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From business to clinical trials: a systematic review of the literature on fraud detection methods to be used in central statistical monitoring

Maciej Fronc[a], Michał Jakubczyk[b]

Abstract. Data-driven decisions can be suboptimal when the data are distorted by fraudulent behaviour. Fraud is a common occurrence in finance or other related industries, where large datasets are handled and motivation for financial gain may be high. In order to detect and the prevent fraud, quantitative methods are used. Fraud, however, is also committed in other circumstances, e.g. during clinical trials. The article aims to verify which analytical fraud-detection methods used in finance may be adopted in the field of clinical trials. We systematically reviewed papers published over the last five years in two databases (Scopus and the Web of Science) in the field of economics, finance, management and business in general. We considered a broad scope of data mining techniques including artificial intelligence algorithms. As a result, 37 quantitative methods were identified with the potential of being fit for application in clinical trials. The methods were grouped into three categories: pre-processing techniques, supervised learning and unsupervised learning. Our findings may enhance the future use of fraud-detection methods in clinical trials.

Keywords: fraud detection, clinical trials, finance, data mining, big data

JEL: C00, C38, C55

1. Introduction

The understanding of the term 'fraud' changes across different fields of study. It can have various potential meanings depending on the scope of the investigated issues, as claimed by Gupta (2013), and West and Bhattacharya (2016). In this paper, however, we define fraud as an intentional manipulation of data (e.g. fabrication, falsification or deletion) or misconduct in the data production process caused by personal motivation of a fraudster or their carelessness.

Fraud is a common problem observed not only in the financial sector but also in everyday life and can expose both transaction parties to huge losses (Al-Hashedi & Magalingam, 2021). According to the US Federal Trade Commission (2022),

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2.8 million fraud cases of different type were registered in the USA in 2021 only, and the total generated financial loss exceeded \$5.8 billion. *PwC's Global Economic Crime and Fraude Survey 2022* (PwC, 2022) showed that 46% of the surveyed companies reported fraud in the last 24 months.

The rapid development of information systems and the progressing digitalisation of data necessitate the development of methods allowing large datasets to be handled properly. Al-Hashedi and Magalingam (2021) explained how the technological revolution extended the opportunities for committing fraud. The transfer of money and related activities became easier as digital technologies developed, which, in turn, has made banking activities vulnerable to deception. As a result, a significant increase of fraudulent schemes in finance is observed. The vast majority of data on financial activities are stored in databases, which causes the volume of such data to increase. Therefore, the application of relevant analytical tools is necessary to mitigate the risk associated with fraud. Moreover, such tools facilitate the decision-making process as to where the resources of an organisation should be allocated most efficiently (Zhou & Kapoor, 2011).

Financial data is relatively common and brings a significant portion of information, which allows us to distinguish activities which are fraudulent from the non-fraudulent ones with the use of analytical tools based on statistics. Registered transactions constitute the main source of financial data. They come from sectors such as banking, the bond market, the securities market, transaction systems, financial statements, etc. (Zhang et al., 2022).

Apart from the financial sector, other fields are also vulnerable to fraud – like clinical trials (CTs). According to the International Council for Harmonisation of Technical Requirements for Pharmaceuticals for Human Use (2016), a CT is 'any investigation in human subjects intended to discover or verify the clinical, pharmacological and/or other pharmacodynamic effects of an investigational product(s)' in order to provide its safety towards the patient as the final recipient. Within the pharmaceutical industry, it is this stage that is the most complex in the drug development process. The execution of a single study produces a tremendous amount of data that are potentially exposed to manipulation. Therefore, keeping the collected data under control is a must and can be achieved through the centralised monitoring of CTs. This monitoring process involves a remote evaluation of the clinical data resulting from a study in order to maintain the high quality of the investigated product (Kirkwood et al., 2013).

Fraud in the context of CTs might be caused by the researcher's carelessness (e.g. making mistakes in the data in the documentation), ambitions or expediency (e.g. enrolling as many patients as possible for extra financial gain even though they had already been enrolled elsewhere). In all the cases, the obtained results and the outcome of the entire study can be affected by the researcher's motivation. Fraud in CTs might result not only in a huge financial loss but it can also undermine the credibility of the trial sponsor (Gupta, 2013; Sakamoto & Buyse, 2016). It is additionally worth noting that the history of investigating fraud in finance is far longer than that of researching fraud in CTs. What is more, this subject is relatively uncommon among researchers, as evidenced by their lack of awareness of the phenomenon (Kirkwood et al., 2013). The implementation of well-developed fraud detection techniques aligned with business objectives increases the efficiency of an organisation. However, the adoption of an approach aiming to minimise the losses caused by fraud is recommended rather than focusing on statistical measures such as likelihood (Höppner et al., 2022). Undertaking preventive measures is better than reacting to failures. Fraud detection in CTs can be further developed through the implementation of the solutions already applied in the field of finance. The aim of our study is to identify the analytical concepts that can be tailored to the specific nature of CTs and applied to detect fraud among clinical data.

The aforementioned goal provides a better insight into the methods currently applied in fraud detection. The methods were extracted and compared through a systematic review of the available literature. The review focused on papers discussing fraud detection based on quantitative methods such as data mining, machine learning, artificial intelligence or econometrics. These methods were evaluated not only in terms of their statistical performance, but also in terms of constraints when considering their potential use. Unsupervised techniques prove more useful when no labelled data is involved and when the outstanding cases are detected across the whole dataset. The outcome obtained by means of unsupervised techniques was compared with the original data labels that were intentionally omitted in the analysis. On the other hand, the performance of supervised techniques may be improved through the use of pre-processing algorithms that can handle imbalanced data. These detection methods ensured a satisfactory level of accuracy (ranging from 60% to nearly 100%) in the context of real-world decision-making problems, which altogether resulted in a more efficient resource allocation.

The paper has a following structure: Section 2 presents the adopted approach within the systematic review, the results of the review are shown in Section 3 (with an additional tabular summary of the identified methods, and final conclusions are presented in Section 4).

2. Methods

2.1. Literature search and methods extraction

We searched two databases: Scopus and the Web of Science. In the search, we used keywords related to fraud or manipulation detection (as a problem to solve) and statistics, data mining, machine learning, artificial intelligence and econometrics (i.e. the kinds of methods that we are interested in). We limited the search to papers published in the years 2018–2022. The search focused on journals in the area of business, management, accounting, decision sciences, economics, econometrics and finance. The search in the Web of Science differed slightly from that in Scopus due to the fact that a different classification was adopted in the former data base. We therefore focused on the following subject areas: business, economics, operations research, management sciences and mathematical methods in social sciences. Eventually, the searches in both databases produced similar results. Considering the manageability of the review and the fact that new fraud detection methods are constantly developed, we believe that such a narrowing was warranted. Specific keywords used in the queries are listed in the appendix.

The papers selected during the search were subsequently analysed, and we included papers which met all the following criteria:

- research or review based on quantitative methods applicable to fraud detection in the aforementioned areas;
- research based on real-life data or analysis-ready datasets;
- papers focusing on detecting committed frauds;
- articles describing algorithms that can be applied to solve related problems;
- articles including fraud detection methods applicable to labeled and unlabeled data;
- articles including methods that handle imbalanced data.

We excluded papers that met at least one of the criteria below:

- duplicated papers;
- articles that do not propose any particular methods of fraud detection.

At the second stage of the selection those articles were excluded that:

- considered fraud in terms of the behavioural aspects of fraudsters' motivation;
- involved methods with a narrow range of application.

2.2. Systematisation of the papers

We extracted information on fraud detection methods from the selected papers. These methods were then categorised according to their use into data pre-processing techniques and supervised and unsupervised methods of fraud detection.

Pre-processing techniques refer to operations performed on an initial dataset in order to prepare raw data for a proper analysis by reducing their inherent complexity. This data modification was necessary to obtain a dataset which would improve the performance of an applied algorithm and provide higher quality results. In our paper, techniques of this kind focused on resampling and attribute selection, which proves useful in handling skewed data.

Supervised learning algorithms use labelled data (training sets) as the basis for patterns recognition among a newly implemented dataset (test set). In our work, the labels represented the particular classes that the new data points were assigned to. For this approach it was crucial to know in advance which predefined classes the training datapoints belong to as the starting point for the learning process.

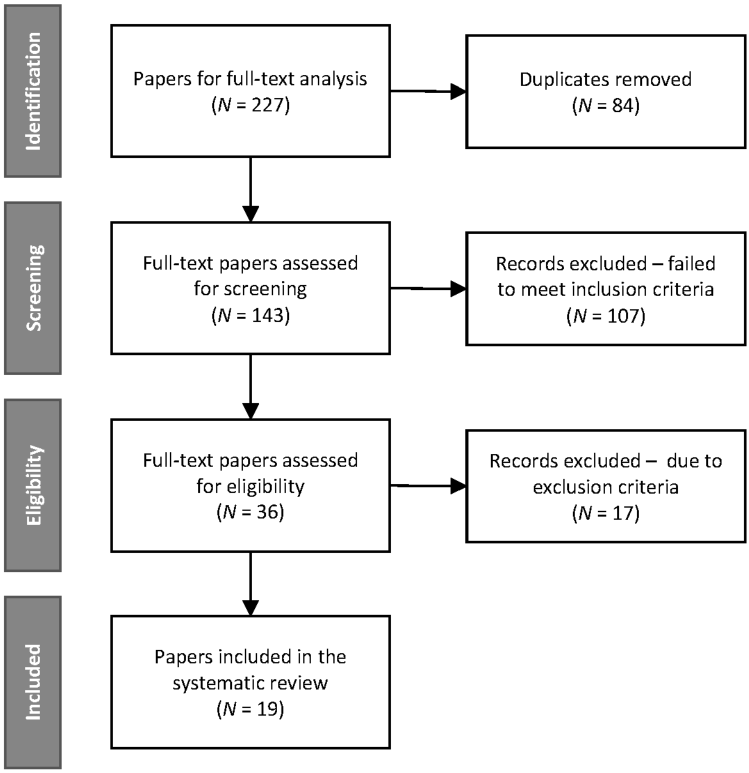
Unsupervised learning enables splitting an initial dataset into subgroups without any *a priori* information about their categories. In contrast to supervised learning, unsupervised learning focuses on the differences and similarities between datapoints in space which are created by their attributes. These kinds of algorithms aim to disclose the hidden patterns from the information included in the processed data.

The proposed division takes into consideration the data characteristics and fraud specificity. In the next section, each of the extracted methods is discussed. A toolbox presented in Section 3 contains the methods that are already used in the central monitoring of CTs, or may potentially be applied as an extension to the current methodology.

3. Results

The systematic literature review allowed the compilation of a total of 19 papers which met the selection criteria. These papers presented 37 quantitative techniques applicable for direct fraud detection or as supportive tools. Figure illustrates the number of publications, *N*, obtained at each stage of the search process. The identified methods were divided into three categories, as specified in the Methods section: pre-processing, supervised learning and unsupervised learning. Unsupervised algorithms (15 techniques) proved to be the most frequently occurring category compared to supervised learning (12) and pre-processing (10). The prevalence of unsupervised techniques might result from the specificity of the available data which were mostly unlabelled (due to the lack of prior knowledge as to the fraudulent activity among the collected data). All these methods are summarised in Table at the end of this section.

Figure. Stages of the search process for a systematic review



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3.1. Pre-processing methods

Ekin et al. (2021) devised a classification of financial frauds committed in the healthcare sector. They studied overpayment issues based on data on healthcare payment claims. The data included billings for the services of physician assistants and interventional pain management providers. The authors focused on coping with imbalanced data, which is typical for problems of this kind; fraud cases in most instances form a minority in the whole dataset. Therefore, this subset should be oversampled to avoid disproportion among the data. Ekin et al. used oversampling of the informative minority data points and undersampling of the non-fraudulent cases. The following oversampling algorithms were used: synthetic minority oversampling technique (SMOTE), majority weighted minority oversampling technique (MWMOTE), and random walk oversampling (RWO). All of these techniques involve generating synthetic data based on minority classes in a dataset. The performance of these techniques depends on the imbalance ratio which refers to a fraction of the minority class in the whole dataset. The study demonstrated that RWO is the most efficient sampling method among all the investigated techniques in terms of the performance measured by AUC (0.84).

As regards undersampling algorithms, only one was applied, i.e. random undersampling (RU). This technique involved removing random cases out of the majority class. RU performed poorer in terms of model quality than the oversampling methods. The exception was the com-putational time which was the shortest for RU, which resulted from the fact that it was the smallest dataset analysed.

Kamalov (2020) investigated kernel density estimation (KDE) to verify the issue of handling imbalanced data. He tested this algorithm on simulated data. KDE is a technique which estimates the unknown probability density distribution based on a sample (Botev et al., 2010). This enables the generation of new datapoints according to the distribution of the minority class in order to remove the data imbalance. KDE is flexible because of the possibility to use different kernel functions, which allows the customisation of the sampling process to be done. This method is popular among researchers and well-investigated, which makes it an attractive solution to implement. Kamalov compared the KDE performance to other pre-processing techniques such as random oversampling (ROS), SMOTE, the adaptive synthetic sampling approach (ADASYN) and NearMiss. ROS creates new data points by simply resampling the minority class. ADASYN works similarly to SMOTE, but it generates more data points at the edge of the minority class. NearMiss undersamples the majority class, which causes loss of information. Each of these algorithms were tested respectively to three imbalance ratios (70, 80 and 90%). Regardless of the performance measure, NearMiss worked the least efficiently, whereas the effectiveness of the performance of the rest of the algorithms was similar. However, KDE performed best while measured by the G-mean and $F1$-score. According to the AUC measured, KDE was the best at an 80% imbalance ratio. For the rest of the ratio values, KDE was the second best.

Przekop (2020) proposed a solution to cope with cases handling too many variables in the form of feature engineering (FE). His experiment was based on real-life data which came from new customers' bank applications. Przekop indicated two different approaches within FE. The first involved using a combination of variables instead of a single one. This allowed the dimensionality of an investigated issue to be reduced as unique combinations of variables were indicated by means of a decision-tree-based algorithm. The second approach involved the segmentation of the population into homogenous peer groups. This made it possible to describe each of the group by a set of variables that were specific to a given segment. The proposed approaches improved the predictive power of the fraud detection models by determining the specific relationships between variables. However, both approaches required expert knowledge about the investigated phenomenon. Przekop also claimed that fraud detection methods tended to be very general and in order to provide the best possible performance of the applied algorithm, the methods required an approach tailored to a specific problem.

Ekin et al. (2021) applied the principal component analysis (PCA) to address multicollinearity between variables. PCA discloses hidden variables represented by principal components that are linear combinations of the original variables, thus reducing the dimensionality of an issue. The choice of the number of the principal components total variance can be controlled. In conclusion, PCA improves the model performance in terms of the computational time and data storage parameters.

3.2. Supervised methods

As already mentioned, Ekin et al. (2021) addressed the problem of financial fraud in healthcare. They also investigated a selection of supervised techniques in terms of their application in fraud detection. Linear discriminant analysis (LDA1) is a classifier based on a linear combination of independent variables. It splits the whole dataset into two classes. LDA1 is dedicated to problems involving dichotomous variables. According to the authors, LDA1 underperforms as a fraud detection method. It copes better with undersampled data, although it is not a distinguishing feature of this method. LDA1 works better with smaller and more homogenous datasets, which causes the method to be resistant to imbalanced data. The authors also proposed the quadratic discriminant analysis (QDA), which is a variant of LDA1. The two techniques therefore share certain characteristics, although in contrast to LDA1, QDA is based on a non-linear combination of independent variables. Moreover, QDA produces better results when dealing with pre-processed data based on sampling and collinearity reduction.

Decision trees (DTs) are one of the most popular methods used for fraud classification in healthcare (Ekin et al., 2021). DTs aim to assign the objects from datasets to their relevant classes. This is a tree-structured classifier where the internal nodes represent features, branches designate the decision rules, and leaves class labels. Each node acts like a test which is a premise to binary classification. The popularity of this technique results from the fact it is relatively easy to interpret. On the other hand, DTs become less readable when too many decision rules occur. The algorithm is a greedy search technique. It does not cope with imbalanced data, nor does it distinguish small classes from the large ones. What is more, branch pruning leads to misclassification due to the use of imbalanced data. In general, DTs achieve poorer results when working on small datasets (Ekin et al., 2021), i.e. datasets comprehensible for humans. As regards collinearity, it does not affect DTs, therefore they do not need any correlation pre-processing. When collinearity does not occur, it makes the code only run faster.

DTs can also be used in an ensembled form as a random forest (RF). This algorithm is based on the average outcome of many DTs obtained through bagging (or bootstrap aggregating), i.e. an algorithm which improves the stability and accuracy of a classifier. RF reduces variance and overfitting. It is resistant to imbalanced data, but not to a high correlation of features. A significant collinearity results in correlation bias, therefore the orthogonalisation of features is necessary (e.g. by using PCA). In contrast to DTs, RFs are intended for processing big data. This method can also be effective with small datasets, however, it would result in a lower variety of patterns. More trees generated within RF leads to a better performance of the algorithm, but on the other hand, it involves a longer processing time. However, if a hyperparameter optimisation is achieved, it makes the RF's performance independent from an increasing number of the generated trees (Wang & Xu, 2018). Ekin et al. (2021) compared the above-mentioned techniques and concluded that tree-based algorithms outperform LDA1 and QDA in terms of AUC and accuracy, but are the most time-consuming.

Wang and Xu (2018) tested the support-vector machine (SVM) as an algorithm supporting text mining within the analysis of vehicle insurance claims. This method is another dichotomous classifier applied in the space of a decision problem. It determines a hyperplane which separates the examples maximising the margin between the two classes. SVM is considered to be one of the best classifiers in terms fraud detection (if relying on references provided by Wang and Xu); therefore, it was included in this study. Although SVMs' performance is poorer than that of deep neural networks, Zhang et al. (2022) concluded that SVM is a better option in terms of classification performance. The algorithm can be combined with others to improve the final recall rate that makes fraud detection more efficient.

The *K*-nearest neighbours (*k*-NN) technique was investigated by Ekin et al. (2021). It classifies objects of an undefined membership to the existing classes. The algorithm uses distance metrics, like the Euclidean distance, to assign the unlabelled objects in the radius of *k* neighbours into the existing classes. The majority of the same class objects in the radius is the criterion of membership. Ekin et al.(2021) demonstrated that this algorithm provided the best accuracy, comparable to that of SVM. The performance of *k*-NN deteriorates as the size of the dataset becomes larger. The algorithm is sensitive to imbalanced data.

