METHODOLOGY OF INDUSTRY STATISTICS: AVERAGES, QUANTILES, AND RESPONSES TO ATYPICAL VALUES

Martin Boďa[1], Vladimír Úradníček[2]

[1] *Matej Bel University in Banská Bystrica, Faculty of Economics, Quantitative Methods and Information Systems Department, Slovakia, ORCID: 0000-0002-7503-6898, martin.boda@umb.sk;*

[2] *Matej Bel University in Banská Bystrica, Faculty of Economics, Quantitative Methods and Information Systems Department, Slovakia, ORCID: 0000-0001-5613-1964, vladimir.uradnicek@umb.sk.*

Abstract: *The paper notices troublesome aspects of compiling industry statistics for the purpose of inter-enterprise comparison in corporate financial analysis. Whilst making a caveat that this issue is unbeknownst to practitioners and underrated by theorists, the goal of the paper is two-fold. For one thing, the paper demonstrates that financial ratios are inclined to frequency distributions characteristic of power-law (fat) tails and their typical shape precludes a simple treatment. For the other, the paper explores different approaches to compiling industry statistics by considering trimming and winsorizing cleansing protocols, and by confronting trimmed, winsorized as well as quantile measures of central tendency. The issues are empirically illustrated on data for a great number of Slovak construction enterprises for two years, 2009 and 2018. The empirical distribution of eight financial ratios is studied for troublesome features such as asymmetry and power-law (fat) tails that hamper usefulness of traditional descriptive measures of location without considering different possibilities of handling atypical values (such as infinite and outlying values). The confrontation of diverse approaches suggests a plausible route to compiling industry statistics that consists in reporting a 25% trimmed mean alongside 25% and 75% quantiles, all applied to trimmed data (i.e. data after discarding infinite values). The paper also highlights the sorely unnoticed fact that the key ratio of financial analysis, return on equity, may easily attain non-sense values and these should be removed prior to compiling financial analysis; otherwise, industry statistics is biased upward regardless of what measure of central tendency is made use of.*

Keywords: *Industry statistics, financial ratios, trimmed mean, winsorized mean, quantile, non-sense values, power law in the tail.*

JEL Classification: *C19, M10, M40.*

APA Style Citation: Boďa, M., & Úradníček, V. (2020). Methodology of Industry Statistics: Averages, Quantiles, and Responses to Atypical Values. *E&M Economics and Management, 23*(3), 120–137. https://doi.org/10.15240/tul/001/2020-3-008

Introduction

The paper studies the somewhat neglected and underestimated issue of constructing industry statistics for the purpose of inter-enterprise comparisons that are an indispensable ingredient for a sensible corporate financial analysis grounded in financial ratios. A comprehensive financial analysis requires that financial ratios computed for an enterprise being analyzed be compared to typical values of financial ratios of enterprises in the same industry. Several approaches are available as to how to obtain typical values, e.g. averages, quantiles, robust measures of location; and, yet, none is generally accepted and widely used. Whereas in other countries it seems that average values are favoured to describe the financial image of an industry, in Slovak conditions the preferred methodology is making use of quantile values that are compiled from financial statements of numerous Slovak enterprises. Whereas CRIF – Slovak Credit Bureau, Ltd. (henceforth referred to as CRIF) uses traditionally three quartile values (with a possibility of extending the report by averages), DataSpot, Ltd. (henceforth referred to as DataSpot) summarizes industries by second deciles, medians and eight deciles. At first glance, it may seem (and it does indeed) that it is an easy task with no methodological trouble that subsumes assembling financial statements from a number of enterprises in an industry, calculating financial ratios and summarizing them with one or a few descriptive measures. Many users of industry statistics (practitioners) as well as instructors of corporate financial analysis (theorists) are oblivious that this ostensibly simple procedure holds numerous pitfalls and the summary figures may be far from being representative of the financial situation in an industry. Several reasons may be singled out.

First, some input financial statements are erroneous (falsified on purpose, or affected by mistakes coming from errors in accounting records or arising in the process of preparing financial statements), and the financial ratios calculated from such statements are misleading. Unfortunately, that financial information disclosed even in audited statements is not free of errors is a notorious fact (e.g. Rezaee, 2005; Markham, 2006; Deloitte Forensic Center, 2009; Firth et al., 2011). Second, a portion of enterprises are not in good financial condition, their operations are atypical and they perhaps face financial distress (e.g. Konstantaras & Siriopoulos, 2011; Harada & Kageyama, 2011; Balcaen et al., 2012; Bhattacharjee & Han, 2014; Inekwe et al., 2018, 2019). In corporate comparisons, one should compare "healthy" enterprises with "healthy" enterprises and eschew comparisons with non-vital enterprises whose operations cast doubt on the faithfulness of the reality represented by financial ratios. Third, also non-sense values of financial ratios exist, and are symptomatic of many enterprises, so they cannot be ignored when the ambition is to give a general description of an industry. Such values arise owing to zero in the denominator (yielding an infinity) or whenever two negative values are divided (yielding a seemingly fortuitous economically favourable positive value). If existent, this signifies a highly non-standard situation to which a comparison should not be made. Fourth, even if the three preceding issues are somehow mended, there still remains great heterogeneity of enterprises reflected in their financial statements, thanks to which the frequency distribution of any financial ratio is frequently heavily-skewed and displays power-law (fat) tails on account of the preponderance of outlying values on either side. The proneness to asymmetry and fat-tailedness casts doubts about an ability of simple descriptive measures to deliver a faithful representation of the situation in an industry.

With a few exceptions, industry statistics is traditionally processed and proffered on a commercial basis by different vendors (credit bureaus and other agencies specialized in keeping business registers), and each vendor has a different approach to tackling these problems. The procedure starts with preliminary screening for anomalous financial statements and mistakes, and then different (sometimes undisclosed) protocols are followed in calculating summary measures. Of course, there are inevitable differences in the way that vendors define financial ratios, but they are of no import to the user granted that he is familiar with the definition.

Odd as it may be, the described issues are overlooked in the academic community, although they do merit attention. This paper is an effort to make amends, it strives to incite discussion amongst practitioners and theorists in this regard by bringing to the forefront of their attention the fact that it matters how industry statistics is calculated. More specifically, the goal of the paper is to demonstrate that the (typical) empirical distribution of financial ratios is too complicated to allow a simple treatment, and to explore different approaches to representing the financial situation of an industry. The reason being, the first ambition follows from the fact that the typical frequency distributions of a financial ratio is inclined to (asymmetric) power-law tails, which mars the usefulness of simple descriptive metrics. This in turn motivates the second ambition and a search for suitable remedies to the situation. Hence, the exploration of fat-tailed properties of financial ratios has its non-negligible role in this paper. To a great extent, the paper takes form of a case study centred upon Slovak corporate conditions. Nonetheless, the lessons learned from this case study are fully transferable to any other economic milieu since the difficulties with the quality of accounting information and heterogeneity of enterprises are shared across all economies.

The paper uses raw financial statements of a great number of Slovak enterprises provided by FinStat, Ltd. (henceforward referred to as FinStat) for two years, 2009 and 2018. Whereas the year 2018 was a period of economic tranquillity, in the year 2009 the Slovak economy was affected by the global economic crisis (e.g. Tóth, 2017; Buček, 2012). For selected industries, eight representative financial ratios defined in line with the methodology of CRIF are considered, and several approaches to calculating industry summaries are compared. Before that, however, the empirical distribution of the eight ratios and its properties are studied to prove the point that these "ugly" properties make common descriptive measures less useful and unsuited. The studied approaches include averages and quantiles used in conjunction with different possibilities of handling atypical values (infinite and outlying values) such as simple removal, trimming or winsorization.

The rest of the paper is organized into five parts. Whilst Section 1 acts as a short literature review and proves the currency of the issue, Section 2 describes the set-up of the case study including the data, the definition of the financial ratios, and approaches to calculating industry summaries. Section 3 presents the results, and is followed by Section 4 that discusses the findings and presents the limitations of the study. Finally, the last part of the paper concludes.

1. Contextual Background

Financial analyses of the enterprise and competitive environment oftentimes require analytical procedures that are based upon average or other typical industry values of selected financial indicators. Sometimes industry values are not needed as an input to the analysis, but are given full appreciation in the interpretations when the position of an industry, or of an enterprise in the industry, is to be assessed. Examples of such financial analyses include Leuz and Verrechia (2000), Serrano Cinca et al. (2005), Sedláček (2007), Bradshaw (2012), Prášilová (2012), Koráb and Poměnková (2014), Skokan and Pawliczek (2014) or Lesáková et al. (2019). There are unavoidable questions regarding the quality of data that are available to analysts for industry comparisons. The heavily used industry characteristics (such as averages, quartiles, deciles) are affected by the methodology adopted in processing financial statements at the level of an industry. Unawareness about the nuances of compiling industry statistics is a pitfall that may lead to erroneous results and unsound conclusions.

