WROCŁAW CONFERENCE IN FINANCE

WROFIN

CONTEMPORARY TRENDS AND CHALLENGES

Book of Abstracts

WROFIN Conference 2022

Gola Dzierżoniowska

16-18 November 2022

Wroclaw University
of Economics and Business

DOFINANSOWANO ZE ŚRODKÓW BUDŻETU PAŃSTWA

DOSKONAŁA NAUKA
Wroclaw Conference in Finance (WROFIN)

DOFINANSOWANIE
70 950 zł

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79 950 zł

Conference Agenda

VIII Wrocław Conference in Finance

Date: Wednesday, 16/Nov/2022

2:00pm - 3:00pm	**Check-in (Uroczysko 7 Stawów, Gola Dzierżoniowska 21, Poland)**
3:00pm - 4:00pm	**Coffee Break (meet together)** Location: **room A**
4:00pm - 6:00pm	**Workshop (Building Personal Brand in Science)** Location: **room A**
7:00pm - 11:00pm	**Supper**

Date: Thursday, 17/Nov/2022

9:00am - 10:30am

Plenary 1 Location: **room A**

Chair: **Krzysztof Jajuga**, Wroclaw University of Economics and Business, Poland

Was tax optimization used in the Ancient Japan?

Magdalena Katarzyna Jerzemowska
University of Gdańsk, Poland

Zombies on the cryptocurrency market

Barbara Będowska-Sójka[1], **Piotr Wójcik**[2]
1: Poznań University of Economics and Business, Poland; 2: University of Warsaw, Poland

Determinants of banking stability in the Czech Republic

Iveta Palečková, **Pavla Klepková Vodová**
Silesian University in Opava, Czech Republic

10:30am - 11:30am

Round-Table Discussions Location: **room A**

11:30am - 1:00pm

Sesion 1A Location: **room A**

Chair: **Jacek Mizerka**, Poznań University of Economics and Business, Poland

Factors of the women's pension gap - comparison of European countries

Ewa Poprawska, **Anna Jędrzychowska**, **Ilona Kwiecień**
Wroclaw University of Economics and Business, Poland

Discussant: **Paweł Galiński** (University of Gdańsk; Faculty of Management)

Income distribution between classes and political polarization: Case of European Union

Ondřej Rolník
Faculty of Business and Economics, Mendel University in Brno, Czech Republic

Discussant: **Ewa Poprawska** (Wroclaw University of Economics and Business)

Key debt drivers of local governments – empirical evidence on municipalities in Poland

Paweł Galiński
University of Gdańsk; Faculty of Management, Poland

Discussant: **Ondřej Rolník** (Faculty of Business and Economics, Mendel University in Brno)

Sesion 1B Location: **room B**

Chair: **Paweł Kliber**, Poznan University of Economics and Business, Poland

Comparison of time series properties for Bitcoin and fiat currencies

Paweł Rokita[1,2], **Radosław Pietrzyk**[1,2]
1: Wroclaw University of Economics and Business, Poland; 2: Empirica sp. z o.o., Poland

Discussant: **Joanna Górka** (Nicolaus Copernicus University)

Explaining the Cross Section of Stock Returns for Companies with crypto-asset exposure

Aleksander Roman Mercik, **Tomasz Słoński**
Wroclaw University of Economics and Business, Poland

Discussant: **Krzysztof Piontek** (Wroclaw University of Economics and Business)

Forecasting volatility during the outbreak of Russian invasion of Ukraine: Application to commodities, stock indices, currencies, and cryptocurrencies

Piotr Fiszeder[1,2], **Marta Małecka**[3]
1: Nicolaus Copernicus University in Torun, Poland; 2: Prague University of Economics and Business, Czech Republic; 3: University of Łódź, Poland

Discussant: **Krzysztof Piontek** (Wroclaw University of Economics and Business)

Sesion 1C Location: **room C**

Chair: **Ewa Majerowska**, University of Gdańsk, Poland

Dynamic Investment Portfolio Optimization with Reinforcement Learning

Grzegorz Tratkowski
Wroclaw University of Economics and Business, Poland

Discussant: **Maciej Wujec** (AI Lab, Science and Technology Park in Opole)

Backtesting comparison of machine learning methods on Warsaw Stock Exchange

Klaudia Kaczmarczyk
Wroclaw University of Economics and Business, Poland

Discussant: **Grzegorz Tratkowski** (Wroclaw University of Economics and Business, Poland)

Textual Analysis of Current Reports: A Deep Learning Approach.

Maciej Wujec
AI Lab, Science and Technology Park in Opole, Poland

Discussant: **Klaudia Kaczmarczyk** (Wroclaw University of Economics and Business)

1:00pm - 2:00pm

Lunch

2:00pm - 3:30pm

Plenary 2 Plenary 2 Location: **room A**
Chair: **Magdalena Katarzyna Jerzemowska**, University of Gdańsk, Poland

Market Risk and Exchange Rate Elasticity of Equity Returns

Lucjan Orlowski
Sacred Heart University, United States of America

Real earnings management, CEO professionalism, family ownership and a presence of big4 auditors - a meta-analysis

Jacek Mizerka, Mikołaj Nowicki, Bartosz Kabaciński
Poznań University of Economics and Business, Poland

Patterns in Corporate Trade Credit Management: A Glance at the Polish Trade Sector

Julia Koralun-Bereźnicka
University of Gdańsk, Poland

3:30pm - 3:45pm

Coffee Break

3:45pm - 5:15pm

Sesion 2A Location: **room A**
Chair: **Sebastian Majewski**, University of Szczecin, Poland

Determination of cap rate using financial data from European REITsMarkett: The Case of the Czech Republic

Dagmar Vágnerová Linnertová[1], **Martin Cupal**[2]
1: Masaryk University, Czech Republic; 2: Brno University of Technology, Czech Republic
Discussant: **Anita Makowska** (Wrocław University of Economics and Busisess)

Effects of capital structure on Jordanian commercial banks' insolvency

Qasim Alawagleh[2], **Abdulnafea Al Zararee**[2], **Tomasz Słoński**[1]
1: Wroclaw University of Economics and Business, Poland; 2: Philadelphia University, Jordan
Discussant: **Julia Koralun-Bereźnicka** (University of Gdańsk)

How properties are getting old - cadastral case

Anita Makowska
Wrocław University of Economics andBusinesss, Poland
Discussant: **Dagmar Vágnerová Linnertová** (Masaryk University)

Sesion 2B Location: **room B**
Chair: **Joanna Górka**, Nicolaus Copernicus University, Poland

Time series properties of liquidity measures in cryptocurrency markets

Krzysztof Piontek[1], **Radosław Pietrzyk**[1], **Paweł Rokita**[1,2]
1: Wrocław University of Economics and Business, Poland; 2: Empirica sp. z o.o., Poland
Discussant: **Ewa Majerowska** (University of Gdańsk)

The correlation between cryptocurrencies and traditional risky assets changes over time. Evidence from developed markets

Aleksander Roman Mercik, **Daniel Cupriak**
Wroclaw University of Economics and Business, Poland
Discussant: **Barbara Będowska-Sójka** (Poznań University of Economics ans Business)

The impact of market value liquidity on the effectiveness of option valuation with the Black-Scholes-Merton model on the example of WIG 20 Index

Michał Prymon
Wroclaw University of Economics and Business, Poland
Discussant: **Daniel Cupriak** (Wroclaw University of Economics and Business)

Sesion 2C Location: **room C**
Chair: **Bogdan Włodarczyk**, University of Warmia and Mazury in Olsztyn, Poland

Hierarchical Risk Parity in Portfolio Optimization – Empirical Evidence

Paweł Kliber
Poznan University of Economics and Business, Poland
Discussant: **Paweł Kuśmierczyk** (Wroclaw University of Economics and Business)

Non-parametric approach to extreme risk estimation on precious metals market

Dominik Krężołek
University of Economics in Katowice, Poland
Discussant: **Katarzyna Kuziak** (Wroclaw University of Economics and Business); katarzyna.kuziak@ue.wroc.pl

Model Risk of Marginal Expected Shortfall: Evaluation on Significant European Banks

Aleksandra Helena Pasieczna
Kozminski University, Poland
Discussant: **Anna Rutkowska-Ziarko** (University of Warmia and Mazury, Poland)

5:15pm - 6:15pm

Round-Table Discussions - cont
Location: **room A**

7:30pm - 11:30pm

Gala Supper

Date: Friday, 18/Nov/2022

9:00am - 10:30am

Sesion 3A Location: **room A**
Chair: **Dominik Krężołek**, University of Economics in Katowice, Poland, Poland

Yield Curve Impact on Energy stocks – preliminary results
Ewa Majerowska[1], **Jacek Bednarz**[2]
1: University of Gdańsk, Poland; 2: Catholic University of Lublin, Poland
Discussant: **Paweł Rokita** (Wroclaw University of Economics and Business)

Dependence analysis for energy ETFs and crude oil – a preliminary study
Katarzyna Kuziak[1], **Joanna Górka**[2]
1: Wroclaw University of Economics and Business, Poland; 2: Nicolaus Copernicus University, Poland
Discussant: **Ranadeva Jayasekera** (Trinity College; University of Dublin); ranadeva.jayasekera@gmail.com

Making Markets work for clean energy proliferation Application on Chinese green bonds
Ranadeva Jayasekera[1,2], **Tianqi Luo**[1]
1: Trinity College; University of Dublin; 2: Judge Business School, University of Cambridge
Discussant: **Marek Szturo** (University of Warmia and Mazury in Olsztyn)

Sesion 3B Location: **room B**
Chair: **Justyna Franc-Dąbrowska**, Warsaw University of Life Sciences, Poland

Information policy and reporting of insurance companies in the context of ESG
Magdalena Chmielowiec-Lewczuk
Wroclaw University of Economics and Business, Poland
Discussant: **Justyna Zabawa** (Wroclaw University of Economics and Business)

Ecological responsibility of banks in the context of ESG requirements
Justyna Zabawa, **Ewa Losiewicz-Dniestrzanska**
Wroclaw University of Economics and Business, Poland
Discussant: **Sebastian Majewski** (University of Szczecin)

Using E from ESG in systemic risk measurement
Marta Karaś[1], **Ewa Dziwok**[2], **Michał Stachura**[3]
1: Wrocław University of Economics and Business, Poland; 2: University of Economics in Katowice; 3: Jan Kochanowski University
Discussant: **Magdalena Chmielowiec-Lewczuk** (Wroclaw University of Economics and Business)

Sesion 3C Location: **room C**
Chair: **Iveta Palečková**, Silesian University in Opava, Czech Republic

Risk attitudes and financial decisions of adult Poles. The results of the combined experimental and survey research
Paweł Kuśmierczyk, **Radosław Kurach**, **Marek Kośny**
Wroclaw University of Economics and Business, Poland
Discussant: **Paweł Kliber** (Poznan University of Economics and Business)

Portfolio Choice during the Covid-19 Pandemic - Evidence from the Frankfurt Stock Exchange
Paweł Kliber[1], **Anna Rutkowska-Ziarko**[2], **Konrad Szydłowski**[2]
1: Poznań University of Economics and Business, Poland; 2: University of Warmia and Mazury, Poland
Discussant: **Radosław Pietrzyk** (Wrocław University of Economics and Business)

The impact of video game industry on economic growth in China, the US and the UK
Natalia Magdalena Romano
Wroclaw University of Economics and Business, Poland
Discussant: **Grzegorz Tratkowski** (Wroclaw University of Economics and Business, Poland)

10:30am - 11:30am

Coffee break / check-out

11:30am - 1:00pm

Plenary 3 + Closing Location: **room A**
Chair: **Barbara Będowska-Sójka**, Poznań University of Economics and Business, Poland

Cash management from a Smart Village perspective
Justyna Franc-Dąbrowska, **Magdalena Mądra-Sawicka**
Warsaw University of Life Sciences, Poland

Crisis phenomena in commodity markets
Bogdan Włodarczyk, **Marek Szturo**
University of Warmia and Mazury in Olsztyn, Poland

Seven decades of the actively managed mutual fund performance
Katarzyna Perez, **Richard Van Horne**
Poznan University of Economics and Business, Poland

1:00pm - 2:00pm

Farewells/snacks
Location: **room A**

Magdalena Jerzemowska

Gdansk University

magdalena.jerzemowska@ug.edu.pl

Was Tax Optimization Used in Ancient Japan?

The aim of the paper is an attempt to examine whether tax optimization was used in ancient Japan. The method of research is analysis of relevant literature. The period under consideration covers the Yamato (250-710), Nara (710-794) and Heian (794-1185) epochs. Thus, the analysis of tax regulations undertaken covers almost one thousand years. During this period, three phases of state development can be distinguished. The first is the period of state centralization, the second is the establishment of the *Ritsuryo* State, and the third is the period of decay of the *Ritsuryo* system and the decentralization of state power. In these three periods, the land was the basis of the economy and a primary source of income. It conditioned the existence of various social groups and was a source of material wealth and political influence for the ruling classes of courtiers, clerics, warriors, and peasants. [1] Thus, the most important problems were related to the ownership of land and the right to taxes levied on it. The research aims to verify the thesis that tax optimization was used in ancient Japan.

The analysis is one of the first attempts in Polish literature to outline taxes and their evolution in ancient Japan. Another novelty is the indication of the possibility of tax optimization on three levels - setting tax policy (state), determining, and collecting tax (local), and generating tax revenue (farmer). An attempt was also made to indicate the consequences of ancient tax practices and rules for the modern Japanese economy. The presented considerations contribute to the recognition and assessment of this interesting and increasingly explored research area.

For the ancient beneficiaries of tax revenues, the most important issue was their optimization, i.e., maintaining and expanding the tax base and striving to increase the income generated from it. For taxpayers, optimization was associated with the possibility of reducing them. Optimization refers to an activity (methodology) or process of doing something as well as possible, that is, as perfectly, functionally, or effectively as possible.[2]

A review of the literature on the subject allowed to conclude that in the analyzed periods, attempts to adjust the tax systems to the turbulent political and economic environment were not always effective. The amount of tax collection changed depending on the state's level of development, its financial situation, the degree of centralization of power and control over land and people, and the land ownership structure. These studies led to the conclusion that tax optimization had been used in Japan since the founding of the *Ritsuryo* State.

There is not much information on taxation in the early Yamato period. Japan was a federation of the clans called *uji*, united under the leadership of a chieftain who claimed descent from a common ancestor (*ujigami*) and worshipped the group's ancestral deity (*kami*). [3] Each clan (*uji*) had its territory and was linked to the main family through loyalty and marriages.[4]

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[1] Frohlich, J. (2003) Land Administration in Medieval Japan: Ito no shô in Chikuzen Province, 1131–1336. *University of Zurich, The Historical Association and Blackwell Publishing Ltd*, file:///D:/Users/wzr/Downloads/Land_Administration_in_Medieval_Japan_It%20(1).pdf

[2] https://dictionary.cambridge.org/dictionary/english/optimization

[3] Britannica; https://www.britannica.com/place/Japan/Rise-and-expansion-of-Yamato#ref276125.

[4] Yamamura, K., Murakami, Y. (1984). Ie Society as a Pattern of Civilization: Introduction, *Journal of Japanese Studies*, 10 (2), 279–363. http://www.jstor.org/stable/132142. p.28.

The chieftain was the lord of the family, and the household, and controlled all the property of the *uji*. He had the right to life and death over the members of the clan. [5] *Uji* can be compared to corporations operating today in a competitive market. It can be assumed that in the period when independent *uji* were ruled by chieftains, tax optimization was not possible (or perhaps not necessary) because the clan worked for its good and that of its leader. The economic activities of the *uji* were carried out by corporations headed by professional managers. Clan leaders focused on increasing tax revenues by improving labor productivity, introducing innovations, and expanding arable land. The chief, who had the right of life and death over clan members, strictly controlled taxes, so the chances of tax optimization by other members of the *uji* were probably very small as well as highly risky.

The Yamato clan established the Yamato Kingdom, a political union of the *uji* of the favoured families. The source of its supremacy were contacts with China and Korea. [6] New technologies, knowledge, and religious systems were acquired from them, including the construction of irrigation systems, the opening of new lands, as well as knowledge about the organisation and functioning of government, the control of land, and the levying of tribute. [7] However, the ancient Japanese implemented only those ideas and practices that suited their needs and preferences[8] (hybridization). At this time there was no annual tax that the king of Yamato regularly imposed on the people, except for occasional general requisitions for public works, festivals, or military operations. He had no right to levy taxes without the consent of the clan chieftains. [9] By the 5th century, the u*ji* associated with Yamato became semi-independent, political, and administrative units approved and controlled by the Yamato ruler until their abolition in 604. [10] The king established unprecedented, centralized control over the *uji* with the implementation of the *uji-kabane* system. [11] It can be assumed that in this period there could already be limited use of tax optimization at the level of clan chiefs.

The situation changed in this regard during the period of centralization of the country, particularly during the operation of the *Ritsuryo* State.

The *Ritsuryo* State was established by the Taika Reform Edict (646), which consisted of four articles that strengthened the emperor ‘s political power. [12] The Taika reform introduced a rational and just tax system. [13] Free farmers were expected to cultivate imperial land in exchange for a rent (lease), which was paid as a tax in the form of agricultural produce, and home-made products (craftsmen), as well as forced labor for the benefit of the community (construction of roads, bridges, etc.). [14] The taxes collected from the farmers were intended for public needs and stipends for the emperor, his family, court members, and distinguished nobles who were appointed as government officials and selected according to established quality

[5] Andressen, C. (2002). A Short History of Japan. From Samurai to Sony, *Allen & Unvin*, Australia, p.28
[6] Totman, C.D. (2014). A History of Japan, 2nd ed. Wiley, 2014. Available at: https://www.perlego.com/book/1006239/a-history-of-japan-pdf, p. 52-53.
[7] Totman, C.D. (2014). A History of Japan, op. cit., p. 53.
[8] Yamamura, K., Murakami, Y. (2014). Ie Society as a Pattern of Civilization…, op. cit.
[9] Ellington L. (2002). Japan. A Global Studies Handbook, ABC-CLIO Inc, Santa Barbara, Denver, Oxford, p.23. Hara K. (1920). An Introduction to the History of Japan, *Yamato Society Publication, G. P. Putnam's &Sons. The Knickerbocker Press*, New York, London, p.42.
[10] Kiley, C. J. (1973). State and Dynasty in Archaic Yamato, *The Journal of Asian Studies*, Nov. 33 (1), 25-49. https://www.jstor.org/stable/2052884
[11] C.D. Totman, *A History of Japan*… op. cit., p.53.
[12] Morton W. S., Olenik J.K. (2005). Japan. Its history and Culture, *McGraw-Hill Companies* Inc, New York, p.24.
[13] Yamamura K. (1974). The Decline of the Ritsuryō System: Hypotheses on Economic and Institutional Change. *Journal of Japanese Studies*, 1 (1) pp. 3–37.
[14] Morton W. S., Olenik J.K. (2005). *Japan. Its history and Culture…op. cit.*, p.24.

criteria.[15] Since labour was the basis for income, following the rules meant that tax optimization was essentially impossible and, more importantly, unnecessary. This system, although rational and fair, did not exist for long.

As a result of these reforms, Yamato's administrative system was replaced by the *Ritsuryo* model administered by officials,[16] which was gradually modified. These adjustments resulted not only from economic realities, but mainly from the desire to obtain privileges that gave financial benefits and higher status to the aristocrats, the former leaders of the clans, and their most prominent members (high state officials). The law became a compromise between the new principles of the *Ritsuryō* system and the old respect for birth.[17] It is an example of the use of hybridization, which is skillfully used to this day.

Throughout the period under review, there was a fierce struggle for power and privileges on all levels of society. In the third phase of the state development, three levels of this rivalry can be distinguished – high i.e., the state level, medium - concerning provinces, and lower administration structures, and low - the farmer's level. At each of these levels, tax optimization was applied, but due to the powers held, to a different extent and effect.

The first level was made up of the most powerful and influential aristocrats and court officials, especially those who had the power to shape the tax policy in the state. Together with the imperial family, they were focused on gaining more and more privileges and income. Due to their power, they could obtain lucrative land grants and various tax exemptions from the emperor.[18] They could plan, impose, and control taxes, and ensure that tax revenues were in line with their expectations and needs.

The desire of the highest state dignitaries to increase income through tax optimization led to the creation of *shoen*, large land estates operating on the basis of enterprises.[19] *Shoen* owners, through court position or connections (relational capital), found ways to obtain land tenure, appropriate tax exemptions, and *shiki* (*shiki* - a specific office or position in the estate that determined the income payable by level in the *shoen* hierarchy).[20] The owners employed professional managers for their *shoen* and ensured proper relations with the provincial governments. *Shoen* were the result of cooperation between the three following aspects of the tax system: policy, the effectiveness of collection, and production base. The deteriorating fiscal situation of the state forced the aristocracy to change the tax law, tax base, assessment, and methods of tax collection. In the tenth century, they applied an innovative method of optimizing their income, i.e., the transition from the personal tax to the land tax (*myo*), which was subject to further modifications.[21] The aristocracy and officials always took great care to apply tax optimization.

[15] Nagata M. L. (2008) Brotherhoods and Stock Societies: Guilds in Pre-Modern Japan. *International Review of Social History*, 53, pp. 121–142. *JSTOR*, www.jstor.org/stable/26405470. Accessed 3 Aug. 2021.

[16] Meyer M. W. (2009). Japan. A Concise History, *Rowman & Littlefield Publishers Inc*, Plymouth, p.41-42. Mason, R.H.P., Caiger J.G (1997). A History of Japan, *TUTTLE Publishing*, p.80.

[17] Murdoch, J. (1910). History of Japan. From the Origins to The Arrival of the Portuguese in 1542 A.D., Volume I, *The Asiatic Society of Japan*, p.171.

[18] Yamamura, K. (1974). The Decline of the Ritsuryō System…op. cit.

[19] The summary of the system is based on Britannica, https://www.britannica.com/place/Japan/The-Taika-reforms#ref168017 21.04.2020

[20] Sato, E. (1979). *Ōyama* Estate and Insei Land Policies Estate and Insei Land Policies. *Monumenta Nipponica*, 34 (1), pp. 73–99. *JSTOR*, https://doi.org/10.2307/2384282. Accessed 23 Aug. 2022.

[21] Kito, K. (1986). Brief history of development of Ancient and Medieval land Systems in Japan, Dialogues d'histoire ancienne Année 12, pp. 457-469. https://www.persee.fr/doc/dha_0755-7256_1986_num_12_1_1735.

To increase control over the settlement and collection of taxes, aristocrats and officials created special audit office (*Kageushi*), and posts such as *zuryo*. The *zuryo*, who had received the governance of the province, was in charge and accountable for its men and public goods.[22]

In the early 670s, provincial governors (*kokushi)* reappeared (dating back to the 5th century) as an integral part of the administrative system.[23] The governor's duties included registering the population, acting as the father to the people, supporting agriculture, hearing complaints, registering households and rice fields, levying, and collecting taxes and serfdom, redressing grievances, and maintaining irrigation systems. No aspect of the lives of the provincial people escaped their notice.[24] However, during the Heian period, ownership, and control of the *shoen* and the provinces became separated. Their masters usually enjoyed life in the capital and did not interfere in the management of their property as long as they obtained the expected income.[25]

A new metropolitan police force spread to the provinces to watch closely all events and activities, especially land ownership and tax avoidance.[26] Systemic changes introduced in the following decades of the existence of the Ritsuryo State enriched the highest elites but significantly reduced their responsibility, involvement, and supervision over the generation of tax revenues. All these changes made local leaders and officials increasingly responsible for valuing and collecting taxes, making them (tax managers) the second tier of the tax system in terms of hierarchy and authority, and members of the group of *wealthy*.[27]
As noted earlier, *shoen* were managed by professional managers whose main task was to meet the financial expectations of the state, the owner of the *shoen*, provincial officials, and farmers. Rich and influential local landowners and farmers were nominated local tax managers or appointed tax collection officials called *fumyo* or *tato*.[28]

The local officials, especially the tax managers, were using tax optimization as a method of increasing their incomes because they were eager to increase their financial and social status. They used various tools to achieve these goals, but such activities had to be consistent not only with the interests of their superiors but also with the applicable laws. The risk of a penalty for failure to comply with the obligations, not to mention penalties for breaking the law, was great.[29]

The government maintained the tax revenue by holding provincial officials responsible for tax losses and instituting a system of incentives to make them deliver the correct amount of taxes on time. A governor who did not provide the full amount owed from his province was disqualified from further official appointments by the Audit Office known as *kageyushi*.[30] The system of *collective reimbursement* was employed in 795.[31] Tax officials, in order to meet the expectations of their superiors, and at the same time increase their wealth (optimize tax

[22] Mass, J.P. (1990). The Kamakura bakufu, In: *The Cambridge History of Japan*, vol.3, *Medieval Japan,* K. Yamamura (ed)…op. cit., p.49.
[23] Hara, K. (1920). An Introduction to the History of Japan…op. cit. London, p.161.
[24] Hérail, F. (2014). The Position and Role of Provincial Governors at the Height of the Heian Period, *French Journal of Japanese Studies*, 3. https://journals.openedition.org/cjs/658.
[25] Hérail, F. (2014). The Position and Rol of Provincial Governors…op. cit.
[26] Sansom, G.B. (1958). A History of Japan to 1334, Volume 1, *Stanford University Press,* Stanford, p.112.
[27] Yamamura, K. (1981). Tara in Transition: A Study of a Kamakura Shoen. *Journal of Japanese Studies,*7 (2), pp. 349–91. https://doi.org/10.2307/132206.
[28] Batten, B. L. (1993). Provincial Administration in Early Japan: From Ritsuryō Kokka to Ōchō Kokka. *Harvard Journal of Asiatic Studies*, 53 (1), pp. 103–34. JSTOR, https://doi.org/10.2307/2719469. Accessed 31 Oct. 2022.
[29] Hérail, F. (2014). The Position and Role of Provincial Governors …op. cit.
[30] Batten, B. L. (1993). Provincial Administration in Early Japan...op. cit.
[31] Hérail, F. (2014). The Position and Role of Provincial Governors …op. cit.

revenues), imposed on peasants more and more burdens, such as *suiko*[32], additional serfdom, used fraudulent measurements or falsified harvest, and population records. [33] Thus, the popular method of tax optimization on the local level was to force, in a lawful and unlawful manner, greater tax efficiency (exploitation) on farmers. These methods were very effective and contributed to a significant increase in the wealth and importance of local notables, and to the emergence of *samurai*.

The third level of tax optimization concerned peasants. However, here the methods of optimization of taxes had serious limitations. Paying the due taxes became the responsibility of the entire village, the community of five, and the family (orders from above). Shared responsibility resulted not only in cooperation, but also ensured strict mutual control. Farmers could reduce the tax burden placed on them (depending on their financial situation) by abandoning farms, land commendation, or armed rebellion. These forms of *tax optimization* were often used and made the elite realize that farmers cannot be burdened with obligations above the level that would ensure their modest existence. They had to be motivated by a small return or else they would lose interest in farming and rebel, causing losses to their superiors, and threatening the existence of the entire tax system.

Despite all efforts, in the Heian era, revenues continued to decline, and the central government's control over the provinces was steadily weakening. The public ownership of land introduced by the *Ritsuryō* system crumbled, causing increasing instability in government, and system of governance. The public ownership of land introduced by the Ritsuryō system disintegrated, causing increasing instability in the government and governance system.

At the end of the 12th century, after the turmoil of wars between the most powerful clans (Fujiwara, Taira, Minamoto) fighting for power, Kamakura *Bakufu* was established by Yoritomo Minamoto, which introduced new rules for controlling the state, provinces, and taxes and their collection.

[32] Hondo, E. (1930). On the Financial Development of Japan. *Kyoto University Economic Review* 5(2 (10)), pp. 66–79. http://www.jstor.org/stable/43216724.

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Zombies on the Cryptocurrency Market

According to the survey conducted on the literature from 2013 to June 2021, 85% of papers on cryptocurrencies have appeared since 2018, which demonstrates the emergency of a new research area (Fang et al., 2022). Fang et al. (2022) state that the number of financial institutions to include cryptocurrencies in their portfolios has accelerated. Thus, unsurprisingly, the coins are highly examined in the academic literature, which in majority focuses on the main leaders. Definitely, less attention is paid to minor losers, those currencies with low capitalization or dying ones.

Such coins, which for the purpose of the paper would be called zombies after Kharif (2022), are rather rarely observed in studies and barely addressed in the literature. Inactive coins appear most often in the context of avoiding survivorship bias. Zombies are also present in the framework of non-fungible tokens (Plachimowicz and Wójcik, 2022). We found a gap in the literature with respect to what are the determinants of becoming inactive and how to predict a coin might become a zombie.

The aim of this paper is to determine what are the predictors of cryptocurrency to disappear from the market or at least to become non-tradable for a period longer than a month. As the regulations of the cryptocurrency market are still in progress and investors are searching for the best investment opportunities, it is reasonable to discuss the risk of losing money invested in coins that become zombies, or at least indicate the possible predictors of such a situation. We focus on the features which are easy to observe, returns, and trading volumes.

The first cryptocurrency, bitcoin, introduced by Nakamoto (2008) appeared on the market in 2010, and its success seems to have fuelled the creation of subsequent cryptocurrencies, which have grown at an almost exponential rate. Unlike with stocks or bonds, taking a cryptocurrency out of circulation does not require lengthy procedures.

The literature related to our research is the following: Agosto and Cafferata (2020) verify whether explosivity in one cryptocurrency leads to explosivity in other cryptocurrencies. They focus on financial bubbles detection. Shahzad et al. (2022) examine price explosiveness in cryptocurrencies and Elon Musk's tweets - bitcoin and dogecoin bubble episodes. Kadziołka (2021) creates a ranking of the cryptocurrency exchanges and identifies groups within them with a similar level of attractiveness. Demir et al. (2018) find evidence that the economic policy uncertainty index of Baker et al. (2016) has predictive power on Bitcoin returns. There is plenty of studies devoted to the prediction of cryptocurrency prices (usually bitcoin) within the ML framework (Oyedele et al., 2022). At the same time, the subject of dying coins is rarely considered.

We use the data from coinmarketcap.com and select coins listed in the database from January 1, 2013, till September 2022 (3462 days) which follows the condition of being listed constantly at least for 210 days. In the first step, zombie coins were detected as those for which trading has stopped. Then for each zombie, we randomly selected two counterparts with similar average market capitalisation from 60 to 30 days before becoming inactive. The final sample consists of 2469 different coins, out of which 823 became inactive and 1646 were active. We divided the whole dataset into training (70%) and testing (30%) samples with 5-fold cross-validation for hyperparameter tuning. We define zombies as those coins for which trading has been halted or which have ceased to be traded for at least a month. All variables, such as returns or trading volume, are obtained for a period up to day zero, defined as the 30th day before the coin disappears. We calculate the usual descriptive statistics for returns and trading volumes in the last month and in the last six-months period ending on a day zero.

The 5-fold cross-validation was applied with optimization based on the Balanced Accuracy metric. Several types of models are considered: linear models, with (1) logistic regression, (2) lasso that penalizes features which have low predictive outcomes by shrinking their coefficients towards zero and setting some to zero, (3) ridge regression which penalizes features that have low predictive outcomes by shrinking their coefficients towards to zero and (4) support vector machine with a polynomial kernel. Among tree-based models, we applied: (5) random forest which combines the predictions of multiple independent decision trees and (6) extreme gradient boosting which combines the predictions of multiple decision trees estimated sequentially.

All measures are calculated on day 0 which is 30 days before a coin becomes inactive. We consider the average return from the preceding 30 and 180 days, average trading volume for 30 and 180 days, medians for returns and trading volumes - 30 & 180 days, minimum, maximum, standard deviation, skewness, and kurtosis. The highly correlated variables are removed from the set.

The predictive ability of models indicating that a cryptocurrency will become inactive is tested. We verify several algorithms in the classification exercise and find that the accuracy differs between particular methods. The best-performing algorithm is a random forest, with top variables such as kurtosis of volume, maximum volume and mean return. The random forest is followed by xgboost. We are able to predict becoming a "zombie" within one month with 70% accuracy.

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Determinants of banking stability in the Czech Republic

The paper focuses on banking stability/fragility. Although the banking sector in the Czech Republic is stable during the last two decades, the Covid-19 period and the unpredictable economic development as well as the rising interest rates and inflation and energy crisis should be a threat to banking stability. Therefore, the paper focused on several internal and external indicators that could influence the banking fragility/stability. The aim of the paper is to estimate the factors that influence the banking fragility in the Czech Republic. The topic is interesting not only for academics, but also for policy-makers, regulators, and bank management. First, the stability of the Czech commercial banks is measured using the summarized index of financial stability. This index is constructed as a weighted sum of selected indicators of performance, liquidity, solvency, asset quality, and affiliation with the financial group (where applicable). Then, we use the generalized method of moments as an estimation method in dynamic panel data analysis.

This paper focuses on one of the most debated topics in contemporary financial economics, i.e., on banking stability/fragility. The term banking fragility is inverse to the term banking stability, so to be able to assess banking fragility, it is necessary to evaluate its ability to withstand shocks. According to World Bank (2021), there are numerous methods for banking stability measurement: (i) financial soundness indicators presented by International Monetary Fund; (ii) Z-score; (iii) Merton´s model; (iv) the KMV model; (v) and other. The aggregated index of financial stability applied in this paper is also possible. The index can summarize complex and multidimensional realities into one number and thus assess easily the overall financial health of the bank. It may enable us to capture also the link between the financial health of a bank and its parent company, which is especially important in the last years when we could observe the increasing interconnection between banks from different countries: many banks offer their services in the domestic country and in other countries through their subsidiaries or branches. The financial health of such banks affects the financial stability of financial systems in different countries. This is also the case of the Czech banking sector, where the banking system is dominated by foreign banks and banks that belong to international financial groups. Therefore, the aim of the paper is to identify the influence of selected factors on the banking fragility in the Czech Republic. Bank fragility will be measured by the aggregated index of bank stability. The paper is structured as follows. The next section provides a review of relevant literature. After that, we describe the methodology and data. The fourth section is devoted to the results of the analysis. The final section offers concluding remarks.