Zhang et al. (2022) used the Naïve Bayes classifier (NB) in text classification as a technique characterised by high classification performance. NB is a probabilistic method based on the Bayes theorem. The technique involves the calculation of the conditional probability of an example belonging to a certain class, assuming the independence of the considered variables. NB is sensitive to imbalanced data and there is no need to remove the collinearity. What is more, the method benefits from correlated attributes (Ekin et al., 2021) and works fast and efficiently only on small samples. It is resistant to the influence of outliers.

Höppner et al. (2022) introduced a novel method – the LASSO-regularised logistic regression (LRLL) – as an extension to the classic logistic regression (LR). The authors tested the algorithm on data produced during card transactions. LR is a classification model with a binary response. Its predictions involve modelling explanatory variables by means of a sigmoid (logistic) function. This method is indifferent to increasing data imbalance (Ekin et al., 2021). The LR outcome is summarised in the confusion matrix. In the context of cost-based modelling, the misclassification of data points can result in a huge financial loss. Therefore, this classification needs improvement. It is possible to achieve this goal and improve the resolution of the LR model through regularisation, i.e. by introducing the penalty function to the basic model. The results of the newly-devised LRLL model allow a more reliable classification which the decision-making process is based on, thus reducing the risk of financial losses.

Höppner et al. (2022) also utilised two methods that can interact with other classifiers to improve their classification performance. The first one is gradient boosting (GB). This technique addresses classification and regression problems by utilising an ensemble of underperforming models to improve their classification capabilities. By combining new models with the existing ones, the algorithm uses the loss function to minimise the overall prediction error. GBs are usually ensembled with DTs by creating gradient tree boosting (GTB). The main problem of DTs is their inaccuracy that impedes predictive learning. GTB improves the precision of trees, in most cases leaving their specific properties that are attributed to data mining intact. These properties include the ability to handle mixed type data, irrelevant outputs and the monotonic transformation of predictors. The improvement, however, at the same time causes the speed, interpretability and resistance to the misclassification of data and overlapping class distributions to decrease. GTB is applicable to cost-related problems where a reliable classification is crucial for the reasonable allocation of financial resources (Höppner et al., 2022).

Extreme Gradient Boosting (XGBoost) is another boosting algorithm based on ensembled simple trees with a weak performance, which enhances the overall performance of this classifier. XGBoost manages to generate more models and process them faster than GTB. Moreover, this model has many other advantages including the ability to handle missing data, scaling according to the dataset size, greater effectiveness than other GB algorithms, and the ability to rank features according to their importance in the model.

Farrugia et al. (2020) applied the XGBoost classifier to find illicit accounts within the transaction history in the Ethereum network. The authors assert that the method has a potential in many areas involving financial data and it allows the prediction of fraudulent activities based on the detected patterns. Farrugia et al. used balanced data and obtained results with satisfying metrics demonstrating a high performance of the method. The data, however, need to be pre-processed.

Rousseeuw et al. (2019) proposed a method of time series monitoring in terms of unusual patterns. Time series (TS) is a sequence of datapoints as a function of time. Measurements are taken at the same time step. TS might be decomposed to the following elements: trend, seasonal variations and random fluctuations. Monitoring the course of the time series allows the detection of outliers with fraudulent causes. This kind of occurrence might be misleading for conventional TS analysis and produce faulty results. Fraud is observed within time series when a temporary anomaly or level shift occurs. Rousseeuw et al. tested their method on airline and trade data. The algorithm adjusts the curve to the time series, although without taking any irregularities into consideration. This way detecting outliers and level shifts caused by fraudulent activities is possible.

Srinivasan and Kamalakannan (2018) analysed financial data with respect to financial risk. They considered financial risk as a multivariate construct which can be interpreted as a multi-criteria decision-making problem. Therefore, they proposed a multi-objective genetic algorithm (MOGA) as a tool for risk analysis and prediction. The algorithm was tested in terms of predicting decisions on credit card and credit applications. In general, the genetic algorithm is biologically inspired by the evolution process. The process involves the progressive adaptation of biological entities enabling them to survive in a certain environment. To transform this approach into a numerical framework, the algorithm searches the computational space to find the best possible solution for the analysed case. Information included in the dataset is incorporated into a chromosome. The searching rules are formulated on the basis of the chromosome's reproduction mechanisms, such as cross-over, mutation and selection. Only those rules which meet the adopted criteria proceed to the next generation. Srinivasan and Kamalakannan found the best solution by the iteration of the algorithm. The iterations make it possible to find the best solution with an accuracy level exceeding 70%, which renders the performance of MOGA satisfying. What is more, the algorithm outperforms other evolutionary algorithms due to the presence of a memory component which makes the analysis more robust.

3.3. Unsupervised methods

Barabesi et al. (2021) proposed a statistical test on Benford's law (BL), which was based on the sum-invariance property with regard to data entries with the same first significant digits. In general, BL relies on the expected distribution of first digits from the sequence of results. It compares the collected data with the theoretical distribution in order to verify their compliance. Significant differences between the two indicate the occurrence of frauds. The distribution takes into account numbers from 1 to 9 and the fact that their occurrence as the first digit decreases logarithmically. According to this rule, small digits appear more frequently among real-world data than the larger ones. The method is helpful in searching data irregularities in the finance and other sectors. BL might also be applied to further digits – individually or at sequence. The conformity of BL with actual data is verified by using statistical tests that measure goodness-of-fit. The solution proposed by Barabesi et al. was tested in the area of fraud detection in international trade to show its application potential. Firstly, the authors verified the performance of the test on synthetic data. Secondly, the test was applied to real-world data taken from customs declarations of two traders. The final results demonstrated that BL is suitable for labelling fraudulent cases.

Bach, Ćurlin et al. (2020) investigated the relationship between suspicious reports of hours-worked claims and specificity of a project in a project-based company. Therefore, they proposed two data-mining models: one based on chi-square automatic interaction detection (CHAID), aimed at disclosing the relationships between the project attributes and the claims, and the other based on link analysis (LA), whose goal was to detect the potential suspicious claims. CHAID is a decision tree based on chi-square test that allows the split of the dataset into the considered variables. The tree is built progressively from the best to the worst decision rule that differentiates examples. CHAID is usually used in marketing research for customer segmentation, but it generally enables segmentation of any kind. LA, on the other hand, evaluates the relationship between attributes that occur together and are conditioned by each other. This linkage creates a node that implies the association of those two items, and it is called the 'association rule'. Both methods produced similar results that indicated the same areas with the highest probability of fraudulent activity. The research provides a practical tool to detect internal fraud. It allows a better insight into the organisation structure and more efficient control over resource allocation.

Abdul Jabbar and Suharjito (2020) conducted research into fraud in telecommunications company based on call detail records as a dataset. The aim of their study was to propose a method that could detect fraud effectively in order to avoid financial loss. Two machine-learning algorithms were tested, i.e. k-means clustering (k-MC), and density-based spatial clustering of applications with noise (DBSCAN), which are similar methods. The difference is that k-MC is based on a centroid as a starting point for making clusters, while DBSCAN creates clusters referring to the density of data points. Out of the two methods, only k-MC needs a pre-defined number of clusters, which can be optimised. k-MC handles large datasets in multidimensional space, but does not work well with outliers. DBSCAN, on the other hand, is less sensitive to outliers, but cannot cope with excessively diverse density, and moreover is applicable only in two-dimensional space. k-MC and DBSCAN are both useful in fraud detection by identifying outlying clusters within the analysed dataset. The research outcome showed that both algorithms work well on this kind of data, but k-MC performs definitely better when it comes to accuracy, precision and recall. Even though the authors proved that k-MC works effectively on data used in the study, this does not necessarily mean that the same method will apply to other cases from the telecommunications industry.

Esen et al. (2019) applied two-step clustering (TSC) to detecting fraud among transactions on a stock market. In this case, fraud was spotted as outlying cases among insider transactions. TSC is a method combining k-MC with hierarchical clustering. The algorithm involves two stages: pre-clustering of data into many small sub-clusters, and hierarchical clustering to the expected number of clusters by means of Bayesian Information Criterion (BIC). TSC is more effective in searching outliers than in simple clustering. It seeks to identify examples of unusual behaviour within a peer group, where outliers do not always stand out of the whole population. TSC handles mixed-type data (numerical and categorical). What is more, this method automatically selects the optimal number of clusters, which makes processing extremely large datasets possible. Another advantage of pre-clustering is reducing the size of the distance matrix. The data-mining part of the research was complemented with financial measures that were used to estimate abnormal returns based on abnormal results detected by TSC.

Eshghi and Kargari (2019) proposed a novel technique called the multi-attribute group decision-making method (MCDM), which can be used to detect fraud. The method is a combination of two components: intuitionistic fuzzy sets and evidential reasoning. Fuzzy logic, in contrast to Boolean logic, takes into consideration real numbers in the range of 0-1. Evidential reasoning, on the other hand, refers to inference based on evidence provided by historical data. Eshghi and Kargari's aim was to solve fraud detection problems effectively using real-world data, which tends to be unlabelled. This is the area where other unsupervised methods do not always produce satisfactory outcomes. Another issue is the lack of sufficient information, which hinders the results of fraud detection. This approach reduces the contribution of expert opinion in favour of information taken from historical data, which eliminates the arbitrariness of decisions. MCDM assigns weights to each attribute based on the provided data only. This method makes it easier to distinguish fraudulent and non-fraudulent cases by taking into account uncertainty as a hesitation margin between these two potential states. Eshghi and Kargari tested their algorithm on bank transaction data. The results showed that MCDM yields satisfactory results with a high level of accuracy and low level of false signals, which makes the fraud detection process based on this method more reliable.

Majadi et al. (2019) investigated an algorithm based on the Markov random field (MRF) called the collusive shill bidding detection (CSBD). They studied its application to identifying fraud based on shill bidding. MRF is a graphical model for inference from noisy data. It is visualised as an undirected graph in which nodes can be in any number of states. There are two types of nodes: the observed nodes and the hidden nodes. The observed nodes are connected with the hidden ones and this relationship is described by the *a priori* belief function. Only hidden nodes are connected with each other, which is described by the compatibility function. The probability of the occurrence of any set of states among the hidden nodes can be calculated using the aforementioned functions. Majadi et al. tested CSBD on synthetically generated auction data charged with shill bidding and on a commercial auction dataset. The algorithm achieved a 99% accuracy in both cases, which renders it an effective tool for colluding shill bidders in online auctions.

Wang and Xu (2018), Zafari and Ekin (2019) as well as Zhang et al. (2022) took up the issue of text mining in the context of fraud detection. Text mining is a part of data mining whose aim is to extract useful information from unstructured data. It is slightly different from traditional data mining due to the nature of the textual data. Semantics presents the main difficulty in text interpretation, which cannot be processed in a computation-based manner. The basis for this approach is the digitalisation of the textual data. The transformed data can then be analysed with quantitative tools.

Wang and Xu (2018) utilised this approach to find fraudulent activity in the automobile insurance industry. Their analysis involved past vehicle insurance claims. The main tool that they used was the latent Dirichlet allocation (LDA2) supported by an AI-driven algorithm. LDA2 was used for feature extraction from the text, which was the initial step of the analysis. The method is based on the decomposition of a text and association of its parts with the main given topics placing them in the context. Wang and Xu combined this method with a deep learning model in order to detect fraudulent behaviours. They used the LDA2 outcome as model input. This approach was compared with two data mining algorithms: SVM and RF. The comparison demonstrated that LDA2 outperforms SVM and RF while keeping the model quality metrics at the level of 90%.

Zhang et al. (2022) proposed the use of the Bag-of-words (BoW) and Word2Vec (W2V) techniques in financial reports. BoW translates a text into a vector which forms the basis for further analyses. The text is split into single words, which then are digitalised into a vector. Its length is equal to the number of words used, i.e. the size of the dictionary. W2V, on the other hand, is an extension of BoW, which overcomes the acknowledged disadvantages of the initial technique. The length of the W2V vector is limited to a fixed number of words and focuses on the most frequent ones occurring in the text while leaving out the most unusual ones. The analysis was performed on financial reports using both methods. The best results were observed for W2V, whilst BoW demonstrated the highest recall (77%), which is significant in the context of audit work. In conclusion, BoW proves effective in the area of fraud detection.

Zafari and Ekin (2019) investigated a case of prescription fraud by using topic modelling (TM) on the Medicare Part D prescription data (a US prescription drug policy). TM is a statistical model which analyses a text in order to find hidden semantic patterns among words. This approach involves clustering used in text analysis. Related words are assigned to the same topic (cluster) creating a semantic group, which makes the text more interpretable from the computational point of view. TM can be extended to other algorithms, e.g. LDA, which was done by Zafari and Ekin (2019). The outcome of the analysis indicated suspicious prescriptions based on some discrepancies in the distribution of the detected topics. The results can help medical investigators to identify prescription fraud during audits.

Artificial neural networks (ANNs) is one the methods investigated by Ekin et al. (2021). ANNs are biologically inspired computing systems imitating information processing which occurs in real neurones. They are built of at least three layers: the input layer, the hidden layer(s) and the output layer. A single-layer ANN is called a perceptron. This solution can be considered either as supervised, unsupervised or even reinforcement learning depending on the analysed case; this part of the review, however, focuses on unsupervised techniques. The ANN technique is a powerful tool that is commonly used in data analytics. Ekin et al. utilised ANNs for detecting fraud in healthcare. ANNs handle noisy data with great efficiency. They work best on smaller datasets with a low variety of hidden patterns. ANNs are vulnerable to overfitting and imbalanced data, which necessitates data pre-processing.

The issue of imbalanced data, i.e. the low number of cases labelled as fraudulent within the whole dataset, and ways of handling such data was raised by Fiore et al. (2019). They proposed generative artificial networks (GANs) to improve the classification effectiveness in the context of credit card fraud detection. The analysis was performed on a publicly available dataset concerning credit card fraud. Technically, GANs are multi-layer ANNs composed of two models – generative and discriminative – which compete against each other. The whole model is used to mimic the minority class generating synthetic datapoints. Learning data patterns and generating synthetic data take place all at once with the aim of obtaining examples indistinguishable from the original class as a form of training for the classifier. The generator attempts to cheat the discriminator using its feedback to create new instances similar to the original one. Subsequently, the new examples can be merged with the original ones into an augmented training dataset. The classifier trained on this set outperforms the classifier trained on the original data, thus increasing the efficiency of fraud detection and improving the sensitivity of the classifier.

Bach, Vlahović et al. (2020) investigated the occurrence of fraud in the leasing industry. They performed clustering by using the self-organising map (SOP), also called the Kohonen map or the Kohonen neural network. The research was based on a client database containing leasing contract details. The method involves searching for similarities among datapoints and organising the neurons in the hidden layer into clusters associated with the pattern hidden among the data. The SOP is also an example of competitive learning. Nodes in the neurones compete to represent the pattern and their performance is described with a neighbourhood function. The function decreases according to the distance to the winning node. Nodes with weight which are the closest to the input vector win. Then, their neighbours have their weights updated when moving towards the input pattern. Finally, the displacement of the nodes and their neighbours leads to obtaining clusters whose number corresponds to the grid size. A higher level of accuracy is observed when the number of clusters is below eight. The results were analysed according to the involved categories and their contribution to each cluster. The fraud gradation among clusters proves informative in the context of implementing preventive actions. Cluster characteristics help define customer profiles and predict the potential behaviours and risks among the groups. Experts from the leasing industry confirmed that these results add value to day-to-day business operations and improve planning both at the tactic and strategic levels.

Table. Summary of fraud detection methods

Method	Reference	Source of data	Data category	Purpose
Pre-processing				
SMOTE	Ekin et al. (2021)	Healthcare payment claims	Real-world data	Balancing data
MMWOTE				
RWO				
Random undersampling				
PCA				Dimensionality reduction
Kernel density estimation	Kamalov (2020)	NA	Simulated data	Balancing data
ADASYN				
NearMiss				
Random oversampling				
Feature engineering	Przekop (2020)	New customers' bank application	Real-world data	Dimensionality reduction
Supervised learning				
Linear discriminant analysis	Ekin et al. (2021)	Healthcare payment claims	Real-world data	Classification
Quadratic discriminant analysis				
Decision trees				
Random forest				
	Wang and Xu (2018)	Vehicle insurance claims		
SVM	Zhang et al. (2022)	Financial reports		Classification into two classes and regression
	Wang and Xu (2018)	Vehicle insurance claims		
k-nearest neighbours	Ekin et al. (2021)	Healthcare payment claims		Classification
Naïve Bayes	Zhang et al. (2022)	Financial reports		
	Ekin et al. (2021)	Healthcare payment claims		
Logistic regression + LASSO regularisation	Höppner et al. (2022)	Card transactions		Classification with better performance than w/o regularisation
	Przekop (2020)	New customers' bank applications		
Gradient tree boosting	Höppner et al. (2022)	Credit card transactions		Classification and regression
XGBoost	Farrugia et al. (2020)	Transaction history (Ethereum network)		
Time series	Rousseeuw et al. (2019)	Trade data / airline data		Forecasting
Multi-objective genetic algorithm	Srinivasan and Kamalakannan (2018)	Credit card and credit applications		Classification

Table. Summary of fraud detection methods (cont.)

<table>
<tr><th>Method</th><th>Reference</th><th>Source of data</th><th>Data category</th><th>Purpose</th></tr>
<tr><td colspan="5">Unsupervised learning</td></tr>
<tr><td rowspan="2">Benford's law</td><td rowspan="2">Barabesi et al. (2021)</td><td>NA</td><td>Simulated data</td><td rowspan="2">Distribution analysis</td></tr>
<tr><td>Customs declaration</td><td rowspan="7">Real-world data</td></tr>
<tr><td>CHAID</td><td rowspan="2">Bach, Ćurlin et al. (2020)</td><td rowspan="2">Working-hours claims and project characteristics</td><td>Classification</td></tr>
<tr><td>Link analysis</td><td>Association rules</td></tr>
<tr><td>k-means clustering</td><td rowspan="2">Abdul Jabbar and Suharjito (2020)</td><td rowspan="2">Call detail records (telecommunication)</td><td rowspan="4">Classification</td></tr>
<tr><td>DBSCAN</td></tr>
<tr><td>Two-step clustering</td><td>Esen et al. (2019)</td><td>Stock market transactions</td></tr>
<tr><td>Multi-attribute group decision-making method (fuzzy-logic-based)</td><td>Eshghi and Kargari (2019)</td><td>Bank transactions</td></tr>
<tr><td>Markov random field (CSBD)</td><td>Majadi et al. (2019)</td><td>Auctions (synthetically generated)</td><td>Simulated data</td><td>Clustering</td></tr>
<tr><td>Laten Dirichlet allocation</td><td>Wang and Xu (2018)</td><td>Vehicle insurance claims</td><td rowspan="7">Real-world data</td><td>Classification</td></tr>
<tr><td>Word2Vec</td><td rowspan="2">Zhang et al. (2022)</td><td rowspan="2">Financial reports</td><td rowspan="2">Association rules</td></tr>
<tr><td>Bag-of-Words</td></tr>
<tr><td>Topic modelling</td><td>Zafari and Ekin (2019)</td><td>Medicare Part D prescription data</td><td>Classification and association rules</td></tr>
<tr><td>ANN</td><td>Ekin et al. (2021)</td><td>Healthcare payment claims</td><td rowspan="3">Clustering</td></tr>
<tr><td>GAN</td><td>Fiore et al. (2019)</td><td>Credit card transactions</td></tr>
<tr><td>Kohonen neural networks</td><td>Bach, Vlahović et al. (2020)</td><td>Leasing contracts</td></tr>
</table>

Note. NA – not applicable.
Source: authors' work.

