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Agnieszka Choczyńska*

Spillovers between European markets

1. Introduction

The topic of financial integration attracted research interest after the Asian and Russian crises in the late '90s, and the Great Financial Crisis (GFC) in 2007–2009. However large the economic benefits of integration are (see e.g. Campos et al., 2019), it also makes it harder for investors to diversify portfolios and shield them from financial shocks and contagion. As noted by Raju and Pavto (2019) most of the articles focus on Asian economies and their relationships with the US or the UK. In Europe, attention focused on Greece and Turkey, as well as the Central and Eastern European (CEE) markets. A large bibliometric study performed by Patel et al. (2022) found the main areas of research interest to have been: I) portfolio diversification; II) equity markets integration; III) the impact of crises and other events on financial linkages; IV) time-varying financial integration; V) co-movements and spillovers between commodities and financial markets.

Financial markets are considered to be integrated if the assets with the same level of risk offer the same expected returns (Bekaert, Harvey, 1995). Integrated markets experience the same sources and levels of risk, which means the expected returns can be explained by covariance with a benchmark world portfolio. In segmented markets, returns depend on other risk factors, and domestic variance becomes important.

Various measures of financial integration have been proposed. Raju and Pavto (2019) mention Johansen's cointegration test, Granger causality, VAR, VECM, impulse response and variance decomposition (spillover) methods as the most popular in the sample of 223 papers between 1972–2018. There were also attempts to utilize machine learning techniques (Akbari et al., 2021), graphs (Bastidon et al., 2020), or panel models (Boubakri et al., 2012).

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A number of studies found evidence for a strong relationship between developed markets in the 20th century (e.g. Koutmos, Booth, 1995; Kim et al., 2004). However, the focus was always on the integration between developed and developing markets, as it provided the opportunity for investors to diversify their portfolios. At the beginning of the 21st century, researchers moved their attention to CEE countries about to access the European Union: mainly Poland, Hungary, and the Czech Republic. Early research reported ambiguous results: some found low or insignificant dependencies between CEE and EU (Kim et al., 2004; Guidi, Gupta, 2009), while some showed a long-run comovement (Jochum et al., 1999; Vizek, Dadić, 2006; Yang et al., 2006). However, the integration between old and new EU seemed to grow stronger over time (Poghosyan, 2009), especially after the episodes of crisis (Yang, Hamori, 2015; Baumöhl et al., 2018). The literature analysis showed that 5 studies found no change in integration among CEE, 1 decreasing integration, and 46 increasing integration: 24 among CEE markets, 13 among European markets, and 9 between CEE and international markets (Inzinger, Haiss, 2006).

Also, regulatory changes may impact dependencies, mostly by opening up the economy for capital flows. Demian (2011) investigated the accession of CEE markets to the EU. He found that the cointegration increased, but accession provided more of an indirect stimulus for the change in financial and economic factors than a direct cause. Similar results were found by Guidi and Gupta (2009).

Baumöhl et al. (2018) performed a network analysis of a large set of 40 developed, emerging, and frontier markets, using Granger causality. They found that interconnectedness peaked during the GFC in 2008. Indirect relationships turned out to be stronger than direct ones; markets' size, liquidity, openness, and whether they are export or import-driven, played a significant role as well.

The aim of this paper is to analyze how the level of financial integration of European markets has changed through time, and what events could affect the dependencies. Integration is measured through the Spillover Index with rolling window, as in Diebold and Yilmaz (2012), that is, the amount of spillover between a given market's MSCI index and the compound European or World index. This strategy allows to observe the fluctuations in spillover through time, in both a regional and global context. Contrary to most studies of financial spillovers, this one takes a broader perspective, including frontier markets which have been little inspected so far. It spans through two decades, focusing on spillover in years after the Global Financial Crisis. Some preliminary observations about the impact of the COVID-19 pandemic are provided as well.

As expected, the more developed the market, the more financial shocks it exchanges with both European and World indices. Spillover levels rise substantially

during the crises, however, in most cases, it falls back to previous levels afterwards. The study does not support the hypothesis, that the spillover between emerging or frontier and developed European markets has risen in long term due to regulatory or economic integration. This is an important property, as it preserves non-developed markets' role in diversification – despite the fact that they will most likely still experience the transmission of financial shocks in case of a crisis.

The broad perspective of this study is also its main limitation. As I analyze the relationships between European market indices and compound indices for the World and Europe, I can only track the spillovers between a given market and its surroundings as a whole. The details of how shocks are transmitted from market to market are lost in aggregation.

2. Data & methodology

2.1. MSCI Indices

MSCI methodology groups countries into three categories: developed, emerging, and frontier, including, respectively, 15, 6, and 8 European countries, as listed in Table 1. The dataset consists of daily quotes in € for these three indices and their components, ranging from 01.01.2000 to 26.11.2021 for developed and emerging markets. Due to lacks in data, quotes of Frontier markets' indices are taken from 30.05.2008 onward.

Figure 1 presents the values of the Compound Indices of developed, emerging, and frontier markets. The latter starts with June 2002, while the former two in January 2001. Despite differences in scale, all of the indices seem to follow a similar path: they dropped down at the beginning of the century, then took a turn in 2002, which can be attributed to recovery from the Asian and Russian crises in the late '90s. The indices peaked in 2007, just before a sharp decline during the GFC. Around 2012 they began to part ways: while the Developed Index rose steadily to reach before-crisis levels at the end of the sample, the other two remained around the post-crisis levels. However, all of them plummeted during the 2020 crisis caused by the COVID-19 pandemic.

Table 2 presents descriptive statistics of daily logarithmic return rates of the MSCI indices. Typically for return rates, most of them concentrate around zero, with a relatively small standard deviation, negative skewness, and large kurtosis. This means that most of the time a return rate would fall just above zero, with few yet severe losses. All of the series are stationary, tested with the Augmented Dickey–Fuller test with a p-value < 0.01.

Table 1

MSCI Market Classification

Developed Markets	Emerging Markets	Frontier Markets
Austria	Czech Republic	Croatia
Belgium	Greece	Estonia
Denmark	Hungary	Iceland
Finland	Poland	Lithuania
France	Russia	Kazakhstan
Germany	Turkey	Romania
Ireland		Serbia
Italy		Slovenia
Netherlands		
Norway		
Portugal		
Spain		
Sweden		
Switzerland		
United Kingdom		

Source: MSCI

Table 2

Descriptive statistics of MSCI indices' returns

Market	Median	Mean	Standard deviation	Skew-ness	Kurtosis	Mini-mum	Maxi-mum
Developed	0.0005	0.0000	0.0132	−0.3866	12.1863	−0.1406	0.1070
Emerging	0.0008	0.0000	0.0177	−0.5236	14.6250	−0.1993	0.1860
Frontier	0.0005	0.0002	0.0114	−0.6861	12.4091	−0.1005	0.0817
World	0.0006	0.0001	0.0102	−0.6305	14.5434	−0.1044	0.0910
Austria	0.0005	0.0001	0.0174	−0.3863	11.6645	−0.1665	0.1335
Belgium	0.0003	0.0000	0.0148	−0.7374	14.1544	−0.1822	0.1066
Denmark	0.0005	0.0004	0.0137	−0.3633	9.8979	−0.1351	0.1071
Finland	0.0001	−0.0001	0.0199	−0.4393	11.3465	−0.2007	0.1591
France	0.0005	0.0001	0.0152	−0.2568	10.7663	−0.1490	0.1184

Table 2 cont.

Germany	0.0005	0.0001	0.0155	−0.2548	9.5576	−0.1509	0.1159
Ireland	0.0002	−0.0001	0.0171	−0.7524	13.2824	−0.1893	0.1360
Italy	0.0003	−0.0001	0.0164	−0.6059	13.7485	−0.2054	0.1247
Netherlands	0.0005	0.0001	0.0144	−0.2951	10.0757	−0.1209	0.1053
Norway	0.0006	0.0001	0.0179	−0.5227	10.8998	−0.1422	0.1539
Portugal	0.0002	−0.0001	0.0141	−0.3303	10.6520	−0.1383	0.1182
Spain	0.0001	0.0000	0.0164	−0.2742	12.4291	−0.1722	0.1601
Sweden	0.0003	0.0001	0.0179	−0.1321	8.5432	−0.1481	0.1405
Switzerland	0.0003	0.0002	0.0115	−0.2221	10.0796	−0.1133	0.0973
UK	0.0004	0.0000	0.0135	−0.3903	14.1749	−0.1421	0.1216
Czech Republic	0.0005	0.0003	0.0163	−0.3394	15.8372	−0.1675	0.1972
Greece	0.0000	−0.0007	0.0233	−0.5241	12.6481	−0.2506	0.1717
Hungary	0.0005	0.0002	0.0205	−0.2014	12.2612	−0.2035	0.2031
Poland	0.0001	0.0000	0.0187	−0.3521	8.6748	−0.1765	0.1423
Russia	0.0006	0.0002	0.0228	−0.4731	15.1032	−0.2559	0.2398
Turkey	0.0001	−0.0002	0.0265	−0.3013	12.1492	−0.2742	0.2201
Croatia	0.0001	0.0001	0.0130	−0.3190	13.4326	−0.1207	0.1059
Estonia	0.0000	0.0002	0.0152	−0.1141	11.1351	−0.1317	0.1254
Kazakhstan	0.0000	0.0003	0.0227	0.0591	11.9553	−0.1530	0.1868
Lithuania	0.0000	0.0000	0.0131	0.8607	46.9624	−0.1466	0.2342
Romania	0.0002	0.0001	0.0186	−1.6035	29.2707	−0.3162	0.1253
Serbia	−0.0003	−0.0005	0.0174	−0.1559	20.9048	−0.1622	0.1889
Slovenia	0.0003	0.0002	0.0136	−0.1568	12.7391	−0.1262	0.1467

Source: own analysis; source of data: MSCI

Most of the developed European countries are members of both the EU and Eurozone. The group of emerging economies contains only one old member with a Euro currency – Greece. The rest of them joined in 2004 and did not adopt the Euro (Czech, Hungary, Poland), or did not join at all (Turkey, Russia). Among frontier economies, there are three that joined in 2004 as well (Estonia, Lithuania, and Slovenia), two that joined later on (Croatia and Romania), and two outside of the community (Kazakhstan, Serbia).

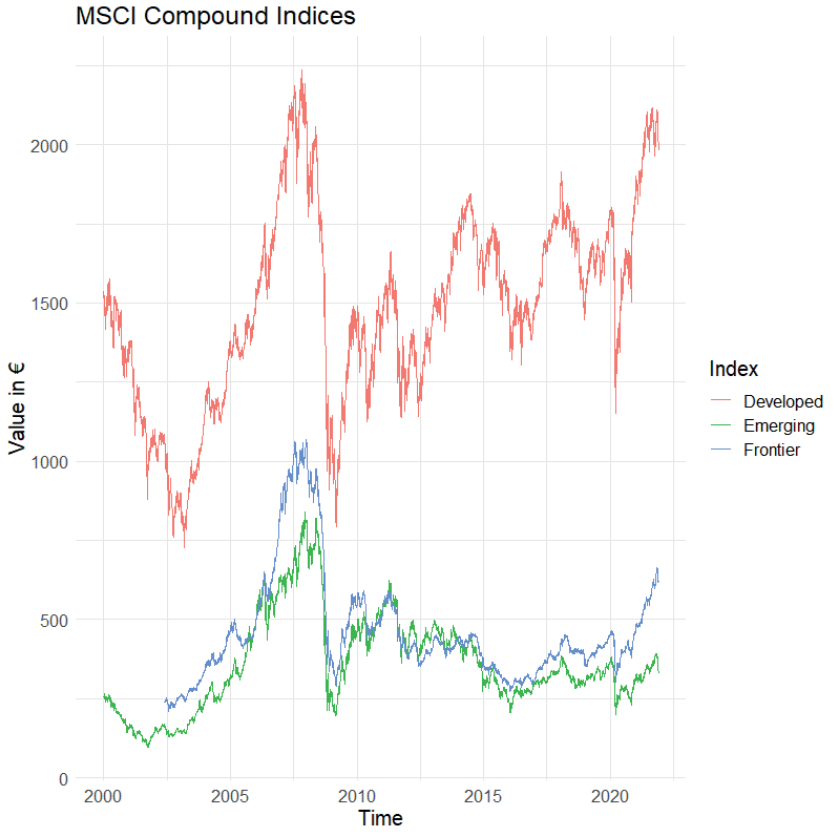

Figure 1. MSCI Compound Indices; source: MSCI

2.2. Financial integration

There are several well-described methods of measuring markets' integration, divided by two main types: *de facto* and *de jure*. *De jure* methods capture the regulations, restrictions, and openness of financial markets (see, for example, Schindler, 2008). It has been noticed, however, that formal restrictions are not the only ones limiting market integration, and financial compatibility is not the same as actual dependence (Quinn et al., 2011; Bekaert, Harvey, 1995). *De facto* methods are typically based on Causality, Correlation, Cointegration, VECM, or VAR models.

The method used in this paper is based on the Variance Decomposition from the VAR model, proposed by Diebold and Yilmaz (2012, 2008), further called the

DY method. In order to omit the problem with variable ordering, their proposition is based on the generalized VAR(p) model (Sims, 1980), given by equation:

$$x_t = \sum_{i=1}^{p} \Phi_i \, x_{t-i} + \epsilon_t \tag{1}$$

where ε is a vector of independently and identically distributed disturbances. It can be expressed as a moving average:

$$x_t = \sum_{i=0}^{\infty} A_i E_{t-1} \tag{2}$$

A_i is an $N \times N$ coefficient matrix:

$$A_i = \sum_{j=1}^{p} \Phi_j A_{i-j} \tag{3}$$

with A_0 being an identity matrix, and $A_i = 0$ for $i < 0$.

