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TRANSFORMATIONAL PROCESSES IN RESOURCE-RICH COUNTRIES: FROM NATURAL RESOURCES TO INNOVATION AND TECHNOLOGY-BASED ECONOMY

ABSTRACT

This paper aims to assess the development pattern of resource-rich countries like Norway, Kuwait, Saudi Arabia, and the Republic of South Africa by analyzing their stock markets. As resource-rich countries have profound implications for the world's sustainable development, it is essential to investigate whether they transform natural resource wealth into sustained growth by reorientation from related to raw material industries to modern ones based on information and technologies. The analysis of resource-rich countries' stock markets allowed us to conclude that partially these countries are on the way to an economy dominated by intangible assets. Nevertheless, despite the declared intentions, some traditional attachments to raw materials are still present. At the same time, most companies in the optimal portfolios of these markets have a long-term non-linear strategy. The impact of the pandemic COVID-19 turned out to be significant, but short-lived. The research was carried out based on R and Python packages.

Keywords: resource-based economy, economic development, machine learning, neural network

JEL Classification: C53, C45, G15, O14

INTRODUCTION

The abundance of natural resources is no longer a guarantee of the successful economic development of any country. Although, natural resources have helped bolster prosperity in some resource-rich countries, at the same time they have made these countries vulnerable to high volatility in natural resources prices, and dependent on revenues from raw materials exports. Moreover, an abundance of natural resources can stimulate the development of extraction industries but hinder the development of hi-tech manufacturing sectors. As a result, many resource-rich countries went through multiple economic crises and experienced so-called "Dutch disease".

It is a common fact, that to gain sustained economic growth, resource-rich countries should use natural resources in a way that is truly a comparative advantage, but not an obstacle to their economic development. The transition to an innovative economy based on intangible assets can be essential to such growth. Reducing dependence on revenues from natural resources exports and strengthening innovative industries will expand the country's economic potential and sustainability.

The stock market can play a crucial role in it by transferring the revenues from natural resources exports to productive investments. With its help, financial resources can be attracted to hi-tech manufacturing sectors to expand the production of their goods and services.

We assume that the stock market can reflect the structure of the economy or at least its transition priorities. The analysis of the stock market structure provides us with information about the share of natural resources-based and high-tech companies; the dynamics of companies' capitalization in new industries; investment in research and development, etc. By analysing it, we can make some assumptions about the country's present and future development patterns.

In this article, we want to follow the development patterns of resource-rich countries like Norway, Kuwait, Saudi Arabia, and the Republic of South Africa by analysing their stock markets in detail. In other words, we want to find out, based on stock market analysis, whether these countries are switching from dominance related to raw material industries to industries with intangible assets.

LITERATURE REVIEW

The idea of the impact of natural resources on the economy and its structure has evolved. While classical ideas from the time of mercantilism viewed natural resources as a factor of economic growth and an opportunity to increase exports and limit imports through significant government intervention, new ideas have emerged over time. In the 20th century, the phenomenon of the "Dutch disease" (Goujon & Mien, 2021); and the "resource curse" (Sachs & Warner, 1995; Ross, 1999, 2015; Adams et al., 2019; Jiang et al., 2021) were actively studied. Another area of research was the study of the development of resource-rich countries in terms of institutional factors (Bhattacharyya & Hodler, 2014; Abdulahi et al., 2019). They emphasized the problems of corruption and military escalation. However, the focus of our attention is on the innovative factors of such countries' development. In the era of digitalization and artificial intelligence, we cannot ignore the impact of innovation and technology on the structural transformation of modern economies (Dwumfour & Ntow-Gyamfi, 2018; Erdoğan et al., 2020; Amin et al., 2024).

Since we are studying resource-rich countries, it is important to define the criteria for their classification. The International Monetary Fund (IMF) defines a country to be 'resource-rich' when exports of non-renewable natural resources such as oil, minerals and metals account for more than 25 % of the value of the country's total exports (Lundgren et al., 2013, p. 6). Lashitew et al. (2021) emphasized the importance of measuring resource wealth. They used such indicators as resource dependence (the share of resources in exports or GDP) and resource abundance (resource rents per person). According to their results, the correlation of indicators of resource dependence and resource abundance with indicators of competitive ability gave different results. The correlation of resource dependence with the indicators of human capital attainment, R&D expenditure, innovation output, and financial access was negative, while the correlation of resource abundance was positive. They also showed that improvements in diversification had rarely been accompanied by a strengthening in competitiveness, especially among extremely resource-rich countries. The study was based on a sample of 42 countries that were the most resource-dependent in the 1970s, for a period of 1981-2014.

Amin et al. (2020) investigated 13 resource-rich countries and 15 resource-scarce countries dividing all of them into sub-groups: resource-rich African countries, resource-rich OPEC countries, resource-scarce Asian countries and other resource-limited countries. The authors analyzed the relationship between technology and long-term economic growth in these countries from 1994 to 2019. The authors found evidence of a "resource curse" symptom between subgroups, as the impact of technology on long-term economic growth was greater in subgroups with limited resources.

"The new economy is not an appearance once an invention or an innovative "break-through" but rather the result of processing the current economy, in a quasi-continuity of physical and human-dominated by knowledge and globally" (Gâf-Deac, 2017). Based on Romania's experience, Gâf-Deac (2017) posed a desirable trend for humanity in transitioning to a new economy oriented on intangible assets.

Earlier, Gioacasi (2015) identified the 80s as an industrial period, which "flourished, having played on the importance of tangible resources and easy access to markets and raw materials." The enterprise theoretical resource approach says that asset competitive advantage is the "fulfilment by it of four conditions: it is valuable, rare, imperfectly imitable and non-substitutable".

The new information market has demonstrated that resources are not creating economic benefits by themselves, but rather the ability of human capital to make use of enterprise resources.

Currently, we are witnessing the development of a new vision for the resources of an enterprise that distinguishes between physical assets and non-financial resources. Modern businesses invest in motivating and training employees to develop innovative products (Gioacasi, 2015).

Labra et al. (2016) concentrated on the essential role of "openness and foreign direct investment to access foreign technologies" as key driving factors. The case of Chile confirmed the importance of intangibles for a country's growth. The weak innovation capability can become a severe blockage for sustained progress.

"Not only absorptive capacities but also innovative capabilities are required in these economies for keeping in the path of a sustainable development" (Labra et al., 2016).

Blomström and Kobbo (2007) considered an industry's success as a mix of "systematic knowledge creation and random technological innovation." According to them, it is not possible to continuously generate breakthrough technologies; however, it is possible to create an environment where winning based on innovations, new markets, and new visions will become the norm.

For raw material-based industries, the innovations are likely to be incremental, and "a large share may be related to changes in demand or international competition, rather than major changes in production technology." In younger industries, fundamental changes in technology will be more common, and the "main challenges are related to the ability to acquire the technical skills necessary to remain competitive" (Blomström & Kobbo, 2007).

The reorientation of the economy has become especially interesting considering rising oil prices in recent years. For some countries, this situation gives incredible opportunities. The government of Saudi Arabia has announced plans to transform the country into an industrial power by 2024. Niblock (2018) paid the most attention to what happened in the first oil boom (1973–1982) in the Saudi Arabian economy. It failed to lead to sustainable non-oil development.

Similarly, Kuwait's economic policy target is to overcome its heavy dependence on oil and the dominance of the public sector. The authorities tried to achieve a two-pronged development strategy: diversifying the country's economic base away from oil and promoting private sector development. The study by Gelan et al. (2021) revealed that diversification and privatization could be possible instruments but in interaction and unity. "The findings indicated that the strength of the primary and secondary oil sectors lies in their forward linkages, supplying other sectors with their outputs, but their backward linkages, rooted in buying inputs from other industries, are not as strong" (Gelan et al., 2021).

The digital economy is the best environment for such a transformation. From the experience of Norway, the fundamental pillars are: "trust-based cooperation across social partners and public and private sectors; the public sector's driving role; cross-organization consolidations and consortia; and application-oriented initiatives." But it also contains several unresolved challenges, such as "better inclusion of local districts, particularly in northern Norway; spectacular failures of digitalization projects; and uneven digitalization in the public sector, where data silos still affect service efficiency" (Parmiggiani & Mikalef, 2020).

Norway led the 2017 Inclusive Development Index, a study of which countries were the best "at delivering growth that lasts for decades, was broad-based across sectors, created jobs for the vast majority of the population and reduced poverty." It had the lowest income inequality in the world, helped by a mix of policies that support the modern education system and innovation process. It also created the world's largest sovereign wealth fund, which manages oil and gas revenues, moving the whole country to long-term economic planning (World Economic Forum [WEF], 2017).

