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Big Data and Energy Security: Impacts on Private Companies, National Economies and Societies

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Abstract: The importance of energy security for successful functioning of private companies, national economies, and the overall society should not be underestimated. Energy is a critical infrastructure for any modern society, and its reliable functioning is essential for all economic sectors and for the well-being of everybody. Uncertainty in terms of the availability of information, reliable data to make predictions and to plan for investment as well as for other actions of stakeholders at the energy markets is one of the factors, which has the highest influence on energy security.

This uncertainty can be connected with many factors such as the availability of reliable data or the actions of stakeholders themselves. For example, the recent outbreak of the COVID-19 pandemic revealed negative impacts of uncertainty on decision-making processes and markets. At the time point when the market participants started to receive real-time information about the situation, the energy markets began to ease. This is one scenario where Big Data can be used to amplify information to various stakeholders to prevent panic and to ensure market stability and security of supply.

In a fast-paced digital world characterized by technological advances, the use of Big Data technology provides a unique niche point to close this gap in information disparity by leveraging the use of unconventional data sources to integrate technologies, stakeholders, and markets to promote energy security and market stability. The potential of Big Data technology is yet to be fully utilized. Big Data can handle large data set characterized by volume, variety, velocity, value, and complexity. The challenge for energy markets is to leverage this technology to mine available socioeconomic, political, geographic, and environmental data responsibly as well as to provide indicators that predict future global supply and demand. This information is crucial for energy security and ensuring global economic prosperity.

Keywords: Energy Security; Big Data; Smart Meter; Security of Supply

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1. Introduction

Energy security and big data are more and more getting intertwined. On the one hand this interlacement brings forth a huge potential for the provision of energy, increasing efficiency in monitoring, and evaluation of current standards. On the other hand, the dependency of energy security on digitalization bears an increased risk exposure concerning cyber-attacks, privacy issues, and dependency on data availability. Nevertheless, the problem of data availability is a vanishing issue since an increasing number of devices measuring energy security-relevant input variables ensure a more and more dense data set which in turn increases energy security. The collection, analysis, and utilization of this collected data set are what we understand nowadays as big data.

The 21st century is the century of data. Big data can be described by the so-called Five Vs: Volume, Velocity, Variety, Veracity, and Value. Big data is characterized by the collection and utilization of huge amounts of data. The process of analyzing and finding patterns in unstructured data is called data mining. Since the vast amount of data is a sufficient condition to call a data set "big data", the first "V" (volume) is a necessary condition to characterize a certain data collection as "big data". The data mining process is associated with the processual ability of the system to actually manage to analyze the data in a reasonable time. Therefore, "Velocity" is a key ingredient for big data to be analyzed and be made useful. The important key characteristic of big data is in this sense the interplay and ability of modern technology to mine these huge numbers of datasets in a reasonable calculation time. Due to the huge size of the data sets, they usually exhibit a "Variety" to some certain degree. The astonishing ability of data mining techniques to identify these varieties in these high volumes and at high velocity is another feature of big data. Since numbers do not lie, "Veracity" is a doubtless characteristic of big data, which makes it so powerful and useful. Substantiated by a huge data set, certain patterns, trends, and forecasts can be solidified and verified. All these factors characterizing big data sum up to an incredible value generated by the collection and analysis of huge datasets.

While energy dependency of society has never been greater, the utilization of big data is increasingly important to secure energy infrastructure and energy market stability.

Considering the high importance of energy security, it is astonishing that a precise definition of energy security still does not exist. The IEA [1] defines energy security as the *"uninterrupted availability of energy sources at an affordable price."* For the IEA, the assurance of energy supply and maintaining the IEA emergency response capability are two key essentials to provide energy security. These capabilities include the maintenance of a *"set of regulations and/or policies that provide a framework for emergency oil stockholding and data reporting, and that facilitate timely participation in IEA collective actions in case of a severe oil supply disruption."*

Nevertheless, definitions such as this have to be looked at carefully. The reason for that lies in the potential conflict of interest of the originator of the definition. Like in the case of the IEA, an organization that represents primarily the interests of energy consumers, a key requirement that ensures energy security according to its definition is affordability. This is of course in the interest of any consumer and should therefore be questioned if this key requirement actually really defines energy security.

On the other side, organizations such as the US Energy Association[2] pursues the mission to *"promote the sustainable supply and use of energy for the greatest benefit of all"*, which overlaps to a certain extent with the mostly found core definitions of energy security. As a representative organization for more than 100 companies and associations in the U.S. energy sector, including the largest Fortune 500 companies, the emphasis for energy providers lies more on the sustainability of the supply of energy, as it is in the energy producers' interest to maximize the price at which they deliver their energy for the longest possible duration of affordability.

The most accurate way to define energy security is to find the common denominator of all definitions provided. However, the only definitions for energy security provided in literature are mainly providing

definitions for indicators of energy security, but not concepts for the actual measurement of energy security. To give a short overview of the most common definitions in the existing literature we first take a look at those indicators.

Kruyt et al. [3] propose to measure energy security via distinct indicators that cover four dimensions: availability, accessibility, affordability, and acceptability. Indicators are then classified to account for energy security accordingly.

Sovacool and Mukherjee [4] define five different dimensions of energy security: availability, affordability, technology development, sustainability, and regulation. They break down these categories into twenty components, which are all related to the security of supply (SOS) and production, dependency, diversification for availability; price stability, access and equity, decentralization, and low prices for affordability; innovation and research, safety, and reliability, resilience, energy efficiency, and investment for technology development; land use, water, climate change, and air pollution for sustainability; governance, trade, competition, as well as knowledge used for appropriate regulation. Furthermore, they list 372 indicators for policymakers and researchers in order to help them in their analysis, measurement, tracking, as well as in making comparisons of national performance on energy security.

Anget al. [5] explain how various energy security indices are being constructed and how the aspect of energy security is being expanded by consideration of factors such as environmental sustainability and energy efficiency. Environmental sustainability is a big issue when it comes to energy security, since the forced energy transition leads to a change in the energy mix, promoting renewable energy at the expense of security of supply (SOS) and market price stability. Chalvatzis and Hooper [6] give an overview of the challenges that various countries face while implementing policies that target addressing two important topics, namely climate change mitigation and improving electricity supply security.

In general, the notion of energy security is subject to variability, which is being discussed e.g. by Yergin [7], Mueller-Kraenner [8], Kruyt et al. [3], and Chester [9].

To construct such indices and to identify synergies within the network these indices require a huge amount of data, ideally generated and processed in real time.

Smart meters are an important tool that is capable of gathering such a huge amount of data in order to improve energy security and market stability, especially for the electricity market. Smart meters represent a type of power grid that is capable of coordinating a conventional power grid and the management of advanced communication networks and pervasive computing capabilities in order to improve the control, increase efficiency, strengthen the reliability and enhance the safety of the grid [10].

