Cluster Method Applying to Covid-19 Event Study for the Largest USA Banks

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Abstract

This paper aims to analyze how the 50 largest banks in the US were affected by the market shock generated by COVID-19. Our analysis is based on the application of clustering within the framework of event study methodology. We have formed a special set of indicators that link together the assessments before and after the shock. The indicators include the bank's total assets, the depth of the shock, the recovery rate, the K-ratio and the ESG scores. These indicators formed the basis of the attribute system for which clustering was performed. Based on the four clusters formed, patterns of banks' shock resilience were identified.

Keywords

Bank, COVID-19, financial shock, clustering, K-ratio, ESG score

1. Introduction

The shock caused by the COVID-19 pandemic had a major impact on various aspects of the global economy. This included a strong impact on the global financial market. This shock was a true "black swan" in Taleb's terminology. The share prices of many companies fell sharply and quite dramatically. At the same time, the characteristics of the decline and the dynamics of the recovery differed across sectors and segments of the stock markets. From a scientific perspective, various methods and approaches have been and are being used to study this phenomenon. The analysis of the manifestation of the impact of the shock on the financial markets COVID-19 objectively incorporates the classical event history methodology. This methodology examines the impact of an event on the financial performance of a security, such as company shares. Our study was designed according to the frameworks of this analysis.

The purpose of our paper is to investigate the specific features of the transition through this shock of large US banks. The banks have been singled out for analysis mainly because they are financial intermediaries and do not produce real output. This has been one of the underlying statements of our research interest.

The conceptual basis of our study was built by constructing a set of indicators. Changes in these indicators during the shock transition provided the basis for clustering. In one group of indicators, we have included shock deepness and recovery rate, which compare the fall and recovery of market prices. The second group includes indicators that reflect consistency and sustainability. For the first indicator we used the K-ratio, which to some extent integrates the dynamics of return and risk. The change in this K-ratio was the indicator included in the clustering. In addition, the indicator of successive changes in ESG scores was used for the banks in question. The result of the study is the distribution of the 50 largest US banks into four clusters with different characteristics.

ProfIT AI 2023: 3rd International Workshop of IT-professionals on Artificial Intelligence (ProfIT AI 2023), November 20–22, 2023, Waterloo, Canada
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The paper is structured as follows. Section 2 reviews the literature related to the topic we investigate. The main methodological aspects of our study are presented in Section 3. In particular, the design of the indicators we used for clustering is presented. Section 4 presents the results of the investigation and their visualization. The fifth section provides conclusions and discussion of the findings.

2. Literature review

Sustainability and corporate governance have become increasingly important concepts in the business world. More and more companies are recognizing the need to act responsibly towards their stakeholders and the environment. The banking industry in particular has come under increasing pressure to adopt sustainable practices and address social issues.

Trinh et al. examined the relationship between CSR (corporate social responsibility) and tail risk in the banking industry using a global sample of 244 commercial banks from 2002 to 2020 [1]. They found that there was no significant effect of CSR on tail risk before 2010, but banks with high CSR had lower tail risk after the financial crisis. This suggests that investing in CSR may help reduce tail risk during market downturns.

A study of US banks shows that ESG (environmental, social, and governance) performance activities constrain earnings management through discretionary loan loss provisions [2]. Banks with better ESG performance show lower levels of earnings management practices, suggesting that social responsibility and corporate governance commitments mitigate opportunistic behavior towards outsiders. The governance and social factors of ESG can effectively constrain banks' accounting misconduct, while the environmental pillar has no significant impact on earnings management behavior.

Chiaramonte et al. examine the impact of environmental, social, and governance scores on bank stability in the European banking sector from 2005 to 2017, particularly during crisis periods [3]. The results show that higher ESG scores reduce bank fragility, particularly in the social dimension, and that sustainability practices can act as an insurance-like risk mitigation device for banks during financial distress.