While choosing methods for the analysis of determinants of bank fragility/stability, we can find studies that used (i) simple panel data regression analysis with ordinary least squares (e.g., Ali and Puah, 2019); (ii) logistic regression models (e.g., Van-Thep and Day-Yang, 2019); (iii) multivariate regression analysis (e.g., RupeikaApoga et al., 2018); or (iv) GMM – generalized method of moments (e.g., Kasri and Azzahra, 2020; Gupta and Kashiramka, 2020; Guidi and Enowbi, 2020; or Karkowska and Pawlowska, 2019). The reasons why we chose the generalized method of moments are described in the section devoted to methodology. The next key task is to choose explanatory variables appropriately. To the best of our knowledge, there exist only four studies that analyse the determinants of financial stability measured by the aggregate index: Ghosh (2011), Pambuko et al. (2018), Shijaku (2016), and Palečková and Klepková Vodová (2022). Regarding the stated goal of this paper, the following narrative will address only selected possible factors: macroeconomic variables were the subject of the previous research (Palečková and Klepková Vodová, 2022), most of the bank-specific variables are included in the aggregated index of financial stability macroeconomic variables. For these reasons, we will focus only on selecting other internal or external factors. We can find studies that include aggregate data from several countries, as well as studies dedicated to only one banking sector. To the best of our knowledge, no study has examined the determinants of financial stability/fragility separately for Czech banks. Mostly, the relationship between a possible internal or external factor and the financial stability/fragility of banks is uncertain. As we can see from Table 1, some empirical studies found a positive link, while other studies suggested a negative impact of the same factor. Therefore, we do not have exact expectations about the direction of influence for individual explanatory variables.

Table 1. A review of empirical research on determinants of bank financial stability

Explanatory variable	Positive impact on financial stability	Negative impact on financial stability
Bank size	Maechler et al. (2007), Ghosh (2011), Shahid and Abbas (2012), Adusei (2015), Karkowska and Pawlowska (2017, 2019), Rupeika-Apoga et al. (2018), Guidi and Enowbi (2020)	Jahn and Kick (2012), Madi (2016), Ali and Puah (2019), Kasri and Azzahra (2020)
Monetary aggregate	Akani and Kingsley (2018), Innocent et al. (2021)	Jahn and Kick (2012), Siddik and Kabiraj (2018), Pham and Doan (2020)
Concentration in the banking sector	Ghosh (2011), Shahid and Abbas (2012), Shijaku (2017), Guidi and Enowbi (2020)	Jahn and Kick (2012), Karkowska and Pawlowska (2017, 2019), Ozili (2018)
Household and corporate indebtedness	Maechler et al. (2007), Siddik and Kabiraj (2018), Pham and Doan (2020)	Maechler et al. (2007), Kasri and Azzahra (2020), Pham and Doan (2020)
Reality price index	Jahn and Kick (2012)	

Source: Authors' processing.

The dataset used for the empirical analysis of this study was obtained from the annual reports of Czech commercial banks and financial conglomerates, statistics of the Czech Statistical Office statistics, and Czech National Bank statistics ARAD. The analysis covered 21 Czech commercial banks within the period 2001-2019. All data are reported on an unconsolidated basis. We used the unbalanced panel data and the sum of the total assets of commercial banks covering more than 75% of the total assets of the banking sector. Due to some missing observations, we have an unbalanced panel of 299 observations over the period 2001-2019.

Bank stability is measured using the aggregate financial stability index. This paper extends the previous authors' studies focused on the construction of the aggregate index of bank stability and a paper estimating the macroeconomic indicators of financial stability of the Czech commercial banks (Palečková and Klepková Vodová, 2022). Therefore, the construction of the aggregate index is detailed as described in Klepková Vodová and Palečková (2022). Briefly, the summary index was constructed as a weighted sum of selected indicators (performance, liquidity, solvency, asset quality, and affiliation with the financial conglomerate where applicable).

Regarding the literature review, numerous studies have concluded that bank-specific factors can determine bank financial stability. According to Adusei (2015) and Pham et al. (2021), bank stability has been typically supported by bank size measured by the natural logarithm of total assets, indicating that the aim of bank size expansion in relation to ensure stability in the financial market has to pursue. We measured bank size (SIZE) using the natural logarithm of the total assets of individual commercial banks. Kim et al. (2013) examined the relationship between some components of monetary aggregates and financial vulnerability. The monetary aggregates can be used as a signal of vulnerability. We used a narrow aggregate (M1), it includes currency, i.e., banknotes and coins, as well as balances, which can immediately be converted into currency or used for cashless payments.

The household sector, like the corporate sector, has the power to influence the overall economy, in part because of its size and its significant exposure to the financial sector. We included in this analysis several household indicators, namely, household and corporate indebtedness (INDEBTEDNESS), household consumption (CONSUMPTION) and average gross nominal wages (WAGE), and average old-age pension/average wage in per cent (PENSION). The growth rate of household and corporate indebtedness is measured by the credit growth rate for households and non-financial companies. The average gross monthly wage is the ratio of wages excl. other personnel expenses per registered employee per month. Old-age pension is calculated as the share of the average old-age pension to the average wage. The average old-age pension per year is based on the average monthly old-age pension paid out excluding the widow/widower pension.

Moreover, financial stability is frequently associated closely with the real estate market. It is generally believed that the boom-bust nature of property price fluctuations has played a role in past business cycles, fuelling the upswing and magnifying the downswing (Zhu, 2005). Therefore, the study includes the real estate (REPI) price index. The Bank stability index is used as a dependent variable and other indicators are regarded as independent variables of the financial stability of the Czech commercial banks.

Empirical analysis of the determinants of bank stability is examined using dynamic panel data analysis. For empirical estimation, we used the econometrics software STATA 16. As a consequence, we specify a dynamic model by including a lagged dependent variable among the regressors, i.e. y_{it-1} is the one-period lagged bank stability. Concretely, we estimated Eq (1) in empirical application:

$$Bank\ stability_{it} = c + \delta_1 Bank\ stability_{it-1} + \beta_{1..it} + \beta_2 GDP_{it} + \beta_3 ER_{it} + \beta_4\ INF_{it} + \beta_5 UR_{it} + \beta_6 GB_{it} + \beta_7 PRIBOR_{it} + \beta_8\ IR_{it} + \beta_9 FD_{it} + \beta_{10} FC_{it} + \varepsilon_{it} \quad (1)$$

where the variable $Bank\ stability_{it}$ is the financial stability of bank measured using the aggregate index of financial stability for bank *i* at time *t*, with *i* = 1, … *N*, *t* = 1, … *T*, *c* being a constant term, variables X_{it} are the instruments presented above and ε_{it} is the disturbance.

We follow the dynamic panel data analysis to assess the determinants of the financial stability of the Czech commercial banks. The estimation in our study is performed using the GMM method in a system. The consistency of the GMM estimator relies on the validity of the used instruments. In this paper, the variables are the lagged values of the explanatory variables and we tested all variables for stationarity using a unit root test (Levin, Lin and Chu test). We used Arellano and Bond test for the assumption of serially uncorrelated errors. Furthermore, we tested the overall validity of the instruments using the Hansen J test and we can confirm the validity of the estimates. The results of the empirical analysis (Table 2) show that five factors influenced bank stability in the Czech Republic. We found that bank size is a significant determinant of banking stability, but we found that bank size negatively influenced banking stability. It means that large banks were lower financially stable during the analysed period.

Table 2 Results of the empirical analysis

Variables	Coefficient	Std. Err.
IndexFSt-1	0.5314513[a]	0.0706576
SIZE	0.1726478[b]	0.0873818
CONCENTRATION	0.157926	0.1032356
M1	0.0508841[c]	0.0304256
INDEBTEDNESS	1.341547b	0.6704174
CONSUMPTION	0.1662599[c]	0.0947332
WAGE	0.0831283	0.0643866
PENSION	0.0494741	0.0810105
REPI	0.0482928[b]	0.019114
Constant	3.027545	5.667051

Note: a denotes significance at the 1% level, b denotes significance at the 5% level, and c denotes significance at the 10% level.

Source: Authors' calculation.

The effect of bank size on bank stability can also be viewed from the perspective of the concentration-stability and concentration-fragility hypotheses (Uhde and Heimeshoff, 2009). Although concentration was not a statistically significant factor of bank stability, the negative effect of size on bank stability is in line with the concentration fragility hypothesis. Moreover, we found that narrow money (M1) positively influenced bank stability. The increase in money lowers the level of interest rate, which makes financing through banking loans much more attractive for low-risk borrowers. The problem of adverse selection is reduced and banks have to solve the lower volume of non-performing loans, which enhance their stability.

We found that the growth rate of loans to households and non-financial companies had a positive and statistically significant impact on bank stability. When the growth rate of loans increases, it positively influences the stability of the Czech commercial banks. Credit growth can enhance bank profitability. Therefore, a decline in credit growth can reduce bank stability because loans are the main source of income in the Czech commercial banks. Traditionally it is considered that excessive credit growth is often considered an indicator of future problems in the financial sector. Therefore, it is necessary and important to determine what is still an optimal credit growth rate that does not threaten financial stability.

Household consumption decisions are associated with savings decisions, where expectations of future income play a determining role. However, the average gross nominal wages and the share of the average old-age pension to average wage were not statistically significant determinants of bank stability, the household consumption has a negative impact on bank stability. It means that when household consumption increase, it leads to a decline in bank stability. Higher consumption may be connected with lower savings and thus lower reserves for unexpected events.

The real estate price index positively influenced bank stability in the Czech banking sector. This situation explained Zhang et al. (2018) who stated that when real estate values change, the collateral values of loans are affected, which in turn affects both borrowing and bank lending behaviour. Well-performing property-related loans and higher returns on real estate investments can encourage banks to further increase their real estate market loans.

The aim of this paper was to identify the influence of selected internal and external factors on the fragility of banks operating in the Czech Republic. First of all, we measured the stability/fragility of Czech banks by the aggregated index of banking stability, based on data over the period 2001-2019. The results show that five factors were statistically significant. We have found that bank stability increases with monetary aggregate M1, corporate and households indebtedness, and real estate price index. Bank fragility increases with bank size and higher households´ consumption.

Our results suggest that large banks are less financially stable. It may signal that they cannot benefit from economies of scale or scope, or they are not able to use their potential to diversify the loan portfolios more efficiently. This negative effect of bank size is also in line with the concentration-fragility hypothesis. The increase in narrow money (M1) reduces the problem of adverse selection which enhances bank stability. Higher households and corporate indebtedness increase bank stability due to higher profits which enable banks to build up capital buffers. On the contrary, banking stability decreases with higher consumption, which leads to lower savings and thus lower reserves for unexpected events. Finally, bank stability is positively affected by the increase of property prices, as the rise of property prices improves the values of loan collaterals. Our results are mostly in accordance with the results of previous studies.

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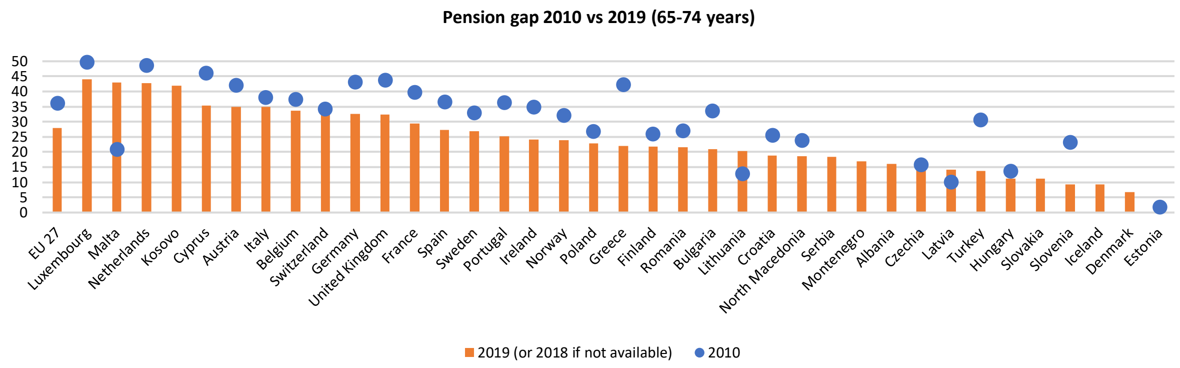
Factors of the women's pension gap - comparison of European countries

The presented research is a part of a broader study on the financial security of the elderly and the risk of poverty (more extensively Kwiecień, Poprawska 2022). Phenomena such as women's longer life expectancy, i.e. longer time running a single-person household, which is more costly than sharing expenses, longer unhealthy life expectancy than men's, poorer health especially in later old age (Murtagh, Hubert 2004, Boerm et al. 2016) and therefore greater need to finance treatment and care and at the same time lower pensions for women make them particularly at risk of poverty at retirement age.

Awareness of the risks that pensioners face with demographic and social changes has led researchers to look for reasons for women's worse retirement situation, primarily the lower pension benefits they receive. The reasons for this can be traced back to demographic, social, and cultural changes and the design of pension systems, most of which in Europe are based on a defined contribution system, which is very much linked to the amount of future pension provision to work history and level of earnings.

The importance of the research undertaken is high, as women are still in a less favourable situation than men in terms of pension benefits (the so-called gender pension gap), a problem which is all the more acute as women in Poland account for around 60% of pensioners, compared to an average of 57% in Europe. The gender pension gap is the difference between the retirement earnings of men and women (most often in %). The women’s pension gap is more than twice as large as the gender pay gap - in the EU 27 in 2020 27.6% vs. 13%. Women pension gap is present in most European countries. The pension and wage gap is narrowing, but their level is still high, and significantly diversified in European countries.



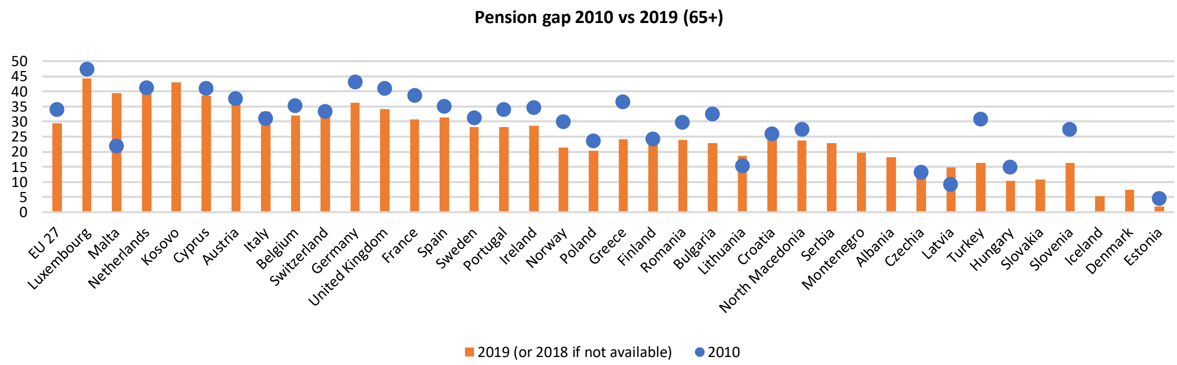


Figure 1. Pension gap in 2010 and 2019
Source: Eurostat data (Gender pension gap by age group – EU-SILC survey [ilc_pnp13])

The pension gap for women is a product of the differences in the course of the professional life of women (here maternity and its consequences are of great importance) and of men, and of the structure of the pension system, which may reduce or enlarge these differences.

The key reasons for the pension gap are as follows (more in Adami et al. 2013; Bettio et al. 2015; Tinios et al. 2015; Samek Lodovici et al. 201; EIGE 2019):

- modern pensions systems based on the DC approach.
- inequalities in the professional life that influence the retirement capital like gender pay gap, lower employment rates.
- over-representation of women in lower-paid professions
- huge over-representation of women in unpaid jobs
- shorter total duration of working life.

Women's fulfilment of social roles such as being mothers and caregivers (women perform these roles more often than men, studies confirm that as daughters, women look after their parents more often than men (e.g. Laditka and Laditka 2001; Ogg and Renaut 2006), 'penalizes' them in terms of pension security (see e.g. M.J. Budig 2014) The Fatherhood Bonus and The Motherhood Penalty: Parenthood and the Gender Gap in Pay. Leave periods related to caring for family members (maternity, parental but also leave related to caring for elderly parents) are calculated very unfavourably in relation to pay. Moreover, they may slow down careers and possibly cause a woman to take up part-time work. The problem for women in Poland is exacerbated by lower retirement age than for men. The majority of Poles and Polish women do not agree with either extending or equalising the retirement age for men and women. Although a significant majority considers the early retirement of women to be fair, most respondents also believe that women should be given the freedom to choose the moment of ending their professional activity. It cannot be considered that the creators and managers of the pension system in PL are not doing anything about this problem. An example of action can be the taxation of non-full-time contracts, but such a period of employment is not included in seniority.

The aim of this study is to compare European countries using factors relevant to building women's retirement capital, excluding the design of the pension system, which are very complex and difficult to compare.

This will then allow us to identify those countries where the factors outside the pension system are similar, but the scale of the pension gap is different, especially those where the gap is small. This may indicate a large role of the structure of the pension system in these countries. Therefore, these are the countries for which it is worth analyzing in more detail the solutions adopted in their pension systems.

Countries similar to each other in terms of the analyzed variables have different levels of the women's pension gap, that suggest the impact of the structure of the pension system. So, it is worth analyzing in detail the elements that compensate the women's pension gap in these systems. The pension gap is calculated for generations of women who are already retired and whose professional activity was covered by other pension regulations (before pension reforms in many countries, change from DB to DC). Demographic changes and projections indicate that young European women will be worse off when they retire than their mothers and grandmothers.

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Income Distribution Between Classes and Political Polarization: Case of the European Union

The paper provides a fresh look at the already existing literature devoted to the emergence of political polarization, its principle, and its connections, especially with redistribution and public finance. This goal will focus mainly on income inequality, specifically on the issue of the poverty risk of the lower income class and its influence on political polarization.

The concept of political polarization will first be defined with the help of existing literature, especially regarding the identification of its determinants. The selected socio-economic determinants will be in accordance with general economic theory, especially the theory of redistribution. Individual ideological spectrums will be used, on which the merit of polarization in the given state will be proven. These are the following spectrums: left-right, liberal-authoritarian, liberal-interventionist, and for or against European integration (EU). The reason for the use of several spectrums of dividing political parties is the development and emergence of new groupings (so-called catch-all parties) that cannot be identified by the most basic and used left-right division.

<u>The link between political polarization and the economic situation of the state</u>

The identification of the connection between polarization and the economic situation in the state is provided by Grechyna (2016). Grechyna considers the disposable income of households to be important. Moreover, polarization has a severe influence on the economic performance of the state and strongly affects investments, fiscal policy, legislative productivity, macroeconomic volatility, income inequality,y and the overall development of the economy. In his research, the state's GDP is shown to be one of the most common indicators of the economy's performance, when its increase has a negative effect on polarization. Grechyna also confirms the negative influence of polarization on the state's international trade and addresses the possible implications arising from the issue of economic policymaking in a polarized state.

Milijkovic and Rimal (2008) address the causality of political polarization and the economic state of the country with consequences for economic-political continuity. Their reasoning is simple. If the socio-economic conditions of the state are perceived positively by the majority of voters, a change in their voting and thus the political garniture is unlikely. For this reason, maintaining economic balance and acceptable growth is important to keep the government in power. Governments can influence the economic growth, rate, and distribution of income to satisfy the electorate. This idea is supported by their further research, in which they confirm the effect of a country's stable GDP growth on political stability, limitation of the number of irregular changes of government, and the satisfaction of society.

Bergh and Karna (2021) study how globalization affects populism (especially in the context of the connection of the Chinese market with Europe). The work finds a connection between the accession to the EU and the decline of left-wing populism, but with the growth of right-wing extremism. Globalization linkage to populism is not significant, even within the framework of purely economic globalization.

Based on these works, indicators of GDP, GNI, disposable income, the openness of the economy, and unemployment will be included as the economic control variables for further analysis.

<u>The impact of the threat of poverty to lower income class on political polarization</u>

The main tested influence of this work on political polarization will be the threat of the lower income class by poverty and, as a result, the voter's decision making. For example, Han (2015) deals with the topic. His research demonstrates the influence of income inequality on political polarization. Parties gain votes by targeting their core voters, which means that extreme left and right parties have then incentive to promote distinct positions from other parties of the spectrum depending on whether they target lower or higher income classes. In more tolerant, democratic political systems, this effect is stronger, political parties can afford to deviate from their original, more moderate positions than in more restrictive political systems. In these more restrictive conditions, on the other hand, parties risk a higher probability of losing mandates than parties relying on their base ideological positions.

The link between income inequality and political polarization is confirmed by Duca and Saving (2016). The main current factor that has an influence on its increased values is technological development, which threatens especially lower income class (less qualified workforce). Progressing globalization and demographic development are identified as other factors. According to Gu and Wang (2022), the threat of poverty to the lower income class increases income inequality in society and leads to higher values of political polarization. As the threat of poverty increases, the affected part of the population begins to adopt risk-averse strategies. This is exploited by extremist and populist parties that adapt ideologically. Ellis and Ura (2008) emphasize the influence of education. If the poorer class has access to education, it reacts to economic issues more strongly, almost strongest across all income classes. On the contrary, without access to education, it is inclined to vote according to cultural and moral values and not to react to changes in the attitude of the political garniture.

Polacko (2021) deals with the withdrawal of political elites from the representation of the class threatened by poverty. The research represents the view that the distribution of income is influenced much more by political decisions than by effective market forces. The trend is that political parties approach the wealthier class, rather than the other way around, and this is causing an increase in income inequality, and higher voter turnout has a positive effect on redistribution. Thus, this failure of political parties perpetuates a cycle of suppressing the participation of lower-income groups, leading to greater representation of the upper-income class and less public effort to combat inequality. It also confirms a possible increase in the number of voters for the radical right, populists, and authoritarians thanks to first-time voters coming from poorer backgrounds.

The premise of using indicators of the threat of poverty and redistribution for further analysis as the main explanatory determinants of polarization is based on this fundamental literature. The paper will use the GINI index of income inequality and poverty line rates.

The unique contribution of this work is the polarization index constructed with data from the ParlGov project. The polarization index is constructed from the left-right, liberal-intervention, and liberal-authoritarian spectrum and from the attitude towards European integration. The general election dates are used for the entire European Union from 1990 to the present.

The index will be constructed as follows. Individual parties are placed by the experts of the ParlGov project on a spectrum from -5 to +5. The given parties on the given election date are grouped according to their value on the spectrum and their election results are added up for the given group. The total electoral result of each of these groups is multiplied by their absolute value of location on the spectrum, where this value represents the 'polarization weight.' The resulting values are added up and divided by 100 for greater clarity. Four different spectrums are used from the ParlGov project; thus, four polarization indexes were calculated according to the previous description, and their average value was calculated for the resulting polarization index, which is the explained variable of the analysis of this paper.

The regression model used for all the studied states of the European Union is of the following form: $Polarization_{i,t}$ as an explained variable where i = 1, 2, . . . , 27 for the given states, t = 1990, 1991, . . . , 2022 for the election years (7–10 observations for given state). The basis of the polarization index is explained before. α_i is the constant, $\beta_{j,i,t}$ the regression coefficients and ε_i the random component. The main explanatory variables are: $poverty\_line\_20_i$ and $poverty\_line\_5.5_i$, the poverty line rate that expresses the share of the population living in poverty at 20 $ and 5.5 $ per day and per capita in 2017 PPP (World Bank, 2022). These values are used due to the different definitions of poverty according to the World Bank (2022), where the rate of $5.5 is considered the poverty line for lower-middle-income countries and the approximate rate of $20 for high-income countries. Further are used: HDIi, Human development index of United Nations Development Programme (2022), consisting of life expectancy at birth in years; expected years of schooling in years; mean years of schooling in years, and gross national income per capita in 2017 PPP $; and GINI_WIDi; GINI_SWIIDi, GINI indexes (World Inequality Database and Solt, 2022). As economic control variables were used: GNI_PPPi, standalone gross national income per capita in 2017 PPP $ (UNDP, 2022), GDP_PPPi, gross domestic product per capita in 2021 PPP € (WID, 2022), $disp\_income_i$, adjusted gross disposable income of households in real terms € per capita (Eurostat, 2022), $unemp_i$, unemployment as % of the total labor force (World Bank, 2022) and $trade\_open_i$, trade openness as the sum of exports and imports of goods and services as % of GDP (World Bank, 2022). Used sociodemographic control variables are: $turnout_i$, voters' turnout in % (National Statistical Offices), densityi, the density of population per km2 of the state (Eurostat, 2022), 65_plusi, the share of population older than 65 years in % (Eurostat, 2022) and edu_terciali, the share of the population with tertiary education in % (Eurostat, 2022). Regarding the sociodemographic variables, the age variable in this context is supported by the works of Stanig (2013) and Hayo and Seifert (2003) that also use population density. Voters' turnout and population state are used for example by Lindqvist and Östling (2010). Education is mentioned for example by Doležalová et. al (2017).

For all the main explanatory variables and control economic variables, the data of the year preceding the election are used in accordance with the research of Stanig (2013), which assumes that voters react to their economic situation from the previous year and not to the current economic state. Variables GNI_PPP_i, GDP_PPP, and $disp\_income_i$ are logarithmized due to greater clarity of the results and simpler analysis using the OLS method. Missing data for all the explanatory variables, especially for the beginning of the 90s of the last century, were calculated as the average deviations of the data available.

During processing, a high correlation was found between the poverty_line_20 and poverty_line_5.5 variables, which was expected, i.e., the variables were used separately in each of the models. The same problem concerned the variables GINI_WID and GINI_SWIID. The economic variables GNI_PPP, GDP_PPP, and disp_income were treated separately, as they are based on a similar basis, and it was examined which of the variables would be the most accurate for describing the economic situation of households, resulting in the usage of 12 different models. When choosing the final model, it was selected among the models with the highest value of the coefficient of determination and least problems with statistical testing. For any of the models is it possible to confirm the connection with the HDI indicator, nor with the GINI coefficients, so it is not appropriate to use these indicators for given states, but these can be useful, for example, for research of the political polarization of developing countries, where higher differences of the level of income inequality and quality of life exist. The variable unemp is significant only in one model. The turnout variable is also not significant in any of the models, voter turnout does not affect polarization in the European Union, i.e., the theory that only voters with stronger, extreme opinions go to the polls. In all selected models, the variable of tertiary education is also not significant, thus for the follow-up research it might be more appropriate to choose the share of the population with completed secondary education as a larger share of the population can have a greater influence on the election results. On the contrary, the poverty_line variable and the economic variables of GNI, GDP, and disposable income play an important role in all monitored models. It can be concluded that these describe the living conditions of the population most appropriately, and redistribution has a high priority for the political garniture within the public finance setting, if the garniture tries to get re-elected while taking political polarization into account. The trade openness variable also has a non-negligible effect in the selected models as its setting behaves as another source of household income. The variable density is significant in each of the models, and it is therefore important to monitor the election results in the context of urban development and its inhabitants. Also, significant for all models is the 65_plus age variable.

The hypothesis about the link between the threat of poverty of the lower income class and political polarization cannot be rejected. The resulting model confirms the positive dependence of polarization on the poverty line rate (20 $), i.e., as the number of people in poverty increases, the degree of polarization rises. This shows that lower class, which is identified within the population by this rate, is prone to elect a more extreme political set, which can use this fact for its re-election and adjusts its electoral program accordingly, which corresponds with the research of Polacko (2021). Moreover, for the chosen model, polarization depends to a lesser extent on the openness of the economy, where more open states move towards less polarization as globalization comes with more economic advantages. The positive dependence of polarization on disposable income is interesting, i.e., with higher values of income, polarization increases. This phenomenon is in contradiction with the broad literature dedicated to polarization, but as this work is devoted almost only to economically developed states, a phenomenon known as loss aversion may be the cause (Kahneman and Tversky, 1979). The population is so sensitive to their income level that when higher values occur, the voters are so afraid of losing it that they vote for more extreme parties that promise to protect them. As for the socio-demographic variables, polarization depends on population density, where states with a higher population density (where is denser urban development, usually of the population with higher incomes) vote less polarized. The influence of the population over the age of 65 is also significant, where a larger share leads to higher values of polarization, as these voters are typically more easily influenced by extreme opinions. This result also corresponds to the influence of redistribution politics, which is directly linked to disposable income – this age group depends not only on their savings but also on pension programs that governments create and adjust. The influence of these socio-demographic changes is consistent with the research of e.g., Stanig (2013). The chosen model explains 48.3 % of polarization variability values, which is satisfactory for a given dataset.

The aim of the paper, i.e., identification of variables that have an influence on political polarization within the context of poverty at risk of the lower class, was fulfilled. For the European Union, the indicator of the share of the population living in poverty at 20 $ per day and per capita, is relevant. Major influence on individual income classes and their decision-making represents the development of disposable income. The openness of the economy also affects the overall wealth of the state. Per the results of socio-demographic variables, the density of the population, and the age composition of the population, especially the share of the over 65 years age group, proved to be of importance.

The polarization index is sensitive to the change in disposable income of households and to the rate of poverty, which corresponds mostly to the voting shifts of the lower income class. For a properly functioning democracy, it is therefore important that public finances are set in a way that the lower class is not left behind and redistribution politics ensure the maintenance of the standard of living of the entire population. Especially at a time when the trend of polarization of the labor market (Náplava, 2019), i.e., the depopulation of the middle class because of technological progress, is progressing, the question of redistribution will be crucial for the growing lower income class, as it may become the main bearer of election results instead of the middle class. At the same time, it is possible to say that the states of the European Union are not homogeneous, each of the democracies has its own historical development, and especially the states formed after the collapse of the USSR had to deal with many economic, sociological, and political changes in a brief time. It is also necessary to investigate other possible influences on its development or to employ weights of individual ideological spectrums into the polarization index according to their significance due to existing literature.

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Key debt drivers of local governments – empirical evidence on municipalities in Poland

In the literature, there are findings indicating both the negative impact of public debt on the economy and the need to use it. It also concerns units operating at the local level of the public sector. Therefore, the growing debt, and finally over-indebtedness of local governments may reduce the living standard of the society.

Thus, the aim of the research is to examine the significance of key debt drivers of local governments on the example of the municipalities functioning in Poland between 2010 and 2021. As a result of the literature review and the examination of the findings, the main hypothesis of the paper is that fiscal capacity, investment activity, budget rigidity and the size of local governments along with spatial associations significantly affect debt level of the local governments and the election cycle.

The study examines the population of 2,414 local governments (municipalities/communes) (N=2,414) operating at the local tier of the public finance in Poland between 2010 and 2021 (T=12). Therefore, panel data analysis is applied. Moreover, the spatial autocorrelation statistics were estimated to reveal spatial associations in the field of the debt burden in the units.

The conducted research shows that there are both financial and non-financial debt drivers of local governments. The level of indebtedness is significantly determined by the first group of factors, i.e., the financial, especially fiscal capacity, investment activity the budget rigidity, as well as the spatial ties. The debt burden is also affected by the election cycle.

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Forecasting volatility during the outbreak of Russian invasion of Ukraine: Application to commodities, stock indices, currencies, and cryptocurrencies*

The Russian invasion on Ukraine on February 24, 2022, sharply raised the volatility in commodity and financial markets. This had an adverse effect on the accuracy of volatility forecasts. The scale of negative effects of the war was, however, market-specific and some markets exhibited a strong tendency to return to usual levels in a short time.

We study the volatility shocks caused by the war. Our focus is on the markets highly exposed to the effects of this conflict: the stock, currency, cryptocurrency, gold, wheat, and crude oil markets. We evaluate the forecasting accuracy of volatility models during the first stage of the war and analyze the methods that have the potential to mitigate the effect of forecast deterioration.

We use robust methods of estimation and a modified Range-GARCH model which is based on opening, low, high, and closing prices. We compare them with the standard maximum likelihood method of the classic GARCH model. Moreover, we employ the MCS (Model Confidence Set) procedure to create the set of superior models.

Analyzing the market specificity during this conflict, we discover the individual nature of the cryptocurrency markets, where the reaction to the outbreak of the war was very limited and the accuracy of forecasts remained at a similar level before and after the beginning of the war. Our findings regarding the suitability of methods in the wartime reveal that the Range-GARCH model compares favourably with the standard volatility models, even when the latter are evaluated in a robust way. It shows that in this period gains from using more market information outweigh the benefits of using robust estimators.

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Dynamic Investment Portfolio Optimization With Reinforcement Learning

One of the basic human activities in the field of economics is investing [Jajuga and Jajuga, 2005]. From the perspective of managing the entire set of investments, it is defined as an ongoing capital commitment to obtain future payments that compensate the investor for time and uncertainty [Reilly and Brown, 2018]. The entire collection of investments in the form of financial or real assets is called an investment portfolio [Ostrowska, 2011], the composition of which changes over time as the investor's expectations of future payouts change. This requires a continuous process of investment portfolio management [Reilly and Brown, 2018], which is divided into:

1) drawing up an investment policy statement,
2) selecting an investment strategy,
3) constructing the portfolio,
4) evaluating portfolio performance.