In Slovakia, the tradition of industry statistics dates back to 1993 and originated under the umbrella of Bankové a zúčtovacie centrum Slovenska, a. s. (Banking and Clearing Center of Slovakia, Plc.), which was later transformed eventually to CRIF – Slovak Credit Bureau, Ltd. The inspiration for instituting the standards of industry statistics in Slovak conditions came from the USA, where similar standards had been adopted and implemented by the American Bankers Association (Profini, 2018, p. 7). CRIF publishes industry statistics for 20 selected financial ratios in printed form in its annual report called *Stredné hodnoty finančných ukazovateľov ekonomických činností v SR* (or *Central values of financial ratios of economic activities in the Slovak Republic*). In addition, more detailed information is available on its web site https://www2.cribis.sk and pertains to another 11 financial ratios. Every financial ratio is represented by three quartile values, the average, and a synthetic indicator called "mental view". The "mental view" for a given financial ratio is obtained by applying the traditional definition of the financial ratio to the aggregated financial statements arising from summing all financial statements in that particular industry. Details on procedures followed by CRIF in detection and removal of false and erroneous financial statements are not divulged. Yet, the definitional formulas referring to particular items of financial statements are fully available to the authors of this study, and are obeyed to the letter in the applicational part. In the case that there is a preponderance of non-defined cases when calculating a financial ratio requires dividing two zeros, CRIF reports a #NA# sign for quartile values. This only reveals that non-defined values enter calculations of quartiles and no trimming or winsorizing procedure protocol is adhered to. A new-comer to the market of business registers is DataSpot, which maintains *Index Podnikateľa* (or *Entrepreneurial Index*). Although the business register operated by DataSpot offers for a selected enterprise a variety of financial ratios, only 10 financial ratios are benchmarked against the second decile, median and eight decile in the industry. Unfortunately, FinStat may also service an extensive business register, provide a collection of raw unprocessed financial statements in a convenient format and calculate for enterprises a number of financial ratios, but it does not occupy itself with compiling industry statistics. This omission is at the cost of a loss in competitive advantage. Needless to say, the definitions of financial ratios implemented by CRIF, DataSpot and FinStat are not identical, although those by CRIF could be righteously deemed for their longevity and tradition as authoritative.

Owing to the relatively small size of the Slovak economy, it is possible to develop and maintain a sort of “national standards”, but outside Slovakia the situation may be much more complicated. An example is the USA where there are several vendors of industry statistics. One of them, the Risk Management Association (formerly Robert Morris Associates), publishes its Annual statement studies that provide ratios for a total of 723 manufacturing, wholesale, retail, and selected service industries in the USA, and are available after the paid registration at https://www.rmahq.org/annual-statement-studies. Selected industry statistics and financial ratios for benchmarking are available for sole proprietorships, S corporations, and corporations from BizStats at http://www.bizstats.com. Another such vendor, IndustriusCFO, provides at http://www.industriuscfo.com benchmarking industry metrics summarized by first deciles, quartile values and last deciles. Finally, industry summaries and scoring by Bizminer at http://www.bizminer.com are developed for various financial ratios and other metrics by dint of averages. Another source is the *Almanac of business and industrial financial ratios*, a printed compendium assembled originally by Leo Troy and later by Philip Wilson, who also authored the latest edition (Wilson, 2016). The almanac gives performance data for 50 operating and financial factors in 199 industries. All these vendors or sources vary in manifold aspects such as the coverage of industries, the population of financial statements, the variety and definition of financial ratios, the procedures necessary to ensure integrity of summary statistics, the selection of measures of central tendency etc. Frequently, methodological details are difficult to track.

A not well-known initiative is BACH (standing for *Bank for the Accounts of Companies Harmonized*), launched in 1985 in order to analyze the financial condition of European enterprises, but harmonized and enhanced in 2010. The BACH project provides industry summaries for 13 European countries (inclusive of Slovakia), and reports industry summaries for 29 financial ratios in addition to numerous balance-sheet and income statements. In step with the agencies that keep business registers for Slovak enterprises, i.e. CRIF, DataSpot and FinStat, the source of input financial statements is the Registry of Financial Statements maintained by the Ministry of Finance of the Slovak Republic. The BACH database is available at https://www.bach.banque-france.fr and for 2018 represents as many as 8.6% of all enterprises (see ECCBSO, 2019, p. 16). The methodology is fairly detailed and described in ECCBSO (2019). The three quartiles and “mental view” are computed to represent financial ratios in an industry (although the term “weighted mean” is used instead of “mental view”). The administration of the BACH database is entrusted to the *Banque de France* (Bank of France) that also maintains the ERICA database of aggregated and harmonised accounting data based on IFRS consolidated financial statements for 8 European countries (exclusive of Slovakia).

Of course, there are many other vendors of financial information outside Slovakia such as Bureau van Dijk (the AMADEUS database), Bisnode (the Albertina enterprise monitor), but in a vein similar to FinStat, they do not compile industry statistics.

The typical empirical distribution of a financial ratio is unsightly and suffers for four chief reasons: (1) Some financial statements are erroneous. (2) Some enterprises tackle financial difficulties and their operations show abnormal values of financial ratios. (3) Non-sensical values of an indicator can arise naturally when both the numerator and denominator are zero, and they do arise. More frequently, only the denominator is zero, in which case a plus or minus infinity is the result. Likewise, a very small value in the denominator makes the financial ratio explode and causes an extreme value. (4) Enterprises even in the same industry are often very dissimilar and so the empirical distribution of otherwise normal values has a tendency towards asymmetry and fat tails. All in all, calculated values of a financial indicator compiled for sundry enterprises in an industry are always to some degree contaminated by errors and their distribution is not well-behaved, typically evincing asymmetric power-law (Paretian) tails. Hence, it transpires that descriptors of classical statistics (averages, or even quantiles) must fare poorly in giving a snapshot of the situation in an industry and robust descriptors must be equal to the task. Indeed, robust methods are devised for use in situations when there are extreme values or where the distribution is highly atypical (highly asymmetric or fat-tailed).

In addition to conventional quantiles, this paper considers two simple robust approaches useful in characterizing the financial situation in an industry: the trimmed (truncated) mean, and the winsorized mean. Despite the existence of a plethora of robust measures of central tendency, these two methods are effective, and conceptually simple with the construction easy and graspable to a layman. They fall into the broad category of L-estimators of location, and have a high breakdown point (Jurečková & Picek, 2006, pp. 66–69). The trimmed mean is a mean applied to the central (trimmed) mass of data that remain after discarding equal portions of data from both endpoints. Similarly, the winsorized mean is a mean applied to the whole (winsorized) mass of data obtained by replacing equal portions of data at both endpoints with the most extreme remaining values. The former is notably used in Olympic judging to prevent impact of a single judge on the overall score (Gaynor et al., 2005), or in calculation of the LIBOR rate (ICE Benchmark Administration, 2019), and both perform well when the contamination at both endpoints is below the set trimming percentage (Wilcox & Keselman, 2003). Nonetheless, the winsorized mean is recommendable for universal situations with no information available about the underlying distribution (Bieniek, 2016).

2. Methodology

As pointed out in the introduction, the paper is built-up as a case study that demonstrates issues in compiling industry statistics with the use of Slovak data. In order to prove more convincingly the point that industry statistics must be related to the empirical distribution of financial ratios, data on Slovak enterprises for two years are employed as the distributional properties of financial ratios vary with business cycles. The year 2009 can be described as turbulent since Slovak corporate financial ratios of that time bore a signature of the erstwhile Great Recession, whereas the year 2018 is a standard year with satisfactory economic growth, low unemployment and normal inflation (National Bank of Slovakia, 2016, p. 15, 2019, p. 16). For either year, the input data represented financial statements of Slovak enterprises collected and provided by FinStat. This analytic agency processes financial statements sourced from web page of the Registry of Financial Statements maintained by the Ministry of Finance of the Slovak Republic (http://www.registeruz.sk). Financial statements for 2009 were mostly scanned and ran through an OCR (optical character recognition) data extraction, and for 2018 were simply downloaded in a structured format from the Registry. In addition to omnipresent commonplace typos and errors in financial statements, the data set of financial statements for 2009 is less trustworthy owing to the digitalization by OCR technology. The input data sets were screened for errors and financial statements with apparent inconsistencies were dropped (the criteria being as follows: the balance sheet identity is violated; either asset or liability components do not add up to declared totals; the numerators or denominators of the financial ratios considered are not non-negative when they must be).

