an efficiency value higher than unity.

Results are then summarized in the following table 4.1 and 4.2.

Table 4.2.1: G-20 Countries ES and SES (1990 – 2000)

Country	ES 1990	SES 1990	ES 1995	SES 1995	ES 2000	SES 2000
Argentina	100	464,84	100	425,04	100	241,5
Australia	100	113,14	100	158,55	100	279,23
Brazil	100	1362,32	100	1462,96	100	650,88
Canada	100	114,69	100	126,18	100	145,77
China	100	1460,26	100	552,57	100	763,87
France	99,6	99,6	99,74	99,74	99,74	99,74
Germany	100	175,43	100	127,61	100	122,36

India	100	213,92	100	196,29	99,39	99,39
Indonesia	100	159,72	100	107,62	99,91	99,91
Italy	100	115,59	100	145,39	100	114,47
Japan	100	117,29	100	112,02	100	104,43
Korea	100	158,11	100	265,61	100	614,28
Mexico	100	162,52	100	108,03	100	146,34
Russia	100	230,95	100	1665,5	100	511,55
Turkey	100	111,23	100	106,85	100	101,14
UK	100	398,27	100	223,64	100	247
USA	100	101,8	100	103,83	98,85	98,85
EU	96,98	96,98	98,41	98,41	99,95	99,95

Source: Dogan and Tucgu, 2015

It can be seen from Table 4.1 that among 18 samples in 1990, 16 countries are efficient and only 2 of them (France and EU) are inefficient. The most efficient country in 1990 is China.

In 1995, similar to 1990, 2 samples are inefficient: France (99.74 %) and the European Union (98.41 %). The most efficient country in 1995 is Russia.

In 2000, 5 countries are found to be inefficient: France, European Union, India, Indonesia, and the United States. China leads the efficient countries.

Table 4.2.2: G-20 Countries ES and SES (2005 – 2011)

Country	ES 2005	ES 2005	SES 2005	ES 2011	SES 2011
Argentina	100	100	224,39	100	273,73
Australia	100	100	177,02	100	112,92
Brazil	100	100	510,2	100	462,53
Canada	100	100	118,57	100	146,7
China	100	100	1049,24	100	682,88

France	99,4	99,4	99,4	100	111,29
Germany	100	100	118,19	100	149,8
India	99,5	99,5	99,5	99,17	99,17
Indonesia	100	100	130,19	100	119,82
Italy	100	100	113,06	100	110,03
Japan	100	100	104,12	100	105,65
Korea	100	100	756,36	100	499,12
Mexico	100	100	118,35	100	131,08
Russia	100	100	202,11	100	1234,91
Turkey	100	100	104,39	100	170,2
UK	100	100	237,7	100	165,14
USA	99,16	99,16	99,16	99,92	99,92
EU	100	100	101,04	99,11	99,11

Source: Dogan and Tucgu, 2015

Looking at table 4.2, in 2005, France, India and the United States are inefficient. China is the most efficient country.

Finally, in 2011 India, the United States and the European Union are inefficient while Russia, China, Korea are the most efficient ones.

2. Second paper

The second work considered is "**Analysing farming systems with Data Envelopment Analysis: citrus farming in Spain"** by Reig-Martinez and Picazo-Tadeo (2004), which covers the topic of efficiency analysis in agricultural production.

The purpose of the article was, starting from a sample of Spanish citrus farms, to identify the decision making units (DMU) that determine the **technological** or **best practice frontier**, and their characteristics are **compared** with those of the **average farm**.

Microeconomic theory considers production processes as the result of **optimization behavior**. Managers decide **what to produce** and **which input-mix to use** in order to achieve **profit maximization**. From an engineering or technical perspective, producers seek to maximize output for a given endowment of resources. Alternatively, producers are assumed to allocate resources efficiently by using the combination of inputs that minimizes the cost of producing the desired level of output.

Therefore they used **CCR Model** to determine**,** for each inefficient production unit, a measure of **relative inefficiency** that can be calculated by comparing its observed behavior either with the behavior of a **reference unit** that belongs to the technological frontier or with a **virtual unit** that is the result of a **convex combination of different efficient units**. The set of units that a decision making unit should look at for improving efficiency, is called **reference set**.

The sample included 33 full production citrus fruit farms with data for one output and nine inputs.

The **output** considered was the **Citrus Fruit Production per Hectare** (measured in tons). The nine categories of **inputs** considered were: **Cultivated Land** (hectares), **Own-Family and Wage-Earning Labor** (annual worker units or AWU), **Own and Hired Agricultural Machinery** (annual hours of use), **Consumption of Nitrogen, Phosphorus and Potassium in Chemical Fertilizers** (in kilograms) and **Expenditure in Pesticides and other Phytosanitary Products** (euros).

The results are the **identification** of the 6 DMUs that belongs to the **efficient frontier**, the **determination** of the **reference sets** for each DMU and the **characterization** of the efficient DMUs.

Table 4.3 shows the characterization of the 6 DMUs lying on the efficient frontier. In brackets there is displayed the number of times that specific DMU appears in the reference set of another DMU.

Table 4.2.3: Characteristics of the Efficient Frontier (2004)

DMU	1 (2)	2 (1)	3 (21)	4 (10)	5 (2)	6 (28)	Average
Output per Ha	25.2	37.6	37.2	44.1	23.3	46.0	30.1
Farm Size	35.0	1.3	16.7	1.1	1.0	1.8	5.7
Own Labor	0.03	0.19	0	0	0	0	0.13
Wage-Earning Labor	0.10	0.02	0.13	0.12	0.20	0.17	0.13
Own Capital	34	0	60	0	74	14	70
Hired Capital	0	0	3	23	0	0	4
Nitrogen	233	148	262	171	306	292	289
Phosphorus	186	91	0	80	59	0	102
Potassium	93	91	0	171	59	0	115
Pesticides	365	1360	305	319	92	243	453

Source: Reig-Martinez and Picazo-Tadeo, 2004

That kind of representation is useful to rapidly compare DMUs and can help in looking for patterns that can explain a greater efficiency level.

3. Third paper

The third article, by Madlener R. et al. (2009), **"Assessing the performance of biogas plants with multi-criteria and data envelopment analysis"** is the closest one to this thesis. It performs an assessment of 41 agricultural biogas plants located in Austria to determine their relative performance in terms of economic, environmental and social criteria by using **DEA techniques** and **Multi Criteria Decision Analysis (MCDA)**.

DEA is the tool generally used to evaluate the **efficiency of decision making units**, while **MCDA** is the tool generally used to **conciliate multiple evaluation criteria**, considering the **preferences** of a decision-maker. In fact, a manager is normally not indifferent to the fact that a DMU turns out to be more efficient by using/producing a different combination of inputs or outputs, and by underweighting inputs and/or outputs of key importance to the business concerned.

The paper computes an **efficiency score** for any given DMU when this particular DMU is compared with all the other DMUs considered. The **relative efficiency** of a DMU is usually defined as the ratio between the sum of its weighted output levels to the sum of its weighted input levels. The weights are not exogenous, but endogenous since they are chosen by the Linear Programming model, such that each DMU is ''shown in its best light".

In DEA, a DMU is considered **efficient** if there is **no other DMU**, or a linear combination of inputs and outputs of several DMUs, **that can improve one input or output, without worsening the value of at least another one**.

The **efficient frontier** is defined by the observed values of the relatively efficient DMUs. If a DMU does not belong to this envelopment surface and lies in its interior, then that DMU is operating inefficiently. DEA models usually return an efficient **projection point** of operation on the frontier for each inefficient DMU, thus identifying the single DMU or the combination of several ones, that can be used as **performance benchmarks** for the **inefficient DMU**.

The DMUs considered are a **representative set of energy crop digestion plants** in Austria, that aim to cover the whole spectrum of plant types and operating conditions. Samples were taken from the substrate, digester, fermentation residues and biogas plant types. Cooling, safe transport and appropriate storage were scrutinized as well. The considered plants are geographically distributed over the country.

They range from small-scale installations using mainly manure and energy crops to larger-scale plants that use considerable amounts of co-substrates.

The **main aspects** that the study shall evaluate, for assessing the efficiency of energy crop digestion plants, are: **Substrate Provision**, **Storage** and **Pre-Treatment**; **Biogas Production** from anaerobic digestion; **Utilization of Heat and Electricity**; **Digestate Handling** and **Disposal**; and **Greenhouse Gas** (GHG) **Emissions**.

The variables considered as **input** were two: **labor** (time) **spent for plant operation** and **amount of substrate used** (organic dry substances, ODS).

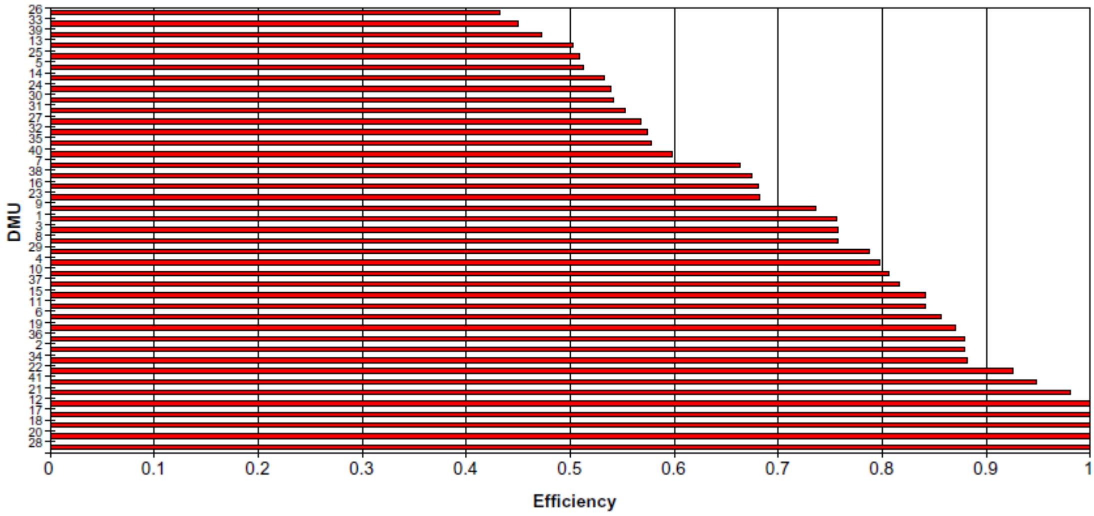
The **outputs**, on the other hand, were: **amount of biogas or net electricity produced** (electricity delivered by the biogas plant and sold for external consumption, subtracting what the plant needs to consume itself); **net heat produced** (for external consumption) and **net GHG emissions** released to the atmosphere (net of the "emissions credits" calculated in case of not having the biogas plant, and measured in CO_2 equivalent).

In the **DEA model** considered in this paper, we have used substrate and labor as traditional inputs and the amount of net external electricity and heat as desirable traditional outputs. **GHG emissions** have been considered as an **undesirable output**. Authors chose to consider these **emissions as an input**, which is a common option to model undesirable outputs, since the DMU to be efficient should minimize GHG emissions (just like other inputs) given a certain fixed level of output.

The considered model was **CCR**, even though the authors suggest the possibility to use the **BCC model** to **benefit DMUs not operating at an optimal scale.**

Fig. 4.2.4 reports paper's DEA results, in which it can be seen that only 5 out of the 41 plants belong to the efficient frontier and thus appear to be considered efficient.

Fig. 4.2.4: Efficiency of 41 agricultural biogas plants located in Austria (2009)



Source: Madlener R. et al. (2009)

4. Fourth paper

The article considered is the one by Sameena B. et al. (2018) "**Significance of Implementing Decentralized Biogas Solutions in India: a Viable Pathway for Biobased Economy**".

This study revolves around the **implementation** of biogas plants in India and the **barriers** that prevent the spread of new plants.

The **first part** of the study focuses on investigating the **biogas solutions** that evolved in India, its installations in rural areas promoted by government and on barriers that hindered the spread of biogas technology due to limited access to information and lack of awareness on the recent scientific innovations.

A **second part** of the study focuses on presenting a **case study** describing the installation and commissioning of the **biodigester** in Bellary (Karnataka, India), operation and maintenance and finally an estimate on its products utility and payback period.

The first barrier is **economic feasibility**. Installing a plant requires large investments and therefore a system in which there are own capital and disposable debt capital.

The **costs associated** with biogas technology can be divided into **initial costs** of construction and installation and **operative costs** for the maintenance of the plant.

Within the first category there are: cost of labor, excavation cost, costs of construction materials, pipes and their set up for biogas supply, transportation cost of materials.

For the maintenance costs there are: costs associated with mixing of feedstock in the slurry tank with water, pH boosters to operate the reactor in stable conditions, collecting the digested slurry from outlet tank, drying the digested slurry to obtain solid fertilizer.

India has implemented a **large biomass energy program**, which involves the promotion of several bioenergy technology programs, called BETP, through several policies, institutional and financial incentives and interventions.

Most of the BETP were implemented with **direct capital subsidy support** from the MNRE (Ministry of New and Renewable Energy), combined with other **policy incentives**, such as income tax reduction, accelerated depreciation, concessional duty/custom duty-free import, soft loans for manufacture and state level policies on wheeling and banking.

Unfortunately, the rate of spread of bioenergy technologies has remained low: only about 3.83 million household biogas plants were installed (till 2006) against a forecasted potential of 12 to 17 million. The reasons behind are attributable to **barriers** such as the limited capacity to assess, adopt, adapt and absorb scientific options, insufficient information and financing possibilities to assess the technological needs.

5. DATA ENVELOPMENT ANALYSIS

5.1. What is DEA?

The origins of DEA methodology date back to 1978, when Professors Charnes, Cooper and Rhodes in their work **"Measuring the efficiency of decision-making units"** applied **linear programming** to estimate, for the first time, an empirical production-technology frontier, building on the work of more than two decades earlier by Farrell, 1957.

Data Envelopment Analysis is a **nonparametric linear methodology** aimed at **evaluating the efficiency** of similar decision-making units (**DMU**), **based upon the inputs and the outputs** associated with these entities (Cooper et al. 2005).

DMUs are the **basic units** of the DEA methodology. The term is very broad and includes within it businesses, hospitals, schools, public institutions, military and police forces, and more. DMUs are defined as any such entity, with each such entity to be evaluated as **part of a homogeneous collection that utilizes similar inputs to produce similar outputs**.

One of the strengths of the DEA methodology is that it is **nonparametric**. This means that it does not need a priori parametric specifications, such as defining a production function.

Data envelopment analysis is so called because it **"envelops" observations to identify a "frontier"** that is used to evaluate the performances of the considered entities. DEA, then, assigns a **performance score** that ranges between zero and one and represents the **"degree of efficiency"** obtained by the entity thus evaluated.

All **the efficient DMUs compose the efficient frontier** where lie the entities that relatively better transform inputs into outputs (“degree of efficiency” = 1).

What is efficiency (and inefficiency) then? We take, at first, the well-known **Pareto-Koopmans Definition of Efficiency** (S. Morteza Mirdehghan, H. Fukuyama, 2016):

Definition 5.1.1: Efficiency

A DMU is efficient **if and only if** it is not possible to improve any input or output without worsening any other input or output.

Definition 5.1.2: Inefficiency

A DMU is inefficient **if and only if** it is possible to improve some input or output without worsening any other input and output.

The following trivial example shows the intuition behind the construction of the efficient frontier in the simplest case possible: firms that produce one kind of output, starting from one kind of input.

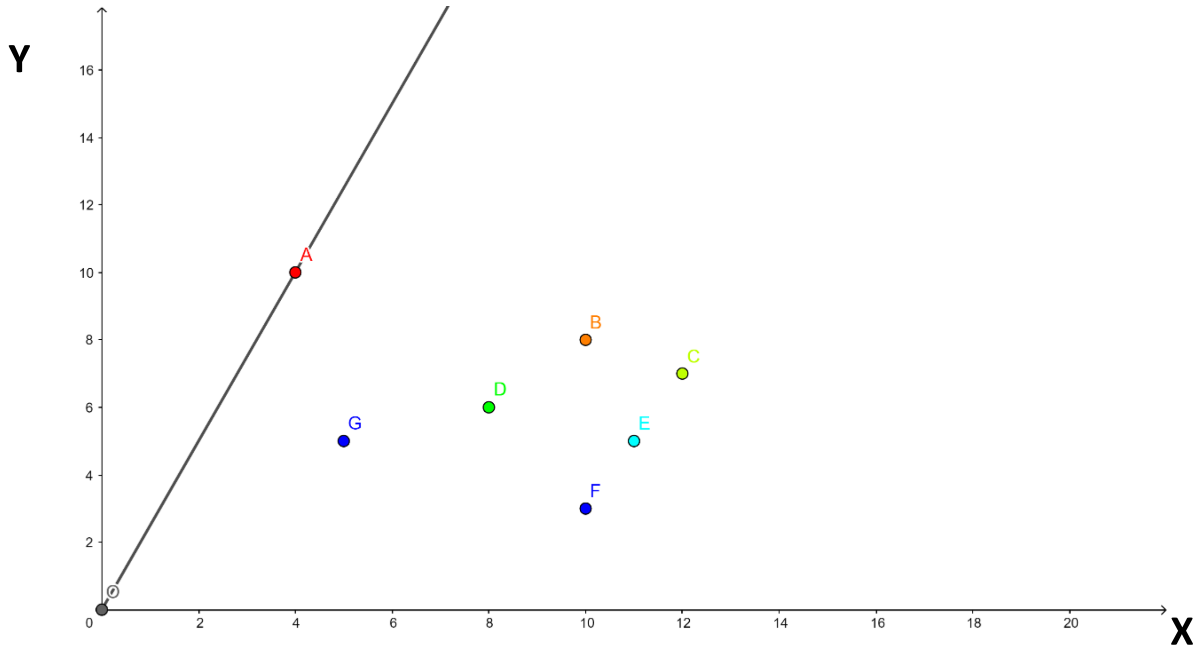
5.2. Example with One Input and One Output

Consider 8 farms (n) that produce t-shirts (y_1) from cloth (x_1). Thus, there are eight DMUs (indexed by i = 1…n) that produce one type of output, starting from one type of input (Cooper, Seiford and Tone, 2005).

