What do you think about those COVID-19 measures? On the extremity and uncertainty of attitudes in business research

Jana Stoklasová[1], Jan Stoklasa*[1,2]

[1]LUT University, School of Business and Management, Lappeenranta, Finland
[2] Palacký University Olomouc, Faculty of Arts, Department of Economic and Managerial Studies, Olomouc, Czech Republic

Abstract: In the paper we explore the link between the extremity of answers provided during the assessment of a specific concept using the semantic differential-type scales and their uncertainty. We investigate whether a more polarized attitude (operationalized by the relative share of extreme scale values in the set of semantic differential scale answers) is linked with less uncertainty present in the answers. The research further extends the applicability of semantic differential in economic and business research. Semantic differential is currently being reintroduced into economic research in the field of strategic management research, risk management, multiple-criteria evaluation and related fields. This paper returns back to the original use of semantic differential, applies its two-scale alternative proposed for the interval-valued semantic differential tool on the assessment of COVID-19 related measures and investigates whether polarization of attitudes seems to result in lower perceived uncertainty of the evaluations being provided. The fsQCA methodology is applied to analyze the data and to see whether polarized attitudes reduce perceived overall uncertainty of the answers and whether a similar effect manifests itself also with specific, more projective and less descriptive scales used in the semantic differential. Implications for the use of generalized versions of semantic differential in economic and business research are discussed.

Keywords: Semantic differential, Extremity, Uncertainty, fsQCA, COVID-19

JEL classification: C44, D81, D91

Grant affiliation: The research was partially supported by LUT AMBI platform.

1. Introduction

Attitudes play an important role in our everyday life and influence (or determine) our choices in many real-life situations. As such the ability to capture attitudes and to reflect them in managerial, economic and business research is of paramount importance. Particularly in those areas of business and social science research that focus on (managerial) decision-making and choice as such. Even though there are several tools for the reflection of attitudes (or their "measurement", as this process is frequently denoted), we apply the semantic differential (SD) introduced by Osgood et al. (1957) as a main research tool. The method has proven useful in social sciences including psychology (Kahneman, 1963), political sciences, economics and business research and even operations research (Stoklasa et al., 2016). The original method by Osgood et al. (1957) method is fully capable of representing the attitudes towards concepts in a three-dimensional semantic space defined by the Evaluation, Potency and Activity dimensions (factors). The partially projective character of SD stemming from the requirement of using scales that are not descriptive for the given concept, however, results in lower comfort of the respondents in the data input process. Stoklasa et al. (2019a) pointed out that the inability to connect the used bipolar-adjective scale with the evaluated concept can result in a random assignment of scale

* Corresponding author's email: "jan.stoklasa@upol.cz"

value (among other issues) and propose an interval-valued SD (IVSD) to deal with this issue and to allow the respondents to express potentially lower certainty of their evaluation and to still be able to use the evaluation in the process of attitudes assessment. The IVSD uses a two-scale input format, where each bipolar adjective scale score is accompanied with an "uncertainty" level reflecting how certain the respondent is concerning the provided value. This format is intended to allow for the distinction between really neutral values (middle point of the evaluation scale) and answers that represent the inability of the respondent to provide an answer/score (stemming from perceived incompatibility of the scale with the concept, a low level of understanding of the scale etc.). The applications of the IVSD method have been proposed for the management of design process (Stoklasa et al., 2019b), in the area of multi-expert evaluation and consensus reaching (Stoklasová et al., 2022) and recently, proposals for the adoption of the IVSD ideas in multiple-criteria decision-making have been made (Stoklasová, 2021).

The ability to reflect the attitudes as well as the uncertainty of the inputs provided by respondents in self-report scales well in our economic, business and social sciences models is important. IVSD provides the needed tools for the reflection of uncertainty in attitudes extraction. Deep understanding of the sources of the uncertainty and its link with other factors relevant in the decision-making and in the attitude expression is, however, also needed. This paper therefore aims on this very aspect of the use of IVSD scales. More specifically we intend to investigate whether extreme values of the scales are linked with low perceived uncertainty of these answers, or in other words whether an expression of an extreme value of the evaluation scale (very low or very high) can be considered an indicator of high level of certainty of the respondent. To be able to investigate this, we will apply the tools of fuzzy set Qualitative Comparative Analysis (fsQCA, see Ragin (2008) or Schneider & Wagemann (2012)). fsQCA is a set of tools that allows for the investigation of the compatibility of IF-THEN rules with the available data. Even though fsQCA can be also used for the theory building purpose (Schneider & Wagemann, 2012), our focus here will remain on the *consistency* of the postulated IF-THEN relationship with the available data and on its *coverage* of the data. More specifically we will apply the recently proposed fuzzified consistency and coverage measures for fsQCA (Stoklasa et al., 2017, 2018) to enable for the IF and THEN parts of the investigated relationships to be fuzzy. These measures have already been successfully applied in the area of strategic management (Kumbure et al., 2020), in academic success prediction capabilities assessment (Stoklasa et al., 2020), in the field of investment decision-making (Welling & Stoklasa, 2021) and others.