Using a time varying BVAR model, Aloui et al. analyzed the behavior of green and brown stocks in the euro area after green QE shocks [4]. They found that the effectiveness of Green QE depends on economic and financial stability and that the policy can be effective in boosting green investment in non-crisis periods. However, the authors also suggest that the policy may lose effectiveness during crises, as shown during the COVID-19 pandemic.

The impact of COVID-19 on the ESG scores of S&P 1500 companies over the period 2020-2021 is examined by Jahani et al [5]. The results show an overall increase in ESG scores, but with industry-specific variations. This is due to the unpredictable impact of the pandemic on ESG spending. The authors conclude that, given the variation in state quarantine policies and enforcement, it is unclear whether COVID-19 had a positive or negative impact on ESG scores.

There are numerous empirical studies (including those using event study methods) that analyze the shocks from Covid-19 in different countries. For example, Aslam et al. [6], Borri & Di Giorgio [7], Kozak [8], Batten et al. [9], Simoens, et al. [10] study European countries, Hevia & Neumeyer [11], Lustig et al. [12] – Latin America, Xie et al. [13], Mohammad & Khan [14] – Asia, Gao & Zhangv [15] – China, Ghosh & Saima [16] – Bangladesh, Hryhoruk et al. [17], Skrypnyk & Nehrey [18], Davydenko et al. [19] – Ukraine.

Researchers are using a variety of approaches in their study of the banking crisis, including time series analysis, regression analysis, machine learning, network analysis, and structural equation modelling.

Applying such different modern approaches to studying banking system is described in [20-26].

Taken together, these studies highlight the complex relationship between ESG, risk management and sustainability in banking.

3. Research methodology

3.1. Data

The focus on the 50 largest US banks by assets was the starting point for using the data in our study. The total assets of this sample of banks exceeded $23.5 trillion at the beginning of 2022 [27]. This asset value exceeds 77% of the assets of the entire US banking system [28]. We, therefore, considered the sample of the top 50 banks to be representative. Data for the indicators used in the clustering process were completed for 47 banks. One bank had missing market prices and we did not have access to ESG scores for two other banks. Obviously, our study does not include a large number of "not big" banks (i.e. less than 50 billion in assets). Looking at the total number of banks in the US (~4.7 thousand), this group of banks obviously has its own characteristics for clustering. At the same time, our sample is representative in terms of the coverage of bank assets in particular. It is possible to use another sampling approach which was designed at the paper of Cherniak and Kaminskyi [29].

That approach integrates together variability of some indicator (total assets volume) and numbers of units at the sample groups. This approach has been limited in our study. Because ESG scoring coverage is complete for 50 largest US banks. At the same time, coverage of the whole group of small banks is not yet complete.

Indicators based on banks' market prices were calculated using data from the resource Investing.com. The SD and RR indicators were calculated using "by the day" data. We have defined the time intervals as follows.

- Before shock period 20.08.2019 - 19.02.2020
- Shock period 20.02.2020 - 30.04.2020
- After shock period 01.05.2020 - 30.10.2020

The exact period of the shock was determined by analyzing the behavior of the S&P 500 and the S&P Banks Select Industry Index. The "Before shock" and "After shock" time intervals were determined by adding 6 months to the edges of the "Shock" period.

To calculate the K-ratio, we used weekly data within two 1.5-year intervals:

- Before shock period Aug 2018 - Jan 2020
- After shock period Jun 2020 - Nov 2021

In our opinion, weekly data over a longer period of time is a better representation of the consistency property (which is presented in the paper on the K-ratio).

For the numerical representation of sustainability, we used the ESG scores calculated by S&P Global. They included 4 score values: integral score and scores by components E, S, G. ESG scores for the years 2018, 2020, and 2022 were used.

The choice of S&P Global as the ESG scoring system was made in comparison to the Refinitiv ESG scoring system. Refinitiv system provides a more detailed scoring presentation with 9 sub-scores. However, we have chosen S&P Global scores. Reason was because we used S&P Banks Select Industry Index and we wanted to have researches data from one provider.

Passing across shock directly: SD-RR correspondence.

