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Emerging interaction of artificial intelligence with basic materials and oil & gas companies: A comparative look at the Islamic vs. conventional markets

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ABSTRACT

As part of the artificial intelligence (AI) industry there are many companies engaged in providing hardware that enhances the use of artificial intelligence technology for big data analysis, along with companies that are involved in data analytics, software, system software, and artificial intelligence software. This paper examines the quantiles-based connectedness and non-linear causality-in-quantiles nexus of AI enterprises with basic materials and oil & gas companies, and their Islamic markets. Formally, we consider two perspectives, including before and after the pandemic of COVID-19 (for period May 18, 2018–June 01, 2022). It is observed that in the network of AI-based investments and companies related to basic materials and oil & gas industries, AI is a net recipient of shocks before and during the COVID-19 era, with a higher intensity of shock-receiving in the normal market and during COVID-19-affected period than in the upper and lower tails and prior to COVID-19 period. However, AI could serve as the cause-in-quantiles of oil & gas-related companies in the Islamic markets (in both pre-COVID-19 and COVID-19 timeframes) and conventional oil & gas firms (only within COVID-19). On the other hand, both the Islamic and the conventional basic materials and oil & gas businesses appear to be a non-linear cause-in-variance of the AI technology in the middle quantiles of the COVID-19 situation. Aside from this, the only causal factors from resources-based markets to AI are Islamic and conventional basic materials companies, as observed only during COVID-19. Based on our analysis, COVID-19 presented an excellent opportunity for improving the involvement of AI innovations with basic materials and oil & gas companies. As a consequence, the basic materials market may be able to provide hardware and software infrastructures to support the technology of artificial intelligence. Also, the inventions that enter the oil & gas industry due to the use of artificial intelligence could have a significant impact on their average performance. In this light, AI could be recognized as a strategic link in the supply chain of basic materials and oil & gas companies. There are many implications arising from these new insights for the developers of AI applications, resource policy-makers and managers, as well as investors who are interested in investing in new technologies.

1. Introduction

The world is in a complex process of changes generated by the challenges implied by environmental pollution but the opportunities offered by technological progress through digitization, industry 4.0, and artificial intelligence (AI). "*AI is a set of comprehensive frontier technologies that can perform activities as human intelligence*" (Liao et al., 2022). The more efficient use of resources in all industries, but especially in the manufacturing industry, has determined the intensification of concerns for the promotion of artificial intelligence, considering "*ability of computer systems to mimic human intelligence in performing various tasks*" like training based on the perception of information,

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processing and using specific data, inference by making conclusions and decisions and self-correction errors in accordance with accumulated experience (Aung et al., 2020).

Taking into account these characteristics of artificial intelligence, its presence in different fields (like transport, agriculture, health, and education) is remarkable, AI being considered the core driving force for the industrial revolution 4.0 (Kuang et al., 2021). or catalyst in the development of innovative services for consumers, public authorities, and companies (Sharma et al., 2020). Computer vision, natural language, virtual assistant, robotic process automation, and advanced machine learning are the main categories of AI (Schilirò, 2020). Considering the multitude of fields in which AI solutions can be applied, researchers consider that AI as a novel method of managing information in a business model (Lüdeke-Freund, 2010), and digital data and information are seen as new oil resources of the world (Sharifi et al., 2021).

Most researchers glorify the positive effects of AI use, such as the increase in productivity, the efficiency of the use of resources, the improvement of product quality, the forecast of demand, supply, prices, and the increase in sales. Some voices draw attention to the negative externalities generated by AI, it being considered a "*tool of power, frequently deepening global inequities and the exploitation of natural resources*" (Dauvergne, 2022). Despite the promotion of the positive results generated by AI through sustainability or CSR (Corporate Social Responsible) reports by large transnational corporations, researchers consider that AI is not a force of sustainability bearing in mind that their main promoters, the transnational companies pursue the maximization of profits, the final result being the deepening of inequities at the micro and macroeconomic level. In addition, the researchers draw attention to the negative externalities related to the development, production, and use of AI taking into account the energy consumption, emissions generated and adverse rebound effects (Hermann, 2021).

The twin transition process is in different stages, the public authorities being concerned both with the predominant use of renewable energies but also with the promotion of digitization and artificial intelligence (Oprea et al., 2020; Apostu et al., 2022; Oprea et al., 2021; Neacșa et al., 2022; Zohuri et al., 2022). The promotion of the two directions can best be seen in the energy industry where artificial intelligence is used to facilitate the energy transition process, the production of energy from renewable sources, and increasing energy efficiency being a priority. The energy industry is in a complex process of metamorphosis considering the challenges generated by the need to ensure access to energy for all citizens of the planet (Sustainable development goal), the reduction of carbon emissions, the predominant production of energy from renewable sources, the geopolitical influences that affect dramatically the national energy security. Changing the energy mix in order to decarbonize national economies, the need to synchronize energy supply and demand considering the characteristics of renewable energy production (volatility of wind and solar) but also power generation from multiple resources requires specific technical solutions, artificial intelligence being the best tool (Jeong et al., 2012; Bucur et al., 2021; H. Li et al., 2021; D'Amore et al., 2022). The use of decision-making software and robots at different stages of the energy value chain can be useful tools to "forecast supply and demand, manage the grid in real time, minimize downtime, optimize returns and enhance customer service as well as end user's experience". (Ahmad et al., 2022). The solutions offered by AI ensure benefits not only economically and socially but also environmentally by reducing costs, increasing efficiency, improving workers' safety, and ecological disasters (Acemoglu and Restrepo, 2018; Hyder et al., 2019; Lv et al., 2020; Yigitcanlar et al., 2020; Liu et al., 2021; Solanki et al., 2021).

In this context, the paper aims to identify the impact of the covid-19 crisis on the adoption of solutions offered by artificial intelligence in two essential areas of economic activity, namely the basic materials industry and the oil and gas industry. The paper examines the quantiles-based connectedness and non-linear causality-in-quantiles nexus of artificial intelligence enterprises with basic materials and oil & gas companies, and their Islamic markets, from two perspectives, before and after the pandemic of COVID-19. The authors have as their main research question "could AI be recognized as a strategic link in the supply chain of basic materials and oil & gas companies?". The results confirm the positive impact of the adoption of artificial intelligence solutions on the performance of companies in the analyzed fields. There is a fourfold contribution made by the authors to the literature. The first step was to develop a hybrid model in order to conduct the connectedness analysis by combining the mean-based measures of Diebold and Yilmaz (2012) with the quantile-based measures of Ando et al. (2018), Khalfaoui et al. (2021), and Ando et al. (2022), to take into consideration three different market conditions. Additionally, we used two different types of investments based on the resources, including two sub-indices within the Dow Jones Global Index, namely Basic Materials and Oil & Gas, as well as the best technology companies associated with artificial intelligence according to the Global X Standard of Finance. Our third step was to divide the period into a crisis period (the COVID-19 era) and a standard time period (the pre-COVID-19 era). Finally, we applied a non-parametric non-linear causality-in-quantiles test between variables to further examine the connection of the variables. The findings identify implications for AI developers, resources policy-makers and managers, and investors who are interested in new technologies.

The work is structured in five parts. After the introductory section in which the main trends in the use of artificial intelligence in economic activity are presented, in the literature review section, the authors identify the research gap based on a review of extant literature. In the data and methodology section, the authors present and justify the choice of the statistical method, the analysis period, and the indicators used. In the discussion section, the authors interpret the results obtained in the context of similar studies that confirm or deny the conclusions of the study. In the conclusions section, the authors present the main elements of the study, highlighting both the limits of the research and the future directions of research, considering that the subject of the implications of artificial intelligence on economic activity is in its infancy.

2. Literature review

The covid-19 crisis has brought to the attention of researchers, companies, and public authorities the importance of using the technologies offered by digitization and artificial intelligence, in the context where physical distancing or even lockdown are the only solutions to stop the spread of the virus (Grigorescu et al., 2021; Khan et al., 2021). For this reason, it is necessary for certain activities or operations to be carried out remotely or to be done by robots. Technical solutions existed but now they are viewed with greater interest by all parties involved who must reflect on their viability from an economic point of view, on their acceptance by consumers and employees but also on the ethical consequences that the use of intelligence artificial can generate (Boddington, 2017; Vu and Lim, 2021). Studies have demonstrated the importance of AI solutions during the covid-19 crisis both for disease prevention and treatment, as well as for crisis management, distance education, payments and collections, energy production, streamlining of supply chains, etc. (Modgil et al., 2021; Piccialli et al., 2021; Sharifi et al., 2021; Nozari et al., 2022). The pandemic not only promoted the large-scale use of artificial intelligence in various fields but also favored the adoption of new solutions that were developed, for objective reasons, much faster, the time period being reduced from a few months to a few days. The solutions found are based on more dynamic algorithms that use a smaller volume of data, considering the lack of information over long periods of time. Therefore, under the impact of the Coivd-19 crisis, we are witnessing a quantitative and qualitative improvement in the development and implementation of AI in the world economy.

Despite the financial difficulties faced by most companies due to the pandemic, considering the important role that AI plays in managing the crisis, the forecasts regarding AI expenses of companies indicate a rise of 33% between 2020 and 2022 (De Vet et al., 2021). Furthermore, the use of AI solutions during the pandemic showed that the symbiosis between AI and the COVID-19 crisis is an important driver, which fuels the transition to Society 5.0 through the implementation of AI (Islam et al., 2020; Sarfraz et al., 2021).

The industry has become increasingly intelligent as a result of the partnerships between manufacturing companies and IT firms, the oil and gas sector standing out through the resounding alliances between Shell, Halliburton, Chevron or Exxon Mobile with Microsoft, or Total with Google or PetroChina with Huawei, Sinopec and CNOOC with Ali. The artificial intelligence is used in specific fields like energy generation, trade, and consumption, increasing resilience in a world under overlapping crisis. The challenges generated by the energy transition, the use of renewable energy and the emergence of prosumers can be managed with the help of artificial intelligence. The productive activity of the companies is in a complex process of metamorphosis under the impact of the use of AI solutions, but we are also witnessing paradigm changes regarding the business model. (Ahmad et al., 2022; Alshater et al., 2022; D'Almeida et al., 2022; Sattari et al., 2022). Nowdays," information is referred to as the new oil" (Jarrahi, 2018), while AI is consider to be "the new power that is able to extract value from this oil" (Chen et al., 2022).