The purpose of this paper can thus be summarized in the following way. We will investigate whether extremity of an evaluation provided on a IVSD bipolar-adjective scale is connected with low uncertainty of such an evaluation as perceived by the given respondent. This allows us to conclude whether extreme answers can be considered to be low-uncertain. We will investigate this on a dataset obtained from university students of business programmes. In the dataset three COVID19-related issues were considered and the attitudes of the respondent towards these issues– the transition from face-to-face to on-line teaching, the restrictions on traveling and the COVID19 vaccination issue. The COVID19 context was chosen to context with affective content and the three topics were chosen to cover areas with which the students did have first-hand personal experience for sure (teaching transition, vaccinations) and also that might have not affected all of them directly (travel restrictions). The effect of different levels of personal experience with the concepts towards which the attitudes are being assessed will also be discussed in this paper.

2. Preliminaries

To be able to describe the results of our analysis and the methods applied to obtain them, we need to shortly recall the basic concepts of fuzzy set theory (see Klir and Yuan (1995) for more) and of the fsQCA (see Schneider and Wagemann (2012) or Stoklasa et al. (2017) for more details). Let U be a nonempty set representing the set of values of the given variable. A fuzzy set A on U is then defined by the mapping $A: U \rightarrow [0,1]$. For each $x \in U$ we call the value $A(x)$ a membership degree of the element x in the fuzzy set A and $A(.)$ denotes the membership function of the fuzzy set A. $\mathrm{Ker}(A) = x \in U | A(x) = 1$ denotes a kernel of A, $A_\alpha = x \in U | A(x) \geq \alpha$ denotes an α-cut of A for any $\alpha \in [0,1]$, $\mathrm{Supp}(A) = x \in U | A(x) > 0$ denotes a support of A. A fuzzy number is a fuzzy set A on the set of real numbers with 1) a nonempty kernel; 2) bounded support and 3) all α-cuts being closed intervals for all $\alpha \in (0,1]$. The real numbers $a_1 \leq a_2 \leq a_3 \leq a_4$ are called significant values of the fuzzy number A if $[a_1, a_4] = \mathrm{Cl}(\mathrm{Supp}(A))$ and $[a_2, a_3] = \mathrm{Ker}(A)$. The negation of a fuzzy set A on U is the fuzzy set A' on U such that $A'(x) = 1 - A(x)$ for all $x \in U$. The cardinality of a fuzzy set A defined on a discrete universe is computed as the sum of the membership degrees of all the members of the universe in A. In this paper we will assume that the membership function of the fuzzy numbers is linearly increasing between a_1 and a_2 and connects the points $(a_1, 0)$ and $(a_2, 1)$ and linearly decreasing between a_3 and a_4 and it connects the points $(a_3, 1)$ and $(a_4, 0)$. In this case we can represent the fuzzy number A by the quadruplet of its significant values and we can write $A \sim (a_1, a_2, a_3, a_4)$. Fuzzy numbers can be used as representatives of (characteristic) features of the elements of the given universe. If we consider that a fuzzy set is defined by a characteristic feature (or a set of characteristic features), then the membership degree of any element of the universe in the fuzzy set can be understood as the level to which the given element of the universe has the feature represented by the respective fuzzy set. Fuzzy sets (particularly fuzzy numbers) can also be used to represent the meanings of linguistic expressions.

