Quantifying the Impact of Sustainable Practices on Business Operations

Ilknur Ozturk[1,*], Festus Victor Bekun[2]
[1]Faculty of Economics, Administrative and Social Sciences, Nisantasi University, Istanbul, Turkey
[2]Istanbul Gelisim University, Turkey
Emails: ilknur.ozturk@nisantasi.edu.tr; fbekun@gelisim.edu.tr

Abstract

Based on the business context, resilience and sustainability seem to have multiple dimensions and connections. Administrative sustainability strategies can help a company develop and become more resilient. With the use of a sustainability maturation index (SMI), this study attempts to analyze how the financial success of a business is affected by its approach to sustainable development. As resilience abilities are closely linked to the SMI, this study proposes to explore the initial integration of both sustainable development and resilience criteria into a single framework. To determine whether there could be an interaction between the SMI and economic performance indices, planned conversations were used to gather data from 35 different firms. The investigation disproves widely circulated claims, demonstrating that there is no meaningful correlation between profitability and sustained business operations. It's noteworthy to point out that market emphasis, organizational size, and firm place of origin do not significantly correlate with SMI. One could argue that to evaluate the effects of environmentally friendly procedures, a company's multi-dimensional performance, which includes both financial and non-financial measurements, should be considered. In addition, more research is required to identify the nonfinancial metrics of success that businesses use to measure resilience and sustainable development to create a cohesive framework that facilitates trade-off evaluation.

Keywords: Sustainability; Business Intelligence; Business Management; Data Analytics; E-commerce.

1. Introduction

The concepts of resilient and sustainable development have many facets and are described differently according to the underlying business operation [1-3]. Sustainable development, in general, is concerned with minimizing adverse effects on the surroundings, both environmental and commercial; resilience, on the other hand, refers to adaptability and recuperation from enforced alteration [4]. According to the literary works, the two ideas are related since they have comparable objectives and certain common methods, even though their relationship might go from seeing them as equivalents to seeing them as separate ideas [3-5]. There are trade-offs between sustainable development and resilience at low levels, which should be examined, and a shared framework developed [4-6]. Sustainable is viewed as an important aspect of resilience in the domains of supply chain administration and company management, meaning that enhancing system integrity increases resilience within the system [6].

The intersection of sustainable practices and business applications has emerged as a key focus at a time of unprecedented global challenges The need to address environmental problems, livelihoods internal welfare and economic development has led to the integration of sustainable development into key organizational processes. At its heart, sustainability encompasses a multifaceted behavior that goes beyond just environmental considerations. It encompasses a wide range of values, combining environmental stewardship with social equity and economic resilience. Companies today take on a complex terrain where profit drives accountability, and success is measured not just by financial returns but by a holistic approach to stakeholders, communities, and the planet. The experimental outcomes of this work demonstrated that the sustainability practices undeniably relate to business. As global consciousness amplifies and consumer preferences pivot towards ethical consumption, companies are compelled to recalibrate their operational paradigms. This shift is not merely a trend; it's a seismic transformation in organizational ethos. Through rigorous analysis and

DOI: https://doi.org/10.54216/AJBOR.110107
Received: June 12, 2023 Revised: October 22, 2023 Accepted: December 08, 2023

synthesis of available data, this paper aims to quantify the ripple effects of sustainable practices, elucidating how they resonate throughout the operational echelons of businesses, influencing decision-making, supply chains, market positioning, and overall resilience. However, amidst the compelling narratives of success, there exist intricate challenges and inherent complexities. Implementing sustainable practices within business frameworks is not devoid of hurdles. Financial considerations, technological adaptations, stakeholder engagement, and regulatory compliance form a complex web that businesses must navigate. This paper recognizes and addresses these challenges, offering a balanced view that acknowledges both the strides made and the hurdles yet to be surmounted in the pursuit of integrating sustainability seamlessly into business operations. The remainder of this work is structured as summarized in Figure 1.