Using new technologies, especially artificial intelligence tools, in the investment portfolio management process, some elements of the process can be improved and automated, as will be shown in this paper.

The first main objective of the paper is to conduct a literature review on the application of machine learning in the investment portfolio management process. The systematic review of the literature is aimed at identifying the research gap and determining the current state of the art on the issues under consideration and verifying the methodology for testing the suitability of using machine learning tools.

Conducting a literature review made it possible to clarify the second main objective of the paper, that is, to verify the effectiveness of constructing a dynamic (multi-period with transaction costs) investment portfolio using a reinforcement learning algorithm in comparison with the classical Markowitz approach. A second literature review already focused only on the use of reinforcement learning methods in investment portfolio optimization allowed the selection of a specific G-learning algorithm, which, according to the author, is the most adapted to the characteristics of financial time series from those currently available. The effectiveness of this algorithm was verified in an empirical study.

Due to the complexity of the second main objective of this work, the following specific objectives were defined:

- Verification of the effectiveness of the selected algorithm on different asset classes (stocks, bonds, currencies, commodities).
- Verification of the impact of investor risk aversion on portfolio efficiency for different asset classes.
- Verification of the effectiveness of different methods of investment portfolio construction depending on the state of the market (ups, downs).

- Polemics with the results obtained on too few instruments or a short-time period, which lead to overly optimistic interpretations of the use of the given tools.

In addition, the indicated main and specific objectives are summarized in the thesis set forth by the author: the use of reinforcement learning methods and consideration of multi-stage decision-making leads to better financial results. The author decided to forgo statistical significance verification due to the high bias of test data selection and the theory of false strategy, which is the reason why it is often not possible to draw generalized conclusions about the effectiveness of a tool in finance [Lopez de Prado and Bailey, 2021].

The first part contains the theoretical foundations of investment portfolio management. In the process of investment portfolio management, the portfolio manager plays an important role, as he decides the composition of the portfolio taking into account the investment policy statement, market situation, and potential financial instruments. Due to the manager's approach, the investment portfolio management process can be divided into passive and active management [Grinold and Kahn, 2000; Swensen, 2009; Elton et al, 2014].

The composition of an investment portfolio and an investor's expectations of future payouts change over time, requiring a continuous process of investment portfolio management. Reilly and Brown [2018] identify four steps in this process:

1) setting an investment policy statement,
2) selecting an investment strategy,
3) construction of an investment portfolio,
4) continuous monitoring of portfolio performance and investor needs.

The second part describes theory from the field of machine learning as an area of artificial intelligence dedicated to algorithms that learn through data analysis. The role of machine learning is discussed from the perspective of the concept of artificial intelligence, as the two concepts are often equated. Understanding the important terms and mechanisms behind machine learning algorithms is key to their correct application.

The most common division is made by the type of learning process itself, i.e. the availability of feedback [Flach, 2012]. On this basis, machine learning is divided into three types: supervised learning, unsupervised learning, and reinforcement learning [e.g., Murphy, 2012; Raschka and Mirjalili, 2017]. Each of the above-mentioned types of machine learning has its own characteristics and applications. However, this division does not exclude the use of different learning methods to solve an identical problem, but the results obtained may be different. It is also possible to combine methods to form hybrids, as exemplified by the use of semi-supervised learning with reinforcement by Finn et al [2016].

The third type of machine learning is reinforcement learning (RL). The very concept of "learning" from a human perspective is defined by the PWN dictionary of the Polish language as the process of acquiring knowledge and gaining skills by learning from experience. Similarly, reinforcement learning is defined as the learning process of choosing the appropriate action depending on the situation in order to maximize the numerically expressed reward [Sutton and Barto, 2018]. The learner, who is called an agent in RL nomenclature, is not told what action he should perform. The agent must discover, based on repeated trials, which action will provide the greatest current reward and subsequent future rewards depending on the state it is in. Jansen [2020] calls reinforcement learning most similar to people taking actions in the real world and observing the consequences of their actions. The premise of learning with reinforcement is that the agent can read the current state of the environment to some degree. Based on this observation, the agent has the ability to take actions that affect this state, and for taking specific actions, the agent can earn a reward which is its overarching goal [Sutton and Barto, 2018]. This goal is completed by finding the optimal policy which maps the state of the environment with agent's actions.

Already having knowledge of the theory of investment portfolio management and the theory of machine learning, a systematic literature review on the use of machine learning in investment portfolio management was conducted. This review was aimed at identifying the research gap, determining the current state of knowledge regarding the issues under consideration, and verifying the methodology for testing the suitability of using machine learning tools.

The first main goal of the paper was achieved, and the several main conclusions of the systematic literature review were withdrawn. The systematic literature review also identified a research gap in the absence of a survey of applications of reinforcement learning algorithms in the construction of investment portfolios.

The third part described reinforcement learning in detail, along with a technical introduction to selected methods. This made it possible to conduct a second critical review of the literature on the use of reinforcement learning for investment portfolio optimization. According to the author of the paper, almost all of the reviewed publications contained a heavily truncated way of testing the algorithms. Selecting individual financial instruments from a specific period is insufficient to draw general conclusions about the effectiveness of the constructed portfolio and the application of a given algorithm. On the basis of the review, the G-learning algorithm was also selected, which, in the author's opinion, is characterized by suitable features for application to the investment portfolio optimization problem. In the last parts of the third chapter, the operation of the G-learning algorithm is described in detail, followed by a proposal for solving the portfolio construction problem using this algorithm.

The last part of the paper presents an empirical study. The author independently designed a test for testing the efficiency of investment portfolios considering: synthetic data, empirical data on different asset classes, randomly selected test periods, and randomly selected financial instruments. The performance evaluation of the G-learning algorithm also took into account the classical Markowitz model, its dynamic extension that takes into account transaction costs, and an equal-weighted portfolio that acted as a benchmark. Synthetic data was generated by a multivariate jump-diffusion model, which allowed the creation of a set of randomly correlated time series with random price shocks. Based on the performance of the portfolios on the synthetic data, the values of the hypothetical investor's risk aversion parameter were determined for both the Markowitz models and the reinforcement learning algorithm.

The empirical part of the study included an assessment of the efficiency of portfolios in terms of the rate of return, the amount of transaction costs, risk, and a combined criterion taking into account all these parameters, namely the rate of return taking into account transaction costs relative to risk. The study was carried out on five datasets of different asset classes: bonds, currencies, stocks, and commodities, as well as on a set combining all classes.

It was verified that, compared with the classical approach, portfolios constructed using the G-learning algorithm obtained, on average, better results for each considered asset class separately and all together. It was also verified that the risk aversion parameter influences the efficiency of portfolios in terms of various evaluation criteria, and at the same time, its influence depends on the characteristics of the asset class. It was also verified that the efficiency of actively managed investment portfolios decreases when the market is in an uptrend, while portfolios show better efficiency during a downtrend. The other conclusions of the empirical study are:

- compared to the classical approach, portfolios constructed using the G-learning algorithm achieved better results on average for each asset class considered separately and all of them combined.
- The results obtained for different values of the risk aversion parameter reach the highest values differently for each asset class. Typically, the riskier the asset class, the higher the value of risk aversion is required to achieve the highest return-to-risk ratio.
- An increase in risk aversion lowers the standard deviation regardless of the method and asset class.
- In three out of five cases considered for different data sets, actively managed portfolios perform better when the overall market is in a downtrend, and better during an uptrend. In the other two cases, the relationship was insignificant or weakly positive.
- Taking into account the dynamics of the problem allows built portfolios to produce better results.
- Strategies following the leader, that is, not taking into account the risk, have the highest volatility.
- The best results are obtained by presenting the investment portfolio optimization problem as a sequential decision-making problem, which takes into account potential decisions in subsequent periods.
- The specifics of reinforcement learning are matched to the characteristics of the problem of constructing optimal investment portfolios.
- It is worth using advanced analytical tools in active investment portfolio management.
- The equally weighted portfolio, treated as a passive investment approach, achieved comparable results to the best performance of actively managed portfolios, which is consistent with the literature.
- It is necessary to test the effectiveness of the investment portfolio on different periods and different financial instruments due to different time series characteristics.

Additionally, based on two literature reviews, the author concludes that there is no established and controlled methodology for testing the effectiveness of investment strategies and portfolios. The bias of data selection, the false-strategy theory, and the drawer effect of published studies make it impossible to properly evaluate these efficiencies and draw general conclusions about the use of a given tool. Currently available publications lead to overly optimistic assumptions from the data use of machine learning algorithms in finance. According to the author of the paper, this justifies the need to create generalized rules for testing the effectiveness of given tools in finance, similar to what is done in testing the effectiveness of drugs in medicine.

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Backtesting comparison of machine learning methods on Warsaw Stock Exchange

Financial decision support is a very important and complex problem. Mathematical, econometrics, financial and other methods are used for this purpose. Contemporary machine learning methods, including Random Forest, are often used. Many research works and practical implementation focus on supporting decisions on stock markets. However, most of them are related to developed markets in the USA or West Europe [1] or Asian stock markets [2]. There is a lack of research related to the comparison of algorithms on a backtesting simulator and on the Warsaw Stock Exchange (WSE), which since 2018 is treated as a developed market [3].

The article aims to analyze the effectiveness of machine learning algorithms about the set initial values of selected time series parameters and technical analysis indicators. Baseline values such as history, expiry, and RSI were selected from initial experiments. It was checked at which bars and expires in random forests the best results were obtained. Then RSI and moving average were added to check if any of them help the algorithm by smoothing the data on the chart. In this way, basic parameters were selected, on which machine learning algorithms selected for experiments were then tested. We focused on six algorithms with basic settings plus an RSI indicator which helps to smooth the price data. The findings are related to determining which of the most popular algorithms have the greatest predictive power for successful transactions on the Polish Stock Exchange. For experiments, we took: Random Forest, Gaussian Naive Bayes, CatBoost, K-Nearest Neighbor (KNN), Logistic Regression, and Support Vector Machine (SVM). The remaining part of the paper is divided as follows: first, the related works on the considered field are analyzed and the methodology of research is presented. Next, the materials and methods, and research experiments are presented. The last part is a discussion and conclusion.

The following methods have been used and analyzed in this research:

- Random Forests (regression and classification) - training a large number of single decision trees and making a prediction based on a majority decision [15].
- Catboost - CatBoost - Categorical Boosting - is the implementation of Gradient Boosting, one of the very popular algorithm. Boosting refers to the ensemble method, which can combine several weak algorithms into one strong. General idea is to train predictors sequentially, each trying to improve their predecessor [16].
- Logistic Regression - some regression algorithms can be also used for classification. For example, logistic regression can be used to estimate the probability that an instance belongs to a particular class [16].
- K-nearest Neighbors (KNN) - simple algorithm capable of clustering datasets very quickly and efficiently [16].

• Naive Bayes - it is strongly competitive in classification and this is a fundamental issue in machine learning. Naive Bayes is the simplest of the Bayesian classifier methods.

The system was created to perform machine learning experiments outputting feature importance metrics. Throughout the system following variables are used [17]: Price; Volume - the total number of papers that have changed their owner; History - how many results we provide back to the algorithm for learning; Expiry - the period after which the shares will be sold if the price does not reach the percentage set Stop Loss or Take Profit; Take Profit - it is a type of order that specifies the price at which a given transaction should be closed to achieve a profit (5%); Stop Loss - an order that is automatically activated when the shares fall to a certain level. It is a defensive order, protecting against too large falls (2%); Minimum profit - the minimum percentage profit that must be made for a transaction to be considered good (2%); RSI - Relative Strength Index – oscillator determining the strength of the trend in the technical analysis [18].

The following metrics were used for performance evaluation [20]:

- Precision - that is, how many real profitable transactions we have (determined by the minimum value in% and TP) for transactions classified by the algorithm to be profitable, i.e. those for which we would get a recommendation to buy. In general, it is the precision of positive predictions, calculated as follows:
- Sharpe ratio – it describes how much excess return we can get for the additional risk.
- A number of transactions - we want the number of transactions to be as high as possible and only statistics on their verifiability are determined on this basis.
- Generalization - to what extent are we able to solve new tasks similar to those we know (Empirical classification methods: Training/test breakdown; Cross-validation or cross-test; Leave one test; Bootstrap test).

The experiment aims to find the best algorithm for stock data by comparing several selected algorithms using a backtesting environment on the same data sets and general parameters.

The broker provides data for 160 companies from the Polish Stock Exchange that meet the liquidity criteria. The data is downloaded in a specific structure. Data is being downloaded from March 2018. The data is minute-long, and because of this there are problems and "holes" in the collected data sets if the company did not achieve specific liquidity. For these reasons, then further processing and augmentation of these data still need to be carried out to fill the gaps. For the needs of this work, a system has been created that allows conducting experiments for selected companies with selected parameters in a backtesting environment. The best results were considered to be those which are distinguished by the precision and Sharpe ratio indicators and the number of transactions carried out. Data ranges: training data range: 03/2018 to 10/2019; test data range: 11/2019 to 02/2020. Transaction costs have also been implemented. Each transaction starts with an entry amount of PLN 2,000. The training and test dataset are a labelled collection of data that the author retrieves from one of the stock market data providers. These are paid datasets. They are not publicly accessible.

Experiments carried out on random forests with expiry 1

Expiry 1 means that if after one day the transaction does not reach TP or SL it is completed. We are checking here which bar sizes (8h, 4h, and 1h) are the best for further experiments. At this stage, the main indicators of a good result were the Sharpe ratio and the cash at the end of the test period (the algorithm makes decisions during this period as the purchase and sale of four companies at the beginning, having at its disposal PLN 10,000).

The selected values of the experiments show that with an expiry as short as 1 there are no good parameters that can cope with such a short period and achieve satisfactory results.

Selected combinations of bars for random forests checked for the value of expiry 5, to allow transactions to reach SL or TP.

With an expiry equal to 5, it can be seen that the algorithm had more possibilities to achieve satisfactory results. You can already notice situations where the Sharpe ratio is positive and the precision reaches a result greater than 0.4. When it comes to the value of the portfolio, we also see a lot of results above PLN 10,000 here.

Adding two moving averages and checking on Random Forest.

Moving average values: 0 - zero values for a given MA (experiment without the mean); 3 - three values given for MA (three values e.g. MA 10 from 8h bars); 5 - five values given for MA (five values e.g. MA 10 from 8h bars); 10 - ten values given for MA (ten values e.g. MA 10 from 8h bar). The differences in the average profit result from the fact that it is the average obtained from the averages for each of the companies. Two different moving averages have been added to the algorithm and the pre-selected bar values, a 10-period average, and a 20-period average to smooth out the price datasets. There was no significant improvement in the results.

Adding two RSIs to random forest experiments to smooth out pricing datasets and see if it helps in getting better results.

There was an improvement in the results after adding the RSI to the algorithm. We have situations where the Sharpe ratio is over 1, the precision is over 0.5 and the portfolio result is over PLN 11,000. The most commonly used RSI values have been added, namely 9, 14, and 21 on the 8h and 1h bars.

Experiments with selected parameters on all algorithms and attempts to improve them - discovering some good basic values from the Random Forest and testing them on other algorithms with their different input settings (to find optimal parameters for each of them).

Only one set of bars makes sense with this algorithm and achieves high Sharpe ratio parameters, over 2. However, when it comes to the number of transactions and the size of the portfolio, these are not satisfactory results.

The CatBoost algorithm did very well on the same data. All of the selected Sharpe ratio values are positive, some values are high and, additionally, the portfolio values all achieved a satisfactory result. If we compare the number of trades with the Naive Bayes algorithm, it is a significant improvement.

The selected values from the experiments with the KNN algorithm show that it is also able to achieve satisfactory values of the Sharpe ratio, the size of the portfolio, and the number of transactions. However, the Sharpe ratio values are lower than those of the CatBoost algorithm.

These are the best results so far obtained when comparing algorithms. We have a large number of transactions among all experiments that achieved a Sharpe ratio above 1. All of the selected experiments achieved a portfolio size above PLN 11,000. The number of transactions also shows that the algorithm made decisions frequently.

The worst results can be seen using the SVM algorithm. The only kernel setup that will give positive results is RBF. Also included for comparison are some selected results with sigmoid, linear, and poly kernels.

The article aimed to check which machine learning algorithms give the best results for given, selected initial values. Four private companies with high liquidity in the technology industry were selected. First, the network was taught on data from the period: from March 2018 to October 2019, then the experiments were carried out on data from the period: from November 2019 to February 2020.

The best results for each of the compared algorithms:

- Random Forest: precision 0.54 and Sharpe ratio 1.011.
- Naive Bayes: precision 0.5 and Sharpe ratio 2.142.
- CatBoost: precision 0.563 and Sharpe ratio 2.017.
- KNN: precision 0.488 and Sharpe ratio 0.995.
- Logistic Regression: precision 0.483 and Sharpe ratio 1.11.
- SVM: precision 0.546 and Sharpe ratio 0.394.

In the presented studies, we do not provide recall and F1 values, because the experiments are carried out on a stock market simulator and not on a classic test set. We can only check how many of those trades that were marked as well made a profit, but we cannot check how many good trades were caught out of all possible. The more transactions we have, the more recall there will be, so it is also an important parameter that should be considered. Each researcher prepares data differently and operates on a different stock exchange and other companies, which makes each data set also different. The results presented by us are difficult to compare with others because the experiments are carried out on a simulator built on a set of test data. In the case of assessing the quality of the algorithm using a standard test set, we have a set of all possible transactions at our disposal. However, when using a simulator, the algorithm gets historical data minute by minute as if it were real stock data and makes decisions in real time. There are many factors due to which the algorithm will never check so many possibilities that are included in the test set, e.g. it cannot open a new transaction when there is already one open position or it lacks funds to open a given position. Therefore, we can adopt the precision metric, which tells us how many profitable trades there are among all the transactions made by the algorithm. It is a comparison of algorithms and each of them works best on different data sets. Here Regression worked best, but it will have to be checked on an even larger data set. The period was sufficient to conduct experiments, often such studies are carried out on much smaller sets, but perhaps for some of these algorithms were not enough to show their capabilities. The data is always tested on a certain selected test period. If the results are satisfactory, you can go to the algorithm check in real time. However, we believe that it is much better to check the algorithms on the simulator and not as it is in most articles only on the test set. The period used during the simulation was not used in the training set, therefore, during the simulation, the algorithm had an environment that was similar to the real one. Experiments give us knowledge on how to approach the creation of new models. Certainly, the research will be repeated on a larger set first to see if the results are similar or if any of the algorithms are not doing better. Then, after confirming which algorithms or algorithm is the best, we will be able to create a model only with the best one and start real-time testing.

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Textual Analysis of Current Reports: A Deep Learning Approach

Textual Analysis is becoming an increasingly important tool used in finance (Loughran & McDonald, 2020). It is based both in practice and in scientific research on deriving word-based features (attributes) like: sentiment, positivity, negativity, readability, riskiness, litigiousness, and complexity from input text. The quantified values of these features are then used for research in many areas of finance such as stock price analysis, rate of return, volatility, earnings, and spreads predictions as well as credit analysis or fraud detection. The latest studies in this area cover such issues as the analysis of the impact of StockTwit tweets on cryptocurrency returns (Chen et al., 2019). The data sources for Textual Analysis vary widely and include primary sources such as regulatory fillings, secondary sources such as newspapers and news sites, and increasingly social media such as Twitter. The amount of unstructured financial data, including text data, is growing dynamically. Only the EDGAR system operated by The U.S. Securities and Exchange Commission (SEC) processes 3,000 publications per day. According to (Ke et al., 2019) in the social sciences, textual data is the fastest-growing data form in academic research. Although on the other hand, the availability of text datasets suitable for comparative research is limited.

The leading practice is to use Dictionary Methods such as Loughran - McDonald word lists to extract features like sentiment from financial texts (Loughran & McDonald, 2020). Dictionaries consist of words lists covering various categories, e.g. positive words, negative words, and litigious words. In this approach, financial texts are usually treated as 'bags of words' and extracting attributes from them is largely based on counting the number of words in the text that can be assigned to a given list within the dictionary. For example, determining the sentiment of a text in this method involves the calculation of a score based on the number of words belonging to positive and negative word lists. Formula 1 represents an example sentiment score.

$$SEN = \frac{WORDS_{POS} - WORDS_{NEG}}{WORDS_{ALL}} \quad (1)$$

where,

SEN – sentiment score,

$WORDS_{POS}$ – number of positive words in the text,

$WORDS_{NEG}$ – number of negative words in the text,

$WORDS_{ALL}$ – sum of the number of positive and negative words (Henry & Leone, 2009)

The results of many studies show that the use of Dictionary Methods brings good results in many cases in the field of finance, and the numerical scores calculated on their basis are correlated with various values characterizing companies (Das et al., 2022). However, despite their usefulness, Dictionary Methods have a number of drawbacks listed below:

1. Dictionaries are not universal and need to be adapted depending on their application to different financial issues or research fields. Also, these domain-specific dictionaries are constantly changing;
2. The process of constructing Dictionaries is largely based on the subjective opinion and experience of the researcher. Therefore, they are different depending on who their creator is. Though recently has an automated approach to the curation of lexicons been presented, which may result in their greater objectivity in the future (Das et al., 2022);
3. Dictionaries cover only part of the vocabulary. For example, the very popular among researchers McDonald Master Dictionary Sentiment Word Lists[34] contains only 4,140 words from the 86,531 in the vocabulary. Such a large reduction in the dimensionality of data even before their introduction into research models undoubtedly translates into the loss of a significant amount of information contained in the analyzed texts;
4. The Dictionary Methods omit the meaning of words and their wider and varied context, which is sometimes crucial for understanding given sentences. The mutual contextual connections between words in a sentence are not taken into account. They assume that counting words in the text will reflect all its complexities;
5. In addition, the Dictionary approach encounters the problem of ambiguity of various words. For example, the word "growth" may have a positive meaning in terms of the company's profit, but a negative meaning in terms of the number of complaints;

In this paper, I propose a new approach to extracting features from financial texts, an alternative to Dictionary Methods. It does not have the drawbacks mentioned above and therefore may potentially bring interesting results beyond the Dictionary solutions in the future. This solution involves transforming the words from the analyzed texts to the form of word embeddings, which are numerical vectors of fixed dimension D. Each word can be imagined as a point in D-dimensional space. None of the words in the text is excluded from the analysis, all words from the defined vocabulary are taken into account. Usually, the size of the vocabulary exceeds 30,000 words. Then, the Deep Neural Network (DNN) model with the built-in Attention Mechanism is used to derive attributes from the text. This mechanism can be represented in the form of Formula 2.

$$attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \qquad (2)$$

where,

Q – query matrix,

K – key matrix,

V – value matrix,

d_k – queries and keys of dimension. (Vaswani et al., 2017)

The intuition behind this equation is as follows: the value of the output vector (V) representing a certain word in a sentence is formed taking into account the value of other words

[34] https://sraf.nd.edu/loughranmcdonald-master-dictionary/

in the sentence (words standing in front and behind). This makes the new representation of the word embedded in a certain context. This new representation is well suited for specifying text attributes such as sentiment or readability. This solution reduces the problem of Textual Analysis to the problem of text classification using DNN. The proposed approach, unlike those used so far, does not require the creation of Dictionaries and is free from the subjective assessment of the researcher. It takes into account the broad context of words and their meaning in financial texts, it also eliminates the problem of ambiguity of words in various contexts.

The DNN model needs to be trained before being applied to real-world issues or research. It should be noted that despite extensive research in the field of automated Textual Analysis in finance, there are very few publicly available datasets containing this type of data. Therefore, as part of my research, I collected financial textual data from the 'EXHIBIT 99' appendices of the 8-K current reports published by the companies included in the S&P 500 index. Often, companies announce their quarterly and annual results at conference calls immediately before or simultaneously with the publication of the report. In such cases, the content presented at the conference call and the summary of the financial reports is contained in this appendix. Textual data cover the period from 2 June 2014 to 31 December 2019. The dataset consisted over 6400 samples from this period. In order for the data to be used in the task of classifying financial texts, they must be properly labeled. For example, in the case of training a model that would automatically determine the sentiment of 8 – K current report, to each text in the training set should be assigned a sentiment value corresponding to it, according to the researcher. Such "manual" data labeling is used in so-called supervised learning. An example fragment of the dataset is presented in Table 1. The first column contains the fragment of text extracted from the appendix 'EXHIBIT 99' to the 8 – K current report. The second column contains the labels of the sentiment classes assigned to this text. The first text concerns Akamai Technologies, Inc. – an American provider of cloud services and the second concerns a company from the transport sector - C.H. Robinson Worldwide, Inc.

Table 1. Illustrative part of the training set

Text	**Class label score**
(nasdaq: akam)… "we were very pleased with our strong finish to the year. both revenue and earnings exceeded our expectations due to the very rapid growth of our cloud security business, robust seasonal traffic, and our continued focus on operational excellence," said dr. tom leighton, ceo of akamai.	1
(nasdaq: chrw) “the third quarter provided challenges in both our north american surface transportation and global forwarding segments. our net revenues, operating income, and eps results finished below our long-term expectations…” said bob biesterfeld, chief executive officer.	- 1

The dataset prepared in this way is transformed into a numerical form, where, as I mentioned earlier, each word takes the form of a vector. The model can then be trained, which means optimizing the weights of the Neural Network (NN). A trained model can predict the sentiment of new financial texts. The sentiment determined in this way can be used, for example, to study its impact on various parameters, such as the volatility of stock prices.

Manually labeling the entire dataset is very time-consuming. Therefore, in my work (Wujec, 2021), I have attempted to automatically label them by assigning to two classes, which can be called UP or POSITIVE, and DOWN or NEGATIVE. Belonging to a given class in this case means whether there is information in the text that may have a positive or negative impact on the share price. Similarly to the authors from the National Bureau of Economic Research Cambridge Massachusetts (Ke et al., 2019) I assumed that the rates of return coexisting with the publication of texts contain information about the features of this text, and therefore can be used as training labels. In this approach, the parameters of the text classification model are being optimized from the joint behavior of current report text and abnormal stock returns. The model used in this study was the BERT model (Devlin et al., 2019) with an inbuilt attention mechanism. For texts belonging to one of the two classes (positive or negative) with the highest probability, this Deep Learning (DL) model gives predictions with a precision of 62% for the positive class and 55% for the negative class. The accuracy for all samples in the validation set was 52.68%. These results are comparable to those achieved with the use of Dictionary Methods for popular test sets such as the Financial Phrase Bank (FPB) or Reddit News dataset (Das et al., 2022). However, it should be noted that the texts used in my research seem much more difficult to analyze than those in the datasets mentioned above. This gives rise to the claim that methods based on the use of embeddings to represent words in texts and the use of DL models with the attention mechanism can successfully compete with models based on 'word count' and the creation of limited Dictionaries.

The most promising future research areas using the DL approach to Textual Analysis are:

1. Event Study;
2. Market efficiency research;
3. Investment strategies;
4. Support for investment analysts using fundamental analysis.

The application of Natural Language Processing (NLP) DL models such as BERT shows that they are easily adaptable to analysis in different languages. Also, research for the Polish financial market depends only on the availability of relevant textual data.

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Market Risk and Exchange Rate Elasticity of Equity Returns: A Non-Technical

Our study has been motivated by the notion that the responsiveness of equity returns to changes in the exchange rate is not constant – and that it is strongly dependent on the levels of market risk. We argue that the exchange rate elasticity of market returns is low and negligible at times of tranquil markets, while it becomes very pronounced at turbulent market periods.

To prove this underlying hypothesis, we examine the elasticity of S&P 500 Futures returns to log changes in EUR/USD exchange rate at various levels of market risk. Our initial hypothesis is that the elasticity is amplified during periods of high market volatility, as defined by elevated levels of the Chicago Board Options Exchange Volatility Index (VIX). We use daily trading data for EUR/USD, S&P 500 Futures, and VIX for the December 31, 1999 – December 31, 2021 sample period.

We first identify three detectable levels or zones of market risk based on VIX by employing a self-exciting threshold autoregressive (SETAR) model. Next, we optimize a vector autoregression (VAR) model that leverages the SETAR model's market risk levels. The corresponding impulse response functions (IRFs) derived from the VAR model show bivariate interactions between shocks in S&P 500 Futures returns and in EUR/USD.

To identify specific periods of jumps to high exchange rate elasticity of equity returns, we employ a two-state Markov Switching Multifractal process. We consider it a further robustness check of our initial hypothesis to detect the time-varying expected durations. Such a model identifies regime35 changes for log changes in the EUR/USD and S&P 500 Futures returns, highlighting statistically significant positive or negative interactions.

Understanding the nature of the relationship between risk and return in the financial markets remains the subject of voluminous studies. While there continues to be significant debate about the characteristics of equity market returns at various levels of market risk, most of them seem to agree that the expected returns should correlate to an investor's willingness to accept risk.

[35] As Herley (2021) noted: Merriam-Webster's dictionary has multiple definitions for the word "regime," which broadly fall into two categories: (1) "a government in power" and (2) "the characteristic behavior or orderly procedure of a natural phenomenon or process." When thinking about a "regime" change here, we mean an equation or model that follows an orderly process of moving to a high exchange rate elasticity of equity market returns from a low or indiscernible exchange rate elasticity of equity market returns and vice versa.

We can trace this debate to Merton's (1973) Intertemporal Capital Asset Pricing Model (ICAPM), which suggests that systemic volatility affects the cross-section of stock market returns, resulting in a positive linear relationship.

Other models examine the relationship between risk and return and focus on the volatility sources in market returns. For example, numerous prior studies employ semi-nonparametric models looking at risk metrics, with VIX as the proxy, compared to the equity returns. Additional papers apply the GARCH class models to explain the non-linear risk-return profile for a given time series.

Irrespective of the model employed to test the relationship between risk and return, the prior research suggests non-linearity and state dependency in their interactions. Several studies examine the dynamics of risk across various time intervals. Notably, Bai and Perron (2003) identify structural breakpoints in interactions between risk and return. Hamilton (1989) shows state-dependency in these interactions in his seminal paper, proposing and testing the Markov Switching Multifractal model.

Most pertinent studies argue that interactions between equity returns and exchange rates are intrinsically unstable. Such a conclusion is confirmed in the prior literature by Grambovas (2003), Syriopoulos (2004), Hau and Rey (2006), as well as Fedorova and Saleem (2010). All of them employ dynamic conditional correlation as well as cointegration with vector error correction tests. Arguing about state-dependency in these relationships, Orlowski et al. (2021) use multiple breakpoint regressions and Markov Switching tests showing discernible structural breaks and phases in the co-movements between equity returns and exchange rates in Central European EU member countries that have not joined the euro area.

Identification of Market Risk Zones

Tong (1990) developed the original SETAR model as an extension of his seminal threshold autoregressive (TAR) model from 1980. We adapt Tong's methodology to identify the market-risk zones based on VIX:

- *Low-market risk*: VIX $<$ 20.229999 (3,427 observations)
- *Intermediate-market risk*: 20.229999 $\leq$ VIX $<$ 24.879999 (973 observations)
- *High-market risk*: VIX $\geq$ 24.87999 (1,128 observations)

Causal Interactions between S&P 500 Future Returns and the EUR/USD Exchange Rate

We then employ VAR tests and the corresponding IRFs to examine causal interactions and the transmission of shocks between the analyzed S&P 500 Futures returns and the EUR/USD exchange rate. Like Sims (1980), we are interested in relationships—not in coefficient estimates, per se, between variables. Hence, we estimate the VAR model at our three-market risk zones for the VIX Index (-9), i.e., high, intermediate, and tranquil, and generate the respective IRFs. An IRF represents a one standard deviation shock to X that causes a significant increase (decrease) in Y for n periods (determined by the length of period for which the SE bands are above 0 or below 0 in case of a decrease), after which the effect dissipates, and vice versa.

Response Pattern at High Market-Risk Zone (Figure 1b)

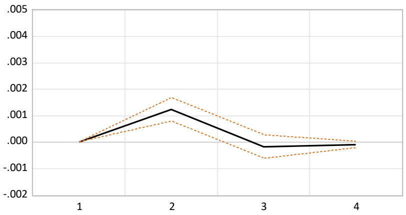
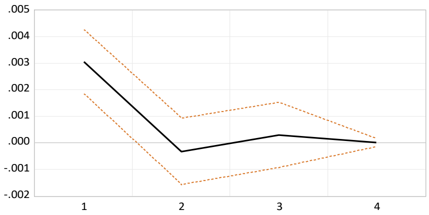


Figure 1b to the left reflects unaccumulated responses of the EUR in the USD exchange rate to (Cholesky one standard deviation) shocks in S&P 500 Futures returns at high market risk, i.e., when VIX≥ 24.87999. We find a pronounced, positive response of the exchange rate to shocks in the S&P 500 Future returns only in the high market risk zone. Similar exchange rate responses to S&P 500 Futures shocks are indiscernible in the intermediate and low market risk zones. In addition, there is a robust two-day transmission of shocks in equity returns into the exchange rate only in turbulent markets. These shocks dissipate relatively quickly, indicating efficient, self-correcting equity and foreign exchange markets.

Response Pattern at High Market-Risk Zone (Figure 2b)



More relevant from the standpoint of the critical objectives of our analysis is the transmission of shocks in the EUR/USD exchange rate into equity market returns. As shown in Figure 2b to the left, there is a robust positive and instantaneous one-day transmission of shocks in the exchange rate into S&P 500 Futures returns in the high market risk zone. We detect no such transmission at the intermediate and the low-risk zones.