Now let us assume that we have a universe U representing our n observations (for example the set of answers provided by our respondents, the set of respondents or any discrete set). Let us define two fuzzy sets A and B on U and let us assume that A represents a feature A of the elements of U and that B represents a different feature B of the elements of U. For any $x \in U$ we can say that $A(x)$ represents the level to which x has the feature A, similarly $B(x)$ represents the level to which x has the feature B. Let us now assume a hypothetical relationship considered to hold in the set of our observations (and technically in general) denoted $A \rightarrow B$ and meaning "the presence of feature A implies the presence of feature B in our observations (i.e. in the elements of U)". Now to assess the validity of such a relationship, we can apply the tools of fsQCA and calculate the so called *consistency* of $A \rightarrow B$ with our data; in other words to assess how large a part of our data support the claim of the existence and validity of this relationship. We can also calculate the coverage of this relationship, that is a value that tells us how much the relationship is relevant for the data (for how large part of the data it is applicable). See Ragin (2008) or Stoklasa et al. (2017) for more details on the fuzzified consistency and coverage measures. In this paper we are going to utilize the full output using all four consistency and coverage measures ($F_1, \dots, F_4$) as suggested by Stoklasa et al. (2017). For better clarity, let us recall at least the basic measures starting with Ragin's original measures (2008):

$$\mathrm{consistency}_{F_1}(A \rightarrow B) = \frac{\sum_{i=1}^{n} \min(A(x_i), B(x_i))}{\sum_{i=1}^{n} A(x_i)}; \quad \mathrm{coverage}_{F_1}(A \rightarrow B) = \frac{\sum_{i=1}^{n} \min(A(x_i), B(x_i))}{\sum_{i=1}^{n} B(x_i)} \qquad (1)$$

For the other measures let us just recall the formulas for the consistencies. The F_2 measure that removes all ambivalent evidence in favour of the given relationship is calculated as:

$$\text{consistency}_{F_2}(A \to B) = \frac{\sum_{i=1}^{n} \min(A(x_i), B(x_i)) - \min(A(x_i), B(x_i), B'(x_i))}{\sum_{i=1}^{n} A(x_i)}. \quad (2)$$

If we remove not only the ambivalent evidence, but also counterevidence, we get the F_3 consistency as a measure of excess support for the rule in the data:

$$\text{consistency}_{F_3}(A \to B) = \max\left\{0; \frac{\sum_{i=1}^{n} \min(A(x_i), B(x_i)) - \min(A(x_i), B'(x_i))}{\sum_{i=1}^{n} A(x_i)}\right\}. \quad (3)$$

All of the above consistency measures have values within the $[0,1]$ interval and the closer the value is to 1, the stronger the support in favour of the given relationship is in the data, still due to the fuzzy nature of the method it is necessary to investigate also the consistency of $(A \to B')$. Stoklasa et al. (2018) also suggested the F_4 measure that has a threshold value of 0.5; values over 0.5 suggest more support for the $(A \to B)$ that for $(A \to B')$ while values below 0.5 indicate more support for $(A \to B')$ in the data.

$$\text{consistency}_{F_4}(A \to B) = \frac{1}{2}\left(1 + \frac{\sum_{i=1}^{n} \min(A(x_i), B(x_i)) - \min(A(x_i), B'(x_i))}{\sum_{i=1}^{n} A(x_i)}\right). \quad (4)$$

3. Data and the operationalization of the investigated relationships

A 7-point bipolar-adjective based IVSD with 17 scales was administered to a group of 57 first-year students of business administration. The method follows the design by Stoklasa et al. (2017), that is each bipolar adjective scale was supplemented by an 11-point uncertainty assessment scale, where 0 meant no uncertainty in the answer and 10 represented 100% uncertainty. Out of the available data 14 questionnaires needed to be discarded because the respondents did not provide all 51 scale values and all 51 uncertainty values. The resulting sample is thus constituted by 43 respondents. Their answers are summarized in Figures 1 and 2 by the concepts the attitudes towards which were assessed, that is separately for "Transition from face-to-face to online teaching during the COVID19 pandemic", "Government/Ministry issued restrictions on travel" and "COVID19 vaccinations".

From Figure 1 we can see that for the teaching there seems to be a clear central tendency. We can also see that the vaccination concept resulted in the highest number of extreme answers (1 or 7), while the teaching concept seems to have resulted in the lowest number of these extreme answers. This can be explained by the perceived limitation stemming from the given concepts for the respondents. In terms of uncertainty, the most completely certain answers are reported for the vaccination issue (Figure 2, right subplot).