As Goertz [11] highlights, there exists a huge difference between indicators and measures, as provided in the literature regarding the definition of energy security, and analytical concepts, which are the foundation for the measurement of a certain variable. The core attributes of a concept constitute a theory of the ontology of the phenomenon under consideration. Concepts are about ontology. To develop a concept is more than providing a definition: it is deciding what is important about an entity. The arguments about why attribute X is an important part of the ontological theory of the object. For this reason, we want to provide an analytical concept for measuring energy security by defining the following lemma:

Lemma: Energy security as a concept mitigates the impact of economic loss for private companies, national economies, and on society by the provision of stable and transparent market prices, cost reduction, homogeneity of trading rules, efficient distribution, and accessibility of energy.

Gerring [12] mentions eight criteria, which need to be met by a concept in order to be perceived as good: (1) familiarity, (2) resonance, (3) parsimony, (4) coherence, (5) differentiation, (6) depth, (7) theoretical utility, and (8) field utility. Our concept of energy security tries to address these eight criteria:

1. The concept of an economic loss is familiar to private individuals, corporations as well as governments due to the commonality of economic principles.
2. The concept of an economic loss resonates within a society, as well as with public and private sector since it serves as a direct feedback loop which triggers immediate call for action.
3. Parsimony reflects the most basic rational behavior and requirement for public and private households to pursue sustainable finances.
4. Since economic practice manifests a common way to facilitate the exchange of needs in every country and society, economic integration of the values of countries or societies provides a solid level of coherence.
5. Our proposed concept of energy security mitigating economic loss for public and private sector, as well as the society differentiates into a significant way from common approaches to break down energy security as a simple connectivity, accessibility and affordability issue by considering the needs and fears of energy consumers and producers.
6. The depth reached by our concept to classify the impact of economic acting into the different branches of public and private sector helps to better understand motives and reactions of agents acting in a certain way, and thus revealing the path to energy security.
7. The strive for economic well-being can be assumed for any rational agent involved in the pursuit for energy security, especially in a theoretical setting.
8. The field utility can be actually measured once energy security is pursued and conducted as it manifests in the economic well-being of countries and societies.

Economic loss occurs in the aftermath of natural or forced disasters and limits societal development. Therefore, resilience of energy systems is a very important key factor. Energy systems need to withstand shocks such as natural disasters, geopolitical conflicts, and new and emerging threats related to the ongoing digitalization of energy systems [1].

We stress in this paper the role of big data as a solution to energy security and investigate its potential impact on private companies, economies, and society. The goal of this paper is to highlight the importance and potential of big data as well as its requirements for implementation and implications on SOS and society. Specifically, this study investigates the role of big data solutions in energy security and market stability to question of "How big data solutions for energy security can impact on private companies, national economies and society, in general". Furthermore, the practical challenges approach in implementing big data solutions for energy security are addressed. While existing literature deals mainly with the identification of certain energy security indices in order to provide SOS, we provide an overview and take a comprehensive look into the role and potential of big data to enhance SOS and market stability. We do this by analyzing the impact of big data as a solution to reduce uncertainty for energy security and market stability. The users of such big data can be companies, national governments, and the overall society. We also present in this paper the evidence of how the usage of big data contributed to SOS. Our contribution to the existing literature is two-folded. First, we develop a framework that considers inclusion and analysis of impacts from the usage of big data on SOS as well as potentials of big data on the meta-levels of energy security and energy market stability. Second, we highlight the implications of big data on energy market stability. The methodology of this paper is based on the meta-study of existing research while summarizing possible benefits from the implementation of big data and their impacts on private companies, national economies, and society, in general. The practical challenge in implementing the big data solution in SOS is also addressed in this study. In Section 2, we give an overview of the role of big data and its impact on private companies. In Section 3, we analyze the impact of the utilization of big data for energy security purposes on national economies. In Section 4, we analyze the impact of big data on society. Section 5 uses real-world examples to discuss challenges in employing big data solutions for energy security assurance.

2. The impact on private companies

Energy security is most often associated with network stability, considering the aggregate production and distribution of energy. On the other hand, big data plays an important role for the assessment of the strengths and weaknesses of this network. By gathering data, forecasting as well as real-time stability evaluations are more accurately possible than forecasts and assessments based on just historical performance. Moreover, big data enables to identify and validate cross relationships of effects that might have remained undiscovered without the use of data mining. Understanding these relationships is crucial, not only for business success but also simply for minimizing disruptions in the network.

Disruptions of energy supply can bring significant economic damages to private companies. They can also bring damages to their reputation. This raises the question about associated costs to maintain at least the critical level of energy supply stability. Jun et al. [13] measure the cost of energy security in terms of supply disruption and price volatility by comparing the supply and demand of energy, which is facilitated through the use of the so-called Hirschman-Herfindahl index (HHI). The index highlights the importance of energy price stability as high-price fluctuations makes it more costly to match supply and demand, thus triggering higher cost of storage or even higher cost of provision. They find several baseload energy technologies as the most competitive energy source. The main reason for this is the prevailing balance in supply and demand of these technologies, which thus ensures a relatively stable price. Moreover, the authors find that economic security dominates supply security and is therefore the main driver for total security cost. This is, where big data can unfold its powerful potential to identify insights of unknown structures that explain certain pillars of economic security such as understanding effects of inflation, unemployment, and economic growth, as well as international geo-economics, a concept that is based on the cross-border economic activity amongst countries (see [14]). Other technologies are more volatile in energy generation and therefore, are more prone to volatility in energy prices. Reduction of uncertainty with such technologies becomes a key for decision-making processes as well as stability of energy supply and stability of energy prices.

For businesses, data extraction, analysis, and representation are crucial for decision making. However, some challenges are coming along with big data mining such as risks to privacy, security and complexity [15]. As traditional mining techniques are not able to provide cost-effective solution besides having inability to leverage parallel processing power of resources, it is inevitable to go for big data mining with newly built data mining technologies. Emerging technologies such as MapReduce that is used by frameworks like Hadoop can help in analyzing big data and bring about business intelligence [16].

Hackl et al. [17] present the Total Site Analysis (TSA) method, which is used to analyze Sweden's largest chemical cluster according to its utility system and the improvement of its energy efficiency. They show that by moderate changes to the process utility system, savings up to 60 MW can be achieved.