Musonda et al. (2019) suggested how to move in the right direction in the development of the built-environment transformation strategy for the South African Republic. Transformation should be "conceptualized with a view to redressing historical imbalances and providing expanded opportunities for worker education and skills development from the grassroots, with attention to the previously disadvantaged" (Musonda et al., 2019).

Summarizing the proposed detailed analysis of the general situation and within the framework of individual countries, there is a necessity to transform the economic development of Norway, Kuwait, Saudi Arabia, and the Republic of South Africa into more innovative, and less dependent on natural resource extraction.

AIMS AND OBJECTIVES

This study aims to analyse the transformation of resource-rich countries' economic structure from resource-based to innovative with the help of their stock markets. The best tool to verify this statement is the analysis of optimal portfolios in chosen developed and emerging markets.

The hypothesis of the study is that raw material-rich countries build their strategies based on reducing gradually the raw material character of their economy and moving to industries with a predominance of intangible assets.

The study consists of two parts. In the first part, we analyse each of the created portfolios based on the following criteria: return, risk, and predictability. The next step of the research was to identify a long-term strategy based on the 5-factor Fama-French model. This model provides a differentiated approach based on the factors for developed and emerging markets. The analysis of the dynamics of risks and investment priorities allows us to make assumptions about the transformation processes in chosen countries. The final stage of the study was modelling based on neural networks. This method allows us to detect nonlinear processes. Since our study is an attempt to explain changes in the structure of

economies through stock markets, we use both macroeconomic and microeconomic theoretical approaches to explain our results.

METHODS

In order to test our hypothesis, we make the assumption that the share of intangible assets in the balance sheet is insignificant for raw materials-based industries. Indeed, if the basis of the company's activity is raw material extraction, then it is not patents, skilled labour, or in-process R&D that prevails, but fixed assets, land plots, the object of a concession, etc. Add to this the fact that the market for intangible in the raw materials-based economies is very weak, and therefore companies mostly disclose such transactions as expenses. This fact significantly complicates the auditor's work. In the approach based on the optimal portfolio, according to the weighting coefficients, we determine the industry's leaders. Next, we do the same ranking assessment by cumulative return.

On the basis of the daily change in return, we test the nature of the stable incomes of such companies from the risk side. It is important to analyze the state of the business precisely in view of the ratio between return and risk (the well-known Sharpe ratio, which we use to build an optimal portfolio).

Machine learning techniques allow us to answer the question of whether these businesses are predictable. On the other hand, the Fama-French model allows us to reveal economic strategies. The most important thing for us is the fact itself of having a working model, which we determine on the basis of the F-criterion (smaller or at least close to 5%). Analysis of individual factors is not the focus of this study. Taken together, these two approaches give us a basis for asserting that our estimates are not a short-term outcome. We expect that the Fama-French model for developing countries will not always work for such a differentiated sample. That is why we have tested the existence of a long-term nonlinear strategy based on a modified Fama-French approach using neural networks. We use, for example, the designations c (6,2) and c (2), respectively, for two hidden layers with 6 and 2 neurons and only one layer with two neurons.

Creating portfolios

First, we create four portfolios based mainly on the ingredients of appropriate stock market indices: MSCI TADAWUL 30, Kuwait Main Market 50, OSE Benchmark, and South Africa Top 40. We analyze these portfolios in relation to profitability, risk, and their ingredients regarding the predictability of their price.

It is applied as a portfolio analysis instrument to the next Python packages: EfficientFrontier, pypfopt, numpy, pandas_datareader, matplotlib.pyplot, yahoo_fin and packages PortfolioAnalytics, fPortfolio, timeSeries of R.

Machine learning methods

Machine learning methods are chosen to estimate business predictability. A random forest is a capable estimator that uses averaging to improve predictive accuracy and control overfitting (Fawagreh et al., 2014). In the case of gradient boosting, in each stage, a regression tree is fitted on the negative gradient of the given loss function (Buhlmann, 2006). The Support Vector Machine Regressor helps us because of our interest in the radial kernel.

To implement prediction models the following packages have been used: sklearn.tree, sklearn.svm, sklearn.linear_model, sklearn.ensemble and others.

Using Fama-French model

Further, we intend to reveal the presence or absence of a long-term strategy based on the 5-factor model of Fama-French (maximum possible period, factors for developed or emerging markets). A five-factor model is aimed at determining at capturing the size, value, profitability, and investment patterns in average stock returns (Fama & French, 2014).

The five-factor model time series regression traditionally has the equation below:

$$R_{it} - R_{Ft} = a_i + b_i (R_{Mt} - R_{Ft}) + s_i \text{SMB}_t + h_i \text{HML}_t + r_i \text{RMW}_t + c_i \text{CMA}_t + e_{it} \quad (1)$$

where R_{it} is the return of one of portfolio i in month t ; R_{Ft} is the riskfree return; R_{Mt} is the return on the value-weight market portfolio; SMB is the return on a diversified portfolio of small stocks minus the return on a diversified portfolio of big stocks (i.e. the size effect); HML is the return spread of cheap minus expensive stocks (i.e. the value effect); RMW is the return spread of the most profitable firms minus the least profitable; CMA is the return spread of firms that invest conservatively minus aggressively; $a_i, b_i, s_i, h_i, r_i, c_i$ – some coefficients; e_{it} is a zero-mean residual.

If the exposures to the five factors, b_i , s_i , h_i , r_i and c_i capture all variation in expected returns, the intercept a_i in (1) is zero for all securities and portfolios i (Fama & French, 2014).

Using modelling based on neural networks

If the approach based on the 5-factor model of Fama-French does not show a result (the necessary criteria are not met), we move on to modelling based on neural networks, rejecting linearity (Tronto et al., 2008).

A modification of the approach based on neural networks used in this study is an attempt to simulate a crisis on the market by adding a hidden layer with an increased number of neurons (factors) as a sign of a crisis on the market. As the object of such analysis, the Fama-French matrix of factors and the adjusted price of shares of the analyzed company are chosen.

Data

This study focuses on several countries: South Africa, Kuwait, Saudi Arabia, and Norway for the period 2019-2023. The last was chosen by the authors due to its unique role in providing oil to European countries regarding Russian aggression against Ukraine and related sanctions against the Russian energy sector. Also, Norway is number one in the Inclusive Economies Index.

We create a portfolio for each country based on the respective stock indices.

All data are derived based on the company's ticker and the corresponding programming language packages.

We get all the data for calculations from the website: yahoo.finance, investing.com, and focus-economics.com based on the tickers of the respective companies and the corresponding Python and R language packages. In most cases, the maximum possible period for analysis is chosen, based on the time the company has been on the stock market. Sometimes this restriction applies to a group of companies.

RESULTS

Risk analysis

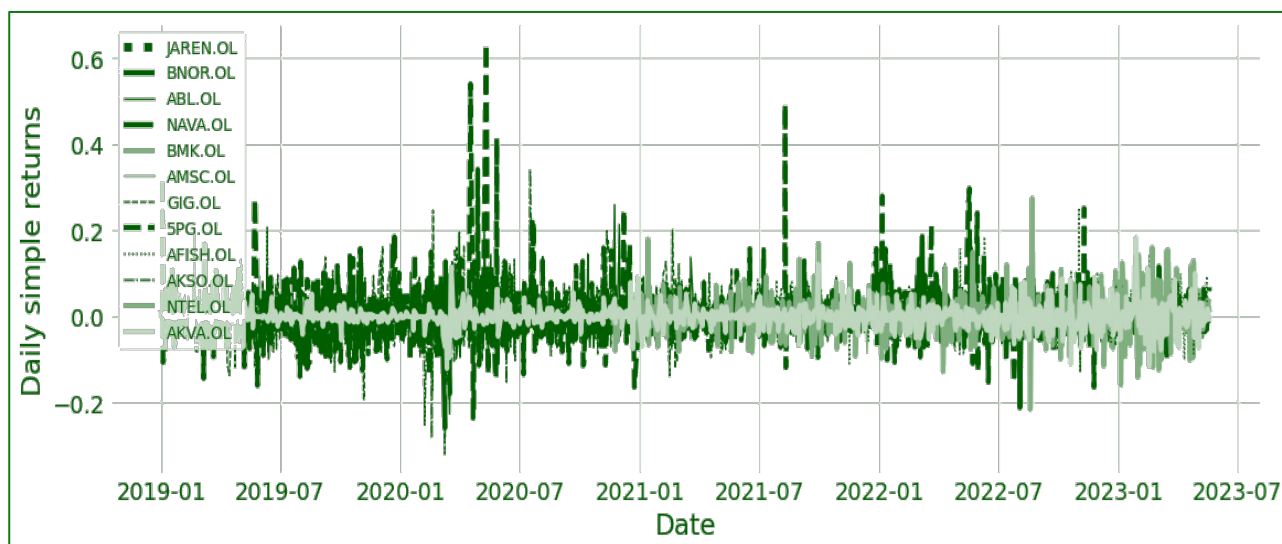


Figure 1. Daily simple return on the Norwegian market. (Source: authors' processing in Python)