We have created a pair (SD; RR) as an indicator that directly describes the passage of the shock. SD represents shock deepness and is a modification of the classical return. The modification of the return consists in transforming the price on a given day into an average value.

$$SD = \frac{Average\ price\ throughout\ period\ "shock"}{Average\ price\ throughout\ period\ \ "before\ shock")} - 1 \quad (1)$$

The idea behind averaging is to "smooth out" random daily/weekly deviations. Typically, prices throughout shocks are quite volatile and can demonstrate high changes even during the day. Price "jitter" is also often observed on the eve of shocks. Of course, the choice of the smoothing period is an important issue. A short period will produce an exaggerated distortion due to random fluctuations. Too long a period can lead to distortions due to the presence of a long-term trend before or after the shock. We have chosen a period of 6 months, as can be seen in section 3.1.

The RR indicator shows the ratio between the average price during the period "After shock" and for smoothed price during the period "Before shock".

$$RR = \frac{Average\ price\ at\ the\ priod\ after\ shock)}{Average\ price\ before\ shock} \qquad (2)$$

The economic nature of the indicators is slightly different. SD has a 'classical return' nature. RR is more focused on the comparison with the price before the shock. This difference is because we compare changes with periods "before the shock". SD corresponds to the "sequence" periods, but RR with periods that separates the shock falling.

Our previous research [30] showed that typically the relationship tends to linear form. The slope of such a trend can be considered as a parameter of clustering (more precisely, as a deviation from it). The examined case shows R^2=0.59 and we have included both indicators in the clustering procedure.

3.2. K-ratio changing after shock

One of the methodological aspects we have used is the inclusion of a K-ratio into the clustering procedures. The K-ratio is a statistical indicator that estimates the increasing/decreasing in value of an investment over the entire time horizon in question. The K-Ratio was developed by Lars Kestner in 1996. There were some upgrades of it in 2003 and 2013 years [31]. We used the 2003-year upgrade of K-Ratio. Generally, it is of no importance for the clustering, because all three K-ratios are perfectly correlated.

K-ratios are estimated on the basis of the so-called Value-Added Time Interval Index (VATII). This index is applied to the time interval [0, T] for some investments. This interval is divided into a number of equal intervals in which investment returns are calculated.

The formal construction of the VATII is as follows:

$$VATII = 1000 \cdot \left(1 + r_{0,1}\right) \cdot \ldots \cdot \left(1 + r_{T-1,T}\right), \qquad (3)$$

where $r_{t-1,t}$ denotes return for the time interval $[t-1; t]$.

The K-ratio formula is then applied to the regression results for VATII. The standard error of the slope indicates the risk, while the slope indicates the return.

We have included the difference in K-ratio values before and after the shock as a parameter in the clustering procedure. It should be noted that the K-ratio is obviously not a linear function. However, the gain indicates whether the change due to the shock is positive or negative.

3.3. ESG scores changing

In recent years, Environmental, Social, and Governance (ESG) criteria have become key factors in business development. Their implementation is closely linked to the concept of sustainability. One of the current questions concerns the influence of ESG criteria implementation on risk-return correspondence. In our study, this question is focused on the transition through the COVID -19 shock. As a parameter, we considered the change in ESG scores from 2018 to 2020:

$$\Delta ESG = 0{,}5 \cdot (ESG_{2020} - ESG_{2018}) + 0{,}5 \cdot (ESG_{2022} - ESG_{2020}) \qquad (4)$$

Such an approach combines the changes before and after the shock with equal weights. Methodologically it can be extended to use both changes in clustering. Or use different weights instead of 0.5.

3.4. Clustering

We have created the following attributes for the application of clustering procedures.

$$(TA; SD; RR;\ \Delta K - ratio;\ \Delta ESG) \qquad (5)$$

where TA - is an indicator of the Total Assets of banks. The other attributes have been defined above.

The correlation analysis applied to the considered sample of 47 banks showed the following results (Table 1).