The development of artificial intelligence platforms by the big oil companies has generated solutions for different stages of design and production activity like E&P, storage & transportation, seismic modeling, supply chain optimization, logging, geophysical exploration, drilling & completion, intelligent fracturing, exploration of oilfields (Kuang et al., 2021). AI has multiple positive externalities in the oil & gas industry through fueling product innovations, increasing the energy efficiency of manufacturing processes, reducing cost reductions, and improvements in fossil energy conversion (Tiwari et al., 2021).

AI represents an IT application, registering a huge development over the last decades (Balcilar et al., 2016; Li et al., 2021; Wipro and Wipro, 2014). It can be used in the activity of exploration and exploitation of oil and gas reserves, but also in the selection process of employees, considering the large number of hires that are made annually and in accounting activity, considering the complexity of the operations carried out by oil and gas companies. (Mukherjee, 2022; Solanki et al., 2021).

The methods using artificial intelligence led to increased work efficiency both in exploration and production-makes, resulting in better performances and less cost (Aung et al., 2020). Gupta and Shah (2021) highlighted the role of artificial intelligence on energy, oil and gas industry, evaluating both technical and non-technical factors affecting the adoption of machine learning technologies. AI easily identifies components and parts of the equipment, meeting the challenges facing the operation, intervention, and production optimization in the oil area (Akanji and Ofi, 2016). AI techniques also ensure better use of the infrastructure, generating better outcomes (Solanki et al., 2021), and additional benefits (Yuan and Wang, 2018). Thus, the growth is maximized, being created value in an interconnected energy system (Rands, 2017).

Since the oil and gas industry is focused on controlled conditions (Wu et al., 2014), the main focus is on creation in order to minimize the costs and the effect of natural dangers (Desai et al., 2021). For this, information volumes have to develop exponentially, reducing the cost, time (Wipro and Wipro, 2014), and loss and increasing profit margins (Akoum and Mahjoub, 2013; Carlson et al., 1992; Hilgefort, 2018; Sousa et al., 2015).

The success of AI projects is based on human intelligence, which is why companies invest more and more in the workforce, trying to attract and maintain AI specialists, considering that the solutions offered by IT companies must be adapted to the specifics of the production activity. Moreover, more and more companies from different fields of activity are trying to create in-house teams composed of data and AI specialists. For these reasons, collaborations with universities are increasingly intense, university labs being nurseries for the development of talents. The exchange of education plans is a necessity, specialists from different fields such as oil and gas must be trained in a modern way that ensures them "strong sense of data science and the ability to identify and design tasks to be solved by AI". (Sircar et al., 2021). The creation of an open and collaborative environment is necessary through the disclosure of data that can be used for AI applications (Choubey and Karmakar, 2021; Sircar et al., 2021).

Most of the studies identified in the mainstream of publications reveals the focus of research on the impact of the covid-19 crisis on several fields such as health, travel and tourism (Fareed et al., 2022; Yan et al., 2022), cryptocurrency and different assets classes (Fareed et al., 2022; Iqbal et al., 2021; Shah et al., 2022; Shuai et al., 2022) and the pharmaceutical industry. For this reason, the authors of this article have focused their research activity on an aspect not yet addressed, namely the impact of the pandemic crisis on the implementation of AI solutions in the oil and gas and basic material industries. The motivation behind the choice of these industries is given by their importance in the world economy, the involvement of all states in the energy transition to manage climate change, the crisis generated by the armed conflict between Ukraine and Russia, which calls into question countries' access to various raw materials traditionally provided by Ukraine or Russian oil and gas as a result of the economic war between democratic countries and Russia.

3. Methodology

3.1. Connectedness analysis at different quantiles

Our empirical approach draws on the quantile connectedness approach provided by Ando et al. (2018), and Ando et al. (2022). While this is an extension of the mean-based measures of Diebold and Yilmaz (2012), recent studies by Chatziantoniou et al. (2021), and Bouri et al. (2021) have used the approach to more accurately evaluate the relationship between various financial assets' quantiles. All of the metrics of connectedness need to be calculated, and the first step involves the estimation of a Quantile Vector Autoregression, QVAR(p), which can be clearly stated that the QVAR(p) works in the following manner:

$$\boldsymbol{y}_t = \boldsymbol{\mu}(\tau) + \sum_{j=1}^{p} \boldsymbol{\varphi}_j(\tau)\boldsymbol{y}_{t-j} + \boldsymbol{u}_t(\tau) \tag{1}$$

In this specific illustrative case, $\boldsymbol{y}_t$ and $\boldsymbol{y}_{t-1}$ are endogenous $k \times 1$ dimensional vectors that are composed of the matrices for the returns. τ represents the target quantile and falls between the [0, 1] range, the QVAR model has a lag length of p, $\boldsymbol{\mu}(\tau)$ is a conditional mean vector that has a dimension of $k \times 1$, $\boldsymbol{\varphi}_j(\tau)$ is a matrix with k dimensions containing coefficients from a QVAR model, and $\boldsymbol{u}_t(\tau)$ shows how the error vector is k $\times$ 1 dimensional with a containing $k \times k$ dimensional variance–covariance matrix (i.e., $\sum(\tau)$).

In order to convert the $QVAR(p)$ into a $QVMA(\infty)$ representation using Wold's theorem, we use $\boldsymbol{y}_t = \boldsymbol{\mu}(\tau) + \sum_{j=1}^{p}\boldsymbol{\varphi}_j(\tau)\boldsymbol{y}_{t-j} + \boldsymbol{u}_t(\tau) + \sum_{i=0}^{\infty}\boldsymbol{\Psi}_i(\tau)\boldsymbol{u}_{t-i}$ as a transformation factor.

Then we calculate a standard decomposition as the H-step forward Generalised Forecast Error Variance Decomposition (GFEVD) according to Pesaran and Shin (1998) and Koop et al. (1996), which demonstrates the influence of a shock in variable j on variable i:

$$\psi_{ij}^{g}(H) = \frac{\sum(\tau)_{ii}^{-1}\sum_{h=0}^{H-1}\left(\boldsymbol{e}_i'\boldsymbol{\Psi}_h(\tau)\sum(\tau)\boldsymbol{e}_j\right)^2}{\sum_{h=0}^{H-1}\left(\boldsymbol{e}_i'\boldsymbol{\Psi}_h(\tau)\sum(\tau)\boldsymbol{\Psi}_h(\tau)'\boldsymbol{e}_i\right)} \tag{2}$$

$$\widetilde{\psi}_{ij}^{g}(H) = \frac{\psi_{ij}^{g}(H)}{\sum_{j=1}^{k}\varphi_{ij}^{g}(H)}$$

In the position ith, $\boldsymbol{e}_i$ corresponds to a vector that is composed of zero with a value of unity. $\boldsymbol{e}_i$ represents a zero vector with unity on the ith position. As a result of this normalization, these two equalities can be obtained, as $\sum_{j=1}^{k}\widetilde{\psi}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{k}\widetilde{\psi}_{ij}^{g}(H) = k$.

We used the total directional connectedness TO others in order to find out the impact variable i has on all variables j, i.e., the total impact of variable j on the other variables:

$$C^g_{i\to j}(H) = \sum_{j=1, j\neq i}^{k} \widetilde{\psi}^g_{ij}(H) \tag{3}$$

As a consequence, the total directional connectedness FROM other variables is used to determine the impact of shocks from all j variables on i variables, as follows:

$$C^g_{i\leftarrow j}(H) = \sum_{j=1, j\neq i}^{k} \widetilde{\psi}^g_{ji}(H) \tag{4}$$

By comparing the total directional connectedness TO others and the total directional connectedness FROM others, we end up with the net total directional connectedness, which can be regarded as the variable i that has the most influence over the network that is being studied.

$$C^g_i(H) = C^g_{i\to j}(H) - C^g_{i\leftarrow j}(H) \tag{5}$$

For the total connectedness index (TCI) and corrected TCI, we follow Chatziantoniou and Gabauer (2021), Chatziantoniou et al. (2021), and Gabauer (2021). The TCI is a commonly used way to express the share of the average forecast error variance that each variable can be attributed to:

$$TCI\ (H) = \frac{\sum_{i,j=1, j\neq i}^{k} \widetilde{\psi}^g_{ij}(H)}{k} \tag{6}$$

According to Monte Carlo simulations, the own variance shares are by definition always greater or equal to all cross variance shares irrespective of the construction of the cross variable. It is important to note that this TCI ranges between 0 and $\frac{k-1}{k}$. If we want to know the average amount of network co-motion in percent, then the number should range between 0 and 1, then we need to make a small adjustment to the TCI:

$$TCI_c\ (H) = \frac{\sum_{i,j=1, j\neq i}^{k} \widetilde{\psi}^g_{ij}(H)}{k-1} \quad , 0 \leq TCI_c\ (H) \leq 1 \tag{7}$$

3.2. Quantile casualty approach

Following Adekoya and Oliyide (2021), Das et al. (2018), and Bhatia et al. (2018), in this study, we analyze a robust approximation to the quantile causality by applying the nonlinear method of Balcilar et al. (2017), and Balcilar et al. (2016). Among the advantages of causality-in-quantiles over traditional techniques, at least two of them stand out. First, using a nonparametric approach to estimate the dependence structure, the optimization of misspecification error probabilities is minimized, and second amuch more sophisticated technique could be applied in order to detect higher order dependencies (mean and variance).

Consequently, the benefits of these techniques include being able to derive additional information about dependencies, information that oftentimes cannot be derived from traditional techniques. It might be stated that causality tests that are based upon mean values may be unable to accurately reflect the actual dependence structure. In order to arrive at the quantile causality approach proposed by Balcilar et al. (2017), they closely align with the frameworks put forward by Nishiyama et al. (2011), and Jeong et al. (2012).

Additionally, a second moment is also considered when it comes to the analysis of causality-in-variance between the financial assets. There may not be causality in the assets' means (as in the first moment), but there may be predictive power in their variances (i.e., the volatility of the assets). This might lead to a greater benefit for portfolio diversification strategies if volatility predictions are more precise (Bhatia et al., 2018).