Table 1. Optimal portfolios. (Source: authors' processing based on Efficient Frontier method and Python packages)

Market	Optimal portfolio	Branches ranking
Norway '2021-09-01' to '2023-05-20'	'JAREN.OL', 0.24032; 'BNOR.OL', 0.16992; 'ABL.OL', 0.13417; 'NAVA.OL', 0.07952; 'BMK.OL', 0.0704; 'AMSC.OL', 0.04955; 'GIG.OL', 0.03845; 'SPG.OL', 0.03327; 'AYFIE.OL', 0.00283; 'AFISH.OL', 0.0213; 'AKSO.OL', 0.01735; 'NTEL.OL', 0.01444; 'ARR.OL', 0.00103; 'AKVA.OL', 0.00051 Expected annual return: 56.7% Annual volatility: 17.4%; Sharpe Ratio: 3.15	Banking, upstream oil & gas, oil & gas products, pharmaceutical, water transport, gambling, toys and games, software, fishing, oil & gas products, wireless telecommunication services, software, precision products
South African Republic '2019-01-01' to '2023-05-20'	'DRD.JO', 0.26732; 'ABSP.JO', 0.26332; 'APH.JO', 0.0844; 'GML.JO', 0.06826; 'DTC.JO', 0.0654; 'ARI.JO', 0.06424; 'LEW.JO', 0.0472; 'GSH.JO', 0.0448; 'AFE.JO', 0.01958; 'ISA.JO', 0.01182 Expected annual return: 31.8% Annual volatility: 20.6%; Sharpe Ratio: 1.45	Gold, banking, food products, gemstones, computer services, general mining, home goods retail, water transport, chemicals, software
Kuwait '2022-01-01' to '2023-05-20'	'JAZEERA.KW', 0.24921; 'TAMINV.KW', 0.2392; 'KFOUC.KW', 0.12875; 'FUTUREKID.KW', 0.0827; 'STC.KW', 0.07529; 'KHOT.KW', 0.06478; 'CABLE.KW', 0.06477; 'CBK.KW', 0.04841; 'KCIN.KW', 0.04024; 'SHIP.KW', 0.00355; 'CGC.KW', 0.00274 Expected annual return: 32.0% Annual volatility: 17.7% Sharpe Ratio: 1.70	Passenger airlines, investment advisors, iron/steel, recreational services, telecommunications, hotels, cable and electrical industries, banking, entertainment, shipbuilding, engineering & construction
Saudi Arabia '2022-09-01' to '2023-05-20'	'9544.SR', 0.14088; '4009.SR', 0.1228; '4142.SR', 0.12239; '9550.SR', 0.12201; '2381.SR', 0.09802; '6015.SR', 0.08951; '4004.SR', 0.05926; '9552.SR', 0.055; '7020.SR', 0.04653; '7204.SR', 0.04455; '2280.SR', 0.02805; '7040.SR', 0.00297; '4013.SR', 0.02593; '4030.SR', 0.02119; '1820.SR', 0.01849; '#9521.SR', 0.00242; Expected annual return: 249.6% Annual volatility: 21.2%; Sharpe Ratio: 11.69	Medical care facilities, electrical equipment & parts, IT services, oil & gas drilling. Restaurants; specialty chemicals; telecommunication; software; packaged foods, shipping, tourism; real estate development

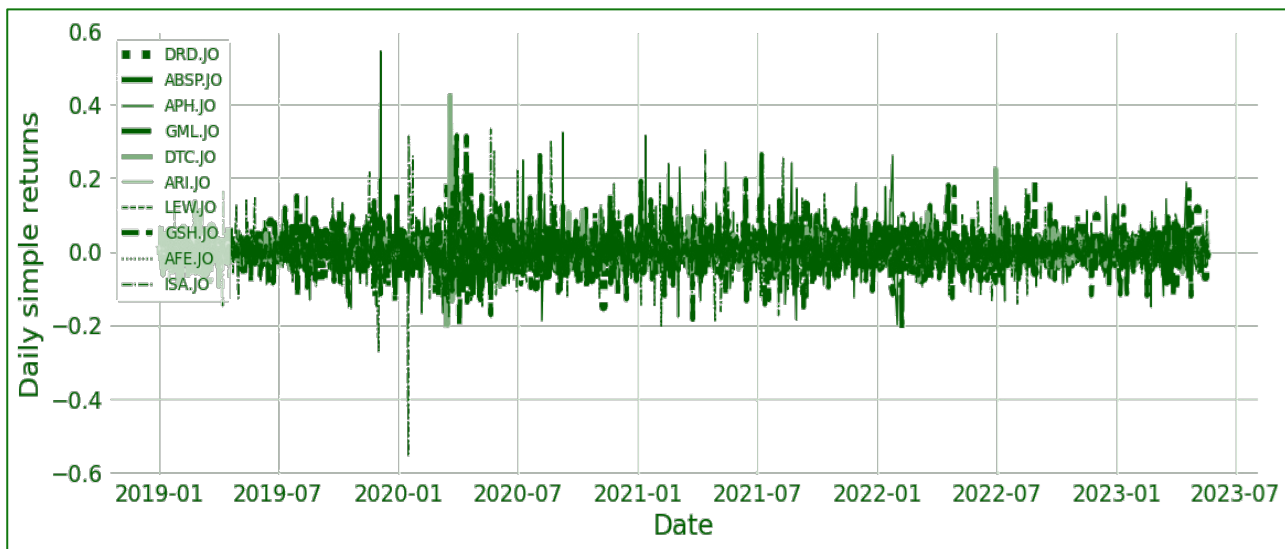


Figure 2. Daily simple return on the South African market. (Source: authors' processing in Python)

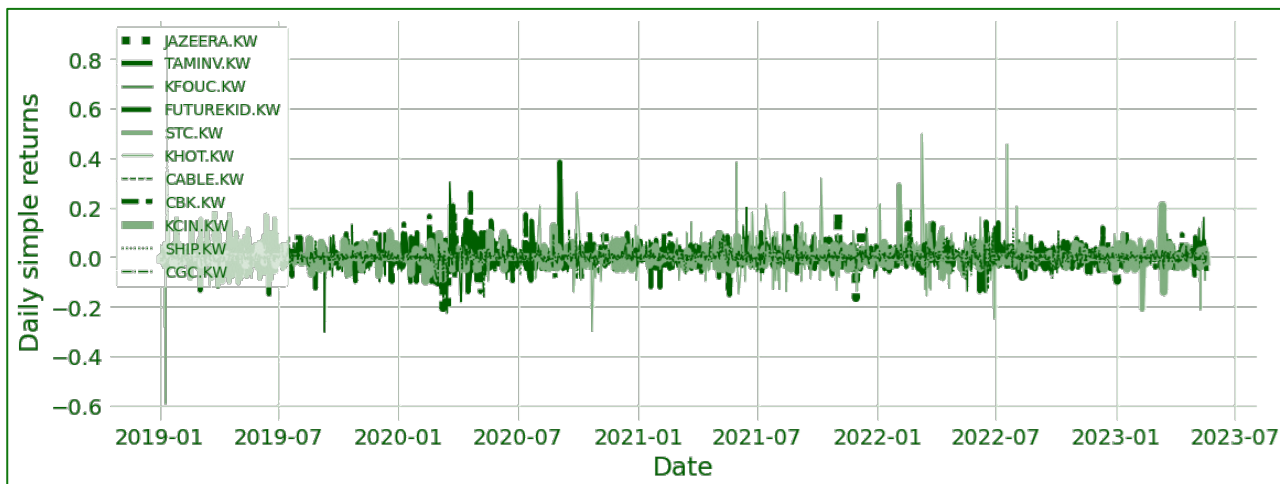


Figure 3. Daily simple return on the Kuwaiti market. (Source: authors' processing in Python)

All the markets we offered turned out to be quite risky (analysis for ingredients of optimal portfolios based on the Efficient Frontier method, Table 1). Except for some marginal cases, the level of risk can be limited to the level of 20%. It is obvious that the greatest outbreaks of risk occurred at the beginning of the pandemic. At the same time, some markets didn't fully recover from that shock (Figures 1-2). Traditionally, such estimates are made on the basis of standard deviation; at the same time, the chosen type of analysis (daily return-based) allows us to assess the dynamics of the process. Interestingly, the situation in all four markets seems to be similar (Figures 1-4).