For simplicity, only 8 ratios were considered respecting the definition and method of computation of CRIF two per each of the four major categories. Their classification, shorthand definitions and abbreviations are provided in Tab. 1.

Note that out of the definitional categories in the numerators and denominators only income before taxes, net income and equity can take negative values, otherwise all the quantities must be non-negative. Note also that L3, ATO, INVDAY, D2ASS must be non-negative or plus infinity, and that WC2INV, INTCOV, ROE and OROS are supported on the real axis or take a value of negative or positive infinity. In addition, with ROE pathological situations may easily happen when both the numerator and denominator are strictly negative, in which case a positive value arises with no economic meaning or sense whatsoever. Unconditionally, such non-sensible values cannot be taken into account when compiling business statistics. A correct approach is to eliminate them in the data set and report that a certain percentage of

Tab. 1: Financial ratios considered in the study

Financial ratio	Code	Notional definition	Category
Liquidity tier 3	L3	$\frac{\text{current assets}}{\text{current liabilities}}$	liquidity
Inventory by net working capital funding ratio	WC2INV	$\frac{\text{current assets} - \text{current liabilities}}{\text{inventory}}$	liquidity
Asset turnover (in sales)	ATO	$\frac{\text{sales}}{\text{assets}}$	activity
Days' sales in inventory	INVDAY	$\frac{\text{inventory}}{\text{sales}} \cdot 360$	activity
Debt to assets ratio	D2ASS	$\frac{\text{debt}}{\text{assets}} \cdot 100$	leverage
Interest coverage	INTCOV	$\frac{\text{income before taxes} + \text{interest expense}}{\text{interest expense}}$	leverage
Return on equity	ROE	$\frac{\text{net income}}{\text{equity}} \cdot 100$	profitability
Operating return on sales	OROS	$\frac{\text{operating income}}{\text{sales}} \cdot 100$	profitability

Source: own

enterprises reported both negative net income and equity and state this percentage alongside the industry representative. It is not known how vendors of business statistics cope with the technical circumstance that emerges with ROE and perhaps with other indicators.

Given the space available, the demonstration is limited merely to one industry recognized according to the industry classification NACE Rev 2 as. “F41.2 – Construction of residential and non-residential buildings”. The choice fell upon this industry to allow a sufficient number of observations on enterprises. Whereas 2018 was rich in the number of available financial statements, 2009 was sparse in terms of effective financial statements. For most industries at the third level of the nomenclature (groups) there were only a few observations in 2009. In truth, all computations were accomplished also for the industry “Q86.2 – Medical and dental practice activities” with findings to a fault similar, but – as the output doubled and became extensive – the analysis for this industry goes unreported.

Eventually, for the two years 2009 and 2018 and the eight financial ratios summarized in Tab. 1 the analysis concentrated upon the following: (i) visual exploration of the frequency distribution of ratios, (ii) demonstration that the frequency distribution of ratios is susceptible to anomalous (outlying) values, and (iii) comparison of different measures of location of the frequency distribution. These aspects are further clarified in the ensuing subsections. Points (i) and (ii) correspond to the goal to demonstrate undesirable empirical properties of the typical distribution of financial ratios with an emphasis upon skewness and asymmetric power-law (Paretian) tails. Points (iii) answers to the goal to explore possible remedial approaches to this situation when a summary measure of location is to be constructed. Whilst elements (i) and (ii) help to prove the assertion that compilation of industry statistics is a complicated task and deserves deeper insights that are obtained through point (iii).

2.1 Visualization of the Frequency Distribution

A visual display of the frequency distribution gives immediate insights into the credibility of simple measures of location upon which the industry statistics is based. For example, it may reveal that the frequency distribution is heavily skewed or is a mixture of distributions, and these are cases in which averages and quantile measures are barely ideal. Financial ratios can be handled as continuous random variables; whereas WC2INV, INTCOV, ROE and OROS are with support on the real axis, the other four ratios L3, ATO, INVDAY, D2ASS are bounded from below at zero. In addition, there are frequent instances when the ratio attains an infinite value owing to zero in the denominator. Values of financial ratios thus resemble censored data and must be treated in this manner, wherein negative and positive infinite values are replaced by the observed finite minimums and maximums, respectively. The knot deletion algorithm of Kooperberg and Stone (1992) is applied to estimate the density of financial ratios by using splines that allows possible boundendess from below at zero (for L3, ATO, INVDAY, D2ASS) and right and left censoring (for all the ratios). Sometimes, additional censoring was needed to assure that the algorithm converges and gives an accurate representation of the frequency distribution. This is implemented symmetrically on both tails of the distribution and the censoring percentages are reported with the censoring percentages arising from the presence of infinite values.

2.2 Power-law (Fat) Tails of the Frequency Distribution

The argument is that the frequency distribution of a typical financial ratio has a tendency towards tails that decay slowly, and is exposed to the occurrence of values extraordinarily distant from the location of the distribution. As the terminology across the statistical community in this respect is not settled, the view adopted here is that a distribution with distribution function F(x) that exhibits a power law in its right tail is a distribution whose complementary cumulative distribution function $S(x) = 1 - F(x)$ can be expressed as $S(x) = L(x) * x^{-\alpha}$ with a small value of $\alpha > 0$ and L(x) such that $\lim_{x\to\infty} L(x)$ equals to a constant. Whereas L(x) is called a slowly varying function, α is positive and required $\alpha < 3$. In such a case, the distribution has a right tail that is heavier than that of an exponential distribution (fat tails) and the probability of extreme values is higher than imposed by the Gaussian law. A similar definition can be adopted for the left tail. The underlying coefficient α is the tail index, and may be employed as a measure of fat-tailedness: the smaller α, the heavier tails a distribution displays. For more details and formal treatment, it is possible to consult Bryson (1974), Nair et al. (2013), Sornette (2006) and Mikosch (2009).

Since in principle a power can be fitted and estimated in the tail of any distribution, it is necessary to inspect whether the data exhibit power-law tail behaviour. Besides informal approaches, there are formal methods for testing rigorously that the frequency of data diminishes in the tail in accordance with the power-law hypothesis. Clauset et al. (2009) recommend a goodness-of-fit test based on the Kolmogorov-Smirnov statistic implemented by dint of a bootstrapping procedure. When a power law is established (and the null hypothesis claiming its presence is not refuted), it is then appropriate to estimate the tail index. Several approaches have been devised to estimate the tail index that captures the magnitude with which the power law presents itself. This paper reports the results of 3 approaches to estimation: the maximum likelihood method (Newman, 2005), and two methods that extend the Hill estimator (Hill, 1975) by an automatic criterion for selecting the cut-off starting off the power-law tail, the method of Danielsson et al. (2016) and of Hall and Welsh (1985). The usefulness of the first method is limited by its reliance on the assumption of Pareto distributed data, whereas the last two Hill-based methods are more general as they only necessitate that the power-law behaviour is exhibited (only) by the tail. Since every method for estimating the tail index has its advantages and drawbacks (Munasinghe et al., 2019), it is prudent to make a comparative use of various methods. The analysis also made use of 3 other methods that are in nature grossly similar to maximum likelihood: the weighted least squares (Nair et al., 2019) alongside the percentile and geometric mean percentile method (Bhatti et al., 2018). These are for the sake of the size limit unreported, and their results are in agreement with the chief 3 methods.

2.3 Measures of Location to Represent the Situation in an Industry

A crucial obstacle to any attempt to characterize the industry situation by a measure of central tendency is the existence of non-defined or infinite values of the financial indicator. The former happens when both the numerator and denominator coincide at a zero amount. An example is when an enterprise is fresh in the business, in which case it may have neither inventory nor sales. The latter arises when only the denominator is zero. Alas, both cases do happen and with some indicators are somewhat frequent. To deal with this issue, the following protocol is adopted: (1) Non-defined values are removed because they appertain to enterprises that do not qualify as a basis for benchmarking and industry comparison. (2) Infinite values are handled in two different ways: either by trimming (truncation) or by winsorization (censoring). Upon trimming, all positive or negative infinities are simply discarded and removed from the calculated values of a financial ratio. In contrast, upon winsorizing, the maximum finite value is substituted for positive infinites, and the minimum value is used instead of negative infinites. Note that whilst an error or inconsistency discovered in the preliminary screening leads to the discarding the erroneous financial statement and affects all the eight financial ratios, the described trimming and winsorization protocol is implemented afterwards for each financial ratio individually.