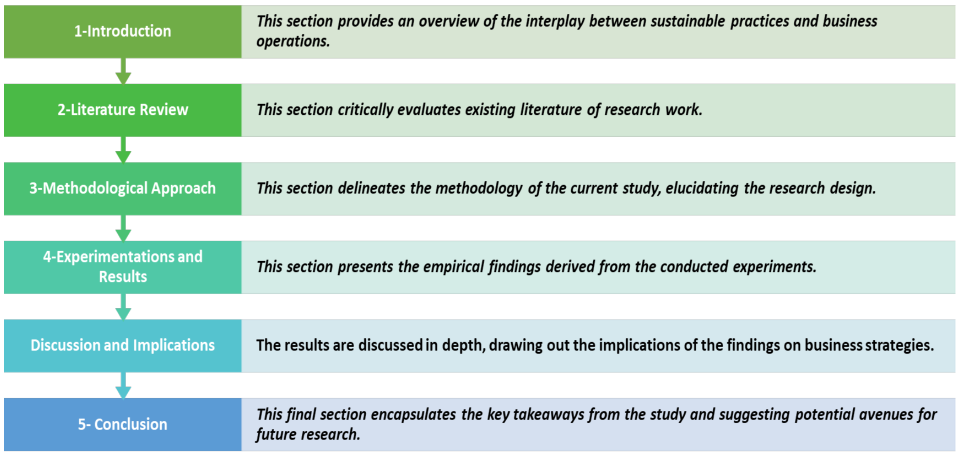

Figure 1: Organization of the paper

2. Literature review

In this section, we provide an in-depth investigation of the literature study with emphasis on those exploring the suitability impact on business operations. For example, Xiaoli et al. [11] studied the role of risk-related big data analytics in improving risk management. In addition, Lam [12] explored the evolution from incentivizing approaches to control apparatuses for improving risk analysis in organizations. In a broad review, Andriosopoulos et al. [13] studied the role of computational approaches and data analytics in financial services. Lemieux [14] discussed the critical role of records and information management in financial analysis and risk management, highlighting critical tasks for effective data governance and social applications Required links between big between data analysis, absorptive capacity, and sustainable supply chain innovation. Rodriguez and Da Cunha [15] proposed a conceptual framework, which sheds light on the use of data analysis for a sustainable supply chain as well as Mashrur et al. [16] carried out a study on machine learning applications for managing financial risks and identified machine learning methods related to risk assessment in a financial context. Furthermore, Saeed [17] presented a classification framework for financial risk management through data mining techniques, proposing a structured approach to classify and manage financial risks. Furthermore, Samuel [18] examined machine learning using information token capabilities for electronic marketplaces, highlighting its impact on behavioral, economic, and big data analysis in information systems and technology management. Chakraborty [19] examined the evolving financial risk management process in the age of digitization, anticipates a paradigm shift in risk management approaches during technological advances. Finally, De Conti et al. [20] introduced a dynamic fractal asset pricing framework for financial risk assessment, resulting in a novel method for analyzing financial risk in an evolving market capitalization environment.

3. Methodological Approach

This section delineates the comprehensive framework employed to ascertain empirical evidence. Drawing inspiration from established methodologies and innovative approaches prevalent in the realm of interdisciplinary research, this study amalgamates quantitative analysis with qualitative insights to traverse the multifaceted landscape of sustainable business operations. Conversations were carried out at the headquarters of 35 organizations during a three-year period, from February 2018 to September 2020. Directors and managers were also given the surveys because they are important players in the development of sustainability. In writing, every company consented to participate in this study provided that their privacy could be ensured. Apart from the questionnaires, qualitative data was also documented for every business, as the subject of operational resilience sparked extensive conversation during the panel discussions, which

DOI: https://doi.org/10.54216/AJBOR.110107
Received: June 12, 2023 Revised: October 22, 2023 Accepted: December 08, 2023

frequently lasted multiple hours. The 35 businesses are spread throughout seven SIC sector classifications and are situated in different countries, where their resumes are displayed in Table 1. The organizations vary in terms of economic achievement, market emphasis, and asset size, as Table 1 shows. Furthermore, their geographical distribution permits meta-analysis by nation, SIC, and stage of industrialization. The present phase of data collection is representative of the study's early stages; the organizations and countries of origin were chosen in an easy and random manner.

Table 1: the summaries of the 35 businesses that were part in this research.