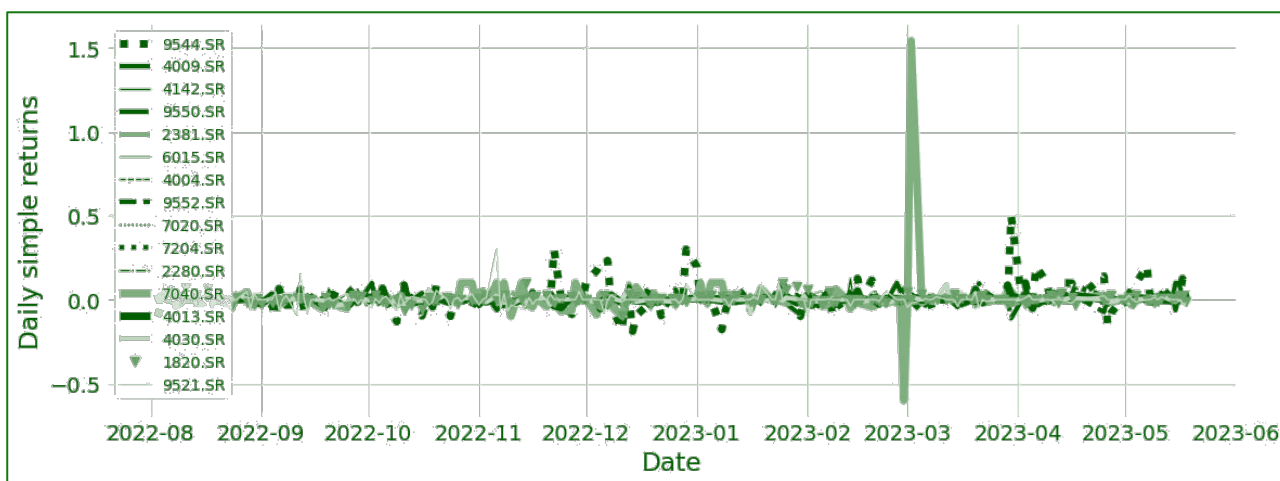


Figure 4. Daily simple return on the Saudi Arabian market. (Source: authors' processing in Python)

Investment growth analysis

For investment growth analysis we also use only ingredients of optimal portfolios for chosen markets (Table 1). Among the leading branches for the Norwegian market, we recognized ABL Group ASA (ABL.OL) – oil and gas products; Navamedic ASA (NAVA.OL) – pharmaceutical; 5th Planet Games A/S (5PG.OL) - toys and games and Jæren Sparebank (JAREN.OL) – banking (Figure 5). A different situation is on the South African market - DRDGOLD Limited (DRD.JO) - gold; Alphamin Resources Corp. (APH.JO) - food products; Grindrod Shipping Holdings Ltd. (GSH.JO) - water transport; Gemfields Group Limited (GML.JO) – gemstones (Figure 6). The most intriguing choice of the market priorities we revealed in Saudi Arabia - Future Care Trading Co. (9544.SR) and Middle East Healthcare Company (4009.SR) - Medical Care Facilities; Riyadh Cables Group Company (4142.SR) - Electrical Equipment & Parts, and Etihad Atheeb Telecommunication Company (7040.SR) – telecommunication (Figure 7). In this last case, our analysis supported trends revealed by Niblock (2018). Now we agree that the Saudi Arabian aim was at least partly achieved. The movement in the same direction could be recognized in the case of Kuwait - KFOUC.KW - iron/steel; Gulf Cable and Electrical Industries (CABLE.KW) - electrical equipment and parts; Jazeera Airways (JAZEERA.KW) - passenger airlines; Tamdeen Investment (TAMINV.KW) - investment advisors (Figure 8).

It seems that Norway, as one of the world leaders in the field of innovative economic development, will stand out completely in comparison with the countries of Asia or South Africa. At the same time, the presence of businesses in such industries as software, telecommunications, and healthcare in the optimal portfolios of all these states suggests a common trend towards the dominance of the economy based on information and knowledge. South Africa stands out somewhat in this group. But when we analyse the smallest participants in the portfolio, an understanding emerges that the same processes are taking place there, but with a certain lag.

Indeed, if we were to turn our attention to South Africa's current commitment to the BRICS association and even the peculiar sprouts of disengagement from developed markets, we might expect that a reverse transformation trend was also quite likely. This is not yet visible in the reaction of the stock market. A similar testing to this one in the next decade will answer this question.

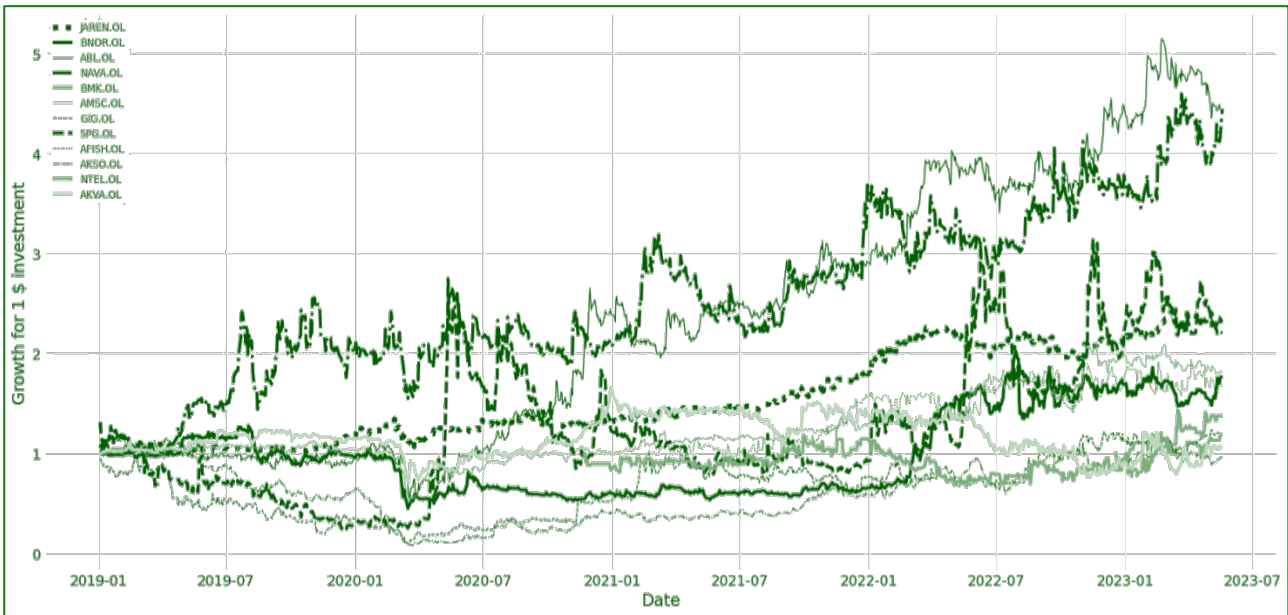


Figure 5. Cumulative return dynamics in Norway. (Source: authors' processing in Python)