The fraction of H-step-ahead forecast error variance of x_i caused by shocks in x_j is defined as follow:

$$\Theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=1}^{H-1} \left(e_i' A_h \sum e_j \right)^2}{\sum_{h=1}^{H-1} \left(e_i' A_h \sum A_h' e_i \right)} \tag{4}$$

As the shocks are not orthogonalized, the sum of variance decomposition elements may not be equal to 1. To achieve this property, they can be normalized:

$$\widetilde{\Theta}_{ij}^{g}(H) = \frac{\Theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \Theta_{ij}^{g}(H)} \tag{5}$$

Directional spillover index can be simply computed as the sum of spillovers transmitted from all markets j to market i, or from market i to all markets j, normalized as above.

High spillover between two given markets can be interpreted as the sign of high integration in the sense most meaningful to investors, i.e. how much the disturbances in one market/instrument will affect the other. However, it could be pointed out that the measure itself depends on the presence of those disturbances. In turbulent times, the integration would be higher, even if *de jure* measures stayed the same (meaning that the restrictions have not change and markets did not become more open).

In this article the financial integration of market i will be defined as the amount of spillover from MSCI Developed Europe index to MSCI index of that country, plus the spillover of country's index to Developed Europe. Highly integrated

markets would be the ones that easily exchange volatility shocks with leading European markets. Such defined Spillover Index will be computed in 260-day-long rolling windows, so that the index's value for a given time point can be interpreted as the amount of spillover between market's index and the Developed Europe index in the last year.

3. Results

Table 3 presents the Total Spillover Index for the period from 2008 to 2021, where all MSCI indices were available. (However, the values for developed and emerging markets computed for the whole period did not differ much). It is apparent, that the markets with high spillover with Europe tend to have high spillover with the World Index as well, however, the spillover with Europe is always higher. Unsurprisingly, the biggest spillovers are found among the largest developed economies. Among emerging markets, some (namely Poland and Hungary) represent levels of spillover similar to smaller developed economies, while Turkey and Greece stay more at the level of frontier markets. EU membership and whether or not a country adopted euro, do not seem to play a role.

The last two columns contain measures of distance between rolling spillover with European and World Indices. Distance is measured with the Dynamic Time Warping method, as described by Giorgino (2009), normalized for series' length. Most Frontier markets (but also Russia and Turkey) have more similar spillovers with both indices, compared to developed and emerging markets, where the discrepancies tend to be bigger.

Next, I compute the rolling spillover in order to analyze changes in time. In result I get a time series for each market, representing the level of spillover in one year time frame. All of the series for developed and emerging markets seem to have a low, but significant positive trend (p-value < 0.001). However, it is most likely due to a huge increase in spillover during the GFC, as the series exhibit a significant structural break, and in the post-crisis period the trend is significantly negative (although still very low). These findings do not support the hypothesis that the spillover increase in time, as the markets integrate – at least in the period considered.

The Rolling Spillover Indices are presented in five groups:

- developed markets that adopted the Euro in 2002 (Fig. 2);
- developed markets that retained their national currencies (Fig. 3);
- emerging markets (Fig. 4);
- frontier markets that adopted the Euro (Fig. 5);
- frontier markets with their national currencies (Fig. 6).

Note that the last two groups only cover the years 2008–2021.

The first group consists of Austria, Belgium, Finland, France, Germany, Ireland, Italy, the Netherlands, Portugal, and Spain. At the beginning of the considered period, values of the Spillover Index cover the span of 0 to almost 50. However, they rise steeply after 2004 to above 20, clearing the lower part of the plot. They also share a similar behavior in times of crisis. There are visible jumps in 2007, 2010, 2011, 2016, and 2020, impacting all of the indices in the same way. Interestingly, the spillover did not fall back after the Euro crisis in 2012. It seems contrary to the decrease of banks' cross-border activity and financial integration (potential channels for spillovers), noted, among others by Lane and Millesi-Ferrati (2018). However, as the authors point out, direct foreign inflows actually increased, mainly due to the expansion of international companies and moving capital to financial centers with favorable taxation.

The second group consists of Denmark, Norway, Sweden, Switzerland, and the UK. Denmark and Sweden belong to the EU, as well as the UK for most of the considered period (up to 2020). The reactions to crisis events are quite similar to those shown in Figure 2, however, the levels of spillover tend to fall back to almost pre-crisis levels.

The emerging group consists of the Czech Republic, Greece, Hungary, Poland, Russia and Turkey. All of the indices follow roughly the same path, with small values at the beginning, the highest and the most prolonged increase during GFC and Eurozone Debt Crisis, as well as shorter jumps in 2016 and 2020.

There are three frontier markets – Estonia, Lithuania, and Slovenia, that have joined EU and adopted euro. Their Spillover Indices are shown in Figure 5. The time series starts in 2009 due to lack of MSCI data from before. The values are generally low (most below 20). At the beginning of the period, they are the highest and most volatile, in the middle (2014–2018) – the lowest. There is a significant jump in 2020 due to the COVID-19 pandemic. All three indices share a similar behavior.

The frontier markets with their national currencies are: Croatia, Kazakhstan, Romania, and Serbia. Here, as well, the spillover is generally low, with higher values before 2014 and spike in 2020, although Romania and Serbia experienced high values also in the period in-between.

In almost all markets, no matter the group, the spike related to the COVID-19 pandemic was one of the steepest in the considered period. In most cases the biggest increase happened on March 12th, which can be attributed to the crash on the American stock market, one of the biggest in history. It is a clear example of how the shocks can be transmitted through the information and investors' panic, as the spillover happened almost instantly in all of European markets, regardless of observed COVID-19 cases or imposed restrictions. Interestingly, the impact of the pandemic on spillovers' levels ended in March 2021, way before the end of the underlying health crisis.

Table 3

Total Spillover Index

Market	Spillover with European Index	Spillover with World Index	Distance (whole period)	Distance (short period)
Austria	19.89	15.56	1.23	2.52
Belgium	20.23	15.65	2.6	1.94
Denmark	18.41	14.34	1.45	1.84
Finland	20.56	15.96	1.96	1.37
France	23.63	18.31	4.53	5.16
Germany	22.97	18.21	3.77	4.81
Ireland	18.09	14.4	2.1	1.48
Italy	22.05	16.31	3.92	4.14
Netherlands	22.61	18.06	2.59	2.77
Norway	19.65	16.09	0.99	1.33
Portugal	18.77	13.9	1.91	1.98
Spain	21.69	16.19	3.36	2.57
Sweden	21.69	17.19	1.98	2.67
Switzerland	21.29	16.74	2.23	2.46
UK	22.77	18.43	2.72	2.1
Czech Republic	15.27	11.95	1.06	1.31
Greece	10.67	8.18	0.8	1.15
Hungary	16.29	12.9	0.85	1.81
Poland	17.49	13.64	0.94	1.9
Russia	14.19	12.75	0.44	1.01
Turkey	11.37	9.45	0.47	0.8
Croatia	10.68	9.19	–	0.74
Estonia	7.8	6.41	–	0.45
Kazakhstan	6.03	6.71	–	0.36
Lithuania	8.52	7.26	–	0.81
Romania	11.72	9.63	–	1.13
Serbia	5.37	5.0	–	0.69
Slovenia	8.78	7.81	–	0.97

Source: own analysis

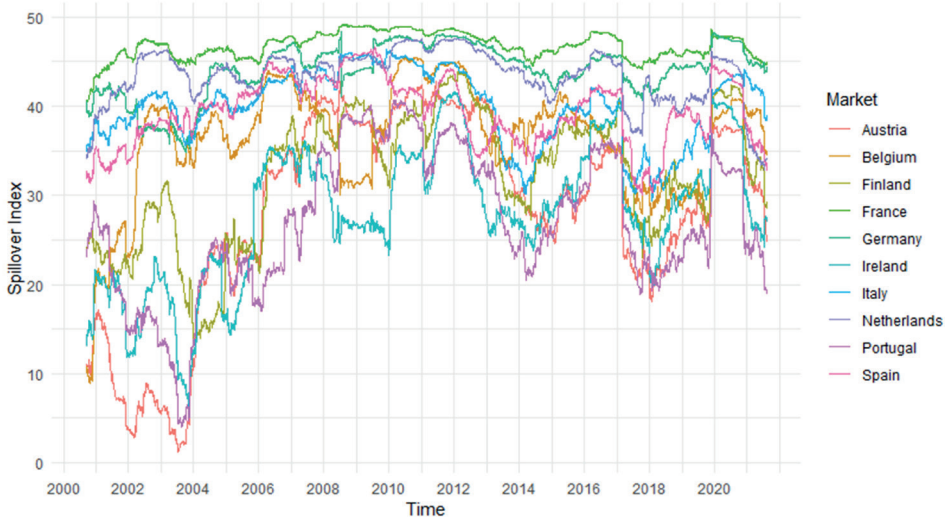

Figure 2. Rolling Spillover Index between European Index and developed markets that adopted euro

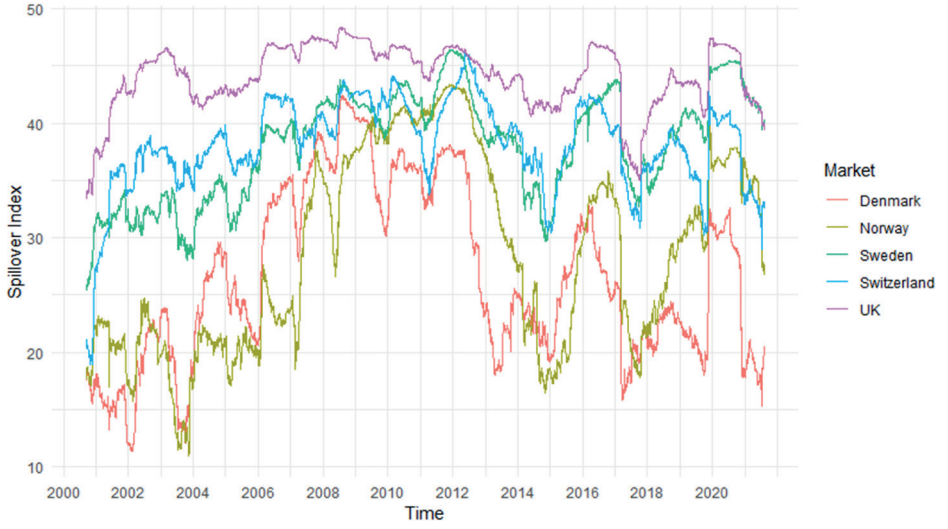

Figure 3. Rolling Spillover Index between European Index and developed markets that have not adopted euro

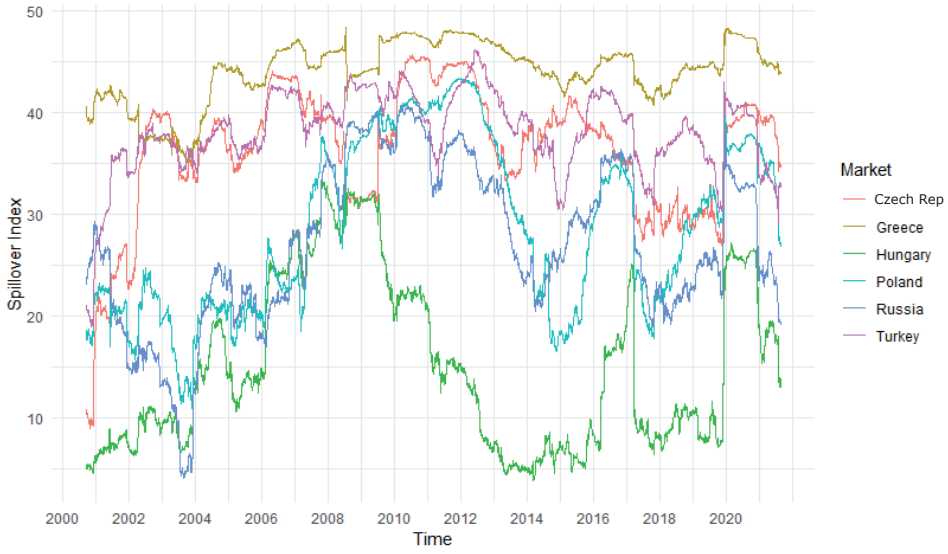

Figure 4. Rolling Spillover Index between European Index and emerging markets

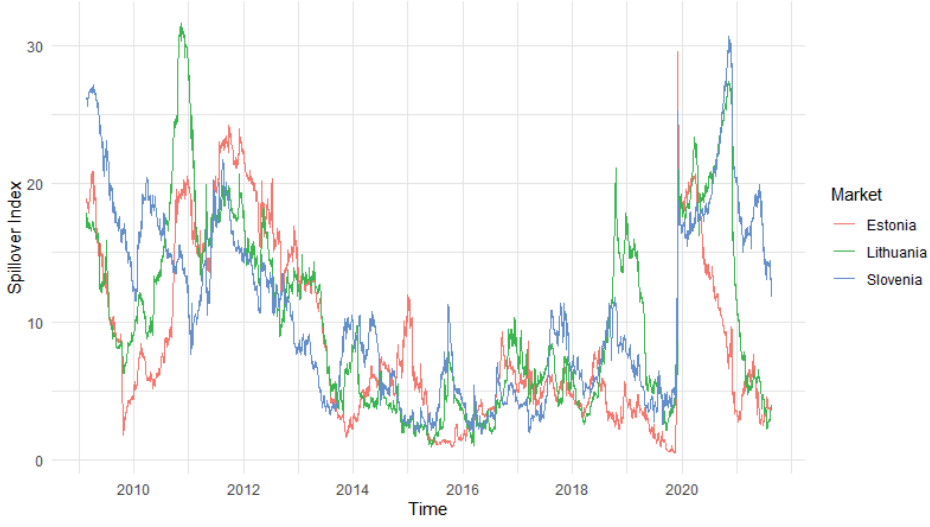

Figure 5. Rolling Spillover Index between European Index and frontier markets that adopted euro