Each DMU is represented into a Cartesian plane with coordinates (x_{1i}, y_{1i}).

The efficient frontier crosses the most efficient DMUs (which are the "northwest-er" ones). Efficient DMUs are defined to be the ones that better translate inputs into outputs. In this case the farms that have the greater t-shirts/cloth ratio (y_1/x_1) are efficient, since from one unit of cloth (input) they can realize the greater number of t-shirts (outputs).

Fig. 5.2.1: One Input, One Output: the Efficient Frontier



Source: Cooper et al. (2005), rework by the author

Thus, is straightforward that **DMUs are efficient if and only if they lie on the efficient frontie**r while these are **inefficient if and only if they lie out of the efficient frontier**.

In Fig. 5.1.1 only the DMU A is efficient, because it is the only one laying on the efficient frontier, since it transforms input (on the x axis) into output (on the y axis) at the best ratio within the DMUs considered. Considered 4 units of inputs, DMU A produces 10 units of output, which means 1.5 units of output per unit of input. The second best, DMU G, only produces 5 units of output starting from 5 units of input: one unit of input produces exactly one unit of output.

In this simple example, the efficient frontier is taken starting from the most efficient DMU A, and it is, in practice, a half line starting from the origin (O) that touches the most efficient points.

$$y = mx \qquad (1)$$

$$m = \frac{y}{x} \qquad (2)$$

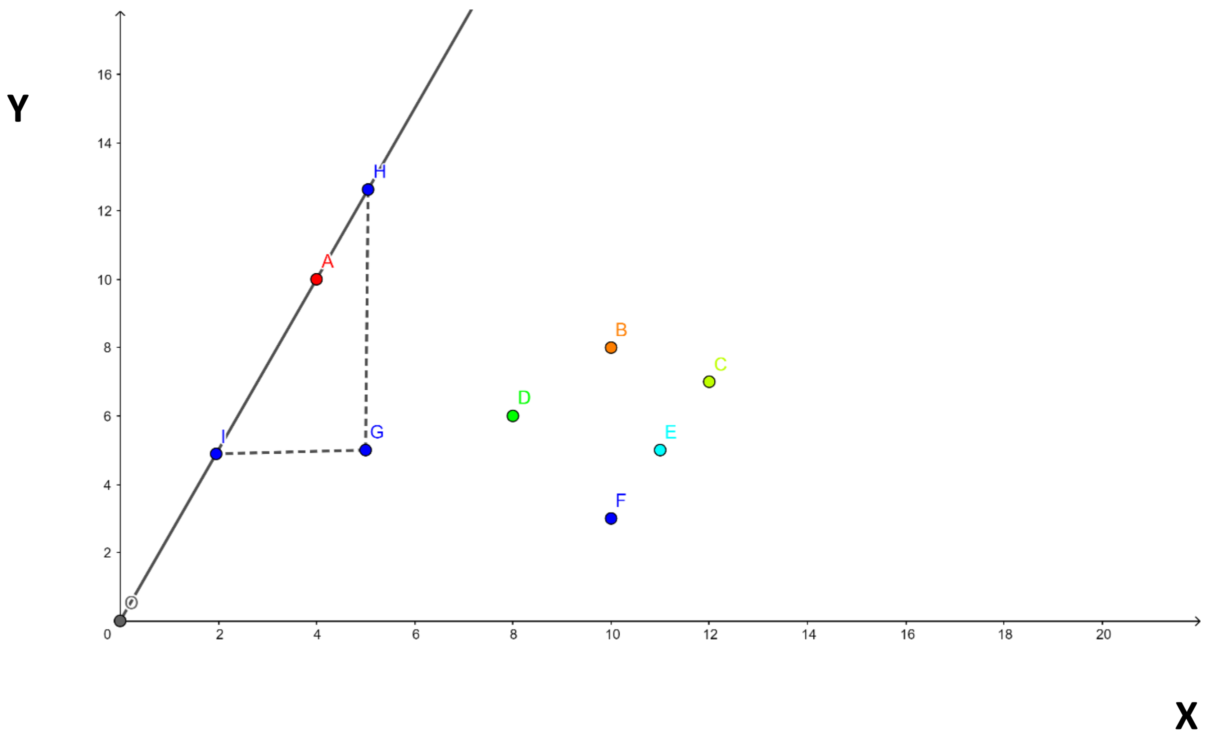
Starting from the equation (1), that crosses the origin the axes, it is straightforward that all the points that lie on this line, with angular coefficient equal to the output/input ratio, have something in common with DMU A: these are all efficient points, with score equals to one.

It is important to note that **efficiency** in DEA is **not necessarily absolute, but it is relative**: in every DEA analysis there will be one, or more, efficient DMU. That does not mean that DMU is efficient in absolute terms, but it means that, among the considered DMUs, it is relatively the most efficient. Slightly changing the set of DMUs may change the set of efficient DMUs.

Given the definition of efficiency, an **inefficient decision-making unit should improve and change its position moving towards the efficient frontier**. For example, point G could, theoretically, reduce the input, keeping fixed the output, until it lays on the efficient frontier (horizontal movement GH); on the other hand, it could fix the input level while being more efficient and enhancing the output level (vertical movement GI).

In the example, DMU G uses 5 units of input (cloth) to produce 5 units of output (t-shirts), given that the “A ratio” is feasible, DMU G should either keep the output fixed and reduce the inputs, or increase the output keeping fixed the level of inputs.

Fig. 5.2.2: One Input, One Output: Improving an Inefficient DMU



Source: Cooper et al. (2005), rework by the author

There are then two perspectives that could be taken in consideration: DEA can be either **output oriented or input oriented**.

In the former case the question is if, using the same number of inputs, a greater outcome can be achieved; in the latter case the question is reversed: given a certain amount of outcome, can this be achieved by using a lesser number of inputs?

5.3. Partial to Total Productivity Measures

The **DEA methodology overcomes a problem** that classical and simpler efficiency analyses have. Often **other systems** for assessing efficiency are based simply on the **single output to single input ratio**.

DEA instead works on **multi-outputs to multi-inputs ratio**.

Examples, **of single output to single input** include cost per unit, profit per unit or satisfaction per unit, which are measures stated in the form of a ratio:

This is a commonly used measure of efficiency. The usual measure of "productivity" also assumes a ratio form when used to evaluate worker or employee performance. "Output per worker hour" or "output per worker employed" are examples with sales, profit or other measures of output appearing in the numerator.

Such measures are sometimes referred to as **"partial productivity measures"**. This terminology is intended to distinguish them from **"total factor productivity measures"**, because the former attributes all the production efficiency to one input: “Output per worker hour” attributes to the input “labor” all the responsibility for producing the output in an efficient way. The latter instead, attempt to obtain an output-to-input ratio value which takes account of many outputs and many inputs.

How is it possible, then, to move from partial to total productivity in this framework? By **combining all inputs and all outputs to obtain a single ratio**. Which means finding two numbers that can reflect all the inputs and the outputs.

However, an attempt to move from partial to total factor productivity measures encounters **difficulties** such as **choosing the inputs and outputs** to be considered: an insufficient number of inputs and outputs leads to a partial analysis that does not reflect the real situation, on the other hand selecting inputs and outputs that are not relevant leads, as well, to an unrealistic situation.

Then, **the weights** that are used to obtain a single-output-to-single-input ratio must be wisely selected: weights are meant to express the **relative importance of the factors** and an inaccurate selection leads to underestimation and/or overestimation of the inputs/outputs.

Moreover, dealing with **multiple outputs and inputs** is something to be cautious with: complexity rises proportionally with the number of inputs/outputs.

Another issue is **comparing different DMUs**: it is not realistic considering all the DMUs “identical”, forcing every DMU to follow the same recipe of inputs/outputs may be misleading.

Now is when Data Envelopment Analysis comes to the aid of the analyst. **DEA does not require the user to prescribe weights** to be attached to inputs and outputs and it also **does not require prescribing the functional forms** that are needed in statistical regression approaches.

DEA utilizes techniques such as **mathematical programming** which can handle large numbers of variables and relations (constraints), and this relaxes the requirements that are often encountered when one is limited to choosing only a few inputs and outputs because the techniques employed will otherwise encounter difficulties. Relaxing conditions on the number of candidates to be used in calculating the desired evaluation measures makes it easier to deal with complex problems and to deal with other considerations that are likely to be confronted in many managerial and social policy contexts.

In section 5.4 is presented the **two inputs and one output case**.

5.4. Example with Two Inputs and One Output

Consider 9 supermarkets (DMU), that have two inputs and one output (Cooper et al. 2005).

Employee (unit is 10 employees) and Floor Area (unit is $1000m^2$) are the inputs while the output is Sale (unit is 100.000$). Inputs for each DMU are normalized to give 1 unit of output.

Table 5.4.1: Two Inputs, One Output

Store		**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**
Employee	X_1	4	7	8	4	2	5	6	5.5	6
Floor Area	X_2	3	3	1	2	4	2	4	2.5	2.5
Sale	Y	1	1	1	1	1	1	1	1	1

Source: Cooper et al. (2005)

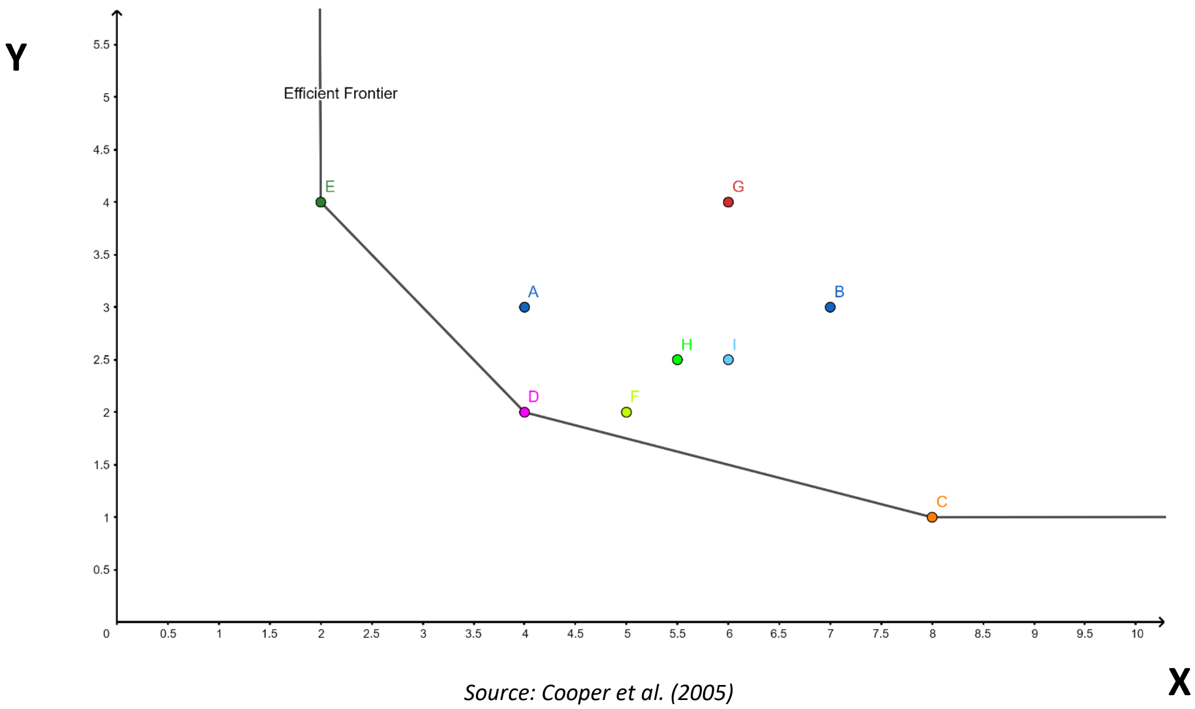
Divide now each Input for the single Output and plot X_1/Y on the X axis and X_2/Y on the Y axis. Each DMU_i can be represented as a point (X_{1i}/Y_i; X_{2i}/Y_i) on the cartesian plane.

To find the efficient frontier link those points that cannot be improved without worsening one of the input/output, i.e., those points that does not have another point placed at west, south or south-west.

We can envelop all the data points within the region enclosed by the frontier line, the horizontal line passing through C and the vertical line through E. We call this region the production possibility set.

This means that the observed points are assumed to provide (empirical) evidence that production is possible at the rates specified by the coordinates of any point in this region. Moreover, the efficient DMUs lying on the efficient frontier can be taken as models for the inefficient DMUs.

Fig. 5.4.1: Two Inputs, One Output: the Efficient Frontier



Source: Cooper et al. (2005)

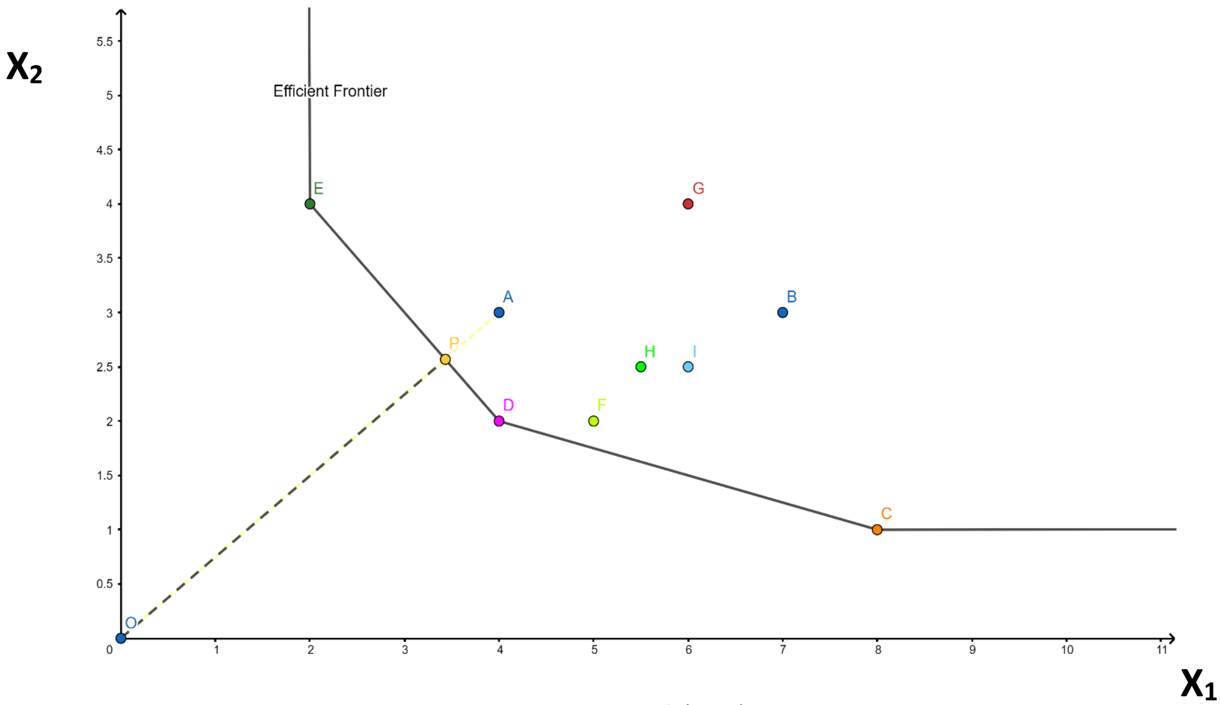
The efficiency of stores not on the frontier line can be measured by referring to the frontier points as follows. For example, A is inefficient. To measure its inefficiency let OA, the line from the origin to A, cross the frontier line at P. Then, the efficiency of *A* can be evaluated by:

$$\frac{OP}{OA} = 0.8571 \qquad (3)$$

This means that the inefficiency of A is to be evaluated by a combination of D and E because the point P is on the line connecting these two points.

D and E are called the **reference set** for A. The reference set for an inefficient DMU may differ from store to store. For example, B has the reference set composed of C and D in Figure. We can also see that many stores come together around D and hence it can be said that D is an efficient store which is also "representative," while C and E are also efficient but also possess unique characteristics in their association with segments of the frontiers that are far from any observation.

Fig. 5.4.2: Two Inputs, One Output: improving Inefficient DMU



Source: Cooper et al. (2005)

Whenever there are multiple inputs/outputs one trick to reduce complexity is to **arbitrarily assign fixed (predetermined) weights.** This simplifies matters for use, to be sure, but raises the question of **justifying the weights**.

Why input i have weight w_i instead of w_i'? This difference in weight may result in significant differences in efficiency.

DEA, by contrast, uses **weights that are not predetermined**. In particular, the weights are derived directly from the data.

The weights are chosen in a manner that assigns a **best set of weights** to each hospital. The term "best" is used here to mean that the resulting input-to-output ratio for each DMU is maximized relative to all other DMUs when these weights are assigned to these inputs and outputs for every DMU. In other words, the system of weight for DMU_0 is meant to put under the **best possible lights** the evaluated DMU_0.

These weights describe more specifically each DMU, emphasizing its own characteristics with respect to the other DMUs.

In the next section there will be a brief explanation of the two most important models in DEA methodology: **CCR** and **BCC model**.

5.5. CCR Model

CCR model was initially proposed by Charnes, Cooper and Rhodes in 1978, named after the initials of its developers.

It is the first model proposed and the most "basic" one. It is a **ratio model** that calculates an **overall efficiency** for the unit in which both its **pure technical efficiency** and **scale efficiency** are aggregated into a single value. It deals with the problem of multi-input and multi-output by relying on virtual input and virtual output.

First of all, let's define what are **virtual inputs** and **virtual outputs**. In short, they represent, within two single values, the **total input contribution** and the **outcome made up by all of the outputs**.