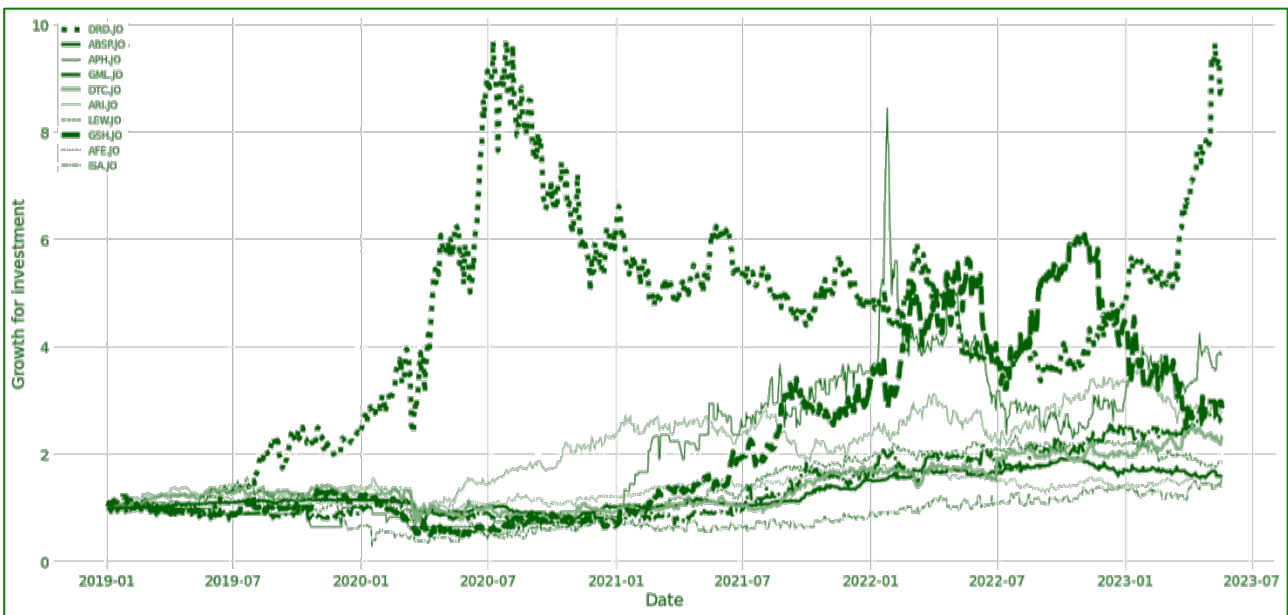


Figure 6. Cumulative return dynamics in South Africa. (Source: authors' processing in Python)

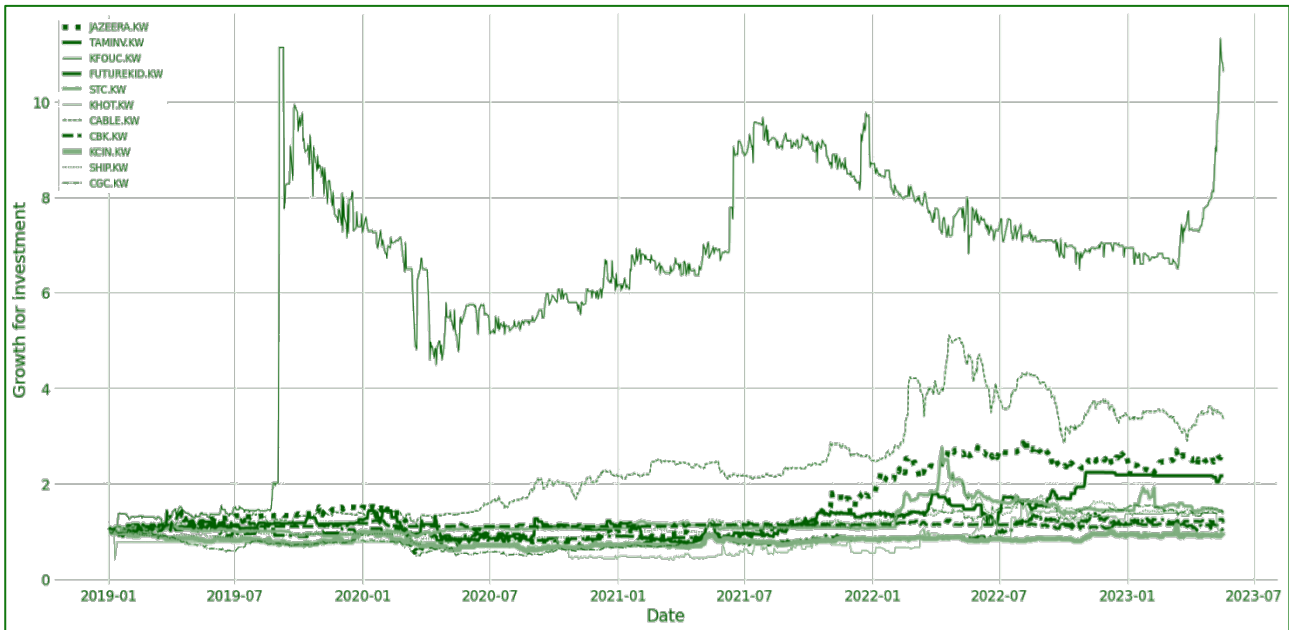


Figure 7. Cumulative return dynamics in Kuwait. (Source: authors' processing in Python)

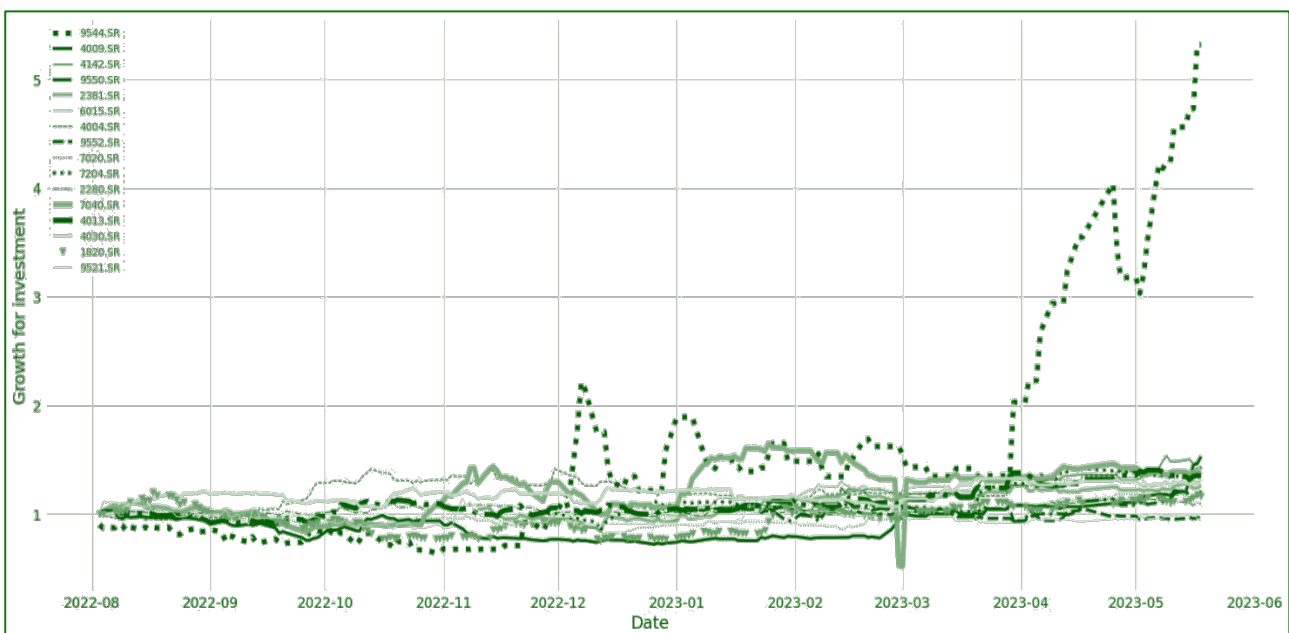


Figure 8. Cumulative return dynamics in Saudi Arabia. (Source: authors' processing in Python)

Predictability analysis

To analyse the predictability of the verified price of the company's shares, we have a whole range of methods. It is the easiest to do this based on linear regression. At the same time, machine learning offers us a much wider and more interesting choice.