The following measures of location are applied to both the trimmed and winsorized data on the eight financial ratios in the years 2009 and 2018: (1) the simple non-robust mean, (2) the trimmed (truncated) mean with 5%, 10%, 15%, 20% and 25% observations discarded from both endpoints of the data sample, (3) the winsorized mean with observations 5%, 10%, 15%, 20% and 25% censored at both endpoints of the data sample, in addition to (4) the quantiles at probabilities 10%, 25%, 50%, 75% and 90%. Owing to the presence of extreme observations that trouble data on a typical financial ratio, there is a need to suppress the effect of observations at the endpoints. Hence, trimmed and winsorized means are preferable over the non-robust mean. Note that 25% trimmed mean is the mid-mean advocated by Tukey (1970) and that the 50% quantile is the median. In addition, the 25% and 75% quantiles define the interquartile range, and indicate the central half of the data that participates in computing the 25% trimmed and winsorized means.

The analysis was in full implemented in program R, version 3.6.0, using the functionalities of the packages `psych`, `logspline`, `ptsuite`, `tea` and `poweRlaw`.

3. Results

After the dismissal of financial statements with obvious errors during the preliminary screening, a total of 101 and 1,109 financial statements were left for enterprises associated with the “construction” industry F41.2. The top parts of Tabs. 2 and 3 identify for the scrutinized financial indicators the frequency of pathological cases when a financial ratio was not defined (“# NA values”), cases when an infinity value was calculated (“# ±Inf values”) and standard cases with finite values. In addition to the eight indicators catalogued in Tab. 1 – L3, WC2INV, ATO, INVDAY, D2ASS, INTCOV, ROE, and OROS – Tabs. 2 and 3 encompass also ROE*, which is return on equity with economically non-sensical values suppressed and designated as non-defined. By comparing the number of NA values for ROE and ROE*, it becomes apparent that there were 18 − 3 = 15 such values (15 / 101 ≈ 14.85%) in 2009 and 124 − 0 = 124 such values (124 / 1,109 ≈ 11.18%) in 2018. This is a fairly high proportion to be simply ignored. As highlighted in Section 2, the non-defined and infinity values were either trimmed, or winsorized. The tables report industry statistics for both versions of data, and label trimmed and winsorized means as “trim mean” and “wins mean”, respectively.

The summaries in Tabs. 2 and 3 point out several notable aspects that appear universal regardless of whether the trimming or winsorizing protocol is adhered to.

- First, to all intents and purposes, the conventional arithmetic mean seems to produce values that are beyond credibility as they are apparently severely affected by extreme values and are overtly distant from values yielded by other metrics. In addition, simple mean values are also less believable from an economic point of view, perhaps with the exception of ATO.
- Second, estimates of central tendency react rather sensitively to the amount of trimming or winsorizing implemented in both endpoints of the distribution. The mean in itself is a 0% trimmed mean as well as 0% winsorized mean, and both the trimmed and winsorized mean in most cases exhibit a strictly monotone trajectory with the increasing trimming or winsorizing factor. Slight exceptions happen with indicators awash with non-defined or infinite values (L3, INVDAY, INTCOV, OROS in 2008,

and WC2INV, INVDAY, INTCOV for 2018). For example, a good many construction enterprises do not report interest expense (and they finance their assets by equity), which renders INTCOV negative. It is perhaps the issue with small entities. There are also situations that are more difficult to explain. For example, 5 enterprises in 2009 reported neither inventory nor sales, and as many as 52 enterprises did not declared sales, which resulted in 5 non-defined and 52 infinite values for INVDAY in 2009. Certainly, a few enterprises may be fresh in the business, but this does not explain why there are so many enterprises with odd values. A similar situation can be detected with other indicators as well, especially with WC2INV for 2018. Nonetheless, this is a snapshot of corporate reality that only proves the point that there will always be a proportion of financial statements liable to be erroneous and that robust or resistant methods are of the utmost appeal to compile industry statistics.

- Third, it is evident that some amount of cutting-off values is desirable. Whereas 5% trimming or winsorizing seems insufficient, 25% trimming or winsorizing aligns calculated values more with median values. The latter is but natural, and implied by the definition.
- Fourth, the presence of odd values is also manifested in quantiles, and especially first and ninth deciles (10% and 90% quantiles) are scourged by values that are not typical and obviously non-representative of the industry situation. Only quartiles (25%, 50% and 75% quantiles) seem to possess some information value.
- Fifth, the trimming protocol may be viewed as more reliable as it produces values that are economically more acceptable and useful for the purpose of comparison. Having said that, the output presented in Tabs. 2 and 3 does not warrant the assertion that the industry statistics compiled by using trimmed data conforms to the true empirical distribution of the scrutinized financial ratios (more closely than the one produced by winsorized data).
- Sixth, the industry statistics for ROE is considerably more favourable than for ROE* when non-sensical values are eliminated. The industry statistics for ROE in both years is artificially biased upward by the presence of non-sensical positive values.

The frequency distributions estimated by logspline are visualized for both years in Figs.1 and 2. The estimated densities are produced with winsorized (censored) data with allowance for the lower bound 0 with L3, ATO, DAYINV, and D2ASS. In some cases, in addition to the trimming owing to the presence of infinite cases, some other additional trimming was sometimes necessary at both ends of the distribution to make the logspline method converge. The needed amounts of trimming are reported with density plots. Figs.1 and 2 display somewhat atypical shapes of frequency distributions and prove the self-evident fact that frequency distributions of financial indicators are not time-invariant, but they change and shift over time. In some cases they are bimodal, and frequently extremely skewed. They depart substantially from the Gaussian paradigm and serve to illustrate glaringly situations where there is an objective need to employ robust metrics of location. The prolonged tails are suggestive of fat tails consistent with a power law.

Indeed, the evidence that in many a case visualized in Figs.1 and 2 a power law is at work is submitted in Tab. 4. The table first reports the results of testing for power-law behaviour in the right tail and (if appropriate also) the left tail for estimates of the tail index α obtained with the aid of maximum likelihood and the Hill estimator combined with the recommendation by Danielsson et al. (2016) and Hall and Welsch (1985). These estimation methods are labelled as “ML”, “Hill_Dan”, and “Hill_HW”. The testing is carried out at the 5% level of significance, and only in a situation when a power law is detected, the respective tail index is reported as a measure of fat-tailedness. This substantiates the claim that financial ratios are naturally exposed to values distant from the centre of their distribution, and tallies with the display of Figs.1 and 2.

4. Discussion

It is very difficult, if not impossible, to formulate a definite instruction concerning how to proceed in compiling industry statistics for the sake of corporate comparisons. Indeed, the ambition of this study is to draw attention to the fact that accounting data from which industry statistics are compiled are not free of mistakes (and are frequently erroneous) and that even errorless financial statements may yield values that are

Tab. 2: Indicators of industry statistics compiled for 2009 for the "construction" industry F41.2