Comparing the high market risk results in Figures 1b and 2b, we can argue that the transmission of shocks from the exchange rate (Fig. 2b) into equities is stronger than the reverse causal effect (Fig. 1b). In addition, the impact of shocks in the exchange rate on equity returns is more instantaneous than the reverse equity to the exchange rate shock transmission. These causal differences underpin our initial assumption of a pronounced impact of changes in the exchange rate on equity returns.

<u>Two-State Markov Switching Process Reflecting Exchange Rate Elasticity of Market Returns</u>

We use the two-state Markov Switching Multifractal model to examine time-varying state dependency in the relationship between equity market returns (log changes in S&P500 Futures) and log changes in the Euro in the USD exchange rate for the entire sample. The estimated State 1 Markov Switching Process reflects the high, positive exchange rate elasticity of equity market returns, as reflected by γ_1 of 3.798, which is statistically significant. In contrast, the estimated elasticity in State 2 is very low (γ_2 of 0.015) and statistically insignificant. Nevertheless, the low elasticity State 2 dominates the Markov process. The Markov Switching estimation suggests that the episodes of high exchange rate elasticity of equity market returns are sporadic. However, the responsiveness of equity returns to the exchange rate at the time of their occurrence is pronounced.

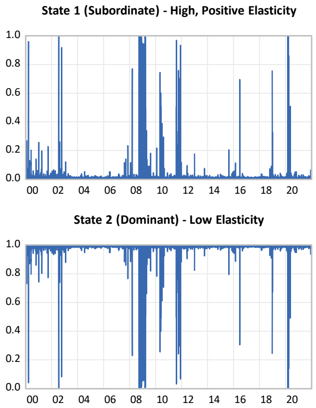


Figure 3: Markov Switching Filtered Regime Probabilities

The filtered regime probabilities derived from our switching regression shown in Figure 3 to the left reflect a more detailed examination of the time pattern of interactions between equity returns and the EUR in the USD exchange rate. The upper graph identifies the probability of remaining in the subordinate high elasticity State 1. In its mirror reflection, the lower graph shows the preponderance of the dominant, low elasticity State 2. The most evident episodes of switching from the neutral State 2 to the high elasticity State 1 coincide with times of high market risk:

Chief among them is the jump to the high elasticity at the peak and the immediate aftermath of the 2008 financial crisis.

The second spike occurred during the August 9, 2011 – November 30, 2011 period, corresponding with the elevated market risk stemming from a range of risks to global financial stability, including the outbreak of the euro periphery sovereign default risk.

The third notable switch to the high elasticity conditions matches the Covid-19 pandemic crisis peak in March and April 2020.

The time patterns shown in Figure 3 indicate the timing of pronounced switches to the high exchange rate elasticity of equity market returns that perfectly match the episodes of considerably elevated market risk.

The key argument of our study is that the sensitivity of equity market returns to exchange rate variations is state dependent. We focus on the EUR in USD exchange rate elasticity of S&P 500 Futures returns and demonstrate that equity returns are responsive to the exchange rate only at times of elevated market risk. We identify three market risk zones by employing a SETAR model with VIX as the risk proxy: tranquil, intermediate, and high (when VIX is at least 24.87999). We subsequently estimate interactions between S&P 500 Futures returns and log changes in the exchange rate in each of the three identified risk zones using a VAR model with IRFs, and the two-state Markov Switching tests. In all tested cases, we only find positive, significant equity returns responsiveness to exchange rate variations in a high market risk environment. The relationship between both variables in the low-risk zone is indiscernible, i.e., equity returns are not associated with exchange rate dynamics during tranquil markets.

Our Markov Switching tests also show that the conditions of low exchange rate elasticity of equity returns are prevalent at tranquil market risk conditions. For example, there are sporadic jumps into the high elasticity at turbulent market periods, most notably during the peak and the immediate aftermath of the 2008 global financial crisis and at the height of the Covid-19 pandemic crisis in March and April 2020.

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Real earnings management, CEO professionalism, family ownership, and big4 auditor presence - a meta-analysis

- Scientific literature focuses increasingly on real earnings management.
- Earnings management occurs when managers use judgment in financial reporting and in structuring transactions to alter financial reports.
- Since the Sarbanes-Oxley act has been passed, companies, in general, have switched from accrual to real earnings management (REM).
- Over time, the types of variables examined in relation to REM have become more specific and sophisticated.
- Results of studies, including beta coefficient values and signs tend to vary greatly.
- Because of that, literature reviews can not establish a consensus about which variables are associated with the reduction of real earnings management practices.
- Study uses Yaari and Ronen's approach and splits corporate governance into three areas: gatekeepers, management characteristics, and ownership structure. Every variable examined belongs to one of the abovementioned areas.
- Meta-analysis methods have been used to determine the association between three variables: CEO professionalism (management characteristics), big 4 auditor presence (gatekeepers), family ownership (ownership structure), and REM.
- Study accounts for geographical, as well as methodical differences between studies, including the type of model used, type of fixed effects, and if a regression model contains certain control variables.
- The study in this article was conducted using an extended meta-regression model, that allows researchers to account for structural heterogeneity.
- Sample includes scientific studies that refer to real earnings management measure as an explained variable. It includes years from 2006 to 2021 and a broad range of

studies including articles in peer-reviewed journals, as well as conference materials and working papers.

- Literature review of three main explanatory variables strengthens conclusions about an ambiguity, because high variability exists both sign-wise as well as in t-statistics.
- In the case of BIG 4 auditor presence and REM – statistically insignificant correlation, no publication bias. Neither type of model nor geographical location changes the value of correlation significantly.
- Family ownership and REM – statistically significant and positive relationship, no publication bias. Estimations with country-fixed effects and models other than OLS show stronger relations. Sign implies that the more family ownership exists in a company, the higher the extent of performing real earnings management. This association is not economically significant being a correlation with about 1% value.
- CEO_PROF and REM – statistically insignificant correlation, no publication bias. This relation might be non-existent or dependent upon other study characteristics than included in a regression model. In studies that control for profitability, the relation between CEO professionalism and REM is weaker in studies that control for leverage.
- Future research should be focused on a broader range of moderator variables, such as an indicator of whether the study has imposed limits on samples, i.e. profitability criteria.
- Splitting regressions into particular geographical regions might be useful in terms of grasping regional specificity better than through binary variables present in an extended meta-regression model.

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Patterns in Corporate Trade Credit Management: Insights into the Polish Trade Sector

The study identifies the multi-sectional regularities in corporate trade credit policies of Polish firms operating in the trade sector. It aims to verify whether the intra-industry effect is more likely to affect corporate trade credit behaviour than the firm size effect. The research is based on yearly data from the ECCBSO trade credit database for three trade industry sub-sections of motor vehicle trade, wholesale trade, and retail trade. It covers four size groups of companies in the period 2005-2017. The rich collection of variables employed enables detailed insights into corporate trade credit management practices. The methods include the analysis of variance, cluster analysis, and multidimensional scaling. The study contributes to the existing literature mainly through the application of the multi-sectional approach to private companies, covering the dimension of time, firm size, and industry sub-section. This offers grounds for detailed multi-layered conclusions in terms of corporate trade credit behaviour in the Polish trade sector. Findings provide evidence that both size-related features and intra-industry specificity are significant determinants of corporate trade credit behaviour. The study also reveals that the industrial breakdown of trade firms into sub-sections is of greater importance in comparison to the size-based classification of firms.

Whenever a delay is arranged between the purchase and the payment, trade credit is created, which constitutes one of the major sources of short-term financing for most businesses (Brick & Fung, 1984). The funds obtained through trade credit may constitute a complementary source of capital, but also a substitute for traditional bank credits (Burkart & Ellingsen, 2004). According to the European BACH database (BACH, 2021), in 2019 trade payables amounted to as much as 28.2% of the assets for a sample of all-sized firms in the Polish trade sector, while the amounts owed to credit institutions accounted only for 8.5%. Given the considerable variations in trade credit usage, terms, and maturity periods across countries and industries, and even within industries, Dary & Harvey (2020) suggest that the research in this area should focus on specific industries. Following this recommendation and taking into account the fact that industry-level studies are relatively rare, this paper concentrates on just one specific sector of trade in Poland.

A number of theories explain the reasons for which on the one hand non-financial companies offer trade credit, and, on the other hand, other firms use this financial instrument. A review of the main trade credit theories can be found in Petersen & Rajan (1997), whereas Bhattacharya (2011) and Dary & Harvey (2020) offer a thorough historical evolution of these theories. A synthetic summary of these considerations can be found in Table 1.

Table 1. Review of theories explaining trade credit

Theory	Literature
Financing advantage	Meltzer (1960); Schwartz (1974); Brennan, Maksimovics & Zechner (1988); Smith (1987)
Liquidity	Meltzer (1960); Schwartz, (1974); Emery (1984)
Financial distress	Wilner (2007); Baxter (1967); Molina & Preve (2012)
Transactions costs	Williamson (1979); Ferris (1981); Emery, (1984); Petersen & Rajan (1997)
Quality guarantee	Smith (1987); Lee & Stowe (1993); Long, Malitz & Ravid (1993); Fafchamps, Pender & Robinson (1995); Deloof & Jegers (1996)
Price discrimination	Brennan et al. (1988); Petersen & Rajan (1997); García-Teruel & Martínez-Solano (2010)
Product differentiation	Nadiri (1969); Wilner (2000); Summers & Wilson (2000); Cheng & Pike (2003)
Market power	Cheng & Pike (2003)
Tax	Brick & Fung (1984); Brennan et al. (1988); Mian & Smith (1992); Desai, Foley & Hines (2016)
Long-term relationship	Nadiri (1969); Ng, Smith & Smith (1999); Wilner (2000); Summers & Wilson (2000); Cuñat (2007)

Source: own elaboration based on Petersen & Rajan (1997), García-Teruel & Martínez-Solano (2010), Bhattacharya (2011), and Dary & Harvey (2020).

As can be inferred from the summary in Table 1, the theories tend to overlap and interrelate rather than be mutually exclusive (Dary & Harvey, 2020). Similar interrelations can be observed in the case of the motives behind trade credit activity. A wide range of factors has been found to affect corporate trade credit policies. The two factors of particular interest in this paper are the firm size and its industrial classification. It appears that the empirical evidence on the effect of firm size and the amount of trade credit granted and received is ambiguous (Dary & Harvey, 2020). A summary of some of the previous research findings in the field can be found in Table 2.

Table 2. Summary of the research findings on the relation between firm size and trade credit

Relation	Trade credit supplied	Trade credit received
+	Petersen & Rajan (1997); Lin & Chou (2015); Carvalho & Schiozer (2015); Bougheas et al. (2009);	Bougheas, Mateut & Mizen (2009); Lin & Chou (2015); García-Teruel & Martínez-Solano (2010); Ferrando & Mulier (2013); Fisman & Raturi (2004)

–	Long et al. (1993); Alarcón (2011); Jaleel, Hui & Jaweria (2014); Wilson & Summers (2002)	Kihanga et al. (2010); Jaleel et al. (2014); Duliniec & Świda (2021)

Source: own elaboration based on Dary & Harvey (2020).

As for the industrial classification of firms as a factor affecting corporate trade credit behaviour, a number of various sector-related firm characteristics can be distinguished. A synthetic summary of such industry-specific factors based on previous literature is presented in Table 3.

Table 3. The industry-related factors affecting trade credit

Factor	Literature involved
Amount of goods purchased	Burkart & Ellingsen (2004)
Liquidity of goods	Dary & Harvey (2020)
Quality verification	Long et al. (1993); Deloof & Jegers (1996); Ng et al. (1999)
Uniqueness of goods	Long et al. (1993)
Market concentration	(Fisman & Raturi, 2004)
Inventory volume	Elliehausen & Wolken (1993)
Production cycle	Long et al. (1993); Fafchamps et al. (1995); Deloof & Jegers (1996); García-Teruel & Martínez-Solano (2010)
Product complexity	Klapper, Laeven & Rajan (2012)

Source: own elaboration based on literature items listed in the table.

Regardless of which industry-specific factor is responsible for the trade credit amount or period, the cross-industry and cross-size variety of trade credit terms is widely evidenced by different studies. A question that remains partly open to debate is which of the two factors prevails in terms of trade credit behaviour. This leads to the formulation of the following research hypotheses:

- H1: trade credit behaviour varies significantly across sub-sections of the Polish trade sector in all size groups of firms;
- H2: trade credit behaviour varies significantly across size groups in the Polish trade sector and its sub-sections;
- H3: the intra-industry specifics is a more important determinant of corporate trade credit behaviour than the firm size in the Polish trade sector.

The analysis of the relative importance of the intra-industry sections and the firm size effect in corporate trade credit behaviour is based on the data from the ECCBSO Trade Credit Database The subdivision of the trade sector into three sub-sections of motor vehicle (MV) trade, wholesale trade (WS), and retail trade (RT) enables deeper insights into the trade credit behaviour of firms in this sector. As for the size breakdown, the data is available for four size groups, i.e. micro, small, medium, and large firms. The time span for Poland covers the period from 2005 to 2017, and the frequency of data is yearly.

The variables involved in the study include the following ratios:

- Days Sales Outstanding (DSO), defined as:

$$DSO = \frac{Trade\ Receivables - Customer\ Prepayments}{Net\ Turnover} \cdot 360, \tag{1}$$

  where the customer prepayments are defined in the 4th EU Directive as: "Payments received on account of orders in so far as they are not shown separately as deductions from stocks";
- Days Payables Outstanding (DPO), defined as:

$$DPO = \frac{Trade\ payables - Advances\ to\ Suppliers}{Purchases} \cdot 360, \tag{2}$$

  where the advances to suppliers are defined in the 4th EU Directive as "Payments on account", and purchases – as a sum of material expense and services rendered;
- Trade Credit Balance (TCB), defined as:

$$TCB = \frac{DSO \cdot Net\ Turnover - DPO \cdot Purchases}{Net\ Turnover}. \tag{3}$$

For each of the three ratios (1) – (3), the following information is provided:

- the percentage share of companies with the ratio value falling into a certain range,
- the ratio's distribution in days,
- the weighted mean based on percentile distribution.

The first stage of the empirical part of the study involves the basic statistical analysis of the diagnostic variables. To evaluate the statistical significance of the ratios' diversity, the one-way analysis of variance (ANOVA) was applied (Fisher, 1954). The following grouping factors were involved in the ANOVA: firm size, industrial sub-section, and year. The heterogeneity of the analysed population, as well as its multidimensionality, imply the need to organise its objects into groups of a clearer internal structure. In this study, two classification algorithms were used, namely the agglomerative cluster analysis and the *k*-means grouping technique (Wishart, 2003) available in the STATISTICA software package. To simplify the data structure, an exploratory technique of multidimensional scaling was applied (Springall, 1978; Mugavin, 2008).

The ANOVA results preliminarily indicate that while the industrial breakdown proves quite meaningful for corporate trade credit behaviour, the firm size appears to be of slightly lower importance. These insights are visualised by a tree diagram in figure 7.

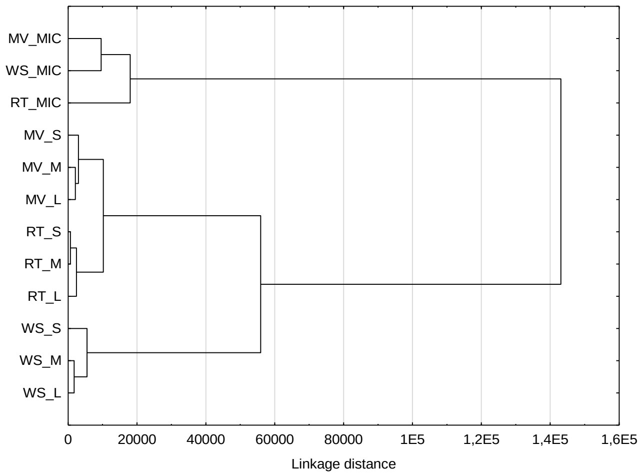

Figure 7. Agglomerative cluster analysis results for trade sub-sections in size groups
Notes: The tree diagram for binomial objects is based on all variables except $DSO_{<0}$, $DPO_{<0}$, and $TCB_{<0}$. The distance between objects was measured with the square Euclidean distance, and the Ward linking method was applied.
Source: own elaboration based on ECCBSO (2020) trade credit database.

If the tree branches were intersected where the linkage distance is around 40000, three clear clusters can be identified, only one of which is a size-oriented one, while the other two are industrially-dominated. The first cluster from the top consists of only micro-firms of all three trade sub-sections. The second cluster contains firms of three different sizes from two trade sub-sections of motor vehicles and retail trade. The last cluster again has the features of sectoral concentration around the wholesale trade. Having identified the structure of clusters, it is purposeful to find what trade credit features are particularly responsible for the differences observed between the groups of objects. Also, given the number of diagnostic variables, some simplification of the data structure seems worthwhile. One of the methods enabling both of the above intentions is the multidimensional scaling (MDS), applied here on the matrix of distances between all variables except $DSO_{<0}$, $DPO_{<0}$, and $TCB_{<0}$. The MDS results in the form of a two-dimensional scatterplot are reported in figure 8.

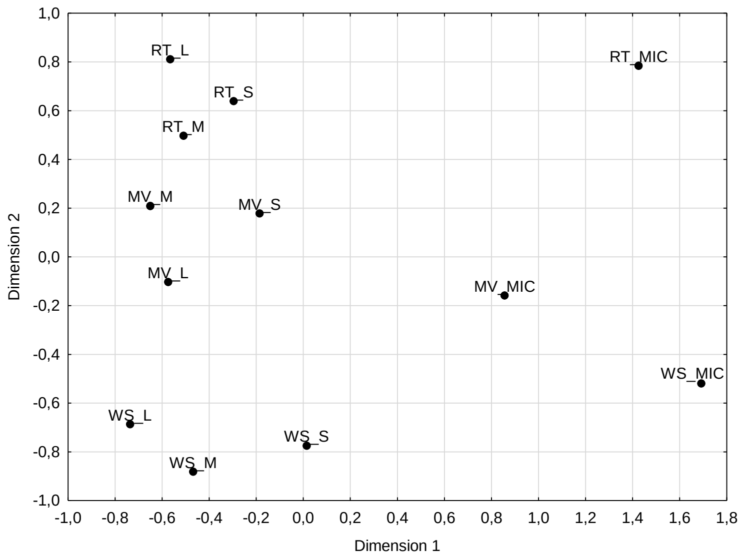

Figure 8. Multidimensional scaling results – scatterplot of binomial objects: trade sub-sections in size groups
Notes: The scatterplot is based on the matrix of distances between all variables except $DSO_{<0}$, $DPO_{<0}$, and $TCB_{<0}$.

Source: own elaboration based on ECCBSO (2020) trade credit database.

The information conveyed by the scatterplot corresponds to the clustering results mainly by demonstrating the dissimilarity of micro firms. A crucial issue in applying the MDS method is to assign meaning to the artificial dimensions which replace the original variables. A closer look at the raw data indicates that the first dimension is likely to correspond to payables management, whose higher values are on the right-hand side of the graph, whereas a reasonable interpretation of the second dimension is the conservatism in receivables collection with the lowest values at the bottom of the scatterplot.

Considerable intra-industry differences identified in trade credit patterns provide support for the first research hypothesis (H1) concerning the significant variability of trade credit behaviour across the sub-sections of trade firms in Poland. As for the cross-size variability of trade credit management policies addressed in the second research hypothesis (H2), the findings indicate that while the firm size is a significant factor affecting corporate trade credit in the Polish trade sector as a whole, the firm size effect is definitely less evident in individual trade sub-sections. As a result, only partial support for H2 has been delivered. The prevalence of the intra-industry effect over the firm size effect in trade credit behaviour reported in the study implies that the third hypothesis (H3) is quite likely to be truthful. Therefore, it can be expected that trade credit management policies should be different across firms operating in different sub-sections of the Polish trade sector, but similar across firms of different size groups, except for micro-firms.

Two main limitations of the study should be highlighted. Firstly, the dataset employed in the research offers aggregated information instead of firm-level data. Secondly, narrowing the research to just one industrial section in Poland makes the study quite specific. Nevertheless, the reported findings might be of interest to those involved in corporate finance management.

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Determination of Cap Rate Using Financial Data from European REITs Market: The Case of the Czech Republic

In the Czech Republic, the discount cash flow approach is widely used for real estate appraisals. This method is based on discounting the expected future cash flows by a proper discount rate (capitalization or cap rate) and is also known as an income approach. In this case, the yield is required minimum rate of return which is required from a real estate property investment on the annual basis. The yield should be based on the analysis of the comparable transaction, but also the recent market situation must be taken into an account. The market situation can be summarized by what is a market and what is expected Shapiro et al. (2013). Valuation models of financial assets can also be applied to the valuation of real estate if certain specifics are respected. However, the valuation of real estate brings with it certain differences compared to the valuation of financial assets. The first difference is their heterogeneity of the subject of valuation and differences in individual characteristics such as size, condition, or location. The fact that real estate is locally bound also creates a problem in valuation based on past (implemented) transactions, which are only exceptionally locally identical to the valued real estate. Another significant difference between real estate and financial assets is liquidity, where financial assets can be sold in a matter of minutes. A significant difference is also the fact that the required minimum investment is significantly higher in the case of real estate.

Empirical analysis of cap rate levels provided by Sivitanides, Torto, and Wheatton (2003) shows the strong effect of interest rates on cap rate levels, and systematic effects of market fundamentals on both cap rate levels and spreads suggesting an ineffective view on the part of real estate investors. Liu and Mei (1992) suggest that the variation in the expected excess returns is predictable and arises from changes in business conditions. They find that REITs are more predictable than all other assets examined, due in part to cap rates which contain useful information about the general risk condition in the economy. Das (2015) focuses on the hotel cap rate and finding that the hotel capitalization rate is a complex combination of macroeconomic and asset-class specific variables such as the cost of capital, capital structure, and growth rate. Further, investors in hotel real estate base their cap rate measures on the performance of corresponding hotel REITs. Peyton (2009) suggests that over short periods of time, cap rates can be predicted using macroeconomic and financial market data with commercial real estate market fundamentals. The effectiveness of this approach increases with the integration of commercial real estate into the larger capital markets. Unbehaun and Fuerst (2018) focus on the German market and the five largest office markets in Germany from 2005 to 2015 findings location is a key determinant of cap rates and risk premia. Similarly can be found in Fisher et al. (2021) who analyse the impact of a property's location as a determinant of its investment performance sing REITs. The results suggest that location density is an important determinant of REIT performance outcomes. Ghysels, Plazzi, and Valkanov (2007) find that about 30% of the fluctuation in the cap rate is explained by the local state variables and the growth in rents, further, using cap rate decomposition they find a positive relation between fluctuations in economic conditions and future returns.

However, a larger and significant part of the cap rate predictability is due to the statistically independent part, which is unrelated to fundamentals. They suggest modelling commercial real estate prices as financial assets and using the discounted rent model for the valuation. Plazzi, Torous, and Valkanov (2010) focus on commercial real estate expected returns and expected rent growth rates are time-varying, finding that up to 30% of the variability of realized returns to commercial real estate can be accounted for by expected return variability, while expected rent growth rate variability explains up to 45% of the variability of realized rent growth rates. Also, rent growth predictability is observed mostly in locations characterized by higher population density and stringent land-use restrictions. Fisher et al. (2021) confirm that location density is an important determinant of REIT performance outcomes, implying that geographical characteristics can drive investment risk and return across commercial real estate markets.

Clayton and MacKinnon (2001) study the sensitivity of equity real estate investment trust (REIT) returns to returns on other asset classes, including real estate, their results show that the relationship between REIT returns and unsecuritized real estate has changed over time. During the 1990s, REITs began to exhibit a direct link to real estate returns, indicating that REITs do provide portfolios with some exposure to the real estate asset class. The strength of this link, however, is cyclical. Fisher et al. (2022) study geographical characteristics of the property portfolios of U.S. equity Real Estate Investment Trusts (REITs) finding that REITs with property holdings in high-density locations experience higher rental growth, carrying the higher systematic risk and also having lower implied cap rates. Results suggest that location density is an important determinant of REIT performance outcomes, implying that geographical characteristics can drive investment risk and return across commercial real estate markets. Between others, investigation of the relationship between REITs and the real estate market can be found in Fisher et al. (2022), Das (2015), Liu and Mei (1992), Capozza and Korean (1995) or Ghysels, Plazzi and Valkanov (2007).

Above mentioned uncovered that the basic problem in the valuation process, regardless of the type of asset, is the appropriate determination of the discount factor. In the case of real estate, we are talking about the so-called capitalization rate, i.e. the minimum required rate of return from a given investment. Considering the inverse relationship between the correct price and the discount factor, a low level of this rate will lead to an overvaluation, and conversely, a high level of the capitalization rate will lead to an undervaluation of the appraised asset (property). Within the Czech Republic, it is possible to use several approaches to determine the capitalization rate.

According to Lusht (2001), the capitalization rate (k), as the rate of return required by investors for their investment in real assets, can be written in this way:

$$k = (r_{minimal} + \pi^e) + r_{risk} + r_{non-risk} \qquad [1]$$

Lust (2001) suggests that the minimum compensation rate could be the same for all market in the range 2 – 3 percent, and the expected inflation could be derived from the yield of long-term bonds and both premiums ($r_{risk} + r_{non-risk}$) could be derived from a historical rate of return on the real estate market.

However, a similar approach can also be found in Hoesli et. al (2006), which determines the capitalization rate in the following way:

$$k = r_f + r_{market} + r_{property} \tag{2}$$

The determination of specific factors (e.g. age or location) can be based, for example, on scoring methods (Amadee-Manesme, 2011).

The building block approach to determining the capitalization rate (k) is based on the sum of the risk-free rate and the determined risk premiums, we can simply write it down as follows:

$$k = r_f + r_{risk\ premium} \tag{3}$$

The risk-free rate of return is usually derived from historical bond market data based on the yield of government bonds. There are two basic types of government bonds suitable for deriving a risk-free rate of return. These are treasury bills and coupon government bonds. The first of the instruments is of course only short-term, with a maturity of up to 1 year, but they are issued as so-called discounted bonds and are therefore not associated with so-called reinvestment risk. Coupon government bonds are long-term in nature, but by paying regular coupon payments, they are at least subject to reinvestment risk. The second way of determining the risk-free rate is through the usage of yield curves. In practice, we tend to use long-term government bonds to derive the risk-free rate of return, while the current yield of these bonds is also used to derive the expected risk-free rate (Pinto et al. (2015)). Bruner et al. (1998) and Truong, et al. (2008) in their research support the preference for using long-term government bonds to determine the risk-free rate in practice, both among companies and advisors.

Expected inflation can be derived on the market based on the yields of financial instruments that are protected against inflation (e.g., TIPS). In countries where it is not possible to use these instruments, the expected inflation is adjusted to the inflation target of the central bank. In the literature, the assumption of illiquidity of the real estate market and thus the demand for a special premium can be found, for example, in Anson (2010), who claims that the real estate market belongs to one of the most illiquid markets, other research supports the premium for illiquidity in the case of the real estate market, when this premium can be derived from the government bond market. Eichholtz (1995) suggests an illiquidity premium between 0.15 to 0.50 percent in van den Bosch (2013).

Our dataset contains 202 REITs with geological focus on the European market from the Bloomberg Database. The yearly prices and dividends from 1990 to 2021 were obtained with more than 6200 observations. To reduce systematic risk and focus only on real estate risk premium we computed the risk premium using the following relationship:

$$r_{premium_t} = r_{total_{jt}} - r_{f_{jt}} \tag{4}$$

Using 10 years moving window and arithmetic (AM) and geometric (GM) we suggest following cap rate for the category of residential and commercial property and particular segments. To distinguish REITs between residential and commercial properties we found the following two main categories of cap rates (Table 1).

Table 1: Residential segment: market risk premium

	Market risk premium 2021	Standard Deviation
Residential AM	3.56%	14.42%
Residential GM	2.59%	9.92%

Source: Authors' based on REITs data from Bloomberg

Table 2: Commercial segment: market risk premium

	Market risk premium 2021	Standard Deviation
Commercial AM	6.52 %	2.70%
Commercial GM	6.95 %	3.05%

Source: Author's based on REITs data from Bloomberg.

Using the built-up approach we obtain the following main capitalization rates as demonstrated in Table 3.

Table 3: Capitalization rates for residential and commercial property, in the Czech Republic

Segment	Market risk premium 2021	Risk-free rate for the Czech Republic36	Cap Rate in 2021
Residential GM	2.59%	2.09%	**4.68%**
Residential AM	3.56%	2.09%	**5.65%**
Commercial GM	6.52 %	2.09%	**8.61%**
Commercial AM	6.95 %	2.09%	**9.04%**

Source: Authors' based on data from Bloomberg and Czech National Bank.

[36] Risk-free rate is derived from the 10Years Czech Government Bonds Yields.

The commercial cap rate represents a large category of different properties. Therefore, in the next step the specific's property segments using REITs was specified for a determination of market segment premium.

Table 4: Segment property premiums

Segment	Market risk premium 2021	Standard Deviation
Accommodation	AM:13.00 % GM:11.42 %	7.65 % 6.27 %
Healthcare	AM: 5.86 % GM: 5,54 %	3.59 % 4.21 %
Shops	AM: 5,61 % GM: 3.76 %	2.33 % 3.70 %
Offices	AM: 5.53 % GM: 5,17 %	1.74 % 2.23 %

Source: Authors' based on data from Bloomberg and Czech National Bank.

The aim of our contribution was to determine the risk premiums for individual segments of the real estate market through the analysis of the European market with REITs. Subsequently, using market data for a risk-free rate we determine the capitalization rate for individual real estate segments using the build-up approach. Based on the analysis carried out, we are also aware of several limitations of our research. This is mainly a limited database, an uneven distribution of data between real estate segments, and volatility in the case of segments with a low representation of REITs. In the case of further research, it is necessary to focus on determining additional premiums that can more closely determine the capitalization rate. This is mainly a premium for illiquidity and a premium for a property location.

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How properties are getting old. Cadastral case

We are creating a demographic pyramid to better manage the pension policy in the future. The process of population aging in the EU is and will be one of the most important problems determining the development of the Member States and the decisions taken at the social and economic levels in the coming years. While society is getting older, aging also applies to everything around. The article answers the question of whether it is equally important to study the aging of housing estates and how to measure it.

Real estate can age both physically and economically. Economic internal aging of real estate is a change in the value of real estate under the influence of factors other than the market (inflation, market condition) and physical ones. Analysis of the aging of housing estates is a useful tool for individual entities, developers, as well as local government units, to build the developer's brand, for investing purposes (two sources of income) or to create tax policy, based on value/zone tax.

The analysis of housing estate aging was based on three databases: purchase and sale transactions of apartments of a selected developer, purchase and sale transactions of apartments on the secondary market, and development investments launched in Wrocław in 2015-2021. The first part of the analysis concerned the verification of whether the value of the property of the selected developer changes faster or slower than the value of average market properties over time. It checked the direction of these changes and compared the results depending on the location (centre vs suburbs). The first part of the analysis concerned the verification of whether the value of the property of the selected developer changes faster or slower than the value of average market properties over time. She checked the direction of these changes and compared the results depending on the location (centre vs suburbs).

According to the main conclusions from the research, developer's apartments age more slowly than those of competitors. The pricing policy of the developer is much more stable, and it is easier to predict changes in value. In terms of investment, it is more profitable to buy an apartment from a developer, located on the outskirts, despite the fact that the prices of these apartments are higher than the prices of apartments from competitors. In order to obtain the greatest return on the invested amount, it is recommended to sell the apartments within 6 years of making profits from them, if the apartment was purchased directly from the developer; in the case of apartments purchased on the secondary market, this period is extended to 12 years after the purchase of the apartment.

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Hierarchical Risk Parity in Portfolio Optimization – Empirical Evidence

Portfolio construction is one of the most important financial problems. The first scientific answer to this problem was given more than 6 decades ago by Harry Markowitz. According to the classical portfolio theory one should consider two criteria of investments: mean return and risk (measured by the returns' variance). When calculating the latter, we should take into account the correlations across alternative investments in order to build a diversified portfolio. The classical portfolio theory provides an efficient portfolios. However the expected returns can rarely be forecasted with sufficient accuracy, many authors have opted for dropping them all together and consider only the risk of the portfolio.

The Hierarchical Risk Parity (HRP) is a method of portfolio construction based on the analysis of the covariance matrix. It takes into account the structure of the correlation matrix and allocates assets according to similarities in their market behavior. The main advantage of this method is that the covariance matrix does not have to be nondegenerate. This allows to use this method for construction of a portfolio with a greater number of assets, based on the estimations on shorter time series.

In the paper, we compare the performance of portfolios built using HRP method with the portfolios constructed using classical portfolio analysis (Markowitz model) and some benchmark portfolios.

Portfolio construction based on statistical methods was proposed 70 years ago, in the seminal paper of Markowitz (1952). The Markowitz classic method was based on risk minimization, when risk was measured by variance or standard deviation of returns. The description of the classical methods can be found, for example, in (Cuthbertson, Nitzsche, 2004). Since the beginning of portfolio optimization, many changes and improvements have been proposed. The review of the literature can be found in (Kolm et al., 2010).

The classical method and its modifications are based on the calculation of variance of the portfolio. To this end, one has first to estimate covariance structure of returns and then make use of some kind of quadratic programming method. As the covariance matrix used for optimization should be nondegenerate, one has to use a sufficiently long time series for the estimation. If one considers a portfolio of N stocks, one needs at least $\frac{1}{2}N(N+1)$ independent observations to obtain a nondegenerate covariance matrix. However, correlations between stocks do not remain constant and estimations based on very remote data can be dubious. On the other hand even the small errors can lead to big changes in the solutions of quadratic programming problems. Thus, the optimal portfolios obtained by classical methods can be very unstable. As it turns out due to this instability even equally-weighted portfolios can have better performance than portfolios based on risk-optimization (De Miguel et al., 2009).