Inputs and outputs are two vectors (X,Y) of dimension (*1xm*) and (*1xs*), where *m* and *s* are respectively the **number of inputs used by a DMU** and the **number of outputs produced by the same DMU**. In DEA models these inputs and outputs are weighted by a **system of weights**: a vector v (*mx1*) containing all the inputs weights and a vector u (*sx1*) containing all the information for the outputs.

Virtual inputs and outputs are then defined by the multiplication of the input/output values times their respective weight. In this way **virtual input/output** it is defined as a **weighted average of the input/output values**.

Virtual input

$$\mathbf{VI} = v_1x_{10} + v_2x_{20} + \ldots + v_mx_{m0} \qquad (4)$$

Virtual output

$$\mathbf{VO} = u_1y_{10} + u_2y_{20} + \ldots + u_sy_{s0} \qquad (5)$$

X_{i0} are the inputs and Y_{j0} are the outputs of the considered DMU_0. V_i and U_j are the multipliers (weights). The index $i \in [0,m]$ and the index $j \in [0,s]$.**The optimal weights may (and generally will) vary from one DMU to another DMU**. Thus, the "weights" in DEA are derived from the data instead of being fixed in advance. Each DMU is assigned the best set of weights.

Suppose there are *n* DMUs indexed by k = 1…n. Let the input and output data for DMUj be (x_{1j}, x_{2j}..., x_{mj}) and (y_{1i}, y_{2i}… y_{si}), respectively. The input data matrix X and the output data matrix Y can be arranged as follows:

$$\mathbf{X} = \begin{vmatrix} x_{11} & x_{21} & \ldots & x_{1m} \\ x_{21} & x_{22} & \ldots & x_{2m} \\ \ldots & \ldots & \ldots & \ldots \\ x_{n1} & x_{n2} & \ldots & x_{nm} \end{vmatrix} \qquad (6)$$

$$
\mathbf{Y} = \begin{vmatrix} y_{11} & y_{21} & \ldots & y_{1s} \\ y_{21} & y_{22} & \ldots & y_{2s} \\ \ldots & \ldots & \ldots & \ldots \\ y_{n1} & y_{n2} & \ldots & y_{ns} \end{vmatrix} \qquad (7)
$$

X is a (*nxm*) matrix and Y is a (*nxs*) matrix, in which **each row** represents the situation of a **specific DMU$_k$** and **each column** reports all the weights assigned to **input *j*** or to **output *i***.

Next step is to **measure the efficiency** of each DMU and hence *n* optimizations are needed, one for each DMU$_k$ to be evaluated.

We solve the following fractional programming problem to obtain values for the input "weights" v_i {i = 1...m) and the output "weights" u_j (j= 1...s) as variables.

Fractional Programming (FP)

Max:

$$
\theta = \frac{u_1 y_{10} + u_2 y_{20} + \ldots + u_s y_{s0}}{v_1 x_{10} + v_2 x_{20} + \ldots + v_m y_0} \qquad (8)
$$

Subject to:

$$
\frac{u_1 y_{1j} + u_2 y_{2j} + \ldots + u_s y_{sj}}{v_1 x_{1j} + v_2 x_{2j} + \ldots + v_m y_{mj}} \leq 1 \qquad (9)
$$

$$
v_1, v_2 \ldots v_m \geq 0 \qquad (10)
$$

$$
u_1, u_2 \ldots u_s \geq 0 \qquad (11)
$$

The constraints mean that the ratio of "virtual output" vs. "virtual input" should not exceed 1 for every DMU. The objective is to obtain weights (v_i) and (u_j) that maximize the ratio of DMU_o, the DMU being evaluated. By virtue of the constraints, the optimal objective value Θ is at most 1.

To put the formalization in words, the objective function **Θ** can be seen as a coefficient that describes the **efficiency in the input-output transformation**. It reflects how much output you can pull out of a theoretical virtual input unit.

Take, for example, the **one input – one output case**. In this specific situation the virtual input and virtual output correspond exactly to the input/output used. And thus:

$$\Theta = \frac{y}{x} \qquad (12)$$

$$\Theta \mathrm{x} = \mathrm{y} \qquad (13)$$

Combining constraint (9) with constraints (10) and (11) and the non-negativity of inputs and outputs, implies that Θ ratio belongs to [0,1].

The objective is to obtain weights v_i and u_j that maximize the ratio of DMU_0, the DMU being evaluated.

By virtue of constraints, the optimal objective value Θ* is at most 1. It is then straightforward, that only DMUs with $\Theta_k = 1$ are efficient and thus they belong to the efficient frontier.

The discussion may end here, but fractional problems are often mathematically not convenient. A very important intuition, proposed by Charnes, Cooper and Rhodes, is the one that permits the linearization (computationally easier) of the above mentioned fractional problem.

Fractional to linear problem

Replace now the above fractional program (FP) by the following linear program (LP).

LP_0

Max

$$\Theta = \mu_1 y_{10} + \mu_2 y_{20} \dots + \mu_s y_{s0} \quad (14)$$

Subject to:

$$v_1 x_{10} + v_2 x_{20} \dots + v_m x_{m0} = 1 \quad (15)$$

$$\mu_1 y_{10} + \mu_2 y_{20} \dots + \mu_s y_{s0} \leq v_1 x_{10} + v_2 x_{20} \dots + v_m x_{m0} \quad (16)$$

$$v_1, v_2 \dots v_m \geq 0 \quad (17)$$

$$\mu_1, \mu_2 \dots \mu_s \geq 0 \quad (18)$$

Constraint (15) imposes that **virtual input of DMU_0** is **normalized as 1**, therefore the fractional program can become linear, canceling the denominator. **Weight μ**, on the other hand, represent an **"adjusted" weight** for output that considers the normalization of the virtual input.

Constraint (16) imposes instead that **virtual output** (weighted by μ) must be **lesser or equal to virtual input** for any *k* (*k* indexes the DMUs, k = 1…n).

Finally, **constraints (17) and (18)** ensure the **non-negativity of weights**.

Theorem 5.5.1

The **fractional problem (FP)** is **equivalent** to **the linear program (LP)**. See the article by Charnes, Cooper and Rhodes (1978) for exhaustive demonstration.

Theorem 5.5.2

The **optimal values Θ_k* are independent of the units of measurement**, provided these units are the same for every DMU.

Definition 5.5.1: Optimality

Suppose we have an **optimal solution of the linear programming problem LP**. We represent this solution by identifying three variables: **ϴ*, v* and μ***.

Where v* and μ* are the vectors of weights that solve the LP under constraints, ϴ* is the value that the objective function takes when maximized.

We can then identify whether CCR-efficiency has been achieved as follows:

Definition 5.5.2: CCR–Efficiency

1. **DMU_0 is CCR-efficient if ϴ* = 1** and there **exists at least one optimal (v*,μ*) that satisfies the constraints** v* > 0 and μ* > 0.
2. **Otherwise, DMU_0 is CCR-inefficient**.

Demanding **ϴ* = 1 condition implies that DMU_0 lies on the efficient frontier**.

By contrast, **CCR-inefficiency** requires that either:

1. **ϴ*< 1**
2. **ϴ* = 1** and **at least one element of (v*, μ*) is zero** for every optimal solution of LP.

Meanings of optimal weights

As mentioned earlier, (v*, μ*) are the set of most favorable weights for the DMU_0 in the sense of maximizing the ratio scale, v_i^* is the optimal weight for the i-th input item and its magnitude expresses how much the item is evaluated, relatively speaking.

The ratio scale is evaluated by:

$$\Theta^* = \frac{\sum_{r=1}^{s} u_r^* y_{r0}}{\sum_{i=1}^{m} v_i^* x_{i0}} \qquad (19)$$

As seen before in eq. (18), the denominator is equal to 1 and hence:

$$\Theta^* = \sum_{r=1}^{s} u_r^* y_{r0} \tag{20}$$

Similarly, u_r^* does the same for the output item r. Furthermore, if we examine each item $v_i^* x_{i0}$ in the virtual input:

$$\sum_{i=1}^{m} v_i^* x_{i0} = 1 \tag{21}$$

Then we can see the relative weight of each item in constructing the virtual input.

The same situation holds for $u_r^* y_{r0}$ where the u_r^* value provides a measure of the relative contributon of the output y_{r0} to the overall value of Θ*.

These values not only show which items contribute to the evaluation of DMU_0, but also to what extent they do so.

Production Possibility Set

Relax now the positive assumption: inputs and outputs are not anymore required to be strictly positive, instead there is a **semipositive assumption**. A vector may contain even **zero value inputs and/or outputs**. For example, let's take two clothing factories as DMUs: both of them produce dresses as single output (y) but the first one uses as inputs workers, silk and machineries, while the second only uses silk and workers. In this case the input x_3 (machineries) for the first DMU is positive while for the second is zero.

Each pair of (x,y) semipositive vectors **is defined as an activity**. The **set of feasible (x,y)** is called the **production possibility set (PPS)**.

The production possibility set has **four properties**:

1) **Observed activities belong to the PPS**.

Clearly, if an activity is observed that means that is feasible.

2) **Linear combinations** (tx,ty) **belong to PPS** if (x,y) belongs to PPS, for every positive t.

Given constant returns to scale, multiplying the inputs and the outputs for the same value means increasing ($t > 1$) or reducing the scale ($0 \leq t < 1$).

3) If (x,y) belongs to PPS, **any (x_1,y_1) such that $x \leq x_1$ and $y \geq y_1$ belongs to PPS**.

Which means that if an activity belongs to PPS, less efficient activities also belong to PPS.

4) **Semipositive linear combinations belongs to PPS**.

$$PPS = \{(x,y) \text{ I } x > X\Lambda,\ y < Y\Lambda,\ \Lambda > 0\} \qquad (22)$$

5.6. The Dual problem

Based on the matrix (X, Y) of inputs and outputs, the CCR model was formulated in the preceding section as an LP problem with row vector v for input multipliers and row vector μ as output multipliers that were treated as variables.

Theorem 5.6.1:

For any linear problem (LP) it is possible to formulate a **partner LP using the same data**, and the solution to either **the original LP** (called primal) **or the partner** (called dual) **provides the same information about the model**.

The dual problem of LP is expressed with a real variable ϴ and the transpose of a non-negative vector $(\Lambda_i \dots \Lambda_n)^T$ of variables as follows:

DLP$_0$

Min $_{(\Theta,\Lambda)}$:

$$\Theta \qquad (23)$$

Subject to:

$$\Theta x_0 - X\Lambda \geq 0 \qquad (24)$$

$$Y\Lambda \geq y_0 \qquad (25)$$

$$\Lambda \geq 0 \qquad (26)$$

DLP has a feasible solution in: $\Theta = 1$, $\Lambda_0 = 1$, $\Lambda_j = 0$ with $j \neq 0$. As before, the optimal Θ, denoted by Θ^*, should not be greater than 1. The constraint $Y\Lambda \geq 0$ forces Λ to be nonzero because $y_0 > 0$, given the semipositive assumption, and thus $y_0 \neq 0$. Putting this all together, we have $0 < \Theta^* \leq 1$.

The **constraints of DLP$_0$ require the activity** (Θx_0, y_0) **to belong to the Production Possibility Set** (PPS) , while the **objective function seeks the minimum Θ that reduces the input vector x_0 radially** to Θx_0 while remaining inside of the PPS.

We are looking for an activity in PPS that guarantees **at least the same output level** y_0 of DMU$_0$ in all components, while reducing the input vector x_0 proportionally (radially) by the Θ multiplier to a value as small as possible.

To summarize, **Θ^* is the coefficient that gives the minimum level of input Θx_0 in order to achieve the fixed level of output y_0**.

If Θ^* is lesser than 1, there is room for improvement and thus the DMU is inefficient, and the activity ($X\Lambda$, $Y\Lambda$) outperforms (Θx_0, y_0).

We define, then, the **input excesses** $s^+ \in \mathbb{R}^m$ and the **output shortfalls** $s^- \in \mathbb{R}^s$ and identify them as **"slack" vectors** by:

$$s^{-} = \Theta x_0 - X\Lambda \qquad (27)$$

$$s^{+} = Y\Lambda - y_0 \qquad (28)$$

To discover the possible input excesses and output shortfalls, we solve the following two-phase LP problem:

Phase I

We solve DLP_0. Let the optimal objective value be ϴ* which is equal to the optimal objective value of LP and is the CCR-efficiency value, also called **"Farrell Efficiency"** (M.J. Farrell, 1957).

Phase II

We solve the following LP using (Λ, s^-, s^+) as variables:

LP

Max **(Λ, s-, s+)**

$$w = es^{-} + es^{+} \qquad (29)$$

Subject to:

$$s^{-} = \Theta^{*} x_0 - X\Lambda \qquad (30)$$

$$s^{+} = Y\Lambda - y_0 \qquad (31)$$

$$\Lambda \geq 0,\ s^{-} \geq 0,\ s^{+} \geq 0 \qquad (32)$$

Where e is a vector of ones.

The objective of **phase II** is to find a solution that maximizes the sum of input excesses and output shortfalls while keeping ϴ = ϴ*.

Definition 5.6.1: Max-slack Solution, Zero-slack Activity

An optimal solution (Λ^*, s^{-*}, s^{+*}) of Phase II is called the **max-slack solution**. If the max-slack solution satisfies $s^{-*} = 0$ and $s^{+*} = 0$, then it is called **zero-slack**.

This condition is also referred to as **"radial efficiency"**, or as **"technical efficiency"** because a value of $\Theta^* < 1$ means that **all inputs can be simultaneously reduced without altering the mix** in which they are utilized.

Definition 5.6.2: CCR-Efficiency

If an optimal solution (Λ^*, s^{-*}, s^{+*}) satisfies $\boldsymbol{\Theta^* = 1}$ and is **zero-slack** ($s^{-*} = 0$, $s^{+*} = 0$), then the DMU_0 is called **CCR- efficient**. Otherwise, the DMU_0 is called CCR-inefficient.

Theorem 5.6.2

CCR Efficiency stated for the primal LP in definition , is equivalent to the partner DLP CCR Efficiency stated in definition.

Given these conditions, inefficiencies can still occur in the process and these inefficiencies, associated with any nonzero slack identified in the above two-phase procedure, are referred to as **"mix inefficiencies"**.

5.7. CCR Example with 2 Inputs and 1 Output

The current section shows an example that deals with the primal LP of a DEA problem with 2 inputs and 1 output. Table 5.3.1 reports 6 DMUs where the output value is unitized to 1 for each DMU.

Table 5.7.1: CCR Example: 2 Inputs, 1 Output

DMU	A	B	C	D	E	F
x_1	4	7	8	4	2	10
x_2	3	3	1	2	4	1
y	1	1	1	1	1	1

Source: Cooper et al. (2005)

The linear problem for DMU_0 is the following:

LP_0

Max

$$\theta = \mu_0 y_0 \qquad (33)$$

Subject to:

$$v_1 x_{10} + v_2 x_{20} = 1 \qquad (34)$$

$$\mu_1 y_{10} \leq v_1 x_{10} + v_2 x_{20} \qquad (35)$$

$$v_1, v_2 \geq 0 \qquad (36)$$

$$\mu \geq 0 \qquad (37)$$

For DMU_A LP is then the following:

LP_A

Max:

$$\theta = \mu_A \qquad (38)$$

Subject to:

$$v_1 4 + v_2 3 = 1 \qquad (39)$$

[A] $\mu_A \leq v_1 4 + v_2 3$ (42)

[B] $\mu_A \leq v_1 7 + v_2 3$ (43)

[C] $\mu_A \leq v_1 8 + v_2 1$ (44)

[D] $\mu_A \leq v_1 4 + v_2 2$ (45)

[E] $\mu_A \leq v_1 2 + v_2 4$ (46)

[F] $\mu_A \leq v_1 10 + v_2 1$ (47)

This problem can be solved by a linear programming code and the (unique) optimal solution is the following: (v_1^*= 0.1429, v_2^* = 0.1429, μ^*= 0.8571, ϴ* = 0.8571)

By applying the optimal solution to the above constraints, the reference set for A is found to be: E_A = {D;E}.

Applying the same method DMU_B is found to be inefficient as well.

An optimal solution for C is {v_1^* = 0.0833, v_2^* = 0.3333, μ* = 1, ϴ* = 1) and C is CCR-efficient by definition (ϴ=1, then it belongs to the Efficient Frontier). However, the optimal solution is not uniquely determined, as will be observed in the next section. Likewise, D and E are CCR-efficient.

Developing the linear problem for DMU F we find that the solution (v_1^* = 0, v_2^* = 1, μ* = 1, ϴ* = 1) is unacceptable because of v_1^* = 0. Therefore, DMU F is inefficient.