The nonlinear causal relationship between one variable, y_t, and the predictor variable, x_t, is examined with the quantile causality test, and then the procedure will be carried out in reverse order. In the view of Jeong et al. (2012), we may define the quantile-based causality as follows, by considering the lag vector as $\{y_{t-1}, ..., y_{t-p}, x_{t-1}, ..., x_{t-p}\}$, when the exhibited x_t does not lead to the observed y_t in the θth quantile:

$$Q_\theta\left(y_t \middle| y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}\right) = Q_\theta\left(y_t \middle| y_{t-1}, \dots, y_{t-p}\right) \tag{8}$$

Moreover, it is possible to assume that x_t will cause y_t to be in the θth quantile taking into consideration $\{y_{t-1}, ..., y_{t-p}, x_{t-1}, ..., x_{t-p}\}$ if:

$$Q_\theta\left(y_t \middle| y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}\right) \neq Q_\theta\left(y_t \middle| y_{t-1}, \dots, y_{t-p}\right) \tag{9}$$

In this case, $Q_\theta(y_t|.)$ refers to the θ th conditional quantile of $y(t)$, has an underlying dependence on the time period t, and it is only possible to assign a quantile to a range between zero and one (i.e., $0 \prec \theta \prec 1$). Taking into account the causal relationship between x_t to y_t in the qth quantile, it may be plausible that the historical values of x_t can assist in predicting the values of y_t in the qth quantile; however, it is not relevant to other quantiles.

4. Data and results

4.1. Data specification

For the purpose of accounting for the impact of the COVID-19 pandemic, we divided the sample size between two periods: May 18, 2018–March 10, 2020 (pre-COVID-19 period) and March 11, 2020–June 01, 2022 (COVID-19 period). In essence, this period coincides with the date when the World Health Organization officially declared COVID-19 to be a pandemic. Additionally, other studies have also applied these criteria, including those conducted by Chemkha et al. (2021), and Kuang (2021). The following variables were used in order to investigate the fast-growing role of artificial intelligence within the basic materials and the oil & gas industries:

We firstly consider the Global X Artificial Intelligence & Technology ETF (hereafter AIQ) to be a representative of the artificial intelligence (AI) technology for our analysis. In order to further enhance and utilize the capabilities of artificial intelligence (AI) technology within the product line and service offerings of companies and give them an edge over their competitors, AIQ is planning to invest in enterprises that will be able to benefit from the development and use of AI technology and provide the hardware for the analysis of big data. There is no doubt that artificial intelligence has been growing exponentially in the past few years. The most innovative companies, whether they are household names or newcomers, are spread across multiple sectors. In this way, AIQ invests regardless of industry or geography, reflecting the needs of the market as a whole. For the purpose of this study, we have used the Global X Artificial Intelligence & Technology ETF as a proxy for the AI industry. To the extent that we are aware, this is the most comprehensive index for considering AI companies that we have seen so far and has included many companies that have a wide range of technological capabilities and high market values, such as Netflix, IBM, Amazon.com, Accenture, Apple, Microsoft, Cisco Systems, Tesla, Alphabet, Oracle, Meituan, Salesforce, Siemens, Samsung, Alibaba, Tencent, Qualcomm, Meta, ServiceNow, Nvidia, Adobe, Intel, Uber Technologies, Thomson Reuters, etc. The fund's investments are made in the public equity markets of the global region as well as in stocks of companies that provide hardware that facilitates the use of artificial intelligence technology for the analysis of big data, together with artificial intelligence and big data companies, information technology, software and services, software, system software, software research, and artificial intelligence software companies. The fund invests in growth and value stocks of companies with a range of market capitalizations and growth potential. It is safe to say that there is no doubt that AI is progressing, and the impact it has on most industries is substantial.

On the one hand, stock indices and ETFs provide relevant information for economic activity, considering the selection criteria that ensure the representativeness of the performances of companies listed on the stock exchange. On the other hand, the companies listed on the stock exchange are considered representative of the business ecosystem on a national and international level, and the transparency criteria that these issuers must meet ensure portfolio investors and other stakeholders such as researchers and economic analysts a basis of rich data that can be used to carry out scientific studies.

In the second stage, we consider two Dow Jones Industry Indices, which are sub-indices of the Dow Jones Global Index, namely the Basic Materials (hereafter MAT) and Oil & Gas (hereafter OIL) sectors, as well as their Islamic markets, i.e., Dow Jones Islamic Market Basic Materials (hereafter IMAT), and Dow Jones Islamic Market Oil & Gas (IOIL). In the basic materials sector, there are sectors such as industrial metals and mining, chemicals, mining, and the forestry & paper sectors, whereas, in the oil & gas sector, there are producers, oil equipment, distribution and services, and alternative energies. While artificial intelligence is still in the process of maturing, it spans a number of business sectors and its most innovative companies come from both household names and newcomers from around the world. Based on the data collected from investing.com, the natural logarithmic returns are computed using the closing price, utilized for connectedness and quantile causality approaches. It is shown in Fig. 1 that the oil and gas companies' performance both on the Islamic and conventional markets has been in line with the index data both in terms of current and past trends.

4.2. Empirical results

A summary of the statistics for the daily returns, as well as the statistics that pertain to the unit root of the returns, can be found in Table 1. Despite the negative mean returns in COVID, all returns are positive in pre-COVID-19 era (except for AIQ), with OIL and IOIL exhibiting the most positive mean returns in COVID-19-affected years, and the lowest mean returns in the pre-COVID-19 time frame. In terms of standard deviations, the riskiest assets are OIL and IOIL, both in COVID-19 and pre-COVID-19 epochs, while the least risky series are IMAT and AIQ in COVID-19 and pre-COVID, respectively. According to kurtosis measures, in the pre-COVID-19 days, there was a definite and all-pervasive leptokurtic distribution that disappeared with the introduction of the COVID-19 era. Both periods are marked by moderate skewness in all variables with the exception of OIL and IOIL, which are marked by high skewedness.

In accordance with the Jarque-Bera (JB) test, we can see that in general, all returns are not normally distributed. Finally, the results of the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) tests also support the find that all series are stationary. Fig. 2 illustrates the daily of the variables considered in the study. Clearly, the volatility of all return series increases by the start of COVID-19-affected days, and continues throughout the COVID-19 era. Particularly in the period during both periods, the returns of AIQ have experienced higher fluctuations than those of other investments.

As the first point of analysis, Table 2 shows AIQ has been a net receiver of shocks both in the pre-COVID-19 era and in the COVID-19 period, but the difference is that the magnitude of that role during the COVID-19 period and the middle quantiles has been larger than the pre-COVID-19 era and the upper and lower tails. This is exactly the case with the MAT, except that the MAT is a shock transmitter. In our analysis of the IMAT connectedness scores, we were surprised to find that IMAT played an entirely different role in the pre-COVID-19 and COVID-19 eras, namely that IMAT is a net receiver of shocks before COVID-19 (except for the two extreme upper quantiles that have exceptionally high positive returns, i.e., 0.95 and 0.9), whereas transform acts as a net transmitter of shocks after COVID-19 and throughout all the quantiles.

In addition, by examining the interrelationship characteristics of the IOIL, it is visible that its major shocks' transmitting nature in the pre-COVID-19 period (which has two exceptions in extreme bear and bull markets) changes to a net shock-receiving function at middle quantiles (i.e., from $q = 0.35$ to $q = 0.75$) in the COVID-19 time frame. The same results could be found for the OIL in both periods, after considering a few exceptions including middle quantiles (which correspond to $q = 0.3$ to $q = 0.6$) and two lower quantiles (i.e., the extreme negative returns for $q = 0.05$ and $q = 0.1$) for the net receipt of shocks. The fact that OIL and IOIL, being the dominant participants in the transmission of shocks at normal market conditions, in pre-COVID-19 days, are now advancing to the follower character at the middle quantiles of the COVID-19 period, makes it evident that the original leading role of OIL and IOIL is diminishing or modifying over time. It is evident that the main leading role of OIL and IOIL in transmitting of shocks at the normal market condition of pre-COVID era modifies to the follower character in terms of shocks at middle quantiles of COVID period. The results of our analysis for the normal period lend credence to the finding of X. Li et al. (2021) that the oil market changed from a net transmitter to a net receiver of shocks to the financial asset in China after the emergence of the COVID-19 epidemic and contradict with the finding of Benlagha and Omari (2022) that the oil is a transmitter of shocks to the five stock

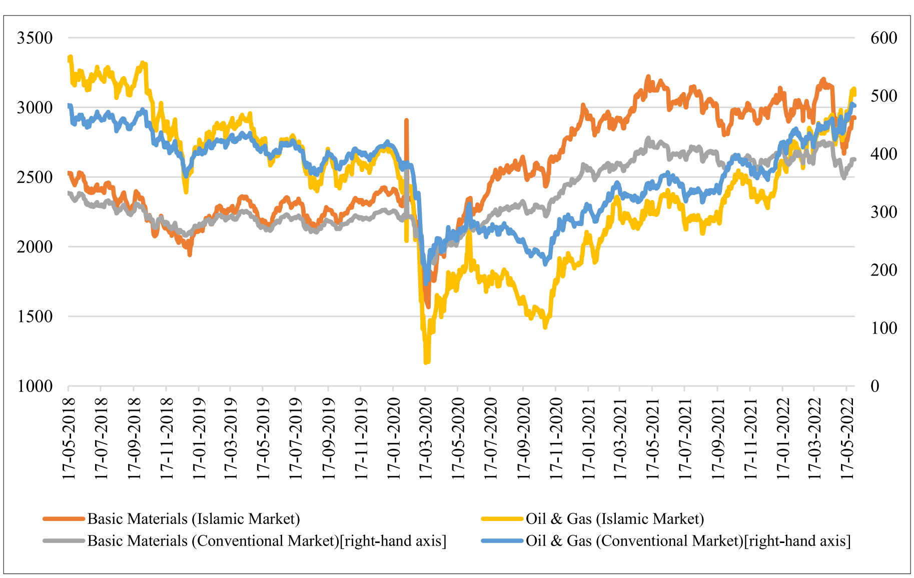

Fig. 1. Islamic and conventional markets in the Basic Materials and Oil & Gas sectors.

Table 1
Descriptive statistics.