#No.	Country	Employees	Operational Income ($)	Net Space	EBT	ROA (%)	ROE (%)
1	AUS	41,876	7952	21.64088	35.62199	-0.13926	12.74157
2	GBR	24,574	2444	26.3622	33.74177	-2.37591	14.37849
3	AUS	952	224	11.82579	16.2011	6.561508	13.28695
4	AUS	1601	177	17.54829	37.37861	8.611247	16.47978
5	AUS	36	23	25.81797	20.20119	6.783939	14.64037
6	JAM	2584	516	20.60323	27.72263	5.3707	15.60722
7	JAM	1934	59.67	3.596013	6.3466	6.543699	9.002578
8	JAM	323	30.37	16.33563	23.75956	24.98879	23.56332
9	JAM	42	2.83	7.486131	5.981576	7.030896	7.857068
10	JAM	2267	132.73	21.62148	25.60065	3.315688	18.18966
11	JAM	274	19.31	12.8835	11.24849	3.327837	9.873451
12	GBR	1524	59	-0.27824	42.87031	3.078969	-1.11266
13	GBR	188	16.12	6.529846	6.158523	10.91917	15.45828
14	GBR	229	-0.25	-66.8407	-72.2394	-44.692	-83.5125
15	GBR	361	2.36	-1.34396	-0.01379	-1.49073	0.275255
16	MHL	577	8.25	19.59078	22.93714	10.81123	20.75378
17	MHL	31	-0.745	7.405356	13.86771	89.72161	14.99891
18	MHL	47	-2.554	13.38394	13.96262	12.56389	14.29514
19	MHL	100	11.34	52.85468	7.930246	91.7848	60.93423
20	ITA	47	5.216	2.1318	7.728862	4.877577	1.720113
21	KIR	3	-1.9158	3.008447	0.561813	4.434946	2.145503
22	KIR	267	20.44	13.38338	29.55009	2.148843	9.458233
23	TUV	35	7.4	3.589671	6.452676	9.395174	9.976875
24	TUV	26	1.42	6.566196	10.08581	10.67039	5.33714
25	GBR	181	12.01	7.141511	7.832639	11.79526	19.24509
26	GBR	1342	46.5	3.415072	38.97437	2.748304	2.417681
27	GBR	45	2.2	11.44914	13.49921	11.82399	15.86321
28	ITA	3	-4.79348	2.35204	2.988542	-1.13909	4.385747
29	AUS	1101	5.93	26.35725	22.2529	2.781067	9.403597
30	AUS	107	9.2	36.63133	13.25634	27.75903	17.93603
31	AUS	70	-1.3	13.21007	2.572075	3.145586	7.984069
32	AUS	141	12.8	0.016885	2.768223	1.111485	4.565224
33	AUS	161	6.2	-0.11463	6.494151	2.802967	2.557374
34	AUS	87	-1.3	5.809304	2.147095	1.937835	0.542293
35	AUS	35	5.9	-1.76155	-1.17609	-0.69018	-0.7532

Asymmetric loss linear regression (ALLR)operates on the fundamental principle that not all prediction errors hold equal weight. Traditional linear regression assumes symmetrical loss functions, treating overestimation and underestimation errors equally. However, in practical scenarios such as evaluating sustainability impacts on business operations, asymmetrical consequences often accompany over or underestimation. This regression method incorporates asymmetric loss functions, assigning different penalties to overestimation and underestimation errors. By assigning greater weight to one type of error over the other, this approach aligns more closely with the real-world implications of misestimation in sustainability assessments within business frameworks (refer to Algorithm 1).

In our study, asymmetric loss linear regression serves as a pivotal tool for quantifying the influence of sustainability indices on various facets of business operations. The choice of this methodology reflects the nuanced nature of sustainability impacts, where overestimating or underestimating these impacts can yield disparate outcomes for

DOI: https://doi.org/10.54216/AJBOR.110107
Received: June 12, 2023 Revised: October 22, 2023 Accepted: December 08, 2023

businesses. By applying asymmetric loss linear regression to our dataset comprising sustainability indices and corresponding operational metrics, we aim to capture and quantify the asymmetric effects of sustainability on business performance. Our implementation of asymmetric loss linear regression involves a two-pronged approach: first, identifying and weighting the significance of sustainability indices based on industry-specific relevance and impact, and second, modeling the relationship between these indices and key operational parameters using asymmetric loss functions. By accounting for the asymmetric nature of potential gains or losses arising from sustainability initiatives, this method enables a more nuanced understanding of how different sustainability indices impact various aspects of business operations.