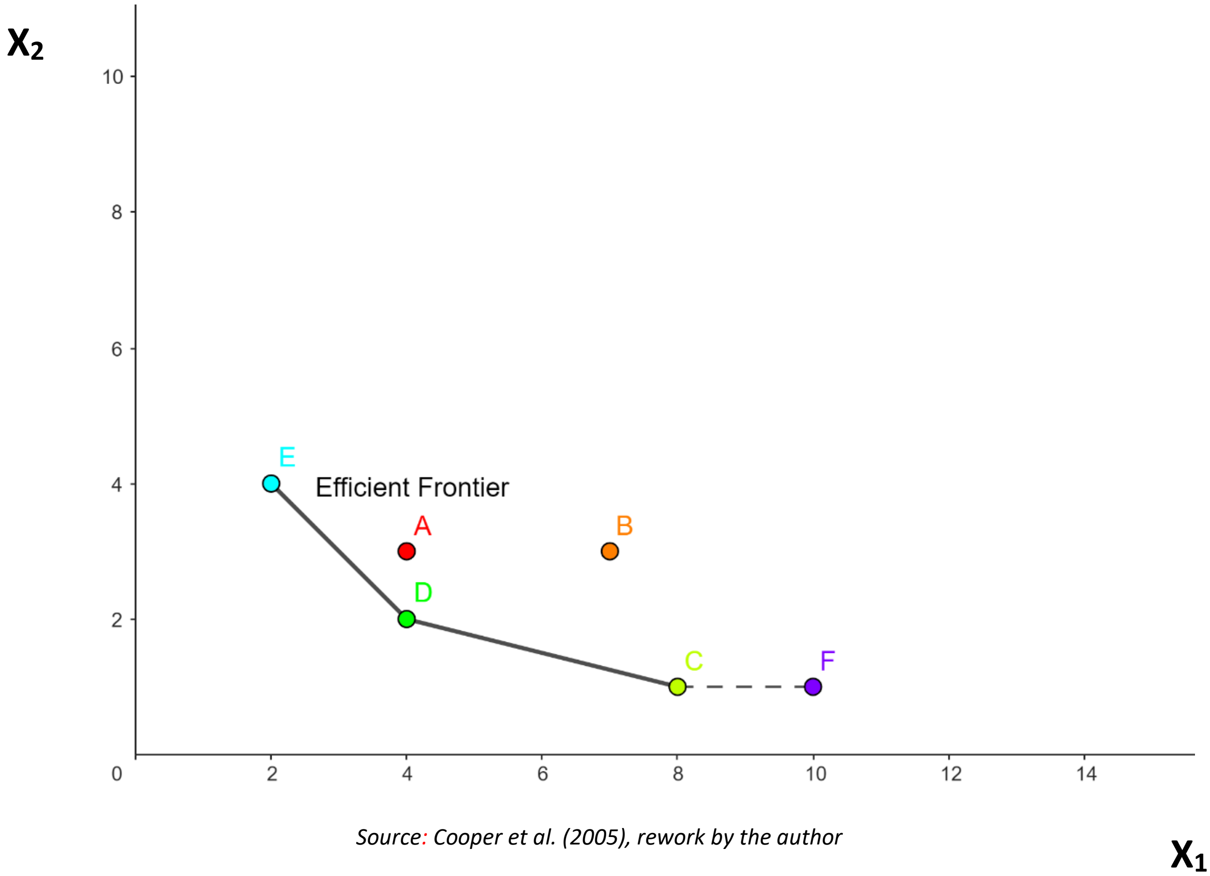
Table 5.8.2 reports the results of Data Envelopment Analysis.

Table 5.7.2: Results of the Example

DMU	x1	x2	y	CCR(ϴ*)	Ref. Set	v_1^*	v_2^*	μ*
A	4	3	1	0.8571	D,E	0.1429	0.1429	0.8571
B	7	3	1	0.6316	C,D	0.0526	0.2105	0.6316
C	8	1	1	1	\\	0.0833	0.3333	1
D	4	2	1	1	\\	0.1667	0.1667	1
E	2	4	1	1	\\	0.2143	0.1429	1
F	10	1	1	1	C	0	1	1

Source: Cooper et al. (2005), rework by the author

Fig. 5.7.1: Example with 2 Inputs, 1 Output



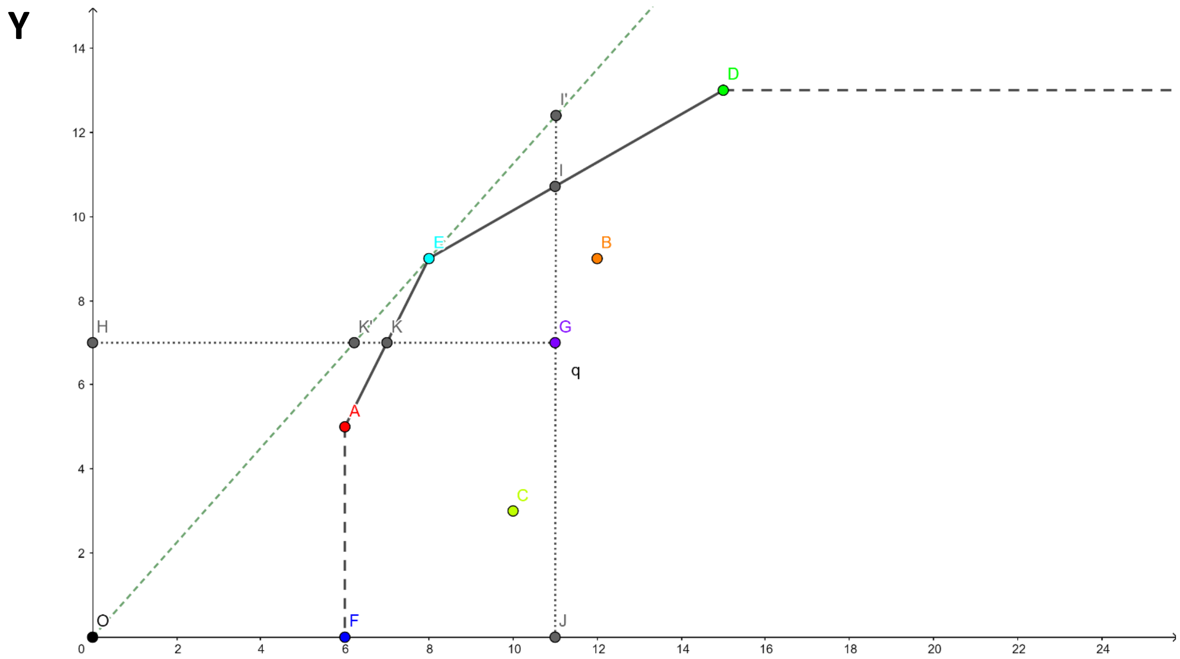
Source: Cooper et al. (2005), rework by the author

5.8. BCC Model

BCC model, originally proposed by Banker, Charles and Cooper in 1984, takes the previous CCR model (1978) and implements a **further condition that shapes in a different way the efficient frontier**.

In the graph below, that portraits the one input – one output framework, it is given the intuition behind the difference between CCR frontier and BCC frontier: the **green dotted line is the CCR efficient frontier**, the **black broken line represents the BCC efficient frontier**. The former has been built around the most efficient DMU_E; the latter takes into consideration even two apparently inefficient DMUs (A; D).

Fig. 5.8.1: BCC and CCR model comparison: one input, one output



Source: Cooper et al. (2005), rework by the author

All the DMUs lying on the frontier are defined to be BCC efficient and those that lie within the frontier are considered inefficient and should aim to position themselves on the efficient line.

Given the different efficient frontier and, consequently, different efficiency definition **BCC and CCR rate inefficiency in two slightly different ways**.

For example, DMU G (11,7) is inefficient in both models but is clear that to reach CCR efficient frontier it is required much more effort. Given an input-oriented perspective (the level of output is fixed) DMU G should reduce its input level by a factor of:

$$\frac{GK'}{GH} \sim \frac{4.777}{11} \sim 0.4343 \qquad (47)$$

In a CCR efficiency framework. While in a BCC framework it should reduce input only by a factor of:

$$\frac{GK}{GH} = \frac{4}{11} \sim 0.3636 \qquad (48)$$

Generally speaking, the distance between an inefficient DMU and the efficient frontier is lower in the BCC model than in the CCR model. The same applies in an output-oriented model, where input is fixed.

These changes are meant to **overcome the constant return to scale assumption** with **a variable return to scale assumption**: a DMU that has the "right" dimension and uses the "right" amount of input and produces the "right" amount of output, is going to have a better combination of inputs/outputs than an undersized or oversized firm. It does not stick to reality the assumption that the sweet combination stays unchanged over DMUs of different size.

That is summarized into a new definition of the Production Possibility Set, which remains identical with the exception of a further constraint:

$$PPS_{BCC} = \{(x,y) \mid x \geq X\Lambda \, ; \, y \leq Y\Lambda \, ; \, e\Lambda = 1 \, ; \, \Lambda \geq 0\} \qquad (49)$$

Where X is the input matrix: $X = (x_{ik}) \in R^{mxn}$ with as many rows as the number of inputs and as many rows as the number of DMUs. Y is the output matrix $Y = (y_{jk}) \in R^{sxn}$ with as many rows as the number of outputs and as many columns as the number of DMUs. The column vector $\Lambda \in R^n$ represents the weight assigned to the DMUs and e is a row vector with all elements equal to 1. Which is the only adjunction to the CCR model (Cooper et al. 2006). The formalization of the linear problem, from its dual perspective, is thus the following:

$DLP_{0(BCC)}$

Min:

$$\Theta_B \qquad (50)$$

subject to:

$$\Theta_B x_0 - X\Lambda \geq 0 \qquad (51)$$

$$X\Lambda \geq y_0 \qquad (52)$$

$$e\Lambda = 1 \qquad (53)$$

$$\Lambda \geq 0 \qquad (54)$$

An optimal solution for BCC is represented by (Θ^*, Λ^*, s^{+*}, s^{-*}), where s+ and s- represent respectively, like in the CCR model, the maximal input excesses and output shortfalls.

Notice that BCC model's Θ^* is not more than the CCR optimal objective value Θ^*, since BCC imposes one additional constraint, $e\Lambda = 1$, so **BCC feasible region is a subset of the feasible region in the CCR model**.

Definition 5.8.1: BCC Efficiency

If an optimal solution (Θ^*, Λ^*, s^{+*}, s^{-*}) obtained for BCC_0 **satisfies $\Theta^* = 1$ and has no slack** (s^{+*}, $s^{-*} = 0$), then the DMU_0 **is called BCC-efficient**, otherwise it is BCC-inefficient.

Proposition 5.8.1: BCC and CCR Efficiency

If a DMU is **CCR-efficient**, then is **also BCC-efficient**.

5.9. Efficiency and Inefficiency Types

In this last section**, three types of efficiency**, and inefficiency, that can arise are briefly presented. Specifically, we speak of **Pure Technical Efficiency**, **Mix Efficiency** and **Scale Efficiency**. **Efficiency and inefficiency can have several meanings and interpretation**, being aware of which kind of inefficiency is acting is crucial to understand how to overcome it.

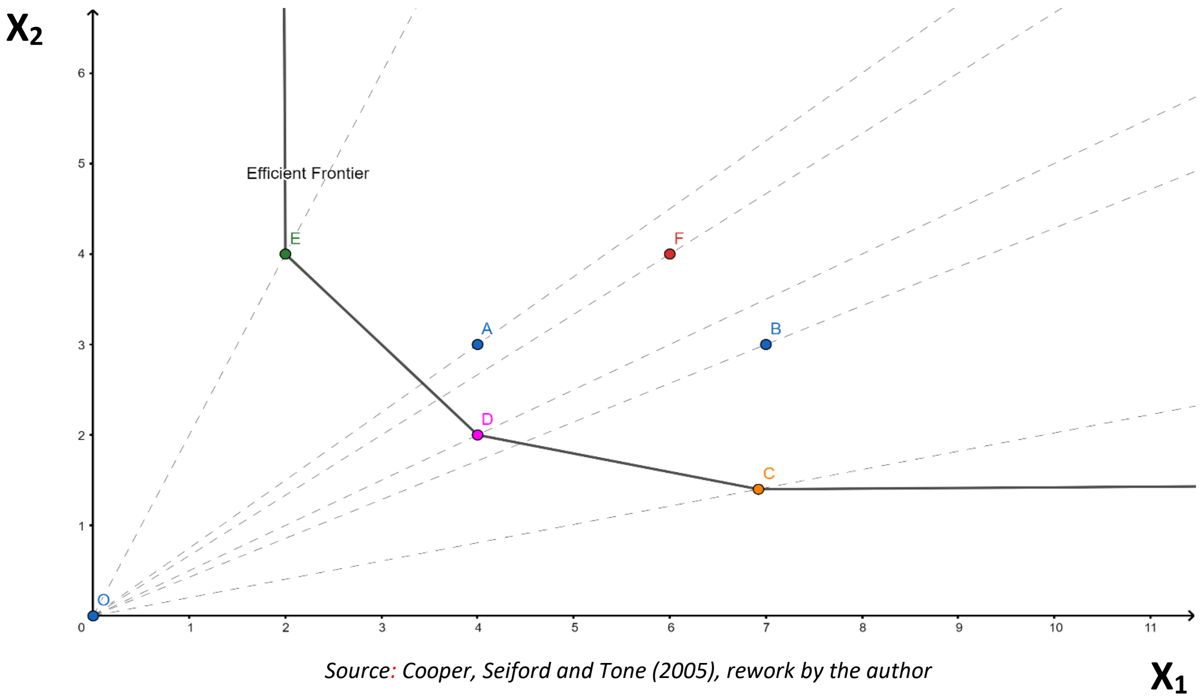
Pure Technical Efficiency

Farrel (1957) defined the pure technical efficiency (PTE) in terms of **radial reduction in inputs** or **radial augmentation in outputs**. DMUs that are already on the frontier are technical efficient, but, if an inefficient DMU can move along its "ray" and therefore reach the efficient frontier, there was a pure technical inefficiency.

In fig. 5.9.1, through an input reduction along the "ray", keeping the same angular coefficient and therefore keeping fixed the input ratio x_1/x_2, also keeping the output level fixed, DMUs A, B and F can improve their efficiency moving towards the origin and the efficient frontier.

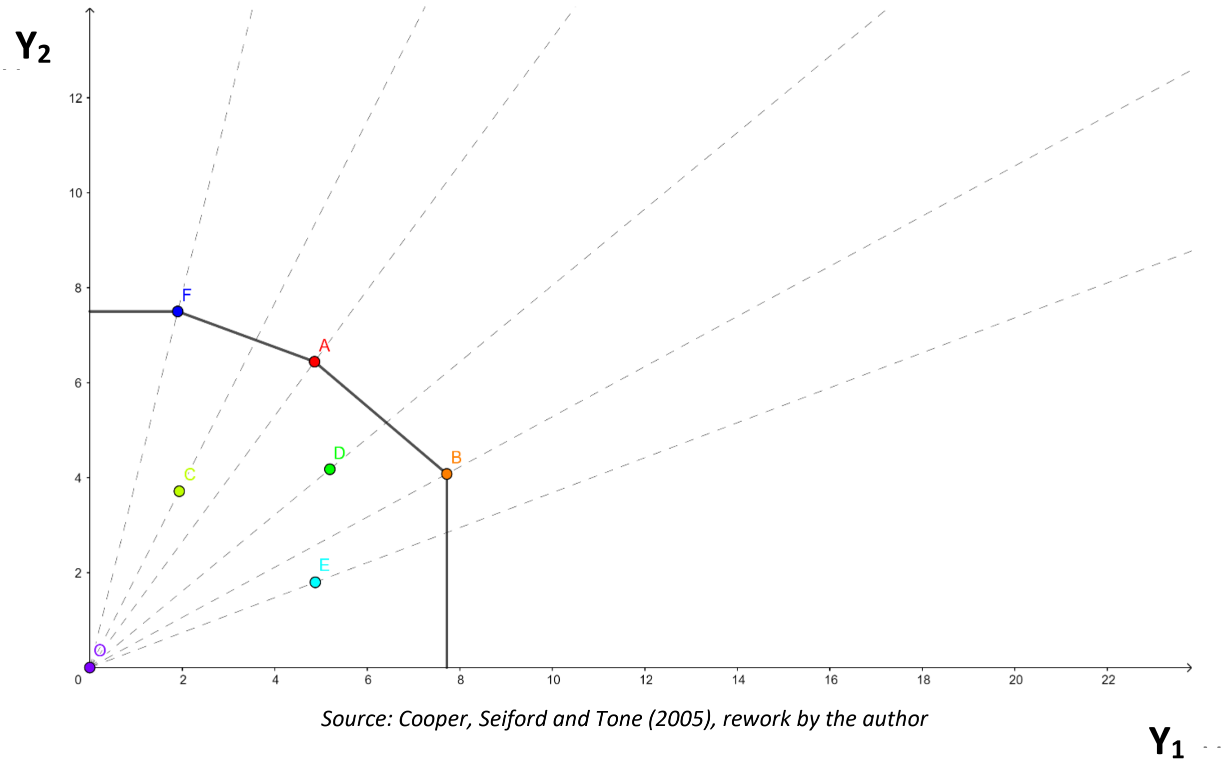
In fig. 5.9.2, DMUs C, D and E can improve their efficiency augmenting their outputs, given that the y_1/y_2 ratio is fixed, keeping the same input level, towards the frontier through the "ray".