A very efficient way to distribute energy between providers and consumers is the smart grid. It facilitates the delivery of electricity between suppliers and energy consumers through a bidirectional electricity and information flow infrastructure by meeting the pre-evaluated demand from consumer, as well as by coordinating the electric power generation through tracking of the terminal electricity consumption, linked real-time to the power market [18]. Efficiency improvement allows reduction of costs for energy providers and consumers as well as to improve reliability and stability of energy supply. Zhou et al. [19] give a detailed overview of how big data drives smart energy management. As big data can be accumulated through application of sensors, wireless transmission, network communication, and cloud computing technologies, they claim that this data can be used for power generation side as well as demand-side management, microgrid and renewable energy management, asset management and collaborative operation.

Interconnectivity, such as achieved through the application of smart grids, also enhance significantly market price stability. The most important factor for energy market price stability is predictive analytics and load classification, which are necessary for the load forecasting, bad data correction, determination of the optimal energy resources' scheduling, and setting of the power prices [20,21].

Moreover, Diamantoulakis et al. [22] stress that the scalability and flexibility can enable efficient processing of the large data volumes, usually faced in dynamic energy management and short-term power demand/supply forecasting, which in turn leads to a reduction in costs and improvement of energy security, as well as market stability. The scalability and flexibility can be ensured by the implementation of robust algorithms and the provision of high-performance computing infrastructure.

An example of the types of innovative approaches to the uses of data to generate real-time supply and demand forecasts lies in shipping. Using big data accumulated in the maritime sector can be a viable tool not only to generate supply forecasts for specific types of maritime fuel and accordingly, prices. More interestingly, if aggregated in real-time, it could provide a current demand profile for that specific sector. A sudden drop in maritime shipping activity could be a viable indicator of sudden supply shocks, as oil markets experienced during the COVID-19 crisis, potentially leading to the economic and fiscal crisis among leading oil-producing countries which in turn could exacerbate negative effects on production and the world economy. It should be noted that in terms of negative effects on fiscal policy, budgetary break-even figures, as opposed to production costs, are most relevant (see, for example, [23]).

Under Article 21 of Regulation (EU) 2015/757 of the European Parliament and the Council on the monitoring, reporting and verification of carbon dioxide emissions from maritime transport, an EU MRV System was introduced to provide a reliable data set to set precise emission reduction targets and to assess the contribution of maritime transport towards achieving a low-carbon economy. As a ship specific Union MRV system, it is based on the calculation of emissions from fuel consumed on voyages to and from Union ports. The regulation applies to ships above 5000 gross tonnage in respect of CO₂ emissions released during their voyages from their last port of call under the jurisdiction of a Member State and from a port of call under the jurisdiction of a Member State to their next port of call, as well as within ports of call under the jurisdiction of a Member State. The European Commission publishes a data set containing the identity of the ship, its technical efficiency, the annual CO₂ emissions, the annual total fuel consumption for voyages, annual fuel consumption per distance and type of cargo, annual time spent at sea in voyages, the method applied for monitoring and related data. All reports can be accessed online and are open source (see: <https://mrv.emsa.europa.eu/#public/emission-report>). For 2018, the report contains more than 9,8 million entries. While certain modifications to the data would have to be made, such as daily aggregation and accessibility, the current data set can provide important insights on the real-time demand pictures and demand shocks brought about by extremely rare and unexpected events, with severe impact on energy security and that were obvious in hindsight, so-called energy security Black-Swans (See, for instance, [25]).

Another viable source for big data to for increased energy security could come from widely applied international trade platforms that serve multi-modal transport. TradeLens [26], a platform and ecosystem to digitize global supply chains that was launched by IBM Blockchain and container giant MAERSK unites a wide range of container-based trading information that could serve as an indicator for global trade movements and therefore produce an accurate real-time data-set of energy usage in the sector, if we breakdown energy consumption per container.

3. The Impact on national economies

How can energy security be measured in a global economic and geopolitical sense? This question is not fully answered by existing literature since there is no agreement on one methodology, which considers the dynamics of international economy. One major characteristic of these dynamics is the occurrence of external shocks, e.g. caused by global financial and economic crises, political conflicts, rebellious or war-like situations, which impact not only energy prices but also the SOS. Radovanovic et al. [27]

propose a new geo-economic concept of energy security. This concept is built upon the common indicators but extends its measurement by taking into account certain measures of economic, financial and political stability, such as sovereign credit rating. These measures are influenced by global factors such as the global trade of energy, or the ability of certain economies to maintain a stable environment to secure a proper energy trading framework. They construct a Geo-economic Index of Energy Security and find that GDP per capita is the most influential factor affecting the value of the Geo-economic Index of Energy Security, while the impact of sovereign credit rating is of less significant value. On the contrary, they find that energy dependence has the least impact on energy security, which is commonly used as a proxy indicator for energy security, as well as the production of energy from renewable sources, even though the latter is defined by the EU policy as one of the methods for the improvement of energy security. The reason why GDP might be identified as a more influential factor for the constructed index measuring energy security than energy dependence might be reflected in the relationship between the capability of a country to afford, promote and pay for energy security and economic development of a country. In other words, if the economic situation of a country allows for the development of more secure energy infrastructure, which in turn contributes to energy security in a sense of more secure energy supply, then a higher level of energy security can be reached than just by a certain level of energy dependency, as energy dependency only reflects the demand of energy, but not to which extent, it can be facilitated.

Big data poses a huge potential to prop up this methodology since the importance of the constituents of such indexes are highly dependent on the identification of influential relationships in the data.

Cherp et al. [28] give a summary of energy issues in the world including their significance: Oil (125 countries)*, Gas (78 countries)*, Coal (45 countries)*, Nuclear (21 countries)**, Hydro (58 countries)***, Electricity (all countries), Transport, Industry (>25% of GDP in 60 countries), residential and commercial (all countries), Cross-country energy supply (all countries).

For each of the affected countries, energy security is achieved differently. It is important to note that 10%, and more of the primary energy depends on the extraction and refinement of oil. While over 5.5 billion people live in 112 countries that depend on oil for more than 18% of their total primary energy supply, energy security is mostly associated with market stability, meaning little or no market price disruptions [28]. Big data could assist in identifying new reserves that could be drilled at cheaper costs than locations that are being found with ordinary procedures.

For countries dependent on natural gas, energy security is being achieved through stabilization of supply as the global supply of natural gas depends upon direct investments in exploration, production, and transportation. These types of investments are usually facing a high risk-return profile since the uncertainty in drilling and production of shale gas fields and other production factors affect significantly the gas prices ([28], p. 342). Big data can help to identify investment regimes under which the investment in natural gas projects is more profitable and secure.

In coal, certain countries are considered especially vulnerable. The main reasons are on the one hand that coal consumption in these countries has been growing more than 5% per year and on the other hand that these economies are very dependent on high coal intensities ([28], p. 345). Big data could help to identify new coal reserves on the one hand, and methods to reduce coal dependency on the other hand.