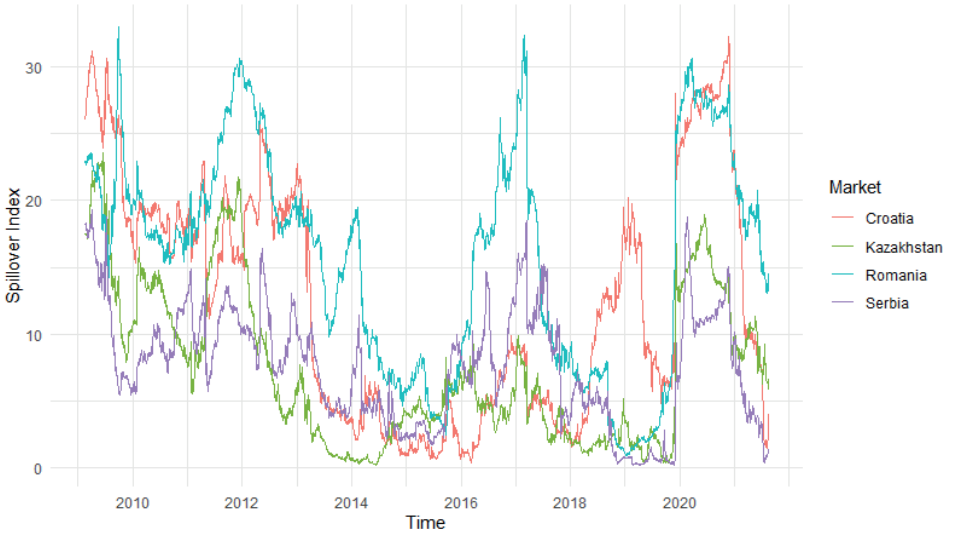

Figure 6. Rolling Spillover Index between European Index and frontier markets that have not adopted euro

The same analysis of rolling spillover between markets and the World Index yielded almost identical results, which can be partly due to a fact that the World and European Index are highly correlated (Pearson's correlation coefficient of the differences equals 0.82). The main difference was noticeable in the group of developed markets with the Euro, presented in Figure 7, where the amount of spillover was substantially lower, and fell back almost to the pre-crisis levels in 2014.

The difference is, that for developed markets, the indices fell down after the 2007–2012 period, while the spillovers with European Index stayed at a high level afterward. Also, the spillover with the World Index was generally lower in the years 2014–2019 and reacted more strongly to the COVID-19 pandemic (especially in non-developed markets).

Figure 8 provides a comparison of the Rolling Spillover Index with Developed Europe Index and the World Index for three chosen markets. As can be seen in Table 3, France had the highest summary difference between the spillovers with Europe and the World. The pattern of ups and downs is quite similar, but the spillover with Europe is always much higher – with the exception of a brief period

at the beginning of the GFC. The Spillover with World Index is also characterized by higher volatility.

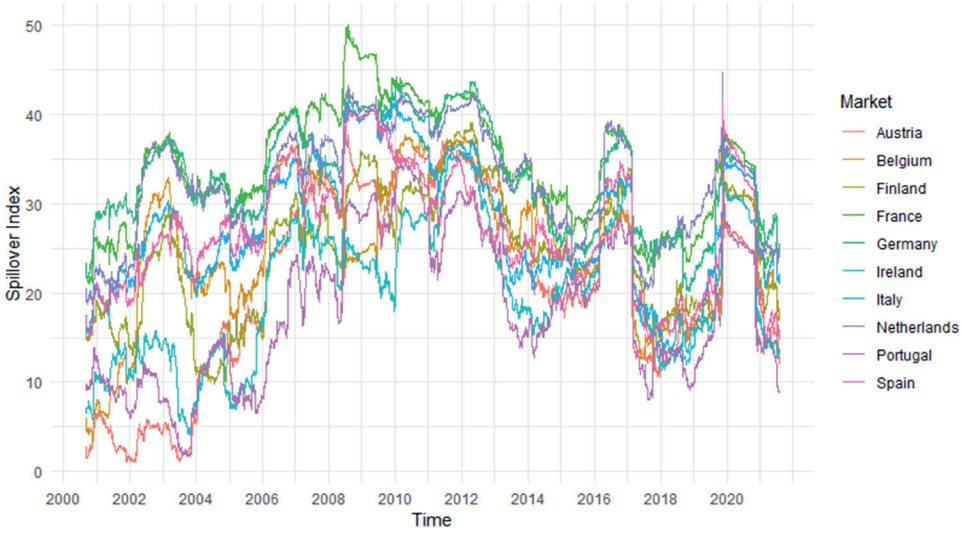

Figure 7. Rolling Spillover Index between World Index and developed markets that adopted euro

Kazakhstan, on the other hand, had the most similar spillovers. The only noticeable disparity was during the COVID-19 pandemic, where the spillover with World Index become higher than with Developed Europe. Among emerging markets, the relation between spillover with World and European Indices is similar. Both follow a nearly identical path and only diverge during the pandemic, when the spillover with European Index went much higher.

In addition to the conclusions from Figure 7 and Table 3, this shows that developed markets are more connected to the region, while the others received the shocks from World and developed Europe in a similar way. In conclusion, the origin of the crisis is more important for developed markets, as they will be more affected if the shocks are transmitted from other developed markets from the region.

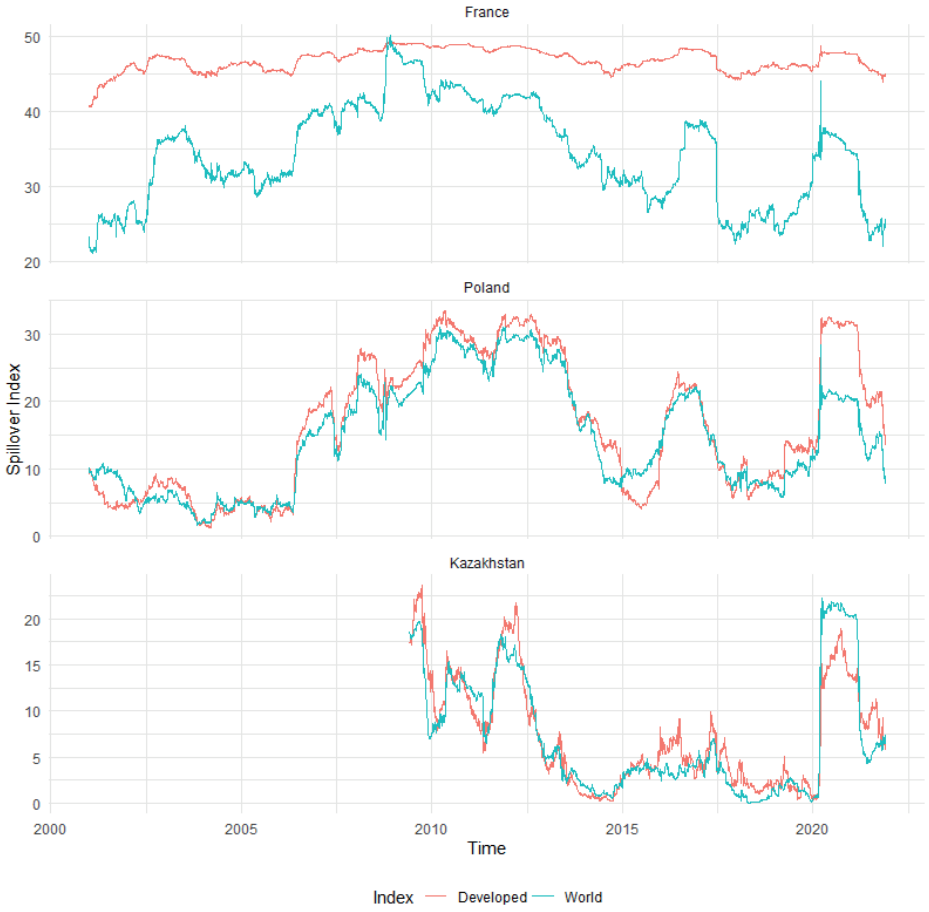

Figure 8. Comparison between Rolling Spillover Indices with World and European Index for three selected markets

4. Conclusions

The aim of this paper was to analyze spillovers between European markets, the European Index, and the World Index, over a period of two decades (2000–2021). Because of the missing data for some of the frontier markets before 2008, they were analyzed in a shorter time frame. All of the indices, as well as market classifications, are provided by MSCI.

In Europe, markets with higher spillover with European Index tend to have high spillover with World Index as well, although the latter is usually lower. Both measures showed a pronounced dependency on crisis events. Especially the turbulent time started by Global Financial Crisis and stretched by the Eurozone Debt Crisis caused higher spillover levels for many years. Between the developed markets and the European Index this shift was even permanent (e.g. lasted at least to the end of the considered period). Some smaller events, like the COVID-19 pandemic, raised the spillover for a while, but plummeted almost to the previous level afterwards.

Changes in spillover in times of Great Financial Crisis, Eurozone Debt Crisis, and the COVID-19 pandemic are noticeable across all European markets. On the contrary, in 2016 there were jumps in spillover in all developed and emerging markets, but the reactions among Frontier markets were mixed.

Three main points can be driven from this analysis.

Firstly, it proves that although European frontier and (to a smaller extent) emerging markets still offer some diversifying potential, they are not fully shielded from the effects of widespread financial and non-financial crises, as the spillover rises substantially in turbulent times. This is an important property for investors, as it can undermine their diversification attempts just when they are most needed. On the other hand, spillover levels in tranquil periods did not substantially increase in the last two decades, despite ongoing integration with developed European markets. It suggests that the transmission of financial shocks may happen more due to stock markets' panic, than the changes in transmission channels – and so the non-developed markets would continue to provide diversification opportunities for the years to come.

Secondly, after a crisis, spillovers usually fall back to roughly pre-crisis levels. The exception was found in the group of developed markets in Eurozone, which continued to have high levels of spillover with European Index after the European Debt Crisis – despite the known contraction of cross-border banks' activity. This can be due to an increase in multinational companies and moving financial activities to the countries with more favorable taxation, which creates cross-border channels for spillovers. The effect was not observed for the World Index, where the spillover reduced after the crisis.

Lastly, I draw some preliminary findings about the effect of COVID-19 pandemic in the context of financial spillovers. In all European markets, its beginning was marked by a high spike in spillovers to the levels observed during the GFC. It lasted about a year and fell back just as suddenly. The almost identical reaction to the pandemic across markets may suggest that a global panic had a more pronounced effect on stock markets than local economic restrictions – although a more precise study would need to be carried out to test this hypothesis.

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Summary

Financial integration has been proven to benefit European economies. However, it may obstruct diversification attempts, and so attracts the attention of investors and researchers. The aim of this paper is to analyze changes in spillovers between European markets, the European Index, and the World Index, over a period of two decades (2000–2021), with regard to the level of development. Mature markets have higher spillovers than emerging and frontier ones. The main finding is that non-developed markets' spillover levels in tranquil periods did not substantially increase in the last two decades, despite ongoing integration with developed European markets. However, spillover rises in time of global or regional crisis (e.g. Great Financial Crisis, Eurozone Debt Crisis, COVID-19 pandemic) for all markets, regardless of economic development, which can undermine diversification attempts just when they are most needed. Afterwards, the transmission of shocks falls back to the pre-crisis level, with the exception of the spillover between Eurozone markets and European Index, which remained very high even after the end of the particular crisis.

JEL codes: F15, F36, G01

Keywords: *spillovers*, *European markets*, *financial crisis*, *financial integration*

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The usefulness of big data in creating innovations. The example of Google Trends

1. Introduction

Over the past century, innovation has become an important management issue, sometimes even referred to as the 'religion of the 20th-century entrepreneurs' (Salter, Alexy, 2014, p. 27–28). When the competition is fierce and market challenges more difficult, innovation in particular is considered a success factor for enterprises, entire industries, and even countries (Akbari et al., 2021). It undoubtedly affects the standard of living of both current and future generations. Implementing innovations – understood as the process of developing and introducing something new, innovative, or advanced with the intention of creating value or benefits (Hisrich, Kearney, 2014) – is a multidimensional process (Baregheh et al., 2009). Moreover, innovation is not something that happens by itself; therefore, it should be a systematic activity that may be learned and practiced. Thus, entrepreneurs must deliberately seek sources of innovation and their symptoms in the environment – this boosts the chances for successful innovation (Drucker, Maciariello, 2014; Shah et al., 2015). It is important from several perspectives, such as creating vacancies, surviving on the market, improving people's standard of living, and building economic growth. Therefore, it may be said that it is not capital and labor that create innovation, but that capital and labor result from innovations.