Algorithm Asymmetric loss linear regression (ALLR)

Inputs: Training data D, number of epochs e, learning rate η, standard deviation σ

Confirm: Weights $w_0, w_1, \dots w_k$

1: Set initial weights $w_0, w_1, \dots w_k$ according to normal distribution
2: For epoch in $1 \dots e$ do
3: For each $(x, y) \in D$ in random order do
4: $\hat{y} \leftarrow w_0 + \sum_{i=1}^{k} w_i x_i$
5: if $(\hat{y} > 1$ and $y = 1)$ or $(\hat{y} < -1$ and $y = -1)$ then
6: continue
7: $w_0 \leftarrow w_0 - \eta 2(\hat{y} - y)$
8: For i in $1 \dots k$ do
9: $w_i \leftarrow w_i - \eta 2(\hat{y} - y) x_i$
10: End for
11: End for
12: End For
13: return $w_0, w_1, \dots, w_k$

4. Experimentations and Results

This volume acts as the empirical focus of this research, reflecting the results of careful research into the impact of sustainable practices on contemporary business.

Eight elements, including SIC categorization, and five sustainability indexes were produced through structured conversations and surveys. Net margin, operating income, employees, and country. Return on Equity (ROE), Return on Assets (ROA), and EBT. The SMI index is displayed together with the five sustainability indexes in Table 2.

Table 2: data that has been obtained for SMI and the five operational sustainability areas.

Total CS	Total HC	Total NC	Total EC	Total SC	SMI Total
158	77	56	97	39	427
157	89	59	105	34	444
111	72	40	74	24	321
74	52	22	54	13	215
92	60	28	69	20	269
75	54	20	69	13	231
119	71	35	80	19	324
50	30	16	48	10	154
47	32	17	44	9	149
159	93	56	104	36	448
148	88	58	106	27	427
114	69	46	81	31	341
154	89	58	108	33	442
163	94	57	106	38	458
135	75	40	80	33	363
144	84	51	89	36	404
140	84	49	77	21	371

DOI: https://doi.org/10.54216/AJBOR.110107
Received: June 12, 2023 Revised: October 22, 2023 Accepted: December 08, 2023

120	90	57	95	16	378
154	91	58	92	31	426
51	60	24	65	15	215
73	45	23	67	15	223
77	43	17	62	18	217
74	41	21	77	12	225
69	50	23	66	15	223
69	45	25	62	15	216
143	93	54	105	34	429
131	80	58	101	33	403
131	75	56	90	40	392
148	94	57	105	41	445
137	87	48	89	27	388
121	75	48	80	34	358
101	40	38	38	16	233
70	47	18	55	13	203
134	89	45	93	32	393
159	89	56	93	39	436

5. Discussion and implications

This section serves as an interpretive site, classifying, comparing, and assessing empirical findings and their broader implications in a complex tapestry of sustainable business practices and business improvement from which insights are constructed empirically expressed on the previous verse.

Given the large number of important events and the challenge in determining which ones were true outliers, the following situations were tested. First, On the initial database, ALLR. Second, the database's ALLR sans the significant spots. Third, On an initial database, robust ALLR. Table 3 shows the ALLR findings for the initial dataset, whereas Table 4 shows the ALLR outcomes for the dataset lacking the important spots. While the t-test uniformity constraints were broken in both situations, the slopes were never statistically distant from 0 and revealed a lack of relationship between the normalized maturity index and financial results and staff members, accordingly. Table 5 suggests alternate robust ALLR outcomes, a bisquare-weighting operation, and no interdependence.

Table 3: Quantitative results of ALLR on the raw data.

Feature	**Operational income**		**Net margin**		**EBT**		**ROA**		**ROE**		**Staffs**	
Parameter	β_0	β_1	β_0	β_1	β_0	β_1	β_0	β_1	β_0	β_1	β_0	β_1
Estimate	2.937	-0.211	1.206	19.033	3.918	18.065	-8.753	26.592	-7.406	24.688	4.877	1.269
Squared Error	1.626	2.067	9.588	13.891	10.103	14.652	10.811	15.731	10.078	14.568	1.201	1.554
t-Statistic	2.168	0.005	0.163	1.496	0.393	1.480	-0.774	1.718	-0.694	1.790	4.677	0.851
p-Value	0.033	1.029	0.968	0.249	0.725	0.337	0.471	0.165	0.682	0.109	0.021	0.534

Table 4: Quantitative results of ALLR on the raw data after removing dominant data elements.