In case of nuclear power, the primary concerns related to nuclear energy infrastructure and technologies. The role of big data could be to identify vulnerabilities in the infrastructure and help developing new technologies to provide a safer generation of nuclear power ([28], p. 345). From a market stability point of perspective, electricity produced from nuclear energy offers a greater protection from fluctuations in raw commodity prices; while doubling uranium prices leads to a 5–10% increase in generating cost for nuclear power, doubling the cost of coal and gas leads to a 35–45% and 70–80% increase, respectively [29].

Hydropower is vulnerable to seasonal and annual variability in hydrological regimes, as well as local weather conditions, temperature, and precipitation in the catchment area. These factors affect not only the availability of water for hydropower production, but also the amount of pressure on water resources in a region from competing uses ([28], p. 348). Big data could assist in forecasting weather changes and hydrological regime changes, as well as in R&D for hydropower optimization.

By taking into account both, supply and demand indicators of cross/sectoral vulnerabilities of energy systems, big data is a fundamental game-changer as it enables the identification of cross relationships and patterns that can be used in order to make the energy supply less vulnerable.

The change towards renewable energy poses certainly a challenge to countries. Nevertheless, via the utilization of big data and 5G, not only the forecasting power of energy-related data can be improved but also real-time adjustments and coordination across different energy providers can be achieved.

The importance of energy supply security is growing due to an increase in electricity dependence, expansion in the coverage of electricity grids in developing nations, an increase in the electrification of energy services, and the advancement of new energy systems that rely on renewable energy sources.

As mentioned in the previous section, economic security is fundamental to achieve energy security. Le and Nguyen [30] find that the opposite holds too in a sense that energy security enhances economic growth, while energy insecurity measured by energy intensity and carbon intensity variables has a negative impact on economic growth. Thus, economic security and energy security are self-reinforcing agendas that need to be pursued in order to improve sustainable economic development.

As the IMF [31] already noted, the improvements in economic security contribute to the rise of private investment and decrease downside uncertainty on the return on investment. Security factors that decrease the uncertainty on the returns on investment across capital goods also directly bear on growth by enhancing the efficiency of resource allocation, independent of their effect on private investment.

The IMF identifies several contributions of big data mining to these improvements, e.g. by gathering and assessing key variables, which influence decisions on private investment, big data helps to define decision-making rules. In terms of government leadership, big data has a huge potential to present inter-relationships of certain dependencies. Moreover, big data has the power to evaluate the external conflict risk and to identify corruption. Therefore, big data can be used to set up rules of law. Other influencing factors on private investment decisions are e.g. racial and ethnic tensions in certain countries. Big data can help identifying causes for these tensions and therefore help alleviating these risk factors.

A very important field of application for big data is the field of political terrorism and civil war threats. As big data comprises an almost unlimited amount of data, political relationships and the emergence and formation of counter-government can be quickly identified, and the corresponding risk for escalation measured.

Furthermore, other areas of expertise can be enhanced and exploited through the application of big data as well, e.g. the evaluation of quality of the bureaucracy or the risk of repudiation of contracts in contractual law. A very important tool big data provides is the assessment of the risk of expropriation by the government, which can be estimated using big data mining techniques. In general, big data can measure the degree of freedom, the possibility to exert political rights, and to measure the status of civil liberties within a country.

4. The impact on society

As in the previous chapters, economic security plays also an important role on society level when it comes to big data induced energy market stability as one needs also to consider the relationship between the shifts from informal to formal arrangements for economic security, on the one hand, and

change in the structural features of the family on the other. Houseknecht and Abdel Aal [32] layout the premise that this shift is associated with variations in the cultural and social structural features of the family. Big data can be useful to assess e.g. the level of the family economic interdependence of workers in industrial or agricultural employment by gathering and analyzing demographic and work status-related statistical data.

Moreover, the economic, and thus energy security can be enhanced by assessing the coverage of formal economic security programs and their relation to the family economic interdependence.

One technical way in order to improve energy security is being done through the creation of a smart grid via smart meters. Smart grid remodels the existing electric power network and infrastructure by connecting communication and information technologies. This communication works based on a wireless sensor network. Smart grid enables both utility providers and customers to transfer, monitor, predict, and manage energy usage effectively and costly [33].

According to a study conducted by Electric Power Research Institute (EPRI), smart metering exhibits several advantages. On the one hand, it supports the behavioral change of a single consumer. On the other hand, the scope of the advantage goes beyond the single consumer and encompasses the society as a whole through the increase in social benefits. While the application of the technology itself does not produce the social benefits, it unfolds its potential when combined with other measures such as the implementation of demand response programs, the revision of outage restoration practices, and the adoption of devices that communicate consumption and price/event information to consumers [34].

Nevertheless, the increased usage of smart meters raises some problems to society as well, as mentioned by Marres [35], who highlights that while digital technologies have enforced the spread of what he calls, a “topological imagination”, they have at the same time created a sort of weak form of this “topological imagination”. Marres understands as topological imagination an imaginary map which maps deterministic ideas about a certain technology as the principal driver of social change.

Liu [33] mentions that the increased application of wireless sensor network raises new security challenges related to privacy issues, connectivity problems, and security management, causing unpredicted expenditures and might potentially cause damage to utility providers as well as consumers.

A major factor that big data plays in the context of energy security and its impact on society is the provision of low-cost energy to parts of society, which would be otherwise excluded from access to affordable energy. By identification of essential variables that lead to reduced access to energy, less available affordable energy, increased availability, and price stability, measures can be taken in order to combat the difficulty of the provision of these key factors to the affected population.

Moreover, the challenge of climate change can get better understood and addressed by the utilization of big data. The impact for society can be a long-lasting one, since better forecasting and modeling techniques of weather phenomena on certain populations can help reducing, respectively mitigating the risk of the unprotected and unexpected impact of immediate as well as prolonged changing weather conditions.

But there are also privacy issues involved in the creation and usage of big data. Zhang [36] mentions the following risks for the society that need to be addressed and considered when using big data to enhance energy security: privacy risks, big data credibility as it needs to be confirmed, big data privacy protection technology is lacking, and threats to data security. In order to come by these risks, he proposes to improve the privacy protection legal mechanism, the establishment of a privacy protection agency, and the improvement of people's awareness and quality of data.