The speed and pace of innovation slow down when the potential combinations of factors are being used up. When this happens, one needs to look beyond the current framework, which nowadays has become easier than ever thanks to the Internet. Currently, the 5G Internet, the Internet of Things and the digitization trends generate more data than ever before, which is why the term 'big

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data' – i.e. huge amounts of data – has emerged. According to a recent study by the International Data Corporation (IDC), the world generated or replicated approximately 64.2 zettabytes of data in 2020, with a projected cumulative annual growth rate of 23% by 2025 (IDC Blog, 2021). Nowadays, personal mobile devices and corporate data centers process more and more information with every passing minute, which is additionally accelerated by remote work (Zhang, 2021). As a consequence, we generate an increasing number of various types of data that can be used by enterprises to develop. A huge amount of data is collected by search engines. According to estimates, the Google search engine, which is dominant on the market, receives approx. 63,000 queries per second, which amounts to 3.5 billion searches per day. Undoubtedly, the data based on queries definitely belongs to the big data category (https://blog.hubspot.com/marketing/google-search-statistics). It should be mentioned that at the end of 2021, Google had 92% of the market, while its nearest competitor, Bing, had less than 3%. It may therefore be concluded that the vast majority of Internet searches are carried out with Google (Google traffic overview, Dec 2021).

The purpose of this article is to prove the suitability of the big data concept for creating and implementing product innovations. The concept of implementing new ideas will be discussed here. The process should start with generating and evaluating these ideas – and this stage is the focus point of this article. The empirical material was data obtained from Google Trends, i.e. data generated by the Google search engine. The author's hypothesis is that the usefulness of the data generated by Google Trends depends on the way the query is entered, which means that the end-user perspective is necessary. The article is structured as follows: presentation of a literature overview on big data and creating innovation; discussion of the research methodology; and a subsequent discussion on the usefulness of the obtained data and conclusions. To the best of the author's knowledge, there have been no published articles to date discussing the differences between the way a query is entered and various periods of analysis.

2. Literature review and conceptual framework

Innovations are the result of invention, i.e. a thought focused on some needs. Innovation itself is rarely an 'absolutely new discovery'; usually it is a creative use of factors and solutions that already existed. It's worth recalling the theorem of Shumpeter (1934), who said that innovation was a 'novel combination' of new or existing knowledge, resources, equipment, and other available factors. Consequently, ideas are created and put into practice (Haberler, 1950; Mazur, Malkowski, 2021).

The nature, sources, and determinants of innovation have occupied researchers for decades. Interestingly, innovation was initially applied to various fields, such as religion, as exemplified by the publication 'Episcopal Innovation; or the test of modern orthodoxy' by Church of England, Diocese of Peterborough in 1820. In 'Gentlemen's Magazine' no. 96 from 1804, one could read about innovations in architecture. In the same period, there were also works related to economic activity, such as 'A Periodical work, Exclusively devoted to Agriculture, and Rural Affairs' from 1805, where readers could learn that the commercial way of charging interest on what is new and uncertain is a common 'financial innovation'. For at least 200 years, innovation has attracted the attention of researchers and practitioners, including businesspeople.

Innovations began to gain popularity in the publications of the 1960s, such as Arnfield's 'Promoting innovation' (1966) or Hayhurst's 'The dynamics of innovation' (1968), which mostly referred to technical changes, but also postulated that innovation should not end with the producer, but be continued by the distributor, and even the consumer, who could take part in product testing. Lack of knowledge about the nature and dynamics of innovation was also seen as a reason for high failure rate of new market entities (Hayhurst, 1968). These issues have remained valid to this day.

Of course, innovations may vary in terms of character. Neirotti and Pesce (2019) wrote that looking from the perspective of the direction of impact, one can distinguish 'inward' process innovations within the company (they improve the effectiveness and efficiency of activities, and therefore relate to technology); there may also be product innovations offered to recipients (they change the company's offer, so they relate to the market). The aforementioned Schumpeter wrote about innovations in the form of a new market, as well as new suppliers, and new forms of organization. A different approach was presented by the Christensen model, which differentiate two types of innovation: incremental innovation and breakthrough innovation (Christensen, 1997; Christensen et al., 2015; Gobble, 2016). Innovations may include functional areas of the enterprise, e.g. marketing. They then concern a product, price, promotion or distribution, and are aimed at meeting the needs of recipients better (Persaud et al., 2021). As may be seen, there are many ways to approach the concept of innovation.

As mentioned before, the creation of innovations is a multidimensional process. Innovation can be generated by employees, engaged customers (especially dissatisfied ones), by benchmarking, and finally – by observing competition. One of the main sources of innovation, as Walder et al. (2006) wrote, are competitors and consumers. The latter may be asked about their expectations and needs using various types of market research. However, it is more difficult to check the innovativeness of competitors before their proposals appear on the market, and

even then, it requires constant tracking of economic information and analyses. On the other hand, enterprises that want to develop have to introduce market innovations. This is due to several reasons – each product sooner or later gets old (as shown in the product life cycle), consumer expectations change, and lastly, new products are introduced by competition (Walder et al., 2006). The need to implement innovations seems indisputable (Mikalef et al., 2019).

The key question to be asked is whether there is any system for acquiring and implementing innovation in the company? Furthermore, if it exists, does it involve external stakeholders – and which ones? No stakeholder group should be underestimated, as each may be a source of new ideas in a dynamic environment. The best product ideas take into account the perspectives of multiple stakeholders and teams, as well as market and customer research (wherever possible). Moreover, a lot depends on management methods and the nature of leadership in the company. Leadership, as Grošelj et al. (2021) wrote, is considered one of the key factors in innovative behaviors at work.

Introducing innovations into the market makes sense when the company has a chance to gain a financial and comparative advantage. On one hand, it requires a search for new ideas, while on the other, an analysis of their profitability. Therefore, every new idea has its source, then it gets developed and evaluated, and finally implemented onto the market. It seems that one of the sources of new ideas may be big data, because modern technologies that collect data have already passed the era of fermentation and development, and nowadays are mature enough to be treated as reliable sources of data and inspiration (Capurro et al., 2021; Sanasi et al., 2021). However, it is worth noting that the current analyzes of the use of big data in business activities are ambiguous and should be approached with appropriate caution, as with any other market research results (Capurro et al., 2021).

This article uses data from Google Trends – a service provided by Google. As already mentioned, the Google search engine is used by 92% of Internet users, which gives the company a central role in gathering market data (Carrière-Swallow, Labbé, 2011; Capurro et al., 2021). Google's infrastructure is just as impressive – it includes hundreds of thousands of servers (estimated to exceed 450,000) spread over thousands of clusters in dozens of data centers around the world (Carr, 2006). When someone types keywords (queries) into Google, the search engine compares them to the index to determine the best matches, and displays links to them along with the relevant cached snippets from web documents. For all of this to work, Google needs to store and analyze a significant proportion of all web content, which is both technically and economically challenging. Yet, on the other hand, it allows the company to collect information known as big data, which is so large and complex that traditional computers are unable to process

it (Carr, 2006). In other words, big data means larger, more complex data sets, especially from new sources. These data sets are so extensive that traditional computing software simply cannot manage them (What is Big Data?). In case of such large collections, large amounts of low-density unstructured data are processed, and the data is generated in milliseconds thanks to networked servers.

Google Trends lists the frequency with which a specific search term is searched in several languages from various regions of the world. To facilitate the comparison of terms, Google normalizes the search data, which means that the search results are normalized to the time and location of the query. The process involves two steps: first, each data point is divided by the sum of the location searches and the time range selected by the user, and secondly, the resulting numbers are scaled from 0 to 100, based on the proportion of the topic to all searches across all topics.

The value of big data becomes clear when we understand that all traditional market data that underpins future decision-making is historical, which should be understood as 'partially out of date' (Carrière-Swallow, Labbé, 2011). In case of data from Google Trends, we know that it is based on the micro-user data; it contains information about a large sample of Internet users (which is a much larger sample than the research agencies could investigate), and is released at high frequency and regular intervals, so it is highly up-to-date (Carrière-Swallow, Labbé, 2011). Big data seems to have become an important form of capital today.

3. Development of hypotheses

Everyone has probably heard about big data, but apart from the high technology industry, few companies use it in their daily activities (Capurro et al., 2021). On the other hand, scientists emphasize the increasing role of big data in better understanding customer needs and in the processes of innovative companies (Nambisan et al., 2017; Mikalef et al., 2019). Therefore, in this article, the author hypothesizes that the usefulness of big data for creating innovation depends largely on the way the query is formulated (here the author refers to the Google search engine and the Google Trends platform). It is crucial to adopt the mindset of the end user – the consumer – and enter queries the way an Internet user would. This corresponds to the vision of creating product or marketing innovations mentioned earlier.

H1: The usefulness of big data for creating innovation depends largely on the way the query is formulated.

Since the area of this study still has many unknowns, the hypothesis adopted herein is non-directional and has an exploratory nature. By using this approach,

the authors wish to show how companies could use big data and what information supporting the innovation process they might obtain. To date, the research of other authors has often focused on companies in digital technology sectors (Liu et al., 2016; Jun et al., 2018), while the authors of this article show the universal possibilities of using big data, regardless of the industry or the level of technological development of a company.

4. Methodology

The aim of this study is to prove that big data analysis in Google Trends may be a useful tool for searching for – and implementing – innovations. The author also wants to prove that the obtained results differ depending on what query is entered and what analysis period is selected. The research method used in this study is content analysis, i.e. the study of the content of messages posted on the Internet and any other written sources and documents.

4.1. Research setting

The study consisted of entering 6 queries (Q1-Q6) into Google Trends (https://trends.google.com) related to the search for new areas for innovation. The user always gets 25 results in so called the TOP category, or fewer if there is insufficient data. The search results are the 25 most frequently entered phrases in the Google search engine, associated with a given query (i.e., if a user enters 'innovations', they will see in the first place 'New Innovations', which is the name of an American company selling medical research software). It is worth noting that these 25 items are based on millions of searches (unfortunately, it is not known exactly how many). Nothing can be said about the group of respondents either as no such data is available. The only clue describing the group of surveyed users is the information as to which Internet users use the Google search engine.

As already mentioned, the study consisted of entering 6 queries – queries Q1 and Q2 were general in nature, and unrelated to any everyday problem. Queries Q3, Q4, Q5 and Q6 related to problems or needs. All inquiries were created solely for this study – the author selected ones associated with introducing changes or searching for innovations.

The key assumption is that when entering search queries into Google Trends, one should adopt the perspective of the end user, the consumer. Therefore, a hypothesis was made (H1) that by entering Q3-Q6 (the end-user perspective), one may get more data on problems and needs, which could be used to create new products or services.

H1: By using the consumer's perspective when formulating a query in Google Trends, one can get more data on problems and needs, therefore it is more useful for creating innovations.

In this study, therefore, a query was entered 6 times for 3 different periods each (5 years, 1 year, 30 days). A total of 18 x 25 results were obtained (with one exception – when there was not enough data for the 30-day period and no results were shown). As a result, 425 variables found in this study were the maximum – there can't be any more since this is the limit to the number that the Google Trends app can display.

The queries entered into Google Trends, which yielded the discussed results (the operation was repeated 3 times for 3 different periods), were as follows:

- Q1 – innovations,
- Q2 – new product,
- Q3 – a problem with,
- Q4 – solve a problem,
- Q5 – how to,
- Q6 – how to easy.

The results for Q1-Q6 were a list of 25 expressions related to the given query. First, the obtained results were analyzed in terms of the content – did the results show a product/service related to the query? Was a specific company name displayed? Was a particular need/problem visible in a specific area? Content that could not be classified as belonging to any of the previously formulated groups was placed under the category 'other' and was eventually excluded from the statistical calculations. This research procedure is a meta-analysis in nature, and is called a 'keyword frequency analysis'. Then, basic descriptive statistics were calculated, and Wilcoxon and Friedman's tests were used, aimed at examining the existence of dependencies and verifying the hypothesis.

So far, companies have commissioned such studies to research agencies, but in case of global companies or universal problems, big data may be used – which is the essence of this article. It is known that the use of big data has its limitations, which will be elaborated on in the Discussion, but the authors wish to show its advantages or opportunities (Capurro et al., 2021).

4.2. Data and data collection

When typing a search term into the Google Trends, e.g. 'innovations', one needs to select a region of interest, the time span analysis, and a category, e.g. 'finance'. One can also leave these parameters as default, i.e. the search term

would be analyzed for the whole world, for the full period (12 years) and for all categories. Google Trends will primarily show graphical data – in Figure 1 it can be observed that the greatest interest in innovations took place in December 2017 but the generated data may also be downloaded in Excel format to analyze it further. This was the approach used in this study, except that the search was performed for periods shorter than 12 years (namely: 5 years, 1 year, and 30 days). Data was collected exactly on December 31, 2021; it is presented in Table 1.

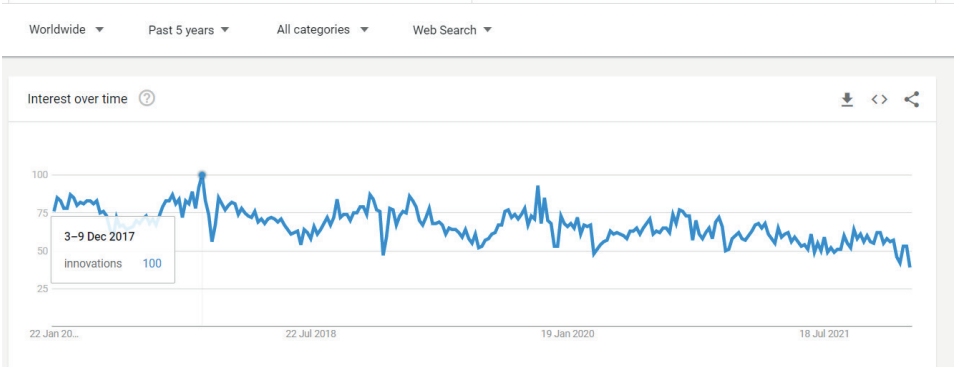

Figure 1. Graphical search results for the term 'innovations' in Google Trends for the period 2017–2021

Source: https://Trends.google.com/Trends/explore?date=today%205-y&q=innovations

Table 1

First collection of data – total results for three measurements

A query	Q1 – innova-tions	Q2 – new product	Q3 – a problem with	Q4 – solve a problem	Q5 – how to	Q6 – how to easy
Product (service) event	18	1	30	9	26	4
Name of a company	25	3	12	3	5	2
Needs in a specific area	11	2	5	7	37	43
Other	54	6	47	19	68	49
Average	27	3	23,5	9,5	34	24,5

As can be seen in Table 1, the first two columns (general) are not related to any problem, while the next four columns (end user) contain phrases which are typical of users looking for a solution to their problem. The authors assumed that the second group of inquiries would yield more results, which quickly was discovered to be untrue. However, on closer inspection, it was found that all the results for the query 'innovation' (i.e. 25 items) simply contained a company name. This type of results may be very useful for tracking competitors' activity; however, it is less useful for finding unmet needs and creating product innovations.