In the paper, we test an alternative method of portfolio optimization based on using a hierarchy of potential investments. The HRP method proposed by De Prado (2016) takes into account the fact that stocks of some companies are very close substitutes, whether some companies can be treated as complementary investments. To disclose this hierarchy clustering methods can be used[37].

The theoretical properties of the HRP methods are well-known. However, to our best knowledge, the method was not tested empirically. In the article, we check this method on the data from Polish and German stock exchanges and compare it with the classical approach.

Hierarchical Portfolio Construction

Below we present a procedure of hierarchical portfolio construction that takes advantage of Hierarchical Risk Parity (HRP). The procedure consists of three steps: clustering, quasi-diagonalization of the covariance matrix, and recursive bisection. First, we present original methods, then our amendments aimed at improving risk diversification.

Step 1 (clustering)

Based on historical data calculate all correlation coefficients ρ_{ij} between stocks' returns. Then define distance measure $d_{ij} = \sqrt{\frac{1}{2}(1-\rho_{ij})}$. Let $D = \left[d_{ij}\right]_{i,j=1,..N}$ be a matrix that consists of all d_{ij} coefficients.

Calculate the Euclidean distance between any two columns of the matrix D:

$$\tilde{d}_{ij} = \sqrt{\sum_{n=1}^{N}\left(d_{ni} - d_{nj}\right)^2}.$$

Create the matrix $\widetilde{D}$ of all coefficients $\tilde{d}_{ij}$.

Find a pair of columns (i^*, j^*) for which the distance $\tilde{d}_{ij}$ is the lowest:

$$(i^*, j^*) = \arg\max_{(i,j),i\neq j} \tilde{d}_{ij}$$

and create the cluster $u[1] = (i^*, j^*)$.

Calculate the distance between the newly created cluster and all columns:

$$d_{i,u[1]} = min\{\tilde{d}_{ij}: j \in u[1]\}.$$

(of course $d_{i^*,u[1]} = d_{j^*,u[1]} = 0$). Update the matrix $\widetilde{D}$ be removing rows and columns i^* and j^*. Add a row and a column with distances to the newly created cluster.

Repeat the previous step by creating the next cluster that consists of indexes of the matrix $\widetilde{D}$ for which the distance $\tilde{d}_{ij}$ is the lowest (the indexes can represent the original variables or clusters). Then calculate the distances between the newly created clusters and all other columns. Update the matrix $\widetilde{D}$. Repeat the procedure of creating clusters until the matrix $\widetilde{D}$ is 1x1. Finally, we obtain the cluster structure, which can be graphically represented by a dendrogram, as in exemplary Figure 1.

[37] See for example (Scitovski et.al., 2021).

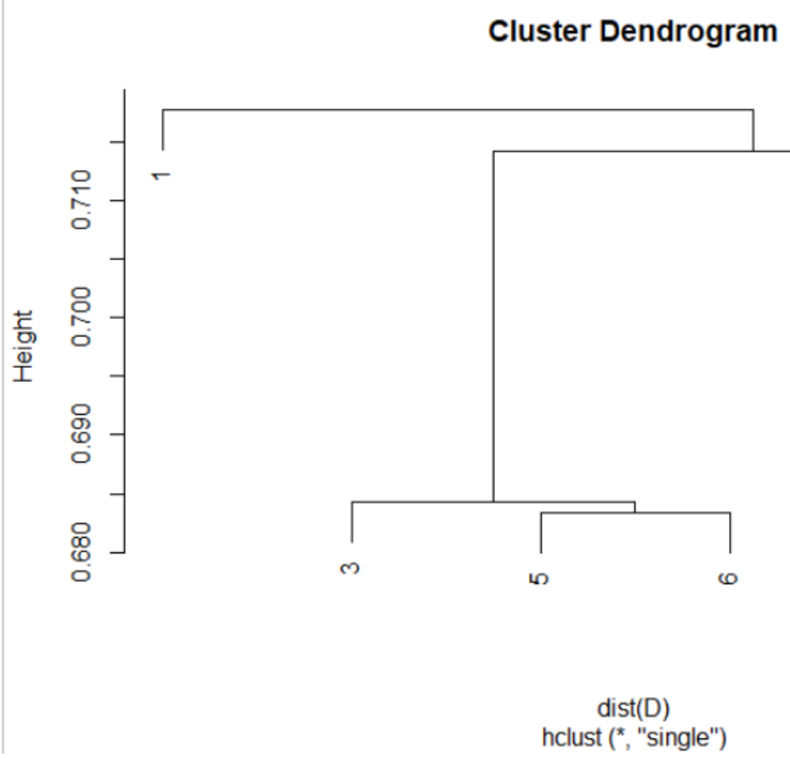

Figure 1. Exemplary cluster dendrogram

Step 2 (quasi-diagonalization)

In the next stage, we rearrange the rows and columns of the covariance matrix according to the obtained cluster structure. The highest values should lie along the diagonal. The detailed algorithm is presented in (de Prado 2016). The obtained matrix has the property that variables (stocks) that are the most similar (i.e. with the highest correlations) are placed together. Variables that are dissimilar are placed far apart. For example, the order for the exemplary cluster structure presented in Figure 1 would be: (1, 3, 5, 6, 2, 4).

Step 3 (recursive bisection)

In this step, we build a portfolio according to the following procedure.

1. Set all weights to 1: $w_n = 1$ for $n = 1, \dots, N$. Create a list containing ordered tuples of indexes of companies. At the beginning, it contains the tuple of all indexes: $L = \{(1, \dots, n)\}$. Let Σ be covariance matrix of all shares.
2. For each element L_i from the list L do the following:
   a. split the tuple L_i into two equal parts L_i^1 and L_i^2 (if the number of the elements in L_i is odd, the tuple L_i^1 is longer then L_i^2 by one element);
   b. define two covariance matrices Σ^1 and Σ^2 by taking rows and columns from the matrix Σ that are in the tuples L_i^1 and L_i^2 respectively;
   c. define the variances v^j $(j = 1{,}2)$ of the elements L_i^j as $v^j = \left(w_i^j\right)^T \Sigma^j w_i^j$, where the weights w_i^j are given by $w_i^j = \frac{diag\left[\left(\Sigma^j\right)^{-1}\right]}{tr\left[diag\left[\left(\Sigma^j\right)^{-1}\right]\right]}$;
   d. calculate the split factor $\alpha_i = 1 - \frac{v^1}{v^1 + v^2}$;

e. multiply the weights w_n of all indexes in L_i^1 by α_i and weights of all indexes in L_i^2 by $1 - \alpha_i$;
f. remove the tuple L_i from the list L. Add the tuples L_i^j if they contain more than one element

3. If the list L is not empty repeat step 2.

The portfolio construction takes advantage of the quasi-diagonalization of the covariance matrix. Weights w_i^j defined in the point 2c are proportional to the inverses of variances. The split factor α_i is the variance-minimizing proportion for a portfolio of two uncorrelated elements.

The original algorithm for the construction of HRP portfolio treats all elements in tuples L_i^1 and L_i^2 as nearly independent. We propose a modification of this procedure, in which we take advantage of a correlation structure. We will refer to the portfolios created with the use of this modified algorithm as HRP1. The changes are in the points 2c and 2e of the algorithm, which have now the following form:

2c'. define the variances v^j $(j = 1,2)$ of the elements L_i^j as $v^j = \left(\tilde{w}_i^j\right)^T \Sigma^j \tilde{w}_i^j$, where $\tilde{w}_i^j$ are weights of variance minimizing portfolio, i.e. the solution of

$\min w^T \Sigma^j w$ subject to $w^T 1 = 1, w \geq 0$;

2e'. multiply the weights w_n of all indexes in L_i^1 by $\alpha_i \tilde{w}_i^1$ and weights of all indexes in L_i^2 by $(1 - \alpha_i)\tilde{w}_i^2$.

The modified method should allow better risk diversification of the portfolio.

To check the performance of the methods based on the risk parity we have calculated numerous portfolios of stocks traded in the Polish and German markets. For the Polish market, we used shares of the companies from WIG20 index. For the German market, we have used stocks of companies from DAX40 index. In both cases, we used companies that were in these indexes in 18.10.2022 and were traded on the stock exchange for sufficient time to obtain good estimates of the returns' parameters.

Data for the WIG20 index cover the period from 6.7.2011 to 18.10.2022. We used the stock prices of 18 companies. Parameter estimation was based on 500 observations and on 100 observations. In the former case, 2271 portfolios of each kind were created. For the shorter estimation period, there were 2671 portfolios of each kind.

Data for the stocks from index DAX cover the period from 1.10.2014 to 18.10.2022, We used stock prices of 36 companies. The parameters were estimated on the basis of 1200 observations (in this case 801 portfolios of each kind were created) and based on 500 observations (which gave 1501 portfolios).

In both cases. covariance matrices estimated based on the longer sets of data were nonsingular while covariance matrices estimated from the shorter sets were degenerated.

We have created portfolios for investments for one month. For each of the investment periods, we have created the following portfolios:

1. equally-weighted portfolio (equal)

2. portfolio minimizing variance (minvar),
3. semivariance-minimizing portfolio (minsemivar),
4. variance-minimizing portfolio with the restriction that expected return should be no lower than 50% of average expected returns of the stocks in the portfolio (minvar0.5),
5. variance-minimizing portfolio with the restriction that expected return should be no less than 75% of average expected returns of the stocks in the portfolio (minvar0.75),
6. HRP portfolio,
7. HRP1 portfolio (based on the modified algorithm).

For the last two types of portfolios, calculations were made two times: once based on nondegenerate covariance matrices (estimated from the longer samples) and the second time based on degenerate matrices (from the shorter samples). For the letter portfolios results are presented as HRPdeg and HRP1deg.

For each portfolio, realized returns were calculated. The summary of the values obtained is given in Tables 1 and 2. Based on the sample of all realized returns we have calculated mean value, median, standard deviation, minimal values, VaR at the level 0.05 (5% quantile), and skewness. All results (except for skewness) are presented as percentage returns.

Table 1. Results for portfolios of WIG20 companies

Portfolio	mean	median	sd	min	Var0.05	skewness
Equal	0.61	0.91	6.16	-39.02	-8.43	-0.51
Minvar	0.38	0.40	5.00	-30.48	-6.85	-0.72
Minsemivar	0.49	0.53	5.11	-27.08	-6.78	-0.40
minvar0.5	0.39	0.43	5.00	-30.48	-6.81	-0.72
minvar0.75	0.40	0.44	5.01	-30.48	-6.85	-0.71
HRP	0.42	0.60	5.25	-34.95	-7.23	-0.92
HRP1	0.12	-0.01	5.67	-31.23	-8.22	-0.47
HRPdeg	0.60	0.93	5.27	-35.66	-7.29	-0.94
HRP1deg	0.69	0.29	6.78	-34.86	-8.62	0.30

Source: own calculations.

Table 2. Results for portfolios of DAX40 companies

Portfolio	mean	median	sd	min	Var0.05	skewness
Equal	0.33	1.01	6.80	-38.50	-9.28	-1.50
Minvar	-0.06	0.74	5.32	-33.72	-7.01	-2.07
minsemivar	0.11	0.85	5.36	-32.04	-7.19	-1.92
minvar0.5	-0.06	0.74	5.32	-33.72	-7.01	-2.07
minvar0.75	-0.05	0.73	5.33	-33.72	-7.05	-2.05
HRP	0.27	1.02	6.20	-37.56	-7.72	-1.81
HRP1	-0.18	0.59	6.62	-37.39	-9.22	-1.16
HRPdeg	0.41	0.96	4.79	-35.92	-6.29	-1.94
HRP1deg	0.42	0.98	5.54	-40.64	-6.88	-1.66

Source: own calculations.

The main conclusion from the results is that any kind of portfolio optimization helps in both markets. Portfolios that uses any kind of systematic approach usually outperforms naïve equally-weighted portfolio – with regard to higher mean returns and lower risk. The second conclusion is that all tested methods of portfolio selection give very similar results. Although there are differences, their magnitude is small and the assessment depends on the criteria which we choose to compare different methods. The portfolios based on HRP method tend to have higher expected mean return but also higher risk than classical portfolios based on variance minimization. For the DAX the HRP methods based on shorter estimation periods performed better than their counterparts based on longer periods. This can mean that there were changes in the correlation structure on the German market. In this case, the usage of the HRP method with more recent data can be advantageous.

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NON-PARAMETRIC APPROACH TO EXTREME RISK ESTIMATION ON PRECIOUS METALS MARKET

Non-parametric methods represent a set of statistical tools that do not require the researcher to specify the form of functions for the models being estimated. Instead, the data inform themselves the resulting model in a specific way. For the estimation of such models, among others, kernel estimation is used. The attractiveness of this method stems from the fact that it lightens the parametric assumptions imposed on the real data generation process and allows the data to determine the appropriate model by itself. The study applies selected kernel estimators to model extreme risk for the returns of precious metals quoted on the London Metals Exchange over the period January 2018 to September 2022. Value-at-risk is estimated for extremely low orders of quantile. Risk is measured using a non-parametric approach, while the results are compared with the assessments obtained for selected probability distributions: t-Student, GED, and alpha-stable distributions. The results indicate that VaR estimates are dependent on the form of the adopted kernel estimator, and on the method of bandwidth selection. Furthermore, it was observed that the estimates obtained by the kernel estimation method are similar (in terms of RMSE error) to the results obtained using alpha-stable models.

Non-parametric models represent tools of statistics and econometrics which do not require the researcher to specify a functional form for the estimated model. Instead, the data inform the form of the output model in a specific way. The simplest non-parametric form of data presentation is the empirical histogram, for which (in the case of parametric methods) an appropriate density function is fitted.

Over the past few decades, non-parametric and semiparametric methods have attracted considerable attention from statisticians. The first published paper on kernel estimation appeared in 1956 (Rosenblatt, 1956), and since then the field has grown rapidly among both theorists and practitioners. The use of non-parametric models is increasing in the analysis of financial data, but nevertheless, their popularity compared to parametric approaches is relatively limited, especially in commodity market analysis. Sam (Sam, 2010) discussed the application of extreme market risk on investment in agricultural commodity futures using nonparametric methods. The agricultural market was also analysed by Ahmed, Aydin and Yilmaz (Ahmed et al., 2022) by using a semiparametric approach to time series analysis. In contrast, Wu, Watada and Xu (Wu et al., 2015) used kernel estimation to analyse the risk of portfolio investments. A non-parametric approach to risk estimation was also described by Huang (Huang, 2009). He proposed and employed the nonparametric kernel estimator technique directly on the tail distributions of financial assets to produce VaR estimates.

Unfortunately, there are few papers on the use of the kernel estimator to estimate risk in the precious metals market. Hence, this study fulfills this gap.

Kernel estimator

Consider a continuous random variable X with a sequence $x_1, x_2, \ldots, x_n$ as its realization. Rosenblatt (1956) proposed a kernel estimator of the density function of the form:

$$\hat{f}_{kernel}(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x_i - x}{h}\right) = \frac{1}{nh}\sum_{i=1}^{n} K(\psi_i)$$

Where the kernel function $K(\psi)$ should satisfy the following conditions:

- $\int_{-\infty}^{+\infty} K(\psi)d\psi = 1$,
- $\int_{-\infty}^{+\infty} \psi\, K(\psi)d\psi = 0$,
- $\int_{-\infty}^{+\infty} \psi^2\, K(\psi)d\psi = \kappa_2 < \infty$, where κ_2 is central moment of second order.

Generally speaking, a kernel function can be any symmetric probability distribution density function with an expected value of zero and a finite variance. Among the most common kernel functions are (Pagan, Ullah, 1999):

- Normal (gaussian): $K(\psi) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\psi^2}{2}\right)$,
- Epanecznikow: $K(\psi) = \frac{3}{4\sqrt{5}}\left(1 - \frac{\psi^2}{5}\right)$ dla $|\psi| < \sqrt{5}$,
- Triangular: $K(\psi) = 1 - |\psi|$ dla $|\psi| < 1$,
- Uniform: $K(\psi) = \frac{1}{2}$ dla $|\psi| < 1$,
- Two-weighted: $K(\psi) = \frac{15}{16}(1 - \psi^2)^2$ dla $|\psi| < 1$,
- Triple-weighted: $K(\psi) = \frac{35}{32}(1 - \psi^2)^3$ dla $|\psi| < 1$.

Apart from the kernel function, an important component in generation of the kernel density function is the aforementioned smoothing parameter h. It determines the degree of smoothing of the estimated density function, while its value is determined by optimising one of the two measures of accuracy of the estimator:

- Mean Square Error (MSE):

$$MSE\hat{f}(x) = E\left[\hat{f}(x) - f(x)\right]^2 = D^2\left(\hat{f}(x)\right) + \left[bias\hat{f}(x)\right]^2$$

where: $bias\hat{f}(x) \approx \frac{h^2}{2} f''(x)\kappa_2$ and $D^2\left(\hat{f}(x)\right) \approx \frac{f(x)}{nh}\int_{-\infty}^{+\infty} K^2(\psi)d\psi$

- Integrated Mean Square Error (IMSE):

$$IMSE\hat{f}(x) = \int_{-\infty}^{+\infty} MSE\hat{f}(x)\,dx = \int_{-\infty}^{+\infty} D^2\left(\hat{f}(x)\right)dx + \int_{-\infty}^{+\infty} \left[bias\hat{f}(x)\right]^2 dx$$
$$= \frac{\int_{-\infty}^{+\infty} K^2(\psi)\,d\psi}{nh} + \frac{h^4}{4}\kappa_2^2 \int_{-\infty}^{+\infty} (f''(x))^2\,dx$$

There are several methods that can be used to estimate the smoothing parameter h. Among them are the reference rule-of-thumb method, the plug-in method, cross-validation or the bootstrap method.

Risk is associated with a decision-making problem in which an agent (decision-maker) is faced with having to choose between at least two decisions. Decisions under risk are described by the fact that each decision involves more than one consequence and a set of possible consequences as well as their probability of occurrence are known. A special type of risk is an extreme risk, i.e. risk that occurs when the probability of a risky event to occur is very low, whereas if it does occur, it entails significant losses. There are a number of measures used to estimate the level of such risks, and the most common is Value-at-Risk.

Using empirical cumulative distribution function $\hat{F}_n(x)$ Value-at-Risk can be calculated using the following formula:

$$\widehat{VaR}_\alpha(X)_n = \inf\left\{x \middle| \hat{F}_n(x) \geq \alpha\right\} = \hat{F}_n^{-1}\,(\alpha)$$

However, using the kernel estimator and the Raphson-Newton iterative algorithm, the VaR estimate is the solution of the following equation:

$$\hat{F}_{kernel}(x) = \frac{1}{n}\sum_{i=1}^{n} K\left(\frac{x - X_i}{h}\right) = \alpha$$

The use of a kernel estimator for extreme risk estimation is presented on the example of daily log-returns of gold and silver quoted on the London Metals Exchange over the period from January 2018 to September 2022. The gaussian kernel function with cross-validation method were used. All estimates were performed for quantiles of 0.005 and 0.001. Three theoretical distributions: t-Student, GED and alpha-stable distribution were chosen as theoretical models, however, the measure of estimation accuracy was the RMSE error. Table 1 shows descriptive statistics for the analysed metal returns.

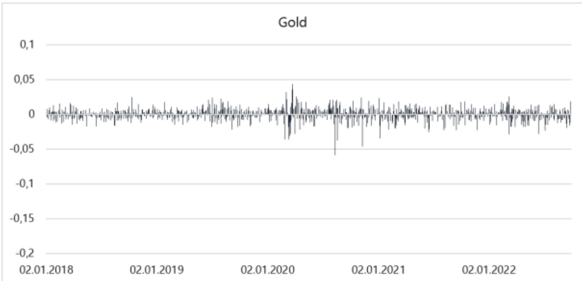
Table 1. Descriptive Statistics

Descriptive Statistics	**Gold**	**Silver**
Mean	0.000189	0.000084
Standard error	0.000250	0.000505
Median	0.000687	0.000276
Standard deviation	0.008739	0.017697
Kurtosis	4.071177	10.435368
Skewness	-0.562188	-0.850348

Range		0.102123	0.237262
Min		-0.058493	-0.158137
Max		0.043631	0.079125
Andeson-Darling test	A-D	10.965	20.871
	p-value	<0.001**	<0.001**

** Statistical significance at 0.01.
Source: own calculation.

Both gold and silver returns performed on average positive returns over the analysed period. The range of volatility of silver returns is more than twice that of gold. The empirical distributions are leptokurtic, left-skewed and differ from the normal distribution. Figure 1 presents the empirical time series of the returns of the analysed metals.



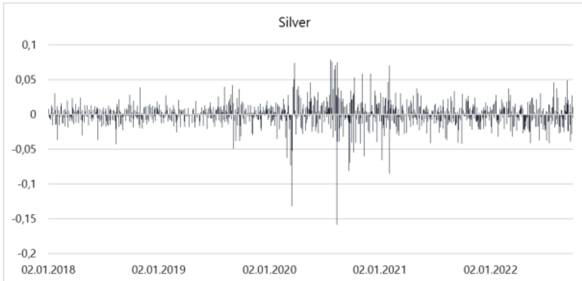


Figure 1. Time series of gold and silver returns
Source: Own calculations.

Analysing the figures above, it is clear that since the WHO announced the SARS-Cov-2 coronavirus pandemic, an increased level of volatility (including variance clustering) has been observed in the time series of gold and silver returns. In addition, significant peaks are observed, indicating the presence of outlier observations. Table 2 shows the parameter estimates for the theoretical distributions. The results of the parameter estimations indicate that the empirical distributions of returns are heavy-tailed and left-skewed.

Table 2. Estimates of theoretical distributions

Metal	Parameter	t-Student	GED	alpha-stable
Gold	$\hat{\mu}$	0.000511	0.000189	-
	$\hat{\sigma}$	0.006159	0.008732	-
	df	3.710495	1.873982	-
	$\hat{\alpha}$	-	-	1.783159
	$\hat{\beta}$	-	-	-0.494995
	$\hat{\gamma}$	-	-	0.005267
	$\hat{\delta}$	-	-	0.000899
Silver	$\hat{\mu}$	0.000411	0.000238	-
	$\hat{\sigma}$	0.010656	0.017033	-
	df	2.886188	0.927775	-
	$\hat{\alpha}$	-	-	1.585329
	$\hat{\beta}$	-	-	-0.102921

	$\hat{\gamma}$	-	-	0.008798
	$\hat{\delta}$	-	-	0.000623

Source: own calculation.

In the next step of the study, the bandwidth for the kernel estimator of the density function was estimated using three methods: reference rule-of-thumb, plug-in and cross-validation, followed by the optimal number of intervals. The results are presented in Table 3.

Table 3. Optimal bandwidth and the optimal number of intervals

Metal	Kernel estimator	Rule of thumb	Plug-in	Cross-validation
Gold	Bandwidth	0.001722	0.001542	0.001514
	No. Intervals	59	66	67
Silver	Bandwidth	0.003118	0.002583	0.002484
	No. Intervals	76	91	95

Source: Own calculations.

The results show that the bandwidth h is determined by the estimation method adopted. The smaller the value of the parameter h, the greater the number of class intervals.

Risk measures were estimated for the assumed theoretical distributions and kernel estimator of the density function were computed using gaussian kernel. In the study, estimates of the h parameter were obtained using cross-validation. The results are presented in Table 4.

Table 4. Estimates of Value-at-Risk

Metal	VaR	Quantile		RMSE	
		0.001	**0.005**	**0.001**	**0.005**
Gold	Empirical	-0.044361	-0.030965	-	-
	Student	-0.041365	-0.025745	0.002996	0.005221
	GED	-0.042831	-0.027541	0.003951	0.003425
	Alpha-stable	-0.045392	-0.032134	0.001031	0.001169
	Kernel	-0.046213	-0.031373	0.001852	0.000409
Silver	Empirical	-0.121531	-0.065242	-	-
	Student	-0.081273	-0.051328	0.040257	0.013914
	GED	-0.092344	-0.053651	0.029186	0.011593
	Alpha-stable	-0.123216	-0.069327	0.001686	0.004085
	Kernel	-0.125394	-0.067351	0.003864	0.002109

Source: Own calculations.

VaR estimates clearly differ due to the distribution proposed for its calculation. The results show that the most accurate estimates, in terms of RMSE error, were obtained for the alpha-stable distribution (gold and silver, quantile 0.001) and the kernel estimator of the density function (gold and silver, quantile 0.005). The t-student and GED distributions strongly underestimate VaR. The reliability of the results obtained was verified using backtesting. For this purpose, one of the most popular statistical tests, the Kupiec Proportion Of Failures test (POF), was used (Kupiec, 1995). The null hypothesis in the test assumes that the number of exceedances should not be statistically significantly different from the established proportions. Assuming the null hypothesis is true, the LRPOF test statistic has an asymptotic chi-square distribution with one degree of freedom. The test results for the analysed metals and the assumed quantile level are shown in Table 5.

Table 5. Test of Kupiec

Metal	VaR	0.001		0.005	
		LR_{POF}	p-value	LR_{POF}	p-value
Gold	Student	0.410051	0.521944	4.409377	0.035742*
	GED	0.410051	0.521944	3.142881	0.076259
	Alpha-stable	0.410051	0.521944	0.002792	0.957871
	Kernel	0.410051	0.521944	0.002792	0.957871
Silver	Student	1.823703	0.176873	4.409377	0.035742*
	GED	0.410051	0.521944	3.142881	0.076259
	Alpha-stable	0.410051	0.521944	0.223478	0.636403
	Kernel	0.410051	0.521944	0.002792	0.957871

* Statistical significance at 0.05
Source: Own calculations.

Kupiec's exceedance test indicates that only if Value-at-Risk is estimated using a Student's t-distribution the null hypothesis stating that the number of exceedances is not significantly different from the determined proportion is rejected. Similarly, a low level of p-value was achieved for the GED distribution. These results are consistent with the accuracy of risk estimation using these two distributions in terms of RMSE error.

The study presented in this paper uses a non-parametric approach to estimate extreme risk. The method based on kernel estimation of the density function (and cumulative distribution function) was used. The motivation for using non-parametric methods is the general difficulty of fitting theoretical distributions to the processes being analysed, as well as the desire to use methods that do not entail such rigid assumptions as in parametric approaches. An important role in the calculation of the kernel estimator is played by the smoothing parameter, which can be estimated using different methods and different kernel functions.

The empirical analysis focused on measuring extreme risk for daily log returns of gold and silver quoted on the London Metals Exchange over the period from January 2018 to September 2022. A gaussian kernel function and cross-validation method were used. Value-at-Risk was estimated for two extreme quantiles: 0.005 and 0.001. t-Student distribution, GED distribution and alpha-stable distribution were chosen as theoretical probability models; however, the RMSE error was used as a measure of estimation accuracy. The results of the analysis show that the time series of gold and silver returns are characterised by a high and varying level of volatility, however, their empirical probability distributions are strongly different from the normal distribution (high leptokurtosis, left-side skewness and heavy tails were observed). Value-at-risk estimates at a given quantile level differ from the adopted model. Silver returns turned out to be significantly riskier, generating (for a quantile of 0.001) loss nearly three times higher than that achieved by gold. The most accurate estimates in terms of RMSE error were obtained for the alpha-stable distribution (gold and silver, quantile 0.001) and the kernel estimator of the density function (gold and silver, quantile 0.005). The t-Student and GED distributions strongly underestimate VaR, which was confirmed by the results of the Kupiec test.

The results show that the choice of the probabilistic model significantly affects the accuracy of extreme risk estimates. Economic time series show that classical assumptions are rarely met, so it seems reasonable to look for alternative, equally effective statistical-econometric methods and models.

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Model Risk of Marginal Expected Shortfall: Evaluation on Significant European Banks

Marginal Expected Shortfall (MES) is a systemic risk (SR) measure that aims to estimate the behaviour of a financial institution (FI) during the worst days of the market. Mathematically, it is defined as the average return of the FI when the reference market returns are in their left tails (Acharya *et al* (2010)),

$$\mathrm{MES}_{\mathrm{i,t}}(\alpha) = \mathrm{E}\left(\mathrm{R}_{\mathrm{i,t}} \middle| \mathrm{R}_{\mathrm{m,t}} \leq \mathrm{VaR}_{\mathrm{m,t}}(\alpha)\right),$$

where α is the Value at Risk (VaR) confidence level for the market, $R_{i,t}$ denotes the returns of the FI *i* at time *t*, and $R_{m,t}$ denotes the returns for the market *m*. Here, the MES is written using the VaR of the market and can easily be rewritten using the Expected Shortfall (ES) of the market. In such a case, MES refers to a FI's marginal contribution to the fall of the market index and looks at the interconnectedness within the system. It should be noted that the sum of MES associated with the firms within the index does not equate the loss indicated by ES, as the size aspect is not included in this metric (Banulescu and Dumitrescu (2015)). If the MES of a FI is estimated with an external market index, then it can represent the performance (sensitivity) of the FI to bad market days, and thus look at how a firm is exposed to systemic risk (Idier and Lamé and Mésonnier (2014)).

In this work, we analysed the model risk of MES in the context of FIs monitored by the European Central Bank (ECB). Model risk refers to the risk that practitioners are exposed to, when using a model that approximates reality, in their work (Derman (1996)). Broadly speaking, model risk signifies the uncertainty due to human error in model application (e.g., parametrization, inapplicability), or intrinsic model shortcomings (such as instability, and sensitivity). We focused on the model risk associated with input parametrization of the model. This type of model risk is often referred to as estimation risk (Christoffersen and Gonçalves (2004), Klein and Bawa (1976)).

The quantitative estimations of model risk generally measure one of two important concepts, accuracy, and precision. The first concept, accuracy, refers to the *systematic shortcoming of the model*, or model performance, and measures the `goodness' or bias of the model. The second concept, precision, refers to the *variability of the model* under different conditions, sometimes referred to as sensitivity analysis in literature (Gourieroux, Laurent and Scaillet (2000)), and measures the repeatability of measurements. Thus, accuracy estimates *closeness of the measurements to a benchmark* (true value), whereas precision or sensitivity estimates the *dispersion of the measurements among each other*. The complete model risk requires knowledge of both concepts. However, accuracy requires a benchmark, something that can be difficult to achieve in SR measures and is an ongoing research area in finance (Banulescu-Radu et al. (2020)). The concept of precision is much more readily applicable, as it requires a comparison of model estimates amongst each other, and thus form the basis of the model risk in this work.

The working approach to measure model risk here relies on measuring the deviation among model estimates, and so we used the following two metrics that aim to capture this deviation based on earlier work (Pasieczna (2021)):

- Ratio – This metric is defined as the ratio of the maximum absolute value of the estimates to the minimum absolute value of the estimates. It has already been used to study the model risk of various market and systemic risk measures (Danielsson et al. (2016)).
- Spread – This metric is defined as the absolute value of the difference between the maximum and minimum estimates, expressed in units of the average estimate. These units allow us to represent the spread metric as a 'band' around the average.

Both metrics are expected to be equivalent up to a multiplicative factor (spread is proportional to ratio - 1). Practically, the ratio can have exceptionally large values, especially if the denominator (the minimum absolute value) is close to zero. In MES estimates, we observed that risk estimates can sometimes be quite low for certain FIs. This can happen, for example, when a FI has small correlations to the reference market index, which imply that the expected returns of the FI will be close to zero under the MES condition, and the ratio then takes arbitrarily large values. The spread metric is thus more attractive.

The list of FIs chosen here was obtained from a list of banks directly supervised by the ECB (ECB, 2021). The various criteria for their choice are also available on the ECB's Banking Supervision website. At the time of this study, (August 2021), 114 FIs were supervised, of which 47 were kept for study. The reasons for rejection included unavailability of data in Bloomberg, unlisted (or pending listing) on the market exchanges, a private company, or having been acquired by an FI already included. We expect survivorship bias in the data, since we considered the list of FIs monitored in August 2021, and not those monitored earlier. Bloomberg terminal was used to download the daily close prices and daily outstanding shares of the chosen FIs. The outstanding shares were necessary to compute the market capitalization of the FIs and, eventually, the artificially constructed market index. Whenever possible, the time series for each FI began on the first of January 2000.

As is evident from the definition of the MES, we require a market index. Instead of using an existing index, such as the Euro Stoxx 50 or Euro Stoxx 600 Banks, an artificial market market-capitalization-weighted index consisting of only the chosen FIs was built. This way, the market movements are solely due to the movements of the chosen FIs, and not exogenous effects. A market-capitalization-weighted index additionally has the advantage of representing the net wealth created of the chosen FIs. To build the index, some cleaning of the data had to be done. Firstly, all missing price and outstanding shares data were forward-filled. This is justified since the market index is supposed to represent the net wealth of the sector. Secondly, the price and outstanding shares of an FI were used with a one-day lag, so that the market information can be used quickly, while still maintaining causality to avoid potential look-ahead biases. The steps to build the index are as follows:

1. For every day within the backtesting period from January 2000 to August 2021, compute the market capitalization for each FI as the product of its last known outstanding shares and price.
2. Add the market capitalization over all FIs present on that day.
3. Normalize this aggregated market value by dividing it by a divisor.

Mathematically,

$$\mathrm{index}_{\mathrm{d}} = \frac{\sum_{\mathrm{i} \in \mathrm{comp}_{\mathrm{d}}} \mathrm{mcap}_{\mathrm{i}}(\mathrm{d})}{\mathrm{divisor}_{\mathrm{d}}},$$

where, indexd, divisord, mcapi(d) and compd are the values of the market index, divisor, market capitalization of FI i, and the market composition respectively, on the day d.