5. Practical issues and challenges

As mentioned above, each energy consumer firm has two major risks related to its energy supply: "changes in energy price" and "energy supply disruption". Changes in energy price increases the firm's total cost and affects the firm's break-evenpoint and profit margin. Energy supply disruption could affect the firm's productivity and damage their brand. In order to manage the energy risks, a firm needs to quantify these risks. Quantifying risk indicators makes it possible to forecast the energy-related risks and identify the risk drivers (factors). For instance, it is logical to assume that the maximum and minimum temperature affects electricity and natural gas price. Thus, it is necessary to forecast the annual temperature to forecast average energy price (to calculate breakeven point, etc.) as well as the worst-case scenario under a given risk level. The worst-case scenario in risk level $\alpha\%$ is a point in which there is an only $\alpha\%$ chance that the energy price will exceed this point. Using worst-case scenario forecasts, a firm can build a portfolio to hedge the energy price risk. As it can be seen in order to successfully hedge their energy price risk, firms need to accurately forecast the risk factors like annual temperature.

To better understand the role of big data analytics for private firms' energy security, let's consider a private firm as medium size electricity or natural gas consumer in Europe. For this example, we are considering the three largest economies in Europe, i.e. Germany, UK, and France. These economies have different energy structures. In Germany, most of the energy supplies come from oil, natural gas and coal. However, UK mostly relies on natural gas and oil while in France, nuclear power and oil are the main sources for energy supply.

Figures 1 and 2 illustrate the energy source's share in total energy supply and their share in generated electricity, in 2019 for these countries. In addition to differences between energy supplies in these economies, their energy consumption patterns and energy firms are different as well. For instance, the most energy consumption in the domestic sector of Germany and UK is used for heating while in France (mostly in the south) is used for both heating and cooling, due to their weather conditions. This means, the lower temperature in Germany and UK increase energy demand in the domestic sector and possibly leads to an increase in energy price (i.e. natural gas and electricity price).

In France, on the other hand, both increases and decreases in temperature leads to higher energy demand and increases the chance of higher energy price. However, since nuclear power is the main source of electricity generation in France, and the fact that households mostly use electricity for air conditioning and natural gas (or heating oil) for heating, we should expect an increase in electricity demand when the temperature rises and increase in natural gas price when temperature decreases. Furthermore, UK and France stock market, there exists large oil and gas upstream companies and dedicated stock market index (FORG index in France and FTUB0500 in the UK) while in Germany, most energy firms presented in oil and gas section are active in midstream fields (distribution, processing, etc).

Figure 1. 2019 Energy Source's Share in Total Energy Supply for France, Germany and UK.

Figure 2. 2019 Energy Source's Share in Electricity Generation for France, Germany and UK.

Using the above discussion, a private firm as a medium-size electricity or natural gas consumer, may consider the annual temperature as a risk factor for its energy security and uses the financial instruments in the oil and gas section of the stock market to hedge its energy risk. Table 1 represents Spearman correlation between temperature, energy price, and some financial instruments in Germany, UK and France, for annual data from 2008 to 2019 (Temperature data is downloaded from Climate Research Unit, University of East Anglia, database [37]). The energy price data is downloaded from the Eurostat database [38]. The Electrawinds SE A stock price (EWI1) from Germany, FTSE ALL Oil & Gas index (FTUB0500) from the UK, and French CAC Oil and Gas (FROG) index data are accessed from investing.com [39]. Since the Frankfurt stock market does not provide an oil and gas index, we used the stock price of an energy firm with the highest correlation with energy price in Germany).

Table 1. Spearman correlation between annual temperature, energy price and some financial instruments in Germany, UK and France.

As it can be seen in Table 1, the annual temperature is a risk factor for energy price in France and Germany, since there is the correlation between annual temperature and natural gas and electricity prices. In the UK, however, the annual temperature is not a risk factor for energy price, since there is not a strong correlation between annual temperature and natural gas and electricity price.

As expected (discussed before), in France, an increase in annual temperature increases electricity price and a decrease in annual temperature leads to increased natural gas price. On the other hand, an increase in temperature leads to a higher return in the France Oil and Gas stocks. Based on this simple analysis, a firm in France may use FROG stocks to hedge their electricity price risk, but not "natural gas price" risk (negative correlation between "annual natural gas price and FROG index suggests that an increase in annual natural gas price may lead to a decreased FROG index level).

In Germany, a decrease in annual temperature results in an increase in electricity and natural gas price (due to negative correlation). Since the "EWI1" price has positive correlation with both natural gas and electricity price, a firm in Germany may use "EWI1" to hedge their energy price risks. In UK, however, the use of financial instrument correlated with annual temperature (like FTUB0500) is not a good strategy to hedge the firm's energy price risk, since the correlation between annual temperature and energy price is low and the correlation between annual temperature and FTUB0500 index is relatively high. Furthermore, the electricity and natural gas prices in the UK does not have a high positive correlation with the market oil and gas index, FTUB0500.

As discussed above, a medium-size electricity or natural gas consumer firm should use different hedging strategies in these countries. In Germany, the firm can use a portfolio of energy firms' stocks like "EWI1" to hedge the energy price risk for both electricity and natural gas. In France, this strategy (using a portfolio of energy firms in "FROG" index) only works for hedging electricity price risk. For hedging natural gas price risk, we should find another financial instrument. In the UK, the strategy of using a portfolio of energy firms in "FTUB0500" index does not help hedging electricity or natural gas price risks. In other words, the firm should find other financial instruments for hedging their energy price risk.

One simple solution for a firm to control their electricity and natural gas price risk is to use a statistical model to forecast electricity and natural gas price and "oil and gas" stock in the market (e.g. "FROG" index in France and "EWI1" in Germany). Using simple linear regression with temperature as a predictor, we would have the following forecasting equations (we used only minimum temperature in France since it has the highest correlation with "Electricity Price" and "FORG" and maximum temperature in Germany). Table 2 shows the estimated forecasting equations with annual temperature maximum and minimum temperature as predictors.

Table 2. Estimated forecasting models for hedging energy price risks.

According to these Table 2, a one Celsius degree increase in annual minimum temperature increases average electricity price by 0.00523 Euros and average FROG index by 65.31 Euros, in France. In Germany, one Celsius degree decrease in annual maximum temperature increases average electricity price by 0.0049 Euros, average natural gas price by 0.0026, and average EWI1 by 2.931 Euros. In order to hedge the energy price risk, the firm can use the "Electricity Price/FROG" coefficient ratio in France and "Electricity Price/EWI1" and "Natural Gas Price/EWI1" coefficient ratio in Germany can be used to build a financial portfolio. For instance, if the firm is estimated to consume N kWh electricity in the next year, in France, they may invest $\frac{0.00523}{65.31}N$ Euros (build a portfolio) in CAC Oil and Gas companies. In

Germany however, the firm may invest $\frac{0.0049}{2.931}N$ Euros for N kWh electricity consumption or $\frac{0.0026}{2.931}N$ Euros for N kWh natural gas consumption, in EWI1.