4. Conclusions

The objective of the systematic literature review presented in this paper was to identify and discuss fraud detection methods that are used in finance and related areas. We were looking for methods based on algorithms utilising statistical knowledge in order to delve into and analyse various kinds of data containing examples of fraudulent activity. Finance and related fields indicated the direction of the search, as they handle big data sets and often use analytical solutions. Generalising data to pure numbers without a context, we can see that the tools already adopted in some areas might also be applied to others. The risk of fraud exists not only in the financial sector, but in CTs as well. Large volumes of data generated by CTs would benefit from being subjected to identified algorithms in order to release the substantial information currently hidden inside them. Our review yielded a set of quantitative methods that were divided into three categories, according to the characteristics of data threatened with fraudulent activity.

The first category comprises pre-processing techniques which are used to prepare imbalanced data for further analysis improving the performance of the applied model. Of course, not all of these methods are sensitive to data imbalance, but the issue must not be neglected. The incidence of fraudulent activities is believed to be usually very low, but its oversight may cause appreciably negative effects. If we ignore the pre-processing, the accuracy of the performed analysis might decrease. Misleading results support wrong decisions that implicate further negative consequences for decision-makers. In the context of CTs, the issue of using unsupervised learning may be a challenge because of a shortage of labelled data. However, it is possible to build a classifier on historical data which could be applied to future studies using data of a similar specificity. Moreover, CTs are embedded in a multivariate space, which allows the reduction of their dimensionality. It can be done not only by means of PCA, but also FE, which needs deeper knowledge about the study to select sensible predictors.

The second category consists of supervised techniques. The key characteristics of these methods is that they need data labelled either as fraudulent or non-fraudulent. However, meeting this condition might be problematic, considering the usual circumstances of committing fraud and the lack of historical data-driven methods for its detection. Therefore, the availability of *a priori* knowledge about which cases are fraudulent and which are not is limited. For this reason, supervised techniques are unlikely to be applicable in CTs, where the knowledge about fraud is usually hidden or unproven. It should be remembered that only supervised algorithms are compatible with the pre-processing ones, as both kinds need knowledge about which data points are fraudulent and which are not. It is then pre-labelled data which makes the application of these kinds of algorithms possible. However, in order to point out fraudulent cases among clinical data, expert knowledge or deep insight into the study specifics and/or a therapeutic area is necessary as well.

The third category, unsupervised techniques, is the largest. These techniques seem to be most useful when only unlabelled data – the most common in CTs – are available. Unsupervised algorithms usually rely on clustering, which leads to obtaining subsets with more homogeneous profiles. The outcome of the application of unsupervised methods enables the indication of cases which might be fraudulent. Basic tools like *k*-MC or Benford's law are a must-have in CTs, but there are also other methods that look promising, such as Markov-random-field-based algorithms or text-mining techniques. The former might be treated as a more sophisticated improvement to clustering algorithms, while the latter seem to be useful in making clinical reports more time-efficient.

The identified methods should be verified in the context of their utility in CTs. There are other methods already used in this area, but mostly they are simpler algorithms relying on a traditional multivariate analysis (Kirkwood et al., 2013; Venet et al., 2012). What has to be remembered is the fact that the impact of fraud erodes confidence in clinical research, and better-performing, more robust analyses are required to ensure that high-quality medicines are offered on the market. In addition, regulators' requirements are becoming increasingly strict, which obliges drug manufacturers to develop more sophisticated solutions. Therefore, research into fraud detection methodologies for clinical data must continue, and the applicability of the identified methods must be further investigated.

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Appendix

Keywords used in the query:
(("fraud" OR "manipulation") AND "detection" AND ("machine learning" OR "data mining" OR "artificial intelligence" OR statistic* OR econometric*))

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Alternative investments during turbulent times – a comparison of dynamic relationships

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Abstract. The COVID-19 pandemic, like the Russian aggression against Ukraine, had a significant impact on many financial markets and asset prices. The latter additionally led to large fluctuations on financial markets. In our paper, we try to compare the performance of 'safe haven' assets during turbulent times, such as the recent global financial crisis, the eurozone debt crisis, the COVID-19 pandemic and the Russian aggression against Ukraine. We investigate the dynamic relationship between indices from several European countries (Czech Republic, France, Germany, Great Britain, Poland, Slovakia and Spain), and popular financial instruments (gold, silver, Brent and WTI crude oil, US dollar, Swiss franc and Bitcoin). The study further estimates the parameters of DCC or CCC models to compare dynamic relationships between the above-mentioned stock markets and financial instruments. The results demonstrate that in most cases, the US dollar and Swiss franc were able to protect investors from stock market losses during turbulent times. In addition, investors from France, Poland, the Czech Republic and Slovakia saw gold as a 'safe haven' asset throughout all the above-mentioned crises. Our findings are in line with other literature which points out that 'safe haven' instruments can change over time and across countries. In the literature, we can find research performed for the USA, China, Canada, and Great Britain, but there is no such research for Poland, France, the Czech Republic or Slovakia. The purpose of this paper is to try to fill this research gap.

Keywords: safe haven instruments, gold, silver, Bitcoin, dynamic correlation, global financial crisis, eurozone debt crisis, COVID-19 pandemic.

JEL: C6, C10, C32, C58, G11

1. Introduction

The world has witnessed several financial crises since the early 2000s. During the COVID-19 pandemic, the eurozone debt crisis and the global financial crisis we could observe huge falls in stock indices and fast changes in prices of many financial instruments. Also, we could see that prices of some instruments, like gold, might rise very quickly. In addition, increased volatility in the financial markets occurred, which was connected with high uncertainty and reduced risk appetite.

The first of the series was the European debt crisis, which began in 2008 with the collapse of Iceland's banking system. In 2009 it spread – mostly to Portugal, Italy, Ireland, Greece, and Spain (PIIGS). That crisis led to the loss of confidence in

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European businesses and economies. By the end of 2009, peripheral eurozone member states like Greece, Spain, Ireland, Portugal, and Cyprus were unable to repay or refinance their government debt (European Stability Mechanism, n.d.). Also in 2009, it turned out that the previous government of Greece had grossly underreported its budget deficit, thus violating the EU policy. This spurred additional fears regarding the stability of the euro and its potential collapse via political and financial contagion (Council on Foreign Relations, n.d.).

The global financial crisis (GFC), which lasted between mid-2007 and the beginning of 2009, was the second financial calamity that ravaged the global financial system. It was caused by a downturn in the US housing market. Its consequence was a crisis which spread from the USA to the rest of the world through links within the global financial system. Many banks all over the world suffered substantial losses and had to use governmental support to avoid bankruptcy. Millions of people lost their jobs as the major advanced economies experienced deepest recessions since the Great Depression of the 1930s. In addition, the recovery from the GFC was slower than in the case of past recessions, because unlike them, it had a financial background.

The COVID-19 pandemic was the third blow to several financial markets and asset prices, which in February 2022 was additionally aggravated by the Russian invasion of Ukraine. As a result, capital markets declined (as demonstrated by their main stock indices), while the prices of gold soared. Most of the European stock indices, especially in Central and Eastern Europe, plummeted. The same happened to European currencies, which depreciated against the US dollar. The prices of Russia- or Ukraine-produced commodities like crude oil, natural gas or wheat rose very fast (Fiszeder & Małecka, 2022).

The European Union, USA, UK, Canada, Switzerland, Japan, Australia and Taiwan imposed several sanctions on Russia. On 8 March 2022, US President Joe Biden signed an executive order banning imports of Russian oil, liquefied natural gas and coal to the United States (Morgan, 2022).

Meanwhile, the Russian ruble reached all-time lows. The Russian stock exchange closed on 25th February 2022 and has not re-opened since then (as of the time of writing this paper). The price of crude oil amounted to 130 USD per barrel (for the first time since 2008), and the gas price climbed to 200 euro per megawatt hour (Dutch TTF Gas Futures) at the beginning of March 2022. Gold prices were boosted by a 'safe haven' demand, and reached the highest level since August 2020.

Let us now look at Baur and Lucey's (2010) definitions of some related terms. According to these researchers, a 'hedge' is an asset that is uncorrelated or negatively correlated with another asset or a portfolio. A 'strict hedge' is an asset strictly negatively correlated with another asset or a portfolio. A 'diversifier' is an asset that is positively (but not perfectly) correlated with another asset or portfolio, whereas a ‘safe haven’ is an asset uncorrelated or negatively correlated with another asset or portfolio in times of market difficulties.

In turbulent times, risk-averse investors turn to precious metals as ‘safe haven’ assets. Interestingly, during the COVID-19 pandemic, and more specifically between January and March 2020, precious metals market fell. Prices of silver and platinum went down by 22% and 26%, respectively. Gold prices did not start rising until the 3rd week of March 2022. Prices of silver and other precious metals began to rebound later in 2020.

Traditionally, investors have used gold as a ‘safe haven’ asset (Baur and Lucey, 2010; Ji et al., 2020). Other precious metals like silver, palladium or platinum have been chosen less often, as their ‘safe haven’ properties seemed to last only over a short time-horizon (Bredin et al., 2017; Lahiani et al., 2021). Some literature finds ‘safe-haven’ properties of gold time-varying (Akhtaruzzaman et al., 2021; Shahzad, Raza et al., 2019) and market-specific (Beckmann et al., 2015; Shahzad, Bouri et al., 2019), while other studies question gold’s safe-haven properties at all (Baur & Glover, 2012; Dee et al., 2013; Klein, 2017).

According to Lucey and Li (2015), the ability of gold to play the role of a ‘safe haven’ asset changes over time. Baur and McDermont (2010) assert that gold can act as a ‘hedge’ or a ‘safe haven’ for major European and US stock markets, but not for other markets. Beckmann et al. (2015) also see ‘hedge’ and effective ‘safe haven’ properties in gold. According to Hood and Malik (2013), gold acts like a weak ‘safe haven’ and a strong ‘hedge’ asset on the US stock markets.

In addition to precious metals, currencies and commodities can also perform as ‘safe haven’ assets on financial markets. According to Ranaldo and Soderlind (2010), the Swiss franc and the Japanese yen often play that role during crises. Several other researchers agree with them regarding the Swiss franc, but also attribute ‘safe haven’ properties to the US dollar (Grisse & Nitschka, 2015; Kaul & Sapp, 2006; Ranaldo & Söderlind, 2010). Bouri et al. (2020) shows that the commodity index is a weak ‘safe haven’ for some stock indices. Commodities, such as crude oil (Xia et al., 2019), are reported to have been behaving differently since the 2008 global financial crisis (Wu et al., 2020). Będowska-Sójka and Kliber (2021) compare the ‘safe-haven’ properties of Ether and Bitcoin displayed during various market turbulences. Łęt and Siemaszkiewicz (2020) investigate the ‘safe-haven’ properties of Bitcoin, gold, and fine wine market against stocks.

This paper attempts to compare the performance of ‘safe haven’ assets during the global financial crisis, the eurozone debt crisis, and the period of the COVID-19 pandemic and the partially overlapping Russian aggression against Ukraine. The author investigates the dynamic relationship between the following European countries: the Czech Republic, France, Germany, Great Britain, Poland, Slovakia, Spain, and the popular instruments: gold, silver, Brent and WTI crude oil, US dollar, Swiss franc and Bitcoin.

2. Data and methodology

The research analysis was carried out using indices of the main stock exchanges, i.e. CAC40 (France), DAX (Germany), FTSE250 (Great Britain), IBEX35 (Spain), PX (Czech Republic), SAX (Slovakia) and WIG (Poland), as well as gold, silver, Brent and WTI crude oil, US dollar, Swiss franc and Bitcoin. We considered three periods: from 1st October 2007 to 31st of March 2009 (sample for the global financial crisis), from 1st January 2010 to 1st June 2012 (sample for the eurozone debt crisis), and from 3rd February 2020 to 30th June 2022 (sample for the COVID-19 pandemic and the Russian aggression against Ukraine). Price rates of metals and crude oil taken from the Thomson Reuters database are quoted in US dollars (continuous futures series). The rest of the data came from the Stooq portal (stooq.pl). We date-adjusted the time series for the observations of indices and metals for particular countries having taken into account holidays during which there was no trading. All the calculations used daily percentage logarithmic returns defined as $r_t = 100 \cdot \ln \frac{P_t}{P_{t-1}}$, where P_t denoted the price of an asset at time t.

Table 1 presents descriptive statistics for the rates of return series on gold, silver, Brent and WTI, US dollar, Swiss franc and Bitcoin, as well as for the CAC40, DAX, FTSE250, IBEX35, PX, SAX and WIG stock exchange indices, in all the studied periods. As regards the first sample (the global financial crisis), the mean value was close to zero: in three cases it was positive, and for the other ten instruments it was negative. The highest volatility as measured by the standard deviation was observed for WTI. The highest skewness was reported for SAX, and it was positive for six instruments. In the other seven cases it was negative, which indicates a long-left tail of the empirical distribution of returns. Surprisingly, the highest kurtosis was observed for SAX, which might be caused by a long period of observation.

In the case of the second period (the eurozone debt crisis), the mean value in eight instances was positive, and in six negative. The highest standard deviation was observed for silver. The highest skewness was reported for IBEX 35: in three cases it was positive, and for the other instruments it was negative. The highest kurtosis was observed for SAX.

As far as the last sample (the COVID-19 pandemic and the Russian aggression against Ukraine) is concerned, the mean value was close to zero: in four cases it was negative, and positive for the remaining instruments. The highest volatility as measured by the standard deviation was observed for WTI, the highest skewness for

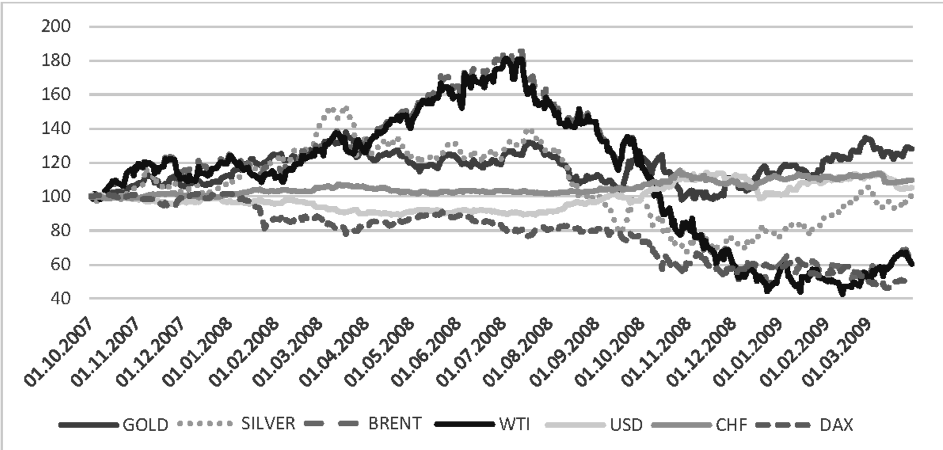
WIG, positive skewness for four instruments, and negative skewness in the remaining cases. The highest kurtosis was reported for WTI.

Table 1. Descriptive statistics for the rates of return series of the analysed instruments

Asset	Min	Max	Mean	St. dev.	Skewness	Kurtosis
Global financial crisis						
GOLD	−6.661	9.235	0.060	1.651	0.155	3.846
SILVER	−12.391	9.786	−0.002	2.473	−0.265	3.121
BRENT	−10.945	12.707	−0.118	3.375	−0.045	1.384
WTI	−12.959	18.587	−0.128	3.567	0.108	2.574
USD	−3.408	2.674	0.018	0.880	−0.355	1.732
CHF	−3.402	2.051	0.025	0.575	−0.691	5.895
CAC40	−9.472	10.595	−0.181	2.273	0.322	4.519
DAX	−7.433	10.797	−0.165	2.152	0.476	5.594
FTSE250	−6.735	7.462	−0.142	1.887	−0.020	1.232
IBEX35	−9.586	10.118	−0.156	2.210	0.145	4.053
PX	−16.186	12.364	−0.231	2.662	−0.337	7.819
SAX	−5.128	11.880	−0.066	1.167	2.403	33.396
WIG	−8.289	6.084	−0.239	1.840	−0.321	1.808
Eurozone debt crises						
GOLD	−5.390	3.568	0.063	0.968	−0.587	3.477
SILVER	−17.050	8.149	0.084	2.077	−1.309	9.164
BRENT	−8.790	5.465	0.032	1.699	−0.315	1.723
WTI	−8.700	5.928	0.003	1.867	−0.386	1.490
USD	−2.310	2.524	0.023	0.716	0.176	0.443
CHF	−8.450	3.035	0.033	0.741	−2.797	32.654
CAC40	−5.630	9.221	−0.046	1.586	0.046	3.056
DAX	−5.990	5.210	0.002	1.466	−0.215	2.124
FTSE250	−5.030	5.262	0.017	1.158	−0.402	1.976
IBEX35	−6.870	13.484	−0.108	1.765	0.508	6.007
PX	−6.130	7.249	−0.044	1.330	−0.272	3.352
SAX	−14.810	4.258	−0.053	1.283	−3.535	33.665
WIG	−6.240	4.579	−0.013	1.181	−0.658	3.851
COVID-19 pandemic						
GOLD	−5.114	4.961	0.020	1.047	−0.426	3.050
SILVER	−16.080	8.243	0.023	2.269	−0.873	7.645
BRENT	−27.976	19.077	0.112	3.395	−1.720	17.584
WTI	−56.859	22.394	0.121	4.728	−3.144	42.165
BITCOIN	−31.877	16.589	0.114	4.592	−0.842	5.989
USD	−1.527	2.485	0.007	0.451	0.173	1.523
CHF	−1.355	1.739	0.009	0.303	0.256	3.998
CAC40	−13.098	8.056	0.002	1.616	−1.013	10.798
DAX	−8.981	7.943	−0.003	1.649	−0.322	6.195
FTSE250	−9.820	8.039	−0.020	1.448	−0.687	8.482
IBEX35	−15.151	8.225	−0.024	1.653	−1.335	14.467
PX	−8.377	7.515	0.025	1.264	−1.176	9.923
SAX	−7.226	6.804	0.008	1.034	0.135	11.593
WIG	−11.347	7.433	−0.009	1.536	1.536	9.781

Source: author's calculations.