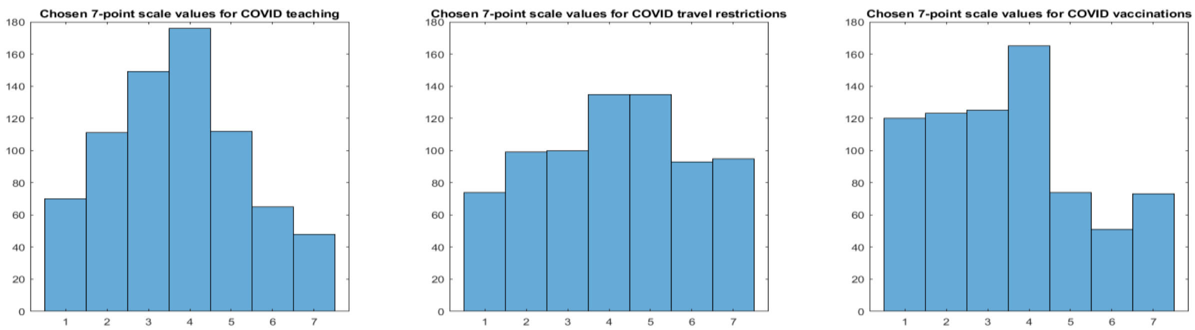

Figure 1: Frequencies of choice of the values of the 17 bipolar-adjective scales (7-point scales) by our 43 respondents by COVID-related topics.

Even though it seems that all three concepts differ slightly in the answering patterns, it is now necessary to define the features representing the relationship between the extremity of the answers and their uncertainty, as it was outlined in the introduction of this paper. We can operationalize the investigated relationship into $A \rightarrow B$, where A represents "high extremity" and B represents "low uncertainty". For any value $x_i \in \{1,2,3,4,5,6,7\}$ the extremity value is calculated as $e(x_i) = |4 - x_i|$ and therefore $e(x_i) \in \{0,1,2,3\}$. High Extremity will therefore be, for the purpose of our analysis, defined as $A \sim (1,3,3,3)$, while Low Uncertainty will be defined as $B \sim (0,0,3,5)$.

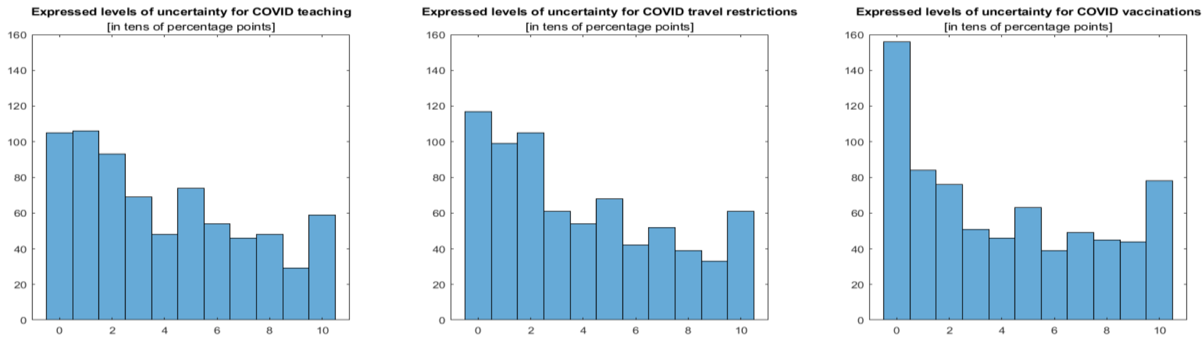

Figure 2: Frequencies of the perceived uncertainties of answers (in tens of percentage points) by our 43 respondents by COVID-related topics.

4. Results and their discussion

Given the definitions above, we have investigated the support for the relationships $A \rightarrow B$ and $A \rightarrow B'$ in our data. Note that A represents "high extremity of the answer" and B represents "low uncertainty of the answer" while B' stands for "not low uncertainty of the answer" (i.e. anything but low uncertainty of the answer). We have performed the fsQCA analysis for all the answers pooled together as well as for the answers grouped by the issues being assessed.