For the purposes of this study, the most important thing was to look for signs of needs, therefore the category 'other' was excluded from further analysis. Moreover, the results of the analysis related to the 'Company name' were commented on. Further analysis encompassed results from Tables 2–4. (It is worth recalling that the maximum number of results displayed by Google Trends for each query is 25; if in Tables 1–4 the sum for a given query is greater than 25, it means that the search result contained more than one category, i.e. for example, both a product and a specific need).

Table 2

The results obtained for the period of 5 years (2017–2021)

A query	Q1 – innovations	Q2 – new product	Q3 – a problem with	Q4 – solve a problem	Q5 – how to	Q6 – how to easy
Product (service) Event	6	0	20	5	6	1
Name of a company	7	1	5	1	1	1
Needs in a specific area	6	0	0	15	15	22

Table 3

The results obtained for the period of 1 year (2021)

A query	Q1 – innovations	Q2 – new product	Q3 – a problem with	Q4 – solve a problem	Q5 – how to	Q6 – how to easy
Product (service) Event	7	1	9	4	9	0
Name of a company	7	2	5	2	3	1
Needs in a specific area	5	1	5	2	3	1

Table 4

The results obtained for the period of 1 month (December 2021)

A query	Q1 – innova-tions	Q2 – new product	Q3 – a problem with	Q4 – solve a problem	Q5 – how to	Q6 – how to easy
Product/service/ event	5	0	1	unavail-able	11	3
Name of a company	11	0	2	unavail-able	1	0
Needs in a specific area	0	1	0	unavail-able	19	20

The main observation to be made at this point is that although the numbers in both tables are relatively small, they are based on huge amounts of searches (possibly even millions). It seems, therefore, worth analyzing them in more depth.

5. Results analysis

In order to determine whether the adopted hypothesis may be confirmed, the authors calculated basic descriptive statistics (mean, standard deviation, median, minimum and maximum), as well as:

1) they checked with the Wilcoxon test whether there were statistically significant differences between the 'end user' and 'general' groups for specific time periods;
2) they used Friedman's test to check whether there were statistically significant differences between the three time periods related to 'end user' and 'general'.

The statistical significance was set at $p < 0.05$. Statistical analysis was performed using the IBM SPSS Statistics 25 suite.

The descriptive statistics are presented graphically in Figures 2, 3 and 4. They illustrate the potential of the data obtained, and allow for the first conclusions to be drawn.

In case of the 5-year period the figure (Fig. 2) is based on the following data:

- for 'end user' – mean M = 7.67, median Me = 8, standard deviation SD = 5.51, minimum Min = 2, and maximum Max = 13;
- for 'general' – mean M = 3.33, median Me = 3, standard deviation SD = 0.58, minimum Min = 3, and maximum Max = 4.

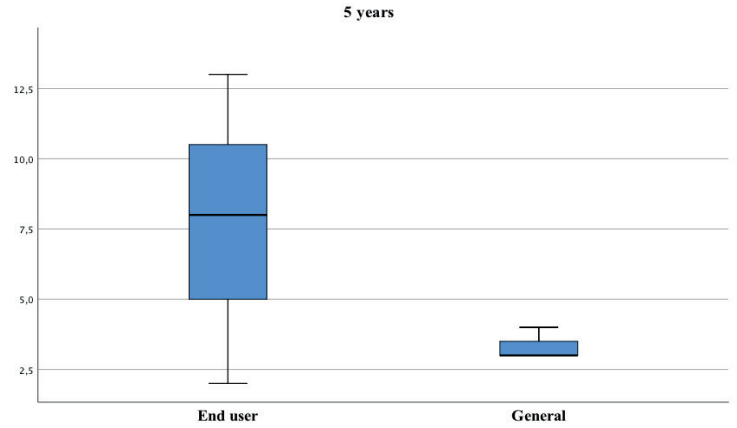

Figure 2. Differences in basic statistical characteristics for 2017–2021

Source: own study

The figure for 1-year period (2021) (Fig. 3) is based on the following data:

- for 'end user' – mean M = 3.67, median Me = 2.75, standard deviation SD = 1.59, minimum Min = 2.75, and maximum Max = 5.5;
- for 'general' – mean M = 3.83, median Me = 4, standard deviation SD = 0.76, minimum Min = 3, and maximum Max = 4.5.

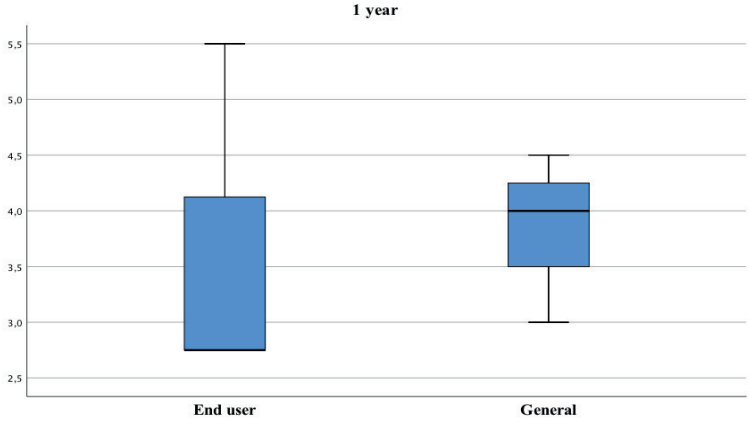

Figure 3. Differences in basic statistical characteristics for a 1-year period

Source: own study

Figure 4 illustrates the data for 1-month period (December 2021). The figure is based on the following data:

- for 'end user' – mean M = 6.25, median Me = 5, standard deviation SD = 6.22, minimum Min = 0.75, and maximum Max = 13;
- for 'general' – mean M = 2.83, median Me = 2.5, standard deviation SD = 2.52, minimum Min = 0.5, and maximum Max = 5.5.

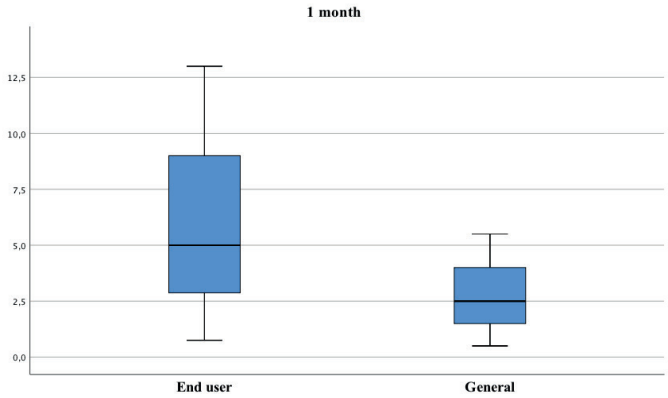

Figure 4. Differences in basic statistical characteristics for a 1-month period

Source: own study

It's known that the median is a better measure for sets with extreme cases, therefore we shall focus on this value. The comparison of all medians is presented in Figure 5.

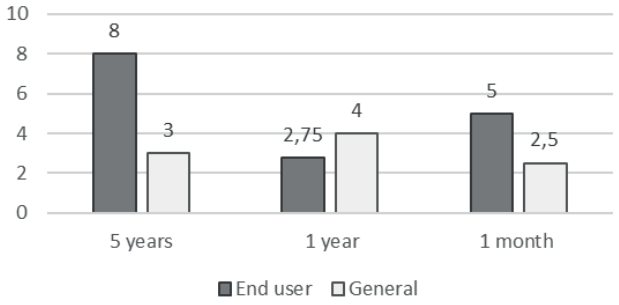

Figure 5. Comparison of the median value obtained for all measurements

Source: own study

Despite the visible differences in the median values, the results of statistical tests (Wilcoxon's test for dependent groups) indicate no statistically significant differences between the individual periods. The test results are as follows: for 5 years – $Z = 1.07$, $p = 0.29$; for 1 year – $Z = 0.54$, $p = 0.59$; for 1 month – $Z = 0.54$, $p = 0.59$.

Using the same data, the question was inverted and it was checked whether there were statistically significant differences between the 3 time periods in the categories 'general' and 'end user' (analysis made with Friedman's test). Figures 6 and 7 illustrate this issue.

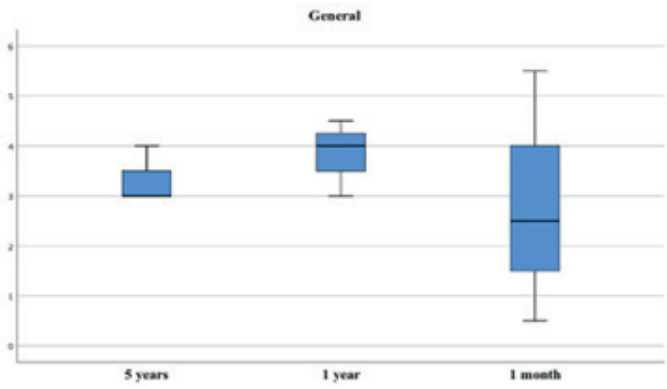

Figure 6. Results obtained for 'General' in particular time spans

Source: own study

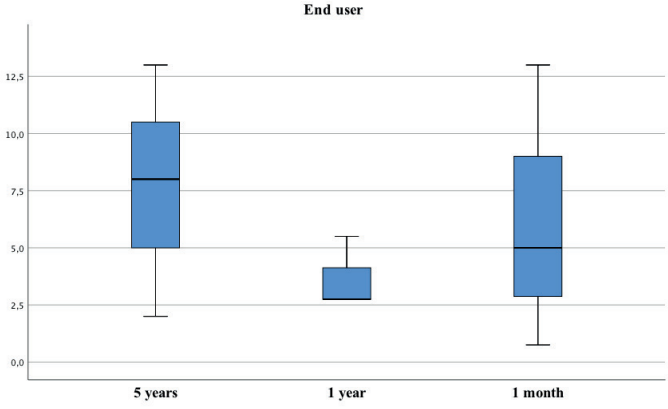

Figure 7. Results obtained for 'End user' in particular time spans

Source: own study

In this study, the authors focused on seeking options that would yield the best results for creating product innovations. By verifying whether there were significant differences between the 3 time spans in the 'General' and 'End user' categories, it may be stated that in case of 'General' queries, the data useful for creating innovations was obtained for a period of 1 month. However, the scope of this data is still worse than for the 'End user' type of queries. For 'General' queries, the average number of useful results in each period fluctuated between 3 and 4, and the highest value – as already mentioned – was obtained for the 1-month analysis. In case of 'End user' queries, the worst average result was obtained for 1 year (3.67), and the best – for 5 years (7.67). For both the 5-year and 1-month period, the maximum amount of data obtained was 13 – compared to 5.5 for 1 year. The median was the highest for the 5-year period. It is worth emphasizing that the best result for the 5-year period for 'End user' was twice as high as the best result in the 'General' category.

Despite significant differences visible in Figures 6 and 7, the results of the analysis for 'general' do not allow for the conclusion that these differences were statistically significant ($\chi^2_F(1) = 1.27$; $p = 0.53$). The same is valid for 'end user' – no statistically significant differences were observed either ($\chi^2_F(2) = 1.64$; $p = 0.44$). This means that, at least from the statistical point of view, the results for both groups and all periods were equivalent.

6. Discussion

In recent years, there has been a debate for and against the use of big data for market decisions. There are studies, such as Carrière-Swallow and Labbé (2011) 'Nowcasting with Google Trends in an emerging market', which confirm that the information from Google Trends allows one to predict trends and phenomena with great accuracy. Similar conclusions were presented by Askitas and Zimmermann (2009), who analyzed the problem of unemployment. On the other hand, there is evidence that predictions and analyzes based on Google Trends fail. For example, Rovetta (2021) emphasized that Google Trends did not provide the right amount of data for the calculations, despite being big data. A different opinion, however, was presented by Medeiros and Pires (2021), who claimed that in order to use Google Trends, one needs to have certain knowledge when entering queries and then analyzing the answers.

Globalization and digitization are currently the main drivers of change (Das et al., 2018) – they can be feared because they change the way market entities operate, but they may also be used to develop the organization. It may be difficult to create breakthrough or radical innovations these days, but introducing changes, as emphasized by Nagano et al. (2016) and Gatignon et al. (2002), is

simply an imperative of our times. Hence, there's a need to look for new sources of innovation.

As already mentioned, innovation is not something that happens by itself, but is a structured or systematic process that requires discipline; it may be learned and practiced. It is also worth being proactive and looking for non-standard sources of innovation – hence the authors' proposal to look at big data and Google Trends. According to the Oracle website (https://www.oracle.com/emea/big-data/what-is-big-data), in relation to big data, the user will have to process large amounts of low-density unstructured data. Its value may be unknown, so only structuring and analysis will help better understand and use it in order to comprehend changes and predict the future (Jun et al., 2018). This is what the authors did by checking the data available in Google Trends.