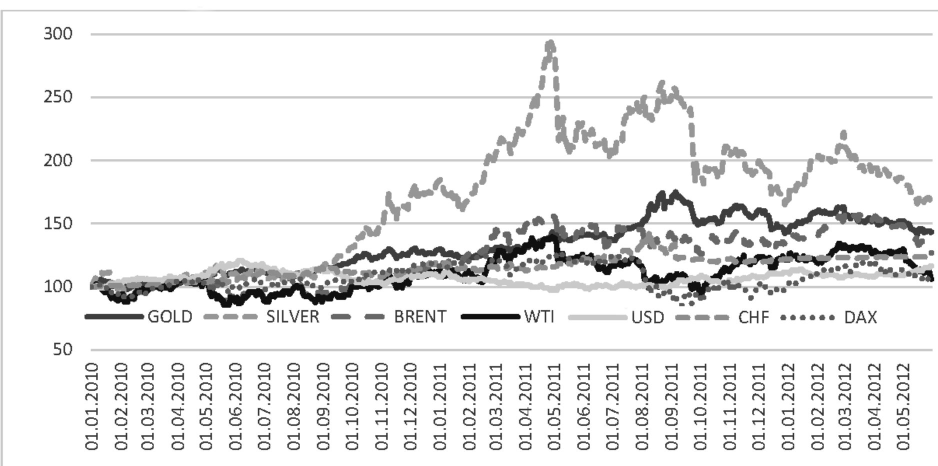
Figure 1. Normalised quotations of gold, silver, Brent, WTI, US dollar, Swiss franc and DAX during the global financial crisis



Source: author's calculations.

Figure 1 presents normalised quotations of gold, silver, Brent, WTI, US dollar, Swiss franc, and the DAX index in the period from 1st January 2007 to 31st March 2009. It shows that obtaining the highest value for investment in gold was possible at the end of the above-mentioned period. Also, the figure indicates the beginning of the downward trend in the value of the DAX index in early February 2008.

Figure 2. Normalised quotations of gold, silver, Brent, WTI, US dollar, Swiss franc and the DAX index during the eurozone debt crisis

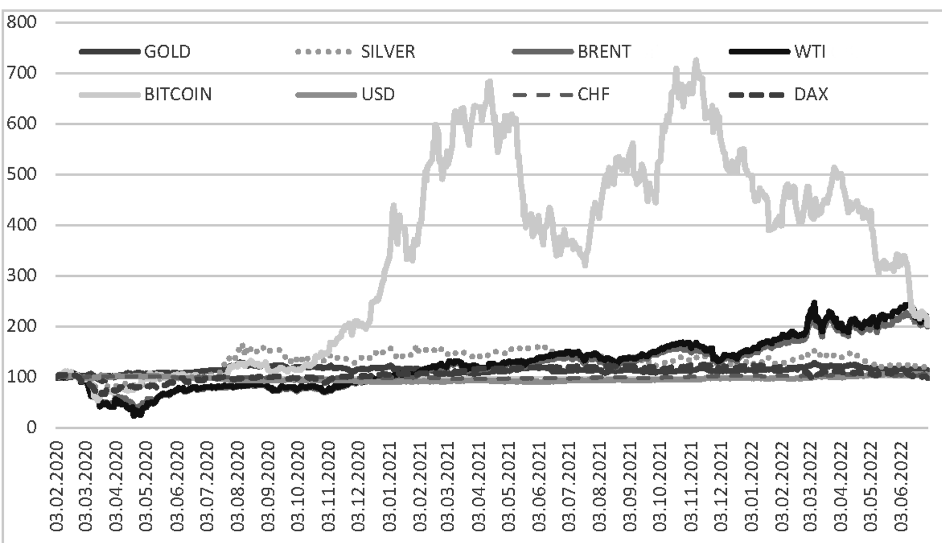


Source: author's calculations.

Figure 2 presents normalised quotations of gold, silver, Brent, WTI, US dollar, Swiss franc, and the DAX index in the period from 1st January 2010 to 1st June 2012. It shows that it was possible to obtain the highest value for investment in silver at the end of the studied period. The figure also indicates the fall in the value of the DAX index at the beginning of August 2011, caused by the European financial regulator's announcement of a ban on all forms of short selling among banks and other financial institutions. The ban was imposed as a result of growing instability on markets, initialled by rumors of French banks risking downgrades and by the concerns of various European banks linked to indebted economies such as Greece.

Figure 3 presents normalised quotations of gold, silver, Brent, WTI, US dollar, Swiss franc, Bitcoin, and the DAX index in the period from 3rd February 2020 to 30th June 2022. According to Figure 3, it was possible to obtain the highest value for investment in Bitcoin at the end of the studied period, and Bitcoin quotations were subject to the most substantial changes.

Figure 3. Normalised quotations of gold, silver, Brent, WTI, US dollar, Bitcoin, Swiss franc and DAX during the COVID-19 pandemic



Source: author's calculations.

2.1. Dynamic conditional correlation and constant conditional correlation models

Let $Y_t = (y_{1,t}, \dots, y_{k,t})$ be the k −sized vector of observation at time *t*. The total number of observations is $n \in \mathbb{N}$. We assume that $E_{t-1}[\varepsilon_{i,t}] = 0$ and $E_{t-1}[\varepsilon_{i,t}, \varepsilon'_{i,t}] = H_t$. The dynamic conditional correlation (DCC) model of Engle (2002) reads:

$$Y_t = \mu_t + \varepsilon_t, \text{with } \varepsilon_t = \boldsymbol{H}_t^{1/2}\mathbf{z}_t, \tag{1}$$

$$\boldsymbol{H}_t = \boldsymbol{D}_t \boldsymbol{R}_t \boldsymbol{D}_t \tag{2}$$

$$\boldsymbol{D}_t = \operatorname{diag}\left(\sqrt{h_{11,t}}, \dots, \sqrt{h_{kk,t}}\right), \tag{3}$$

where μ_t is the k-dimensional conditional mean structure, $\boldsymbol{H}_t$ denotes the $(k \times k)-$ sized conditional variance matrix, $\mathbf{z}_t$ is a k-dimensional vector of independent and identically distributed random variables with zero mean and unit variance, $\boldsymbol{R}_t$ is the dynamic correlation matrix of size $(k \times k)$ from which we obtain the time-varying correlation coefficient estimates, and $\boldsymbol{D}_t$ is the diagonal matrix of conditional standard deviations of ε_t. We assume that $\mathbf{z}_t \sim St - t_v(0, I_k)$. Let $z_{i,t}$ denote the standardised residual with respect to the idiosyncratic volatility given as $z_{i,t} = \varepsilon_{i,t}/\sqrt{h_{ii,t}}$. The dynamic correlation matrix then decomposes to

$$\boldsymbol{R}_t = (\operatorname{diag} \boldsymbol{Q}_t)^{-1/2} \boldsymbol{Q}_t (\operatorname{diag} \boldsymbol{Q}_t)^{-1/2}, \tag{4}$$

where $\boldsymbol{Q}_t$ denotes the covariance matrix of the standardised residuals $z_t = \left(z_{1,t}, \dots, z_{k,t}\right)$. Engle (2002) introduced a GARCH (1,1)-like structure on the elements of $\boldsymbol{Q}_t = [q_{ij,t}]_{i,j=1}^{k,k}$ with

$$\begin{aligned} q_{ij,t} &\coloneqq \bar{\rho}_{ij} + \alpha\left(z_{i,t-1}z_{j,t-1} - \bar{\rho}_{ij}\right) + \beta\left(q_{ij,t-1} - \bar{\rho}_{ij}\right) = \\ &= \bar{\rho}_{ij}(1 - \alpha - \beta) + \alpha z_{i,t-1}z_{j,t-1} + \beta q_{ij,t-1}, \end{aligned} \tag{5}$$

which is a mean reverting as long as $\alpha + \beta < 1$, and where $\bar{\rho}_{ij}$ is the unconditional expectation of $q_{ij,t}$ with $\bar{\rho}_{ii} = 1$ for all $i = 1, \dots, k$. An estimator for the dynamic correlation is then obtained by calculating:

$$\begin{aligned} \rho_{ij,t} &= \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} = \\ &= \frac{\bar{\rho}_{ij}(1 - \alpha - \beta) + \alpha\xi_{i,t-1}\xi_{j,t-1} + \beta q_{ij,t-1}}{\sqrt{1 - \alpha - \beta + \alpha\xi_{i,t-1}^2 + \beta q_{ii,t-1}}\sqrt{1 - \alpha - \beta + \alpha\xi_{j,t-1}^2 + \beta q_{jj,t-1}}}. \end{aligned} \tag{6}$$

The difference between DCC and the constant conditional correlation (CCC; Bollerslev, 1990) models is shown in Equation (2), in which $\boldsymbol{H}_t$ is defined as

$$\boldsymbol{H}_t = \boldsymbol{D}_t \boldsymbol{R} \boldsymbol{D}_t, \tag{7}$$

where $\boldsymbol{H}_t$ is a conditional variance matrix and $\boldsymbol{R}$ is the constant conditional correlation matrix of process ε_t.

The vector GARCH (p, q) process of ε_t is defined as (Nakatani & Teräsvirta, 2008)

$$\boldsymbol{h}_t = \boldsymbol{a}_0 + \sum_{i=1}^{q} \boldsymbol{A}_i\, \varepsilon_{t-1}^{(2)} + \sum_{j=1}^{p} \boldsymbol{B}_j\, h_{t-j}, \tag{8}$$

where $\varepsilon_{t-1}^{(2)} = (\varepsilon_{1,t}^2, \dots, \varepsilon_{N,t}^2)', \boldsymbol{a}_0$ is a k-dimensional vector, and $\boldsymbol{A}_i$ and $\boldsymbol{B}_j$ are $(k \times k)$ matrices with elements such that $h_{ii,t}$ in $\boldsymbol{h}_t$ are positive for all *t*.

Equations (1), (2) and (8) jointly define the k-dimensional CCC-GARCH (p, q) model if $\boldsymbol{A}_i$ and $\boldsymbol{B}_j$ are diagonal for all *i* and *j*.

In 1986, Engle and Bollerslev proposed an integrated GARCH (IGARCH) model. Many studies have shown that the sum of the parameters in GARCH models is almost always close to unity. In the IGARCH model, we assume the sum of the parameters to be equal to one, which means that the return series is not covariance-stationary, and there is a unit root in the GARCH process (Jensen & Lange, 2007). Jensen and Lange pointed out that 'the conditional variance of the GARCH model converges in probability to the true unobserved volatility process even when the model is misspecified and the IGARCH effect is a consequence of the mathematical structure of a GARCH model and not the property of the true data-generating mechanism'.

The condition for IGARCH is $\sum_{i=1}^{q} \alpha_i + \sum_{i=1}^{p} \beta_i = 1.$ For the IGARCH model, Equation (5) assumes then the following form:

$$q_{ij,t} = (1-\lambda)\left(z_{i,t-1} z_{j,t-1} \right) + \lambda q_{ij,t-1}, \tag{9}$$

where $\lambda = 1 - \alpha = \beta$. Then the DCC model is called an 'Integrated DCC'.

The GJR-GARCH was proposed by Glosten et al. (1993). This model assumes the revelation of and taking into account the asymmetry properties of financial data by means of obtaining conditional heteroscedasticity (see Glosten et al., 1993). The general form of the GJR-GARCH (q, p) is

$$\sigma_t^2 = w + \sum_{i=1}^{q} (\alpha_i + \lambda_i\, I_{t-i}) \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2, \tag{10}$$

where I_{t-i} is an indicator function taking the value of one if the residual is smaller than zero and the value of zero if the residual is larger than or equal zero, i.e.

$$I_{t-i} = \begin{cases} 1 \text{ if } \varepsilon_{t-i} < 0 \\ 0 \text{ if } \varepsilon_{t-i} \geq 0 \end{cases}.$$

3. Results and discussion

This part of the paper presents the research results for the CAC40, DAX, FTSE250, IBEX35, PX, SAX, and WIG indices obtained using the methodology described earlier in the article. As mentioned before, we considered three periods: 1st October 2007 to 31st of March 2009 (sample for the global financial crisis), 1st January 2010 to 1st June 2012 (sample for the eurozone debt crisis), and 3rd February 2020 to 30th June 2022 (sample for the COVID-19 pandemic and the Russian aggression against Ukraine).

Table 2. Static correlation between the studied instruments for the period of 1 Oct 2007–31 March 2009

Instrument	GOLD	SILVER	BRENT	WTI	USD	CHF
SILVER	0.768	1				
BRENT	0.219	0.149	1			
WTI	0.177	0.137	0.817	1		
USD	–0.127	–0.099	–0.008	–0.006	1	
CHF	–0.065	–0.090	–0.231	–0.291	–0.057	1
DAX	**–0.150**	**–0.041**	0.024	0.028	**–0.027**	**–0.074**
FTSE250	**–0.093**	0.056	0.026	0.042	**–0.030**	**–0.080**
CAC40	**–0.173**	**–4.8E–05**	0.003	0.016	0.034	**–0.081**
IBEX35	**–0.163**	**–0.046**	**–0.003**	0.018	0.009	**–0.059**
WIG	**–0.016**	0.027	0.050	0.063	**–0.038**	**–0.091**
PX	0.132	0.015	0.341	0.283	**–0.051**	**–0.209**
SAX	0.027	**–0.003**	0.040	0.021	**–0.024**	0.006

Note. Numbers in bold indicate that the instrument can be considered as a 'safe haven' for a given asset.
Source: author's calculations.

Table 2 presents the static correlation between the studied financial instruments during the sample period for the global financial crisis. We can see that gold, the USD and the CHF were able to act like 'safe haven' instruments, and the correlation coefficient was negative (bold numbers).

Table 3. Static correlation between the studied instruments for the period of 1 Jan 2010–1 June 2012

Instrument	GOLD	SILVER	BRENT	WTI	USD	CHF
SILVER	0.727	1				
BRENT	0.130	0.234	1			
WTI	0.108	0.217	0.857	1		
USD	–0.109	–0.149	–0.431	–0.441	1	
CHF	0.070	–0.009	–0.214	–0.243	0.337	1
DAX	0.014	0.158	0.443	0.466	**–0.395**	**–0.205**
FTSE250	0.090	0.227	0.498	0.496	**–0.345**	**–0.178**
CAC40	0.019	0.158	0.467	0.470	**–0.409**	**–0.210**
IBEX35	**–0.028**	0.105	0.402	0.389	**–0.451**	**–0.245**
WIG	**–0.030**	**–0.034**	0.003	0.004	**–0.024**	0.029
PX	0.057	0.208	0.364	0.334	**–0.255**	**–0.164**
SAX	0.008	0.012	0.012	0.027	**–0.056**	0.008

Note. Numbers in bold indicate that the instrument can be considered as a 'safe haven' for a given asset.
Source: author's calculations.

Table 3 presents the static correlation between the analysed financial instruments during the sample period for the eurozone debt crisis. We can see that the USD and the CHF assume the role of a 'safe haven' here.

Table 4. Static correlation between the analysed instruments for the period of 3 Feb 2020–30 Jun 2022

Instrument	GOLD	SILVER	BRENT	WTI	BITCOIN	USD	CHF
SILVER	0.604	1					
BRENT	0.058	0.220	1				
WTI	0.008	0.191	0.837	1			
BITCOIN	0.054	0.250	0.198	0.162	1		
USD	–0.149	–0.126	0.081	0.078	–0.050	1	
CHF	0.086	0.056	–0.086	–0.051	–0.023	0.319	1
DAX	0.021	0.174	0.219	0.154	0.244	**–0.075**	**–0.094**
FTSE250	0.058	0.228	0.255	0.167	0.277	**–0.077**	**–0.113**
CAC40	**–0.022**	0.203	0.375	0.265	0.251	**–0.073**	**–0.150**
IBEX35	**–0.055**	0.127	0.290	0.202	0.292	**–0.028**	**–0.145**
WIG	0.087	0.155	0.120	0.075	0.268	**–0.063**	**–0.036**
PX	0.103	0.037	0.016	0.027	0.082	**–0.172**	**–0.112**
SAX	**–0.006**	0.019	**–0.024**	0.002	0.001	0.002	0.055

Note. Numbers in bold indicate that the instrument can be considered as a 'safe haven' for a given index.
Source: author's calculations.

Table 4 presents the static correlation between the studied instruments during the sample period for the COVID-19 pandemic. The USD and CHF were able to act like a 'safe haven' in that period. Gold displayed similar properties, but only for investors from France, Spain and Slovakia.

We obtained the estimation of DCC or CCC model parameters by means of OxMetrics professional program by Jurgen A. Doornik. Every consecutive table describes models which could be estimated.

Table 5. Parameter estimates of DCC or CCC models (the covariance part) of pairwise synchronised return data of a chosen instrument and the CAC40 stock index for the studied periods. Robust standard errors are available upon request

Instrument	**01.10-2007–31.03.2009**				
	Model	$\bar{\rho}$	α	β	ν
GOLD	DCC-IGARCH	**−0.855689**	0.435508	0.548063	35.437678
SILVER	DCC-IGARCH	0.864911	0.372007	0.610552	17.843321
BRENT	DCC-IGARCH	0.813531	0.363481	0.635019	28.651271
WTI	DCC-IGARCH	0.818750	0.356349	0.641856	27.722282
USD	DCC-GARCH	**0.007485**	0.167051	0.722181	5.217730
CHF					no model
	01.01.2010–01.06.2012				
	Model	$\bar{\rho}$	α	β	ν
GOLD					no model
SILVER					no model
BRENT					no model
WTI					no model
USD	DCC-GARCH	**−0.363442**	0.270696	0.729167	2.389826
CHF	DCC-GARCH	**−0.151098**	0.133705	0.866278	2.389103
	03.02.2020–30.06.2022				
	Model	$\bar{\rho}$	α	β	ν
GOLD	DCC-GARCH	**−0.011460**	0.011930	0.867722	5.278174
SILVER	DCC-GARCH	0.147659	0.013062	0.945512	4.323866
BRENT	DCC-GARCH	0.280304	0.027201	0.906151	4.820194
WTI	DCC-GARCH	0.258318	0.044729	0.835777	4.323945
BITCOIN	DCC-GARCH	0.115494	0.012011	0.938783	4.307042
USD	DCC-GARCH	**−0.091039**	0.010536	0.922120	6.868912
CHF	DCC-GARCH	**−0.104849**	0.040353	0.905463	5.556040

Note. Numbers in bold indicate that the instrument can be considered as a ‘safe haven’ for CAC40.
Source: author’s calculations.