Fig. 5.9.1: Two Inputs, One Output: Pure Technical Efficiency



Source: Cooper, Seiford and Tone (2005), rework by the author

Fig. 5.9.2: One Input, Two Outputs: Pure Technical Efficiency



Source: Cooper, Seiford and Tone (2005), rework by the author

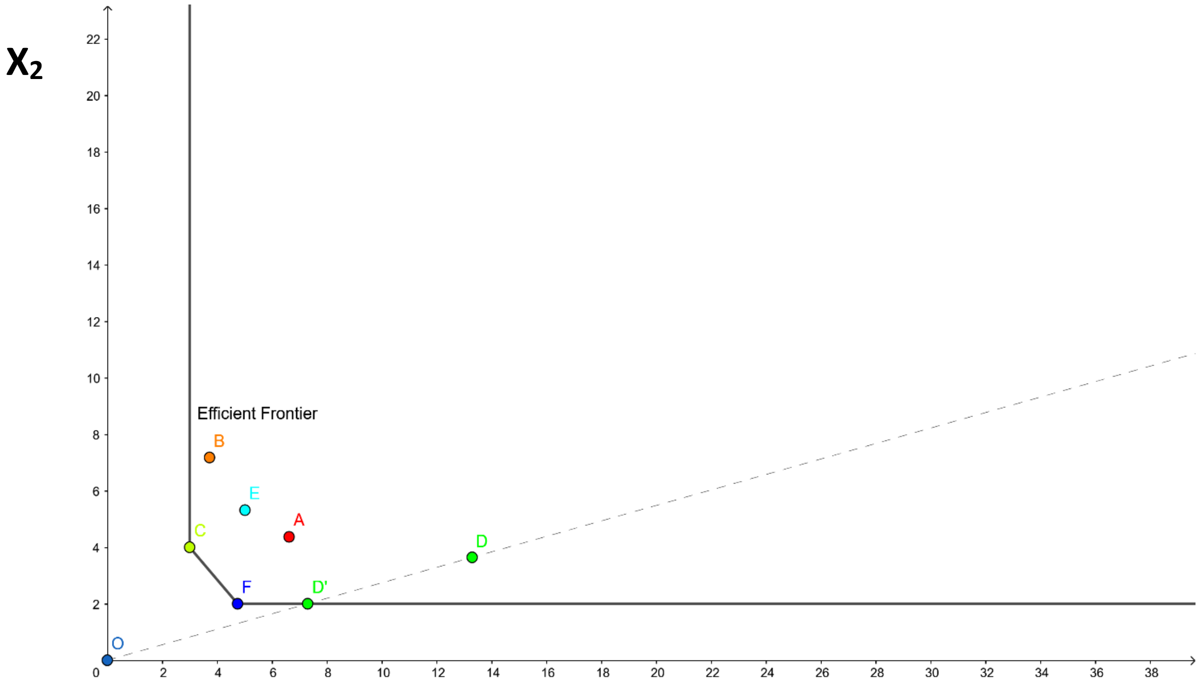
Mix Efficiency

To understand mix efficiency it is convenient putting it backwards, by looking instead at mix inefficiency. Mix inefficiency is the **inefficiency due to a wrong composition of the inputs or the outputs**, i.e. the ratio x_1/x_2 or y_1/y_2 is suboptimal and changing the ratio grants a higher efficiency.

In figure 5.5.3, the DMU D can reduce its inputs x_1, x_2 to reach the efficient frontier in D' but there is clearly the possibility to make another improvement: simply reducing input x_2 the point D' could move towards point F and, given the fact that inputs are costly, reducing the costs of inputs, being therefore more cost-efficient.

That is because the combination (mix) of the inputs was itself inefficient.

Fig. 5.9.3: Two inputs, One Output: Mix Inefficiency



Source: Cooper, Seiford and Tone (2005), rework by the author

X_1

Scale Efficiency

Scale efficiency relies on the **economies of scale theory**, that is the **changes in returns from increasing, or decreasing, the scale of production**.

The most common and intuitive result is the average reduction of cost when increasing the size of the firm. That mainly result from spreading a firm's fixed cost over a larger volume of output. So that the associated cost of one unit of output will be:

$$C = VC + TFC/n \qquad (5)$$

Where C is the unitary cost, VC is the variable unitary cost, FC is the total fixed cost required divided by n that is the number of units of output that "utilizes that fixed cost".

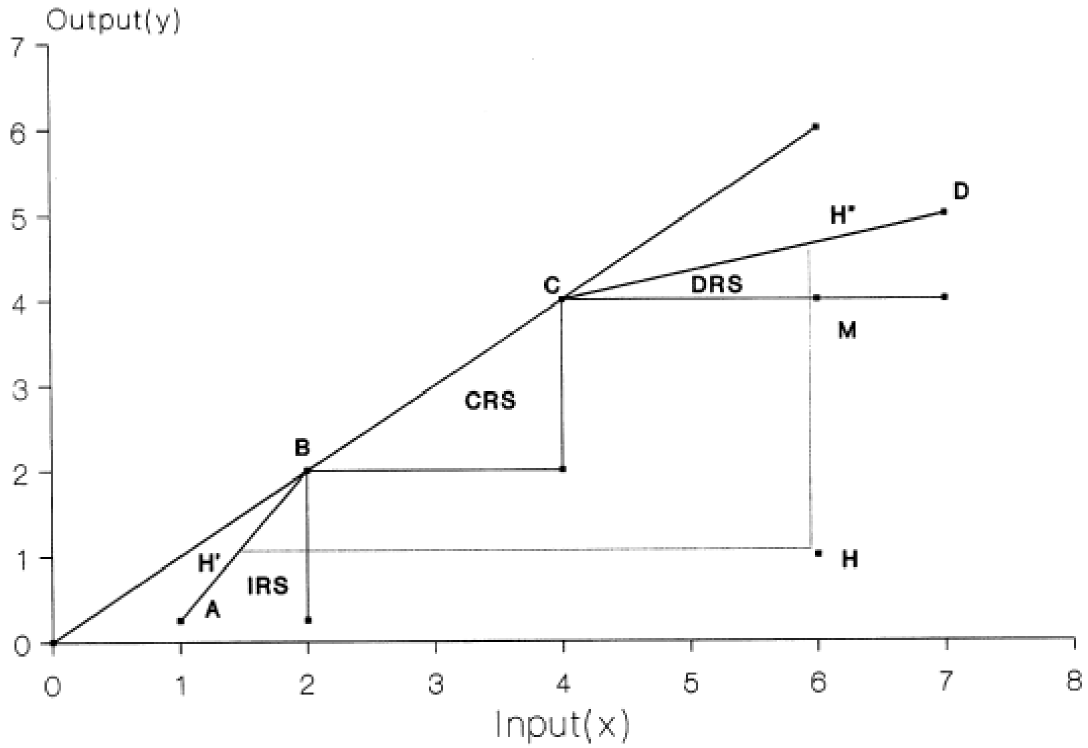
Economies of scale can be of two different types:

- **Constant Return to Scale (CRS)**
- **Variable Return to Scale (VRS)**

Constant returns to scale imply that as inputs increase, outputs will increase proportionally steadily. In the CCR model, only CRSs are allowed. On the other hand, Variable Scale Yields can be increasing (IRS), constant (CRS) or decreasing (DRS). The BCC model allows VRSs and in this it differs from the CCR model.

Figure 5.9.4 (Seiford and Zhu, 1999) graphically summarizes the difference between CRS and VRS, highlighting the different efficient frontiers of the CCR and BCC models.

Fig. 5.9.4: CCR and BCC scale returns compared



Source: Seiford and Zhu, 1999

Suppose we have six DMUs: A, B, C, D, H and M as shown in Fig. 5.9.4. The segment OBC is the **CCR efficient frontier**, exhibiting CRS. On the other hand, the three segments AB, BC and CD constitute together the **BCC efficient frontier** and exhibit IRS, CRS and DRS respectively.

Note that some DMUs, say B and C, are located at the intersections of different RTS frontiers. In this situation, CRS have the first priority. Then, B and C should exhibit CRS rather than IRS and DRS, respectively.

Note also that the concept of **RTS may be ambiguous unless a DMU is on the BCC efficient frontier**. We classify, then, the RTS for inefficient DMUs by their BCC projections. For instance, by applying the BCC projection to point H, we have a frontier point H0 on the line segment AB and thus H exhibits IRS. However a different RTS classification may be obtained if a different projection, or model, is utilized. This is due to the fact that the input-based and the output-based BCC models yield different projection points on the VRS frontier. For example, the point H is moved onto the line segment CD by the output-based BCC model and thus DRS prevail on the point H0. However, some IRS, CRS and DRS regions are uniquely determined no matter which BCC model is employed.

6. DATA, MODEL AND RESULTS

This chapter discusses the **data regarding the farms** and then defines what are the **specifications of the model** used, in the next chapter, for the efficiency analysis.

Section 6.1 describes what is the **FADN/RICA database** from which the entirety of the data considered was collected, the manner in which these data were collected, and finally some brief history of the FADN institution. **Section 6.2** discusses the **need for clean data**, specifically when talking about a DEA model. **Section 6.3**, then, **describes the sample** by showing some statistical information in order to put the data in context. **Section 6.4** specifies what the **characterizations of the model** are: the purpose, the specifications, the inputs and the outputs considered. **Section 6.5**, then, reports the **results of the model** and their **statistical distribution**, further breaking down DMUs by macro area, altitude, economic size and economic orientation. **Section 6.6** focuses on the distinction between **farms that produce renewable energy and farms that do not**. **Section 6.7** characterizes **efficient DMUs** and their distribution, again taking care to distinguish renewable energy companies. Finally, **section 6.8** reviews the steps of the analysis and **comments on the results** obtained.

6.1. The FADN Database

Data are collected from the **Farm Accountancy Data Network (FADN)**, which is a **European institution** that **monitors farms' income and business activities**. In particular, the data used comes from the Italian section of FADN, which is called RICA.

RICA ("Rete di Informazione Contabile Agricola") consist of an **annual sample survey** established by the European Economic Commission in 1965, by EEC Regulation 79/65 and updated by EC Reg. 1217/2009. It has been carried out in Italy since 1968, with a similar approach in all EU Member States.

The FADN/RICA survey does not represent the entire universe of farms surveyed in a given territory, but only those that, due to their economic size, can be considered **professional** and **market oriented**. The methodology adopted aims to provide representative data on three dimensions: **region**, **economic size** and **technical-economic order**.

There are **more than 86,000 farms** in the FADN Community, and they represent nearly 5 million Union farms that cover 90% of the agricultural area and 90% of the standard production. Table 6.1 below shows the evolution of the FADN Community as the European Union enlarges: from 1968 onward, the states that now make up the FADN were added as they came along.

Table 6.1: FADN Sample Size per Country (1968 – 2013)

Country	**1968**	**1973**	**1981**	**1986**	**1995**	**2004**	**2007**	**2013**
Italy	2,750	3,500	12,000	18,000	18,000	17,000	16,300	11,106
Germany	2,000	2,000	3,500	4,500	4,500	7,000	7,000	8,800
France	3,000	3,000	6,100	6,100	6,100	6,100	6,100	7,640
Netherlands	900	900	1,500	1,500	1,500	1,500	1,500	1,500
Belgium	550	550	870	1,000	1,000	1,000	1,000	1,200
Luxembourg	50	50	125	300	300	300	300	450
United Kingdom		1,600	1,650	2,500	2,500	2,500	2,500	2,500
Denmark		1,450	1,555	2,000	2,000	2,000	2,000	2,000
Ireland		550	700	1,300	1,300	1,300	1,300	900
Greece			3,000	7,200	7,200	7,200	7,200	5,500
Spain				12,000	10,100	10,100	10,100	8,700
Portugal				1,800	3,000	3,000	3,000	2,800
Austria					2,000	1,800	1,800	2,000
Finland					1,100	1,100	1,100	1,100
Sweden					600	1,025	1,025	1,025
Poland						12,100	12,100	12,100
Czech Republic						1,000	1,417	1,417

Slovakia						600	600	562
Hungary						1,900	1,900	1,900
Slovenia						500	908	908
Cyprus						400	400	500
Malta						300	300	536
Estonia						400	400	658
Lithuania						1,000	1,000	1,000
Latvia						800	800	1,000
Romania							1,000	6,000
Bulgaria							2,000	2,202
Croatia								1,251

Source: FADN, 2022

Currently, the **Italian FADN sample** is based on a reasoned sample of about **11,000 farms**, structured to represent the different production types and sizes found in the country. It allows a **national average coverage** of 95% of Utilized Agricultural Area (UAA), 97% of Standard Production value, 92% of Labor Units, and 91% of Livestock Units.

FADN's primary task is to meet the information needs of the European Union for the definition and evaluation of the **Common Agricultural Policy** (CAP). FADN data are the main source of information for both the European Commission and member countries to assess the impact of proposed changes to the

CAP by simulating different scenarios on farm sustainability (economic, environmental, social and innovations).

The FADN is used for policy evaluation of **public aid to agriculture co-financed by the European Union**. The information collected with the FADN also makes it possible to meet the **needs of research and business advisory services**, through a series of variables and indices on the technical, economic, capital and income characteristics of farms.

For each farm in the sample, are collected on average about **1,000 variables**, that becomes **more than 2,500 for the Italian FADN**. Then, the Community farm return is compiled and outlined in its basic structure by specific regulatory measures of the Commission.

The variables surveyed concern:

- **Physical and structural data** (location, area, herd size, farm labor, services offered, etc.)
- **Economic data** (revenues from sales, farm redeployments, ending stocks, purchases of technical means, etc.)
- **Financial and asset data** (debts, credits, public aid, production rights, acquisition and disposal of assets, etc.)

The information framework of the Italian FADN, which is much broader than the institutional requirements of the European Commission, allows for analysis on a variety of issues ranging from farm productivity to production costs, from environmental sustainability to the role of the farm family.

Farm Accountancy Data Network (FADN) consists of a **Community network** and each participating member State has its **own national network** with its own characteristics. For Italy there is a concordance between the two, at least historically. Even at the beginning of the survey, the implementation took place in different ways, the ambition of the Community device was very great if one considers the poor situation of agriculture and bookkeeping in the 1960s, especially in Italy.

Historical Notes

Some of the founding countries of the European Community, had already been investigating farm accounting for several decades. The Netherlands had set up an accounting network in 1942, Germany in 1956, and **for Italy the first accounting survey on farms was initiated in 1928** by the then nascent INEA ("Istituto Nazionale di Economia Agraria", that stands for "National Institute of Agricultural Economics"), an activity strongly desired by minister Serpieri and included in the Institute's statutes.

The surveys, on a sample of only a few hundred farms, were later discontinued as a result of war events. In 1962, at INEA's proposal, the collection of accounting data on a sample of 1,500 farms was resumed, but the proposal failed to find the necessary financial resources.

In **1965** there was the **establishment of the Community FADN**, and INEA was designated, by Presidential Decree (Presidential Decree 1708/65), as the liaison body for the Italian state, as the only public institution suitable for this role.

The FADN was established just after the birth of the Common Agricultural Policy, precisely to accompany it on its long journey to support the European agricultural system. The initiative aimed to create an **information tool that met the criteria of uniformity in surveys**, how values were assigned and how the sample was represented.

The dissemination of the FADN in Europe has gone hand in hand with the process of EU enlargement, eventually covering the current 28 states where the survey is regularly carried out. To the EU countries, one can add the accounting surveys carried out with the same FADN methodology in Switzerland and Norway for several decades. Moreover, recent requests for implementation of the FADN survey has been proposed by Turkey, the Balkan countries in pre-accession to join the EU (Serbia, Albania, Macedonia and Montenegro) and some states of the former Soviet Union (Azerbaijan).

Italy, thanks to the prestige of great agricultural economists such as Baldini (INEA president from 1962 to 1972), was one of the main promoters towards the European Community for the establishment of an information network on agricultural accounting as a data collection tool to develop policy in the sector on a scientific basis.

6.2. Data Accuracy and Errors

Data collection is a very important issue for all kind of analysis: incorrect data can lead to large misunderstandings. All analysis should start with **reliable data**, but errors in databases are anything but rarities. In practice, there are different types of errors: from missing or irrelevant data to values that are theoretically possible but completely out of scale.

Errors can arise at the time of collection, at the time of database entry to even at the time of data analysis.

To minimize errors at the time of collection, strict procedures must be followed to determine the data with certainty. Surveys are a relatively simple and quick method to perform but often lack the accuracy of documents, which on the other hand are more challenging and expensive to complete. The database entry step is often left to the manual entry procedure, which brings with it errors and inaccuracies. Ultimately, the analyst should be careful to treat the data he or she receives well, trying to skim those that are reliable from those that need to be evaluated.

Since Data Envelopment Analysis builds its efficient frontier on a **deterministic basis**, data collection is even more crucial. In fact, **all deviations** from the efficiency frontier are indeed attributable to **inefficiencies of various kinds**.

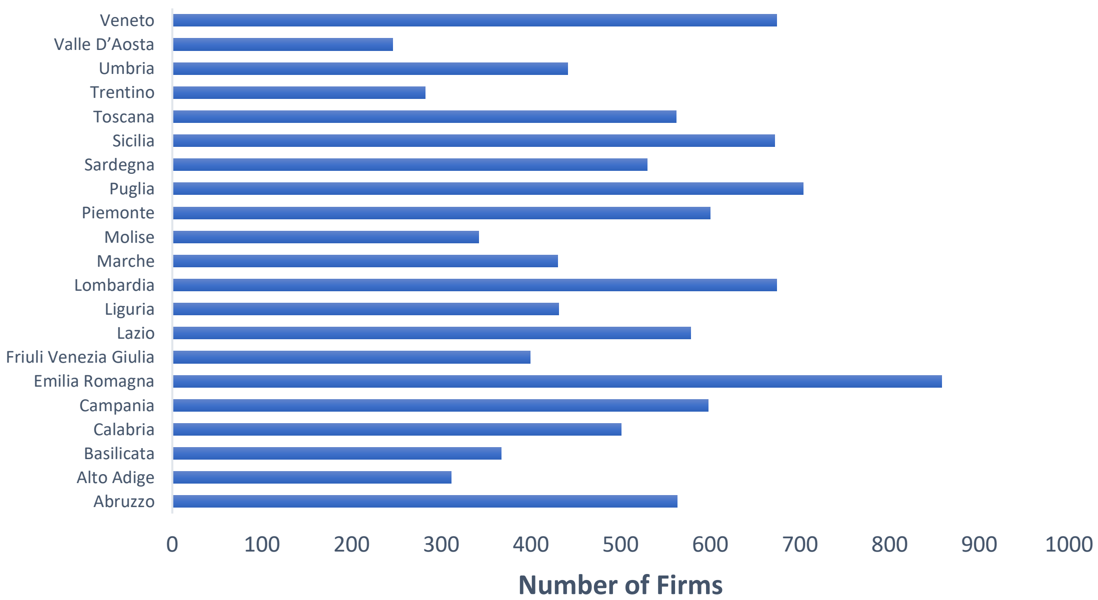
In contrast, **if the frontier were stochastic** then data collection might be a little looser, since the **deviation** from the frontier **might be attributable to a random factor** that also collects, within a certain extent, errors in data collection.