	L3	WC2INV	INVDAY	ATO	D2ASS	INTCOV	ROE	ROE*	OROS
# NA values	1	1	5	0	0	20	3	18	14
# ±Inf values	39	5	52	0	0	71	8	8	43
# finite values	61	95	44	101	101	10	90	75	44
Trimmed data									
Mean	25.39	−11.24	776.37	4.51	1,597.04	49.67	−81.93	−104.70	7.55
5% trim mean	12.04	0.29	262.08	1.39	155.07	49.67	−1.08	−9.09	−18.29
10% trim mean	9.27	1.36	98.14	0.89	89.47	29.87	−1.21	−7.01	−4.47
15% trim mean	7.66	1.59	81.23	0.48	67.96	29.87	−0.74	−5.01	−1.98
20% trim mean	6.69	1.66	70.11	0.32	63.62	2.40	−0.17	−3.44	−1.12
25% trim mean	5.91	1.69	57.87	0.18	64.34	2.40	0.11	−2.54	0.28
5% wins mean	14.60	−0.52	466.94	1.87	270.59	48.18	−1.48	−11.19	−32.28
10% wins mean	12.17	0.99	124.21	1.53	124.79	46.68	−1.11	−10.20	−8.21
15% wins mean	9.72	1.35	102.47	0.82	82.58	31.14	−1.75	−8.35	−3.65
20% wins mean	8.97	1.57	87.75	0.66	65.84	11.57	−0.60	−6.33	−2.93
25% wins mean	7.44	1.60	71.44	0.44	59.15	2.62	0.06	−4.57	−1.79
10% quantile	0.01	−3.15	8.70	0.00	0.00	−12.50	−52.01	−63.58	−70.27
25% quantile	0.43	1.00	27.08	0.00	7.95	0.21	−7.44	−15.28	−11.68
50% quantile	4.87	1.81	45.48	0.00	71.55	1.75	0.00	0.00	0.63
75% quantile	17.62	2.00	142.94	1.42	99.77	6.12	7.46	1.75	3.98
90% quantile	48.03	2.00	483.99	8.27	535.66	240.38	50.67	15.19	19.40
Winsorized data									
Mean	155.62	−38.00	7,330.57	4.51	1,597.04	29.17	−681.29	−810.18	−432.16
5% trim mean	152.95	−12.87	7,411.58	1.39	155.07	18.25	−422.06	−512.81	−582.30
10% trim mean	149.61	0.53	7,535.49	0.89	89.47	4.63	−16.02	−133.36	−582.59
15% trim mean	145.31	1.37	7,694.82	0.48	67.96	−12.81	−6.21	−13.26	−580.97
20% trim mean	139.53	1.59	7,908.17	0.32	63.62	−35.95	−3.77	−8.83	−578.70
25% trim mean	131.36	1.64	8,209.73	0.18	64.34	−58.03	−2.02	−6.18	−575.47
5% wins mean	155.62	−38.80	7,330.83	1.87	270.59	29.17	−686.84	−817.54	−581.45
10% wins mean	155.62	−1.43	7,332.04	1.53	124.79	29.17	−33.77	−669.36	−584.23
15% wins mean	155.67	0.81	7,333.17	0.82	82.58	29.17	−11.31	−26.50	−585.30
20% wins mean	155.82	1.36	7,334.87	0.66	65.84	29.17	−8.57	−15.79	−585.79
25% wins mean	155.98	1.54	7,335.90	0.44	59.15	−45.52	−4.85	−11.48	−585.92
10% quantile	0.07	−20.50	24.37	0.00	0.00	−68.00	−272.11	−6,017.79	−1,195.49
25% quantile	1.88	0.90	47.69	0.00	7.95	−68.00	−22.51	−35.66	−1,195.49
50% quantile	26.15	1.77	12,876.43	0.00	71.55	−68.00	0.00	−1.86	−201.29
75% quantile	359.31	2.00	12,876.43	1.42	99.77	2.58	6.82	1.09	1.25
90% quantile	359.31	2.00	12,876.43	8.27	535.66	325.77	35.07	14.36	12.53

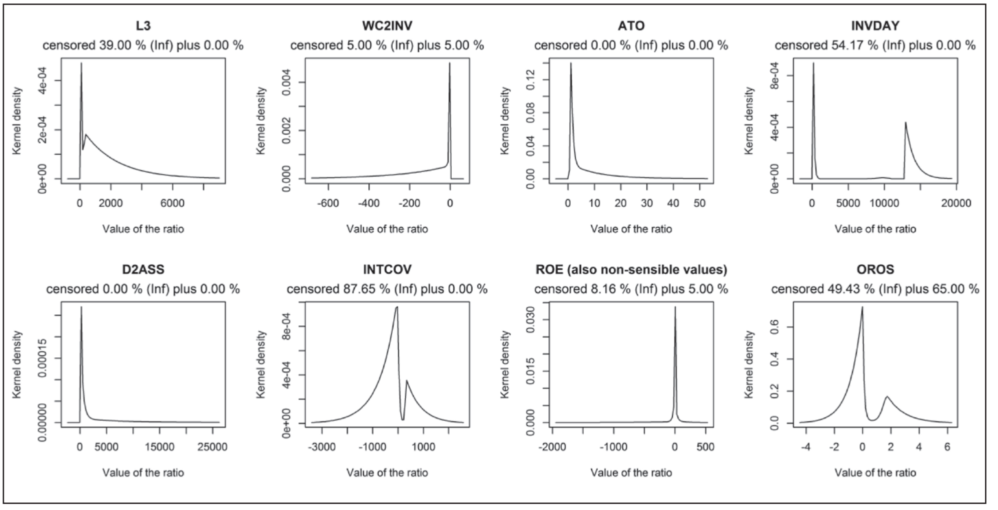
Source: own

Tab. 3: Indicators of industry statistics compiled for 2018 for the "construction" industry F41.2

	L3	WC2INV	INVDAY	ATO	D2ASS	INTCOV	ROE	ROE*	OROS
# NA values	1	1	160	0	0	57	0	124	70
# ±Inf values	49	521	53	0	0	532	0	0	143
# finite values	1,059	587	896	1,109	1,109	520	1,109	985	896
Trimmed data									
Mean	30.18	114.79	517,861	2.11	146,859	−145.98	−303.89	−368.52	3,537.93
5% trim mean	2.49	10.14	54.63	1.24	69.24	20.07	11.65	6.69	1.88
10% trim mean	1.75	3.07	22.04	1.13	66.98	13.48	11.18	7.74	3.29
15% trim mean	1.49	1.50	12.94	1.06	67.84	9.34	10.16	7.54	3.50
20% trim mean	1.36	1.12	8.30	1.00	69.26	6.72	8.97	6.73	3.42
25% trim mean	1.29	0.90	5.37	0.97	70.41	5.29	7.71	5.83	3.25
5% wins mean	3.62	25.95	124.37	1.36	74.89	29.58	10.51	3.83	−0.56
10% wins mean	2.28	8.07	44.39	1.26	66.85	20.62	12.59	7.33	2.41
15% wins mean	1.83	2.81	24.98	1.19	64.95	16.30	12.63	8.83	3.59
20% wins mean	1.57	1.78	17.12	1.11	66.20	11.95	11.80	8.91	3.67
25% wins mean	1.43	1.42	11.23	1.02	68.01	7.61	10.55	7.95	3.72
10% quantile	0.22	−14.99	0.00	0.00	5.52	−24.45	−33.53	−40.53	−26.83
25% quantile	0.69	−0.98	0.00	0.04	35.78	0.21	−1.29	−2.74	−0.15
50% quantile	1.15	0.54	0.72	0.93	71.56	3.65	4.81	3.24	2.67
75% quantile	2.46	4.89	34.19	2.12	95.46	19.65	28.09	22.88	8.52
90% quantile	8.68	71.70	269.19	3.60	127.19	122.87	70.10	51.90	24.56
Winsorized data									
Mean	363.82	4,009.80	24,894,390	2.11	146,859	−6,126.42	−303.89	−368.52	−134,274
5% trim mean	9.06	3,888.11	3,609,331	1.24	69.24	−5,185.00	11.65	6.69	−157,067
10% trim mean	2.41	3,736.27	65.39	1.13	66.98	−3,986.17	11.18	7.74	−52,790
15% trim mean	1.76	3,537.44	23.80	1.06	67.84	−2,475.26	10.16	7.54	−3.83
20% trim mean	1.52	3,077.57	13.86	1.00	69.26	−423.59	8.97	6.73	0.94
25% trim mean	1.39	1,690.02	8.77	0.97	70.41	1,240.24	7.71	5.83	1.99
5% wins mean	38.78	4,009.80	24,894,390	1.36	74.89	−6,126.42	10.51	3.83	−239,059
10% wins mean	4.11	4,009.80	239.81	1.26	66.85	−6,126.42	12.59	7.33	−239,062
15% wins mean	2.45	4,009.80	57.57	1.19	64.95	−6,126.42	12.63	8.83	−27.34
20% wins mean	1.92	5,756.33	29.08	1.11	66.20	−6,126.42	11.80	8.91	−3.22
25% wins mean	1.60	5,841.50	18.87	1.02	68.01	7,580.91	10.55	7.95	0.81
10% quantile	0.23	−9,765.62	0.00	0.00	5.52	−57,516.00	−33.53	−40.53	−1,984,600
25% quantile	0.72	−7.42	0.00	0.04	35.78	−257.15	−1.29	−2.74	−8.65
50% quantile	1.22	1.09	1.47	0.93	71.56	4.34	4.81	3.24	2.14
75% quantile	2.88	19,993.40	57.98	2.12	95.46	28,100.33	28.09	22.88	7.89
90% quantile	21.71	19,993.40	1,892.64	3.60	127.19	28,100.33	70.10	51.90	25.93