Statistics	AIQ	IMAT	MAT	IOIL	OIL
Pre-COVID					
Mean	0.0233	−0.0548	−0.0709	−0.1538	−0.1372
Std. Dev.	1.4187	1.7594	1.9076	1.9082	1.4777
Skewness	−0.5551	0.6332	0.7661	−1.5277	−6.0625
Kurtosis	4.9931	107.4194	125.7367	51.0870	82.6349
Jarque-Bera	98.686***	206740.8***	285638.4***	44015.44***	123015.6***
ADF	−21.948***	−28.9132***	−29.1513***	−24.0158***	−19.1332***
PP	−21.9507***	−29.4006***	−29.6258***	−24.0092***	−19.1960***
KPSS	0.0617	0.1036	0.0945	0.3043	0.2911
COVID					
Mean	0.0541	0.0702	0.0859	0.1098	0.1109
Std. Dev.	1.8340	1.3098	1.3535	2.2403	2.2627
Skewness	−0.5255	−0.6498	−0.8515	−0.5407	−0.6002
Kurtosis	6.7713	16.4388	14.6576	11.9114	14.7222
Jarque-Bera	358.9225***	4268.61***	3250.22***	1886.96***	3251.43***
ADF	−26.6663***	−22.4028***	−21.9138***	−26.33***	−24.8291***
PP	−26.7539***	−22.4243***	−21.9138***	−26.3451***	−24.8277***
KPSS	0.2015	0.2239	0.2159	0.0473	0.0571

Note: (***) indicates the significance at 1%.

markets.

As a final point of clarification, according to Fig. 3, TCI (TCI_c), i.e. total network connectivity, represents the level of risk that the network system faces, is between 80.81% and 95.49% (64.65% and 76.39%) for pre-COVID-19 era, and ranges from 72.80% to 95.37% (58.24% and 76.29%) for COVID-19 period. Therefore, all TCIs were found to have decreased during the COVID-19 pandemic period and to have increased during the lower and upper quantiles, which contrasts with the findings of Chatziantoniou et al. (2022) who noted an increase in TCIs during the period, and is in accordance with the findings of Bouri et al. (2021) who pointed out an increase in TCIs in extremely positive and negative returns. Lastly, the TCI explains that on average, the co-movement of AI and resources-based investments, as well as the risk equality of the whole system, is 86.70% and 82.46%, respectively, in pre-COVID-19 and COVID-19 eras, which on the basis of TCI_c, it is conclusive to say that on average 69.36% and 65.97% of the variance of the forecast error variance of the investments under study can be explained by the influence of others during the preceding periods.

Figs. 4 and 5 show the results of the causality-in-quantiles test between AIQ and basic material, and oil and gas investment returns, respectively. As a result, the Panel A of the figures corresponds to a null hypothesis that the first variable does not Granger-cause the second variable to the mean, and Panel B corresponds to the null hypothesis that the first variable does not Granger-cause the second variable to the variance. The vertical axis indicates the non-parametric causality test statistics and the horizontal axis shows the corresponding quantiles. On the basis of the solid horizontal line, a value of 1.95 equates to a critical level of significance for the study at a level of 5%.

It can be seen from Fig. 4 that even though there is no causal link between MAT (IMAT) and AIQ prior to COVID-19, the causal effect from MAT (IMAT) to AIQ becomes profound only at the time of the COVID-19 pandemic, which has been found in some middle quantiles for both causality-in-mean and causality-in-variance cases, and the results were also extended to all of the quantiles only for causality-in-variance from IMAT to AIQ. As outlined in these results, we find that the Islamic basic material market takes a prominent role in the support of AI-enabled products in all market states, including bear, normal, and bull markets, especially on days where COVID-19 has a considerable impact on the market. The results add new insights to studies of Sha et al. (2020), Sun et al. (2021), Guo et al. (2021), Huang et al. (2021), Lopez-Bezanilla and Littlewood (2020), Sagdic et al. (2022), and Abbasi Moud (2022), who concentrated on the effective synergy of AI and advanced or basic materials.

A closer examination of Figs. 4 and 5 is necessary to find that the only causality amongst all resources-related companies and AIQ in the pre-COVID-19 era is attributed to the leading role of the Islamic oil and gas business to AIQ. After taking a closer look at Figs. 4 and 5, it is interesting to note that one can see that the only direction of causality from AIQ to the under-study indices is the one of causality-in-mean from AIQ to the Islamic and conventional oil and gas investments at the COVID-19-impressed times, a direction that is found in all lower, middle, and upper quantiles. This result is supporting the great and effective participation of AI in the oil and gas industry highlighted by Cedeno et al. (2022), Choubey and Karmakar (2021), Hijji (2022), Sircar et al. (2021), Nguyen et al. (2020), Gupta and Shah (2021), and Rahmanifard and Plaksina (2019). The last point that should be noted is that since both versions of the oil and gas industry could be the cause-in-variance of the AIQ observed in COVID-19 period, there is no doubt that the COVID-19 pandemic has serious implications for the interactions across the AIQ and resources-driven markets, as it may alter the global business cycle, which, in turn, might affect risk perceptions and potentially cause a variety of risks among global financial markets (Adekoya and Oliyide (2021).

5. Conclusion

The solutions offered by AI are increasingly accepted by society despite the fears and disruptions they can generate on the economic, social and environmental levels, existing concerns at an international level for increasing responsibility in the use of AI considering the ethical problems that can be generated through improper handling of data or through decisions made by robots. The use of artificial intelligence has been growing exponentially in the past few years, with companies allocating important amounts from the budget for testing and developing AI solutions for different fields of activity. The COVID-19 crisis has generated an intensification of the innovation process in the field of AI from the need to solve some pressing problems related to the imposition of specific restrictions - physical distancing and lockdown or solving specific problems for the rapid detection of cases of COVID- 19. Therefore, this crisis gave an impetus to innovation in the field of AI, the world being in a complex process of metamorphosis. Companies reconfigure their production processes, personnel selection or financial accounting activities using AI solutions, managing information in the new business model. This study demonstrated that the AI is a net recipient of shocks with a higher intensity of shock-receiving in the normal market and during COVID-19- period.

The importance of AI and its extensive use is demonstrated by the emergence of specialized companies but also by the existence of stock indices and ETFs that include companies in the AI field. Taking into account these considerations, for this study, Global X Artificial

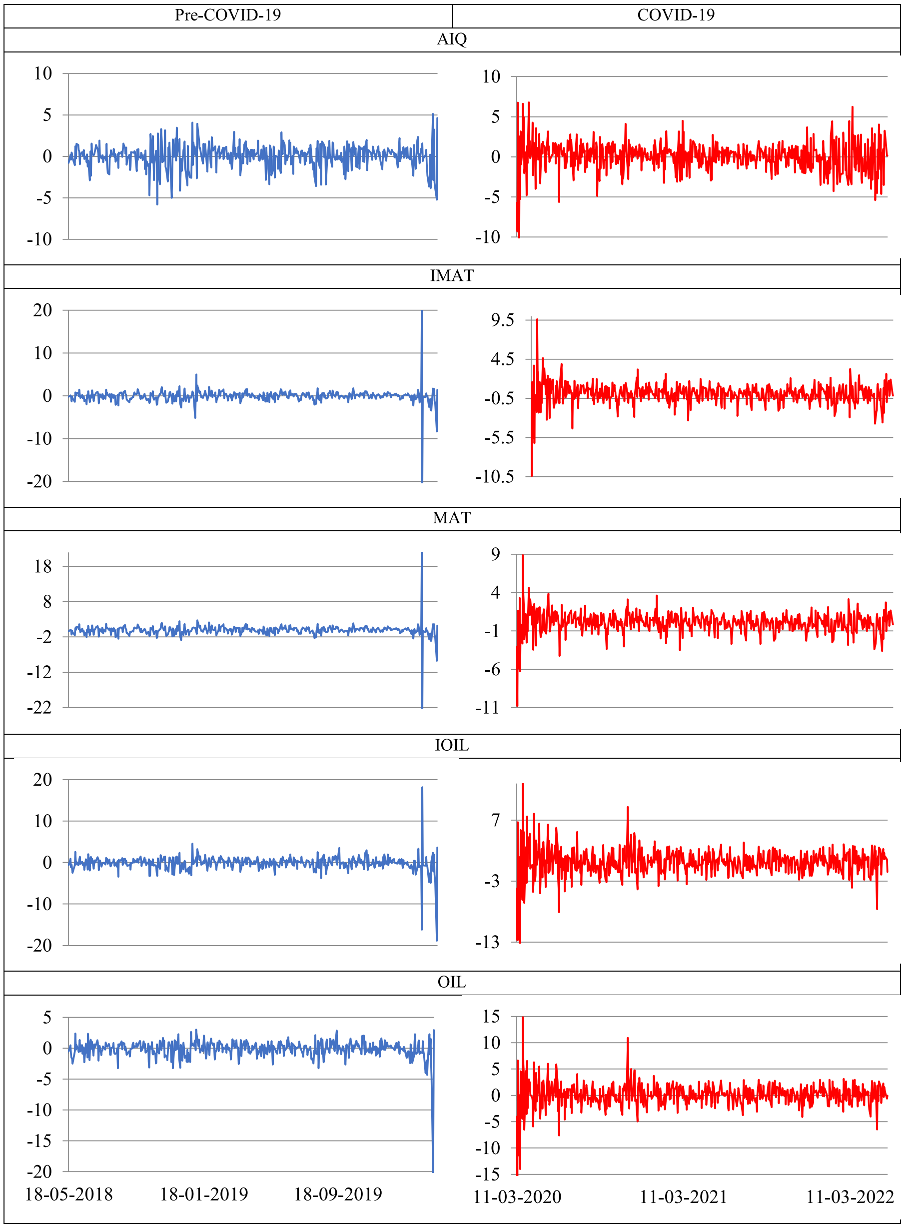

Fig. 2. Plot of returns.

Intelligence & Technology ETF was used as a representative of the artificial intelligence (AI) technology. To follow the evolution of the industrial activity, the authors selected Dow Jones Industry Indices, which are sub-indices of the Dow Jones Global Index, for two sectors - the Basic Materials and Oil & Gas sectors. In order to monitor the impact of the covid-19 crisis on the use of AI solutions, the authors considered the specific situation of the Islamic market, which is why Dow Jones Islamic Market Basic Materials and Dow Jones Islamic Market Oil & Gas were observed. In the basic materials sector, there are sectors such as industrial metals and mining, chemicals, mining, and the forestry & paper sectors, whereas, in the oil & gas sector, there are producers, oil equipment, distribution and services, and alternative energies. In order to evaluate the impact of the COVID-19 pandemic, the analysis period was divided into two stages: May 18, 2018–March 10, 2020 (pre-COVID-19 period) and March 11, 2020–June 01, 2022 (COVID-19 period).