Feature	**Operational income**		**Net margin**		**EBT**		**ROA**		**ROE**		**Staffs**	
Parameter	β_0	β_1	β_0	β_1	β_0	β_1	β_0	β_1	β_0	β_1	β_0	β_1
Estimate	3.201	-0.085	1.442	18.973	3.912	18.041	-8.625	26.448	-7.328	24.830	4.886	1.246
Squared Error	1.693	2.037	9.688	13.771	10.146	14.596	10.948	15.598	10.057	14.625	1.214	1.596
t-Statistic	2.155	0.058	0.298	1.690	0.707	1.475	-0.731	1.959	-0.732	1.782	4.784	0.922

DOI: https://doi.org/10.54216/AJBOR.110107
Received: June 12, 2023 Revised: October 22, 2023 Accepted: December 08, 2023

p-Value	0.305	1.077	0.973	0.376	1.022	0.348	0.656	0.123	0.555	0.340	0.270	0.456

Table 5: Quantitative results of robust ALLR on the raw data.

Feature	**Operational income**		**Net margin**		**EBT**		**ROA**		**ROE**		**Staffs**	
Parameter	β_0	β_1	β_0	β_1	β_0	β_1	β_0	β_1	β_0	β_1	β_0	β_1
Estimate	2.963	-0.248	1.295	18.987	3.960	18.067	-8.727	26.468	-7.367	24.701	4.712	1.264
Squared Error	1.513	2.048	9.568	13.888	10.201	14.577	10.993	15.611	10.169	14.441	1.106	1.652
t-Statistic	2.162	0.004	0.234	1.504	0.442	1.389	-0.768	1.726	-0.749	1.832	4.510	0.890
p-Value	0.073	1.057	1.058	0.299	0.893	0.365	0.448	0.267	0.483	0.119	0.164	0.491

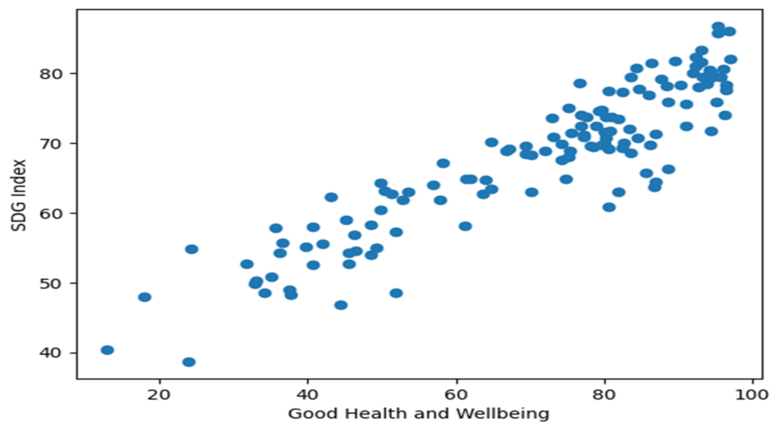

Figure 2: visualization of predictions from ALLR

The regression on the initial dataset is offered as an idealistic situation, in which all probable anomalies are retained, perhaps resulting in misleading relationships. The regression on the initial dataset excluding significant spots is offered as a conservative situation, in which any possible anomalies have been eliminated and the slope of the regression becomes less obvious. As a middle situation, robust linear regression is presented; the robust design appropriately weights any outliers. To determine which model slopes were substantially distinct from zero, a t-test was done for every case and regression. The findings revealed that the linear framework assumption was incorrect. Furthermore, we visualize the prediction of ALLR for sustainability index.

6. Concluding Remarks

This research investigation depends on a data collection that is still being developed and includes 35 firms that varied in financial size, market emphasis, profitability, and geographical locations, with main emphasis on the choice of companies and nation in a random fashion. It generates a sustainable maturity index by constructing a model of operational sustainability competence. The ALLR approach, generalizability, and rigor were initially tested in financial services businesses in advanced as well as developing nations. The statistical analysis conducted contradicts commonly accepted contentions: we demonstrate that prosperity has no meaningful association with long-term strategic aim. As a result, while we demonstrated that our model is suitable for resilient aims, we cannot assume that an organization's resilience characteristics affect the competitiveness of businesses.

References

[1] Kim, A., Yang, Y., Lessmann, S., Ma, T., Sung, M. C., & Johnson, J. E. (2020). Can deep learning predict risky retail investors? A case study in financial risk behavior forecasting. *European Journal of Operational Research*, *283*(1), 217-234.