Table 1
Correlation analysis

Correlation	TA	SD	RR	ΔK-ratio	ΔESG
TA	1,000	0,158	0,039	-0,131	-0,396
SD		1,000	0,770	0,179	0,009
RR			1,000	0,397	-0,137
ΔK-ratio				1,000	-0,189
ΔESG					1,000

The correlation matrix demonstrates absent or very low correlations between attributes. This mean that formed attributes estimates bank from "uncorrelated" indicators.

It was applied K-means method of clustering. K-means has the advantage that has a linear complexity of O(n). This is because all we are really doing is calculating the distances between the points and centers.

From other point of view, K-means has a couple of disadvantages. First, it is necessary to choose the number of clusters. This is not always trivial since the point is to get some insight into the data. K-means also starts with an arbitrary choice of cluster centers and therefore may produce different clustering results on different runs of the algorithm.

4. Results and discussion

An initial visualization of the shock path of the S&P Banks Select Industry Index and the S&P 500 is shown in Figure 1. For comparison purposes, the indices have been normalized to 1,000 at the beginning of 2019. The S&P Banks Select Industry Index comprises stocks in the S&P Total Market Index that are classified in the GICS Asset Management & Custody Banks, Diversified Banks, Regional Banks, Other Diversified Financial Services, and Thrifts & Mortgage Banks sub-industries.

Figure 1: Comparable dynamics of normalized (by Jan 2019) indices S&P500 and S&P banks Select Industry Index

The figure shows the difference between the shock experienced by the banking sector and the companies included in the S&P 500. Visually, the difference can be characterized by the fact that the S&P500 shows a V-type, while the S&P Banks Select Industry index tends to be W-type [32].

The first result concerns the estimation of the pair (SD; RR). The values of this pair are shown in Figure 2. There is a pattern of "greater decline - less recovery". Using a linear trend shows an angular dependence coefficient of 1.09. However, the linear relationship is not very strong (based on R^2).

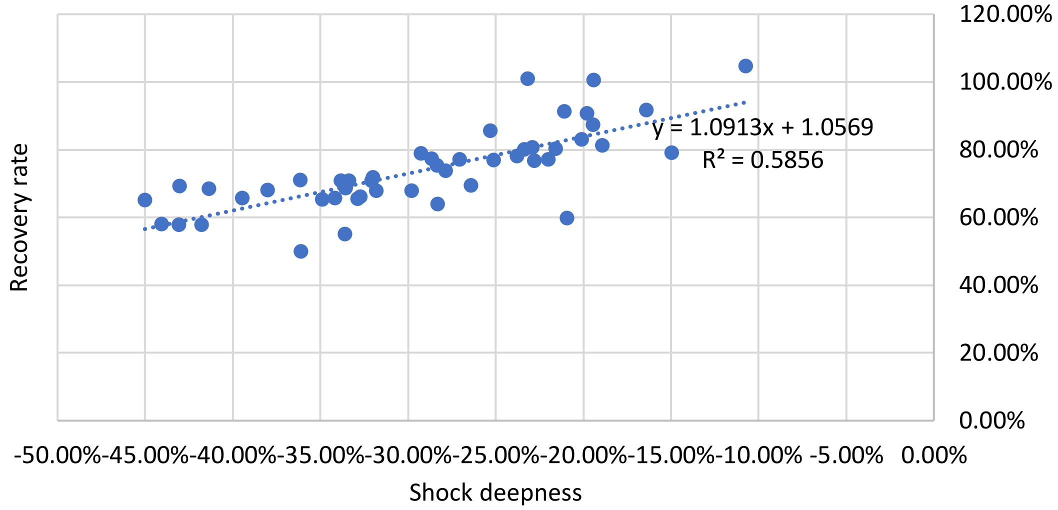

Figure 2: Interdependency between SD and RR

Consideration of the K-ratios before and after the shock initially shows a sharp increase in the K-ratios after the shock. The chart in Figure 3 shows a shift of the K-ratio distribution to the right. All bank stocks have higher K-ratios after the shock than before the shock. In fact, all increases were positive.