This simple example shows the number of practical issues in managing the energy price risk. The first issue is finding the risk factors. As it can be seen in Table 1, while the annual temperature can be used as an energy price risk factor in some economies (like Germany and France), there are other risk factors in other economies (like UK). Even in Germany and France, the annual temperature only explains some of the variations in energy price (correlations or not close to 1 or -1). Low correlations between annual average temperature and energy prices indicate that there are risk factors other than annual temperature. Using big data mining, one can find other energy risk factors (e.g. social, economic, or environmental factors) for a given firm, although employing such solutions need access to multiple socio-economic and environmental databases.

Another issue is forecasting risk factors. As it can be seen in Table 2, risk factors (such as annual temperature) are predictors in forecasting models for energy price and related financial instruments. To utilize these models, one should first forecast the risk factors. Using big data analytics makes it possible to find an accurate forecast for risk factors[40]. For instance, big data solutions are widely used to forecast the climatic variables [41]. GEFS (Global Ensemble Forecast System), GFS (Global Forecast System) and ECMWF (European Center for Medium range Weather Forecast) are some of the famous platforms providing such forecasts. However, the forecasts from these models are not necessarily the same. These forecasts usually need to be combined using existing climatic big data (observed data from weather stations, satellite data, etc.) and probabilistic methods [42]. Although big data solutions are well developed for forecasting some risk factors (like weather conditions), there are not many solutions for other forecasting other risk factors. For instance, forecasting socio-economic variables affecting energy demand is a challenge itself[43].

Estimating energy price and its worst-case scenario is another issue in managing energy risks. The relation between energy price and its risk factors is not necessarily linear. Many researches in energy demand forecasting have shown the nonlinear behavior in energy demands[44,45]. Using big data mining and machine learning algorithm, one can find a nonlinear dynamic models to estimate the energy price's drivers and its worst case scenario [46,47].

Finally, finding right financial tool to hedge the energy risk, is another self. For instance, oil and gas index can be used to hedge electricity price risk in France, whilst it is not appropriate for hedging natural gas price risk (since, according to Table 1, FROG has positive correlation with electricity price, but negative correlation with natural gas price). In UK, however, the oil and gas index is not useful for hedging either of electricity or natural gas price risk (since, according to Table 1, the FTUB0500 does not have large positive correlation with electricity or natural gas price). In Germany, on the other hand, the situation is different.

As the stoke market does not provide an oil and gas index, one should find another financial instrument. In above example, we searched the entire energy section in Frankfurt stock market to find a suitable instrument with high positive correlation with electricity and natural gas price. As it can be seen from this example, there is not a unique financial instrument or hedging strategy, and to build the appropriate portfolio to hedge energy risks, one should analyze the stock market and finds relations between stock prices and energy risk factor movements. In practice, one financial instrument can be used to hedge some energy risks and increase other risks at the same time. For instance, as discussed above, FROG can be used to hedge electricity price risk, however, it will increase the natural gas price risk, since it has negative correlation with natural gas price. There is a growing literature proposing big data solutions for risk management[48].

The advantage of using big data solutions in risk management, is their ability for fusing quantitative data (like financial variables, stock price, etc.), and qualitative data (like sentiment data from social networks, published policy documents, etc.)[48,49]. In energy risk context, however, the use of big data

solutions is relatively novel. For instance, Cerchiello and Giudici [50] proposed a big data solution to use financial analysis (on financial data) and sentiment analysis (on related news feeds) for managing financial risks in Italian banks. Specific solutions to hedging energy price risks are proposed based. Kou et al. [51] provides a comprehensive list of methods for and objectives for developing systematic risk analysis based on big data solution. Although there are large number of researches proposing the machine learning methods (as it is suitable for big data analytics) for hedging energy price risks (see, [52,53] for example), there are not many studies focusing on developing big data solutions, specifically for the energy price risk. The main challenge in developing such solutions, is to access the multiple data warehouses and fusing the results from different sources[53].

In a larger scale, the policy makers need to manage country's energy-related risks. As mentioned before, instability in energy resources has a negative impact on socio-economic variables. As an immediate consequence of increased energy prices or disruption in energy supply, the rate of energy poverty increases in society. Accordingly, it increases social distress, healthcare costs and affects households' ability to provide work force and contribute to the economy [43].

Furthermore, an increase in energy prices affects the global economy through its effect on private firms (as discussed). Governments and policymakers, use different approaches to reduce energy risks and secure energy supply, from supporting energy supply firms and reduce their operational risks (e.g. geopolitical risks, cash flow risks, etc.) to investing in new technologies for renewable energies, even supporting households and small firms against energy risks. Policymakers need to have a comprehensive understanding of energy risk factors and energy supply situations, to choose between policies and approaches. For instance, if the policymakers choose to invest in renewable energy sources for long term energy supply, they should first investigate the availability and sufficiency of such resources [43].

One needs to have the driver factors of energy demand, amount of accessible energy resources, and the variables related to the final cost of energy supply to find the cost-efficient and sustainable energy policies. Using this information, policymakers can estimate how much energy they need to achieve sustainable development in long term and from which sources they can provide the cost-efficient energy for their economy and society [43]. For instance, before choosing solar, wind, or hydro energy as the main energy source for a given region, policymakers should have long term climatic forecast (let's say for the next 30 years) for the region. If the forecasts show low precipitation in long run, hydropower energy would not be an efficient choice. On the other hand, if climatic forecast shows a large number of cloudless days with high solar radiation (illumination) rate, investing in solar power plant might be a proper policy. If the historical data trend, in a region shows an increase in clouds during day, policymakers will focus their policy on other recourses for the long-term energy supply.

As an example, let us consider the climatic variables in France. Figure 3 shows the annual average of "Evapotranspiration" measured as millimeter per day (top left), "Precipitation" measured as millimeter per month (top right), "Cloud Cover Percentage" as a percentage of the sky covered by clouds, daily, (bottom left) and "Temperature" measured as daily mean in Celsius degree (bottom right). The historical data is accessed from Climate Research Unit, University of East Anglia, database [37]. These four climatic variables are selected in this example since they have known relations with renewable energy sources and have effects on the performance of some electric power plants.

For instance, an increase in "Precipitation" could, potentially, increase the water inlet flow in hydroelectric power plants and consequently improve their performance. Increased "Evapotranspiration" and/or "Temperature", on the other hand, can increase water evaporation in dams and decrease the performance of hydroelectric power plants. Increase in " Cloud Cover Percentage" in a region, can decrease the solar radiation (illumination), since the clouds can block the solar radiation, and decrease the performance of solar power plants. As it can be seen, the "Evapotranspiration" and "Temperature" show an increasing pattern, while the "Precipitation" and "Cloud Cover Percentage" has

a steady state. Increasing "Evapotranspiration" and "Temperature" may reduce hydropower plants when the precipitation is not increased.