The results indicated that AI could serve as the cause-in-quantiles of Islamic oil & gas-related companies (in both pre-COVID-19 and COVID-19 timeframes) and oil & gas firms (only within COVID-19). The causality-in-mean from AIQ to the Islamic and conventional oil & gas investments at the COVID-19 times (in all lower, middle, and upper quantiles) was detected, the result being supported by the great and effective participation of AI in the oil and gas industry all over the world. In addition, both of the Islamic and the conventional basic materials and oil & gas businesses appear to be a non-linear cause-in-variance of the AI technology in the middle quantiles of the COVID-19 situation. Furthermore, the only cause-in-quantiles from resources-based markets to AI is accounted for by Islamic and conventional basic materials companies, as observed only at the COVID-19 era. In accordance with this study, during the COVID-19 crisis, an important opportunity for basic materials and oil & gas companies was to improve and use the AI innovations, a fact that generated an increase in the financial performance of these companies and the rise in stock market indices. So, the AI could be a strategic weapon for basic materials and oil & gas companies which has to face more and more challenges generated by black swan events such as the COVID-19 crisis.

Due to the fact that artificial intelligence will increase productivity and decrease losses, the oil and gas industries have invested a considerable amount of resources in artificial intelligence and other data

Table 2
Net spillovers.

q	pre-COVID-19					COVID-19				
	AIQ	IMAT	MAT	IOIL	OIL	AIQ	IMAT	MAT	IOIL	OIL
0.05	-3.5	-1.07	2.47	2.43	-0.33	-3.36	1.13	2.82	0.03	-0.62
0.1	-3.48	-1.36	4.03	-0.2	1.01	-7.31	3.08	4.24	0.29	-0.3
0.15	-5.26	-1.67	4.36	0.54	2.02	-11.28	3.35	6.18	1.35	0.4
0.2	-7.32	-2.26	4.79	1.66	3.12	-13.23	3.15	7.24	2.34	0.5
0.25	-8.17	-2.84	5	2.46	3.55	-13.96	4.02	8.39	1.17	0.38
0.3	-9.03	-2.97	5.03	3.23	3.75	-13.09	4.02	8.82	0.27	-0.01
0.35	-8.66	-3.72	5.01	3.26	4.1	-12.18	3.79	9.59	-0.3	-0.89
0.4	-8.99	-3.46	4.85	3.17	4.43	-11.93	3.83	9.85	-0.68	-1.07
0.45	-9.37	-3.19	4.7	3.53	4.34	-11.87	3.95	9.78	-0.9	-0.95
0.5	-9.39	-3.5	4.61	3.65	4.63	-12.48	4.21	9.76	-0.68	-0.8
0.55	-9.77	-3.34	4.57	3.65	4.89	-13.44	4.69	10.4	-0.65	-1
0.6	-9.79	-3.43	4.24	3.94	5.04	-14.04	5.03	10.72	-0.8	-0.91
0.65	-9.95	-3.1	3.88	4.3	4.88	-14.91	5.27	10.44	-0.84	0.03
0.7	-9.53	-2.48	3.45	3.99	4.58	-14.92	5.47	9.75	-0.82	0.51
0.75	-8.89	-1.94	3.82	2.68	4.33	-14.86	5.42	8.85	-0.16	0.75
0.8	-8.15	-1.16	3.54	1.78	4	-15.02	4.83	8.41	0.66	1.12
0.85	-7.05	-0.65	2.62	1.57	3.51	-14.28	3.66	7.45	1.88	1.3
0.9	-5.7	0.28	2.78	0	2.65	-12.02	2.63	6.13	2.14	1.12
0.95	-4.45	5.74	1.05	-2.2	-0.14	-4.86	0.51	3.19	1.12	0.05

Note: By increasing the shock's net transmitting power, the color changes from red to yellow, and then green.

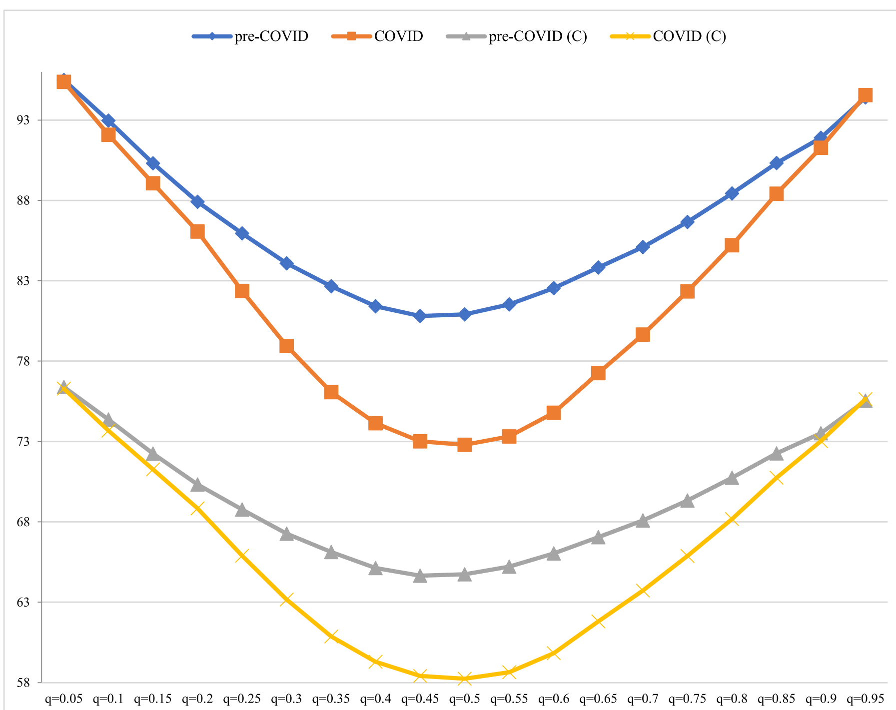

Fig. 3. Total connectedness index and its corrected version (distinguished by "C" in brackets).

technologies in order to ensure their future competitiveness in an environment which is rapidly changing. Using artificial intelligence, the Oil and Gas industry is able to increase operational efficiency, reduce costs, enhance data intelligence, improve safety measures, and discover and drill new resources, which can have a significant impact on their bottom lines while improving their efficiency. As technologies come together, they will have an impact on the oil and gas industry, helping to develop advanced applications to assist in infrastructure management and maintenance, identifying new oil wells, and enhancing worker safety over the next few years. As a result of the potential of artificial intelligence in the sectors analyzed, it is crucial for the innovation process to be intensified by establishing partnerships between companies, universities, and government agencies in order to ensure both the appropriate training of specialists and the conception of solutions that are both ethically acceptable and economically efficient. Furthermore, artificial intelligence, in conjunction with green manufacturing, could present new opportunities and challenges for companies in the process industry (Mao et al., 2019) as well as cleaner energy companies

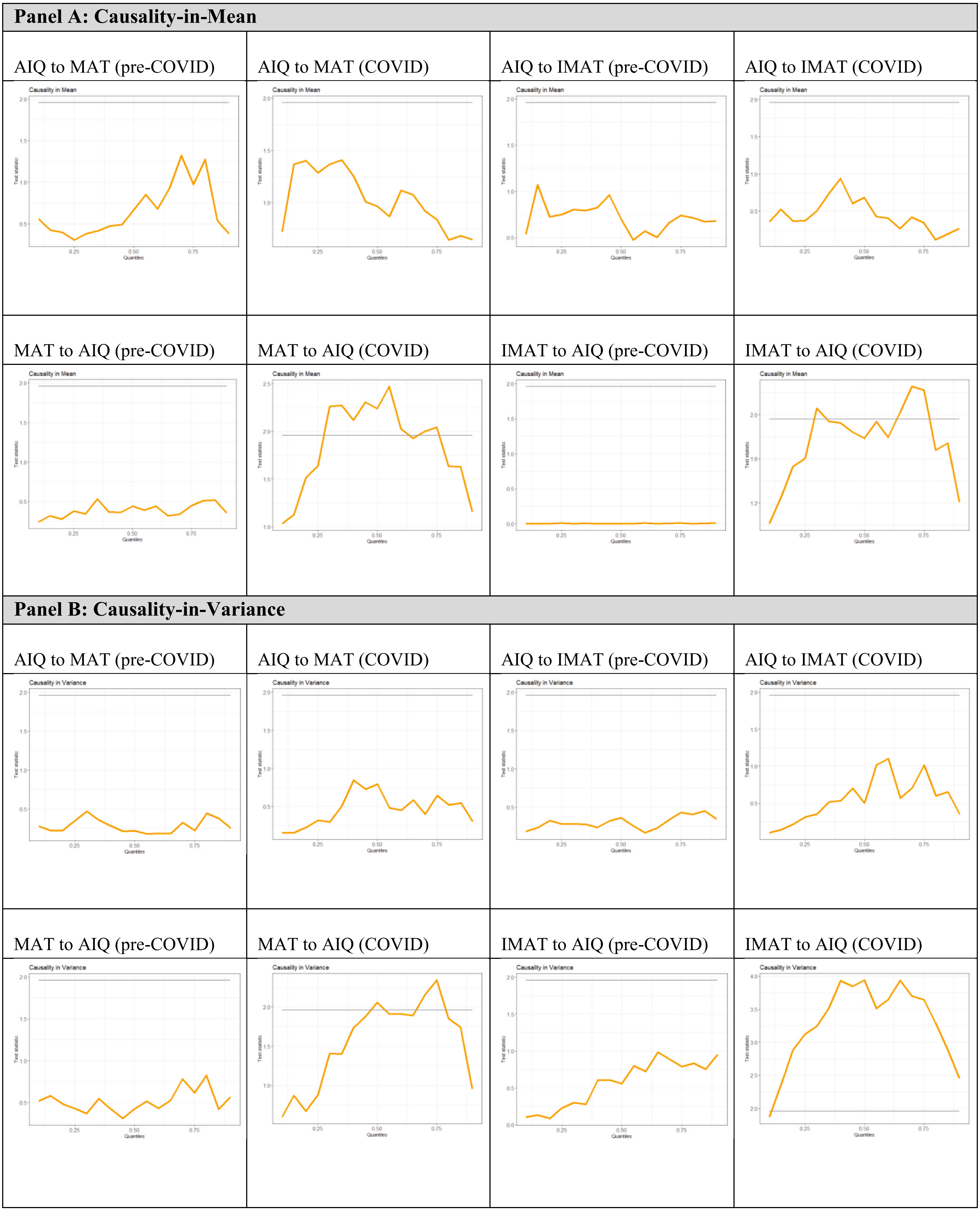

Fig. 4. Causality-in-quantiles nexus of AIQ and MAT (IMAT).