DOI: https://doi.org/10.54216/AJBOR.110107
Received: June 12, 2023 Revised: October 22, 2023 Accepted: December 08, 2023

[2] Bahrami, M., & Shokouhyar, S. (2022). The role of big data analytics capabilities in bolstering supply chain resilience and firm performance: a dynamic capability view. *Information Technology & People*, *35*(5), 1621-1651.

[3] Phan, D. T., & Trang Tran, L. Q. (2022). Building a Conceptual Framework for Using Big Data Analytics in the Banking Sector.

[4] Zhu, X., & Yang, Y. (2021). Big data analytics for improving financial performance and sustainability. *Journal of Systems Science and Information*, *9*(2), 175-191.

[5] Rasmussen, J. (1997). Risk management in a dynamic society: a modelling problem. *Safety science*, *27*(2-3), 183-213.

[6] Clintworth, M., Lyridis, D., & Boulougouris, E. (2021). Financial risk assessment in shipping: a holistic machine learning based methodology. *Maritime Economics & Logistics*, 1-32.

[7] Dicuonzo, G., Galeone, G., Zappimbulso, E., & Dell'Atti, V. (2019). Risk management 4.0: The role of big data analytics in the bank sector. *International Journal of Economics and Financial Issues*, *9*(6), 40-47.

[8] Shih, D. H., Hsu, H. L., & Shih, P. Y. (2019, April). A study of early warning system in volume burst risk assessment of stock with Big Data platform. In *2019 IEEE 4th international conference on cloud computing and big data analysis (ICCCBDA)* (pp. 244-248). IEEE.

[9] Haile, I. M. (2020). *Data Analytics in Financial Institutions: How Text Analytics Can Help in Risk Management* (Doctoral dissertation, Colorado Technical University).

[10] Kothandapani, H. P. (2023). Applications of Robotic Process Automation in Quantitative Risk Assessment in Financial Institutions. *International Journal of Business Intelligence and Big Data Analytics*, *6*(1), 40-52.

[11] Xiaoli, W., & Nong, N. B. (2021). Evaluating Big Data Strategies for Risk Management in Financial Institutions. *Journal of Computational Social Dynamics*, *6*(3), 34-45.

[12] Lam, J. (2014). *Enterprise risk management: from incentives to controls*. John Wiley & Sons.

[13] Andriosopoulos, D., Doumpos, M., Pardalos, P. M., & Zopounidis, C. (2019). Computational approaches and data analytics in financial services: A literature review. *Journal of the Operational Research Society*, *70*(10), 1581-1599.

[14] Lemieux, V. L. (2012). Records and information management for financial analysis and risk management: An introduction. In *Financial analysis and risk management: Data governance, analytics and life cycle management* (pp. 1-13). Berlin, Heidelberg: Springer Berlin Heidelberg.

[15] Rodriguez, L., & Da Cunha, C. (2018). Impacts of big data analytics and absorptive capacity on sustainable supply chain innovation: A conceptual framework. *LogForum*, *14*(2), 151-161.

[16] Mashrur, A., Luo, W., Zaidi, N. A., & Robles-Kelly, A. (2020). Machine learning for financial risk management: a survey. *IEEE Access*, *8*, 203203-203223.

[17] Saeed, T. (2020). The Application of Data Mining Techniques for Financial Risk Management: A classification framework. *IJCSNS*, *20*(8), 84.

[18] Samuel, J. (2017). Information token driven machine learning for electronic markets: Performance effects in behavioral financial big data analytics. *JISTEM-Journal of Information Systems and Technology Management*, *14*, 371-383.

[19] Chakraborty, G. (2020). Evolving profiles of financial risk management in the era of digitization: The tomorrow that began in the past. *Journal of Public Affairs*, *20*(2), e2034.

[20] de Conti, B., Gisin, V., & Yarygina, I. (2021). Dynamic Fractal Asset Pricing Model for Financial Risk Evaluation. In *Risk Assessment and Financial Regulation in Emerging Markets' Banking: Trends and Prospects* (pp. 355-367). Cham: Springer International Publishing.

DOI: https://doi.org/10.54216/AJBOR.110107

Received: June 12, 2023 Revised: October 22, 2023 Accepted: December 08, 2023