As Jun et al. (2014) have noted, Google Trends undoubtedly offers an almost instantaneous reflection of the needs, desires, requirements and interests of users; plus, the tool is easy to use and provides various options for comparison. In this study the authors assumed that big data analysis in Google Trends may be a useful tool for searching for – and implementing – innovations. They also wanted to prove that the obtained results differed depending on what query was entered and what analysis period was selected. Unfortunately, the adopted concept of statistical analysis did not prove the hypothesis that the usefulness of big data for creating innovation largely depends on the way the query is formulated. However, it must be emphasized that it was not possible to confirm significant statistical differences for different ways of formulating the query, which means that all the obtained results were equivalent. Perhaps other analyzes should be carried out, ones better suited to the specifics of the study, and possibly more data is needed.

On the other hand, basic statistical measures such as mean, standard deviation, median, minimum and maximum values clearly show differences in the obtained results and encourage the hypothesis to be maintained. In this study, when the method of asking the question was the variable, the obtained results were as follows:

1) for the 5-year period (2017–2021), for the 'general' query, the average was 3.33 of the useful result, and for the 'end user' query, the average was 7.67, which is twice as high; moreover, the median for 'end user' was three times higher;
2) for the 1-year period, the results for both approaches were similar – no significant differences were found (the mean for 'general' was 3.83, and for 'end user' 3.67);
3) for the 1-month period, for the 'general' query, the average was 2.83, while for the 'end user', the average was 6.25, meaning twice as much data was obtained; the median was also twice as high.

Therefore, despite the lack of statistical significance, it may be concluded that if the end-user point of view was adopted and queries over the 5-year period analyzed, one would get more useful data than for other entries (here called 'general') as well as other analysis periods. It should also be noted that in the Q1 query – 'innovations' in the 'general' group, there were company names which included the word 'innovations' in the name. Such data was not excluded from the analysis, but if it had been done, the search values in the 'general' group would have been even smaller.

By focusing not on the type of query entered, but on the comparison of the analysis periods, it may be stated that the queries for 1 year in the 'general' category do have some value, but they are still worse than the results of the 'end user' category. From the perspective of the usefulness of data in the implementation of innovations, the best among the three analyzed periods was the 5-year period, followed by the 1-month period.

Much better results for 'end user' queries allowed the authors to adopt the preliminary research hypothesis that the usability of big data is influenced by how one formulates the query. However, as already mentioned, further statistical analyzes need to be carried out on more data.

7. Conclusions

Thanks to modern technologies, we generate more and more amounts of various types of data that may be used for the development of organizations. A huge amount of data is collected by search engines, which leads to the creation of big data. In this study the authors assumed that big data analysis in Google Trends may be a useful tool for searching for – and implementing – innovations. They also wanted to prove that the obtained results differed depending on what query was entered and what analysis period was selected. Over 400 responses were received in the form of phrases typed by Internet users all over the world, and the results of the conducted analysis allowed for the identification of differences and the selection of specific ways of entering queries and certain periods. The authors believe that the obtained results prove sufficiently that the end-user perspective should be adopted as it gives more useful information relating to needs and problems. Undoubtedly, such information is necessary to successfully implement market innovations.

7.1. Theoretical implications

The basic descriptive statistics highlight differences in favor of the hypothesis but it has not been statistically verified. From the theoretical point of view, other

methods of conducting the analysis should be considered, and perhaps more data should also be collected. The authors notice a potential for further considerations and research on the use of big data. It is also worth adding that hypotheses are made on the basis of theoretical premises, and the theory involving the use of big data in various areas of knowledge has not yet crystallized, which places this work in the domain of exploratory studies.

7.2. Practical implications

Discovering human needs and searching for answers to them is not only the domain of entrepreneurs, therefore this study may have a fairly broad practical applications. By adopting the general assumptions, i.e. ones that do not refer to specific products or industries, the authors showed that the presented path may be recreated by both entrepreneurs and creators of political programs, as well as leaders of non-governmental organizations.

Additionally, it may be stated that by analyzing Google Trends, the authors noticed market opportunities, new needs, and current problems – all this may be a source of innovation, understood as new products, new services, or new approaches to problems. Interestingly enough, one may also obtain insights on the successes or failures of competitors, which is very valuable from a management point of view. So, one can say that an access to big data thanks to Google Trends enables better decision-making.

7.3. Limitations and future studies

It must be remembered that Google Trends is an imperfect tool, mainly because it does not take into account the irrational behaviors of people and does not display many connections. Moreover, the obtained data is highly averaged and it is often difficult to relate it to specific, local solutions. It must also be kept in mind that the smallest change of the query in Goggle Trends changes the obtained results, so it does matter whether we enter 'innovation' or 'innovations'. In addition, two people entering the same query, but in different countries, may obtain different results. This means that the data presented in this article, as well as all the data obtained from Google Trends, is difficult to verify, but it is also a field for further research on the possibilities of using big data.

In conclusion, it may be said that the performed meta-analysis (i.e. the analysis of the frequency of keywords) could be used to examine changes in consumer behaviors and identify new areas for innovation. On the other hand, however, it does not show many connections and dependencies, so it is worth combining keyword analyzes with other data collection methods.

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Summary

A huge amount of data is collected by search engines. According to estimates, the Google search engine, which is dominant on the market, receives billions of search requests daily. Of particular note is that a large part of the collected data is available through the Google Trends service. As a consequence, various types of data can be used by enterprises for their development but they often do not take advantage of this opportunity. Therefore, the purpose of this article is to prove the suitability of the big data concept for creating and implementing product innovations, using the example of Google Trends. Discovering human needs and searching for answers to them is not only the domain of entrepreneurs, therefore this study may have a fairly broad practical applications. By adopting general assumptions, i.e. ones that do not refer to specific products or industries, the author has shown that the presented path may be recreated by both entrepreneurs and creators of political programs, as well as leaders of non-governmental organizations who need to implement innovations. The results revealed the selection of specific ways of entering queries in Google Trends and certain periods of analysis which are the most useful for creating innovations. Descriptive statistics (such as median) clearly show that the results typed in Google Trends are better when taken from a user perspective and can be used to create innovations. Despite substantial differences, the results do not allow for the conclusion that these differences were statistically significant. Thus, preliminary data supports the hypothesis, but more research is needed.

JEL codes: C44, D81, M1, O31

Keywords: *better decisions*, *identifying needs*, *keyword analysis*, *product innovation*, *sources of ideas*

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Tightening tax policy and changes to tax efficiency on the example of companies listed on the Warsaw Stock Exchange

1. Introduction

Tax efficiency is shaped by two opposed forces: (1) companies intensify behavior aiming at tax planning and (2) the legislator changes the tax law in order to seal the tax collection system, thereby increasing revenues to the state budget and limiting the behavior of companies balancing on the edges of the law. On the Polish market these two forces have collided very dynamically. The interest of enterprises in the issue of tax management has been systematically growing since 2004, as evidenced by the research conducted (Famulska, 2015) as well as reports from the specialist press on the unprecedented growth of the tax advisory market (Zalewski, 2015). At the same time, after the change of the ruling elite in Poland in 2016, some intensive legislative activities aiming at tightening tax laws have been observed. The declared goal of these changes by their legislators is: (1) tightening of the income tax system and (2) ensuring that the amount of tax paid by large enterprises, in particular international enterprises, is linked to the actual place of their income. Most of these changes effectively impacted the tax results and taxes reported by enterprises for the first time in 2018.

The impact of these changes on the behavior of enterprises and their tax efficiency is indisputable but it should be noted that there is little research on tax efficiency concerning the Polish market. Most concerns individual case studies

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and opinion polls, while quantitative research on the tax efficiency of enterprises has practically not been conducted on the Polish market as of yet.

The aim of the article is to analyze the effectiveness of income tax management among companies listed on the Warsaw Stock Exchange (WSE) and to verify the hypothesis that the changes in tax regulations introduced since 2017 have affected the tax efficiency of Polish listed companies. The author adopted the following specific research goals:

- quantitative assessment of the impact of changes in tax law introduced since 2017 on the tax efficiency of companies listed on WSE,
- identification of groups of enterprises for which the scale of the impact of legal changes on tax efficiency is the highest,
- formulation of directions for further research on tax efficiency.

The article is organized in the following manner. The first section presents the synthetic results of the research on tax efficiency to date. The second presents the research sample and discusses the methods of analysis used. The third part presents the obtained results and their discussion in two main areas: (1) changes in tax efficiency in the audited period and (2) analysis of the relationship between the observed changes in tax efficiency and selected characteristics of enterprises. The work ends with a summary in which directions for further research are proposed.

2. Review of the current state of knowledge

The global research concerning taxation are conducted in the areas of balance sheet law and tax law, economics as well as corporate finance. Hanlon and Heitzman (2010) indicate four key areas in global taxation research: (i) tax reporting, (ii) tax planning and tax avoidance, (iii) tax impact on corporate decisions, including investment, debt and eligibility, and (iv) the impact of taxation on the valuation of assets. The vast majority of empirical research focuses on the two middle ones and concerns a broadly understood notion of tax efficiency.

The literature defines many different measures of tax efficiency that support different research goals (Kowalski, 2016). The most popular measure of tax efficiency is the effective tax rate (ETR). The effective tax rate is the quotient of the income tax and balance sheet income before tax. It should be noted that the income tax presented in the financial statements includes the amount of the calculated tax liability commensurate with the results of a given period, additionally adjusted by deferred tax. As a result, if there were no permanent differences between the balance sheet and tax recognition, and no temporary differences for which deferred tax was not established, the effective tax rate should be equal to the nominal tax rate. The formation of permanent differences will result in the

ETR exceeding the nominal rate and proves the tax ineffectiveness of the enterprise. The fundamental advantage of the effective tax rate may also be regarded as its most significant disadvantage for the purposes of tax control. The emergence of temporary differences may be independent of managerial decisions, an element of tax planning or even a tool for shaping financial results (Buk, 2014). This is one of the reasons why ETR has been the subject of much criticism in the literature on the subject as a measure of tax efficiency both from the perspective of enterprises and tax authorities. Omer et al. (1991) indicate in their research examples of Fortune 500 companies that, despite their high ETR values, they have paid little or no tax over the years.

The indicated disadvantages of the effective current tax rate mean that the effective tax rate (CETR) is a measure of tax efficiency widely promoted in the literature (Heltzer, 2009). The effective tax rate of the current tax is calculated as the current income tax divided by the balance sheet income before tax, i.e. the gross result. Literature reports mention the advantages of an effective current tax rate, especially important for applications in controlling. First of all, as Graham (2013) points out, it is the measure preferred by managers. CETR is the most frequently used measure of tax efficiency used in incentive systems of people responsible for tax aspects (Armstrong et al. 2012). A positive correlation was found between the reported CETR and the share price and market value, CETR is used as a parameter in most profitable valuation models, moreover, CETR is often used in banking covenants and determines debt capacity (Graham et al., 2011).

Research on factors affecting tax efficiency has a long history in developed markets. Among the factors positively affecting tax efficiency is, among other things, the size and profitability of enterprises (Lisowsky, 2010), low indebtedness, and concentration of ownership, including family businesses (Desai, Dharmapala, 2009; Chen et al., 2010). Undoubtedly, one of the most important determinants of tax efficiency is the involvement of enterprises in tax planning (Mills, 1998; Frank et al., 2009). Lisowsky (2010) showed the relationship between tax efficiency and the number of foreign operations, the presence of entities in tax havens and the number of court disputes with tax authorities recognized as the consequences of tax planning.

The literature introduces many terms to describe the activity of enterprises focused on the analysis and further shaping of tax burdens. On the rocky poles there are terms: tax planning or tax management and tax avoidance or tax – aggressiveness, sheltering, evasion, noncompliance, etc. Some researchers have defined tax planning as exerting an active and legal influence on the amount of tax burdens (Szlęzak-Matusewicz, 2013), or an organized response of a company to the tax regulations (Poszwa, 2017). Tax avoidance is defined broadly as the reduction of explicit taxes. This definition does not distinguish between real activities that are tax-favored, avoidance activities specifically undertaken to reduce taxes, and targeted tax benefits from lobbying activities.

Global research identifies and discusses examples of tax strategies. Lisowsky (2010) distinguishes three main groups: (i) regarding increasing the value of assets, (ii) increasing costs and (iii) deferring revenues. The literature also indicates examples of tax strategies specific to Polish conditions and the tax system (Famulska, 2013, 2015; Wyciślok, 2013; Szlęzak-Matusewicz, 2013). The scale of using these strategies was examined in Poland in the form of collecting and analyzing opinions (Ciupek, Famulska, 2013), but I am not aware of quantitative research on the impact of using a tax strategy on tax efficiency. Particularly significant, and possibly the only work in recent years on tax efficiency in the conditions of companies listed on the WSE, has been the research of Sztuba (2016). The research covered the years 2008–2010 and was aimed at a comparative assessment of the level of fiscalism in Poland compared to other countries.

Tax planning is the most common reaction of enterprises to tax burdens, including changes in tax regulations. Research by Famulska (2015) on a group of 50 companies showed that the most common response to the tax burden was the implementation of a tax strategy, and not the payment of the due tax or tax evasion.

Tax efficiency is determined, on the one hand, by the attitudes of the taxpayer who strives to minimize the burden and, on the other hand, by the mechanism of imposing and enforcing taxes by the public authority. Ciupek and Famulska (2013) pointed out that tax and legal relations are a natural axis of the conflict of interests between public authorities and enterprises. In the example of the Polish market, we can observe the intense clash of these two forces.