Suppose the **case of a typo** that slightly changes an output: instead of 90 units of output, the careless collector transcribes only 80. In the **case of a stochastic frontier**, the error would be **relatively unimportant** because the system itself considers random deviations and the anomaly would not indelibly spoil the results. In our **case of a deterministic frontier**, unfortunately, that error results in a **misleading result**. In fact, that DMU could be inefficient because of the very error, or even more inefficient than it already was. But even in the case where it still turns out to be efficient, it would be a distortion of reality and a problem for the other inefficient DMUs that should be inspired by it in order to become efficient.

6.3. The Italian Sample (RICA)

This section describes the sample in order to obtain an **overall view of the constituent companies** and to check the sample for bias due to an inappropriate choice of companies. The sample consists of **10,764 companies**, investigated in 2020, from every area of Italy with a variety of characteristics that, according to the RICA database, make a fair representation of the population.

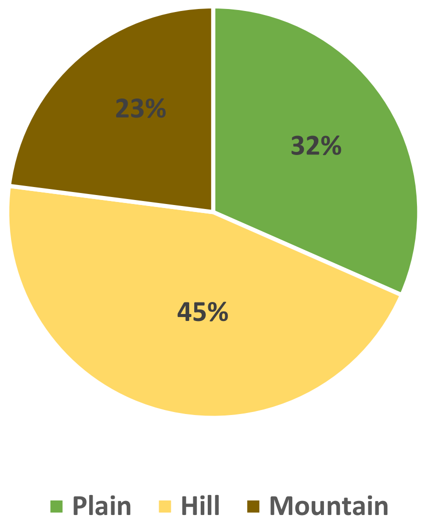
Fig. 6.3.1: Sample Geographical Distribution, by Region (2020)



Source: RICA (2022)

In figure 6.3.1 and in table 6.3.1 it is possible to see that the most represented region is Emilia-Romagna, with 858 surveyed firms on its territory, followed by Puglia, with 704 firms, and then by Veneto and Lombardia, both with 674 firms.

Fig. 6.3.2: Sample Geographical Distribution, by Altitude (2020)



Source: RICA (2022)

Moreover, in figure 6.3.2 and in table 6.3.2 it is possible to see the distribution among altitude, sorted by plain, hill and mountain. The largest slice of the Italian farms surveyed, 45%, belongs to the hills, 32% to the plains, and 23% to the mountains.

As can be seen by comparing Figure 6.3.2 with Table 6.3.1, the distribution of farms in the three altitudes is different with respect to the percentage of Italian territory belonging to each altitude. The mountains have a greater presence as a territory than the share of Italian farms located in the mountains; in contrast, the plains and hills have a greater share of farms relative to their percentage of land occupancy.

Table 6.3.1: Sample Geographical Distribution

	Plain	**Hill**	**Mountain**	**Italy**
Area (Ha)	6,978,265	12,543,385	10,611,208	30,132,858
%	23.16%	41.63%	35.21%	100%

Source: Istat (2022)

Table 6.3.2: Sample Geographical Distribution (2020)

Region	Firms	%Firms	Plain	%Plain	Hill	%Hill	Mountain	%Mountain
Abruzzo	563	5,23%	0	0,00%	356	7,29%	207	8,38%
Alto Adige	311	2,89%	0	0,00%	0	0,00%	311	12,60%
Basilicata	367	3,41%	65	1,91%	175	3,58%	127	5,14%
Calabria	501	4,65%	109	3,21%	290	5,94%	102	4,13%
Campania	598	5,56%	140	4,12%	255	5,22%	203	8,22%
Emilia-Romagna	858	7,97%	598	17,60%	205	4,20%	54	2,19%
Friuli-Venezia Giulia	399	3,71%	256	7,53%	123	2,52%	20	0,81%
Lazio	578	5,37%	93	2,74%	413	8,45%	72	2,92%
Liguria	431	4,00%	0	0,00%	278	5,69%	153	6,20%
Lombardia	674	6,26%	565	16,63%	75	1,54%	31	1,26%
Marche	430	4,00%	0	0,00%	384	7,86%	46	1,86%
Molise	342	3,18%	0	0,00%	204	4,18%	138	5,59%
Piemonte	600	5,57%	272	8,00%	246	5,04%	79	3,20%
Puglia	704	6,54%	468	13,77%	234	4,79%	2	0,08%
Sardegna	530	4,92%	155	4,56%	327	6,69%	48	1,94%
Sicilia	672	6,24%	93	2,74%	417	8,54%	162	6,56%
Toscana	562	5,22%	65	1,91%	402	8,23%	95	3,85%
Trentino	282	2,62%	0	0,00%	0	0,00%	281	11,38%
Umbria	441	4,10%	0	0,00%	402	8,23%	39	1,58%
Valle D'Aosta	246	2,29%	0	0,00%	0	0,00%	246	9,96%
Veneto	674	6,26%	519	15,27%	99	2,03%	53	2,15%
Total	**10763**	**100,00%**	**3398**	**100,00%**	**4885**	**100,00%**	**2469**	**100,00%**

Source: RICA (2022)

Table 6.3.2 shows the distribution by **economic dimension**, calculated according to the standard gross income, the largest mass resides more or less evenly in the ranges from €4,000 up to €500,000 while only 737 (less than 7% of the total) have a larger size.

Table 6.3.2: Sample Distribution by Economic Dimension (2020)

Economic Dimension	**Number of Firms**	**%**
€4.000 - €25.000	2232	20.74%
€25.000 - €50.000	2468	22.94%
€50.000 -€100.000	2499	23.22%
€100.000 - €500.000	2824	26.25%
€500.000 or more	737	6.85%

Source: RICA (2022)

Table 6.3.3 reports the classification of companies according to their economic orientation. The main categories are: farms specialized in crops, in livestock and mixed.

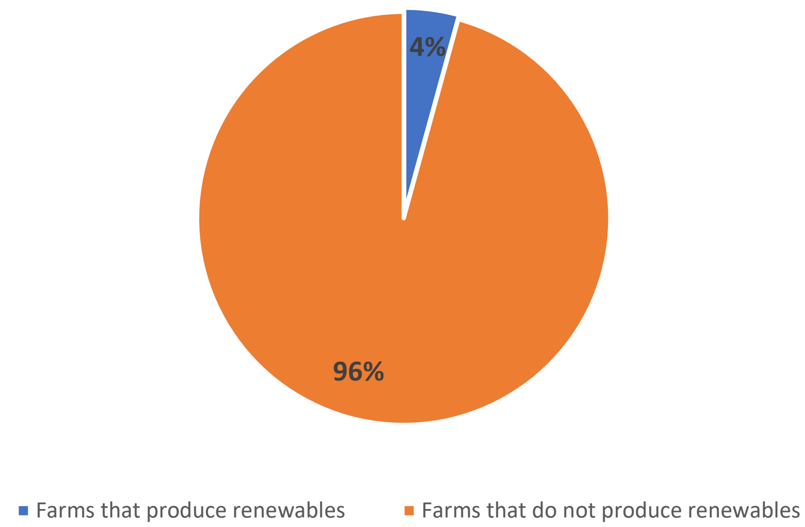
Table 6.3.3: Sample Distribution by Economic Orientation

Farm type	**Number**	**%**
Mixed	497	4.62%
Livestock	2919	27.12%
Crop	*7347*	*68.26%*

Source: RICA (2022)

Looking now at renewable energy companies, of the entire sample of 10,764 farms, only 459 produce renewable energy as a primary or complementary activity. On the other hand, 10,305 farms do not produce renewable energies.

Fig. 6.3.3: Farms that do and do not Produce Renewables (2020)



Source: RICA (2022)

Of these 459 farms, which is 4.3% of the sample, Table 6.3.3 shows that the majority, 405, exploit solar power, then 28 produce Biogas, 11 use as source the wind power, 5 wood and 10 other sources.

Table 6.3.4: Renewable Energy Production Farms (2020)

Energy Source	**Number**	**%**
Other	10	2.18%
Biogas	28	6.10%
Eolic	11	2.40%
Wood	5	1.09%
Solar	405	88.24%
Total	459	100%

Source: RICA (2022)

6.4. Purpose and Model Definition

The current section covers the definition of the DEA model, regarding the **purpose of the analysis** and then the choice of model, the choice of returns, the choice of orientation, and, finally, the choice of inputs and outputs.

Purpose of the analysis

The objective of this analysis is to **assess the efficiency of all farms** included in the database, to understand **whether renewable energy production in agriculture**, ceteris paribus, **improves the overall efficiency** of these farms.

The question this analysis seeks to answer is whether the renewable energy farms are, on average, more efficient. In addition, the results will be read with different keys of interpretation, separating the results into categories to check whether, for example, the farms that belong to southern Italy are, on average, more or less efficient. Efficiency will be evaluated by scoring the following DEA model run on the MAXDEA program.

Model Specifications

Among the various DEA models, the chosen one is an **output oriented BCC** (Banker, Charnes and Cooper 1984), that has **VRS** (variable return to scale).

The **BCC model** has been selected for two reasons: the first one is that because, alongside with CCR, is a well-known, basic DEA model and, most important, because it allows for **variable return to scale**. The reason for choosing the **VRS** is that farms belong to various fields that are extremely different from each other and thus constant returns to scale would probably not optimally represent the reality.

Finally, the choice to use the **output oriented** model is a choice due to the fact that farms, often rely particularly on **land inputs and capital inputs that are not easy to change**. Therefore, for farms it is better to try to optimize the inputs they have to get the best possible result, rather than trying to minimize their inputs to get the same result.

Inputs

Table 6.4.2 shows the inputs values of the first ten DMUs, indexed by the "Id" column.

Table 6.4.1: Inputs for DEA (2020)

Id	Working Hours	Net Current Costs	Multiyear Costs	UAA	Crop Pollution Costs	Breeding Emissions
1	2160	26310	1525	47.57	0	4950
2	2880	23991	3520	27.02	4417	2574
3	7080	97193	6712	32.93	7880	5445
4	2720	12415	616	8.28	0	2040
5	2400	105055	2262	14.64	8639	1856
6	3840	58482	5019	88.25	25909	0
7	3840	99473	25073	20.38	1681	3861
8	2800	8555	3276	8.21	0	1287
9	2720	13659	3410	7.03	0	1089
10	6700	22605	1812	35.21	8524	0

Source: RICA (2022)

As it is possible to see, there are six different inputs. The following list briefly explain the reasons behind those choices and if the values are directly imported from the RICA database or whether there has been some manipulation.

- **Working Hours**: That is the **total number of working hours during the whole year**. This input refers to **labor as a productive factor**.
- **Net Current Costs**: this input item includes all **current expenses** that the farm pays during the year, net of the specific septage for herbicides, pesticides, and pesticides that have already been considered separately.

- **Multiyear Costs**: **total deferred costs for the year**, calculated as the sum of depreciation and provisions.
- **UAA:** Utilized Agricultural Area, it refers to land as productive factor. UAA is the sum of farm areas devoted to agricultural production and it is calculated in hectares.
- **Crop Pollution Costs**: this input can be either considered as an input or as an undesirable output. In fact, it is something that is actively used with the purpose of obtaining the output but is also an environmental cost that is an indirect consequence of the purpose of support the crops growth. In any case, it is **something that farms want to minimize**. It is a composed variable, obtained by the **sum of the costs for fertilizers, herbicides and pesticides** collected through the income statement table, in the RICA database, of each DMU. This input can be greater or equal to zero, where a farm does not use pesticides, herbicides, and pesticides by choice or because they are unnecessary, such as for breeding farms that do not grow crops.
- **Breeding Emissions**: as before this input can be considered as an **undesirable output**. Livestock emit polluting agents, especially **methane**, that are an **unnecessary consequence of breeding**. Methane is not a necessary input to livestock farms, but an unavoidable externality that is an environmental cost. Not all emissions are inevitable waste, however; in fact, methane emission occurs at two main stages: the enteric fermentation and the manure management. Each animal species has a methane emission coefficient per livestock unit (Yusuf et al, 2012), separated into enteric fermentation and manure management. **The value of breeding emissions is thus:**
  - $BE_{id} = n * (EF_j + MM_j)$ (1)
- Where BE stands for Breeding Emissions, the index *id* refers to the DMU, n is the number of livestock, EF_j is the coefficient for Enteric Fermentation for the animal species *j* and MM_j is the coefficient for Manure Management for the animal species *j*.

Table 6.4.2 summarize the coefficients for the animal species.

Table 6.4.2: Emission Coefficients by Animal Species

Animal Species	EF	MM
Cattle-Dairy	68	31
Others	47	1
Buffalo	55	2
Sheep	5	2
Goats	5	0.22
Pigs	1	7
Horses	1.80	2.19
Poultry	0.02	0.02

Source: Yusuf et al. (2012)

EF is generally nonrecoverable while MM can be managed through biogas plants that use animal slurry to produce energy. For this reason, farms that produce energy through biogas plants have the MM coefficient changed to zero.

Outputs

Table 6.4.4 reports the outputs for Data Envelopment Analysis. These outputs should not be mistaken for model outputs. In fact, in Data Envelopment Analysis the "model inputs" are both the inputs that a company uses to produce its outputs and these outputs. On the other hand, the "model outputs" are the efficiency scores.

Table 6.4.3: Outputs for DEA (2020)

Id	GSP	GSP Renewables	Complementary Activities Revenues
1	103357	0	0
2	54934	0	0
3	151803	0	0
4	16825	0	0
5	138995	0	0
6	93090	0	0
7	130407	0	95263
8	28713	0	0

9	30063	0	0
10	45431	0	1491

Source: RICA (2022)

There are three distinct outputs: GSP, GSP Renewables and Complementary Activities Revenues. These three variables are the addends that when added together produce total business revenues.

- **GSP**: Gross Saleable Production, that is calculated as the sum of sale of products, stock variation, EU aids, increase in fixed assets and self-consumption and gifts. These addends refer to **revenues closely related to agricultural activity**.
- **GSP Renewables**: GSP obtained from **on-farm renewable energy sources**.
- **Complementary Activities Revenues**: Income from **activities complementary to agricultural activities**. This input is calculated as the sum of farmhouse revenues, contracting, rental income and other complementary revenues.

6.5. Scores Distribution

The analysis was conducted on a sample of 10,764 farms that were assigned a score between 0 and 1. Farms with an **efficiency score of one** are those considered **efficient,** while all others are considered with some degree in inefficiency, the more as they are close to zero. Remember that Data Envelopment Analysis methodology defines efficiency as a relative measure, based upon the best performers in the sample.

Overall, **204 farms** (1.91%) were found to be **efficient** while the other **10564** (98.09%) had some sort of **inefficiencies**. DEA identifies as relatively efficient only those DMUs that lay on the efficient frontier, and they thus have a score equals to one. Remember, though, that a score that is close to one, despite being significantly better than a score close to zero, is still considered inefficient by DEA. Nevertheless, DEA scores can be ordered from zero to one to create an efficiency ranking.

The **lowest score** value was 0 for the DMU identified with the number 7.231, which recorded positive or zero input values, but all three output values of zero. Excluding this last particular case, the DMU with the second lowest score was number 9.686 with a value of 0.004586.

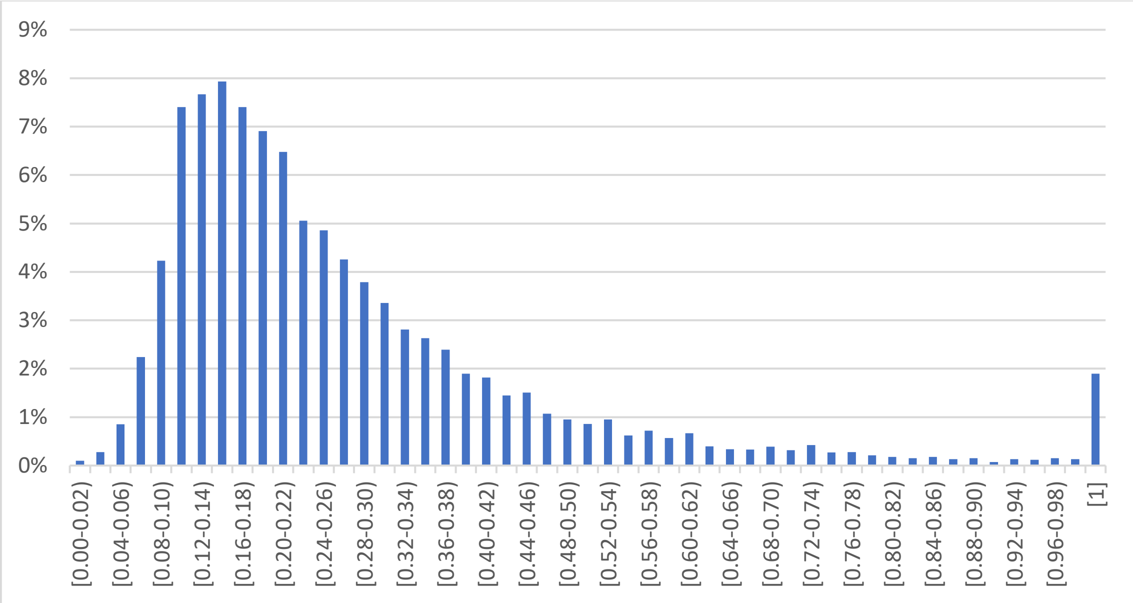
As previously mentioned, by the model definition, the highest value was obviously 1, obtained in 204 cases. The mean value was 0.273275, the median value was 0.215128 and the standard deviation was 0.191385. Table 6.5.1 summarizes these values.

Table 6.5.1: Scores Statistical Indicators

Indicator	**Value**
Minimum Value	0.004586
Maximum Value	1
Mean Value	0.273275
Median Value	0.215128
Standard Deviation	0.191385

Figure 6.5.2 shows the frequency distribution of the results, through **50 equidistant intervals of value 0.02 and a final singleton** in [1]. Each interval, except the last one, is closed on the left and open on the right. Most of the mass resides in the first half of the possible values, the density initially increases from zero to a peak in the range [0.14-0.16), from which it then falls gradually and with decreasing steepness to the range [0.98-1.00). Finally, in the last interval [1.00] the curve steeply rises again.