On the other hand, a high percentage of cloud cover indicates a low performance in solar power plants. According to the historical data, assuming the recent trend will continue for a long time, making policy to consider hydropower or solar energy as primary energy resources may increase energy-related risks and cause energy insecurity in the future. On the other hand, since natural gas is usually used for heating and electricity for cooling, in households, an increasing pattern in temperature suggests that in the future France will need more electricity and less natural gas in the domestic sector. Thus, developing more power plants to produce electricity, encouraging the use of high-performance central heating/cooling systems in buildings, and using natural (or liquid) gas for cooking purposes could increase energy security in the future.

Figure 3. Annual average of climatic historical trends for France.

As mentioned earlier, there is a big data solution to forecast climatic variables. There are also many other variables affecting energy policies; consumer cultures, economic growth rate, environmental and ecological risk, to name a few [43]. Although using big data solutions can help policymakers to design appropriate policies to reduce energy-related risks and provide sustainable energy resources for their society and economy, collecting data for big data solutions could be challenging, especially for social variables [43]. Another challenge for energy policymakers is to measure, quantify and forecast some risk factors, like geopolitical risks and related government policies.

Once all the energy risk factors and energy demand drivers are estimated, we can design a suitable energy policy for a sustainable energy supply. Furthermore, once the risk factors are estimated, we can use financial instruments to hedge the energy risk and ensure the economic and social results of any energy crises.

In addition to building and using big data solutions to reduce the effects of instability in the energy market, the governments and policymakers should provide a private firm access to big data resources. Using this access, a private firm will be able to manage and hedge their energy risks (as discussed earlier in this section). Providing these accesses not only helps private firms, but it also can reduce energy crisis negative impacts on society and the economy.

6. Conclusions

This paper focuses on the leverage big data can unfold in energy security. Considering the provision of security of supply, as well as its geopolitical and societal implications, big data has an enormous potential in improving energy security as well as energy market stability. While modern energy distribution and management as well as geo-political and technological developments almost necessitate the usage of big data, there is still a significant lag in the realization of certain data and technology utilization. We identify the key needs for the implementation of relevant technology for data generation and collection by analyzing several use cases and highlighting the implications of big data usage on private companies, national economies, and society (Table 2).

Table 3. Benefits from the usage of big data.

The most common approach to measure energy security is through indices, which take into account dimensions such as economic conditions, environmental sustainability, and energy efficiency. The explanatory power of these indices can be significantly improved by the identification of cross relationships and patterns in endogenous as well as exogenous variables. Therefore, the utilization of big data can lead to significant insights.

For firms, big data can help combating energy supply disruptions by identifying vulnerabilities and dependencies in energy production. Moreover, it can help handling the tradeoff between cost reduction and securing energy supply, e.g. through the utilization of smart grids.

The impact of big data on economies is a broader one. One of the most fundamental prerequisites for energy security is economic security. Big data enhances the ability to understand economic causalities and how the integration of renewable resources can be conducted without causing energy supply disruptions.

While the utilization of big data seems mainly to be a technical or political question for firms and economies, it poses a bigger challenge for society in terms of availability, accessibility, affordability, and acceptability. On the one hand, society can benefit from big data generating devices such as smart meters in terms of cost reductions and automated, and thus optimal handling of energy usage, however, this raises issues such as the risk of data privacy violations, fraudulent use or even broader misconduct such as deliberate and targeted manipulation of consumer behavior e.g. by identifying certain consumption behavior through surveillance and subsequent price manipulation.