Table 5 presents the parameters of DCC or CCC models of pairwise synchronised return data of a chosen instrument and the stock exchange index from France in the studied periods. The analysis of the first sample shows that gold and the USD (the bold number of $\bar{\rho}$) acted like ‘safe haven’ instruments. If we had been able to estimate the CCC model alone, we would have obtained only the values of $\bar{\rho}$ and ν. In the first sample, we could not estimate the parameters of the model for the CHF (no model in Table 2). If the number $\bar{\rho}$ is written in bold, it means that the instrument can be considered as a ‘safe haven’ for a given financial market. We received such estimations for the second sample (the eurozone debt crisis). Here the USD and the

CHF performed as 'safe haven' instruments. For the third sample (the COVID-19 pandemic and the Russian aggression against Ukraine) it was gold, the USD and the CHF.

During all the studied periods, we were able to observe changes in the 'safe haven' instruments. Parameter ν is the Student-t degrees of freedom, which is also highly significant for all the analysed markets.

Table 6. Parameter estimates of DCC or CCC models (the covariance part) of pairwise synchronised return data of a chosen instrument and the DAX stock index for the studied periods. Robust standard errors are available upon request

Instrument					
	01.10–2007–31.03.2009				
	Model	$\bar{\rho}$	α	β	ν
GOLD					no model
SILVER	DCC-IGARCH	0.747367	0.339874	0.637354	42.714842
BRENT					no model
WTI					no model
USD	DCC-GARCH	**0.017794**	0.225868	0.717877	6.044658
CHF	DCC-GARCH	**–0.279713**	0.237167	0.762818	6.121240
	01.01.2010–01.06.2012				
	Model	$\bar{\rho}$	α	β	ν
GOLD	DCC-GJR	0.100388	0.456954	0.539041	17.435560
SILVER	DCC-GARCH	0.872968	0.403194	0.586336	21.966551
BRENT	DCC-GJR	0.214342	0.448220	0.546723	29.576535
WTI	DCC-GJR	0.561504	0.395476	0.596793	32.800047
USD	DCC-GARCH	**–0.601568**	0.430806	0.557005	49.887258
CHF	DCC-GARCH	**0.002928**	0.311602	0.307095	4.937210
	03.02.2020–30.06.2022				
	Model	$\bar{\rho}$	α	β	ν
GOLD	DCC-GARCH	**0.012609**	0.024982	0.884302	5.255967
SILVER	DCC-GARCH	0.100165	0.045367	0.884028	4.510034
BRENT	DCC-GARCH	0.218921	0.087742	0.766783	5.065991
WTI	DCC-GARCH	0.196299	0.095173	0.760282	4.488492
BITCOIN	DCC-GJR	0.172001	0.022321	0.630662	4.776805
USD	DCC-GARCH	**–0.042095**	0.014063	0.945218	7.509458
CHF	DCC-GARCH	**–0.044364**	0.006699	0.976591	5.405469

Note. Numbers in bold indicate that the instrument can be considered as a 'safe haven' for DAX.
Source: author's calculations.

Table 6 presents the parameters of DCC or CCC models of pairwise synchronised return data of a chosen instrument and the stock exchange index from Germany for the analysed periods. We can observe that for the first sample (the global financial crisis), the CHF acted as a 'safe haven' instrument, and the USD like a diversifier. We could not, however, estimate any model for gold, Brent or WTI crude oil, which means that the parameters were non-significant. For the second sample (the eurozone debt crisis), the USD and CHF played the role of 'safe haven' instruments. During the COVID-19 pandemic, German investors identified gold in addition to the USD and the CHF as 'safe haven' instruments.

Table 7 presents the parameters of DCC or CCC models of pairwise synchronised return data of a chosen instrument and the stock exchange index from Great Britain for the analysed periods. We can see that for the first sample gold, the USD and the CHF performed like 'safe haven' instruments. For the second sample, none of the analysed instruments were able to act as a 'safe haven'. In the last sample, it was the USD and the CHF that assumed that role. However, we could only estimate the CCC model for them.

Table 7. Parameter estimates of DCC or CCC models (the covariance part) of pairwise synchronized return data of a chosen instrument and the FTSE250 stock index for the analysed periods. Robust standard errors are available upon request

Instrument	01.10-2007–31.03.2009				
	Model	$\bar{\rho}$	α	β	v
GOLD	DCC-GJR	**−0.773008**	0.395823	0.592608	57.149371
SILVER	DCC-IGARCH	0.870617	0.417034	0.565477	55.851490
BRENT	DCC-IGARCH	0.974320	0.431575	0.548935	46.912669
WTI					no model
USD	DCC-GJR	**−0.777718**	0.415172	0.573252	133.804185
CHF	DCC-IGARCH	**−0.151108**	0.126566	0.873424	5.755777
	01.01.2010–01.06.2012				
	Model	$\bar{\rho}$	α	β	v
GOLD	DCC-GJR	0.922608	0.376621	0.603970	39.889827
SILVER	DCC-GJR	0.936172	0.421873	0.551708	38.252471
BRENT	DCC-GJR	0.905833	0.393996	0.589547	49.618297
WTI					no model
USD	DCC-GJR	0.408277	0.313151	0.686770	5.151887
CHF	DCC-GJR	0.202545	0.187833	0.812147	5.166961
	03.02.2020–30.06.2022				
	Model	$\bar{\rho}$	α	β	v
GOLD	DCC-GARCH	0.061356	0.012497	0.952665	6.429651
SILVER	DCC-GARCH	0.167862	0.027387	0.932724	5.121025
BRENT	DCC-GARCH	0.217322	0.037338	0.864430	5.414050
WTI	DCC-GARCH	0.191069	0.050345	0.822635	4.703665
BITCOIN	DCC-GARCH	0.191768	0.057980	0.444974	5.016487
USD	CCC	**−0.128980**			9.000909
CHF	CCC	**−0.112000**			6.465939

Note. Numbers in bold indicate that the instrument can be considered as a 'safe haven' for FTSE250.
Source: author's calculations.

Table 8 presents the parameters of DCC or CCC models of pairwise synchronised return data of a chosen instrument and the stock exchange index from Spain for the analysed periods. The table shows that for the first sample, the USD and the CHF were ‘safe haven’ instruments. For the second sample, all the considered instruments besides gold and silver acted like a ‘safe haven’. We were not able to estimate any model for them, which means that the parameters were non-significant. As regards the last sample, gold, the USD and the CHF assumed the role of a ‘safe haven’.

Table 8. Parameter estimates of DCC or CCC models (the covariance part) of pairwise synchronised return data of a chosen instrument and the IBEX35 stock index for the studied periods. Robust standard errors are available upon request

Instrument	**01.10–2007–31.03.2009**				
	Model	$\bar{\rho}$	α	β	v
GOLD					no model
SILVER	DCC-IGARCH	0.864608	0.393670	0.586732	26.478605
BRENT	DCC-IGARCH	0.952832	0.342216	0.650269	69.919609
WTI	DCC-IGARCH	0.948066	0.392836	0.596922	72.438051
USD	DCC-IGARCH	**–0.140535**	0.144989	0.854918	6.435076
CHF	DCC-GARCH	**–0.153448**	0.136317	0.863666	5.802824
	01.01.2010–01.06.2012				
	Model	$\bar{\rho}$	α	β	v
GOLD					no model
SILVER					no model
BRENT	DCC-IGARCH	**–0.823470**	0.350473	0.642149	18.957779
WTI	DCC-GARCH	**–0.721551**	0.368481	0.619947	20.007171
USD	DCC-GARCH	**–0.744959**	0.489767	0.479076	36.974216
CHF	DCC-GARCH	**–0.175427**	0.078289	0.921689	5.155858
	03.02.2020–30.06.2022				
	Model	$\bar{\rho}$	α	β	v
GOLD	DCC-GARCH	**–0.027057**	0.014252	0.884740	5.737603
SILVER	DCC-GARCH	0.051029	0.035763	0.890887	4.889897
BRENT	DCC-GARCH	0.201075	0.013149	0.977917	5.794954
WTI	DCC-GARCH	0.190250	0.040868	0.886720	4.991259
BITCOIN	DCC-GARCH	0.141693	0.050887	0.562657	4.784661
USD	DCC-GARCH	**–0.065973**	0.009620	0.911343	8.038629
CHF	DCC-GARCH	**–0.115954**	0.031190	0.901819	6.147031

Note. Numbers in bold indicate that the instrument can be considered as a ‘safe haven’ for IBEX35.

Source: author’s calculations.

Table 9. Parameter estimates of DCC or CCC models (the covariance part) of pairwise synchronised return data of a chosen instrument and the PX stock index for the studied periods. Robust standard errors are available upon request

Instrument	01.10.2007–31.03.2009				
	Model	$\bar{\rho}$	α	β	ν
GOLD					no model
SILVER	DCC-IGARCH	0.461011	0.531922	0.447429	14.932472
BRENT	DCC-IGARCH	0.779160	0.354647	0.641090	19.581309
WTI	DCC-GJR	0.849292	0.458906	0.521793	69.450220
USD	DCC-GJR	**–0.833320**	0.451201	0.531993	83.810415
CHF	DCC-IGARCH	**–0.564010**	0.379333	0.620657	6.382970
	01.01.2010–01.06.2012				
	Model	$\bar{\rho}$	α	β	ν
GOLD					no model
SILVER					no model
BRENT	DCC-IGARCH	**–0.383056**	0.500989	0.479729	41.086390
WTI	DCC-GARCH	**–0.645584**	0.336861	0.658189	67.495692
USD	DCC-IGARCH	0.448988	0.739845	0.259919	5.123791
CHF	DCC-GARCH	**0.002803**	0.090534	0.774052	3.152850
	03.02.2020–30.06.2022				
	Model	$\bar{\rho}$	α	β	ν
GOLD	DCC-GARCH	**0.038179**	0.013889	0.925150	5.395398
SILVER	DCC-GARCH	**0.014474**	0.019279	0.915615	4.895346
BRENT	DCC-GARCH	0.175833	0.059475	0.863947	5.297923
WTI	DCC-GARCH	0.178175	0.066614	0.844744	4.727693
BITCOIN	CCC	0.116920			4.682146
USD	DCC-GARCH	**–0.008366**	0.030781	0.909490	8.121857
CHF	DCC-GARCH	**–0.063639**	0.035200	0.737096	5.818132

Note. Numbers in bold indicate that the instrument can be considered as a 'safe haven' for PX.
Source: author's calculations.

Table 9 presents the parameters of DCC or CCC models of pairwise synchronised return data of a chosen instrument and the stock exchange index from the Czech Republic for the analysed periods. The USD and CHF turned out to be 'safe haven' instruments for the first sample (the global financial crisis). For the second sample (the eurozone debt crisis sample) it was silver, Brent, WTI and the CHF. We could not, however, estimate any model for gold. The analysis of the last sample (the COVID-19 pandemic) identified the USD and the CHF as 'safe haven' instruments, while gold and silver acted like diversifiers.

Table 10. Parameter estimates of DCC or CCC models (the covariance part) of pairwise synchronised return data of a chosen instrument and the SAX stock index for the studied periods. Robust standard errors are available upon request

Instrument	01.10-2007–31.03.2009				
	Model	ρ	α	β	v
GOLD	DCC-IGARCH	0.380580	0.532207	0.418066	14.480247
SILVER	DCC-IGARCH	0.872840	0.329076	0.649137	9.467602
BRENT	DCC-IGARCH	**–0.235311**	0.633031	0.292223	12.999959
WTI	DCC-IGARCH	**–0.112323**	0.692290	0.250241	10.650810
USD	DCC-IGARCH	0.824149	0.556674	0.443281	4.057933
CHF	DCC-IGARCH	0.693377	0.562151	0.437838	4.063121
	01.01.2010–01.06.2012				
	Model	ρ	α	β	v
GOLD	DCC-GJR	**–0.643940**	0.268954	0.729471	9.192191
SILVER	DCC-GARCH	**–0.677970**	0.271991	0.726189	11.312298
BRENT	DCC-GJR	**–0.659567**	0.265811	0.731917	11.699329
WTI	DCC-GARCH	**–0.476157**	0.337293	0.657481	11.367734
USD	DCC-GARCH	**–0.698326**	0.507687	0.451662	14.047624
CHF	DCC-EGARCH	**–0.184411**	0.360978	0.631185	16.040608
	03.02.2020–30.06.2022				
	Model	$\bar{\rho}$	α	β	v
GOLD	CCC	**–0.004145**			3.581142
SILVER	CCC	**0.010773**			3.377403
BRENT	CCC	**–0.013781**			3.771008
WTI	CCC	**0.008540**			3.466948
BITCOIN	CCC	**0.037810**			3.288803
USD	DCC-GARCH	**0.042724**	0.013815	0.946996	4.278525
CHF	CCC	0.073189			3.922210

Note. Numbers in bold indicate that the instrument can be considered as a 'safe haven' for SAX.
Source: author's calculations.

Table 10 presents the parameters of DCC or CCC models of pairwise synchronised return data of a chosen instrument and Slovakia's stock exchange index for the analysed periods. The first (GFC) sample indicated Brent and WTI as 'safe haven' instruments. Within the second (EDC) sample, all the studied instruments acted like a 'safe haven'. For the last (COVID-19 pandemic) sample, gold and Brent were identified as 'safe haven' instruments, while silver, WTI, Bitcoin and the USD behaved like diversifiers.

Table 11. Parameter estimates of DCC or CCC models (the covariance part) of pairwise synchronised return data of a chosen instrument and the WIG stock index for the analysed periods. Robust standard errors are available upon request

Instrument	**01.10-2007 – 31.03.2009**				
	Model	$\bar{\rho}$	α	β	v
GOLD	No model				
SILVER	DCC-GJR	**–0.018615**	0.286464	0.683628	6.580985
BRENT					no model
WTI	DCC-GARCH	**–0.845865**	0.248803	0.751086	32.588449
USD	DCC-GJR	**–0.423791**	0.436192	0.560037	32.740343
CHF	DCC-GARCH	**–0.862167**	0.605918	0.369927	3.950087
	01.01.2010 – 01.06.2012				
	Model	$\bar{\rho}$	α	β	v
GOLD	DCC-GJR	**–0.399642**	0.378022	0.619880	31.564120
SILVER	DCC-GJR	**–0.686526**	0.364487	0.632018	61.217814
BRENT	DCC-GJR	**–0.622894**	0.381311	0.615699	56.010843
WTI	DCC-GJR	**–0.305956**	0.323458	0.674095	28.673782
USD	DCC-GJR	0.412603	0.266950	0.731978	7.410154
CHF	DCC-EGARCH	**0.000015**	0.089062	0.910396	5.695479
	03.02.2020– 30.06.2022				
	Model	$\bar{\rho}$	α	β	v
GOLD	DCC-GARCH	0.072622	0.006643	0.905773	6.133009
SILVER	DCC-GARCH	0.153195	0.021415	0.850993	4.905963
BRENT	CCC	0.190343			5.632020
WTI	CCC	0.182339			4.904768
BITCOIN	CCC	0.198206			4.679099
USD	DCC-GARCH	**–0.045457**	0.013421	0.9222542	9.729939
CHF	DCC-GARCH	**–0.034920**	0.012046	0.790507	6.192595

Note. Numbers in bold indicate that the instrument can be considered as a ‘safe haven’ for WIG.
Source: author’s calculations.

Table 11 presents the parameters of DCC or CCC models of pairwise synchronised return data of a chosen instrument and Poland’s stock exchange index for the analysed periods. As regards the first sample, all the studied instruments except gold and Brent were able to act like a ‘safe haven’. For the second sample, gold, silver, Brent, WTI and the CHF were considered as ‘safe haven’ instruments, while for the last one, it was the USD and CHF.

Table 12. Number of countries (stock exchanges) in which we were able to identify the analysed instruments as a 'safe haven'

Instrument	**01.10–2007 – 31.03.2009**	**01.01.2010 – 01.06.2012**	**03.02.2020– 30.06.2022**
GOLD	2	2	4
SILVER	1	3	1
BRENT	1	4	1
WTI	2	4	1
BITCOIN	–	–	1
USD	6	4	7
CHF	5	6	7

Source: author's calculations.

Table 12 presents the number of countries in which the studied instruments were able to act like 'safe haven' assets during all the analysed time samples. The USD and the CHF were the dominant 'safe haven' instruments throughout the studied crises. We were also able to observe that 'safe haven' instruments were changing during different downturn periods. The largest number of the analysed instruments were identified as a 'safe haven' during the eurozone debt crisis, probably because all the countries were sampled from Europe. Surprisingly, in only one country (Slovakia), Bitcoin was considered as a 'safe haven' instrument. This might be the result of the specific characteristics of Bitcoin: during the COVID-19 pandemic, its quotations were subject to sharp fluctuations, while it is common knowledge that only those financial instruments can be considered a 'safe haven' that are not risky themselves.

4. Conclusions

During turbulent times such as financial crises or pandemics, searching for safe haven instruments becomes an important task for financial market investors. Due to the recent Russian aggression against Ukraine, we witnessed substantial hikes in the crude oil and natural gas prices, while at the same time stock indices were falling. Difficult times bring about great uncertainty.

This paper examined the performance of gold, silver, Brent, WTI, the USD and CHF as 'safe haven' assets during the global financial crisis, the eurozone debt crisis, and the COVID-19 pandemic combined with the war in Ukraine.

The results demonstrate that it was the USD and the CHF that were best able to protect investors from stock market losses during turbulent times. However, we could observe changes in 'safe haven' instruments throughout these crises. For example, during the eurozone debt crisis, silver, Brent, WTI, the USD and the CHF acted like a 'safe haven' for most of the analysed countries. Bitcoin, on the other hand, was considered as a 'safe haven' only by investors from Slovakia.

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Consumption-led expansions lead to lower future output growth

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Abstract. When assessing future growth prospects, does the current structure of demand matter, i.e. does it affect the future growth? This question is analysed in our paper using global and EU panel data. The result is quite striking: consumption-led growth – either in terms of private or public or total consumption – is slower than investment-led or exports-led growth. The same qualitative result is obtained irrespectively of the length of the past growth period (lag window), yet the more often the past is characterised by consumption-led growth, the slower the growth rate is in the future. In this context, our research provides important insights for both structural and cyclical policies.