Figure 6.5.1: Score Frequency Distribution (2020)



Distribution by Geographic Area

Italy is often divided geographically into five areas: **northwest, northeast, center, south and islands**.

Table 6.5.2 summarizes some characterizing statistics of different areas in Italy: area, population, density, GDP, percentage contribution to total GDP and GDP per capita. It can be seen that the center is the largest area in terms of area, but northwest is the more populated and the densest, it also contributes with the largest share of GDP and it has the highest GDP per capita.

Table 6.5.2: Italian Areas Statistics (2019)

Area	**Surface**	**Inhabitants**	**Population Density**	**GDP (billion €)**	**% GDP**	**GDP per capita**
Northwest	57,950 km^2	16,113,972	278.07 inh./km^2	591.15	33.05%	€36,937
Northeast	62,310 km^2	11,660,998	187.21 inh./km^2	413.85	23.10%	€35,420
Center	68,884 km^2	12,995,601	188.66 inh./km^2	418.34	23.38%	€32,192
South	62,391 km^2	12,180,295	195.22 inh./km^2	240.29	13.42%	€19,728
Islands	49,801 km^2	6,598,884	132.49 inh./km^2	124,61	6.94%	€18,886

Source: Istat (2019)

Table 7.1.3 shows mean, median, standard deviation, minimum and maximum values, number of efficient farms, total number of farms, and percentage of efficient farms overall, divided by the above mentioned five macro-areas. It can be seen that companies in the northwest are on average more efficient than those in other areas, and the percentage of efficient companies in the total is significantly higher. On the other hand, central Italy turns out to be the area with the lowest average score and the lowest percentage of efficient companies in the area.

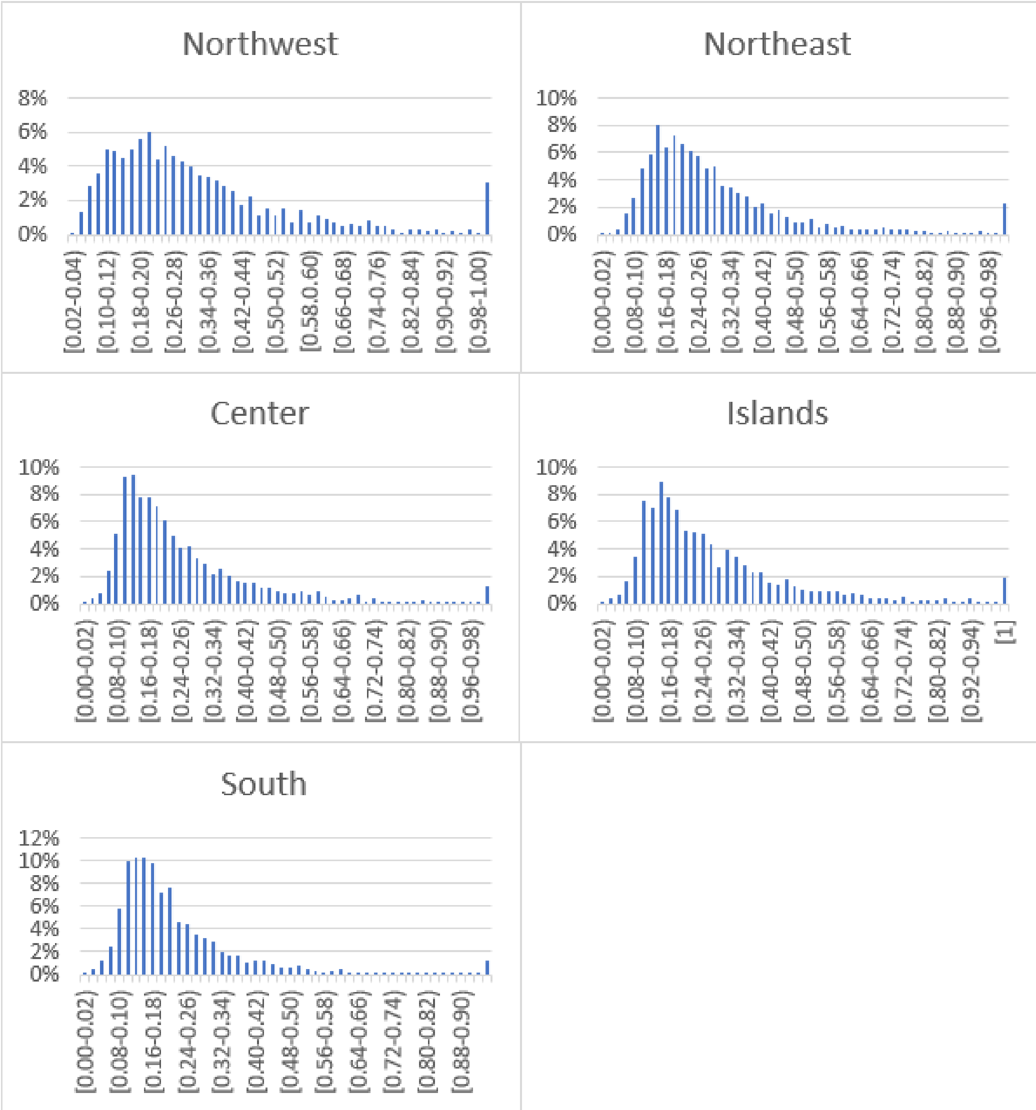
Table 6.5.3: Score Statistics, by Area

Area	Average Score	Median Score	Standard Deviation	Min. Value	Efficient DMUs	DMU Number	% Efficiency
North west	0,32419	0,267719	0,218016	0,024771	60	1950	3.07%
North east	0,294668	0,240737	0,194811	0,018826	58	2524	2.30%
Center	0,258034	0,199775	0,183707	0,015907	33	2,573	1.28%
South	0,235701	0,187742	0,159541	0,038605	29	2,010	1.44%
Islands	0,280227	0,223185	0,193038	0,004586	23	1,202	1.91%

Source: Istat (2019)

As can be seen from the distribution curves in fig. 6.5.2, for the center and south the bulk of the mass is toward zero. This fact is also true for the north and the islands, but the difference is that in the latter two cases the curve drops less rapidly going right toward the higher scores. Also, above the 0.5 score, many more firms tending trough efficiency are appreciable in the northern distribution.

Fig. 6.5.2: Score Frequency Distribution, by Area (2020)



Distribution by Altitude

When it comes to farms, a very important quality variable is **altitude**: it is very different, indeed, to run a farm in the **plains, hills or mountains**.

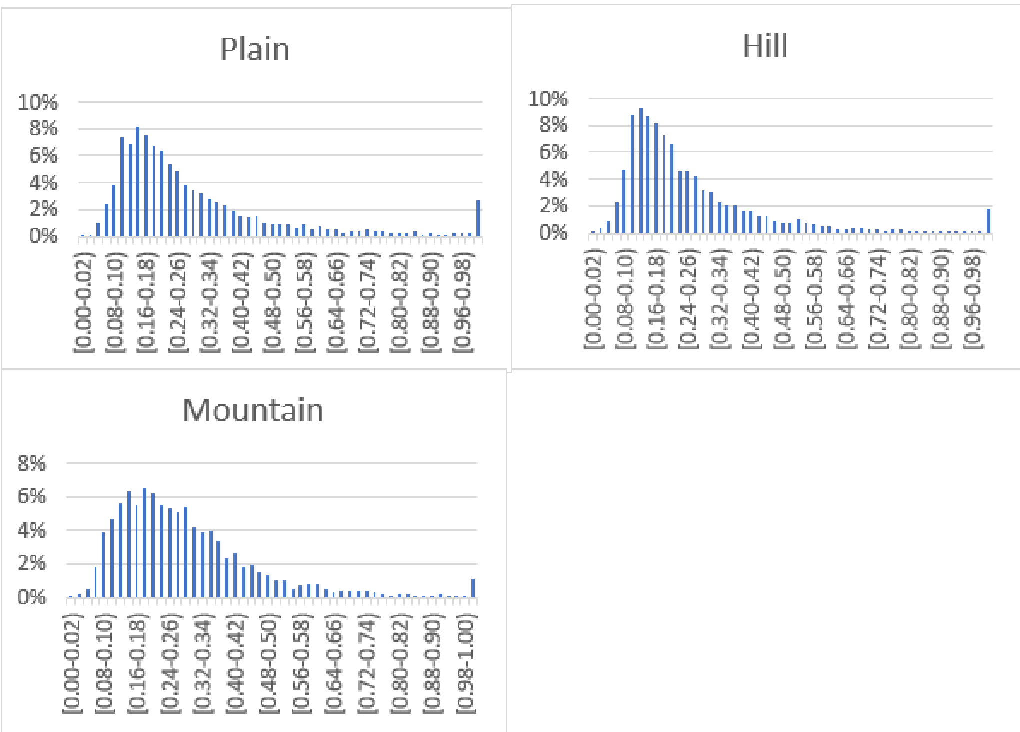
As mentioned in chapter 6, the majority of the farms, 45%, reside on the hills, while 32% in the plains and 23% on the mountains. This current section tries to understand whether altitude could be an exogenous factor capable of determining a significant difference in the efficiency score.

Table 6.5.2 shows some descriptive statistics of the distribution of scores, separated by altitude, while figure 6.5.3 shows the distribution of scores, separated by altitude.

Table 6.5.3: Score Statistics, by Altitude (2020)

Altitude	Average Score	Median Score	Standard Deviation	Min. Value	Efficient DMUs	DMU Number	% Efficient DMUs
Mountain	0,290115	0,252772	0,175402	0,004586	28	2,468	1.13%
Hill	0,255095	0,198649	0,182823	0,015907	86	4,883	1.76%
Plain	0,28735	0,217995	0,211282	0,016933	90	3,397	2.65%

Fig. 6.5.3: Score Frequency Distribution, by Altitude (2020)



As for the average score, the mountains have the highest value, but instead have the lowest percentage of efficient DMUs in the total. The supremacy belongs to the plains, which not only has the highest percentage of efficient farms out of the total with 2.65 percent but is also the altitude with the highest absolute number of efficient DMUs, despite having only 3,399 DMUs compared to the 4,883 farms in the hills.

Distribution by Economic Orientation

Farms can have different **economic orientations**, the choice of this section is to divide them into three macro-categories: **crop, mix and livestock**.

The average score is higher for livestock farms, while the number of most efficient DMUs belongs to crop farms. Anyway, the category that has relatively the highest number of efficient DMUs (3.01%) is the mix one.

Table 6.5.4: Score Statistics, by Economic Orientation (2020)

Orientation	Average Score	Median Score	Standard Deviation	Min. Value	Efficient DMUs	DMU Number	% Efficient Farms
Crop	0,255741	0,199322	0,183365	0,004586	116	7345	1.16%
Mix	0,237769	0,175192	0,195039	0,023988	15	497	3.01%
Livestock	0,323661	0,274462	0,201065	0,031772	73	2917	2.50%

Fig. 6.5.4: Score Frequency Distribution, by Econ. Orientation (2020)

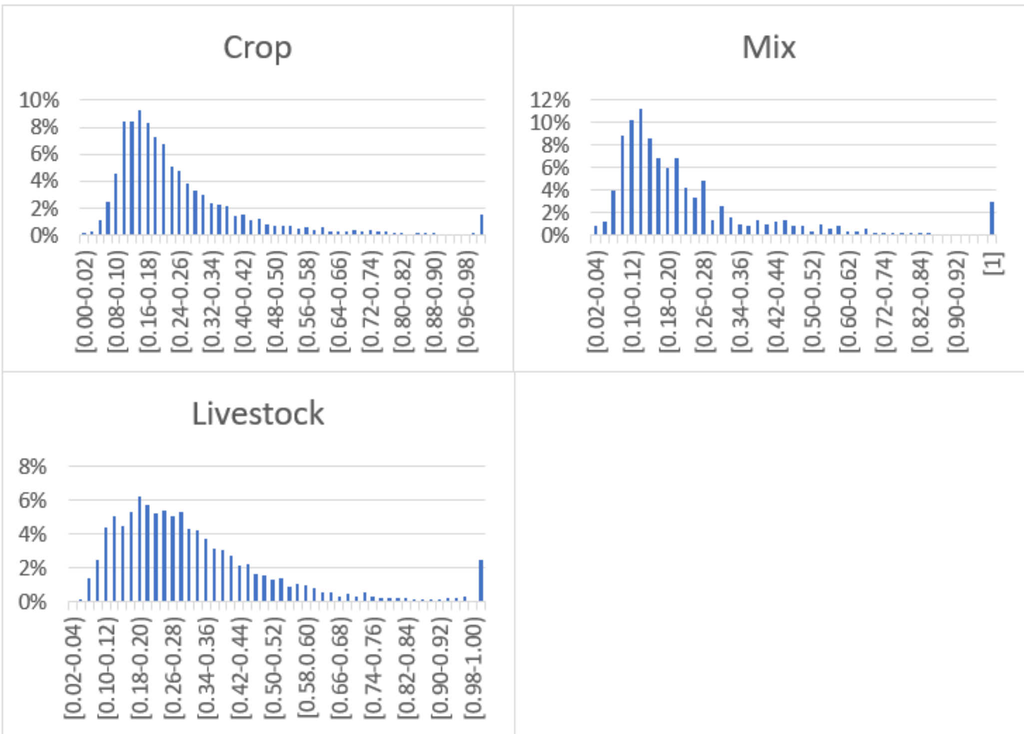


Table 6.5.4 shows some descriptive statistics of the distribution of scores, separated by the economic orientation, while figure 6.5.4 shows the distribution of those scores.

Also from the distribution density graph it is possible to guess what the statistics in Table 6.5.3 show: indeed, it can be seen that the mass of the livestock distribution is less shifted toward the left end, resulting in a higher mean score than the other two distributions. In addition, it is clearly seen that the mix and livestock distributions have more elements, relative to the total number, in the last singleton [1.00], thus resulting in a higher percentage of efficient farms over the relative population.

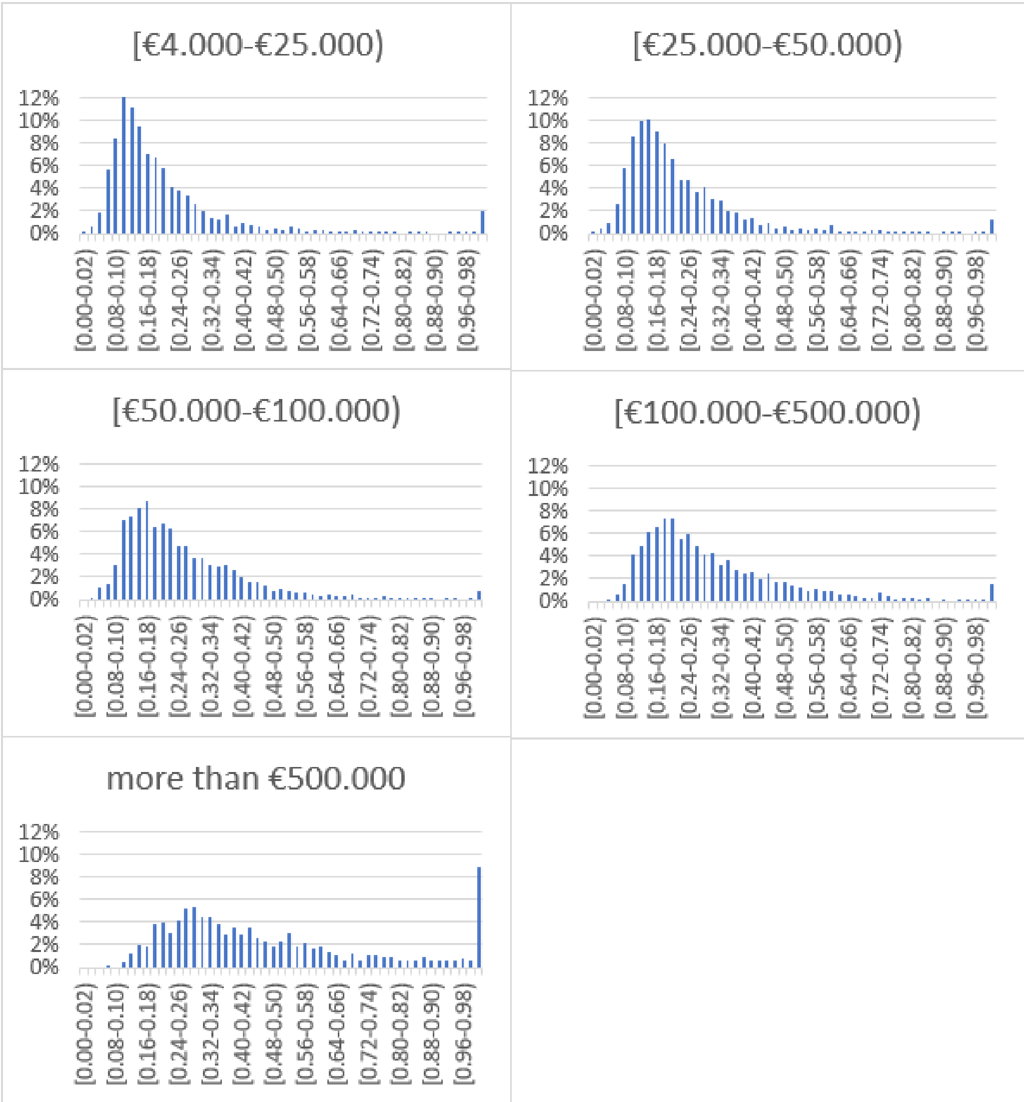
Distribution by Economic Dimension

As in the previous section, farms were divided by class of **economic size**, indexed from 1 to 5. Table 6.5.5 shows that the average score increases as the economic dimension class increases.