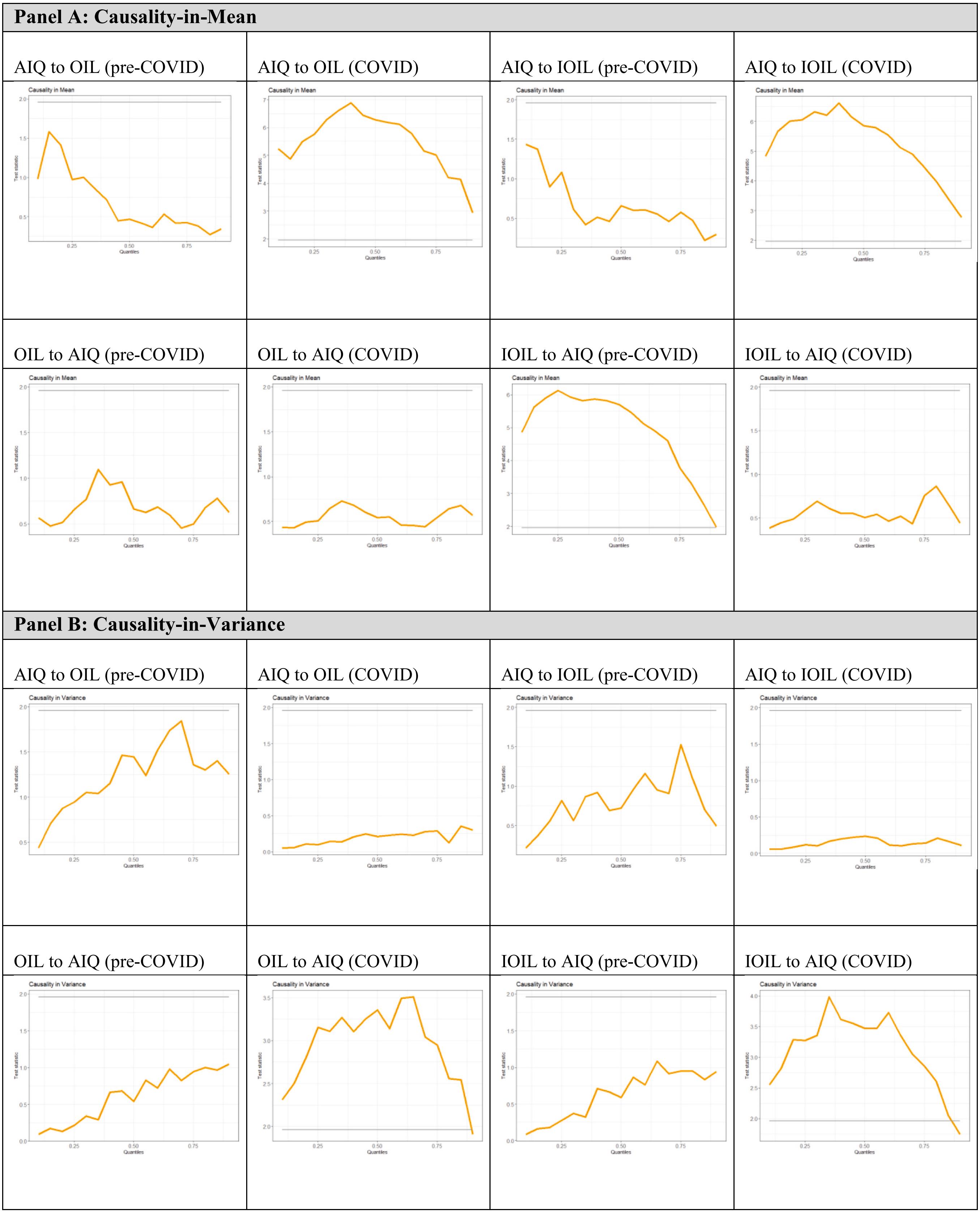

Fig. 5. Causality-in-quantiles nexus of AIQ and OIL (IOIL).

(Mazzeo et al., 2021; Zhang et al., 2021).

The authors are aware of the limits of the research carried out considering the indicators used, the period was chosen for the analysis, and the targeted markets. For this reason, the authors consider the continuation of this research in several future directions, taking into account the existing concerns at the level of the European Union for the promotion of AI solutions among companies and public authorities.

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Credit author statement

Umer Shahzad: Conceptualization, Original draft preparation, Methodology, Software. Mahdi Ghaemi Asl: Conceptualization, Original draft preparation, Reviewing and Editing, Supervision. Mirela Panait: Visualization, Data Curation, Reviewing and Editing. Tapan Sarker: Validation, Reviewing and Editing, Supervision. Simona Andreea Apostu: Methodology, Software, Supervision.

Data availability

Data will be made available on request.

Appendix

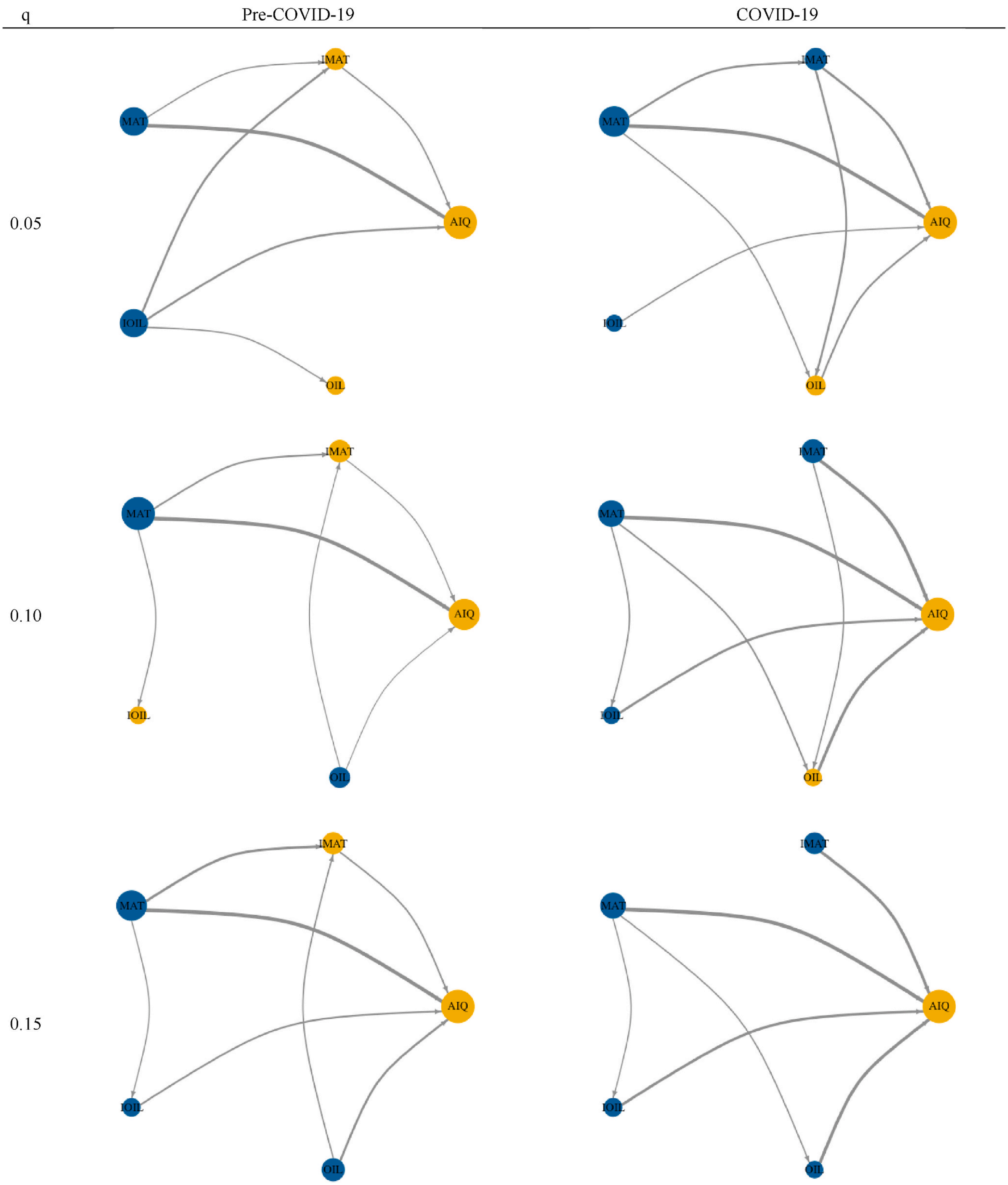


Fig. A1. Network of connectedness

Note: There are two sets of results described: the network of connectedness (shown in Figure A1), and the net spillovers (depicted in Table 2); Both of these results show that the network of connectedness and the transmission (receiving) patterns of shocks can vary accordingly as a function of moving from one quantile to another, and moving from pre-COVID-19 days to COVID-19 periods. It is also possible to observe the same pattern by emphasizing the net pairwise directional transmission dominance, highlighted in different rows and columns of Figure A1. Based on Figure A1, shocks' net transmitter (receiver) is represented in navy blue (mustard) nodes. Weighting is calculated by averaging net measures of directional connectedness between pairs of vertices. Nodes are sized based on their net total directional connectedness, which represents the weighted average of their respective sizes.