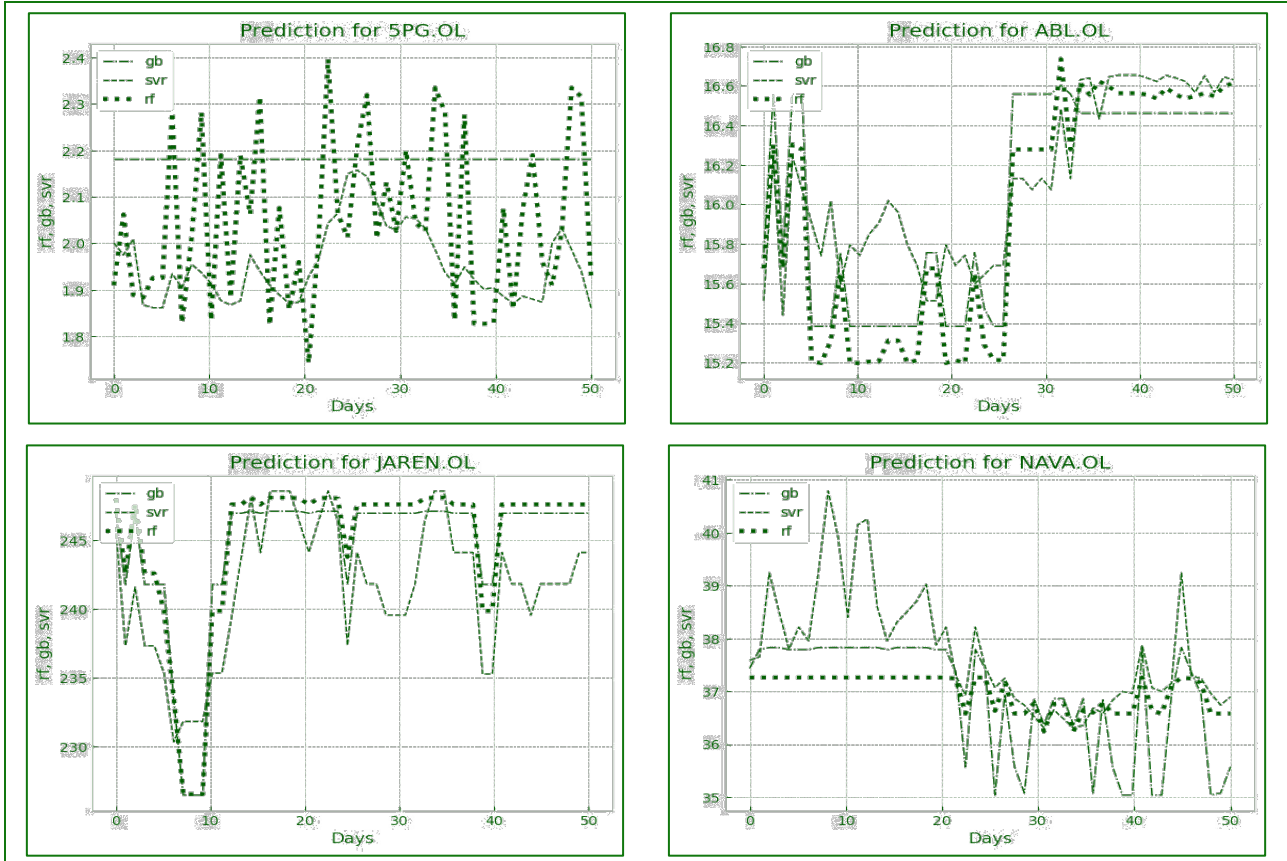


Figure 9. Machine learning based predictability analysis for Norway. (Source: authors' processing in Python)

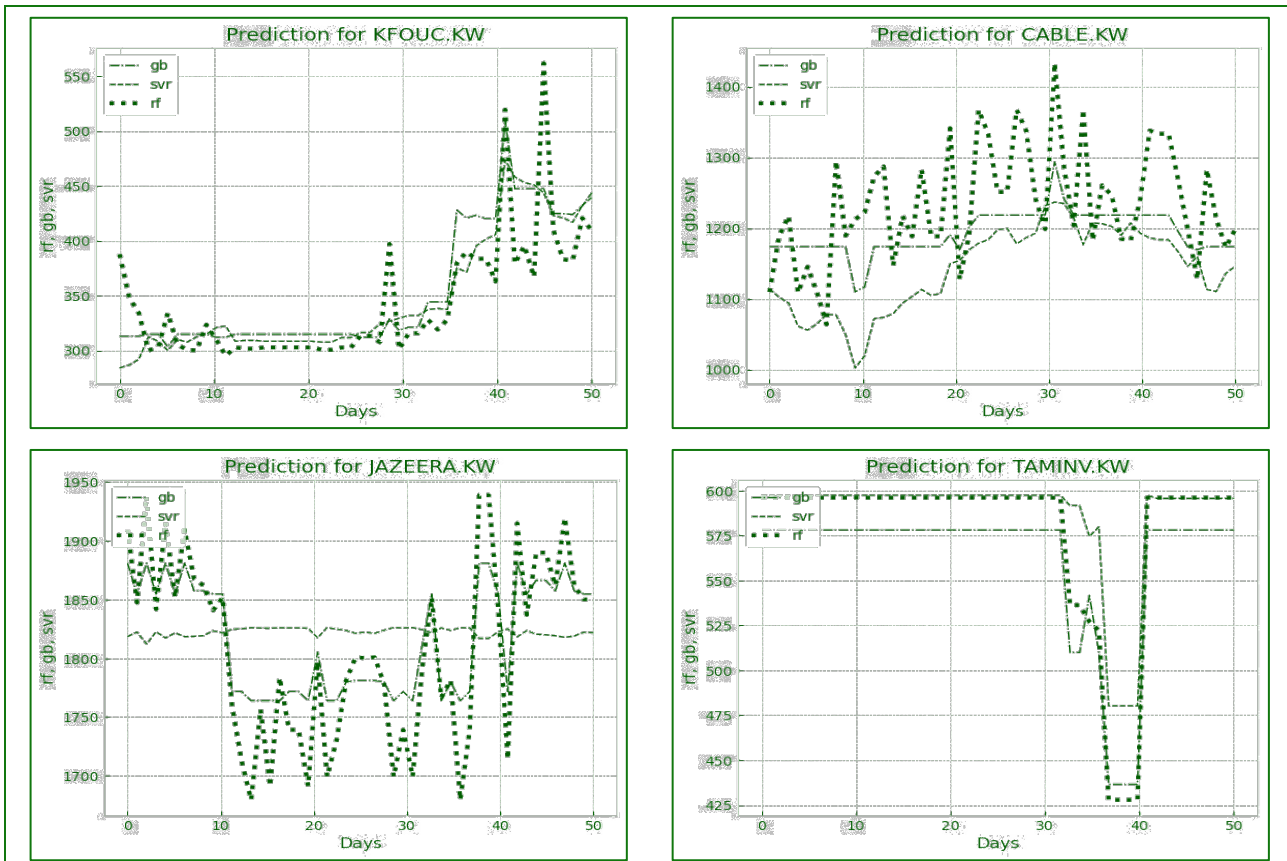


Figure 10. Machine learning based predictability analysis for Kuwait. (Source: authors' processing in Python)