Table 6.5.5: Score Statistics, by Economic Dimension Class (2020)

Dim. Class	Economic Dimension	Average Score	Median Score	Standard Deviation	Minimum Value	DMU Number	Efficient DMUs	%
1	**4.000€ - 25.000€**	0,212283	0,158722	0,173512	0,004586	2232	45	2.02%
2	**25.000€ - 50.000€**	0,231117	0,185918	0,159427	0,015907	2468	30	1.21%
3	**50.000€ - 100.000€**	0,264584	0,219938	0,165375	0,019242	2499	21	0.08%
4	**100.000€ - 500.000€**	0,31391	0,259011	0,188823	0,019109	2824	43	1.52%
5	**500.000€ or more**	0,473684	0,397901	0,255394	0,061459	737	65	8.81%

Fig. 6.5.4: Score Frequency Distribution, by Econ. Dimension (2020)



Although the first four dimensions are definitely the most populous, dimension 5 (€500,000 or more) has the largest number of efficient firms and the highest percentage of efficiency. Of all the distinctions made so far, dimension class 5 is the one that by far accommodates the largest percentage of efficient firms and the highest average score.

Looking at the density distributions in Fig. 6.5.5, one can see the gradual shift of mass to the right that justifies the growth of the average score.

The density distribution of dim. class 5 (500.000€ or more) is markedly different from the previous ones; in fact, the last interval [1.00] is the densest one, and the mass distribution in the other intervals is more homogeneous than the other distributions that place most of the companies below the score of 0.5.

6.6. Renewable Production Scores

This section will compare data on the **efficiency of companies that produce, and do not produce, renewable energy.** **Internalized energy production** in itself is already a factor that is expected to enhance a farm's efficiency, since, on the one hand, it **reduces costs for energy** that is no longer purchased from providers and, on the other hand, it **adds positive cash flow** to normal farming activities. In some cases, renewable energy production is a complementary activity that complements "regular" farming practices, while in others it is so important that it becomes the core business.

In some cases, producing renewable energy requires a huge investment and produces returns big enough to become the core business. Is the case, for example, of some plants that generate biogas, with a cost that can range from €800,000 up to €15 million (Birchsolutions, 2021).

Table 6.6.1 shows some statistics characterizing the distribution of efficiency scores: on average, farms producing renewable energy get a higher score by almost 13 percentage points, moreover, relatively many more efficient DMUs are found among these farms.

Table 6.6.1: Score Statistics, by Renewable Production (2020)

Farm Type	Average Score	Median Score	Standard Deviation	Min Value	DMU number	Efficient DMUs	%
Renewable	0,395412	0,310379	0,26453	0,046651	459	40	8.71%
Non Renewable	0,267795	0,211974	0,185616	0,004586	10302	164	1.59%

The result then tells that **companies that produce renewables** are, on average, **more efficient** than those that do not, and that the **chance of a company being efficient is more than five times higher in farms that produce renewables** than those that do not.

Table 6.6.2 collects data divided by type of renewable energy production. It can be seen that **most of the companies in the sample use solar energy** and only about one ninth of them produce energy from different sources. Among those that produce **solar energy** the **average score is lower than the other renewables** but still **significantly higher than those that do not produce**, the **efficiency rate** is similarly **lower than the other sources** but **higher than those that do not produce renewables**.

There are only 26 **biogas companies** in the sample, and it should be noted that the **numerical scarcity could lead to inaccuracies in the results**. The **same argument applies** even more to the companies gathered in the **"others"** field: of the 27 collected 11 exploit wind power, 5 produce energy from wood, and the remaining 11 are classified as "others" directly in the FADN database. In any case, according to the sample data, biogas companies are by far the most efficient with an average score of more than 0.83 and an efficiency rate of 53.84 percent. As for "others," they rank ahead of solar farms but significantly behind biogas farms.

Table 6.6.2: Score Statistics, by Renewable Source (2020)

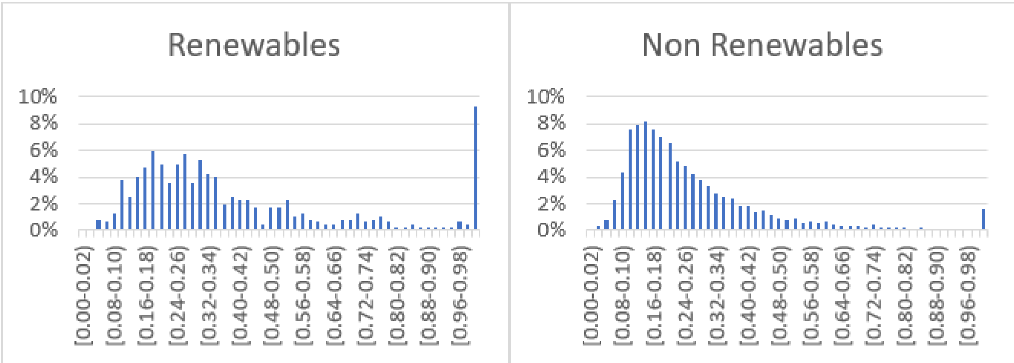
Renewable Source	Average Score	Median Score	Standard Deviation	Min Value	DMU Number	Efficient DMUs	%
Solar	0,366451	0,292722	0,243148	0,046651	406	25	6.15%
Biogas	0,838021	1	0,207368	0,345107	26	14	53.84%
Others	0,419337	0,391872	0,239736	0,052873	27	1	3.7%

As in the previous section the next figures show the density distribution of the efficiency scores, that are gathered into 50 intervals from zero to one.

Figure 6.6.1 shows that the **distributions of farms that produce renewable energies scores and farms that do not produce renewable scores looks very different**, but with some common features: they both have a large mass in the first half and then they both have the last interval more populated than the previous ones. In any case, it is clear that

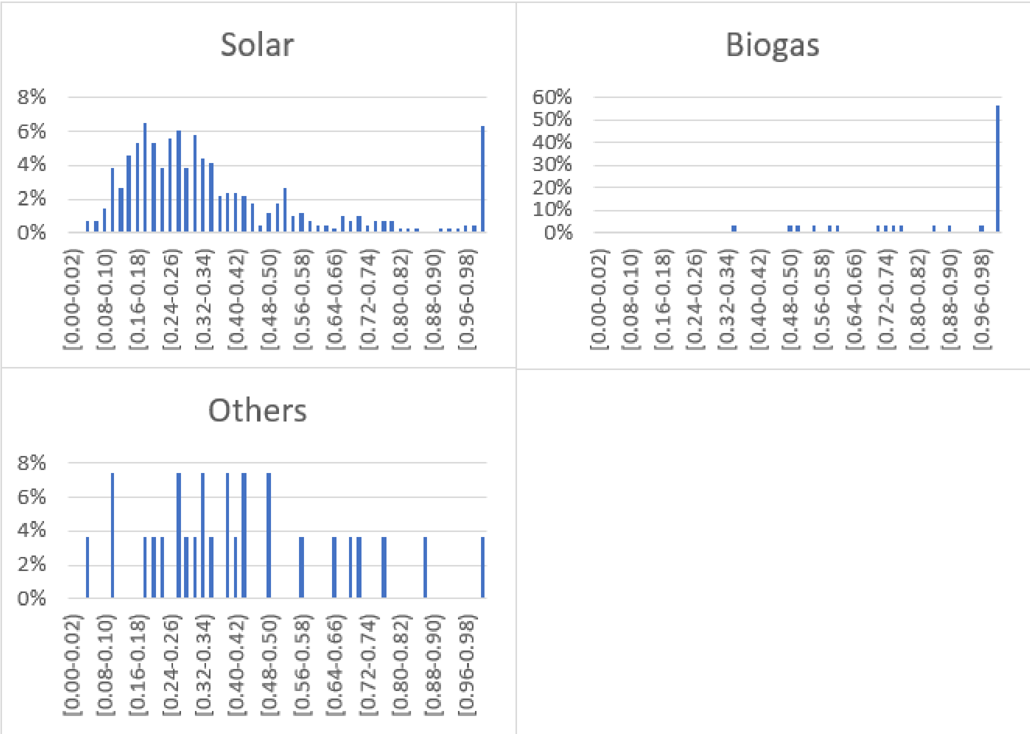
renewables are on average more efficient and that is more plausible finding an efficient DMU among those that produce renewables energies.

Fig. 6.6.1: Score Frequency Distribution, Farms producing R. E. and Not producing R. E. (2020)



In figure 6.6.2 are shown the distribution of the three renewable sources. Since solar covers for more than 88 percent of the producing renewable farms, visually its scores distribution looks a lot like the renewables one. Looking at the biogas and "others" scores distribution it is clear that the sample is very limited and every consideration built upon must be very cautious. Even with few data, these distribution look very different than the other ones. In particular the distribution of biogas scores that has almost its entire mass in the right side of the scores. The other sources distribution looks like it is shaped in a more uniform manner.

Fig. 6.6.2: Score Frequency Distribution, by Renewables Source (2020)



6.7. The Efficient DMUs

As said before, only those DMUs that have a score equal to one belong to the efficient frontier and therefore are considered to be efficient. This section aims to present and describe those DMUs.

Of all 10,764 farms only 204 are considered efficient. The next tables show those **efficient DMUs, divided by renewable production and then by macro area, altitude, economic size, and orientation, respectively**. This distinction is necessary to understand whether indeed the higher score of renewable companies is also influenced by other factors within the sample.

In Table 6.7.1 we see that most of the efficient companies producing renewables are located in the North, which, as seen above generally has higher efficiency than other regions. Specifically, of 40 efficient farms, 29 are located in the North, or 72.50 percent.

Table 6.7.1: Efficient DMUs, divided by Ren. Source and Macro Area (2020)

None	**164**	**%**
Center	25	15%
Islands	21	13%
Northwest	55	34%
Norteast	34	21%
South	29	18%
Biogas	**16**	**%**
Center	3	19%
Northwest	3	19%
Northeast	10	62%
Others	**1**	**%**
Northwest	1	100%
Solar	**23**	**%**
Center	5	22%
Islands	2	9%
Northwest	1	4%
Northeast	14	61%%
South	1	4%

In Table 6.7.2, with regard to renewables we see a clear preponderance toward the hills and plains. Specifically, no efficient biogas-producing farm is located in the mountains.

Table 6.7.2: Efficient DMUs, divided by Ren. Source and Altitude (2020)

None	**164**	**%**
Hill	67	41%
Mountain	25	15%
Plain	72	44%
Biogas	**16**	**%**
Hill	5	31%
Plain	11	69%
Others	**1**	**%**
Mountain	1	100%
Solar	**23**	**%**
Hill	14	61%
Mountain	2	9%
Plain	7	30%

Table 6.7.3 shows that efficient farms that do not produce renewables are mostly crop farms, while on the other hand, efficient farms that produce renewables are livestock farms. The statistical trend is completely reversed here, and it would certainly be interesting to investigate this fact further.

In Table 6.7.4 it comes out clearly that efficient biogas companies have an economic dimension at least above €100,000 and, in the vast majority, above €500,000. As seen before, farms larger than €500,000 tend to be more efficient than smaller farms. There is also a tendency to see relatively fewer farms with average economic size, between €25,000 and €100,000. Specifically, there is no average size farm that produces renewables in the DMU efficient list.

Table 6.7.4: Efficient DMUs, divided by Ren. Source and Economic Orientation (2020)

None	**164**	**%**
Crop	107	65%
Livestock	44	27%
Mix	13	8%
Biogas	**16**	**%**
Crop	4	25%
Livestock	11	69%
Mix	1	6%
Others	**1**	**%**
Livestock	1	100%
Solar	**23**	**%**
Crop	5	22%
Livestock	17	74%
Mix	1	4%

Table 6.7.4: Efficient DMUs, divided by Renewable Source and Economic Dimension (2020)

None	**164**	**%**
[€100.000 - €500.000)	33	20%
[€25.000 - €50.000)	30	18%
[€4.000 - €25.000)	40	24%
[€50.000 - €100.000)	21	13%
€500.000 or more	40	24%
Biogas	**16**	**%**
[€100.000 - €500.000)	2	13%
€500.000 or more	14	88%
Others	**1**	**%**
[€4.000 - €25.000)	1	100%
Solar	**23**	**%**
[€100.000 - €500.000)	8	35%
[€4.000 - €25.000)	4	17%
€500.000 or more	11	48%

6.8. Results and discussion

In light of what has been addressed in this chapter, it can be said that the **farms defined as efficient by the DEA model are relatively few**, only 1.91 percent, and that **most of the farms in the sample are relatively inefficient**, since they mostly rank far from score 1 representing efficiency and instead closer to score 0.

The distribution of scores in almost all cases takes on a **characteristic shape** that grows rapidly from zero and finds its peak toward the first third of the distribution, then decreases rapidly and finally grows back to the last value it can take in its domain, which is 1.

Next, the distribution of scores was divided into categories, and these were analyzed separately to see **whether certain characteristics could be determinants of efficiency scores**.

As a first step, companies were divided according to their **macro geographical area**, and it was seen that companies in the northwest are generally more efficient than those in the northeast, center, south and islands. Then, farms were divided according to altitude. Then, farms were separated by **economic orientation** into crop, livestock and mix. Crop farms were found to be the most efficient on average, and mix farms were found to be the least efficient on average. But looking at the number of efficient farms in the total, the mix farms had the highest relative number of farms. Next, the farms were divided into **five economic size classes**, and it was seen that the average score increases as economic size increases. Instead, the relative share of efficient farms in the total is higher at the extremes, especially toward the largest class farms, and for the middle class farms it decreases to almost zero.

Finally, the companies were divided between **those that produce renewable energy and those that do not**. The result in this case is strongly different: in fact, the **companies producing renewable energy obtained a significantly higher average score**, and also from a relative point of view, **there are relatively many more efficient companies among those producing renewables**.

Specifically of the 459 renewable companies, the **vast majority operate in the solar energy sector** and only a few use other facilities. The other companies are divided between **biogas producers and "others"** due to an insufficient number of companies in the sample.

Of these, companies **producing solar energy and "others" are more efficient on average** than those that do not produce renewables, while **farms producing biogas are extremely more efficient**, both from the average point of view and from the point of view of efficient companies out of the total.

It should be noted that a **sample of only 26 biogas** companies has **limited statistical significance**. In addition, it was noted that biogas companies are part of the two largest economic size classes, which, as mentioned earlier, are relatively more efficient than the smaller ones.

That being said, it is possible to say that, according to the DEA model specified in Chapter 6, **renewable energy producing farms**, that belong to the Italian RICA sample, **are economically more efficient than those that do not produce renewables instead**.

7. CONCLUDING REMARKS

The result of the analysis is, basically, that **farms that produce renewable energy appear to be more efficient than those that do not**. How does this result translate into practice?

Starting from a point of view close to **neoclassical economics**, the significance of this thesis statement could be of interest both to **farms as a unit** in an economic system and to **policy makers** in resources allocation.

On the one hand, **farms might consider solutions that allow them to produce renewable energy**, not only out of a desire for the environment to be better, but also **to gain an economic return** in terms of efficiency. In addition, given the **emergency situation** in the energy market to date February 2023, the related **energy prices have risen disproportionately** and the choice to **internalize energy production** turns out to be **relatively more convenient than before**.

Thus, an educated guess might be that **farms will tend in the future**, due to the nature of the market itself, to **produce more renewable energy**.

This statement should not be understood as an exact prediction of the future, as many factors and possible market failures could come into play. For example, as noted, biogas farms are of considerable economic size, and barriers to entry in this market sector may be too high and prevent the full realization of equilibrium.

On the other hand, Italian and European **policy makers** might be interested in injecting **more funds** specifically for **farms producing renewable energy**. In fact, the relatively higher efficiency found on farms producing R. E., compared with those that do not produce them, implies that, at the overall level, if many more farms decided to produce renewable energy, then the **overall economic efficiency of the sector would increase**. This means that this **support would not be a mere subsidy** but would become, from a macroeconomic point of view, an **investment that would promote growth**.

Again, therefore, it is natural to think that policy makers would act in this way, and indeed, as seen in section 3.3 with NRRP funds, actions in this direction are already in place.

Turning to a **more modern economic point of view**, in which utility does not depend only on the consumption of goods, but also on hard-to-quantify factors related to **well-being and quality of life**, the expectation is the same, namely a **likely gradual increase in renewable energy producing farms**.

In fact, as seen in Chapter 2, the current dependence on **fossil fuels** is not only time-limited due to resource scarcity, but also **produces harm for human beings**, from an ecological point of view, also from a geopolitical point of view. Thus, the **maximization of social welfare**, which should be the ultimate goal of policy makers, **also comes through the conversion of farms to renewable energy production**, since, as stated earlier, renewable production both **increases the economic efficiency** of companies, thereby **increasing social welfare**, but also **offers a clean alternative solution** to fossil fuels and their negative externalities and **would reduce social malaise**.

A proliferation of renewable energy farms would surely be good, but there are **risks**.

Undoubtedly, the energy situation at today's date (February 2023) is a further push toward this ecological transition. However, it must be kept in mind that the hurry resulting from the emergency situation could bring **problems related to landscape constraints**.

Recent Italian legislation, following the worsening of the energy crisis, has expanded the areas suitable for production plants from renewable sources and this could lead to a **degradation of the agricultural landscape**. The systems and connection works to be built in agricultural areas are, in fact, today declared to be of public utility and so far, subject to accelerated administrative procedures, in which the administrations in charge of landscape and archaeological protection must express their opinion, but their opinion is not binding.

In conclusion, the results of this paper have the **advantage and limitation of being general**, that is, referring to a population of farms that represent Italian farms as a whole. There are farms from all parts of Italy, located in mountains, hills and plains, of different economic size classes and with different economic orientations.

Thus, it would be interesting to develop further research in which to evaluate the specific efficiency of farms in a full producing renewable energy sample, based on a larger volume of data, maybe European, in order to understand the efficiency of the different sources associated with different farms' own characteristics.

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