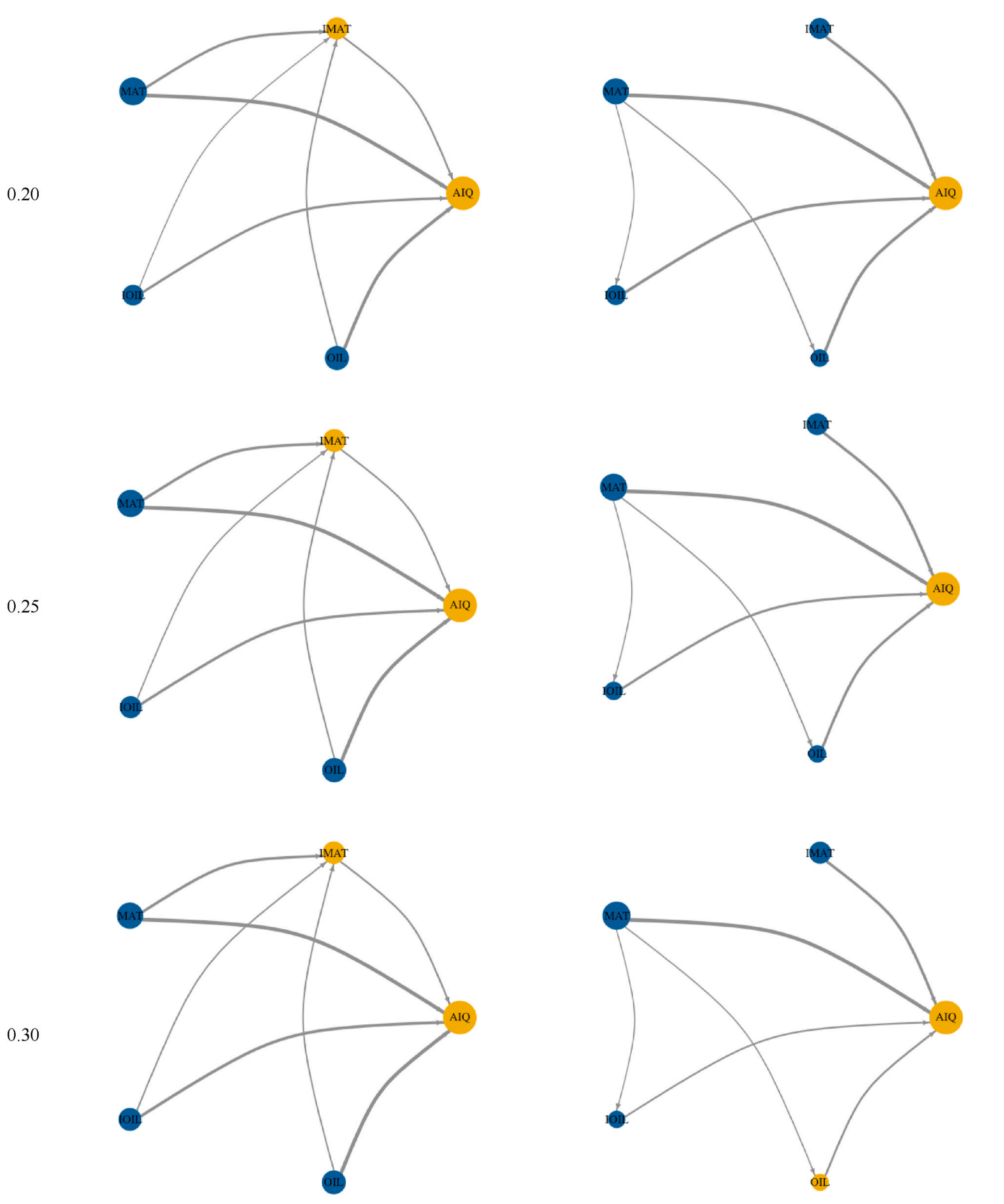
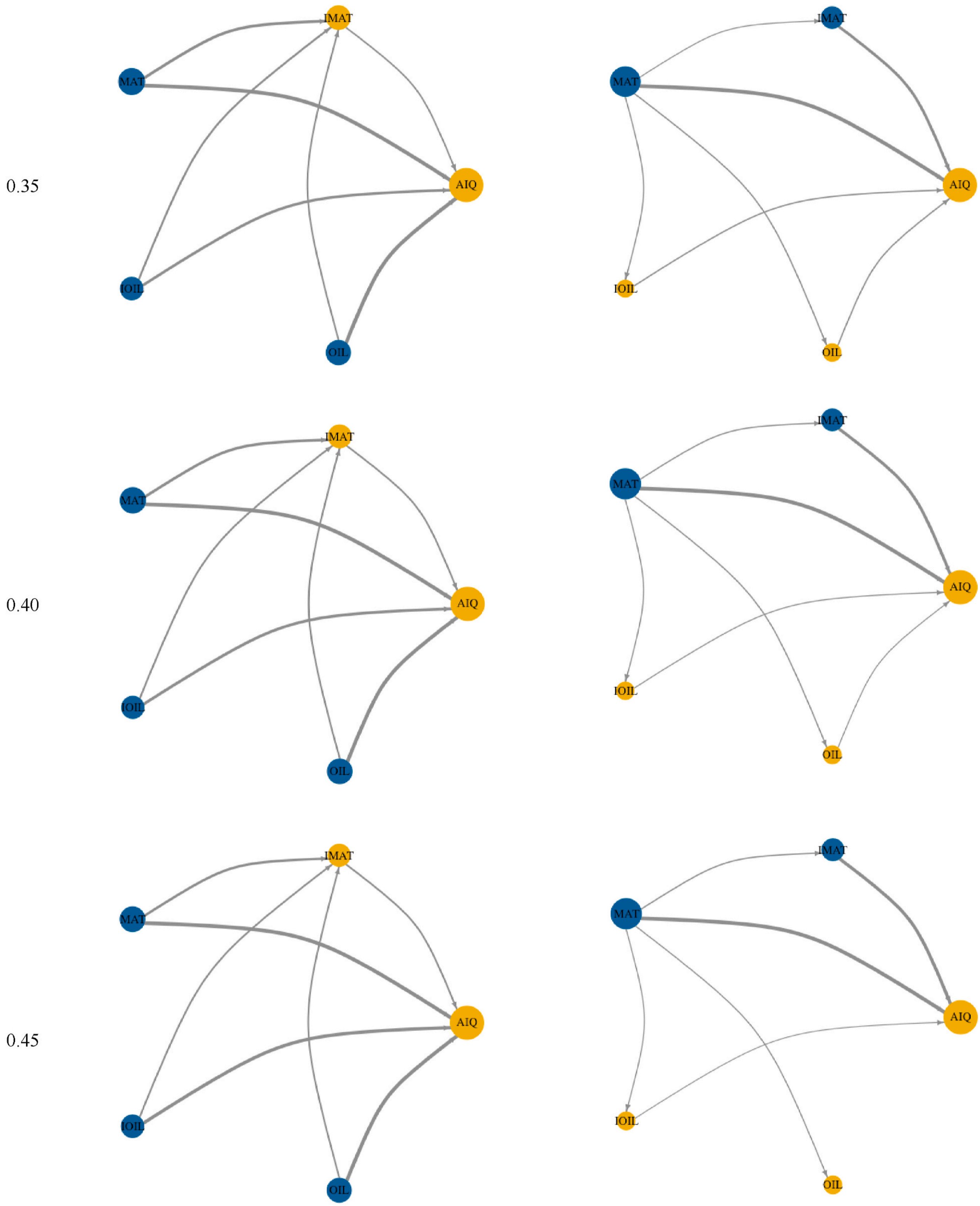


Fig. A1. (*continued*).



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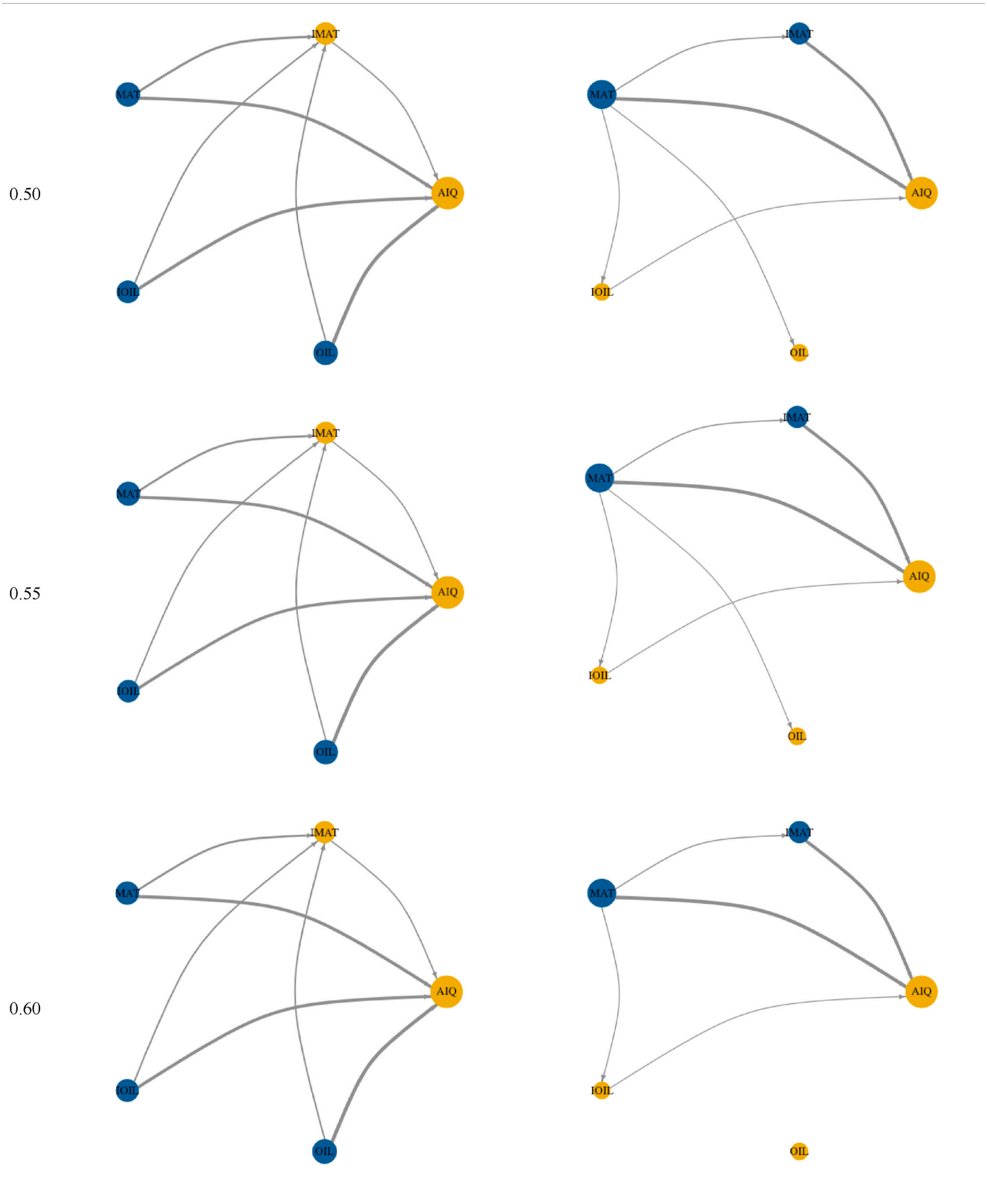