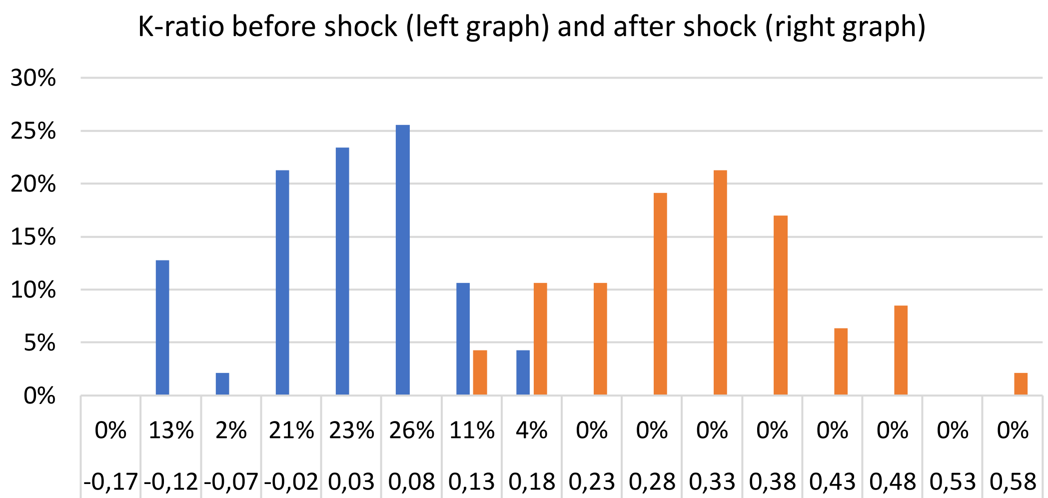

Figure 3: Distribution of K-ratio values before shock and after shock

An examination of the changes in ESG scores reveals the multidirectional nature of the changes (Figure 4). This is evident in the economic explanation of cluster characteristics.

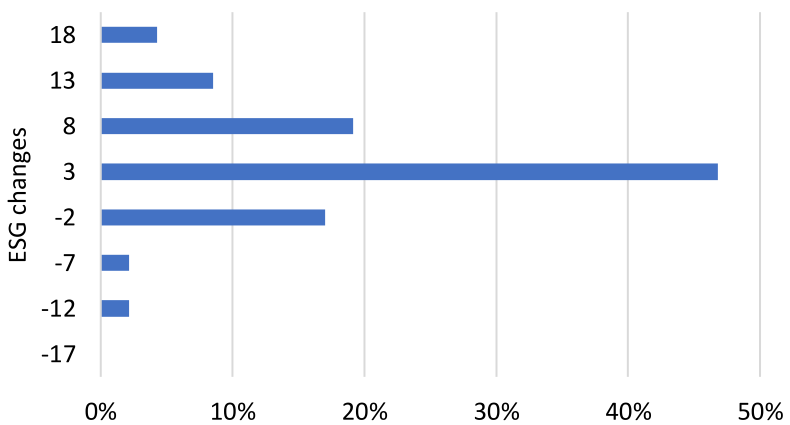

Figure 4: ESG scores changes

In the application of the clustering procedure, options from 2 to 7 clusters have been used. As a result, we believe that clustering with 4 clusters provides the most transparent economic explanation. The distribution of clusters is shown in Table 2.

Table 2
Clustering results

Cluster 1	Cluster 2	Cluster 3	Cluster 4
JPMorgan Chase & Co (JPM)	U.S.Bancorp	Goldman Sachs Group Inc	Well Fargo & Co
Bank of America Corp (BAC	Truist Financial Corp	Morgan Stanley	PNC Financial Services Group Inc.
Citigroup Inc	HSBC North America Holdings Inc.	Charles Schwab Corp	Capital One Financial Corp.
	Citizens Financial Group Inc.	TD Group US Holdings LLC	KeyCorp
	M&T Bank Corp.	Bank of New York Mellon Corp.	Santander Holdings USA Inc.
	Fifth Third Bancorp	State Street Corp.	Discover Financial Services
	Ally Financial Inc.	BMO Financial Corp	Zions Bancorp. NA
	Huntington Bancshares Inc.	SVB Financial Group	Comerica Inc.
	Regions Financial Corp.	UBS Americas Holding LLC	Webster FINANCIAL Corp
	First Citizens BancShares Inc.	American Express Co.	Western Alliance Bancorp.
	Synchrony Financial	First Republic Bank	Synovus Financial Corp.
	New York Community Bancorp	RBC US Group Holdings LLC	Wintrust Financial Corp.
	Popular Inc.	Northern Trust Corp.	
	Valley NATIONAL Bancorp.	Signature Bank	
	Cadence Bank	Raymond James Financial Inc	
		CIBC Bancorp USA Inc.	
		East WestBancorp Inc.	