The tax law regulations introduced in 2017 were intended to limit the use of those strategies that result from legal imperfections. A anti-avoidance clause was introduced, as well as numerous changes to the Income Tax Act (Act of October 27, 2017), aiming to tighten the tax system, among other things,: separate taxation of income from capital sources, limiting the possibility of including expenses for certain intangible services or expenses related to debt financing as tax costs. The purpose of these changes is to increase the efficiency of the tax system in Poland, and to increase income tax revenues (Wyrzykowski, 2019).

Kowalski (2017) conducted research on the tax efficiency of companies listed on the WSE in the years 2004–2014. The study showed an increase in tax efficiency of the surveyed companies in the analyzed period, but it was observed for entities with average effectiveness values. A negative correlation was demonstrated between tax efficiency and the scale of operations and profitability, which could be related to the use of tax strategies and tax management instruments. The presented study covered the years 2012–2019. The selection of the period was related to the sample analyzed in previous studies (Kowalski, 2018) and to some extent is their continuation.

3. Sample and research method

The survey covered enterprises listed on the main market of the Warsaw Stock Exchange. The analysis used annual financial statements. Data for analysis were collected from the EquityRT databases.

Efficiency is a concept that is not clearly defined, being a category used as a criterion for assessing the activity both at the level of the entire enterprise, as well as in relation to its individual areas. Efficiency is most often analyzed as a reciprocal relationship between inputs and outputs. With regard to tax efficiency, the effect will most often be expressed differently in terms of tax burden, tax loss, assets or tax liability. This value will be related to the basis of comparisons most often representing different categories of the financial result. Two measures of tax efficiency were analyzed: effective tax rate (ETR) and current effective tax rate (CETR). ETR was calculated as 'income tax' divided by profit/loss before tax presented in income statement. The main advantage of an effective tax rate is the ease of its calculation.

CETR was calculated as income tax, the current part divided by profit/loss before tax is presented in an income statement. A higher value of ETR and CETR means that the company calculates in the current and future periods (in the case of ETR), shows as an obligation to pay in the current period (in the case of CERT) more tax burdens. Thus, the higher the ETR and CERT value, the lower the tax efficiency.

Income tax was not included in financial statement presented in EquityRT data, so it was measured based on other data. First, the deferred part of income tax was calculated as delta year to year position 'deferred income tax' presented in assets in balance sheet statement and delta year to year position 'deferred tax liabilities' posted in equity & liabilities. To calculate current income tax, the income tax presented in income statement was reduced by the deferred part. The correctness of these assumptions was verified on the basis of a dozen or so companies. During the verification, the obtained result was compared with the data contained in completed financial statement issued on company web sites. CETR is a measure of tax efficiency propagated in the literature (Heltzer, 2009). Graham (2013) indicates that this is the measure preferred by managers.

The sample originally included 6,161 financial statements. Excluded from the database were banks and enterprises conducting financial activity due to different standards of financial statements. When calculating CETR, companies that recorded tax losses and did not report current tax were omitted. Ultimately, the sample included 3,416 observations for ETR and 2,215 observations for CETR. The database was supplemented with the characteristics of companies used in the further analysis (for example, industry, capitalization, auditor). The characteristics of the tested sample are presented in Table 1.

Table 1

Sample descriptive statistics

Year	N	SALES [mPLN]		EBIT [mPLN]		ASSETS [mPLN]		ROA [%]		ROE [%]		D/E [ND]		Capitalization [mPLN]	
		AVG	MED	AVG	MED	AVG	MED	AVG	MED	AVG	MED	AVG	MED	AVG	MED
2019	268	1 787.1	207.4	128.4	17.2	2 001.1	256.8	8.4	4.8	18.0	10.3	1.67	1.17	1175.5	117.1
2018	289	1 864.0	186.2	152.5	14.9	2 234.8	247.2	33.7	4.5	32.2	10.1	1.30	1.07	1162.5	105.7
2017	292	1 651.3	189.9	159.2	15.3	2 019.5	218.2	6.7	4.5	14.5	10.4	1.17	1.02	1100.7	99.7
2016	292	1 460.1	180.0	131.1	14.9	1 778.1	222.0	7.3	5.0	9.7	10.5	1.21	1.05	1112.4	97.4
2015	289	1 258.0	174.4	93.1	15.0	1 246.9	195.0	7.9	5.1	19.2	10.8	1.54	0.93	1044.0	100.6
2014	279	1 177.5	176.0	115.1	14.2	1 661.4	208.3	9.0	4.9	19.1	10.5	1.87	0.94	956.2	117.6
2013	266	1 628.1	171.5	112.1	14.0	1 773.8	195.7	6.7	4.8	13.3	9.6	1.20	0.87	920.8	122.3
2012	240	1 901.8	168.6	137.2	13.7	1 883.4	192.0	7.2	5.2	14.4	10.5	1.37	0.92	907.7	133.4

N – number of observations, AVG – average, MED – median

Then the prepared database was analyzed and statistically deduced, with the Statistica package used for the analysis.

The first part of the research was aimed at assessing whether, after the introduction of changes related to the tightening of the state's tax policy, there were cracks in the measures of tax efficiency. The analyzed sample was divided into quartiles in terms of ETR and CERT. The division was made because earlier studies showed that companies with different tax effectiveness were characterized by the strength of its changes over time.

The sample was purified from outliers. Then, the possibility of conducting an analysis of variance was verified. The Shapiro–Wilk test verified whether the distributions of each group were characterized by a normal distribution. The homogeneity of variance in each of the selected groups was then tested using the Brown-Forsythe test (Brown, Forsythe, 1974). Due to the fact that the assumptions about the normality of the distribution were not confirmed for each of the groups, further studies were carried out using non-parametric Kruskal–Wallis tests (Kruskal, Wallis, 1952). Significance of differences between the measures of tax efficiency between the distinguished classes was made using posthoc tests (Dunn, 1964).

In the next step, the scale of CETR changes in 2018–2019 was analyzed, i.e. when changes to the tax law aimed at tightening it came into force in relation to the recorded by the companies in 2016–2017. The variable Z is given for the analysis and is defined as Z = (CETR AGV 2018–2019/ CETR AGV 2016–2017) – 1, where CETR AGV 2018–2019, CETR AGV 2016–2017 means the average CETR value for the company achieved in 2018–2019 and 2016–2017, respectively.

Subsequently, the relationship between Z and the characteristics of companies was tested, taking into account such features as Sales, EBIT, Assets, ROA, ROE, D/E, Capitalization. The aim of the research was to verify whether enterprises with different characteristics have different changes in tax efficiency in the analyzed period. The enterprises were grouped into quartiles of the observed measures and the defined measure Z was analyzed in each group. The same procedure as presented in the first step was carried out.

The factors positively influencing tax efficiency include: the size and profitability of enterprises (Lisowsky, 2010), low debt to equity ratio an ownership concentration (Desai, Dharmapala, 2009; Chen et al., 2010). It was analyzed whether these features may affect the level of changes in tax efficiency after the entry into force of the amended regulations. It was also analyzed whether features such as revenues from sales, CETR, profit income (EBIT), assets, debt to equity, return on assets, return on equity, capitalization, occurred. The sample was divided into groups, where a given group denoted a quartile in terms of

a given feature. The statistical significance of the observed differences was tested using the Kruskal–Willis tests.

It should be assumed that the amended regulations will affect the CETR of companies involved in aggressive tax planning. Identifying that a given company has carried out tax planning is not easy. Miles (1998) assumed that companies audited by auditors from the so-called big four are more likely to use the services of tax advisers and apply tax strategies although the correctness of this assumption may be questionable and was criticized by Frank et al. (2009). Lisowsky (2010) showed a relationship between tax efficiency and the number of investment operations that can be identified on the basis of financial statements. In addition, changes to the tax law should have a greater impact on the efficiency achieved by holding companies, on which regulations such as limiting intangible costs and internal financing costs should have a greater impact.

For this reason, in this step, the Z value was analyzed from the point of view of the characteristics of whether the company was audited by a big four auditor, whether the company created holding structures, or whether the company implemented capital investments. The aim of the research was to verify whether the indicated features affect the observed changes in tax efficiency in the analyzed period. Because the sample was divided into two groups in this experiment, the statistical significance of the obtained results was tested with the classic t statistic.

4. Results and discussion

Tables 2 and 3 present the results of the ETR and CETR values obtained during the analyzed period. The results for the entire sample and groups based on ETR and CETR quartiles are presented. Additionally, the results are presented in Figures 1 and 2.

Table 4 presents the pairwise comparison analysis. The results obtained in individual years were compared in terms of whether they differ in a statistically significant manner. The non-parametric Kruskal–Wallis tests were used for the assessment of differences in tax efficiency between the selected groups, the analysis was supplemented with post hoc Dunn tests. The obtained results indicate that for ETR there is no reason to reject the hypothesis that all groups are characterized by the same tax efficiency. However, in the case of CETR, the null hypothesis that all groups are characterized by the same tax efficiency should be rejected. Significant differences between CETR were obtained for all examined quartiles.

Table 2

ETR by years

ETR	Total			Q1			Q2			Q3			Q4		
	AVG	MED	StDev	AVG	MED	StDev	AVG	MED	StDev	AVG	MED	StDev	AVG	MED	StDev
2019	24.0	20.5	36.5	41.8	30.2	65.5	22.1	20.5	5.2	20.5	18.4	15.2	11.5	9.9	18.9
2018	35.5	20.3	161.1	78.5	29.3	307.8	20.6	20.2	5.5	21.2	19.0	15.6	21.9	17.2	87.6
2017	33.6	19.8	149.2	51.3	25.6	80.8	20.1	20.0	7.1	17.0	17.4	14.7	45.9	16.5	286.8
2016	40.2	19.5	403.4	122.5	23.7	803.8	18.8	19.5	8.3	11.2	16.3	37.0	8.3	6.8	31.1
2015	22.5	19.6	119.8	58.5	23.0	186.4	26.1	20.1	74.1	12.7	15.1	11.5	−6.8	10.5	124.0
2014	0.9	19.0	131.8	-18.9	24.1	199.8	17.9	20.2	14.4	20.9	18.4	42.5	−16.1	2.9	163.3
2013	14.7	18.9	26.7	28.0	26.4	23.9	17.9	19.9	11.5	8.0	13.5	25.0	4.8	3.0	34.7
2012	22.8	19.2	139.5	58.1	22.6	270.7	17.4	20.2	13.9	13.7	14.3	12.0	1.9	9.6	58.2

ETR in percentage, AVG – average, MED – median, StDev – standard deviation, Total – whole sample.
Q1, Q2, Q3 – companies asses to first, second, third quartile of ETR

Table 3

CETR by years

CETR	Total			Q1			Q2			Q3			Q4		
	AVG	MED	StDev	AVG	MED	StDev	AVG	MED	StDev	AVG	MED	StDev	AVG	MED	StDev
2019	16.2	16.9	11.1	32.3	31.0	6.3	21.0	21.0	1.9	13.6	14.1	2.9	2.3	2.3	3.5
2018	16.2	17.1	11.7	33.2	31.5	7.6	21.0	20.9	1.9	13.4	13.7	3.1	1.3	0.4	4.0
2017	13.3	14.2	11.2	29.1	26.5	6.7	18.4	18.1	2.1	9.5	9.8	3.4	−-0.6	0.5	4.9
2016	13.6	14.1	11.4	29.8	28.7	5.9	18.4	18.4	2.3	10.5	10.6	2.9	−-0.7	0.3	5.2
2015	15.0	15.2	12.6	32.6	29.9	8.6	19.5	19.4	2.0	10.4	10.5	3.5	−0.5	0.1	3.8
2014	14.7	15.7	12.9	32.8	30.7	7.3	20.1	20.0	2.5	10.2	9.9	3.7	−1.4	0.3	6.5
2013	14.5	15.2	13.2	32.8	29.8	8.3	19.4	19.2	2.3	9.5	9.3	3.9	−1.6	0.0	5.7
2012	13.4	13.4	11.3	29.6	27.6	6.9	18.0	18.1	1.9	9.8	9.7	2.9	−0.4	0.4	4.4

ETR in percentage, symbols analogical as in Table 2

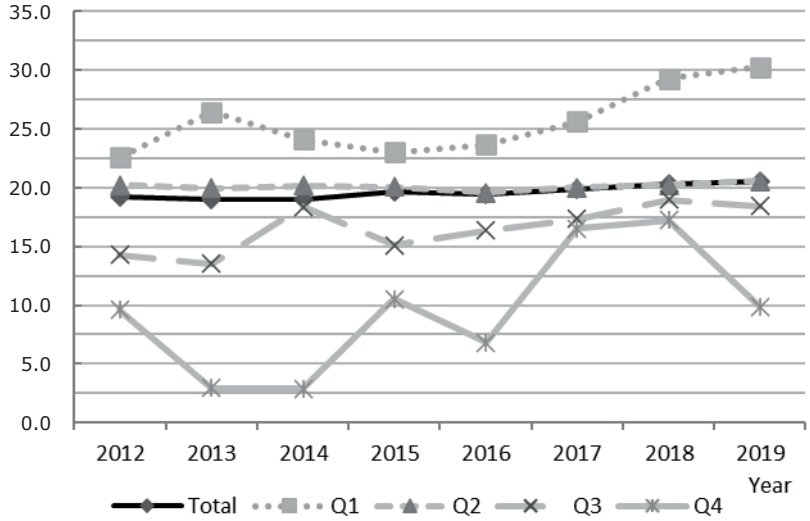

Figure 1. Effective tax rate – median [%]