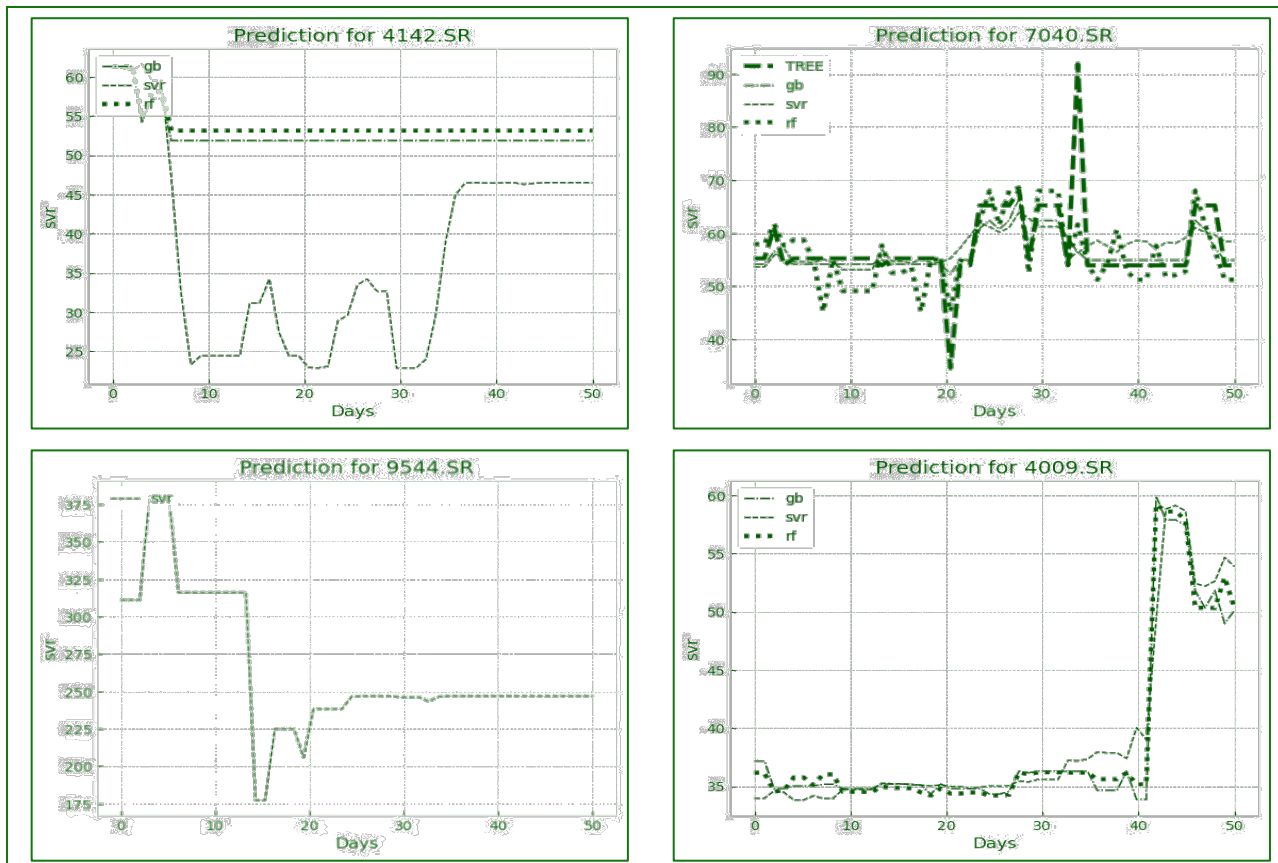


Figure 11. Machine learning based predictability analysis for Saudi Arabia. (Source: authors' processing in Python)

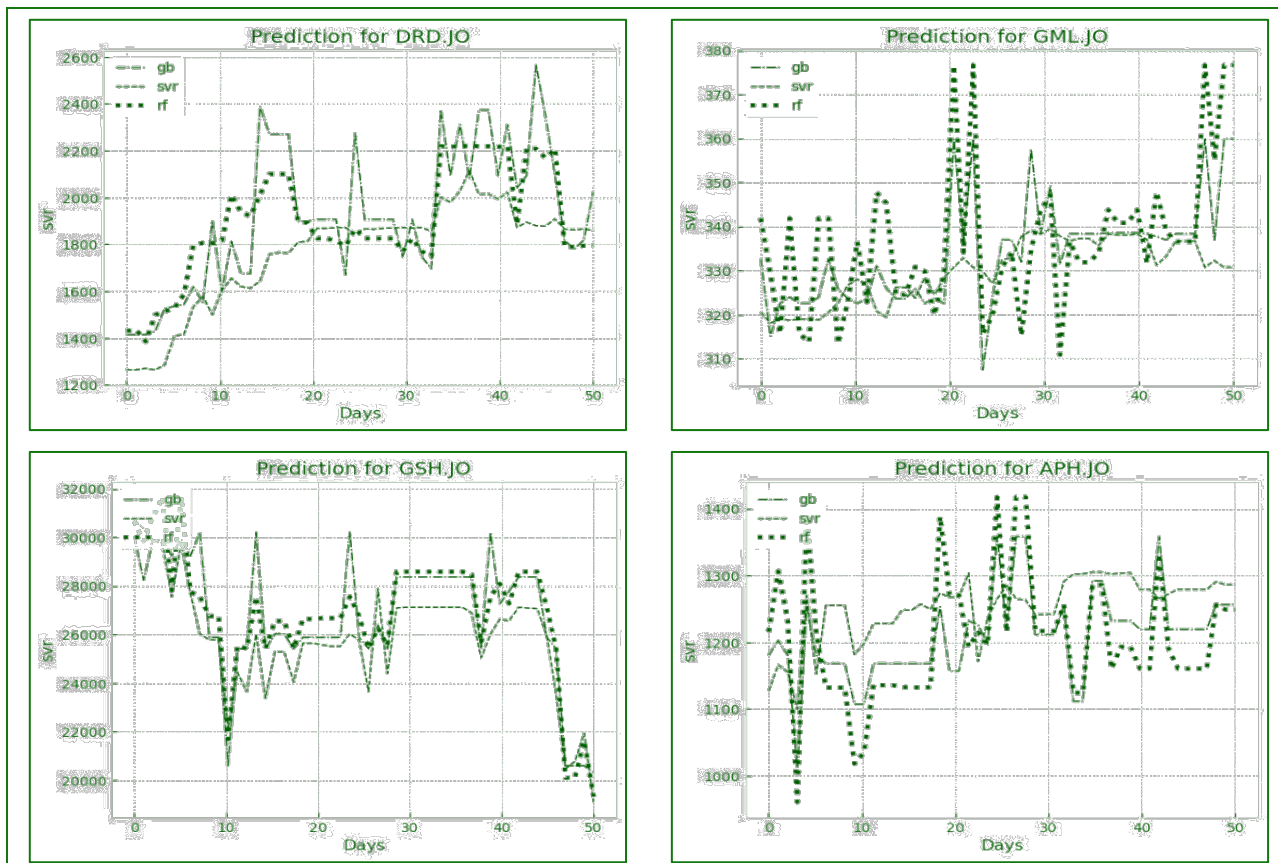


Figure 12. Machine learning based predictability analysis for South African Republic. (Source: authors' processing in Python)

Analysing the price charts of companies' shares for the next 50 days (Figures 9-12) we note the obvious absence of clear trends. Such methods of machine learning as random forest (rf), gradient boosting (gb), and support vector regressor (svr) are a very much suitable instrument for it. The argument for such a conclusion is a high coefficient of determination, or in other words, good accuracy of the models (Table 2).

Table 2. Accuracy level of prediction models (R^2). Notes: gb – Gradient Boosting, rf – Random Forest, svr – Support Vector Regressor. (Source: authors' processing in Python)

Ticker	gb	Svr	rf	Ticker	gb	svr	rf
ABL.OL	0.944	0.933	0.9425	9544.SR	-	0.51	-
NAVA.OL	0.909	0.897	0.907	4009.SR	0.833	0.786	0.821
SPG.OL	0.919	0.905	0.912	4142.SR	0.928	0.959	0.953
JAREN.OL	0.990	0.988	0.993	7040.SR	0.675	0.549	0.676
CABLE.KW	0.921	0.919	0.927	DRD.JO	0.825	0.820	0.825
JAZEERA.KW	0.972	0.957	0.974	APJ.JO	0.923	0.873	0.926
TAMINV.KW	0.692	0.638	0.726	GSH.JO	0.884	0.848	0.875
KFOUC.KW	0.938	0.928	0.941	GML.JO	0.792	0.766	0.796

Machine learning based approach allows to indicate the absence of a clear transformational strategy in the market (like traditional industries are steadily losing, new industries are steadily gaining, or vice versa), or such a process exists, but at the same time, it is not linear. Perhaps the explanation is a certain jump in the market's interest in business based on Internet platforms, online learning, and software during the pandemic, which was largely minimized in the post-pandemic period. On the other hand, let's not forget about the fleeting impact of pandemic restrictions. At the same time, for the selected companies, we have shown the short-term impact of the pandemic on these companies, based on risk and investment growth. In this way, we approached the possibility and necessity of describing the strategies of the elements of our sample, which can traditionally be done based on the Fama-French analysis.

Fama-French model

In Fama - French analysis we take the factors for Norway as for developed markets, and for other participants as for emerging markets (Table 3).

Table 3. Fama-French model. Note: used portfolio based on ingredients of main indices with a maximum possible period. In case of not sufficiently small Prob. (F - criterion) the model is not working. In the case of the significance of individual factors, the probability is given in parentheses. (Source: authors' processing in Python)

Ticker	Fama – French model description
CABLE.KW (industrial electronics)	Adj R2 = 0.018, prob. (F) = 0.0804, HML = 0.659 (0.07), D_W = 2.015
JAZEERA.KW (passenger airlines)	Prob. (F) = 0.858
KFOUC.KW (iron/steel)	Prob. (F) = 0.748
TAMINV.KW (investment advisors)	Adj R2 = 0.05, prob. (F) = 0.01, HML = 1.67 (0.01), SMB = 1.06 (0.06), D_W = 1.75
ABL.OL (oil and gas)	Prob. (F) = 0.768
NAVA.OL (medical distribution))	Prob. (F) = 0.810
SPG.OL (gaming)	Adj R2 = 0.09, prob. (F) = 0.02, HML = -3.8 (0.006), SMB = 2.5 (0.003), D_W = 1.7
JAREN.OL (banking)	Prob. (F) = 0.186
DRD.JO (gold)	Prob. (F) = 0.5
APH.JO (industrial metals & mining)	Prob. (F) = 0.654
GSH.JO (shipping holding)	Prob. (F) = 0.334
GML.JO (precious metals & mining)	Prob. (F) = 0.568
7040.SR (telecommunication)	Adj R2 = 0.065, prob. (F) = 0.01, HML = -7.38 (0.05), CMA = 12.12 (0.01), D_W = 2.09
4009.SR (medical care facilities)	Prob. (F) = 0.64

As we can see, the Fama-French model is not functional in most cases. Only for some businesses we can find out some details about growth or value stock (HML), big or small (SMB), conservative or aggressive (CMA). Perhaps it would be possible to improve the result somehow, using not monthly, but daily statistics. However, it is unlikely that this would solve the problem since it is practically impossible to bring such different markets under a single average model.