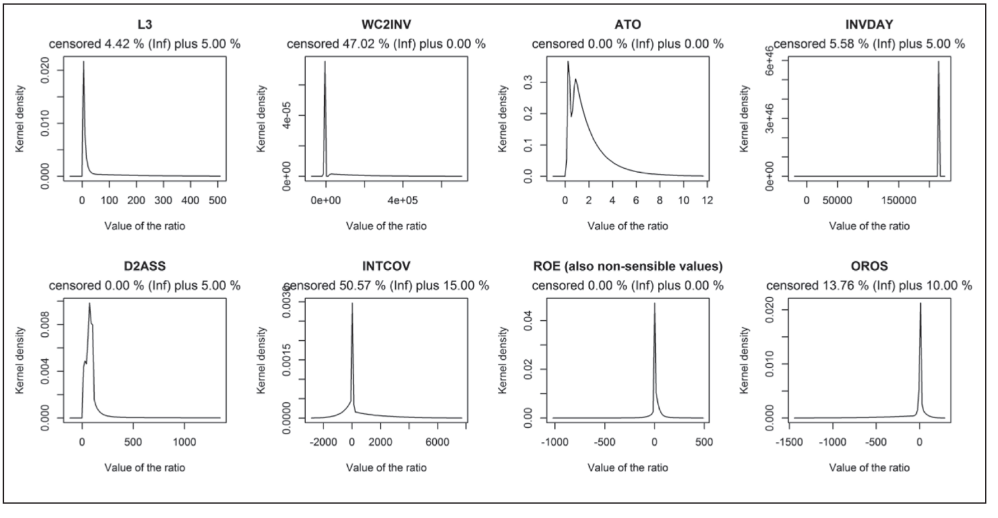
Source: own

Fig. 1: **Estimated densities of financial ratios for 2009 for the "construction" industry F41.2**



Source: own

Fig. 2: **Estimated densities of financial ratios for 2018 for the "construction" industry F41.2**



Source: own

Tab. 4: Presence of power laws in financial indicators for the "construction" industry F41.2 and tail indices for cases where a power law cannot be rejected

	L3	WC2INV	INVDAY	ATO	D2ASS	INTCOV	ROE	ROE*	OROS
Year 2009: the right tail									
ML	0.00	0.68 α = 0.451	0.00	0.15 α = 0.216	0.49 α = 0.201	0.28 α = 0.479	0.08 α = 0.366	0.44 α = 0.390	0.15 α = 0.359
Hill_Dan	0.83 α = 0.946	0.00	0.68 α = 1.269	0.76 α = 0.541	0.81 α = 0.646	0.00	0.24 α = 1.386	0.39 α = 1.052	0.49 α = 0.469
Hill_HW	0.87 α = 0.924	NA	0.33 α = 0.996	0.73 α = 0.508	0.72 α = 0.560	NA	0.23 α = 0.680	0.39 α = 1.052	NA
Year 2009: the left tail									
ML	bounded from below by zero	0.53 α = 0.306	bounded from below by zero	bounded from below by zero	bounded from below by zero	NA	0.37 α = 0.184	0.37 α = 0.184	0.14 α = 0.251
Hill_Dan		0.00				NA	0.84 α = 0.788	0.84 α = 0.788	0.74 α = 0.705
Hill_HW		NA				NA	0.83 α = 0.566	0.83 α = 0.566	0.69 α = 0.431
Year 2018: the right tail									
ML	0.00	0.00	0.00	1.00 α = 0.123	1.00 α = 0.136	0.00	0.00	0.00	0.25 α = 0.163
Hill_Dan	0.46 α = 0.702	0.48 α = 0.922	0.18 α = 1.765	1.00 α = 0.408	1.00 α = 0.410	0.54 α = 0.784	0.57 α = 0.743	0.00	0.95 α = 0.751
Hill_HW	0.11 α = 0.747	0.70 α = 1.175	0.04	NA	1.00 α = 0.559	0.34 α = 1.075	0.07 α = 1.259	0.00	0.96 α = 0.815
Year 2018: the left tail									
ML	bounded from below by zero	0.00	bounded from below by zero	bounded from below by zero	bounded from below by zero	0.00	0.21 α = 0.138	0.21 α = 0.138	1.00 α = 0.184
Hill_Dan		0.30 α = 1.013				0.34 α = 0.535	0.52 α = 0.754	0.52 α = 0.754	1.00 α = 0.594
Hill_HW		0.64 α = 1.741				0.26 α = 0.516	0.51 α = 0.734	0.51 α = 0.734	1.00 α = 0.426

Source: own

difficult to grasp (infinities) and non-sensical (non-defined). In the experience of the authors of this study, many do not realize that industry measures do not come easy, but necessitate a number of subjective decisions whose purpose is to isolate the frequency distribution of financial ratios and capture its central tendency or other characteristics. The task is not a simple empirical exercise or a mere statistical analysis by reason of the absence of information about the underpinning frequency distribution. In fact, this must be reconstructed from available data, and the plausibility of the measures of location chosen to represent the situation in an industry must be assessed through economic judgement as an inevitable input to the entire process. Such economic judgement provides guidance in adjudging which of the explored elements of the methodological procedure are sound and preferable.

Albeit the empirical demonstration focuses on an only industry of the Slovak economy, it is both the contention and experience of the authors, that the results of the previous section are universal and do not deviate in troubles from the patterns identifiable in other industries and in industries of other economies. The references made in the introduction prove that issues with financial statements or usefulness in corporate comparisons are not particular only to Slovak economic conditions, but are international. The results proved firmly that analysis of financial ratios requires a robust methodology as data – even after addressing the problem with infinite values (either by trimming or winsorization) – teem with extreme values that make the arithmetic mean useless. Each of the examined financial ratios showed a tendency towards a power law at least in one tail, or in other words, towards at least one Paretian tail, which signalizes the failure of standard measures of central tendency. In spite of using more common sense and subjective reasoning than objective knowledge as explained afore, the recommendation is to stick to the trimming protocol and to summarize the remaining data through the interquartile range and 25% trimmed mean, possibly in conjunction with the 50% quantile. On the one hand, winsorization may be deemed as more friendly in regard to the information encompassed in infinite values since the information about the direction of data is preserved by clipping the infinite values off to the nearest finite values. On the other hand, the results obtained after the winsorization protocol still display less credible values that cannot be reasonably employed in industry comparisons. The trimming protocol is in this respect more suitable as it produces more interpretable and credible values of financial ratios. Hence, it transpires that there is no benefit in trying to spare information that may be recoverable from infinite values. The interquartile range applied to such trimmed data then specifies the boundaries of the middle half of data, the 25% trimmed mean is their arithmetic average, and the 50% quantile is their mid. The recommendation advanced for discussion is thus to use only the middle half of the ordered data rid of infinite values, and to apply a measure of central tendency to them. The 25% trimmed mean is also called the midmean or interquartile mean, whereas the 50% quantile is the median.

In one respect, the recommendation to employ the three quartile measures, i.e. the 25%, 50% and 75% quartiles, is no improvement over the methodology of CRIF. In another respect, it is a confirmation of the soundness of the methodology they use. That being said, also their quartile summaries suffer from extreme values as is apparent in too frequent an occurrence of −#INF# or #INF# signs that are used in place of values of a ratio lower than −100,000 or greater than 100,000. Nonetheless, the firm does not disclose the measures taken to ensure integrity of their summary numbers, how they deal with infinite values or to what extent they cleanse input financial statements. That thorough cleansing is needed is corroborated by the fact that the number of erroneous financial statements is not negligible. For instance, Profini (2018, p. 33) reports for 2015 to 2017 from 12.48% to 13.22% erroneous financial statements published for enterprises that keep accounts on a double-entry basis. For both years, 2009 and 2018, Tab. 5 contrasts the summary statistics provided by CRIF and the summary statistics recommended in this study. There is a huge disproportion in the numbers of financial statements out of which these summaries were calculated. Whereas CRIF calculated their statistics using 2,229 and 7,082 financial statements for 2009 and 2018, this study employed respectively 101 and 1,109 financial statements that remained after the preliminary screening for errors. It is not clear whether the counts 2,229 and 7,082 appertain to the effective number of financial statements or the input data set before any removal of dubious financial statements. In addition, CRIF does not report any adjustment regarding non-sensical values of ROE. The differences between the summary statistics are striking and unsettling. On the one hand, the quartile measures and arithmetic mean reported by CRIF emerged from a considerably higher sample of financial statements (yet, they still do not represent the full population of construction enterprises), which might be suggestive of better accuracy or cogency. On the other hand, the method of disposing of erroneous or suspicious financial statements and the approach to coping with infinite values is not communicated. The glaring discrepancies between mean and median (50% quantile) values indicate extremely skewed frequency distributions, in which case the mean is of little avail to corporate comparisons since it fails to capture the central tendency. Obviously, the methodology recommended here for the sake of compiling industry statistics seems more coherent as there are petit differences between 25% trimmed mean and median (50% quantile) values in comparison to the preceding commented discrepancies. Nonetheless, it is not possible to state which one is more relevant. Yet, the point is made. Note that it is not possible to add into this comparison the industry statistics prepared by DataSpot since their definitional convention differs.