Keywords: economic growth, demand management, consumption-led growth

JEL: E21, E32, E50, F43, O40

1. Introduction

In a crisis situation, it is almost always argued that some demand stimulus is necessary. More precise policy proposals are less often put forward, and if they are, they are motivated by practical or public policy reasons. But there are good reasons to think that 'just more demand' is not a sufficient recipe for an effective policy, as demonstrated e.g. by Kharroubi and Kohlscheen (2017). They show that consumption-led expansions of output tend to be significantly weaker than when growth is driven by other components of aggregate demand. Their analysis was based on forecasts from a model where the time path of output growth was predicted by consumption-led expansions and various controlling variables like house prices and household loans. It turned out that the slowdown of growth was particularly significant when important imbalances co-existed with the expansion of consumption. The fact that the structure of demand has important long-run consequences was also pointed out in Bughin et al. (2018). Additionally, the relatively large differences in fiscal multipliers (see e.g. Kilponen et al., 2015) with respect to different policy variables suggest that changes inside aggregate demand are all but trivial in terms of economic importance.

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In this paper, we concentrate on the comparative effects and focus not only on consumption, but on all demand components. We compare their impact on the future output growth. For that purpose, we carry out a horse-race test for the different demand components where we use the world and the EU data. Both data sets demonstrate that consumption-led economic expansions – public as well as private – result in a slower future output growth than investment- and exports-led expansions. The EU subsample of the world data is scrutinised separately, because it is likely to be less akin to outlier observations. Even though we use panel data, we focus solely on individual countries and ignore the potential cross-country spill-over effects (even though they are not trivial, see e.g. Ilori et al., 2022).

Why then should today's expansion of different demand components affect the future growth in different ways? To some extent, the answer is simple. Most of the consumption has no effect on productive capacity and thus on future output. An increase in consumption might even take place at the expense of savings, which lowers resources for the future consumption. In addition, consumption booms are often financed by debt, so eventually the debt-service costs are likely to depress consumption.[1]

Unlike consumption, investment increases productive capacity and output in subsequent periods, whereas income from exports makes it possible to expand capacity and output in the future. Higher exports growth might also signal higher export market shares that led to the continuation of growth of exports in future periods as well as to other side effects, particularly in productivity (see e.g. Shepherd and Haddad, 2011). The question of the pros and cons of exports-led growth has been under scrutiny for long, but no consensus among researchers seems to have been reached yet. Most analyses of this kind of growth focus on structural and long-term effects, which is slightly different than our analysis.

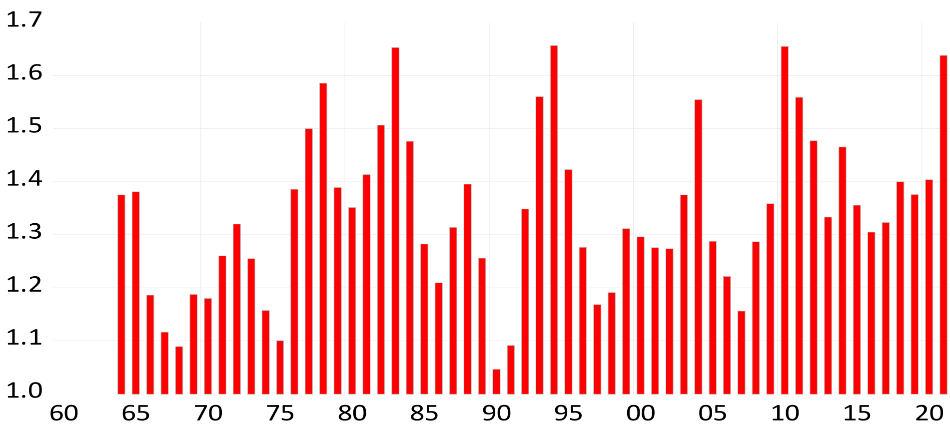
2. Empirical analysis

We apply the Kharroubi and Kohlscheen (2017) definition of consumption-led growth (or growth fuelled by some other component of demand) by selecting the observations where the growth rate of a specific demand component exceeds the growth rate of GDP in year $t-1$, or $t-2$ (in fact, Kharroubi & Kohlscheen use a three-year window for the expansion period). Altogether we analyse four demand components: private consumption, public consumption, (total) investment and

[1] This issue might actually be more complex, because some part of private and public consumption can be treated as investment (e.g. education, healthcare). On the other hand, residential investment does not necessarily have much impact on productive capacity or growth.

(total) exports. This gives us four indicator variables: cq, gq, iq and ex. For example, private consumption indicator cq is computed as $cq = 1$ if $100 * \Delta log(CQ) > 100 * \Delta log(GDP)$. We also use total consumption denoted by ca, which is used instead of private and public consumption in some specifications.

Figure 1. Number of consumption-led expansions in the world data



Note. The numbers are for a three-year period.
Source: author's calculation.

Figure 2. Mean values of indicator variables for three consecutive years

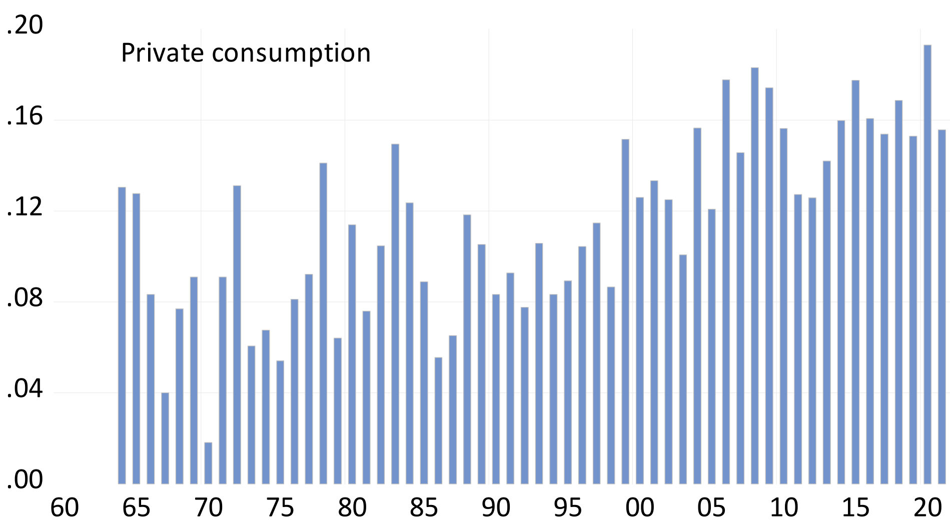
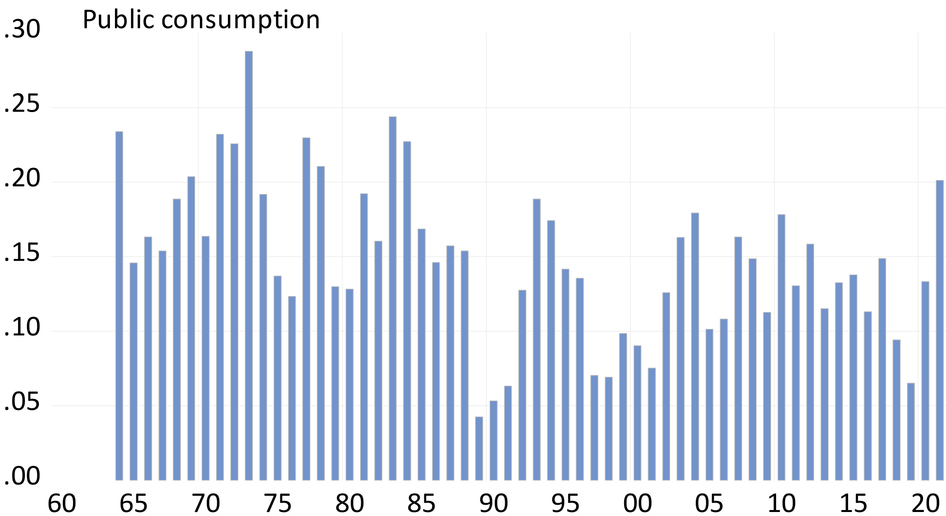


Figure 2. Mean values of indicator variables for three consecutive years (cont.)



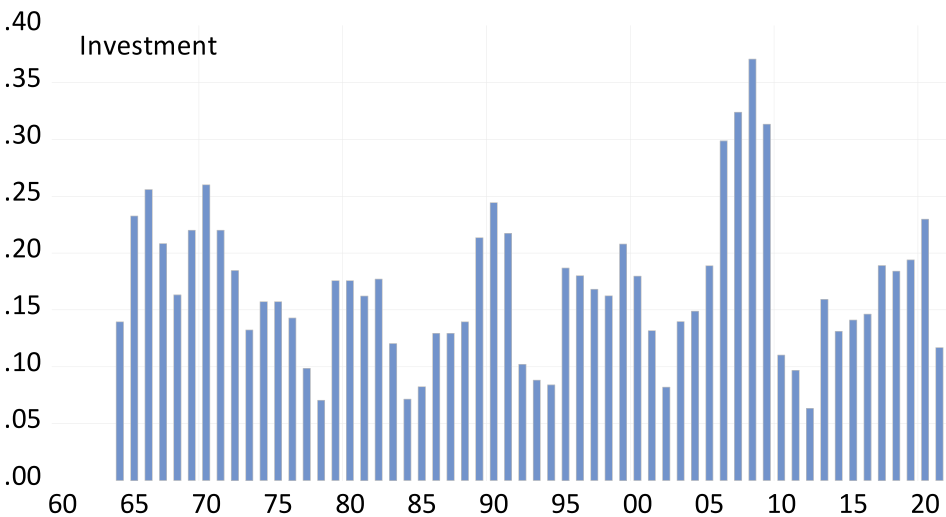
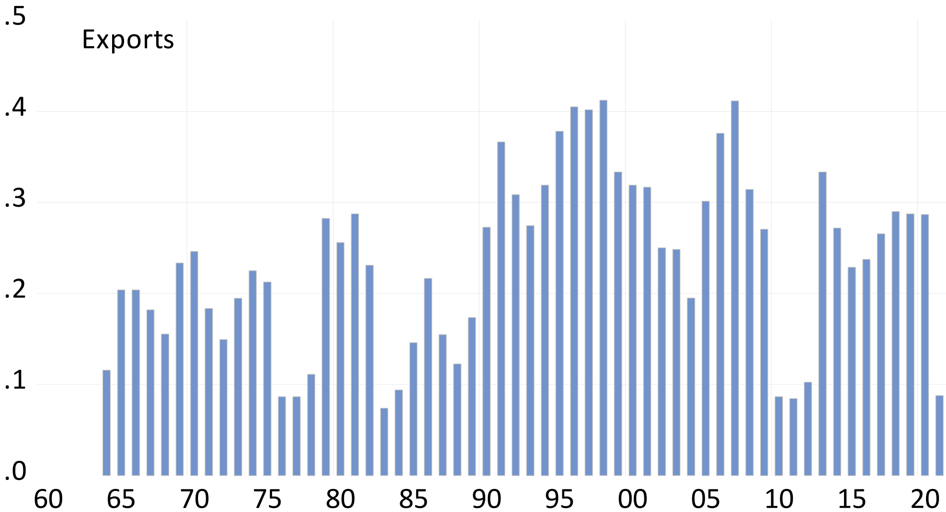


Figure 2. Mean values of indicator variables for three consecutive years (cont.)



Note. The values indicate the average share (in the cross-country panel) of cases where the growth rate of demand component x exceeded the GDP growth rate in all the three consecutive years prior to period t.
Source: author's calculation.

The average values of this indicator are presented in Figures 1 and 2, (there is a three-period lag window in each of them). Figure 1 presents the sum of periods in which the growth rate of demand component x exceeded the growth rate of GDP. In Figure 2, we show the share of cases where the above condition was met for three consecutive periods (years). The correlation matrix of indicator variables is shown in Table 1.

Table 1. Correlations between indicator variables

	cq	gq	iq	ex
cq	1.000			
gq	0.056	1.000		
iq	−0.177	−0.110	1.000	
ex	−0.091	−0.134	−0.052	1.000

Source: author's calculation.

Table 2. Type of demand growth pattern in current period

	gdp	$gdp > 0$	$gdp \leq 0$	gdp
cq	0.470	0.448	0.594	3.04
gq	0.484	0.438	0.745	1.53
ca	0.456	0.421	0.690	
iq	0.541	0.586	0.298	4.88
ex	0.589	0.607	0.495	3.49

Note. Values in columns 2–4 indicate how often (the share of all values of) growth rates of different demand components exceed the growth rate of GDP for all the values of GDP as well as for increasing and declining values of GDP. The last column shows the values of GDP in those cases where the growth rate of demand component x is higher than all the other demand components. Please note that GDP is not exactly the sum of demand components, because it is measured from the production accounts and there is always a statistical error between the production and the use accounts.

Source: author's calculation.

In Table 2, we show some descriptive statistics of the growth patterns of demand components. In short, this table shows that during economic depressions, growth is fuelled by consumption (private and public), while when GDP rises, growth is powered by investment and exports.

Subsequently we run a regression equation for the growth rate of GDP, such that the set of RHS variables consists of lagged values of the variables of this indicator (dummies) and the lagged value of the GDP growth rate, and the level of GDP *per capita* in USD is denoted by ytc plus fixed country and time effects. Thus, the estimating equation takes the following form:

$$gdp_{it} = \alpha_{0it} + \alpha_1 gdp_{it-1} + \alpha_2 cq_{it-1} + \alpha_3 gq_{it-1} + \alpha_4 ig_{it-1} + \alpha_5 ex_{it-1} + \\ + \alpha_6 log(ytc_{it}) + u_{it},$$

where u_{it} is the error term. As regards lags, we computed them up to five years, but only the values of the first two lags turned out to be significant. The (annual) data cover the period of 1960–2020.

Table 3. Sample mean values of GDP growth conditional to previous year's growth pattern

Demand component growth higher than GDP growth	World	EU	Demand component growth lower than GDP growth	World	EU
private consumption	3.27	2.74	private consumption	3.80	2.62
public consumption	3.34	1.98	public consumption	3.74	3.16
total consumption	3.09	2.34	total consumption	3.78	2.86
investment	4.03	3.13	investment	2.08	2.09
exports	3.70	2.71	exports	2.50	2.51

Note. Here, the private consumption row indicates the average GDP growth rate conditional to $cq_{t-1} > gdp_{t-1}$ (the first two columns) or $cq_{t-1} \leq gdp_{t-1}$ (the last two columns). Similar notation applies to other variables. The data cover the period of 1960–2021. The number of data points in the world panel data is 5,754, and 1,069 in the EU panel data. Please note that this condition does not exclude the possibility that at the same time, some other demand component grows faster (slower) than GDP. If this possibility is excluded, the results slightly change (in most part, the values for the consumption-led expansion decrease), see Figure A1, Appendix.

Source: author's calculation.

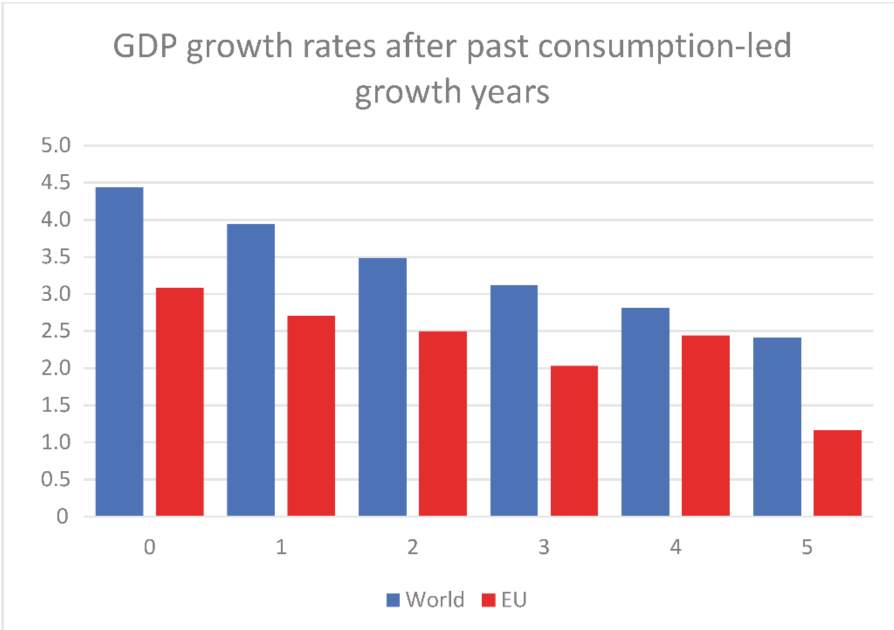
Some idea of the results might be obtained by scrutinising the conditional mean values of GDP growth with respect to different lagged values of demand components (Table 3). It can clearly be seen that GDP growth is lower following periods when the consumption growth (private or public) exceeded GDP growth. If we reverse the inequality condition in the sample selection, the results become almost opposite, indicating, for instance, that low-consumption growth periods are followed by high GDP growth periods. By the same token, periods of low-investment or low-exports growth are followed by those of low GDP growth (see Table 4 for details).

Table 4. Effect of the past demand structure on current and future demand growth

	GDP	CQ	GQ	CA	IQ	EX
Indicator variables lagged by 1 period, effect on the current period variable						
full sample	3.72	3.41	3.11	3.31	4.38	5.00
$cq_{t-1} > 0$	3.13	5.12	2.82	4.54	2.72	3.08
$gq_{t-1} > 0$	2.76	2.75	6.12	3.34	1.93	3.20
$ca_{t-1} > 0$	2.70	4.55	3.74	4.42	1.50	2.33
$iq_{t-1} > 0$	4.35	3.82	3.34	3.71	11.24	5.35
$ex_{t-1} > 0$	3.76	3.08	2.75	2.93	3.99	9.02
Indicator variables lagged by 3 periods, effect on the current period variable						
$cq_{t-1} > 0$	3.15	3.28	2.69	3.13	3.57	4.17
$gq_{t-1} > 0$	3.54	3.36	3.90	3.38	4.42	4.80
$ca_{t-1} > 0$	2.82	3.00	3.09	3.02	3.34	3.63
$iq_{t-1} > 0$	4.25	4.05	3.56	3.99	5.33	4.98
$ex_{t-1} > 0$	3.44	3.11	2.50	2.93	4.63	5.89
Indicator variables lagged by 3 periods, effect on the average of current and future (2 periods) variables						
$cq_{t-1} > 0$	3.05	3.16	2.90	3.00	3.97	4.34
$gq_{t-1} > 0$	3.45	3.51	3.70	3.31	4.73	5.15
$ca_{t-1} > 0$	2.95	3.33	3.10	3.08	4.12	4.11
$iq_{t-1} > 0$	3.95	3.93	3.84	3.83	4.82	5.21
$ex_{t-1} > 0$	3.25	3.21	2.77	3.00	4.53	5.43

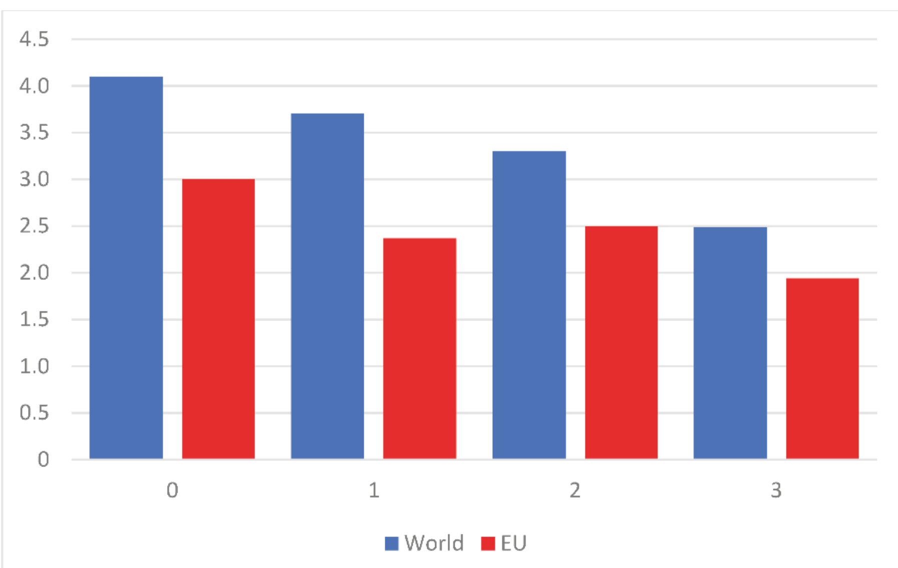
Source: author's calculation.