Overall (complete dataset)			
	A=>B		A=>notB
F1 consistency =	0.701065	F1 consistency =	0.318242
F1 coverage =	0.440217	F1 coverage =	0.239719
F2 consistency =	0.676431	F2 consistency =	0.293609
F2 coverage =	0.276756	F2 coverage =	0.149448
F3 consistency =	0.382823	F3 consistency =	0
F3 coverage =	0	F3 coverage =	0
F4 consistency =	0.691411	F4 consistency =	0.308589
F4 coverage =	0.434156	F4 coverage =	0.232447

F2F->online teaching due to COVID19			
	A=>B		A=>notB
F1 consistency =	0.674757	F1 consistency =	0.356796
F1 coverage =	0.350126	F1 coverage =	0.22006
F2 consistency =	0.643204	F2 consistency =	0.325243
F2 coverage =	0.191436	F2 coverage =	0.125749
F3 consistency =	0.317961	F3 consistency =	0
F3 coverage =	0	F3 coverage =	0
F4 consistency =	0.658981	F4 consistency =	0.341019
F4 coverage =	0.34194	F4 coverage =	0.210329

Government/Ministry issued travel restrictions			
	A=>B		A=>notB
F1 consistency =	0.722642	F1 consistency =	0.301887
F1 coverage =	0.468215	F1 coverage =	0.248447
F2 consistency =	0.688679	F2 consistency =	0.267925
F2 coverage =	0.294621	F2 coverage =	0.150621
F3 consistency =	0.420755	F3 consistency =	0
F3 coverage =	0	F3 coverage =	0
F4 consistency =	0.710377	F4 consistency =	0.289623
F4 coverage =	0.460269	F4 coverage =	0.238354

COVID19 Vaccinations			
	A=>B		A=>notB
F1 consistency =	0.7	F1 consistency =	0.305357
F1 coverage =	0.502564	F1 coverage =	0.250733
F2 consistency =	0.689286	F2 consistency =	0.294643
F2 coverage =	0.344872	F2 coverage =	0.171554
F3 consistency =	0.394643	F3 consistency =	0
F3 coverage =	0.001282	F3 coverage =	0
F4 consistency =	0.697321	F4 consistency =	0.302679
F4 coverage =	0.500641	F4 coverage =	0.248534

Figure 3: Consistencies and coverages of the investigated relationship and its negation in the whole dataset and also grouped by the issue being assessed.

Figure 3 shows that in the overall dataset (in all the answers) there seems to be much more evidence in favour of the relationship $A \rightarrow B$ than there is against it. This can be interpreted as evidence of the co-incidence of extreme answers and low uncertainty of these answers ($\text{consistency}_{F_1}(A \rightarrow B) = 0.701065$, also rather high F_2 and F_4 consistencies and nonzero F_3 consistency). Overall we can say that when the respondent selects an extreme value of the IVSD bipolar-adjective scale, then this value is considered by the respondent to be low-uncertain. This is consistent with our expectations. It is, however, good to understand that this just points to a decent strength of the claim that extremity of the answer is a sufficient condition for low uncertainty of the answer. It is by no means a necessary condition for low uncertainty.

When we take a closer look at the results grouped by the assessed issues, we can see that the shift in the teaching approach, travel restrictions and vaccinations follow the overall pattern rather closely, vaccinations having almost identical support for extremity of the answer leading to low uncertainty as the full sample, travel restrictions having an even stronger support that the overall sample. Surprisingly the transition to on-line only teaching, an issue with which all the participants had first-hand experience, has a weaker support in favour of extremity being linked with low uncertainty. This can, however, be explained by the fact that first-year university students most probably did not have experience with any other mode of university-level teaching and as such they were lacking a reference framework to apply in the assessment of this situation. In this case it is reasonable to assume that the main source of uncertainty of the answers was not necessarily the scale irrelevance, but also the lack of direct experience with an alternative to the concept being assessed.

Even though this is one of the first insights into the link between extremity of answers and their uncertainty in the IVSD setting, it seems to confirm the reasonability of the IVSD data input format. However, several points of interest for future applications of the IVSD stand out – first the instruction for the respondents needs to be clear and more effort needs to be made to get full data without any missing values. It can be achieved, though. Also, our results suggest that while the assessment of well known concepts and the attitudes towards them works in the predicted way, where extreme answers can be assumed to be rather certain, when the concepts are less familiar or when a reference framework or experience with an alternative is missing, extreme answers with lower certainty can be produced too. These can be methodologically tricky to process.

5. Conclusions

We have set to investigate the relationship between the extremity of the answers in the IVSD setting and their perceived uncertainty. On our sample we have confirmed that the extreme answers tend to be perceived as low-uncertain ones, but we have also identified some evidence that extreme and not low-uncertain answers can also be produced. We hypothesize that the exception manifests itself when the inability to assess the concept fully due to the missing experience with anything but the concept becomes the main (or significant) source of uncertainty in semantic differentiation. The obtained results confirm the reasonability of the IVSD input method setup, and stress the need for more insights into the sources of uncertainty in semantic differentiation.