A methodological issue that remains is that, if an enterprise shows a non-sense value in one financial ratio, only this particular value should

Tab. 5: Comparison of the industry statistics using the methodology of CRIF and the recommended methodology for the “construction” industry F41.2

	L3	WC2INV	INVDAY	ATO	D2ASS	INTCOV	ROE	ROE*	OROS
Year 2009									
Year 2009: methodology of CRIF									
25% quantile	0.59	−3.20	0.00	0.07	12.00	−#INF#	−4.77		−5.93
50% quantile	1.10	0.11	0.00	0.99	56.75	15.51	2.93		1.51
75% quantile	2.38	4.08	8.62	2.27	90.98	#INF#	26.55		6.34
Mean	15.78	18.24	159.60	5.67	320.09	6,872.04	−44.10		−117.24
Year 2009: recommended methodology									
25% quantile	0.43	1.00	27.08	0.00	7.95	0.21	−7.44	−15.28	−11.68
50% quantile	4.87	1.81	45.48	0.00	71.55	1.75	0.00	0.00	0.63
75% quantile	17.62	2.00	142.94	1.42	99.77	6.12	7.46	1.75	3.98
25% trim mean	5.91	1.69	57.87	0.18	64.34	2.40	0.11	−2.54	0.28
Year 2018: methodology of CRIF									
25% quantile	0.91	−1.54	0.00	0.01	19.23	−7.53	−9.53		−8.99
50% quantile	1.72	#INF#	0.00	1.13	69.30	2.08	3.01		2.30
75% quantile	8.90	#INF#	4.82	2.36	97.11	16.51	29.45		11.28
Mean	26.64	32.44	9,098.47	5.83	212.83	−101.48	−246.52		−241.52
Year 2018: recommended methodology									
25% quantile	0.69	−0.98	0.00	0.04	35.78	0.21	−1.29	−2.74	−0.15
50% quantile	1.15	0.54	0.72	0.93	71.56	3.65	4.81	3.24	2.67
75% quantile	2.46	4.89	34.19	2.12	95.46	19.65	28.09	22.88	8.52
25% trim mean	1.29	0.90	5.37	0.97	70.41	5.29	7.71	5.83	3.25

Source: own, CRIF – Slovak Credit Bureau, Ltd.

be dropped from the database or the values for all financial ratios should be discarded. At present, the cleansing procedure is applied for every financial ratio separately. The cleansing procedure must include also cases when a financial ratio attains not so obviously incorrect values. Such an issue arises with the frequently used and popular return on equity, ROE, which indicates a positive (desirable) value even in economically distressed situations when both net income and equity are negative. A snapshot provided by the empirical demonstration is alarming as it proves that these unacceptable situations are rather common and their disregard is at the risk of putting the profitability in an industry into a more positive light.

An obvious shortcoming shared by the discussed approaches to compiling industry statistics is unidimensionality. This paper, CRIF, DataSpot and other vendors consider every financial ratio individually and separately from others at the expense of ignoring simultaneous links that exist between different financial ratios at a time. An avenue worthy of exploration is consideration of these relationships, e.g., in the spirit of multivariate medians (and similarly multivariate measures of location). Small (1990) surveys different definitions of the median in a multivariate case, and Chaudhuri (1996) and Hallin et al. (2010) exemplify multivariate extensions of the concept of quantiles.

Finally, industry statistics should encompass not only information about the central tendency of financial ratios, but also about their variability. A proper interpretation should take into account also the level of dispersion of a financial ratio in the industry. Given the noted and observed heterogeneity of enterprise values, conventional non-robust measures will scarcely be useful. Nonetheless, a robust measure of variability can be easily extracted from 25% and 75% quantile values as their difference (the interquartile range) or half their difference (the quartile deviation). In the methodology of CRIF and the recommended methodology, 25% and 75% quantile values are immediately available.

Conclusion

Motivated by the practical needs of corporate financial analysis when it comes to benchmarking and comparison with an industry, the paper studies methodological subtleties of compiling industry statistics. In this respect, the paper contributes to the methodology of financial analysis in no less than three ways. First, it challenges the semblance that compiling industry statistics is a simple task that leads to trustworthy figures to which an enterprise can be compared. The converse is true for input data are drawn from financial statements with varying veracity and financial ratios have distributions with power-law (fat) tails to say nothing of the existence of relatively frequent infinite or non-defined values. Second, it explores different methodological choices underlying compilations of industry statistics and suggests that after the preliminary screening for errors in financial statements data should first be trimmed (truncated) in order to rid them of infinite values and then summarized by three quartiles (especially the 25% and 75% quantiles) as well as the 25% trimmed mean. It seems that with typical frequency distributions of financial ratios winsorization is substantially inferior to trimming, in both suppressing infinite values and representing the central tendency of a financial ratio. Albeit quartile values are conventional metrics of industry statistics in Slovakia in the methodology of CRIF, their methodology does not appreciate the trimming protocol and does not make use of a trimmed mean. Third, the paper calls attention to the defective feature of return on equity, ROE, which is the ultimate indicator of accounting profitability and of somewhat obligatory use. ROE becomes positive, which is interpreted as a good situation, also when both net income in the numerator and equity in the denominator are negative. Yet, this is the worst possible scenario. If this is not reflected in the trimming protocol before values of ROE are summarized, the calculated metrics of central tendency are biased upward.

The study has implications not only for the methodology of industry statistics, but also for corporate and banking analysts as end users of financial information compiled for different industries. Whereas in Anglophone countries there is an inclination to averages, in Slovakia the golden standard instituted by CRIF prefers quantiles. Although any such descriptive gives a snapshot of where an industry stands in terms of its financial position, its computation requires a set of steps associated with cleansing data and ensuring that computed values are usable, at least at first glance. An analyst should understand that a particular value of an industry statistic actually does not appertain to all firms in a given industry, but to those whose financial ratios are well-behaved to some degree. Thus, comparability is inevitably limited, and a reasonable approach to analysis is to use quartiles rather than (traditional) averages to assess the position of a firm for the former are less sensitive to atypical values thanks to their resistance. That said, this only testifies the prudence of the quartile-based approach of CRIF.

A seeming limitation of the initiative is that the point is made through a case study oriented upon Slovak enterprises falling into the “construction” industry F41.2 for two years, 2009 and 2018. Nonetheless, in no manner is this orientation restrictive since lessons are of universal validity all over the financial world. The reason being, financial statements are full of errors, enterprises vary in operations and are extremely heterogeneous, and some of them find themselves in financial distress. The caveat placed upon the methodology of industry statistics is of concern elsewhere, and the raised issues deserve special attention on the agenda of international management.

Acknowledgement: *The paper arose in partial fulfilment of VEGA project No. 1/0767/18 and would not have come into existence without the encouragement of the late prof. Ing. Mária Uramová, PhD. The authors regret her sudden demise and are grateful to her for the idea to write this paper.*

References

Balcaen, S., Manigart, S., Buyze, J., & Oooghe, H. (2012). Firm exit after distress: differentiating between bankruptcy, voluntary liquidation and M&A. *Small Business Economics, 39*(4), 949–975. https://doi.org/10.1007/s11187-011-9342-7

Bhattacharjee, A., & Han, J. (2014). Financial distress of Chinese firms: Microeconomic, macroeconomic and institutional influences. *China Economic Review, 30,* 244–262. https://doi.org/10.1016/j.chieco.2014.07.007

Bhatti, S. H., Hussain, S., Ahmad, T., Aslam, M., Aftab, M., & Raza, M. A. (2018). Efficient estimation of Pareto model: Some modified percentile estimators. *PLoS ONE, 13*(5), 1–15. https://doi.org/10.1371/journal.pone.0196456

Bieniek, M. (2016). Comparison of the bias of trimmed and winsorized means. *Communications in Statistics – Theory and Methods, 45*(22), 6641–6650. https://doi.org/10.1080/03610926.2014.963620

Bradshaw, M. T. (2012). Discussion of "Analysts' industry expertise". *Journal of Accounting and Economics, 54*(2–3), 121–131. https://doi.org/10.1016/j.jacceco.2012.09.003

Bryson, M. (1974). Heavy-Tailed Distributions: Properties and Tests. *Technometrics, 16*(1), 61–68. https://doi.org/10.1080/00401706.1974.10489150

Buček, J. (2012). Crisis in Slovakia 2009–2010: from saving the economy to saving public finance. In G. Gorzelak, K. Fazekas, & C.-C. Goh (Eds.), *Adaptability and change: the regional dimensions in Central and Eastern Europe* (pp. 334–359). Warszawa: Wydawnictwo Naukowe Scholar.