Figure 3. GDP growth and number of past years of consumption-led growth



Note. The x-axis indicates the number of years with consumption-led growth during the past five years.
Source: author's calculation.

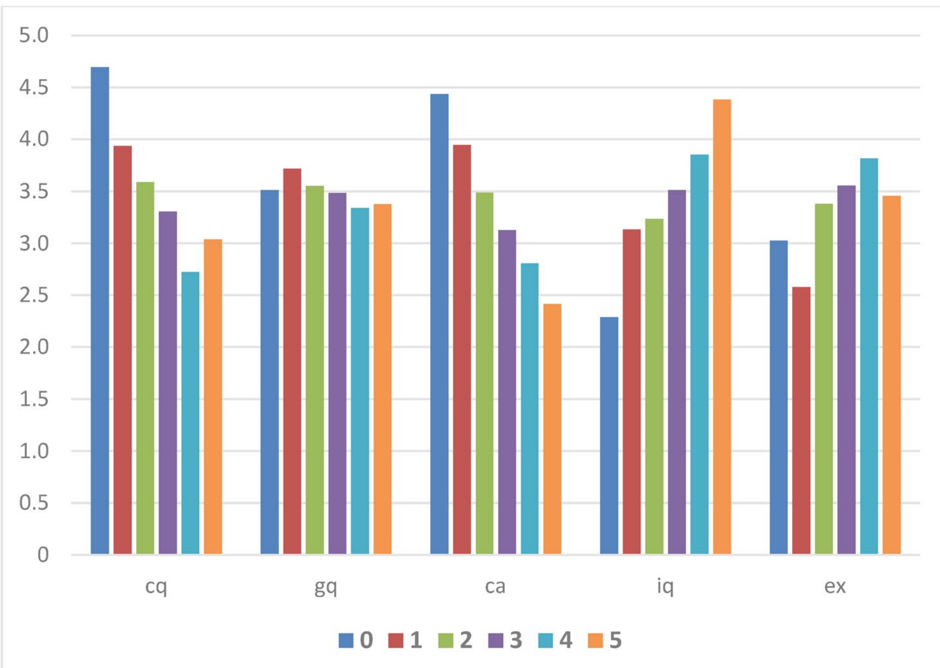
Figure 4. GDP growth and number (3) of past years of consumption-led growth



Note. This is the same as Figure 1, but computed with a three-year window.
Source: author's calculation.

The pattern does not really depend on the length of the lag window (see Figure 4 for values from a 3-year window). Thus we conclude that the more frequent consumption-led growth periods were in the past, the lower the subsequent output growth rate is. The figure illustrates the situation for total consumption, but the outcome is very similar for both the private and public consumption. Not surprisingly, the opposite outcome is the case when we focus on investment-led or exports-led growth. The more often they take place, the higher the growth rate in the future (see Figure 5).

Figure 5. GDP growth after all past demand-led growth years



Note. Figure 5 is the same as Figure 3 but includes all demand components (not only the effects of total consumption). Numbers 1–5 under the Figure denote consecutive future periods; 0 is the current period.
Source: author's calculation.

The same result is obtained when we estimate the model so that all the indicator variables of demand components are on the right-hand-side when using Equation (1). The model fits the data comparatively well (see the R^2s), given the fact that the explanatory variables are basically dummies. When estimating the equation, we included several additional control variables, but only the current value (not the lagged one) of the terms of trade turned out to be significant in the basic equation. However, it did not make any difference in terms of other coefficients.[2]

Table 5. Effect of different demand patterns on GDP growth

	World1	World2	World3	World4*	World5*	EU1	EU2	EU3	EU4*	EU5*
constant	−.077	−.068	−.084	−.088	−.051	−.228	−.220	−.293	−.301	−.289
	(2.53)	(2.28)	(2.67)	(2.56)	(1.50)	(2.45)	(2.38)	(3.17)	(3.00)	(2.69)
$cq_{t-1>0}$	.071		.004	−.013	−.080	.239		.234	−.095	−.071
	(0.60)		(0.03)	(0.20)	(1.59)	(1.47)		(1.42)	(0.93)	(0.86)
$cq_{t-2>0}$			.026					−.154		
			(0.22)					(0.93)		
$cg_{t-1>0}$	.247		.267	−.006	−.027	−.089		−.037	−.010	−.058
	(1.78)		(1.91)	(0.87)	(0.51)	(0.51)		(0.21)	(0.10)	(0.79)
$cg_{t-2>0}$			−.243					−.064		
			(2.01)					(0.34)		
$ca_{t-1>0}$		.108					.157			
		(0.89)					(0.91)			
$ca_{t-2>0}$										
$iq_{t-1>0}$	.675	.646	.644	.301	.181	.353	.325	.330	.139	.036
	(5.49)	(5.30)	(5.23)	(4.16)	(3.21)	(2.03)	(1.97)	(1.95)	(1.29)	(0.41)
$iq_{t-2>0}$			.258					−.028		
			(2.00)					(0.17)		
$ex_{t-1>0}$	.503	.527	.470	.353	.239	.463	.431	.384	.343	.194
	(3.80)	(4.10)	(3.59)	(4.49)	(4.05)	(2.18)	(2.05)	(1.85)	(2.81)	(2.03)
$ex_{t-2>0}$			.360					.346		
			(2.67)					(1.60)		
gdp_{-1}	.266	.247	.250	.239	.249	.315	.330	.291	.298	.306
	(6.80)	(6.41)	(5.91)	(5.87)	(5.69)	(5.34)	(2.92)	(4.73)	(4.58)	(4.67)
$log(ypc_t)$	1.124	1.022	1.189	1.157	.820	2.399	.001	3.037	3.087	2.985
	(3.11)	(2.91)	(3.19)	(2.98)	(1.80)	(2.57)	(2.92)	(2.26)	(3.05)	(2.78)
R^2	0.302	0.300	0.305	0.307	0.325	0.596	0.594	0.597	0.593	0.600
SEE	4.134	4.099	4.100	4.045	3.913	2.362	2.362	2.328	2.327	2.303
DW	1.959	1.984	1.920	1.908	1.924	1.970	2.001	1.913	1.926	1.891

Note. The dependent variable is GDP growth. All equations include country- and time-fixed effects. Numbers inside parentheses are robust t-values. Variables in columns 1–3 and 6–8, except for gdp and ypc, are indicator variables of the $(x_{t-1} - gdp_{t-1}) > 0$ type. cq refers to (the indicator for) private consumption (expansion), gq to (the indicator for) public consumption, ca to (the indicator for) aggregate consumption, iq to (the indicator for) investment, and ex to (the indicator for) exports. * In columns World4 and World5 as well as EU4 and EU5, the RHS variables are the number of years during which particular demand component x led past expansions during a 3-year or a 5-year period. The number of data points in the World panel data is 5,754, and in the EU panel data 1,069.

Source: author's computations.

[2] The respective t-value was 2.41. The variable could be motivated by the observation of Montiel (2000), which proves that it is the terms of trade alone that is the key determinant of consumption booms. We also had the lagged value of the (total) consumption/GDP share as a control variable, but its coefficients were not significant in any of the estimating equations, and thus it was not included in the final specification. The same outcome was obtained by introducing the lagged value of the standard deviation of the growth rate of different demand components or the lagged value of the current account/GDP ratio. We also constructed indicator variables so that the growth rate of the demand component is λ times larger than the growth rate of GDP. That did not make any noticeable difference to the results, either. The same was true when the sample was divided into two according to the $gdp > 0$ and $gdp \leq 0$ criterion. Moreover, we estimated the model by the (Huber) Robust estimator and the Quantile estimator, but the qualitative results did not change in any meaningful way. Finally, we estimated the basic equation World1 in Table 5 with GMM. The produced results were very similar to those with panel OLS (see column 5 in Table 6).

The results are reported in Table 5, which consists of five sets of equations (both for the world and the EU), i.e. a pair for one period lag effects (World1, EU1), a pair for aggregate consumption lagged effects (World2, EU2), a pair for one and two period lag effects (World3, EU3), a pair with the number of years for demand-component x-led growth with a three-year lag window (World4, EU4), and a similar pair, but with a five-year lag window (was World5, EU5). In almost all cases, we found that consumption-led periods were followed by either lower growth rates or the growth effect was simply zero (i.e. the coefficients were not statistically different from zero). This is especially clear when we consider aggregate consumption (ca) in the same way as in Table 2.[3] The future outcome is different for investment- and exports-led expansion periods. The effects for the first lagged year were all positive and significant, as were most of the second-year effects. Moreover, because we have the lagged dependent variable in the model, the long-run future effects do in fact go beyond two periods.

If we use a longer window for past values of demand growth following Kharroubi and Kohlscheen (2017), and instead of using individual indicator (dummy) variables, we count the number of years during which component x of the demand led growth, we receive more affirmative results, as shown in Table 5 (columns World4 and World5 as well as EU4 and EU5). The outcome is illustrated in Figure 3 for the (whole) consumption-led growth case. Quite clearly, consumption-led growth is disadvantageous for the future performance of the output growth. One reason for this is the fact that past consumption-led growth expansions result in higher consumption/GDP shares in the future, while higher exports-led expansions translate into much lower consumption/GDP shares in the future.

This is also indirectly demonstrated by the fact that when we estimate the equation for the future values of GDP growth (for gdp_{t+1} or gdp_{t+2} instead of gdp_t), the qualitative results remain approximately the same. So, the current 'demand policies' have long traces on the future growth performance. Similarly, if we use the average GDP growth rates for the periods of t, $t+1$ and $t+2$, or even t, $t+1$, $t+2$, $t+3$ and $t+4$ as the dependent variable, the effect of demand structure is more or less the same. It is only that in such a case, the importance of the negative effect of private consumption-led growth is more pronounced, and the investment-led growth effect less so (Table 6 and Figure 6).

[3] This is also true when we use five lagged values of the first difference of the consumption/GDP share as the only determinant of GDP growth in an alternative model specification (see Figure A2, Appendix). The five lags are clearly negative (although declining in size).

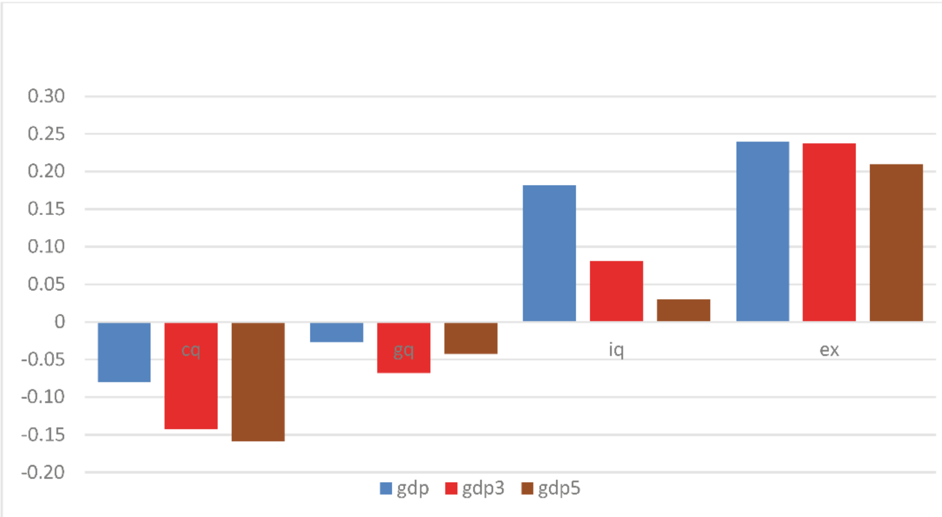
Table 6. Some additional estimates

	1	2	3	4	5	6
constant	7.680	7.213	21.117	29.516		−1.158
	(2.46)	(2.24)	(3.66)	(1.82)		(4.64)
$cq_{t-1}>0$	−.057	−.112	−.142	−.157	.985	.016
	(0.48)	(0.63)	(3.89)	(5.26)	(1.41)	(0.20)
$gq_{t-1}>0$	−.018	−.083	−.068	−.043	−.143	.097
	(0.12)	(0.46)	(1.82)	(1.39)	(0.24)	(1.19)
$iq_{t-1}>0$	.500	.396	.082	.030	4.452	−.291
	(3.90)	(2.65)	(1.84)	(0.88)	(9.86)	(3.57)
$ex_{t-1}>0$	.539	.385	.237	.210	3.767	−.3.08
	(4.34)	(2.91)	(5.75)	(5.98)	(6.25)	(3.82)
gdp_{t-1}	.251	.254	.112	.068	.207	.127
	(6.19)	(6.44)	(4.67)	(4.21)	(7.01)	(9.78)
log(ytc)	1.180	1.144	−2.181	−3.140	1.354	.003
	(3.19)	(2.99)	(8.38)	(14.52)	(4.51)	(0.11)
R^2	0.301	.306	0.368	0.460	..	0.061**
SEE	4.109	4.056	2.639	2.014	4.761	0.342
DW	1.925	1.943	0.688	0.419	0.872*	..
Dependent variable	gdp GR	gdp GR	average of 3 gdp GRs	average of 5 gdp GRs	gdp GR	Pr(gdp<0)
Indicator variables	for the past 2 consecutive yrs.	for the past 3 consecutive yrs.	sum of the past 3 x-led years	sum of the past 5 x-led years	past year	past year
Estimator	OLS	OLS	OLS	OLS	GMM	LOGIT

Notes: In columns 1 and 2, indicator variables equal 1 if the respective growth rate exceeds the growth rates of GDP for all 2 (or 3) consecutive years. In columns 3 and 4, the average growth rate of GDP for years t to $t+2$, or alternatively t to $t+4$, are the dependent variables. Indicator variables are the numbers or years the growth rate of demand component x exceeded the growth rate of GDP for the last five years. GMM estimates (with orthogonal deviations) are reported in column 5. * is the marginal probability of the *J*-statistic. The set or (additional) instruments include lagged consumption and investment ratios. Finally, Logit estimates for the probability of a depression (negative GDP growth) is reported in column 6. ** is the MacFadden pseudo R^2 value. All results are from the world panel data.

Source: author's computations.

Figure 6. Effect of demand structure on current and future GDP growth rates



Note. The values are coefficient estimates of the indicator variables. gdp denotes one-year growth, while $gdp3$ ($gdp5$) stands for the average growth rate for periods t, $t+1$ and $t+2$ (t, $t+1$, $t+2$, $t+3$, and $t+4$) in the estimating equation. In this equation, the RHS variables are the five-year sums of the indicator variable of the respective demand component (i.e. the number of years in which the growth rate of demand component x exceeded the GDP growth rate). The values of gdp correspond to column World5 in Table 3. The values of $gdp3$ and $gdp5$ have been computed in a similar way (see columns 3 & 4 in Table 4).
Source: author's calculations.

We also considered the effects of the persistent patterns of demand growth by constructing the indicator variables in such a way that they show whether the same type of demand-led growth continued over consecutive periods (years). The results are not significantly different from a one-year-lag case, except yielding a slightly weaker outcome for the consumption led-growth. It is interesting that according to Figure 2, the frequency of these cases grew over time in the cross-country panel. Could that be the explanation for the output growth rate deteriorating overall?

For the purposes of robustness, we used the Barro and Ursua (2010) historical data for 41 countries covering the period of 1790–2009 (with the average sample period of 112 years). The data are obviously very volatile, but the results were relatively similar to those presented above. This was particularly true when a robust (Huber) estimator was applied. The results are available upon request from the author.

Finally, we analysed how accurately it is possible to predict a depression (negative GDP growth in period t) on the basis of the past demand pattern while using a logit regression with the same RHS variables as in Equation (1). The results are reported in Table 6 (column 6), and they demonstrate that when growth in period $t-1$ is driven by investment or exports, the probability of a depression is much lower. If growth is fuelled by consumption in the past, the opposite holds true, but the results are relatively imprecise, so strong conclusions cannot be drawn. The same result applies if we look at longer time horizons or deeper depressions.

3. Conclusions

We have seen that the pattern of aggregate demand growth indeed affects the future values of GDP growth. Therefore, in difficult economic times, increasing demand cannot be proposed as the only remedy, because the structure of demand makes a significant difference, too. If aggregate demand growth is mainly consumption-led, the subsequent output growth rates are much lower than in the case where aggregate demand growth is fuelled by investment or exports. This should be kept in mind when public policies intended to boost output are drafted, as the ultimate goal is to obtain permanent results. Even though boosting consumption seems easier and quicker than doing the same with investment or exports, the latter should be preferred.[4] Our analysis does not mean that the level of consumption should permanently be kept low; it rather implies that excessive consumption booms should be avoided.