References

Kahneman, D. (1963). The Semantic Differential and the Structure of Inferences Among Attributes. The American Journal of Psychology, 76(4), 554–567.

Klir, G. J., & Yuan, B. (1995). Fuzzy Sets and Fuzzy Logic: Theory and Applications. Prentice Hall.

Kumbure, M. M., Tarkiainen, A., Luukka, P., Stoklasa, J., & Jantunen, A. (2020). Relation between managerial cognition and industrial performance : An assessment with strategic cognitive maps using fuzzy-set qualitative comparative analysis. Journal of Business Research, 114(June 2020), 160–172. https://doi.org/10.1016/j.jbusres.2020.04.001

Osgood, C. E., Suci, G. J., & Tannenbaum, P. H. (1957). The Measurement of Meaning. University of Illinois Press.

Ragin, C. C. (2008). Redesigning Social Inquiry: Fuzzy sets and Beyond. University of Chicago Press.

Schneider, C. Q., & Wagemann, C. (2012). Set-Theoretic Methods for the Social Sciences: A Guide to Qualitative Comparative Analysis. Cambridge University Press.

Stoklasa, J., Luukka, P., & Talášek, T. (2017). Set-theoretic methodology using fuzzy sets in rule extraction and validation - consistency and coverage revisited. Information Sciences, 412–413, 154–173. https://doi.org/10.1016/j.ins.2017.05.042

Stoklasa, J., Talášek, T., & Luukka, P. (2018). On consistency and coverage measures in the fuzzified set-theoretic approach for social sciences: dealing with ambivalent evidence in the data. In L. Váchová & O. Kratochvíl (Eds.), Proceedings of the 36th International Conference on Mathematical Methods in Economics (pp. 521–526). MatfyzPress.

Stoklasa, J., Talášek, T., & Stoklasová, J. (2019a). Semantic differential for the twenty-first century: scale relevance and uncertainty entering the semantic space. Quality & Quantity, 53(January 2019), 435–448. https://doi.org/10.1007/s11135-018-0762-1

Stoklasa, J., Talášek, T., & Stoklasová, J. (2019b). Reflecting emotional aspects and uncertainty in multi-expert evaluation: one step closer to a soft design-alternative evaluation methodology. In L. Chechurin & M. Collan (Eds.), Advances in Systematic Creativity: Creating and Managing Innovations (pp. 299–322). Palgrave Macmillan. https://doi.org/10.1007/978-3-319-78075-7

Stoklasa, J., Talášek, T., & Stoklasová, J. (2016). Semantic differential and linguistic approximation - identification of a possible common ground for research in social sciences. Proceedings of the International Scientific Conference Knowledge for Market Use 2016, 495–501.

Stoklasová, J. (2021). Interval-valued semantic differential in multiple criteria and multi-expert evaluation context: possible benefits and application areas. Annals of Computer Science and Information Systems, 29 (Recent Advances in Business Analytics. Selected papers of the 2021 KNOWCON-NSAIS workshop on Business Analytics), 53–61. https://doi.org/10.15439/2021B3

Stoklasová, J., Talášek, T., & Stoklasa, J. (2022). Attitude-Based Multi-expert Evaluation of Design. In P. Luukka & J. Stoklasa (Eds.), Intelligent Systems and Applications in Business and Finance (pp. 1–16). Springer Cham. https://doi.org/10.1007/978-3-030-93699-0_1

Stoklasa, J., Talášek, T., & Viktorová, L. (2020). Do we have crystal balls? A case study of the possibility of predicting academic success using fsQCA. In P. Slavíčková & J. Stoklasa (Eds.), KNOWCON 2020, Knowledge on Economics and Management, Conference Proceedings (pp. 215–221). Palacký University Olomouc. https://doi.org/10.5507/ff.20.24457987

Welling, F., & Stoklasa, J. (2021). Possible drivers of high performance of European mutual ESG funds - an fsQCA view on sustainable investing. Annals of Computer Science and Information Systems, 29(Recent Advances in Business Analytics. Selected papers of the 2021 KNOWCON-NSAIS workshop on Business Analytics), 63–73. https://doi.org/10.15439/2021B2