Chaudhuri, P. (1996). On a Geometric Notion of Quantiles for Multivariate Data. *Journal of the American Statistical Association, 91*(434), 862–872. https://doi.org/10.2307/2291681

Clauset, A., Shalizi, C. R., & Newman, M. E. J. (2009). Power-law distributions in empirical data. *SIAM Review, 51*(4), 661–703. https://doi.org/10.1137/070710111

Danielsson, J., Ergun, L. M., de Haan, L., & de Vries, C. G. (2016). *Tail index estimation: quantile driven threshold selection* (Discussion Paper Series 58). London: London School of Economics and Political Science. https://doi.org/10.2139/ssrn.2717478

Deloitte Forensic Center. (2009). *Ten things about financial statement fraud: A review of SEC enforcement releases, 2000–2008* (3rd ed.). London: Deloitte Development. Retrieved December 31, 2019, from https://assets.corporatecompliance.org/Portals/1/Users/169/29/60329/10%20Things%20about%20financial%20statement%20fraud.pdf

ECCBSO [European Committee of Central Balance-Sheet Data Offices]. (2019). *BACH userguide summary*. BACH Working Group. Retrieved December 31, 2019, from https://www.bach.banque-france.fr/index.php?page=telechargementFile&file=Summary_Userguide.pdf

Firth, M., Rui, O. M., & Wu, W. (2011). Cooking the books: Recipes and costs of falsified financial statements in China. *Journal of Corporate Finance, 17*(2), 371–390. https://doi.org/10.1016/j.jcorpfin.2010.09.002

Gaynor, J., Engel, J., Long, L., Auxier, S., & Goldman, L. (2005). *Judges training manual for the ISU Judging System*. Colorado Springs, CO: US Figure Skating. Retrieved December 31, 2019, from https://www.usfsa.org/content/module4pgs30-34.pdf

Hall, P., & Welsh, A. H. (1985). Adaptive estimates of parameters of regular variation. *The Annals of Statistics, 13*(1), 331–341.

Hallin, M., Paindaveine, D., & Šiman, M. (2010). Multivariate quantiles and multiple-output regression quantiles: From L_1 optimization to halfspace depth. *The Annals of Statistics, 38*(2), 635–669. https://doi.org/10.1214/09-AOS723

Harada, N., & Kageyama, N. (2011). Bankruptcy dynamics in Japan. *Japan and the World Economy, 23*(2), 119–128. https://doi.org/10.1016/j.japwor.2011.01.002

Hill, B. (1975). A simple general approach to inference about the tail of a distribution. *The Annals of Statistics, 3*(5), 1163–1174.

ICE Benchmark Administration. (2019). *ICE LIBOR methodology (Approved July 9, 2019)*. London: ICE Benchmark Administration. Retrieved December 31, 2019, from https://www.theice.com/publicdocs/ICE_LIBOR_Methodology.pdf

Inekwe, J. N., Jin, Y., & Valenzuela, M. R. (2018). The effects of financial distress: Evidence from US GDP growth. *Economic Modelling, 72,* 8–21. https://doi.org/10.1016/j.econmod.2018.01.001

Inekwe, J. N., Jin, Y., & Valenzuela, M. R. (2019). Financial conditions and economic growth. *International Review of Economics & Finance, 61,* 128–140. https://doi.org/10.1016/j.iref.2019.02.001

Jurečková, J., & Picek, J. (2016). *Robust statistical methods with R*. Boca Raton, FL: Chapman & Hall/CRC.

Konstantaras, K., & Siriopoulos, C. (2011). Estimating financial distress with a dynamic model: Evidence from family owned enterprises in a small open economy. *Journal of Multinational Financial Management, 21*(4), 239–255. https://doi.org/10.1016/j.mulfin.2011.04.001

Kooperberg, C., & Stone, C. J. (1992). Logspline density estimation for censored data. *Journal of Computational and Graphical Statistics, 1*(4), 301–328. https://doi.org/10.2307/1390786

Koráb, P., & Poměnková, J. (2014). Financial crisis and financing constraints of SMEs in Visegrad countries. *Ekonomický časopis, 62*(9), 887–902.

Leuz, C., & Verrecchia, R. (2000). The economic consequences of increased disclosure. *Journal of Accounting Research, 38,* 91–124. https://doi.org/10.2307/2672910

Lesáková, Ľ., Ondrušová, A., & Vinczeová, M. (2019). Factors determining profitability of small and medium enterprises in selected industry of mechanical engineering in the Slovak Republic – the empirical study. *E&M Economics and Management, 22*(2), 144–160. https://doi.org/10.15240/tul/001/2019-2-010

Markham, J. W. (2006). *A Financial History of Modern U.S. Corporate Scandals: From Enron to Reform.* Abingdon: Routledge.

Mikosch, T. (2009). *Non-Life Insurance Mathematics: An Introduction with the Poisson Process* (2nd ed.). Berlin: Springer. https://doi.org/10.1007/978-3-540-88233-6

Munasinghe, R., Kossinna, P., Jayasinghe, D., & Wijeratne, D. (2019). *Fast Tail Index Estimation for Power Law Distributions in R (Vignette to the R package ptsuite).* Retrieved December 31, 2019, from https://cran.r-project.org/web/packages/ptsuite/vignettes/ptsuite_vignette.pdf

Nair, J., Wierman, A., & Bert, Z. (2013). The fundamentals of heavy-tails: properties, emergence, and identification. *ACM SIGMETRICS Performance Evaluation Review, 41*(1), 387–388. https://doi.org/10.1145/2465529.2466587

National Bank of Slovakia. (2016). *NBS monthly bulletin: March 2016.* Bratislava: National Bank of Slovakia. Retrieved December 31, 2019, from https://www.nbs.sk/_img/Documents/_MonthlyBulletin/2016/ mb0316en.pdf

National Bank of Slovakia. (2019). *NBS monthly bulletin: March 2019*. Bratislava: National Bank of Slovakia. Retrieved December 31, 2019, from https://www.nbs.sk/_img/Documents/_MonthlyBulletin/2019/ mb0319en.pdf

Newman, M. E. J. (2005). Power laws, Pareto distributions and Zipf's law. *Contemporary Physics, 46*(5), 323–351. https://doi.org/10.1080/00107510500052444

Prášilová, P. (2012). Determinants of capital structure within Czech companies. *E&M Economics and Management, 15*(1), 89–104.

Profini. (2018). *Analýza súčasného stavu odvetvových štandardov na Slovensku a ich využitie na zefektívnenie verejných politík* (Research report on Project NFP314011L717). Bratislava: Profini. Retrieved December 31, 2019, from http://www.profini.sk/informacie-o-projekte-nfp314011l717

Rezaee, Z. (2005). Causes, consequences, and deterence of financial statement fraud. *Critical Perspectives on Accounting, 16*(3), 277–298. https://doi.org/10.1016/S1045-2354(03)00072-8

Sedláček, J. (2007). Analysis of the development of financial efficiency of enterprises in the Czech Republic. *Ekonomický časopis, 55*(1), 3–18.

Serrano Cinca, C., Mar Molinero, C., & Gallizo Larraz, J. L. (2005). Country and size effects in financial ratios: a European perspective. *Global Finance Journal, 16*(1), 26–47. https://doi.org/10.1016/j.gfj.2005.05.003

Skokan, K., & Pawliczek, A. (2014). Lifecycle dynamics of Czech and Slovak enterprises in selected regions. *Ekonomický časopis, 62*(7), 728–742.

Small, C. G. (1990). A Survey of Multidimensional Medians. *International Statistical Review, 58*(3), 263–277. https://doi.org/10.2307/1403809

Sornette, D. (2006). *Critical Phenomena in Natural Sciences: Chaos, Fractals, Selforganization and Disorder: Concepts and Tools* (2nd ed.). Berlin: Springer. https://doi.org/10.1007/3-540-33182-4

Tóth, P. (2017). When are we in recession? Estimating recession probabilities for Slovakia. *Biatec, 25*(4), 31–35.

Tukey, J. W. (1970). Some Further Inputs. In D. F. Merriam (Ed.), *Geostatistics: Computer Applications in the Earth Sciences* (pp. 163–174). New York, NY: Plenum Press. https://doi.org/10.1007/978-1-4615-7103-2_12

Wilcox, R. R., & Keselman, H. J. (2003). Modern robust data analysis methods: measures of central tendency. *Psychological Methods, 8*(3), 254–274. https://doi.org/10.1037/1082-989X.8.3.254

Wilson, P. (2016). *2017 Almanac of Business & Industrial Financial Ratios* (48th annual edition). Chicago, IL: Wolters Kluwer.