Acknowledgements

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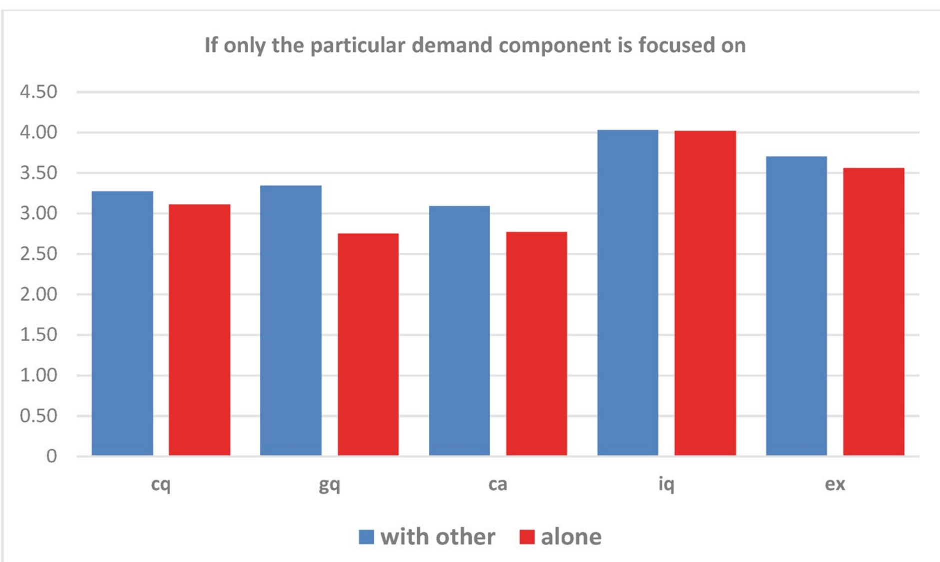
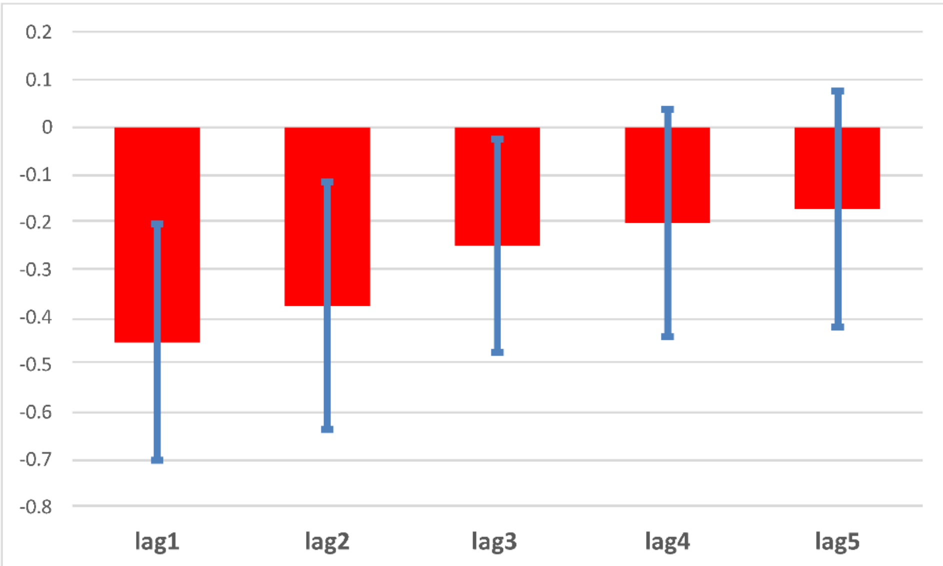
Appendix

Figure A1. Difference between demand component-led growth 'alone', and demand component-led growth with some other demand component



Source: author's calculation.

Figure A2. Coefficients of lagged values of first difference of aggregate consumption share (+/−2SD)



Note. Red bars denote the coefficient estimates and the blue lines the corresponding confidence intervals.
Source: author's calculation.

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In memory of Professor Maria Podgórska

Bartosz Witkowski[a]

Source: photo by Maciej Górski

On 2 December 2022, professor Maria Podgórska passed away unexpectedly at the age of 73. Her whole professional career was connected with the SGH Warsaw School of Economics (SGH). Professor Podgórska was a renowned and commonly liked scholar, known to the entire econometric society in Poland. Being her successor in the position of the director of the Institute of Econometrics at SGH, but most of all – having the honour of being her friend – I would like to share a few words about her brilliant research, and, most importantly about what kind of person she was.

Professor Podgórska obtained her PhD in 1976, then her post-doctoral degree in 1991, and the title of professor in 1999. The pace at which she earned the professorship is stunning, given that at the same time she was the director of the Institute of Econometrics at SGH (1993–2019), the head of the Probabilistic Methods Unit in the same institute (1994–2013) and the dean of the undergraduate studies at SGH (1992–1993). It should be emphasised that the organisational aspect of her job became additionally challenging at the beginning of the 1990s, when SGH was completely restructured.

At the same time, Professor Podgórska was an active teacher. She supervised numerous master theses and eight PhD theses. She actively taught a number of courses which concentrated on her scientific interests: econometrics, Markov models

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and their applications, probabilistic methods and financial mathematics. Since the aforementioned reform of the SGH, the students decide which courses to participate in and are free to select their teachers. It was a common occurrence that more students were willing to participate in Professor Podgórska's courses than the available number of seats permitted, despite the high level of her tests and exams. The students were well aware that participating in her lectures was worth the effort. She also co-authored seven handbooks, some of which were written in collaboration with her students or former students. This says so much about this incredible person: it was typical of her to co-operate with younger generations, to provide every possible opportunity to support them and, most of all, she strongly believed in them.

Last but not least, Professor Podgórska remained an active scholar throughout her professional life. Her scientific interests varied and, to some extent, transformed over time. At first her research mostly concentrated on probabilistic models and Markovian processes, then her interests gradually drifted towards financial and, in particular, actuarial mathematics. At the same time, she started collaborating with the Research Institute for Economic Development at SGH which lasted for over 25 years and resulted in a substantial number of publications based on the results of analyses of the economic situation mostly in Poland. She was the author and co-author of a few dozen articles and five monographs, which attests to the fact that her research was indeed extensive.

To me however, the above-mentioned facts are far less important than knowing what kind of person she really was. First of all, Professor Podgórska always appreciated and respected others. Rarely would she criticise others, never would she do any harm to anyone. In fact, the opposite was true: she would devote most of her energy to helping others. While her academic record is impressive, reaching the top of the scholar's career, it is worth noting not just *what* she achieved, but also *how* she did it and what she was able to do with it. As the director, she would always allocate the small budget that the Institute received to those who were working on their PhDs or post-doctoral degrees, allowing them to cover publication costs and participate in any necessary conferences.

She would pay particular attention to the youngest people she worked with. The pioneering initiative of writing a book together with her students is just one such example. At the same time, she always took all the possible measures to provide support to young scholars in their academic careers. One of her plans was for the young employees to take over the Institute of Econometrics. Step by step, young professors in their fourties or even thirties would become heads of units. Professor Podgórska believed that, just as the reform of the SGH at the beginning of the 1990s was performed by her and the then younger generation of scholars, it was also time for young scientists to decide about the school's future. Therefore, she resigned from the position of the director of the Institute as she felt it was high time to let the next generation take over, while she saw herself as a mentor and advisor. Professor Podgórska always supported her employees and showed her appreciation for the fact that the next generation is more knowledgeable in some areas than her and her generation. Others might find it a reason for envy, yet for her it was something to be proud of. She understood that it was the natural course of events – she would remain the mentor with extremely valuable experience and routine, while the younger generation, brought up in a computerised environment, would be technically more efficient and knowledgeable. While this mindset seems logical, it does not seem common among scientists. Was Professor Podgórska right to have adopted such a policy? Well, the Institute of Econometrics currently employs 7 university professors and 4 full professors in their fourties who are likely to conduct research for another 20 years and who reached their scientific goals thanks to her support. In addition to Professor Podgórska's publications, this is also part of her legacy.

She worked until September 2022 and decided that she would finally take some well-deserved rest. Still, we would spend a lot of time – sometimes hours – discussing different issues on the phone: university policies, politics, children, dogs... In fact, it would probably be easier to mention what we *did not* talk about rather than what we *did*. Her unusual intelligence, knowledge, respect for others and great sense of humour made her the perfect interlocutor. I will miss these talks just as much as I will miss her.

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Report from the 31st Scientific Conference of the Classification and Data Analysis Section of the Polish Statistical Association

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The 31st Scientific Conference of the Classification and Data Analysis Section (SKAD) of the Polish Statistical Association took place on 7–8 September 2022, in Warsaw, Poland. The conference was organised by the Classification and Data Analysis Section of the Polish Statistical Association and the Department of Econometrics and Statistics of the Warsaw University of Life Sciences. Basic information about the conference is available at: https://skad2022.conference.ieif.sggw.pl/.

Monika Zielińska-Sitkiewicz, PhD, was the chairman of the Organising Committee, consisting of Mariola Chrzanowska, PhD, Paweł Kobus, PhD, DSc, Joanna Landmesser-Rusek, PhD, DSc, Łukasz Pietrych, PhD, Ewa Wasilewska, PhD, Tomasz Woźniakowski, PhD, Dorota Żebrowska-Suchodolska, PhD, and Stanisław Jaworski, PhD.

The following topics were addressed during the conference:

- the theoretical aspects of taxonomy, discriminant analysis, linear ordering methods, multivariate statistical analysis, methods of analysing continuous variables, methods of discrete variables analysis, symbolic data analysis, graphical methods;
- the application of the financial data analysis, marketing data analysis, spatial data analysis, and other areas of data analysis application, i.e. in medicine, psychology, archaeology, etc., computer application of statistical methods.

The main objective of the SKAD conference was to present the current research and to create a platform for exchanging ideas related to the theoretical and applied

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aspects of classification and data analysis. This annually held forum provides an opportunity to present and promote state-of-the-art research and to indicate the possible directions for its development.

The conference featured 65 participants – faculty members and doctoral students of the following universities and institutions: WSB University at Dąbrowa Górnicza, Pomeranian University in Słupsk, Carnegie Mellon University, Rzeszów University of Technology, Warsaw University of Life Sciences, SGH Warsaw School of Economics, University of Economics in Katowice, Cracow University of Economics, Poznań University of Economics and Business, Wroclaw University of Economics and Business, University of Gdańsk, Adam Mickiewicz University in Poznań, Lodz University, Poznań University of Life Sciences, University of Szczecin, University of Wrocław, and the Statistical Office in Poznań.

During the conference, 30 presentations introducing research results on the theory and application of classification and data analysis were delivered in three plenary sessions and six parallel sessions. Six poster presentations were given during the poster session. The sessions were chaired by Józef Pociecha, Grażyna Dehnel, Marek Walesiak, Krzysztof Najman, Andrzej Dudek, Krzysztof Jajuga, Tomasz Klimanek, Jacek Batóg, Bolesław Borkowski.

Below is a list of all the papers presented during the conference:

- Grażyna Dehnel, Marek Walesiak, *Assessment of changes in the aging process of the population in the EU countries in 2001–2020 with the application of a dynamic relative taxonomy*;
- Andrzej Dudek, *Use of a synthetic control method (SCM) to estimate benefits and costs of Poland as a member of European Union*;
- Rebecca Nugent, *Optimizing and Clustering Data Science Workflows*;
- Grażyna Trzpiot, *Extended Gini regression coefficient as robust estimator of systematic risk in post Covid time*;
- Tomasz Klimanek, Sylwia Filas-Przybył, *Geospatial dilemmas of improving the survey on commuting to work*;
- Krzysztof Dmytrów, Beata Bieszk-Stolorz, *Application of the dynamic time warping method to compare the dynamics of the degree of fulfilment of the sustainable development goal SDG8 in the EU countries*;
- Iwona Markowicz, Paweł Baran, *Convergence in the mirror data of intra EU trade*;
- Rafał Topolnicki, Niklas Hellmer, Paweł Dłotko, *TopoTests. Use of topology methods to construct multivariate goodness of fit tests*;
- Stanisław Jaworski, *Comparison of the maximum likelihood estimator to the unbiased estimator of a fraction of sensitive questions in the model of nonrandomized cross-questions*;

- Barbara Kijewska, Katarzyna Raca, *Analysis of the violence against politicians on Twitter*;
- Agata Majkowska, Krzysztof Najman, Kamila Migdał-Najman, Katarzyna Raca, *Identification of age groups based on the formatting of text messages of Twitter users*;
- Agata Dobranowska, Paweł Lula, Magdalena Talaga, *Analysis of the social impact of research activities carried out in the area of selected social disciplines in Poland and in the UK*;
- Jerzy Korzeniewski, *Unsupervised sentiment analysis of texts in Polish language*;
- Jacek Batóg, Barbara Batóg, *Long term local development: impact of economic crises*;
- Barbara Batóg, Katarzyna Wawrzyniak, *Investigation of the stability of the classification of West Pomeranian counties with regard to the economic situation in years 2007–2021*;
- Aneta Ptak-Chmielewska, Agnieszka Chłoń-Domińczak, *Analysis of social and economic conditions of microenterprises using taxonomy methods*;
- Aleksandra Łuczak, Sławomir Kalinowski, *Hard and fuzzy linear ordering methods in the evaluation of subjective household poverty*;
- Małgorzata Just, Krzysztof Echaust, *Application of tail index of return distributions to the evaluation of gold of safe haven of stock investments*;
- Dominik Krężołek, *Does the pandemic of COVID-19 influence the precious metals market? Analysis of extreme risk*;
- Joanna Landmesser-Rusek, *Network analysis of the foreign exchange market using minimum spanning trees constructed from the DTW distance measure*;
- Adam Juszczak, *Use of scrap data to determine the changes of cloth and shoe prices*;
- Barbara Pawełek, Józef Pociecha, *Analysis of the impact of the method of missing data estimation on the effectiveness of company bankruptcy prediction*;
- Dorota Rozmus, *Stability measures in the choice of the number of clusters in the aggregate approach using spectral measures and similarity propagation*;
- Marcin Szymkowiak, Wojciech Roszka, *Analysis of publishing efficiency of Polish scientists based on the integrated sources of information*;
- Adam Korczyński, *Bayesian predictive probability design – theory and practical example in a prospective study*;
- Piotr Sulewski, *New members of the family of Johnson distributions: properties and applications*;
- Marcin Salamaga, *Analysis of the impact of export specialization and investment attractiveness on the processes of innovation diffusion in the processing industry in Poland*;

- Wioletta Grzenda, *Estimating the probability of taking up employment for people aged 50 years or older in Poland – the assessment of predictive accuracy over time for censored data*;
- Jacek Szołtysek, Grażyna Trzpiot, *Subjective risks assessment in safety of elderly persons in cities*;
- Jacek Brożyna, Marek Sobolewski, *Factors influencing regional differences in excess mortality in Poland in 2020*.

In the poster session six posters were presented:

- Adam Sagan, Marcin Pełka, Justyna Brzezińska, Mirosława Sztemberg-Lewandowska, *Segmentation of university networks in Europe*;
- Danuta Strahl, Małgorzata Markowska, *Dynamic classification of EU countries with regard to employment rate – evaluation of classifications in sectors and with regard to gender*;
- Marcin Szymkowiak, Tomasz Józefowski, Kamil Wilak, Grażyna Dehnel, *A taxonomic analysis of the labour market variation in functional urban areas of provincial capital cities*;
- Monika Zielińska-Sitkiewicz, Mariola Chrzanowska, *Analysis of the electrical energy consumption in Poland using prediction models and artificial neural networks*;
- Dorota Żebrowska-Suchodolska, *Elimination of open-ended equity funds characteristics*;
- Rafał Topolnicki, Paweł Dłotko, Simon Rudkin, *Local regression based on mappers. BallMapper Regression method*.

The members of SKAD held an annual meeting on the first day of the conference. The meeting was chaired by Krzysztof Jajuga, PhD, DSc, ProfTit, and its agenda included the following items:

- report on the SKAD activities;
- information on the planned domestic and international conferences;
- organisation of SKAD conferences in 2023 and 2024;
- elections to the SKAD Council for the term of 2023–2024;
- other issues.

A report on the activities undertaken by SKAD was presented by the Secretary of the SKAD Council, Barbara Pawełek, PhD, DSc, Assoc. Prof. at the Cracow University of Economics. According to the report, SKAD has currently 234 members, and any by-laws and membership applications are available on the SKAD website.

Subsequently, Prof. Pawełek introduced information related to a book containing papers presented during the previous SKAD conference (which was held in Poznań on 8–10 September 2021). Prof. Pawełek also mentioned that the report concerning that SKAD conference could be found in issue 3/2021 of the *Przegląd Statystyczny. Statistical Review* journal.

Prof. Barbara Pawełek announced that Marcin Pełka, PhD (Wroclaw University of Economics and Business), nominated by the Council of SKAD, was elected to the Council of the International Federation of Classification Societies (IFCS) (https://ifcs.boku.ac.at). He will serve as an Additional Member of the IFCS Council until 1 February 2026.

Prof. Barbara Pawełek also stated that Prof. Krzysztof Jajuga was a member of the Scientific Programme Committee during the IFCS 2022 Conference (Porto, Portugal, 19–23 July 2022), while Professors Krzysztof Jajuga, Andrzej Sokołowski, and Andrzej Dudek chaired the sessions. In addition, Polish participants presented nine papers and four posters during this conference.

The following conferences are planned in years 2022–2024: the 40th International Conference on Multivariate Statistical Analysis (7–9 November 2022, Łódź, Poland), the 16th Aleksander Zeliaś International Conference on the Modelling and Forecasting of Socio-Economic Phenomena (8–11 May 2023, Zakopane, Poland), ECDA 2022 (14–16 September 2022, Naples, Italy), CLADAG 2023 (11–13 September 2023, Salerno, Italy), ECDA 2023 (Antwerp, Belgium), ECDA 2024 (Gdańsk, Poland), IFCS 2024 (15–19 July 2024, San Jose, Costa Rica).

Subsequently, the issue of the organisation of the next SKAD conferences was discussed. Prof. Grażyna Trzpiot of the University of Economics in Katowice declared that the University would host the conference in 2023.

The next part of the meeting was devoted to the election of the members of the SKAD Council for the 2023–2024 term. Prof. Danuta Strahl chaired this part of the meeting. Dr. Mariola Chrzanowska and Dr. Marcin Pełka were assigned to the ballot counting committee. Prof. Krzysztof Jajuga declared the following persons as the candidates: Krzysztof Najman, Barbara Pawełek, Paweł Lula, Joanna Landmesser-Rusek, Grażyna Dehnel, Andrzej Dudek, and Marek Walesiak. Prof. Józef Pociecha declared Krzysztof Jajuga as a candidate. Then a secret voting was conducted, eighteen persons participated. The candidates received 18 and 17 votes 'for', which meant that all candidates were elected. The meeting was then closed.

The newly elected SKAD Council held its first meeting. The following board was elected:

Andrzej Dudek – Chairman of the Council, Paweł Lula – Vice-Chairman of the Council, Barbara Pawełek – Secretary of the Council, Grażyna Dehnel, Krzysztof Jajuga, Joanna Landmesser-Rusek, Krzysztof Najman, Marek Walesiak – Members of the Council.

During the ceremonial dinner, Prof. Krzysztof Jajuga informed the members about the composition of the SKAD Council for the 2023–2024 term and about the possibility to publish the presented papers. He invited the members to the next SKAD conference to be held in Katowice.