The divisor is updated each time a new FI enters the market and is used from the following day. The expressions for updating the divisor and the starting divisor are:

$$\mathrm{divisor}_{d+1} = \mathrm{divisor}_{d} \frac{\sum_{i \in \mathrm{comp}_d} \mathrm{mcap}_i(d)}{\sum_{i \in \mathrm{comp}_{d-1}} \mathrm{mcap}_i(d)}; \quad \mathrm{divisor}_2 = \frac{1}{100} \sum_{i \in \mathrm{comp}_1} \mathrm{mcap}_i(1).$$

The starting market value (on day d = 1) is thus set to 100, and the index growth is compared with this number. Within our dataset, the composition was updated 42 times, and the final market index used for estimating the MES is provided in Fig. 1.

Fig 1. Evolution of the market index built from the FIs within the dataset
Note: Reference value of the index is 100 points on the first day, and values represent wealth growth with respect to this value.

Monte Carlo (MC) methods were used to compute MES for each FI, an extension of an earlier implementation for VaR and ES (Pasieczna (2021)). Four MC parameters are studied:

1. Inter-FI dependence: Independent (no consideration of the inter-FI correlation matrix), multivariate (numbers are generated from a multivariate distribution).
2. Distribution type: Normal, Student's-*t* (allows for heavier tails through a degrees-of-freedom parameter).
3. Estimation window type: Rolling (simple moving average window), Exponentially weighted moving (EWM, timescale using the centre-of-mass (com) parameter where the weight decreases by com/(1+com) per day).
4. Historical time period: 125D (0.5 years), 250D (1 year), 500D (2 years).

We thus have 24 MC variants (2x2x2x3), corresponding to the 24 MES estimates per FI per day for which we can estimate the ratio and spread. The algorithm to estimate the MES at 95% for each FI on each day d is given below (log-returns are used in this work):

1. Estimate the empirical mean, standard deviation, and the inter-FI correlation matrix on the returns of all FIs were estimated. A distribution shape parameter was computed for each FI each day as a way to `fatten' the tails for the case of the Student's-*t* distribution. For the

independent FI approach, the correlations of each FI with the market index, the market's mean, and the market's standard deviation were estimated.

2. These statistical quantities and distribution choices were used to generate random returns for *all* FIs for day $d + 1$, 20000 times, the number of MC iterations.

a. Independent: We generated random numbers using a bivariate process similar to that used by Brownlees and Engle (2012), but where the two random numbers for the FI and the market are obtained from the distribution choice (normal, Student's-*t*). The process can be expressed as:

$$r_{m,d+1} = \sigma_{m,d}\varepsilon_{m,d}$$

$$r_{i,d+1} = \sigma_{i,d}\rho_{im,d}\varepsilon_{m,d} + \sigma_{i,d}\sqrt{1-\rho_{im,d}^2}\varepsilon_{i,d}$$

where $\varepsilon_{m,d}$ and $\varepsilon_{i,d}$ represent the random numbers generated corresponding to the market and the FI, respectively.

b. Multivariate: Here, random numbers for the FIs were drawn from the multivariate distributions directly. For simplicity of implementation, standard multivariate distributions with the correlation matrix were used to draw random numbers, which were then scaled by the standard deviations and shifted by the means.

3. For each MC iteration, generate the FI returns, corresponding FI price, market returns, and corresponding market index for day $d + 1$ using the MC sampling process.

4. Compute the MES as an average over the MC iterations satisfying the condition required. Estimate the VaR of the market as the 95th quantile from the 20000 simulated market index values, and then average the simulated returns of the FI for those MC iterations when the simulated market returns were below this VaR

5. Compute the ratio and spread over these estimates for each FI on each day.

To avoid numerical issues, days were skipped for a given FI if estimates are missing, or if any of the risk estimates are above -0.5%. The temporal evolution of the model risk was studied by estimating the model risk across all FIs per day. Parameter contribution to model risk was estimated by computing the model risk over risk estimates with parameters *fixed* to a given value (e.g., window type fixed to EWM), and then averaging the drop in model risk overall values of this parameter. If the drop was *larger* (lower model risk by fixing the parameter), the parameter contributed *more* to the model risk.

The model risk results of the MES are provided in Table 1. We see that the model risk for MES is non-zero (no model risk implies a ratio of 1 and a spread of 0) and that all parameters contribute to the model risk. The largest contribution comes from the historical period parameter. This is intuitive as this parameter defines the length of the data that enters the distribution parametrization, and as the MC model is sensitive to how the MC distribution is parametrized, this parameter becomes important. The lowest contribution is from the inter-FI dependencies parameter, indicating an equivalence of the multivariate the independent-FI approaches. The independent-FI approach still has interactions through the market and the low contribution to the model risk implies that the interaction of the FIs and the market can be captured with a multivariate distribution and a rebuilt index. The rankings of the parameter contributions are additionally identical for both model risk measures.

Table 1. Model risk metrics

	Ratio			**Spread**		
	Model risk	**Change**	**Average**	**Model risk**	**Change**	**Average**
All	2.259	-	-	0.677	-	-
Inter-FI dep.						

Independent	2.202	-0.057	-0.203	0.660	-0.017	-0.096
Multivariate	1.910	-0.349		0.503	-0.174	
Distribution type						
Normal	1.726	-0.533	-0.403	0.384	-0.293	-0.189
Student's-*t*	1.986	-0.273		0.593	-0.084	
Window type						
Rolling	2.079	-0.180	-0.341	0.587	-0.090	-0.136
EWM	1.756	-0.503		0.495	-0.182	
Historical period						
125D	1.545	-0.714	-0.673	0.336	-0.341	-0.289
250D	1.595	-0.664		0.391	-0.286	
500D	1.618	-0.641		0.437	-0.240	

Note: ratio and spread for the MES at 95% overall MC variants and over variants when one parameter was fixed.

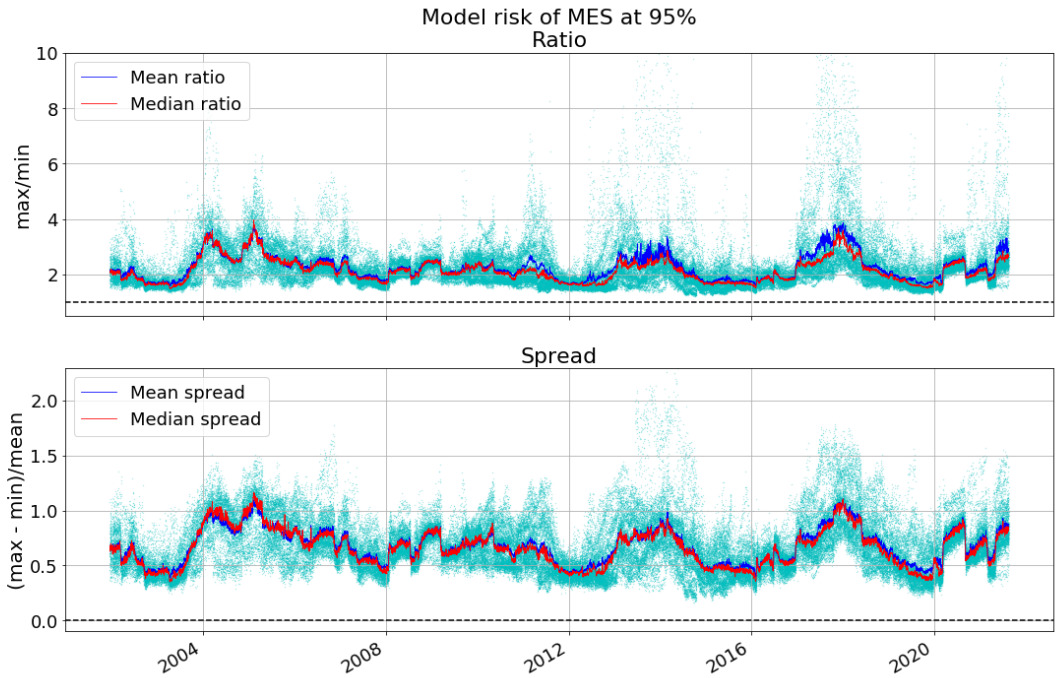

Fig. 2. Temporal evolution of the model risk (ratio and spread) of MES at 95%

The model risk of individual FIs per day are shown in cyan dots. The median (in red) and mean (in blue) are provided to highlight that the ratio measure is more right-skewed than the spread measure.

The temporal evolution of the model risk measures is shown in Fig. 2. We observed similar trajectories for both measures. The model risk tended to increase *after* the crises (2008 crisis, the 2012 Greek financial crisis, the recession of 2018, and the 2020 Covid crash) while remaining low during the crisis periods, something not in agreement with the literature (Danielsson *et al.* (2016)). The model risk increase in the post-crisis period can be attributed to the historical period parameter, since this parameter introduces delays in incorporating latest information. The mean (blue) and median (red) lines show a larger right-skew for the ratio measure as compared to the spread measure. This indicates the sensitivity of the ratio to outliers, which is not the case for the spread. The spread seems to be a better model risk measure due to this stability.

In this work, we computed the model risk of MES at 95% using two model risk measures: ratio (value of 2.3) and spread (value of 0.7). These values indicate that the lowest and highest risk estimates vary by a factor of 2 and that the distance between the lowest and highest risk estimates is 70% of the average. Both measures have similar temporal aspects, with the spread being more stable than the ratio to outliers. The model risk was observed to increase after crisis periods, an effect attributed to the historical time period parameter that reacts to events at different speeds. Finally, we studied the sensitivities of the MC process to four parameters and found that the historical time period contributes the most, whereas the inter-FI dependence parameter contributes the least. To the best of our knowledge, analysis of parameter sensitivities using model risk is not done in the literature, and we believe that this approach can be of use for practitioners trying to refine their models.

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Do energy stocks react on interest rates shifts? – preliminary results

The energy sector plays important role in sustaining social and industrial infrastructure. Since the sector is the capital intensive and long-term investing is required for its development, it is interesting to test sensitivity of rates of return of energy stocks on long-term interest rates changes.

The paper deals with the problem of possible energy stock reactions to shifts within the interest rate curve. For the analysis, the Sao Paulo Stock Exchange quotations were selected. The GARCH-type models are applied.

The GARCH(1,1) model, described in the seminal paper of Bollerslev (1986), is:

$$y_t = \mu + \varepsilon_t \quad (1)$$

$$\varepsilon_t | I_{t-1} = N(0, h_t) \quad (2)$$

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \quad (3)$$

where symbols are: h_t - conditional variance, I_t - set of all available information, ε_t - error term.

For the purpose of the analysis, equation (4) is introduced:

$$y_t = \mu + \delta \mathrm{x}_t + \varepsilon_t \quad (4)$$

where x_t represents differences between ten-years and five-interest rates (10Y minus 5Y).

This variable x_t we include also into the variance:

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma x_t \quad (5)$$

The first analysis of this type was presented in Majerowska, and Bednarz (2020).

Five energy companies operating in Brazil were selected for analysis. The specification of selected companies is presented in Table 1. Wednesday-to-Wednesday observations from January 2012 to the beginning of March 2021 were employed.

Table 1. List of companies

Company	Abbreviation
Companhia Energetica de Sao Paulo	CESP3
Companhia Energetica de Minas Gerais	CMIG4
Companhia Energetica do Ceara	COCE5
CPFL Energia SA	CPFE3
Companhia Paranaense de Energia	CPLE3

Source: own presentation.

The results of the estimates are given in Table 2 and Table 3.

Table 2. Results of the estimation of the GARCH(1,1) model with the conditional mean equation

	Conditional mean		Conditional variance			Conditional density
Companies	μ	δ	ω	A	B	H
CESP3	-0.004	0.009**	0.000	0.013	0.997***	2.677***
CMIG4	-0.001	0.007	0.000**	0.132***	0.763***	5.455***
COCE5	0.001	-0.000	0.001***	0.319**	0.268*	3.872***
CPFE3	0.003**	-0.002	0.000	0.284*	0.825***	3.009***
CPLE3	0.001	0.003	0.002***	0.193***	0.007	7.611***

*) **) ***) statistically significant at 0.1, 0.05 and 0.01 significance levels respectively
Source: own elaboration.

Table 3. Results of the estimation of the GARCH(1,1) model with the conditional mean equation and conditional variance equation (Y10-Y5)

	Conditional mean		Conditional variance				Conditional density
Companies	μ	δ	ω	γ	α	B	H
CESP3	-0.004	0.008**	0.000	-0.000	0.011	0.963***	2.752***
CMIG4	-0.001	0.007	0.000**	-0.000	0.129***	0.763***	5.501***
COCE5	0.001	0.000	0.001***	0.000	0.319**	0.253*	3.937***
CPFE3	0.003**	-0.002	-0.000	0.000	0.264***	0.847***	2.924***
CPLE3	0.002	0.002	0.002***	-0.001	0.187**	0.005	7.814***

*) **) ***) statistically significant at 0.1, 0.05 and 0.01 significance levels respectively
Source: own elaboration.

It can be concluded that the changes of the long-term interest rates have no significant impact on the energy stocks listed in Sao Paolo. Presented results are very preliminary so they could be treated with caution. It seems valuable in addition to analyse the impact of lower financing costs, i.e. lower than market interest rates.

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Dependence analysis for energy ETFs and crude oil – a preliminary study

This study investigates the effects of crude oil on energy stock portfolios. We consider returns of portfolios of energy companies approximated by energy ETF and returns of crude oil. To study the relationship between crude oil and ETFs we apply Granger causality and Dynamic Conditional Correlation. The research hypothesis about a dependence between energy ETFs and the underlying energy risk factor – crude oil – and therefore the existence of hedging or diversification opportunities was verified. Our empirical findings indicate that crude oil has a low effect on energy ETFs, therefore hedging opportunities using crude oil is weak, but opportunities for risk diversification are still possible.

The purpose of this paper is to investigate the transmission from oil price changes to energy portfolio returns. We examine the following research hypothesis: there is a strong dependence between energy ETFs and the underlying energy risk factor – crude oil.

To analyze dependence the following tools were used in the paper:

1) Causality relationship

Granger first introduced the concept of causality (Granger, 1969). Since then, many different methods for testing causality in Granger's sense have emerged. In practice, vector autoregressive models (VAR) are most commonly used to study causality in mean.
Hong (2001) proposed test statistics, which included tests proposed by (Cheung, Ng, 1996) and (Granger, 1969). As dynamic relationships between variables can change over time, a time-varying Granger-causality test is also used in the empirical literature. For this purpose, Lu et al. (2014) propose a simple and intuitive approach to estimating Hong tests in rolling subsamples.

2) Dynamic conditional correlation (DCC)

DCC-GARCH model (Engle, 2002) is estimated using the Quasi Maximum Likelihood (QML) in two stages. In the first stage, univariate GARCH models are estimated for each asset series (Engle 2002, Engle, Sheppard 2001, Tse 2002). In the second stage, residuals, transformed by their standard deviation estimated during the first stage, are used to estimate the parameters of the dynamic correlation.

The research hypothesis on the existence of a dependence between energy ETFs and crude oil was verified. The hedging opportunities are weak, but diversification is possible.

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Information policy and reporting of insurance companies in the context of ESG

The concept of a sustainable economy, which is associated with the introduction of sustainable development, is relatively young. It emerged in the second half of the 20th century. However, its importance has increased in recent years, as solutions have been regulated and implemented to intensify sustainability development. These have also extended to the insurance market.

The basis for the regulation of sustainable development is the agenda, which was endorsed by a UN General Assembly resolution in 2015. It identifies 17 goals that cover many areas of social and economic life.

Currently, the two most important pieces of legislation that regulate the role and tasks of insurance companies in the context of sustainable development are:

- REGULATION (EU) 2019/2088 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 27 November 2019 on sustainability-related disclosures in the financial services sector.

- DIRECTIVE 2014/95/EU OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 22 October 2014 amending Directive 2013/34/EU as regards disclosure of non-financial and diversity information by certain large undertakings and groups.

The specific nature of the activities of insurance companies determines the many roles that these institutions play in a sustainable economy. Three of the most important can be identified. Indeed, insurers act as:

- investors,
- risk managers,
- underwriters.

Table 1. Definition of the roles of insurance companies in a sustainable economy

Role	Definition
Investors	They participate in directing capital flows both as direct investors and as intermediaries in accordance with the principles of sustainable development (sustainable investments)
Risk managers	Participate in the orientation of risk management activities, both insurance and other risks, in line with

	the principles of sustainable development (risks for sustainable development)
Underwriters	Take steps to select and classify insurance risks in accordance with the principles of sustainable development

Source: own study.

The carrying out of the indicated roles by insurance companies determines the direction of change in areas related to their operations, influences management and determines their place in the modern economy.

The purpose of the research was to check the scope, availability, and transparency of information on the area of sustainable development that is published by insurance companies in Poland on their websites. However, it was not the purpose of this research to assess the activities of insurers in the area of sustainability.

The research included all insurance companies that operated in Poland in 2022 in the form of a joint stock company or mutual insurance company. Information on these insurance companies was taken from the website of the Polish Financial Supervision Authority (as at 31.10.2022).

The research assessed 24 entities in the life insurance companies group and 28 entities in the non-life insurance companies group. Due to the fact that some entities belong to groups and the information that relates to sustainability is presented for the group as a whole and not for individual entities, the entities were divided into: insurance groups, life insurance companies, and non-life insurance companies with the division into joint-stock companies and mutual insurance companies.

The research carried out to prove the thesis that contemporary market conditions related to the role of insurance companies in a sustainable economy require insurers to publish information in this area, which influences the formation of their image as a public trust institution.

The research was conducted from September to November 2022. The information published on insurers' websites was assessed. This information took the form of content presented on the websites, as well as additional files that were attached. The most recent reports that dealt with sustainability were also considered, in most cases they were from 2021, for a couple of insurers they were from 2020. These reports were the result of insurers' compliance with the requirements imposed by the EU Sustainable Finance Disclosure Regulation ('SFDR').

The study used the following methods: statistical method - counting the number of pages, subpages on websites and the number of pages in documents and qualitative method - document analysis to examine the scope and the content of the information.

After completing the research was noted that some of the sustainability information is published for the group and not for individual insurance companies. Therefore, the entities were divided into:

- 9 groups,
- 15 life insurance companies,

- 17 non-life insurance companies.

Thus, the total is 41 entities.

In assessing the scope, availability, and transparency of information, 4 levels were identified:

- Low (no information, information not available),
- Minimal (information presented is only due to regulatory requirements, the only information that needs to be published is available);
- Good (information presented is not only due to regulatory requirements, but additional information is also published in the form of content on the website or files, is available);
- Very good (the scope of information presented is very broad, a report on sustainable development is published, all information is accessible, readable, and clearly drafted).

Table 2. Results of the research for each group of entities

Level	Low	Minimal	Good	Very good	Number of pages (web, in files)
Groups					
COMPENSA		X			1
ERGO HESTIA				X	60
ALLIANZ POLSKA			X		7
EUROPA			X		2
GENERALI				X	170 (report in English)
SANTANDER ALLIANZ			X		5
SIGNAL IDUNA POLSKA			X		1
PZU				X	150
WARTA				X	150 (report in German)
Life insurance companies					
NNLIFE TUnŻiR S.A			X		13
AEGON TU na ŻYCIE S.A.			X		27
CA ŻYCIE TU S.A.		X			1
CARDIF POLSKA S.A		X			1
INTER-ŻYCIE POLSKA S.A		X			1
NATIONALE-NEDERLANDEN TUnŻ S.A.			X		13
OPEN LIFE TU ŻYCIE S.A			X		1
PKO ŻYCIE TU S.A	X				
POCZTOWE TUnŻ S.A.	X				
SALTUS TU ŻYCIE SA	X				

UNIQA TU na ŻYCIE S.A.				X	60
UNUM ŻYCIE TUiR S.A.			X		4
VIENNA LIFE TU na ŻYCIE S.A. Vienna Insurance Group			X		2
POLSKI GAZ TUW na ŻYCIE		X			1
REJENT-LIFE	X				
Non-life insurance companies					
CREDIT AGRICOLE TU S.A.				X	60 (report for bank)
INTER POLSKA S.A.	X				
INTERRISK TU S.A. Vienna Insurance Group			X		
KUKE S.A.			X		23
LINK4 TU S.A	X				
NATIONALE-NEDERLANDEN TU S.A.			X		17
PARTNER TUiR S.A.	X				
PKO TU S.A.		X			1
UNIQA TU S.A				X	60
WIENER TU S.A. Vienna Insurance Group			X		1
ZDROWIE S.A.	X				
AGRO UBEZPIECZENIA TUW	X				
CUPRUM			X		30
POLSKI GAZ TUW	X				
SALTUS TUW			X		7
TUW		X			1
TUZ TUW	X				

Source: own study.

Table 3 Final results

Level	Low	Minimal	Good	Very good
Total	11	7	16	7
Groups	0	1	4	4

Life insurance companies	4	4	6	1
Non-life insurance companies	7	2	6	2

Source: own study.

Following the research, the following conclusions were formulated:

- Sustainability information is best presented by groups, which usually include insurance companies of both divisions as well as other financial institutions. Thus, in such a situation, it is difficult to clearly attribute the information presented to a specific group entity. The sustainability policy is closely linked to the strategy of the group as a whole.
- The fact that a fairly large number of entities present sustainability information at a good level can be regarded as a positive development. As this is a relatively new challenge for insurers, it bodes very well for the future, as it can be presumed that the process will develop and in the next years insurance companies will improve the way and extent of the information presented.
- The rather large number of non-life insurers with a low level of presentation of sustainability information is a cause for concern. However, it should be noted that these entities are primarily mutuals, whose business purpose is different from that of joint stock companies. This may have an impact on the fact that mutuals have less need to present this information and it is not an important part of their business.
- There is a wide range and variation in the level of presentation of sustainability information. There are insurance companies that do not publish this type of information at all, or the information is not available. However, there are also those that publish such information very extensively. They are often presented in the form of extensive reports, which are prepared in a form that is very clear and readable for the audience.
- Having analysed the scope and content of this information, it can be seen that the most common information related to sustainable development concerns climate, ecological and environmental issues; less frequent are those related to respect for human rights and discrimination.
- It can be observed that, for most insurance market players, sustainability issues are relevant, as they are considered in their operational strategy and designated mission.

The presented summary allow us to conclude that the thesis that the contemporary market conditions related to the role of insurance companies in a sustainable economy require insurers to publish information in this area, which influences the formation of their image as a public trust institution is true. Undoubtedly, insurers have started to publish sustainability information. However, the scope and availability of this information vary greatly, and the process still needs to be improved.

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Ecological responsibility of banks in the context of ESG requirements

In the last decade, public consciousness has been growing on a wide range of issues, including climate change, water and food crises, modern slavery, poverty and conflict. Currently, society has increasing expectations of the role businesses should play in tackling some of the planet's biggest challenges [PWC, 2022]. Institutions are expected to not only minimise their negative impacts, but to also contribute positively to both society and the environment. Corporate sustainability is therefore all about creating long-term value by implementing strategies that incorporate environmental, social, and governance (ESG) dimensions, in addition to economic ones. For many, ESG brings to mind environmental issues like climate change and resource scarcity; however, in reality and in the literature the topic is much broader and considers social and governance matters too. From a social perspective, issues like a company's labour practices, talent management, work conditions, human rights, product safety, and data security are covered. From a governance perspective, topics like board diversity, executive pay and business ethics are discussed, thus forming an integral part of a company's sustainability agenda. For that reason ESG reporting is all about the disclosure of information, data or metrics that explain a business's impact and added value in these three areas.

We can find a large number of foreign and domestic literature concerning CSR (Corporate Social Responsibility) and the banking sector but only a few papers which concern ESG, green finance and financial efficiency in the banking sector. There are also only a few papers presenting in which way we can find the link between environmental responsibility and financial performance.

In the context of new regulation from the European Union, we would like to focus in our paper on the aspect concerning environmental responsibility in the banking sector. Additionally, what we mentioned, in the literature we can observe a gap of scientific papers connected with the environmental responsibility of banks as a one of the dimensions in ESG strategies, in the context of their financial effectiveness.

The selected EU Regulations concerning ESG aspects, with particular emphasis on environmental responsibility, which should be applied by banks: 2014/95/EU Directive of Non-Financial and Diversity Information by Certain Large Undertakings and Groups (NFDR), the Corporate Sustainability Reporting Directive (CSRD), EU Taxonomy, The Sustainable Finance Disclosure Regulation (SFDS), Sustainable Development Goals (SDG).

The problems of environmental responsibility of business institutions, including banks, become especially important in the light of the EU strategy already mentioned and the 2014/95/EU. Directive on disclosure of non-financial information, including environmentalist actions. These laws come into force for Polish institutions on the 1st of January 2017 and include public interest institutions, commercial banks among them [Zabawa, Kozyra, 2022]. All member countries had until the 6th of December 2016 to implement the directive. According to the Directive text, the public interest institutions, including banks, must disclose, in their reports or separate documents, important information concerning environmental data, social and human resources (HR) data, respecting human rights and counteracting corruption and bribery [Zabawa, 2018], [Directive 2014/95/UE]. Companies are free to choose the means of reporting that suit them and their standards. The most popular guideline standards for social reporting were established by the Global Reporting Initiative (GRI), with their newest standard being GRI Standards.

The Corporate Sustainability Reporting Directive (CSRD) is the new EU legislation requiring all large companies to publish regular reports on their environmental and social impact activities. CSRD will apply to all large EU companies, including banks, exceeding at least two of the following criteria: - more than 250 employees; - a turnover of more than 40 million euro; - total assets of €20 million euro. CSRD will significantly expand the scope and content of the EU's existing non-financial reporting regime under the Non-Financial Reporting Directive (NFRD). Under Article 8 of the EU Taxonomy Regulation, entities in scope of NFRD are also required to report on their Taxonomy alignment. The amendments made by CSRD therefore mean that a broader range of entities will also be required to make disclosures of their Taxonomy alignment. Another key difference between NFRD and CSRD is that the new rules will introduce a mandatory audit and assurance regime to ensure the reliability of data and avoid greenwashing and/or double accounting [Stehl et al., 2022].

In our paper, we used a variety of sources, including scientific articles and statistical data, financial and ESG reports of banks, and reporting principles (e.g., Global Reporting Initiative—GRI Standards) as well. The importance of the line of research used here is confirmed by the recent (2018) award of the Bank of Sweden's Prize in Economic Sciences in Memory of Alfred Nobel to William D. Nordhaus (Yale University) for the inclusion of climate change into the long-term macroeconomic analyses (the prize was shared with Paul M. Romer of New York University).

Modern banking institutions, as public trust entities, are bearers of special responsibilities. These responsibilities arise, on the one hand, from the dominant role of the banking sector in the financial segment and, on the other hand, from its role as a main depositary of financial assets held by households, institutions, and other entities. Activities focused on the protection and improvement of resources defined in the area of ESG aspects, although largely voluntary in this context, such as those expressed in the reporting obligations of non-financial information.

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E from ESG Applied to Systemic Risk Measurement

The paper discusses how the ESG data may be a source of information for systemic risk analysis. We use the environmental ("E") factor, but the framework is universal and can utilize any factor extracted from an ESG score. New empirical research of the banking sector combing ESG data and risk, and the upcoming standardization of ESG reporting standards make our model feasible.

We use our own definition of environmental risk: potential of adverse consequences for human and ecological systems that arise from impacts of environmental factors, including climate change, and the human responses to these consequences (compare: Reisinger, Howden and Vera, et al. 2020).

Despite the significance of environmental factors for systemic risk, there are very few models quantifying this impact and it is difficult to measure the impact of changes in environmental variables on financial institutions' risk exposures and losses (compare Nieto 2017). Firms do not possess analytical frameworks to combat environmental risk using financial management tools (Toma and Stefanelli 2022). Policy frameworks for dealing with climate change are impaired because risks are very uncertain and efficient price discovery is almost impossible (Battiston 2019, Chenet, Ryan-Collins, and van Lerven 2021).

When we talk about econometric systemic risk measures, none includes all environmental risk aspects. Jung et al. (2021) develop the CRISK model to incorporate climate risk exposure in financial stability analysis. Unfortunately, CRISK depends on proprietary data and considers a fraction of the environmental risk only. Other models include Battiston et al. (2021), who study contagion in stylized networks, and Sohag et al. (2022), who demonstrate that green investments are sensitive to geopolitical risk.

There is an opportunity to incorporate ESG data in systemic risk measurement. To do that, we can take the exposure approach and use the environmental E-score for information about exposure to environmental risks. A benefit of this method is cost efficiency – using the data that gathered by banks for other purposes and pre-processed by external specialists.

Even if ESG scores are prone to green-washing, there is no better readily accessible data to be used for quantifying the E (but also S and G) factor for systemic risk analysis. Also, the E-factor is most fact-based, and the least diverse in calculation, which makes it the most objective among the scores (compare: Boffo, Marshall, and Patalano 2020). Lastly, the upcoming IFRS framework changes aim to objectivize sustainability and environmental exposure reporting giving way to further improvements in ESG data quality.

Let us discuss how to extract the environmental risk factor from the ESG score and how to augment a systemic risk measure with it. For this purpose we use a beta-independent exposure-based approach. If SRM is a systemic risk measure that we use, we add E-factor to this measure, obtaining E_SRM measure. Equation 1 shows that the lower the E-score is, the stronger the increase of the E_SRM:

$$E\_SRM_{i,t} = SRM_{i,t} + \beta(100 - E_{i,t})SRM_{i,t}, \tag{1}$$

$SRM_{i,t}$ - the estimated value of the SRM of the i-th institution on t-th trading day.

$E_{i,t}$ - the value of the E-score of the same institution on the same day.

β - a coefficient scaling the E-factor influence.

In our model, β coefficient may be time-varying and be a function of time, and it may differ from one bank to another.

Let us illustrate the application of our model on data stylized using a sample of more than fifty systemically important European banks for the period from 2007 to 2022. We provide only some examples of the study results in this abstract. For full results please refer to the full version of the paper. Figure 1 shows the mean SRM and E_SRM of the Baltic and Nordic systemic banks depicting their reaction to the global financial crisis. It was the most significant manifestation of systemic risk in these countries.

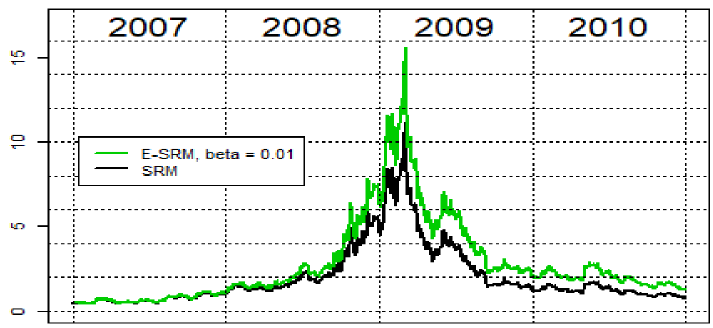

Figure 1. Nordic and Baltic banks 2007-2010

Financial stability in the Nordic-Baltic region is generally high. Throughout the 15-year period, the SRM remains between 0 and 5%, showing low systemic fragility. Still, during the global financial crisis, there was a large risk spike that subsided relatively fast – in one year.

We show how the falling E-factor (increasing environmental risk exposure) increases the systemic risk (green line). Our model increases the effect of such exposure automatically when SRM rises – which is justified theoretically and expected empirically. In this example, even though β is very small (1%), the impact of the E-factor reaches 5% – almost 1/3 of systemic risk in its peak in early 2009.

Figure 2 refers to the systemic banks of these European countries which were strongly impacted by the public debt crisis in years 2010-2013. The risk materialized not only in Greece but also in other Southern European and Balkan countries. Systemic risk reaction was sequential to CDS market reactions.

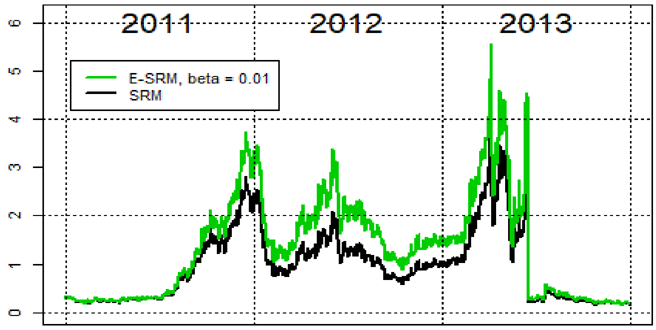

Figure 2. Banks affected by the European debt crisis 2011-2013

Figure 2 shows the SRM of systemic banks where the reaction to the European debt crisis was stronger than to the global financial crisis. For these banks, systemic risk spikes are U-shaped and recurring. They also have a more prolonged impact than in the previous example. Interestingly, the sudden drops in risk coincide with rescue measures (emergency assets programs, bail-outs, mergers, and take-overs) aimed at the straggling banks. Here, we stylize the E-factor with a temporary drop that effects from the governments stopping subsidies and tax reliefs stimulating green innovation and decarbonization. The effect on systemic risk is smaller than in the previous case but still significant.

Figure 3 shows SRM of some selected systemic banks in varied geographic locations, but all of these banks had a very strong reaction to the COVID-19 pandemic.