Table 3 shows the characteristics of the clusters obtained in terms of the mean values of the parameters. The values of the E, S and G scores in 2022 are also included for completeness analysis.

Table 3
Means of cluster attributes and E, S and G in 2022

	TA	SD	RR	ΔK-ratio	ΔESG	E	S	G
Cluster 1	3195,67	-0,27	0,73	0,18	-9,83	48	44	50
Cluster 2	207,57	-0,31	0,70	0,19	6,33	27	32	43
Cluster 3	393,56	-0,22	0,86	0,38	0,44	42	43	51
Cluster 4	314,19	-0,37	0,63	0,31	-0,08	23	30	40

5. Conclusions

From the analysis performed, we conclude that the chosen attributes and clustering method allow a transparent division into 4 clusters. The first cluster comprises the three banks with the largest assets by 2022. However, the banks in this cluster lose an average of 10 ESG score when they pass the shock. This is significant changes. However, it should be noted that the banks in this cluster have, on average, the highest scores across all components: E, S, G.

Clusters 2, 3 and 4 have a market capitalization below the sample average (which is around $493 billion). However, the banks in Cluster 2 showed an increase in ESG scores and had the lowest average TA score. It is the only cluster to show such an effect. At the same time, its current E, S and G scores are still quite low.

Cluster 3 differs from the others in that it has a low average SD and a high average RR. This means that the shares of these banks fell the least and had a (relatively) high rate of recovery to pre-crisis levels. Moreover, the increase in the K-ratio of the banks in this cluster is two times higher than in clusters 1 and 2. It should be noted that in cluster 3 the values of E, S, G are significantly higher than in clusters 2 and 4.

Cluster 4 is characterized by the largest drop (maximum SD value across clusters) and the smallest recovery rate. When compared to the average E, S and G scores, it appears to be the lowest in this cluster.

In general, the following conclusions can be drawn. The results of the clustering on the basis of the suggested attributes are in line with certain patterns. In particular in relation to the E, S, G scoring values. Looking at clusters 2,3,4, we see that the scoring order correlates negatively with the level of SD and positively with RR. To some extent this interrelate well with the notion of sustainability. However, it should be noted that these clusters are similar in terms of TA value. Where there is a significant difference in asset size (as in cluster 1), this may be different.

The changes in ESG scores are interesting. Large banks in Cluster 1 had relatively high scores. During the shock, it was difficult for them to adjust. The "S" and "G" scores were "hit". A very interesting influence of the ESG factor on "average" banks (clusters 3 and 4). The E, S and G scores are higher in cluster 3 than in cluster 4. Banks in cluster 3 show a better correspondence between SD and RR. It is also interesting to note that small banks from cluster 2 had a better match of SD and RR than the banks from cluster 4. Our explanation is that these banks started to actively deal with E, S, G. Thus, the worst ratio of SD and RR showed banks from 4 clusters that had the lowest values of E, S and G scores and did not improve them. This confirms the importance of E, S and G factors for sustainability.

One point of discussion in our study is that clustering is only performed for the 50 largest banks. One hypothesis is that homogeneity patterns vary across groups with different asset sizes. A possible solution could be to divide the banks into several groups (e.g., 4-6) according to asset size. And perform clustering in each of the groups separately. This could make the patterns associated with the level of ESG scoring more visible.

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