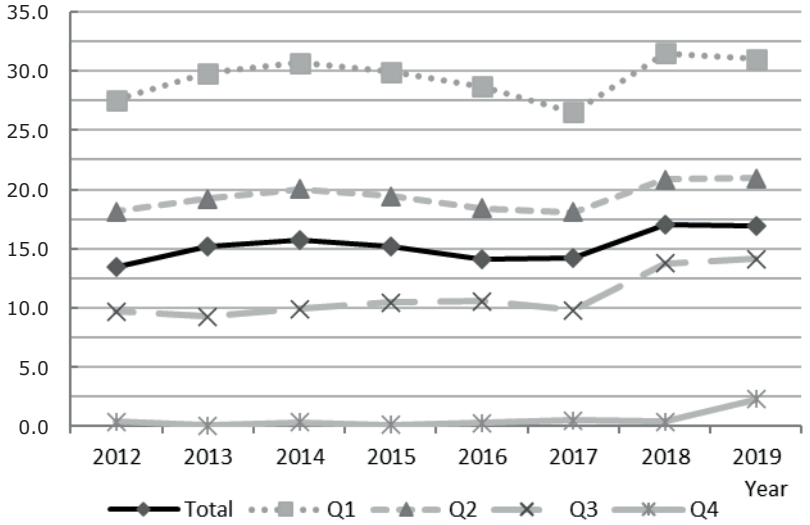

Figure 2. Current effective tax rate – median [%]

Table 4

Results of significance test

ETR	Total	Q1	Q2	Q3	Q4
	H = 7.757 p = .0513	H = 4.878 p = .180	H = 6.735 p = .080	H = 6.692 p = .082	H = 2.745 p = .432
2019 vs 2018	1.000	1.000	1.000	1.000	1.000
2019 vs 2017	1.000	1.000	0.643	0.796	1.000
2019 vs 2016	0.145	0.715	0.061*	0.312	1.000
2018 vs 2017	1.000	0.886	1.000	0.597	1.000
2018 vs 2016	0.069*	0.334	1.000	0.217	0.859
CETR	H = 13.116 p = .0044	H = 15.919 p = .0012	H = 72.238 p = .0000	H = 68.425 p = .0000	H = 13.131 p = .0044
2019 vs 2018	1.000	1.000	1.000	1.000	0.667
2019 vs 2017	0.043**	0.011**	0.000**	0.000**	0.031**
2019 vs 2016	0.060*	0.200	0.000**	0.000**	0.005**
2018 vs 2017	0.066*	0.005**	0.000**	0.000**	1.000
2018 vs 2016	0.091*	0.112	0.000**	0.000**	0.502

The table presents the results of the statistical analysis of the significance of differences between the results in the years 2016–2019 for ETR (Panel A) and CETR (Panel B) using the Kruscal-Wallis tests. The value of the H statistic and the p-significant level are presented. The paired comparisons of indicators in individual years were presented using Dunn's post-hoc test and the significance level obtained. Sign * indicate significance of results at the level of $0.05 < p \leq 0.1$ and ** at $p < 0.05$.

The highest CETR values were recorded in 2019 and 2018, both in the entire sample and in the companies included in Q1, Q2 and Q3. The highest values in these years were recorded both in relation to the average and the median CETR. The significance analyzes carried out indicate that in the entire sample, the CETR values recorded in 2019 and 2018 are statistically significantly higher than those recorded in 2016–2017 at the level of $p < 0.1$. Thus, the obtained results confirm the thesis that the changes introduced to the tax law resulted in a decrease in the tax efficiency of the surveyed companies.

The scale of this mechanism is not the same. While the increase in CETR is observed in all quartiles, the statistical significance is confirmed especially for companies Q2 and Q3, i.e. half of the surveyed population recording CETR closest to the average. In the group of companies that bear the highest tax burdens (Q1 the highest CETR value), the differences between the CETR values are visible, but the tests confirm their statistical significance only when compared with 2017. Companies with the highest tax efficiency, the lowest CETR, do not show clear trends, probably due to taxation being close to zero in this group and relatively high volatility of results.

The obtained ETR values are characterized by high variability, therefore few conclusions are confirmed with statistical significance. Median ETR for the whole sample observed in years 2019 and 2018 is the highest in the whole analyzed period. Similar relationships were observed for Q1 and Q3. This leads to the conclusion that not only did the current tax liabilities increase, but that tax burdens are also the highest after taking into account deferred tax. This means that businesses are less likely to create deferred tax assets that is, recognizing that certain items of expenses or revenues will be deductible in the future.

It is worth noting that the median CETR for 2018 is higher than 2019 both in the entire sample and in the Q1, Q2, Q3 groups. Similarly, the CETR observed for the entire sample and for the Q1 group is higher in 2018 than in 2019. Although the observed differences between 2019 and 2018 in tax efficiency measures are not statistically confirmed, the improvement in tax efficiency in 2019 compared to 2018 may indicate that enterprises are adapting to the changed law and are gradually taking steps to improve tax efficiency. Subsequent analyzes were aimed at identifying those companies for which the observed decrease in efficiency was the greatest. The analysis gives the variable Z indicating the % decrease in tax efficiency measured with CERT recorded in a given entity in 2018–2019 compared to the one recorded in 2017–2018. The results are presented in Table 5. Research has shown that the hypothesis that changes in tax efficiency in all efficiency groups are the same should be rejected. The average CERT value recorded in the years 2018–2019 in the analyzed sample was 19.4%, and in 2016–2017, i.e. before the changes to the tax law, 17.3%. The introduced changes to the tax law resulted in a decrease in the tax efficiency of companies measured by CETR by an average of 17.7%, the median of 14.8%. The statistical significance of the differences between the 2018–2019 and 2016–2017 effectiveness was confirmed statistically at every significance level. The decrease in efficiency is related to the achieved efficiency. The lower the efficiency (higher CERT), the greater the recorded changes. This relationship was statistically confirmed at $p = 0.04$.

A high variability of the observed changes in effectiveness was observed depending on the characteristics of the companies studied. Among the analyzed features, only in the case of the value of assets should one reject the null hypothesis that companies of different sizes are characterized by the same change in tax efficiency. Large companies with the highest sales, assets and capitalization recorded the greatest decrease in efficiency (increase in CETR). The level of profitability as well as debt seems to be irrelevant to the level of recorded changes in tax efficiency.

The third analyzed thesis has not been confirmed. The conducted research did not allow the rejection of the null hypothesis that the observed changes in tax efficiency are identical in groups distinguished on the basis of the auditor examining the enterprise, belonging to a holding, or conducting capital investments. Companies that had financial statements audited by the big four suffered from

fewer drops in efficiency than others. Therefore, the thesis that companies surveyed by the big four are more likely to use tax planning and are more influenced by the changed regulations is not confirmed. The data suggests, however, that the changes in regulations had a greater impact on capital groups and enterprises involved in capital investments. However, the presented results have not been sufficiently confirmed by the statistical tests and should therefore be treated as preliminary theses for verification in subsequent studies.

Table 5

Change in CETR between 2019–2018 and 2017–2016

Panel A delta CETR 2019–2018 vs 2017–2016			
Change	AVG	MED	StDev
AVG 2019–2018	19.4	17.1	23.6
AVG 2017–2016	17.3	15.7	21.8
Z (delta)	17.7	14.8	53.0

Panel B: feature analysis											
Indicators	Q1	Q2	Q3	Q4	K-W	p	Q1 vs Q2	Q1 vs Q3	Q2 vs Q4	Q2 vs Q3	Q3 vs Q4
CETR	30.3	23.5	12.7	-0.6	8.30	0.040**	*	**	*	**	–
Sales	2.8	19.6	22.9	21.3	2.27	0.516	–	–	–	–	–
EBIT	15.1	12.4	5.4	-2.5	5.77	0.122	–	–	–	–	–
Assets	13.5	13.6	7.3	34.2	8.53	0.036**	–	–	*	–	**
ROA	8.3	9.1	12.1	1.2	2.65	0.448	–	–	–	–	–
ROE	14.7	14.8	25.6	15.5	2.5	0.446	–	–	–	–	–
D/E	17.4	12.1	17.3	24.1	0.4	0.929	–	–	–	–	–
Capitalization	12.3	7.9	11.6	28.7	6.2	0.103	–	–	–	–	–

Group	YES	NO	F	p
Auditor Big4	8.9	28.9	1.184	0.277
Holding	23.0	15.2	0.487	0.486
Investment	22.1	13.4	0.9	0.344

Panel A presents descriptive statistics on the average CETR value in 2018–2019 and 2016–2017. The Z variable represents the percent change in CETR between

these periods. Panel B presents the values of the variable Z for companies with different characteristics. The values Q1, Q2, Q3, Q4 represent companies grouped in the quartiles according to the indicated characteristics such as sales, capitalization, etc. Auditor Big4 refer to companies having audited financial statements by the four largest professional services networks, Holdings companies that form capital groups, Investment companies for which capital activities. Panel B presents the results of tests indicating whether the Z values are statistically different in the analyzed groups. When comparing multiple groups, the values of the H statistic for the Kruskal-Wallis tests and the corresponding confidence level were given. For parameters with statistically significant differences between the groups, the results of the Duun tests for stochastic dominance among multiple pairwise comparisons were presented, * indicate significance of results at the level of $0.05 < p \leq 0.1$ and ** at $p < 0.05$.

When comparing two groups, the value of the F statistic and the corresponding confidence level p for the t-test were given.

5. Summary

The conducted research confirms that changes in tax law in Poland since 2017 clearly aimed at tightening the tax system and limiting tax planning practices have affected Polish companies. After a few years increase in tax efficiency indicated in the previous research (Kowalski, 2018), in 2018 and 2019 it started to decrease. Changes in tax law caused a reduction in the tax efficiency of companies. The presented research results may indicate the relationship between changes in tax law and tax efficiency and enterprises and the value of the tax burden incurred. When interpreting the results, the influence of other, not studied factors, cannot be ruled out. However, the observed dependencies may be a source of further research.

Tax efficiency for companies listed on WSE measured by ETR as well as CETR in years 2018 and 2019 was the lowest in the whole analyzed period embracing years 2012–2019. On average, the tax efficiency measured by CERT decreased in the sample in years 2018–2019 by 17,7% (median 14,8%) compared to the one observed in years 2016–2017. The decrease in efficiency is especially noticeable for companies with average tax values included in the second and third quartile of CETR.

Higher CETR values were recorded in 2018, i.e. the first year of the application of the most restrictive regulations. A small but clearly marked decrease in CETR in 2019 may mean that enterprises started to adapt to new legal regulations. Thus, the research preceded the thesis, already proven in the literature, that the change in standards triggers a reaction in the form of tax management (Famulska, 2010).

Similarly median ETR in 2019 (20,5) and 2018 (20,3) was the highest in whole analyzed period 2012–2019. Volatility ETR in the sample was much bigger than

the volatility of CERT and consequently the increase in ETR was not statistically confirmed. However, the data may suggest that changes in the law that observed change in tax efficiency is permanent, and that enterprises do not see the possibility of lowering the tax burden in the future. The propensity of enterprises to create deferred tax assets is decreasing.

At the same time, the results in the field of ETR confirm previous studies indicating a surplus of the effective tax rate over the nominal tax rate, while it should be noted that the surplus is deepening. This may indicate a further complication of the tax settlement system and an increase in the number of titles that cause permanent differences between the tax and balance sheet results (Sztuba, 2016).

The initial results suggest that large companies (classified by the first quartile of revenue, assets and capitalization) have noted the largest decreases in tax efficiency, as well as companies that exist as holding structures and those engaged in capital investment.

Undoubtedly, the preliminary research indicates that the Polish market is an interesting arena in which we can observe the clash between enterprises and authorities on a very intense scale. In this context, studies of this market can provide interesting conclusions for research on taxation, particularly in developing markets. Further research may concern the impact of individual regulations on taxation and help to find an answer to the question of which of the introduced changes to the law contribute to the decline in tax efficiency to the greatest extent. Another important question seems to be which companies have experienced drops in efficiency, as this will make it possible to assess whether the changes to the tax law act are as intended by the legislator or if they have caused a much wider impact not only aiming against multinationals and transfer taxation abroad.

The noted phenomena of changes in tax efficiency may have wide further consequences on the operating results of companies, their propensity to invest and the behavior of markets, including share prices. Although these phenomena have been extensively presented in the literature (Desai, Dharmapala, 2009; Hanlon, Slemrod, 2009; Hanlon, 2015), their observation in the conditions of such intense clash between company and ruler behavior may provide fresh, interesting conclusions.

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Summary

The article presents an analysis of changes in the tax efficiency of companies listed on the Warsaw Stock Exchange. After 2017, some changes to the tax law aimed at tightening the regulations on an unprecedented scale were introduced.
The research conducted showed that since 2018 there has been a decrease in tax efficiency measured with effective tax rate (ETR) and current effective tax rate (CETR). On average, in 2018–2019, the efficiency measured with CETR dropped by 17.7%, the median by 14.8% compared to the previous years. In 2018 and 2019, the value of the CETR was the highest in the entire analyzed period, i.e. from 2012 to 2019. At the same time, the propensity of companies to create deferred tax assets is declining, and the effective tax rate is also growing. The changes mainly concern companies with average tax efficiency, large entities forming capital groups, and companies implementing capital investments. The article presents a discussion on the observed trends and formulates directions for further research.

JEL codes: F38, H2, K34, M4

Keywords: *tax management, tax efficiency, tax policy, tightening tax policy, effective tax rate – ETR, current effective tax rate – CERT, Warsaw Stock Exchange*

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