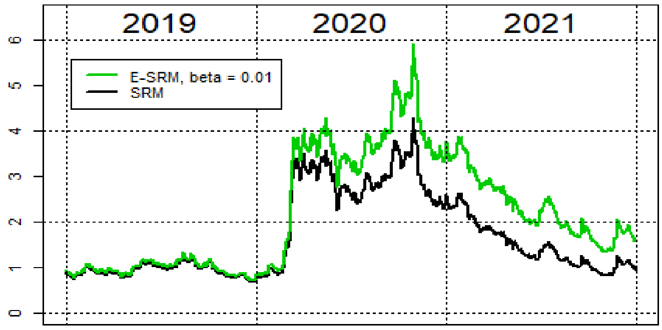

Figure 3. Banks most affected by the COVID-19 pandemic

Many bigger banks, especially in the CEE region are characterized by high fragility during COVID-19 pandemic. This example shows also the recent and ongoing materialization of transition risk and how significant this risk may become in a crisis scenario.

Our model has significant utility and many possible empirical applications by macroprudential regulators, central banks, investors, systemic banks themselves and other stakeholders of the financial system. The transparent and simplistic construction of our model makes it appropriate for network-based stress-testing analyses and financial stability analyses of all sorts, especially that augmentation may be performed on both: individual banks and banking networks, where systemic risk contagion may be observed. Using ESG data is cost-efficient, and it is also the only feasible solution for frontier and emerging markets, where data is very limited. With the increasing ESG data quality related to the IFRS reform in 2023, the utility of our model will significantly rise.

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Risk attitudes and financial decisions of adult Poles. The results of the combined experimental and survey research*

The paper shows the results of the research aimed at measuring the risk attitudes of adult Poles, which was carried out applying two popular approaches: an incentivized multiple-choice lottery (field experiment treatment), and the non-incentivized self-assessment of risk attitude (survey treatment). These two methods are the most often applied when measuring people's risk attitudes. We use them simultaneously providing an insight into their relationship and efficiency. Using a large set of data, we were able to analyse the distribution of both risk attitude measures, depending on age, gender, education, height, and income, as well as to demonstrate the applicability of them in predicting risky financial decisions.

There is a huge amount of papers devoted to the problem of measuring risk attitude, theoretical as well as empirical. In the latter case, the research can be based on experiments (laboratory or field, incentivised or non-incentivised), surveys or the analysis of the real-life decisions. A good summary of the research can be found in (Jamison et al., 2012), (Lönnqvist et al., 2015), or (Harrison & Cox, 2016). As most authors agree that risk aversion is common, they disagree on almost everything else. Consider the role of gender: (Barsky et al., 1997), (Dohmen et al., 2011) or (Liu, 2013), in line with the dominating view, find women to be more risk-averse, but (Harrison et al., 2007), (Guiso & Paiella, 2008), as well as (Tanaka et al., 2010) find this characteristic to be insignificant. Consider the role of education: (Guiso & Paiella, 2008) and (Dohmen et al., 2011) demonstrate that the higher the education, the lower the risk-aversion, (Liu, 2013) reports it to be insignificant, whereas (Harrison et al., 2007) show the opposite (that more educated people are more risk-averse). Finally, consider the role of age: (Dohmen et al., 2011) demonstrate that the older the person, the more risk averse (s)he is, whereas (Harrison et al., 2007) show the youngest respondents to be the most risk-averse (and the middle-aged ones to be the least risk-averse). Similarly to (Jamison et al., 2012), we conclude that there is a substantial amount of heterogeneity in risk attitude, which could be due to non-observed characteristics, methodological issues, or simply population-specific.

The research was conducted at the end of 2019 as a part of a bigger questionnaire study concerning pension system preferences and carried out on a representative sample of 1069 adult

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Poles. This enabled us to compare the results of the risk preferences study with other economic and demographic parameters characterizing the respondents.

The sole research on risk attitudes comprised two separate methods. Firstly, we asked the respondents to self-assess their risk attitudes using the 7-point Likert scale, applying a general risk assessment question (Self_risk_gen), as well as a question-based in the financial domain (Self_risk_fin). Specifically, the respondents were requested to say to what extent they agree with the following statements[38]: *I'm a person ready to make risky decisions* (Self_risk_gen), *I'm a person ready to make risky financial decisions* (Self_risk_fin). At the end of the survey, about 30 minutes after the risk attitudes self-assessment questions, respondents were presented with the experimental part. To test the risk attitudes experimentally we applied the multiple-price list approach (Hey & Orme, 1994), (Holt & Laury, 2002), with few modifications: instead of the random-lottery incentive scheme, we used the pay-all scheme, rewarding the participants with the (positive) pay-out, being the sum of the payments from all decisions made. As we wanted the payments to have a significant financial meaning, we decided that we will pay out the total payoffs, but we will randomly choose the respondents who get the real payoff, paying the money out only to 1/10 of respondents. The respondents were informed that their final payoff is guaranteed to be positive, and that the maximal possible reward is 160 PLN.

All the choices within the gains domain had the same structure: the first variant was the safe one (S), with equal chances of winning x_{S1} or x_{S2}, and the latter was the risky one (R), with equal chances of winning x_{R1} or x_{R2}. To facilitate the choices that we presented the participants with, we kept the same values of x_{R1} and x_{R2}, and changed only the values of x_{S1} and x_{S2}, making the safe option less and less attractive. An exemplary choice that the respondents were provided with, looked like this:

Choose the variant which you prefer more:

- *Variant A: You have equal chances of winning 20 zł or winning 21 zł*
- *Variant B: You have equal chances of winning 5 zł or winning 35 zł*

Table 1 presents that data we applied, as well as some other statistics concerning the lotteries. The last parameter results from applying the CRRA utility function.

Table 1: Lotteries used to assess risk attitude, gains domain

Lottery	x_{S1}	x_{S2}	$E(X_S)$	$\sigma(X_S)$	x_{R1}	x_{R2}	$E(X_R)$	$\sigma(X_R)$	r
L1	20	21	20.5	0.5	5	35	20	15	-0.08
L2	16	20	18	2	5	35	20	15	0.31
L3	14	19	16.5	2.5	5	35	20	15	0.53
L4	12	18	15	3	5	35	20	15	0.76

A small number of lottery pairs, that the participants are choosing from, makes it impossible to assess precisely the value of the r parameter. For that reason, a better measure of the degree of risk aversion is S_choices which counts the number of safe choices that each individual takes (Holt & Laury, 2002). This measure is not directly linked to the specific form of the utility function, i.e. does not assume the CRRA form. One more benefit of using the S_choices measure, instead of estimating the r value, is that this measure is immune to the problem of non-monotonic switches.

[38] With 1 meaning "Definitely no", and 7 meaning "Definitely yes".

Results: the distribution of the risk attitude measures

Let us start with the non-incentivized, survey questions. Figure 1 presents the distribution of answers.

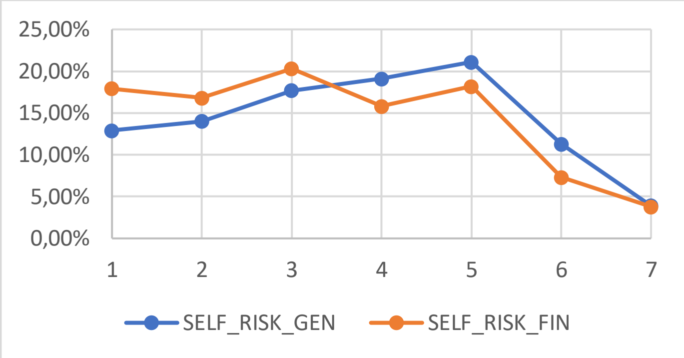

Figure 1: Self_risk_gen &Self_risk_fin distribution

Using the 7-point Likert scale, we interpret the values 1-3 as reporting risk aversion, 4 as reporting risk-neutrality, and 5-7 as reporting risk-loving. We conclude that the largest number of respondents claim to be risk-averse, both in the general domain (44.6%) as well as in the financial domain (54.9%). These numbers are significantly lower than the proportion of risk-averse Germans (78%) reported by (Dohmen et al., 2011). Surprisingly, a relatively high number of adult Poles find themselves to be risk-loving: 36.3% in case of the general risk attitude, and 29.3% in the financial domain. For comparison, only 9% of adult Germans were reported by (Dohmen et al., 2011) to be risk-loving. For further analyses, we will use only the Self_risk_fin measure.

Let us now move on to the experimental method, starting with the lotteries in the gains' domain. Figure 2 shows the distribution of the S_choices variable in our study.

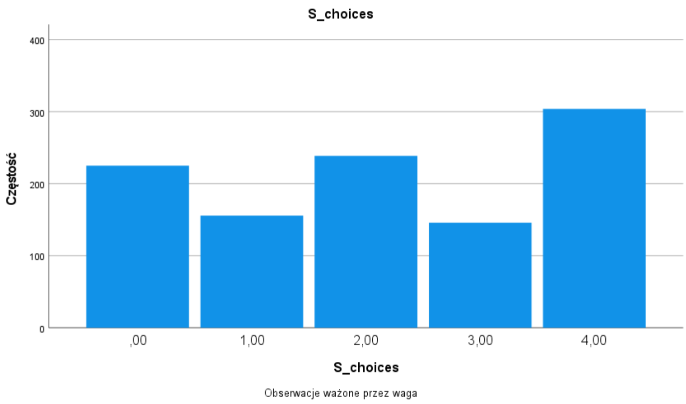

Figure 2: S_choices distribution

The average value of the S_choices variable is 2.17, i.e. the average Pole chose the safe option about 2 times. Knowing from Table 1 that the SSRR choices indicate that $r \in (0.31, 0.53)$ we could conclude that the average Pole is (weakly) risk-averse. Now, if we look at the distribution of safe choices, we conclude that: 20.8% of Poles are risk-loving (S_choices = 0), 13.6% of Poles are risk-neutral or very mildly risk-averse (S_choices = 1), 65.6% of Poles are risk-averse (S_choices > 1). The latter results indicate that the proportion of risk-averse Poles is a number between 65.6% and 79.2%, this time the number closer to the results of other studies.

Applying two risk attitude measures simultaneously allows for their comparison. Figure 3 shows the relationships between S_choices and the self-assessment of risk attitude provided by the Self_risk_fin measure.

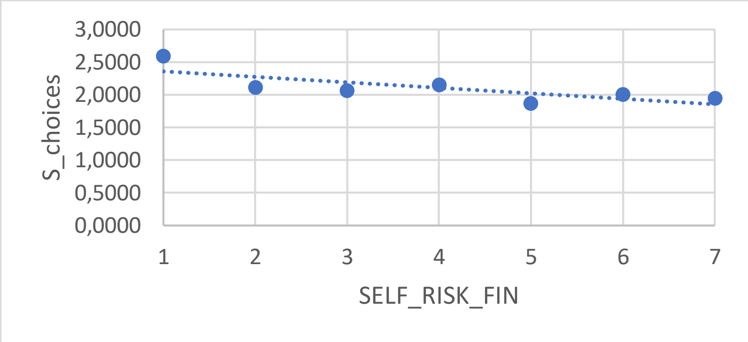

Figure 3: S_choices vs Self_risk_fin

Figure 3 shows that there is an apparent relationship between the number of safe choices in the lotteries and self-assessment of risk attitude in the case of financial decisions. A negative relationship was expected as a high value of Self_risk_fin indicates risk-loving, whereas high value of S_choices shows risk aversion.

Let us now look at the correspondence in between the demographic characteristics and the values of the Self_risk_fin and the S_choices variables. Table 3 presents regression coefficients (significant at 5% level) with the exogenous demographic variables: age, gender (coded: 0 for male, 1 for female), education, and height, as well as one variable that is partly exogenous and partly endogenous, i.e. income. Due to the design of the risk attitude measures, the regression coefficients in the case of the self-assessment measures and the S_choices are expected to have reversed signs.

Table 2: D-Somers regression coefficients between demographic variables and risk attitude measures

Variables	Self_risk_fin	S_choices
Age	-0.111	-
Gender	-0.108	0.074
Education	0.11	-
Height	0.128	-0.1
Income	0.201	-

In case of the self-assessment measure, all demographic variables are significant. The risk aversion is the highest in case of older people, women, less educated people, shorter people, and for less-affluent people. All of these results are in accordance with the common knowledge expectations. On the other hand, in the case of the S_choices measure the only significant factors turn out to be the gender (women are more risk averse) and height (short people are more risk averse). The age, the education, and the income level showed up to be insignificant.

Results: the applicability of risk measures to predict risky behaviour

An efficient risk attitude measure should be a good indicator of the actual decisions that people make, when facing a risky choice. The data collected in the survey allowed us to run regressions between the risk attitude measures and some declared financial decisions.

When considering the financial decisions, we decided to look at 5 areas: retirement planning, risky investments, willingness to save money, willingness to buy insurance products, and employment decisions. As all these decisions concern the financial area, we use Self_risk_fin as the measure of risk attitude's self-assessment. Tables 3-7 present the results (D-Somers regression coefficients, significant at 5%).

Table 3: Retirement planning and risk attitude measures

Variables	Has a plan to save for retirement	Will save enough to increase pension
Self_risk_fin	0.174	0.176
S_choices	-	-

Table 4: Risky investments and risk attitude measures

Variables	Looks for new investment opportunities	Invest pension contributions in capital markets?	Invests in:			
			invest. funds	stocks	real estate	other material
Self_risk_fin	0.38	0.065	0.05	0.04	-	0.05
S_choices	-0.08	0.09	-	-	-	-

Table 5: Willingness to save and risk attitude measures

Variables	Saves for a rainy day	Proud of ability to save	Careful with handling money	Saving for future	Does your household save money?
Self_risk_fin	-	0.2	-0.075	0.16	0.09
S_choices	-	-	-	-	-

Table 6: Willingness to buy insurance products and risk attitude measures

Variables	Eager to buy insurance against losing job	Has insurance product				
		Life insurance	Private liability	Motor hull insurance	Health when going abroad	Real-estate
Self_risk_fin	0.253	0.132	0.078	0.166	0.077	-
S_choices	-	-0.065	-	-	-	-

Table 7: Employment and risk attitude measures

Variables	Has a risky employment
Self_risk_fin	0.059
S_choices	-

In our research, we compared the field applicability of two risk attitude assessment methods: the questionnaire (based on self-assessment of risk attitude), and incentivized experiment (based on the multiple lottery choice). Both measures demonstrated that most adult Poles are risk averse, even though a significant proportion of subjects turned out to be risk-loving.

Even though there exists a significant correlation between both measures, our study suggests that self-assessment by a simple question is a more efficient way of learning risk attitudes than a multiple-choice list approach.

First of all, there are significant relationships between all demographic characteristics that we considered and the Self_risk_fin measure; moreover, their direction is in line with the expectations. In the case of the S_choices measure only gender and height turned out to be significant.

Secondly, the experimental S_choices measure is very weakly related to any financial decisions and declarations, whereas the Self_risk_fin is highly correlated with many economic and financial activities. In particular, it seems to be a good indicator of decisions concerning risky investments (risk-loving subjects have more investments of this type), as well as the employment (risk-loving subjects have more risky employment). Having said that, it is a bit more difficult to explain decisions/declarations in the other areas. In particular risk loving subjects save more in general and save more for retirement; additionally, they buy more insurance products. We believe that the explanation of these puzzling results lies in the correlations with other variables. Risk-loving participants are younger, better educated and richer, which could be a potential explanation for the observed phenomenon.

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Portfolio choice during the Covid-19 pandemic - Evidence from the Frankfurt Stock Exchange

The classical models for the construction of an investment portfolio take into account only two criteria for assessing investment opportunities: expected return and risk measured with a variance. This approach can be criticized for several reasons. First, it takes into account only information that is revealed in the market prices of the stock. However, a more detailed analysis of the situation of a company, based on some fundamental indicators, can provide more clues about possible risks and opportunities connected with investing in its stocks. Second, variance can be a poor measure of risk in the situation of large jumps in stock prices, when the distribution of returns differs much from the normal distribution. Third, the disadvantage of the variance is that it treats in the same way negative and positive deviations from the expected return.

In the paper, we consider some extensions of the classical portfolio theory and try to evaluate them in the situation of a crisis. We consider some additional criteria for portfolio selection, based on the market multiples, which represent the overall situation of companies. Additionally, we consider semi-variance as an alternative measure of risk. We construct a range of portfolios of companies from the German stock market which were built using different criteria for risk and fundamental values. Then we compare their returns during the crisis after the outbreak of the Covid-19 pandemic.

In the construction of portfolios with an additional, fundamental criterion, we looked for efficient solutions with respect to three criteria: profitability (measured with expected return), risk (measured with variance or semi-variance of returns) and a market ratio of companies in the portfolio (measured by one of four market multiples). The usefulness of portfolio selection models during the Covid-19 epidemic was analyzed. This period has been divided into five subperiods due to the changing situation on the Frankfurt Stock Exchange.

The portfolios were built in subperiods of different stock market situations, and the selection methods of the portfolio components were also different. To analyse the performance of portfolios we used realized rates of return, based on which we calculated overall assessments of different types of portfolios.

In the entire analyzed period, the highest rates of return were generated by portfolios built on the basis of market indicators. Similar trends were observed in the subperiods with the highest DAX index growth dynamics. On the other hand, in periods of mild growth, the highest rates of return were characteristic of portfolios built on the basis of the principle of equal shares. In the period of collapse, the highest (negative but lowest looking at absolute value) rates of return generated risk-minimizing portfolios.

The individual portfolios also differed in terms of risk. Its highest level was observed for portfolios built on the basis of market indicators. This phenomenon was characteristic of all analyzed subperiods. On the other hand, the lowest level of risk was observed for portfolios unconditionally minimizing risk (measured with variance or semi-variance).

The results from empirical research for the major companies traded on the Frankfurt Stock Exchange reveal that:

• investors can receive better investment results by adding to the Markowitz model an additional criterion connected with market ratios, such as book-to-market, earnings-to-market, or others. However, this applies to periods characterized by a strong upward trend. In periods of smooth growth and periods of decline, the classic Markovitz model, as well as other analyzed models, had the better performance;

• using semi-variance instead of variance gives better results for investors. However, this is a phenomenon typical of periods of decline;

• fundamental portfolios with the minimum semi-variance seem to be a useful tool of choosing investment strategy during periods of significant market uncertainty. This is undoubtedly the situation for investors during the Covid-19 pandemic.

The results of the research indicate a further need to explore the problem and look for new possibilities for the development of classic models of portfolio construction.

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The impact of video game industry on economic growth in China, the US, and the UK

Economic growth is one of the most important economic categories. Despite the criticism that the level and rate of growth do not always reflect the real level of a population's living standards, it remains the primary measure of prosperity. Economics seeks to answer the question which factors influence economic growth and to what extent. For this, it uses quantitative models - models that can be compared with empirical data. A widely accepted measure of economic growth is the growth of Gross Domestic Product (GDP). Components of GDP include consumption, investment, government purchases, and net export. The main drivers of economic growth include labor, natural resources, capital (including physical, financial and human resources), and technology.

The gaming industry is the youngest representative of the creative sector, and is characterized by a high potential for creative work, innovation, high quality products, and great flexibility in adapting to expectations, requirements or tastes (Warzecha, 2018). It includes enterprises that create, distribute and disseminate creative goods and services. The gaming industry has become one of the key branches of the entertainment and media sector over the past decade. The most popular games bring their creators revenues that run into millions of dollars. The game industry is one of the fastest growing branches of computer technology and the global entertainment sector. The number of gamers is steadily increasing every year, thus increasing the value of the industry itself as well as its revenues. The game industry employs many skilled professionals, such as programmers, designers, graphic designers and game testers. Figure 1 shows the global game market by revenue of game companies by region.

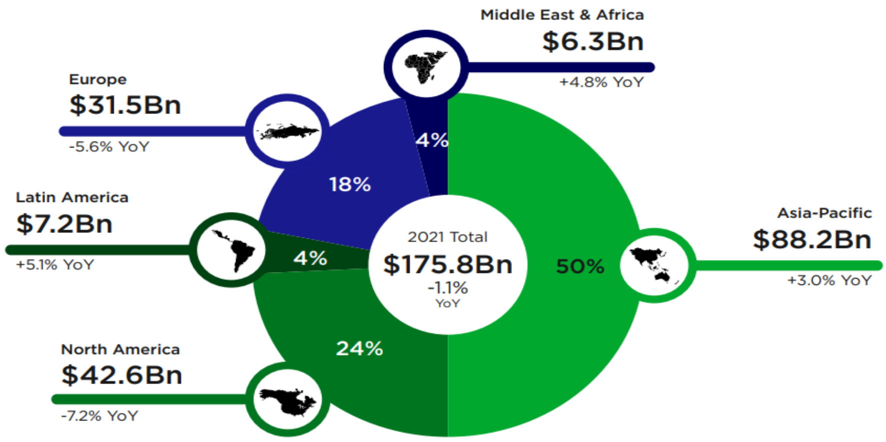

Figure 4. Global Games Market in 2021, per region
Source: Newzoo, Global Games Market Report. The VR & Metaverse Edition, taken from: https://newzoo.com/insights/trend-reports/newzoo-global-games-market-report-2022-free-version. Date 05.11.2022

According to analyst firm Newzoo, the global gaming market is divided into 5 regions: Asia-Pacific, North America, Europe, Latin America, Middle East and Africa. The Asia-Pacific region has the largest share of the global gaming market (50%). In second place is North America (24%), followed by Europe (18%). The representative for the Asia-Pacific region will be China, for North America will be the U.S., while for Europe it will be the UK. The countries were selected based on the leading gaming markets worldwide in 2022, by gaming revenue.

The study used the Hellwig's method and linear regression to model the impact of the gaming industry on the economic growth of selected countries. The dependent variable is economic growth, described by the economic GDP index. The following were taken as explanatory variables: revenue from the game industry, the number of video game users, average revenue per user, the value of video game exports, the market capitalization of the single largest company in the market, and the number of employees working in the game industry. The relationship between the dependent variable and the explanatory variables will show the impact of the game industry on economic growth. In the table below presented the dependent variable - Y and the explanatory variables labeled X1, X2, X3, X4, X5, and X6, respectively.

Table 8. Dependent variable and explanatory variables in the economic model

Y	**GDP** (in million dollars)
X1	**Revenue of video game industry** (in billion dollars)
X2	**Number of video game users** (in millions)
X3	**Average revenue per user of video game** (in dollars)
X4	**Value of games export** (in billion dollars)
X5	**Market capitalisation of one the biggest company on stock market exchange** (in billion dollars)
X6	**Number of employees in the video game industry** (in thousands)

Source: own elaboration.

Figures for the dependent variable and explanatory variables can be found in Appendix 1 of this study. The data are from the period 2017-2021.

Based on a pre-selection by coefficient of variation, one variable with the smallest coefficient for each country was discarded. Table 2 shows the coefficients of variation for all variables for China, the U.S., and the UK.

Table 2. Volatility coefficients for China, U.S. and UK

Country	**Y**	**X1**	**X2**	**X3**	**X4**	**X5**	**X6**
	GDP (in million dollars)	**Revenue of video game industry** (in billion dollars)	**Number of video game users** (in millions)	**Average revenue per user of video game** (in dollars)	**Value of games export** (in billion dollars)	**Market cap of one the biggest company on stock market exchange** (in billion dollars)	**Number of employees in the video game industry** (in thousands)
China	13,57%	19,47%	13,83%	15,18%	211,37%	23,08%	**6,71%**
U.S.	6,13%	28,33%	**3,71%**	24,91%	9,97%	26,31%	10,57%
UK	6,54%	26,61%	11,05%	13,14%	**10,54%**	61,57%	17,58%

Source: own elaboration.

The coefficient of variation shows the level of variation in trait values and is used to compare the variation of specific traits. For China, the variable "Number of employees in the video game industry" has the least variation. In contrast, for the U.S. it is „Number of video game users" and for the UK it is „Value of games exports". The mentioned variables were discarded and not taken into account in the further estimation of the impact model.

Using Hellwig's method, optimal variables were selected for a model describing the impact of the gaming industry on economic growth. Table 3 shows the optimal combinations of variables for China, the U.S., and the UK.

Table 3. Optimal combinations of variables for the model of the impact of the gaming industry on economic growth in China, the U.S. and the UK selected based on the Hellwig method

China	
Y	GDP (in million dollars)
X2	Number of video game users (in millions)
X4	Value of games export (in billion dollars)
U.S.	
Y	GDP (in million dollars)
X6	Number of employees in the video game industry (in millions)
UK	
Y	GDP (in million dollars)
X3	Average revenue per user of video game (in dollars)

Source: own elaboration

Of the variables considered, the variables "Number of video game users" and "value of game export" have the greatest impact on economic growth in China. In the U.S., the variable "Number of employees in the video game industry" has the greatest impact, while for the UK it is "Average revenue per user of video game".

Linear regression was calculated for the most optimal sets of variables, selected using Hellwig's method. It is a method of estimating the expected value of a variable with known values of another variable or variables. The regression function is used to estimate the expected value of a variable with known values of another variable or variables. It is a mathematical function that approximates the actual relationship between data (Central Statistical Office).

Below is the equation of the linear function of China's economic growth depending on the number of players and the value of video game exports. R square for these variables is 0.947.

$$\hat{y}t = 6247978 + 7481 * X2 + 1649 * X4$$

where: $\hat{y}t$ – GDP (in millions of dollars), X2 – Number of video game users (in millions), X4 - Value of games export (in billion dollars).

If the number of players increases by 1 million, the value of economic growth will increase by $7481 million, and if the value of exports increases by $1 billion, economic growth will increase by $1649 million.

The following is the equation of the linear function of U.S. economic growth, dependent on the number of employees in the video game industry. R square for this model is 0,819.

$$\hat{y}t = 9999726 + 46565 * X6$$

where: $\hat{}yt$ – GDP (in million dollars), X6 – Number of employees in the video game industry (in thousand).

If the number of workers in the video game industry increases by 1 thousand, the value of economic growth will increase by $46 565 million.

The linear function equation below shows the dependence of economic growth on the average revenue per user of the video game industry and the value of video game exports in the UK. R square for this model is 0.649.

$$\hat{}yt = 1726784 + 4498 * X3$$

where: $\hat{}yt$ – GDP (in million dollars), X3 – Average revenue per user of video game (in dollars).

If the average revenue per video game user increases by $1, the value of economic growth will increase by $4498 million.

The main aim of the study is to show what impact the video game industry has on economic growth in selected countries of the regions. According to the estimated model, the economic growth of China, the U.S., and the UK is influenced by other factors (explanatory variables). The number of video game users and the value of game exports have the greatest impact on economic growth in China. In the case of the U.S., the value of economic growth is largely dependent on the number of employees, employed in the video game sector. In contrast, for the UK, the greatest relationship of economic growth is with the average revenue per video game user.

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Appendix 1

Data for dependent variable and explanatory variables for China, the U.S. and the UK from 2017 to 2021

CHINA							
	Y	**X1**	**X2**	**X3**	**X4**	**X5**	**X6**
t	**GDP (in milion dollars)**	**Revenue of video game industry (in billion dollars)****	**Number of video game users (in millions)**	**Average revenue per user of video game (in dollars)****	**Value of games export (in billions)**	**Market capitalisation of one the biggest company on stock market exchange (billion dollars) - TENCENT**	**Number of employees in the video game industry* (in thousands)**
2017	12 310 409,37	31,21	884,1	53,52	17,6	493,31	6,31
2018	13 894 817,55	31,18	948,1	49,84	17,2	381,65	6,8
2019	14 279 937,50	33,15	1 023,50	51,72	14,2	460,66	6,97
2020	14 687 673,89	42,67	1 164,30	64,18	14,2	699,78	6,18
2021	17 734 062,65	46,64	1 231,00	70,01	13,8	562,84	7,25
U.S.							
	Y	**X1**	**X2**	**X3**	**X4**	**X5**	**X6**
t	**GDP (in milion dollars)**	**Revenue of video game industry (in billion dollars)**	**Number of video game users (in millions)**	**Average revenue per user of video game (in dollars)**	**Value of games export (in billion dollars)**	**Market capitalisation of one the biggest company on stock market exchange (billion dollars) – Activision Blizzard Inc.**	**Number of employees in the video game industry (in thousands)**
2017	19 479 620,06	25,34	189,4	133,8	6,9	47,87	208,216
2018	20 527 156,03	28,29	188,5	150,1	6,78	35,55	225,857
2019	21 372 572,44	32,99	188,2	175,2	6,39	45,67	229,12
2020	20 893 743,83	42,43	201,9	210,2	5,34	71,75	250,384
2021	22 996 100,00	49,68	201,7	246,4	6,77	51,81	273,379
UK							
	Y	**X1**	**X2**	**X3**	**X4**	**X5**	**X6**
t	**GDP (in milion dollars)**	**Revenue of video game industry (in million dollars)**	**Number of video game users (in millions)**	**Average revenue per user of video game (in dollars)**	**Value of games export (in million dollars)*****	**Market capitalisation of one the biggest company on stock market exchange (billion dollars) – Games Workshop Group**	**Number of employees in the video game industry (in thousands)**
2017	2 699 016,72	2964,28	35,58	218,5	2,31	1,14	292
2018	2 900 791,44	3428,73	35	239,12	2,41	1,25	338
2019	2 878 673,91	3755,61	36,82	251,54	2,42	2,61	387
2020	2 756 900,21	4634,11	42,26	269,95	2,44	5,00	408
2021	3 186 859,74	5717,84	44,54	307,74	1,87	4,41	465,7

*Data for years 2010, 2012, 2014, 2016, and 2018
**Revenue of video game industry and average revenue per user of video game in China was converted at the CNY USD exchange rate as of Dec. 31 of each year.
***Value of games export for UK was converted at the GBP USD exchange rate as of Dec. 31 of each year.

Source: Statista, Total revenue of video game industry in China from 2008 to 1st half of 2022 (in bilion yuan), taken from: https://www.statista.com/statistics/322200/video-game-revenue-in-china/. Date 05.11.2022., Statista, Number of video game users in China 2017-2025 (in milions), taken from: https://www.statista.com/forecasts/456604/video-games-users-in-china-forecast. Date 05.11.2022., Statista, Average revenue per user of video games in China from 2014 to 2021 (in yuan), taken from: https://www.statista.com/statistics/1287724/china-video-game-average-revenue-per-user/. Date 05.11.2022., OEC, Value of Exports in Video and Card Games - China (in bilions), taken from https://oec.world/en/profile/hs/video-and-card-games#trade. Date 05.11.2022., Companies Market Cap, Tencent, https://companiesmarketcap.com/tencent/marketcap/. Date 05.11.2022., Statista, Number of IT employees in digital creative industry in Hong Kong from 2010 to 2018 (in thousand), taken from: https://www.statista.com/statistics/631348/hong-kong-cultural-creative-industry-workforce/. Date 05.11.2022., Statista, Video game market revenue in the United States from 2017 to 2027 (in bilion U.S. dollars), taken from: https://www.statista.com/forecasts/1275477/revenue-video-game-united-states. Data 05.11.2022., Statista, Video game average revenue per user (ARPU) in the United States from 2017 to 2027 (in US dollars), taken from: https://www.statista.com/forecasts/1275501/per-user-video-game-revenue-in-the-united-states. Date 05.11.2022., Statista, Export value of toys, games and sports requisites of the United States from 2011 to 2021 (in billion U.S. dollars), taken from: https://www.statista.com/statistics/616638/toys-games-export-value-united-states/. Date 05.11.2022., Activision Blizzard Inc., taken from: https://companiesmarketcap.com/activision-blizzard/marketcap/. Date 05.11.2022., Statista, Number of employees in the video games industry in the United States from 2010 to 2022 (thousand), taken from: https://www.statista.com/statistics/1175322/video-game-employment/. Date 05.11.2022., Statista, Number of video game users in the United States from 2017 to 2027 (in milions), taken from: https://www.statista.com/forecasts/1277728/physical-or-digital-core-gamers-in-the-us. Date 05.11.2022., Statista, Digital video game revenue in the United Kingdom (UK) from 2017 to 2027, by category (in milion US dollars), taken from: https://www.statista.com/forecasts/461236/video-games-revenue-in-the-united-kingdom-forecast. Date 05.11.2022., Statista, Digital Market Outlook: digital gaming ARPU in the UK 2017-2027 (in US dollars), taken from: https://www.statista.com/statistics/460473/digital-video-arpu-type-digital-market-outlook-uk/. Date 05.11.2022., Statista, Value of toys, games and sports requisites exported from the United Kingdom (UK) from 2001 to 2021 (in million GBP), taken from: https://www.statista.com/statistics/375103/exports-of-toys-games-total-value-in-the-united-kingdom-uk/. Date 05.11.2022., Companies Market Cap, Games Workshop Group, taken from: https://companiesmarketcap.com/games-workshop-group/marketcap/. Date 05.11.2022., Statista, Total numbers of programmers and software development professionals in the United Kingdom (UK) from 2011 to 2021 (in 1,000s), taken from: https://www.statista.com/statistics/318818/numbers-of-programmers-and-software-development-professionals-in-the-uk/. Date 05.11.2022., Statista, Number of digital video game users in the United Kingdom (UK) from 2017 to 2027 (in milions), taken from: https://www.statista.com/forecasts/461253/digital-games-users-digital-market-outlook-uk. Date 05.11.2022., The World Bank Data, GDP (in milion dollars) for China, taken from https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?locations=CN. Date 05.11.2022., The World Bank Data, GDP (in milion dollars) for United States, taken from: https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?locations=US. Date 05.11.2022., The World Bank Data, GDP (in milion dollars) for United Kingdom, taken from: https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?locations=GB. Date 05.11.2022.

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Cash management from a Smart Village perspective

The concept of Smart Villages concerns rural areas and communities that use their strengths and resources for development enhanced by digital technologies, innovation, and better use of knowledge for the benefit of residents and businesses (EU action for Smart Villages, 2017).

Implementing electronic distribution channels in the form of trading platforms supports the shortening of supply chains (Köhler, Pizzol, 2020). It increases food safety through access to knowledge for producers, primary producers (farmers), retailers, and consumers.