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Figures

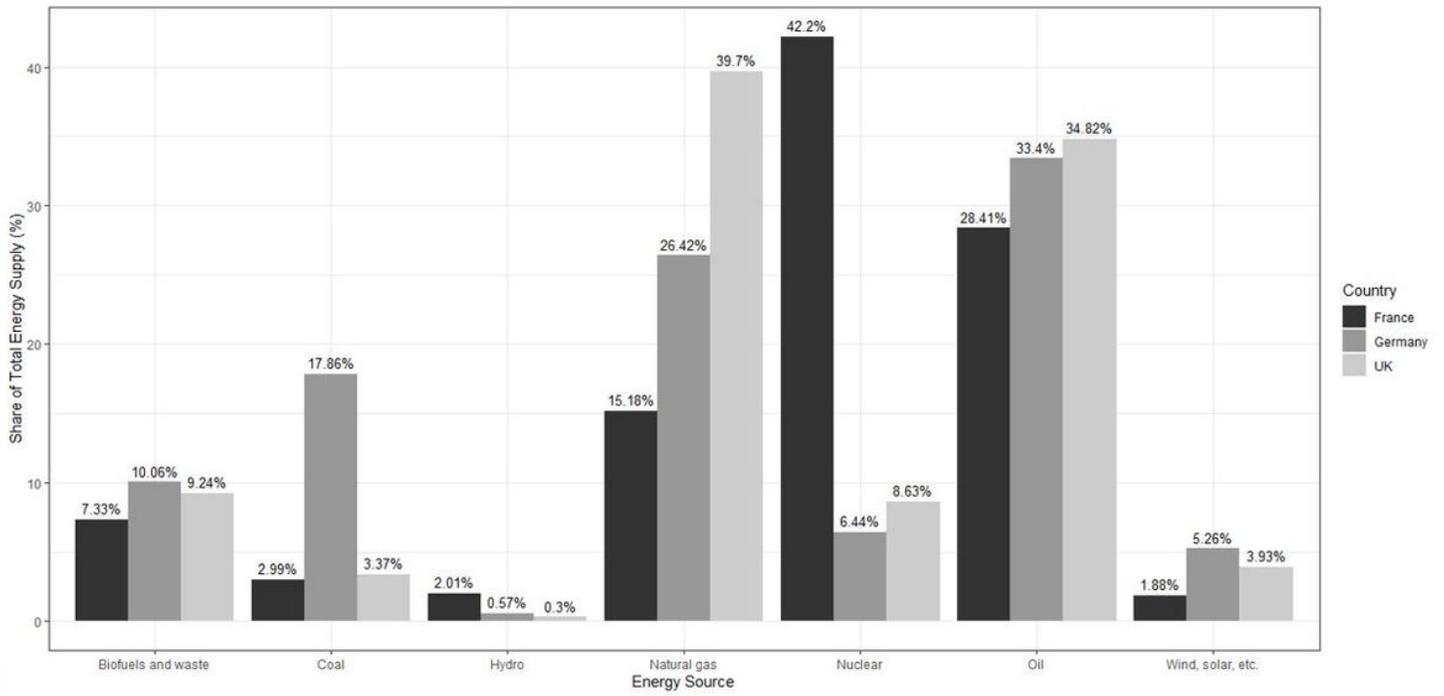


Figure 1

2019 Energy Source's Share in Total Energy Supply for France, Germany and UK.

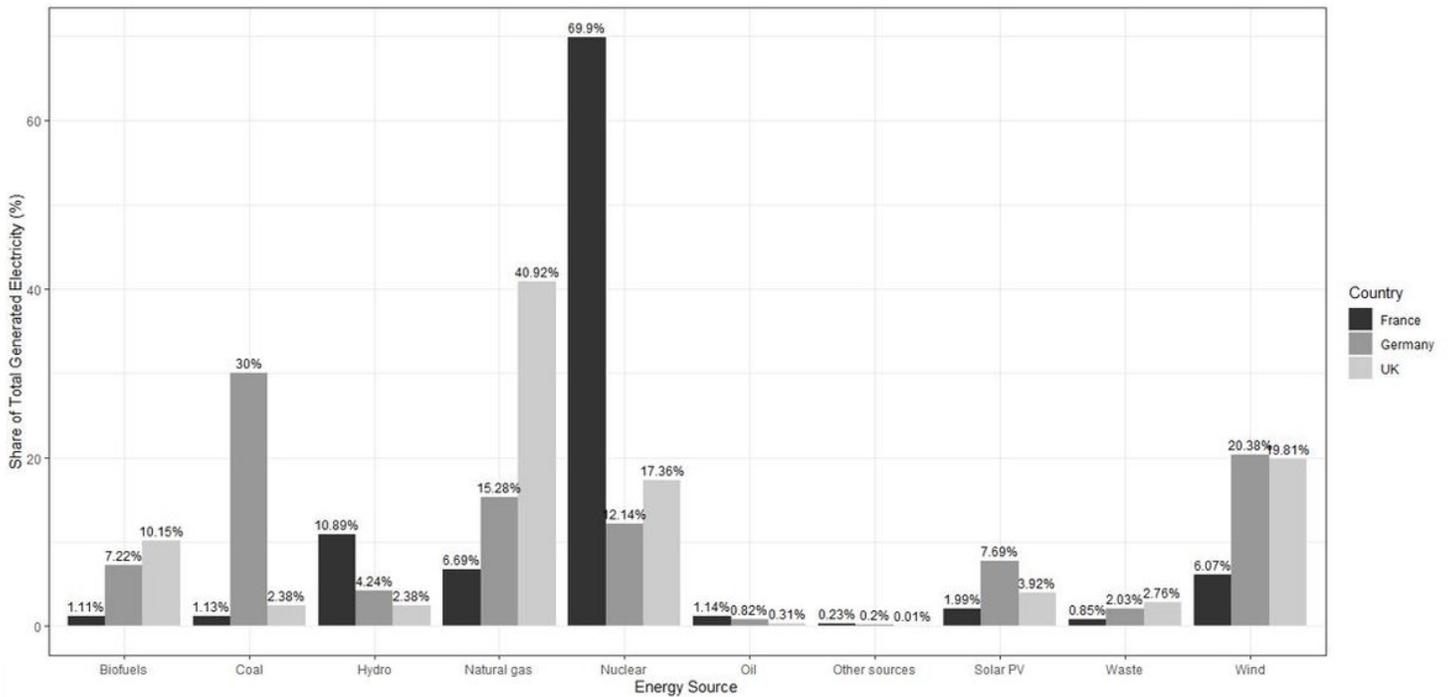


Figure 2

2019 Energy Source's Share in Electricity Generation for France, Germany and UK.

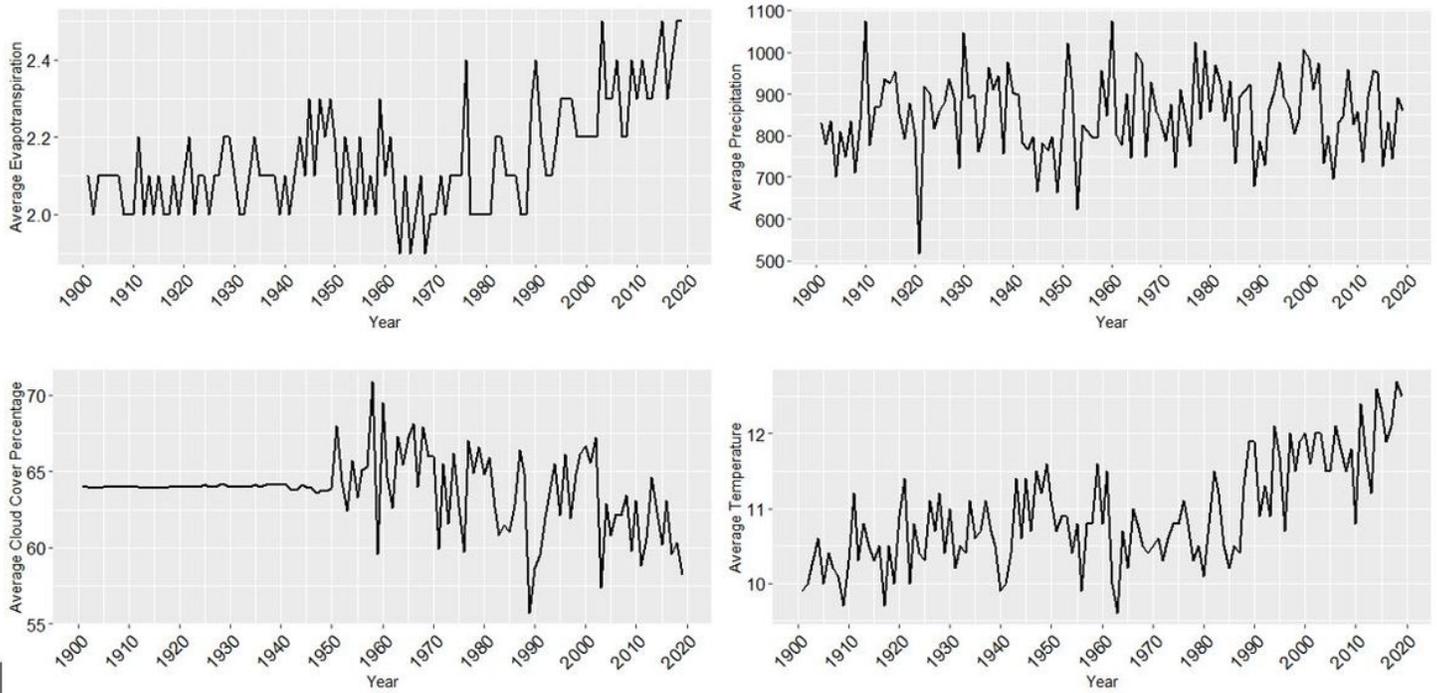


Figure 3

Annual average of climatic historical trends for France.