Neural network-based approach

Let's try to abandon linearity and use a non-linear mechanism. By manipulating additional hidden layers with different sets of neurons and algorithms provided by R packages (neural net and others), this can be done.

Table 4. Neural network-based analysis. Note: * Jazeera Airways returns to profitability in record time. The companies (strategies) least affected by the crisis according to our approach are highlighted. (Source: authors' processing in Python)

Ticker	2 neurons	c(6,2)
CABLE.KW (industrial electronics)	Acc. = 0.9838, er. = 0.4419, steps = 11	Ac. = 0.9857 (↑), er. = 0.4419, steps = 19
JAZEERA.KW (passenger airlines)	Acc. = 0.9882, er. = 1.3259, steps = 15	Ac. = 0.9866, er. = 1.3268, steps = 16*
KFOUC.KW (iron/steel)	Acc. = 0.584, er. = 20.3656, steps = 16	Ac. = 0.594 (↑), er. = 20.3616, steps = 12
TAMINV.KW (investment advisors)	Acc. = 0.9725, er. = 1.4064, steps = 15	Ac. = 0.9695 (↓), er. = 1.4094, steps = 12(↓)
ABL.OL (oil and gas)	Acc. = 0.8704, er. = 0.5782, steps = 7	Ac. = 0.8729, er. = 0.5782, steps = 16
NAVA.OL (medical distribution)	Acc. = 0.782, er. = 1.2365, steps = 18	Ac. = 0.775 (↓), er. = 1.2372, steps = 22
SPG.OL (gaming)	Acc. = 0.591, er. = 1.3034, steps = 36	Ac. = 0.589 (↓), er. = 1.305, steps = 26(↓)
JAREN.OL (banking)	Acc. = 0.961, er. = 0.1327, steps = 19	Ac. = 0.959, er. = 1.327, steps = 27
DRD.JO (gold)	Not appropriate R2 of the model	
APH.JO (industrial metals & mining)	Acc. = 0.793, er. = 0.6058, steps = 9	Ac. = 0.8006 (↑), er. = 0.6057, steps = 17
GSH.JO (shipping holding)	Acc. = 0.52, er. = 0.9249, steps = 55	Ac. = 0.5565 (↑), er. = 1.08743, steps = 21(↓)
GML.JO (precious metals & mining)	Acc. = 0.7937, er. = 0.4965, steps = 18	Ac. = 0.789 (↓), er. = 0.497, steps = 14(↓)
7040.SR (telecommunication)	Acc. = 0.59, er. = 23.7, steps = 181	Ac. = 0.578 (↓), er. = 23.7, steps = 109(↓)
4009.SR (medical care facilities)	Acc. = 0.974, er. = 0.237, steps = 14	Ac. = 0.97, er. = 0.237, steps = 19

We can see that the pandemic crisis had an impact on most of the identified portfolio leaders but did not change crucially their long-term strategy. For some businesses, it is not even useful to enter the crisis identifier additional variable (6th neuron) into the model.

So, we try to influence the business strategy based on the traditional set of factors with a financial crisis, which is simulated by an additional hidden layer with a set of neurons that is more painful than the original set of factors. If it affects the business significantly (decrease in model steps, increase in model accuracy), it means that the crisis could significantly change the company's strategy. We consider the company's strategy to be the interaction of factors obtained from the 5-factor Fama-French model. Only for JAZEERA.KW, NAVA.OL, JAREN.OL and 4009 SR (Middle East Healthcare Company) the introduction of the crisis into the model damaged it, and therefore it turned out to be inappropriate. The chosen approach is based on an algorithm slr (smallest learning rate).

The most significant conclusion of the last model is the presence of a long-term non-linear strategy for the majority in our sample. Only for two enterprises, such an analysis did not give results due to the too short period of the presence on the stock market.

DISCUSSION

The basis of the discussion is the choice between the improvement of the traditional Fama-French model with the use of daily statistics, smoothing of curves, input into the model of the additional factors or rejection of linearity and the analysis of applied algorithms based on neural networks. Both approaches have their pros and cons. In our opinion, the non-linear nature of the interaction between the Fama-French factors and the verified price of the company's shares is a more accurate method. A special advantage of this method is the inclusion of additional hidden layers in the model with a number of neurons (factors) manipulation.

In this way, the rejection of hypotheses or restrictions regarding the linearity of processes, strategies, and trends allow to significantly increase the viability of theoretical models, making it difficult to assess the influence of individual factors.

Based on the Fama-French method, it was possible to analyse long-term strategies for only four companies in our sample. At the same time, it does not mean that companies do not have such a strategy. It can be obtained based on nonlinear models using neural networks. The impact of the crisis caused by pandemic restrictions is proposed to be embodied with the help of an additional hidden layer using a larger number of neurons than at the initial layer. The absence of such influence was found only in industries which are capable of effective local development (regional banking, medical facilities, etc.). The contradictory case of the Jazeera airline is an exception, which can be explained by the very quick resuscitation of the company after certain losses related to the pandemic.

Expectations regarding Norway and its special role in providing Europe with oil and gas in critical situations turned out to be exaggerated. This significant change in external factors obviously affected the weighting coefficients of representatives of the extractive industry in the optimal portfolio but did not transfer them to the status of clearly prevailing.

The next debatable issue is accepting the stock market environment as a reflection of the country's economy. It proved to be true for developed countries, but for emerging markets, it is partially correct.

CONCLUSIONS

According to the machine learning-based approach, there is no clear transformational strategy on the market of Norway, Kuwait, Saudi Arabia, and the Republic of South Africa or that such a process exists, but at the same time it is not linear. The analysed resource-rich countries are gradually switching to intangible assets although some traditional attachments to raw materials are still present. In any of the proposed optimal portfolios natural resources companies are not dominant.

The transformation processes on the stock markets of Norway, Kuwait, Saudi Arabia, and the Republic of South Africa turned out to be quite similar in the aspect of risk dynamics and investment priorities.

With rare exceptions, most of the companies in the optimal portfolios of these countries are predictable businesses with a long-term nonlinear strategy according to machine learning methods. The impact of the pandemic COVID-19 on them turned out to be significant, but short-lived.

ADDITIONAL INFORMATION

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CONFLICT OF INTEREST

The Authors declare that there is no conflict of interest.

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ТРАНСФОРМАЦІЙНІ ПРОЦЕСИ В БАГАТИХ НА РЕСУРСИ КРАЇНАХ: ВІД ПРИРОДНИХ РЕСУРСІВ ДО ІННОВАЦІЙ ТА ЕКОНОМІКИ, ЗАСНОВАНОЇ НА ТЕХНОЛОГІЯХ

Метою цього дослідження є вивчити трансформаційні процеси в економіках багатих на ресурси країн, таких як Норвегія, Кувейт, Саудівська Аравія та Південно-Африканська Республіка, за допомогою аналізу їхніх фондових ринків. Оскільки багаті на ресурси країни мають вагомий вплив на сталий розвиток світу, важливо з'ясувати, чи перетворюють вони доходи від продажу природних ресурсів на формування стійкого зростання шляхом трансформації структури їхніх економік у напрямі збільшення частки галузей, що базуються на інформації та технологіях. У результаті проведеного дослідження зроблено висновок, що частково ці країни трансформують структуру своїх економік у напрямі домінування галузей із нематеріальними активами. Проте, незважаючи на задекларовані наміри, сировинні галузі все ж присутні. При цьому більшість компаній в оптимальних портфелях цих країн мають довгострокову нелінійну стратегію. Вплив пандемії COVID-19 виявився значним, але короточасним. Дослідження проведене на основі пакетів R і Python.

Ключові слова: ресурсоорієнтована економіка, економічний розвиток, машинне навчання, нейронна мережа

JEL Класифікація: C53, C45, G15, O14