The project Smart Village realized by the Warsaw University of Life Sciences concerns issues related to developing solutions aimed at supporting communities and rural areas of the Mazowieckie Voivodeship. Its aim also covers strengthening traditional and creating new networks of connections between stakeholders using modern means of communication and raising social awareness related to the development of rural areas.

Farms that conduct production activities on a smaller scale supplement capital shortages with loans from the family. Farmers use available internal funds, especially accumulated savings or borrowed from family, as a substitute for debt (Enjolras, et al., 2021). On the other hand, farmers indicate the need to increase the level of debt in the event of insufficient income. The demand for external financing is therefore diversified due to the scale of production and its type. Subsidies from the funds allocated for implementing the Common Agricultural Policy (CAP) of the European Union (EU) aim to increase the demand for Polish agri-food products in the single European market and increase investment outlays in agriculture. Agriculture also faces the challenge of transformation towards local and supra-regional food systems, adapted to the needs in terms of the profile and quality of production (Wasilewski, et al. 2021). Investments in agriculture are related to the modernization and technological modernization of farms and also relate to the processes of digitization of agriculture.

Cash management functions show the tendency of a partial shift away from physical money almost in every sector of the economy. In the agriculture sector, it can observe the synchronization of payments for purchased raw materials and products sold in such a way as to ensure financial security for the farmer/producer. Thus, the financial balance between the farm and the household was maintained. It is related to the observation that farmers show conservative attitudes or even risk aversion to increasing debt. The use of credits and loans is limited among smaller farms and purchases in farms are made in specific time intervals (Łukaszuk, 2020).

The study aimed to analyze the farmer's attitude to cash management from the perspective of receivable and payables transfers and cash investment issues. The sample for the cash management evaluation was drawn as a part of a more extensive questionnaire conducted for broader Smart Village project purposes. In the study main set of data is based on questionnaires. The questionnaire was carried out on the webankieta platform. In order to verify the correctness of the prepared questionnaire, test research was carried out in February 2022. The analysis was conducted from March 29 to August 1, 2022. Respondents for the study were recruited using the snowball method in cooperation with the Mazovian agricultural advisory centre. The selection was non-random and was made using the elimination method. The database of surveys has 290 items. However, the filtering question verifying the residence place in the Mazowieckie Voivodship's rural areas and the final number of responders for the "cash management part" was 136 questionnaires. The analyzed smart village issues related to cash management concern purchasing materials - payment practices, payments for purchased materials necessary to run the farm, and farm savings. Farmers also assess the frequency of indicated behaviour regarding payment transfers.

The moment of purchasing materials necessary to run a farm is presented in figure 1. The result brings the main observation that farmers faced limited possibilities of making purchases of raw materials transactions in advance and limited use and even access to price discounts. What is more, farms' expenses are related to the seasonality of production, and having free cash does not determine farmers to make purchases in advance, which can be a result of the relatively high level of uncertainty when it comes to production decisions. In addition, expenses incurred are related to the seasonality of production and fluctuations in the economic situation in agriculture. It also limits the freezing of cash in inventories in the event of periodic shortages. Delays in payments occur in agriculture often due to "fortuitous events" or are related to the problems of crop failure. Most transactions between individual farms with a small scale of activity are carried out in the form of current settlements.

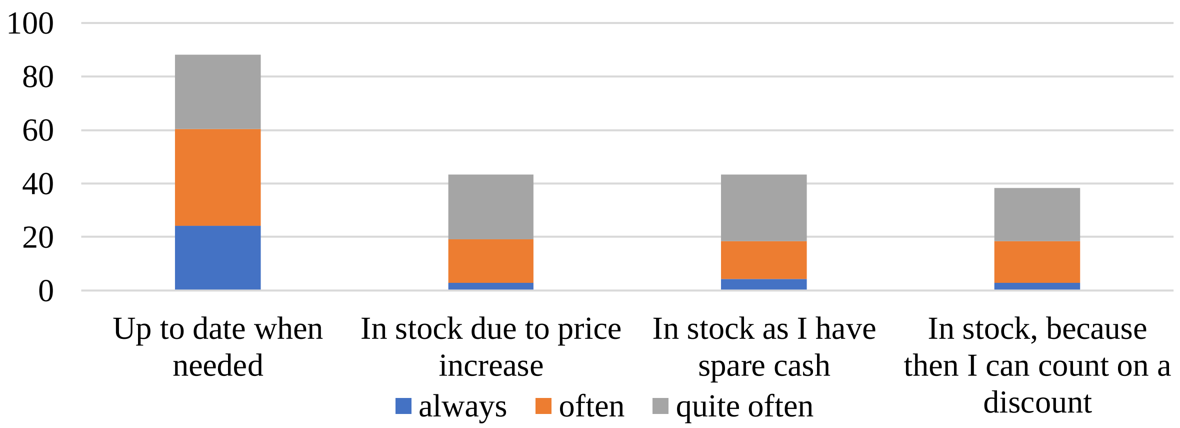

Figure 1. How to purchase materials necessary to run a farm (136 answers)
Source: Own research.

Figure 2 presents the period of payments for purchased materials necessary to run the farm. Most transactions between individual farms with a small scale of activity are carried out in cash or card. Purchases of materials took place "often" through cash payments and card payments. The increase in the level of non-cash payments in agriculture may also be influenced by the development of settlements carried out with blik payments.

Making payments by transfer at the post office or via a bank within 14 days was, in the opinion of the villagers, "rarely" (30.15%) and "never" (35.29%). A similar relationship was found in the case of payments by bank transfer or bank transfer within 30 days or longer, which was assessed by rural residents as a situation not occurring in 53.68% of indications and "rarely" in 29.41%. It indicates a limited possibility of using deferred payment terms in purchases of farm materials. This situation may change as many marketplaces implement the possibility of late payments.

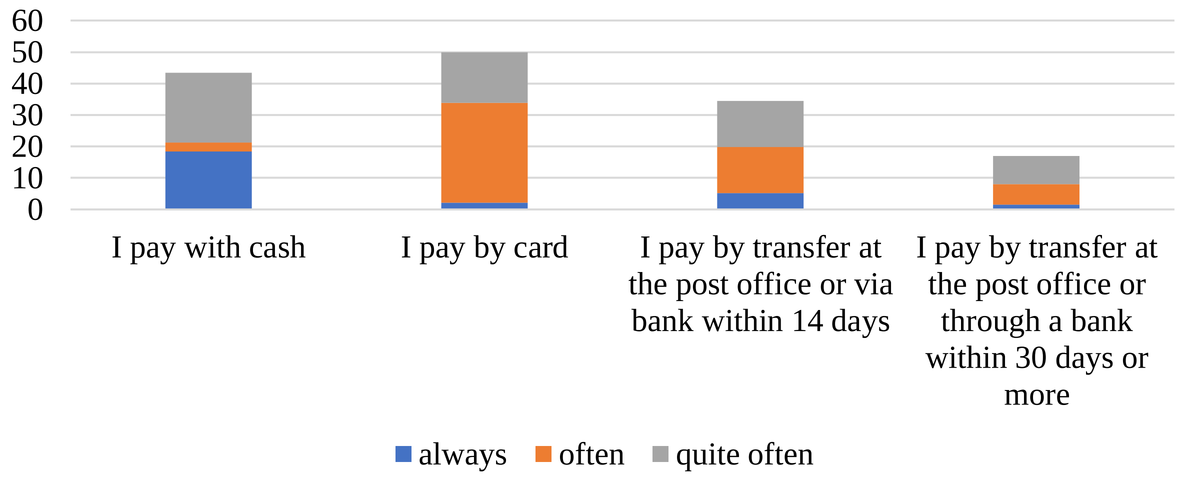

Figure 2. Method of making payments for purchased materials necessary to run a farm (136 answers)
Source: Own research.

The type of farm payment for the sale is presented in figure 3. In the opinion of rural residents, these payments are usually made in cash, which is confirmed by the number of responses "often" (37.50%) and "always" in the case of 14.71% of people. With the answer that recipients pay by bank transfer within 14 days, there was a split of responses, according to which this practice was indicated as "frequent" by 26.47%, and "rare" by 27.21%. The share of these answers is similar, which may indicate a differentiated settlement method depending on the recipient. Definitely, payments made by transfer by the recipient in the period from 14 to 30 days are not very frequent, as the occurrence of such a situation was rated as "rare" in 40.44% of responses and "never" in 29.41% of responses. 44.85% of rural residents indicated the lack of settlements by bank transfer for more than 30 days. Such situations also occurred "rarely" in the opinion of 38.24%. It indicates the reduction of long settlement terms for sales in farm activity. Farmers attach great importance to ensuring financial liquidity and generally have no problems with meeting the deadlines for the payment of liabilities.

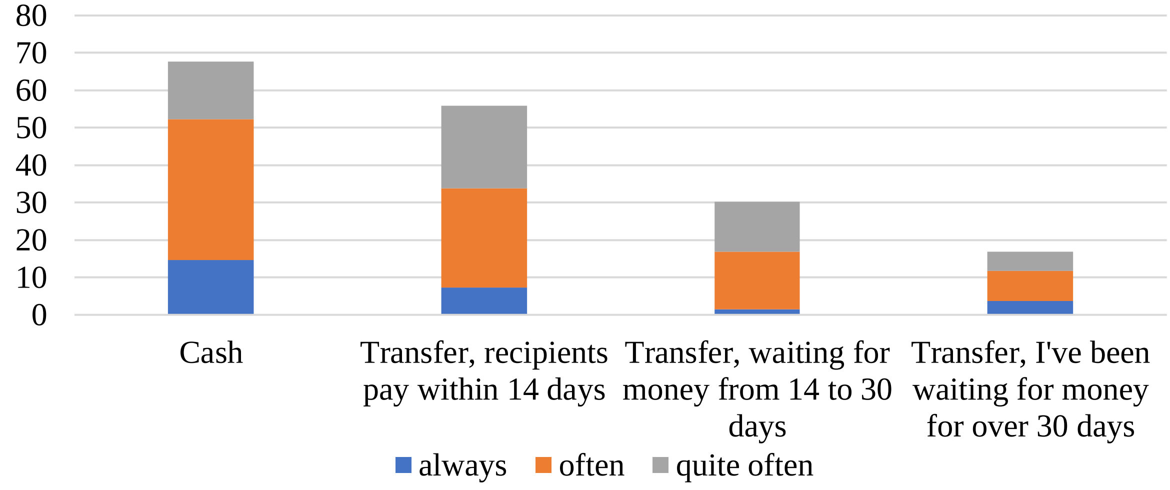

Figure 3. Type of payment for sales (136 replies)
Source: Own research.

Farmers collect their own funds through savings, which act as a buffer securing operations in situations of limited liquidity. Savings held by rural residents of the Mazowieckie voivodship are "rarely" deposited in the bank and "rarely" allocated for the purchase of the land (41.91%) (figure 4). The inhabitants of rural areas pointed to the "quite frequent" allocation of savings in investments related to fixed assets (34.56% of responses). In the survey, the largest number of responses indicated having no savings "never" (37.50%) and "rarely" (34.56%). It proves the organic possibilities of creating savings by farms. Inhabitants of rural areas also do not use other forms of investing in savings, which indicates limited possibilities in terms of allocating surpluses and maintaining their high liquidity in the event of their occurrence. As part of "other" forms of savings, rural residents pointed to investments in current assets, but also in financial instruments (such as deposits, bonds, cryptocurrency, and investment funds) or making savings to regulate current expenses of the family, maintain the family or accumulate savings for children/grandchildren.

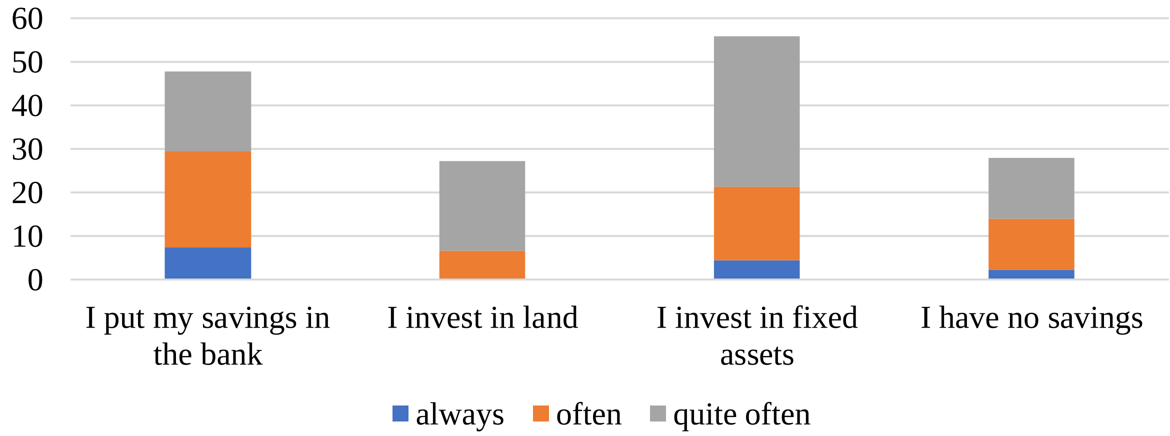

Figure 4. How to invest savings (136 replies)
Source: Own research.

According to a cross-section analysis of inflow and outflow transfers, in farmers' opinion, “cash transactions” still lead to the type of financial settlements (table 1). It constitutes 58,8% of all transactions. Thus, the regularity of liquidity preferences is clearly visible both on the purchase and sales sides when cash dominates in trading in raw materials and agricultural products. One of the reasons for this state of affairs is the problem of payment backlogs, which have affected farmers for many years, and may also result in bankruptcy. Farmers prefer a conservative approach and the precautionary motive of keeping cash and making payments in this form.

Table 1. Cross questions analysis (%)

Item		payment for the sale is in the form of cash	
		always, quite often, often	rarely, never
purchases materials by paying in cash	always, quite often, often	58,8	14,0
	rarely, never	8,1	18,4

Source: Own research.

Within the framework of smart financing models, it is possible to consider recommending relatively low-risk investments of free cash resources related to the level of risk individually accepted by the farmer. The development of information technologies accelerated by the pandemic may, in the long run, lead to changes in production and distribution organisations. Blockchain technology allows taking advantage of technical and technological progress in both.

For the agricultural sector, the risk related to payment backlogs, which is a problem when extending payment terms, is important. Agricultural entrepreneurs maintain high quick and immediate liquidity ratios, and their decisions are conservative and prudent (Franc-Dąbrowska, 2008). In addition, payment backlogs are particularly noticeable in the agricultural sector, as the increasing share of receivables is partly the result of delaying the receipt of funds due from recipients and the increasing scale of sales revenues (Franc-Dąbrowska, 2010). As part of possible transactions, enterprises cooperating with farms prefer cash settlements in order to reduce financial risk.

In farms in the Mazovian rural area, the purchase of raw materials for cash or payment card dominates. This observation is consistent with the known regularities indicating that agricultural entrepreneurs prefer cash payments, especially from smaller farms. The possibility of postponing the payment deadline is rarely used (to a much lesser extent).

Blockchain technology can provide a decentralized platform that gives transaction history and a reliable farmer's identity. Furthermore, digital information could enable farmers to acquire loans (FAO, 2020).

Blockchain technology can support economic development by creating new business opportunities (Schinckus, 2020). Franc-Dąbrowska and Drejerska emphasize the importance of a holistic approach in the search for a broadly understood balance in the agri-food sector, starting from natural conditions, through production processes, fair exchange conditions, financial balance and social well-being (Franc-Dąbrowska, Drejerska, 2022; Kamilaris et. Al, 2019; Feng et al., 2020). Blockchain technology allows taking advantage of technical and technological progress in farm activity's production and financial spheres. It will enable technical and technological advancement in operational and financial activity.

Study limitation concerns that the field of observation covers only rural areas of the Mazowieckie Voivodeship. The project was dedicated to the multidimensional aspects of socio-economics rural living conditions. Thus, cash management was not the primary goal. The main challenge of the smart village finance issue is to combine existing solutions into one platform and integrate them with blockchain technologies to support the activities of small producers, regional circular economy, and food safety. These integrations should follow the internet, Data Analytics, Artificial Intelligence, cloud-based technologies, interactions between users, and Cybersecurity support of regional food production, circular economy issues and local consumption.

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Crisis phenomena in commodity markets

The current global socio-economic situation is governed by the course and dynamics of the post-covid crisis, Russian war in Ukraine and by the multifaceted consequences thereof. The condition of world economies and the situation on international markets are molded by state interventionism, social solidarity as well as the efficiency and effectiveness of system solutions aiming to restrain the adverse effects of the pandemic and sanctions. Widespread restrictions limiting the operations of business enterprises and many public institutions implicate a change in the current paradigm of how markets and societies functions. One might say that the re-assessment of individual, social and market values will change the face of our world.

The costs of economic recovery after the coronavirus pandemic and the war situation in Ukraine have a negative impact on the global economy. At the same time, we can observe a reduced activity of the Chinese economy and related Asian economies, as well as disturbed functioning of global value chains, which include companies from the European Union and the United States. The OECD forecasts a sharp weakening of the global economy. Growth estimates hover around 3% in 2022 and 2.8% in 2023 (OECD, 2022). The war in Ukraine is having a devastating effect on the global distribution of food and energy, among other things, causing higher inflation and threatening low-income countries. At the same time, the global outlook is heavily influenced by China's zero-Covid policy, lowering economic growth and further disrupting global supply (Igan, Kohlscheen, Nodari, Rees, 2022).

Negative consequences of the pandemic are also seen on financial markets. A continuation of declines in global stock markets is now being observed. This was mainly the result of rate hikes by central banks. The deterioration in investor sentiment was also influenced by further revelations of the conflict in Ukraine. As a result, major stock indexes have recorded negative returns since the beginning of 2022. The U.S. S&P500 fell 25.0%, the Nasdaq fell 33.9%, and the DAX corrected 23.0%. Fluctuations are also seen on the monetary market, where mainly the US dollar gains in worth. The highest losses were observed in emerging markets. The uncertain future of the global economy further depresses the mood prevalent among investors and weakens the investment drive (World Bank, 2022).

This phenomenon of the global crisis also affects the situation on commodity markets. Russia and Ukraine are both major suppliers of energy, fertilizers, some grains, and metals. Russia is the world's biggest exporter of natural gas, nickel, and wheat, while Ukraine is the biggest exporter of sunflower oil (FAO, 2022).

Considering the above observations, this research was launched to evaluate the situation on commodity markets during the post-subprime, post-pandemic, and war crisis.

The study applied a comparative approach to the long-term dynamics of future commodity prices over the period from April 6, 2006 to September 30, 2022. In addition, time series of daily price changes were presented. WTI crude oil, natural gas, wheat, soybean oil, copper, and gold prices were used for comparison. The source of the data is the Refinitiv Eikon database. The price charts mark the periods of the 2008 financial crisis and the 2020-2022 crisis.

Prices in global commodity markets are currently (October 2022) experiencing the declines. However, starting in the spring of 2020, this asset class began a bull market that lasted until mid-June 2022. At that time, the value of the CRB index was at its highest level in more than 10 years. Prior to that, the bear market in commodities lasted nearly 9 years (Fig.1).

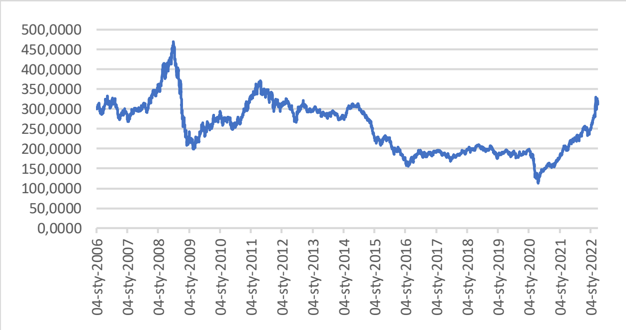
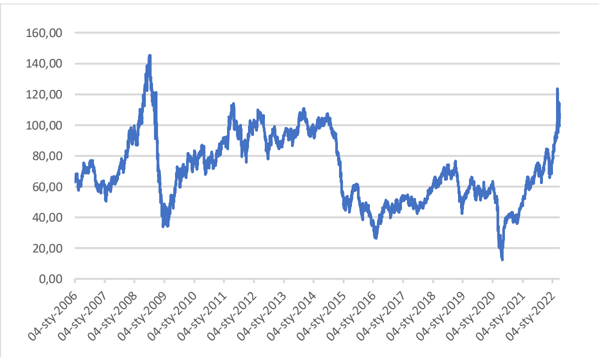


Fig. 1. Refinitiv/CoreCommodity CRB® Index
Source: Refinitiv Eikon database.

Russia invaded Ukraine on February 24, 2022, and in early March oil prices exceeded $120/125 (Brent/WTI) per barrel and were at their highest level since 2008. In June 2022, they approached these values again, and now the rates are at similar levels as before the outbreak of war in Ukraine. The rise in oil prices in the early stages of the crisis reflects fears of declining oil production. Declines in oil prices in the later phases of the crisis are caused by assessments of economic slowdowns, such as the current slowdown in the Chinese economy (Fig.2).



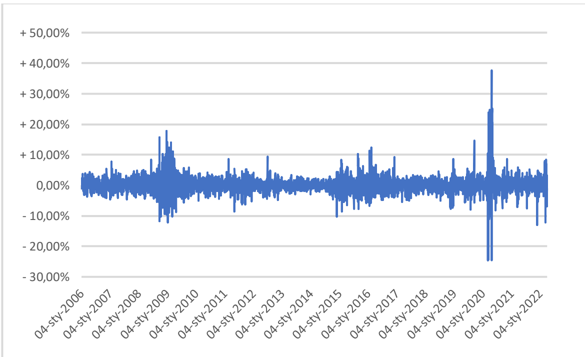


Fig. 2. NYMEX Light Sweet Crude Oil (WTI) Future Continuation Price History and Daily Price Changes
Source: Refinitiv Eikon database.

Since 2008, the decline in gas prices has been due to the increasing availability of gas. Currently, among the group of commodities whose quotations remain at high levels are gas prices. Gas prices were particularly influenced by information on the degree of supply of countries with this raw material (Fig.3). According to Gas Infrastructure Europe, European gas storage facilities are filled to about 88 percent, i.e. above the 5-year average.

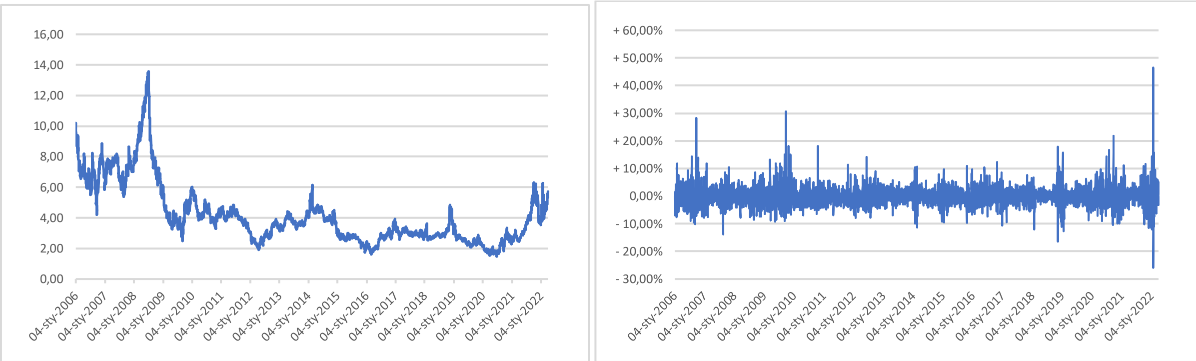


Fig. 3. NYMEX Natural Gas Future Continuation Price History and Daily Price Changes
Source: Refinitiv Eikon database.

With relatively steady global demand for grains (wheat), the supply side is guiding the overall direction of prices. The main reasons for rising wheat prices are fertilizer costs and climate change. Added to this is the war in Ukraine, which has led to a sharp decline in grain exports to the world market (Fig. 4). Given the level of global wheat stocks, which are under pressure from weather conditions and export restrictions, the risk of price increases is a major threat.

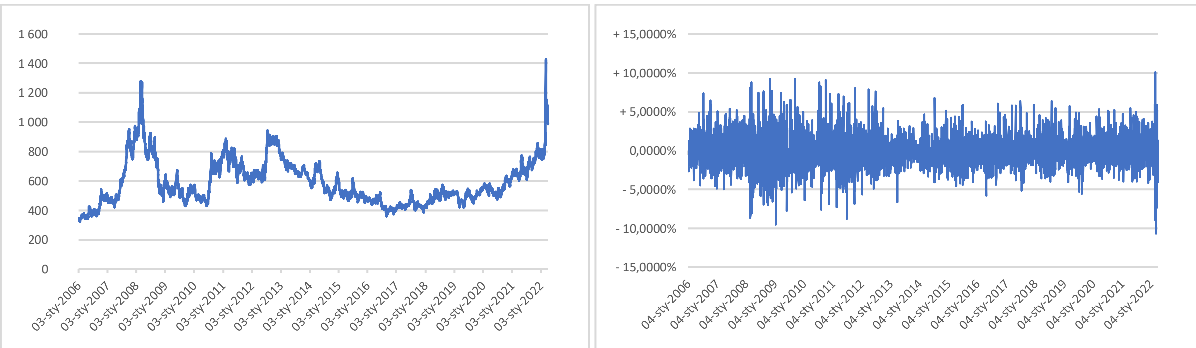


Fig. 4. CBoT Wheat Composite Commodity Future Continuation Price History and Daily Price Changes
Source: Refinitiv Eikon database.

The current crisis is a period of extremely expensive food. High global food prices were the result of a number of factors. The increase was caused primarily by vegetable oils. The reason for such high oil prices was a combination of unfortunate events. Droughts in South America hit soybean oil production. Bad weather reduced canola oil production in the US and Canada. In turn, the war in Ukraine intensified pressure on sunflower oil prices. The crisis of 2008 was different in this regard (Fig. 5).

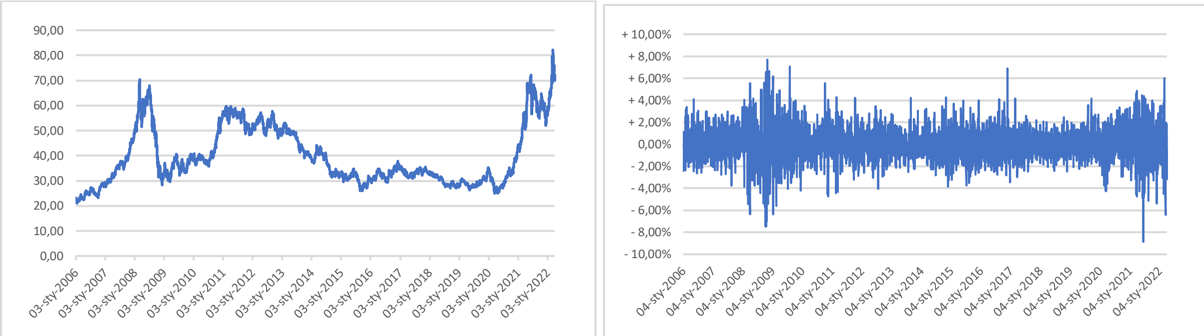


Fig. 5. CBoT Soybean Oil Composite Commodity Future Continuation Price History and Daily Price Changes
Source: Refinitiv Eikon database.

Copper is among the most actively used metals and has a very wide range of consumption, that is why the change in copper prices quite clearly reflects the state of the global economy. Over the past decade, the copper prices have varied widely. After the global financial and economic crisis of 2008-2009, the copper prices recovered very quickly and upsurged until 2011. After that, a lengthy period of decline was recorded until 2016 amid a slowdown in the development of the Chinese economy. In 2021, the copper market began its rapid growth which continued in early 2022, but at a more moderate pace (Fig. 6). This is due to the possibility of significant investment in the development of the global energy sector.

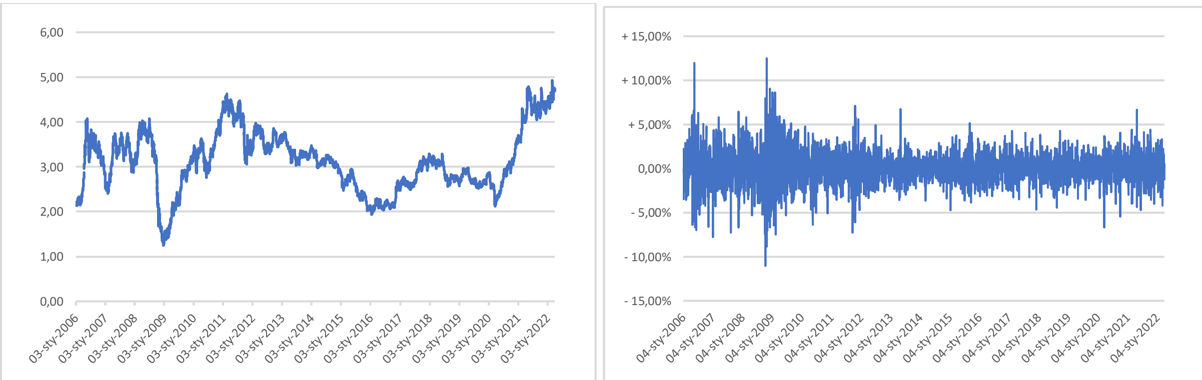


Fig. 6. COMEX Copper Composite Commodity Future Continuation Price History and Daily Price Changes
Source: Refinitiv Eikon database.

The price of gold is shaped by the demand for a safe investment asset. It depends directly on the exchange rate of the U.S. dollar and the effectiveness of U.S. anti-inflationary policies. Changes in the price of gold during crises are a reaction to predictions of further development of the crisis scenario (Fig. 7).

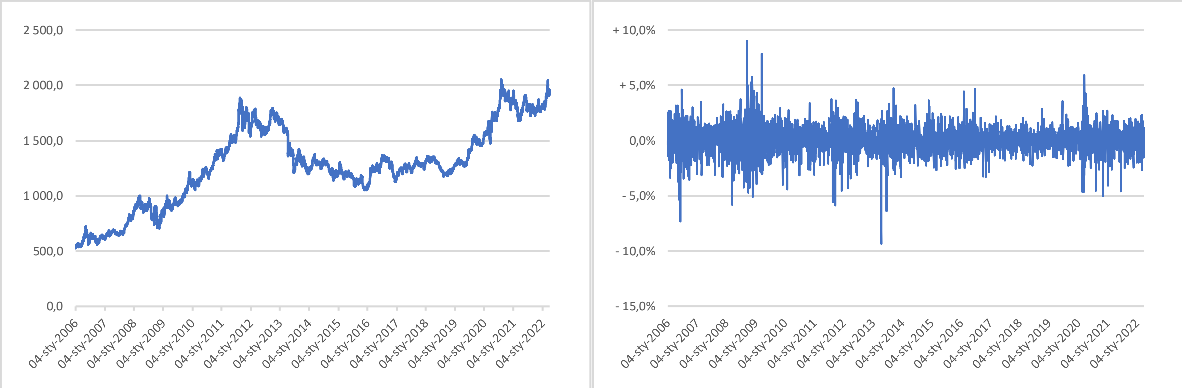


Fig. 7. COMEX Gold Composite Commodity Future Continuation Price History and Daily Price Changes
Source: Refinitiv Eikon database.

The presented results allow us to the following conclusions:

1) The reasons for the rise in commodity market prices during the current crisis are the difficulties associated with transportation and storage (oil, natural gas) and the prospect of infrastructure investment activity (copper) in the electric industry.

2) The main reason why prices on commodity markets have decreased during the current crisis is the economic downturn, which has a direct impact on the demand for commodities (slowdown in the Chinese economy).

3) Commodity which has definitely gained in value during the crisis is gold, owing to the role it is assigned as an asset protecting one's wealth in times of high volatility on stock markets and high inflation.

4) The long-term investment scenario for commodity markets foresees, in the face of growing inflation pressure, the re-birth of commodities as investment assets, especially when the profitability of investing in government bonds on the biggest markets decreases. Scales of growths in prices and rates of return will depend on many factors, including the available supply of raw materials and the starting level of prices. Among commodities, the assets which can become targeted by investors are industrial metals, such as copper and aluminum.

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Seven decades of the actively managed mutual fund performance

2022 marks the seventieth anniversary of Modern Portfolio Theory by Harry Markowitz (1952). That theory has become an inspiration for other scientists such as William Sharpe (1964, 1966), Michael Jensen (1968), Eugene Fama and Kenneth French (1993, 2015, 2018) or Mark Carhart (1997), all of whom have successfully moved the portfolio analysis into the practical ground of mutual funds. During these seventy years, the active mutual fund industry has gone through many changes and has faced many challenges, including notably the recent rising competition from passive funds and then the advance of the exchange-traded funds.

In this article we summarize seventy years of active mutual fund performance as measured by risk adjusted return. We look at actively managed equity mutual funds in the USA across the seven decades in 10-year increments (i.e., 1952-1962; 1962-1972; etc. until 2012-2022). We measure Alpha in a Fama-French-Carhart 4-factor model. We find that the vast majority of mutual funds have Alpha that cannot be distinguished from zero in a statistical sense (at the 95% confidence level) with a few funds producing positive Alpha and a cohort of funds with statistically significant negative Alpha (i.e., funds that destroy investor value through active management). We fail to find significant patterns in the results that could shed light on characteristics that would distinguish "positive Alpha" funds from "negative Alpha" funds or from "zero Alpha" funds or that could explain how these dynamics may change over time. We mention some lessons for investors that can come out of this analysis of the history of Alpha over the past seventy years. We also try to identify index closet funds among the actively managed cohort that have tighter or looser relationship to the equity market.

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