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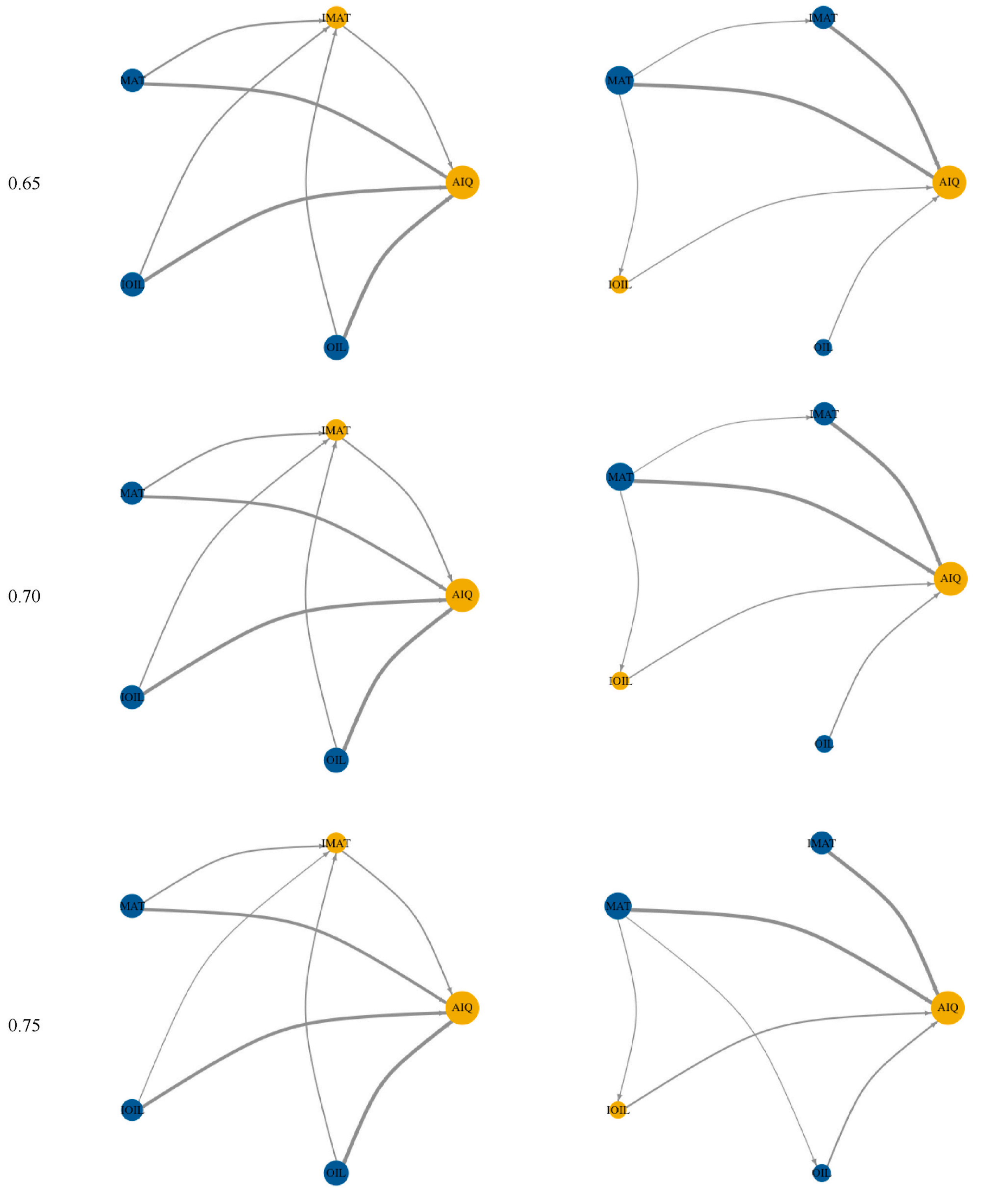

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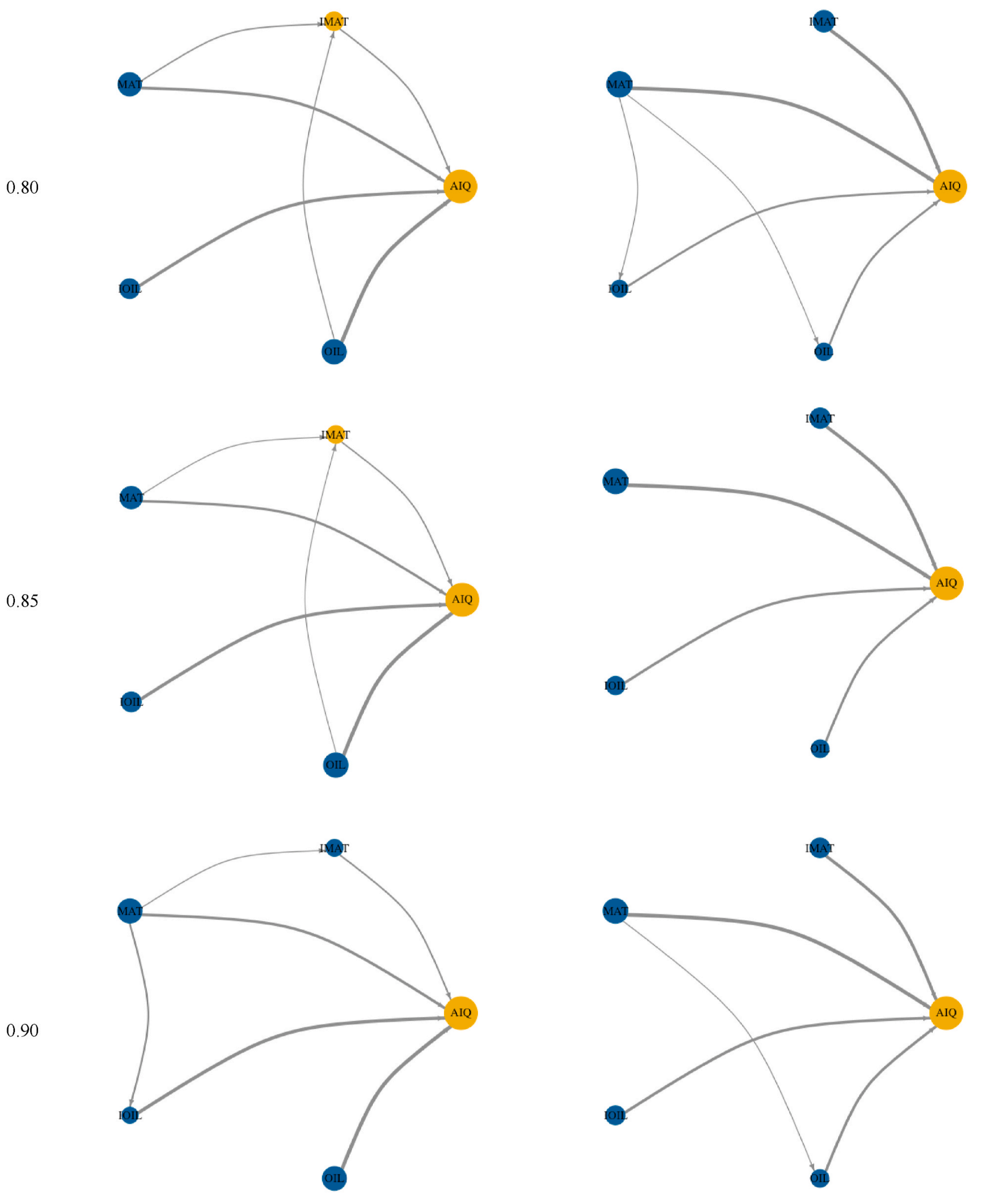

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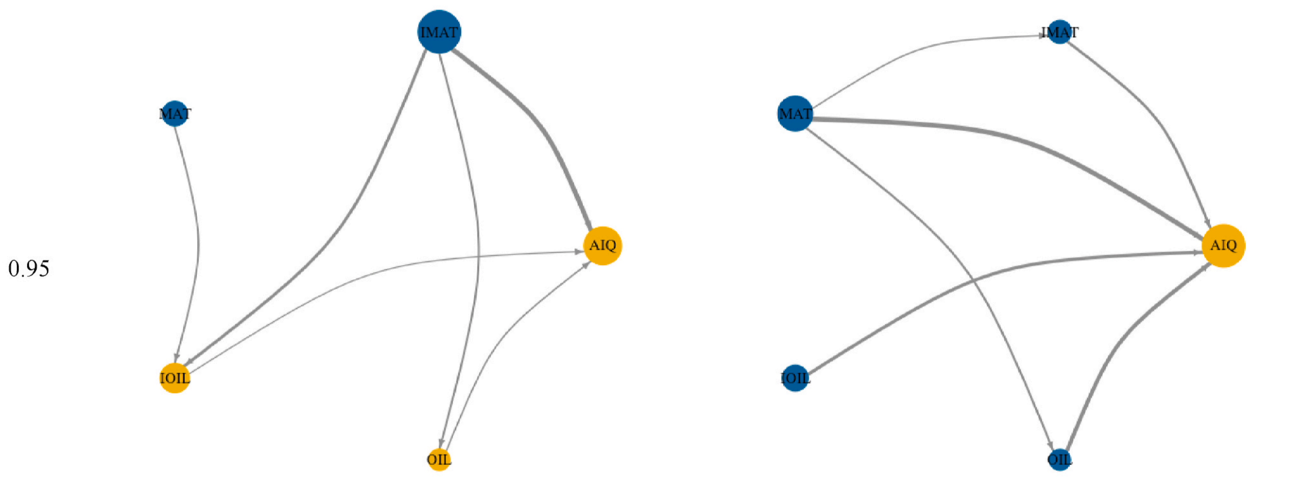

Fig. A1. (*continued*).

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