The Mean May Not Mean What You Think It Means: The Use and Misuse of Measures of Central Tendency

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Analysis of business studies often involves the quantification of qualitative data to derive meaningful insights and making informed decisions. One such challenge is the inappropriate use of the arithmetic mean in economic and financial modeling. The arithmetic mean is a widely used statistical measure of central tendency that sums up a set of values and divides it by the total number of observations. While the arithmetic mean is simple and intuitive, its appropriateness in financial and economic modeling highly depends upon the nature of the data and the specific research question being addressed. This creates a dilemma. Despite the business community traditionally emphasizing quantitative research modeling, the growth of artificial intelligence and big data make qualitative research more desirable, particularly in areas such as ESG scorecards and financial literacy surveys. This paper discusses the challenges presented with analyzing studies after quantifying qualitative data and provides examples of how ordinal regression and other techniques could be used to analyze qualitative variables. This is especially applicable in undergraduate education.

Keywords: business statistics, financial literacy, sustainability, ordinal regression, ESG

INTRODUCTION

The arithmetic mean is an important statistical measure that is widely used in business, economics, and financial research for a variety of reasons. First, it summarizes the data via a single value that represents the typical or central observation. In that sense, it allows analysts to understand the average behavior or performance of a typical group. Second, the arithmetic mean provides standardization of aggregate data comparisons across many business cases. This is useful when analyzing financial ratios, leading and lagging economic indicators, or market returns. Third, the arithmetic mean has a straightforward interpretation which is easy to communicate to a number of interested groups, such as policymakers, academics, and other stakeholders. Fourth, the arithmetic mean can be easily calculated by statistical software packages and as a result, the arithmetic mean provides a baseline for estimating parameters, trends, or future values.

While the arithmetic mean has many benefits to its use in business models, there are situations where it may not be appropriate. When working with skewed or non-normal distributions, outliers, or categorical and ordinal variables, alternative measures may be more suitable. Also, when researchers attempt to quantify qualitative data, there is a risk of losing the rich contextual understanding provided by the original data. Subjective judgments and interpretations can introduce bias and impact the analysis, leading potentially to incorrect conclusions and hence, the implementation of an incorrect policy action or decision. With the growing availability of large and diverse datasets, finance and economic researchers are being confronted more often with data that includes categorical variables with ordered categories. As research in business continues to evolve, there is an increasing recognition of the importance of categorical data analysis and academic journals and conferences are embracing techniques such as ordinal regression or textual analysis. Acquiring the skills to analyze and interpret categorical data is also becoming more important for professionals and researchers. The degree to which business schools are preparing undergraduate students to analyze categorical data may be limited in scope, even at AACSB (Association to Advance Collegiate Schools of Business) accredited business schools. While AACSB schools aim to provide comprehensive education preparing students for a comprehensive education which addresses the demands of the business world, business school curricula tend to prioritize quantitative methods, focusing on statistical analysis, econometrics, and data modeling. Emphasizing the historical significance of quantitative analysis in business decision-making may provide undergraduate researchers with incomplete skillsets for tackling categorical datasets. In addition, AACSB schools may have a set curriculum which does not have the possibility of developing courses or electives that delve into the nuances of categorical data development. Quantifying qualitative data and the evolving nature of data analytics requires an understanding of various concepts that are only covered superficially in undergraduate curriculum. While business education recognizes the importance of categorical data analysis, the lack of coverage in curriculum may also be due to course curriculum constraints, competing priorities, and the perceived demand that the skillset for categorical demand analysis is lower than other areas of business analytics, such as predictive modeling or data visualization. We anticipate the demand for categorical demand analysis changing, however, due to extensive data exploration recently made possible through ever expanding machine learning and artificial intelligence. Therefore, the qualitative analysis presented in this paper represents a strong step in anticipating future market and student needs.

Categorical data analysis provides valuable insights into various business phenomena and without adequate preparation in this area, undergraduate students who will be the researchers of tomorrow may miss out on opportunities to explore and contribute to research. Categorical data analysis is an emerging area in economics, finance, human resources, and supply chain management. Business school graduates may be limited in their ability to express interest in conducting rigorous, comprehensive, and quality research in this area. Studies which evaluate customer satisfaction ratings, Likert scale responses in surveys, credit rating categories, and environmental, social, and governance (ESG) or sustainability scores are becoming more prevalent in academic and business. To effectively analyze and interpret such data, researchers may need to employ statistical techniques which support categorical data.

This paper will utilize examples from the financial literacy and ESG literature to highlight techniques to quantify qualitative data and, as a result, help business students begin to prepare for careers in qualitative research. The paper proceeds as follows. First, a literature review is presented highlighting the need for qualitative research analysis and categorical data analysis within business education in light of accreditation. Second, an overview of variable classifications, specifically ordinal variables, is presented. Third, the qualitative nature of financial literacy survey data is used to highlight qualitative modeling techniques, such as the Mann-Whitney U tests and Kruskal-Wallis tests. Fourth, ordinal regression techniques as a mechanism for treating ordinal variables are presented via the use of credit score data and ESG scores. Fifth, the paper concludes with directions for the future.

LITERATURE REVIEW

Literature on qualitative research techniques in the social sciences is "meager" (Aspers and Corte, 2019) and, in fact, qualitative research is an "umbrella term" for a number of various approaches and the subset of methods used to assess qualitative data is less defined than quantitative methods. De Villiers (et al., 2022) defines qualitative research as "misunderstood" in fields such as accounting and finance and it tends to face criticism in academia primarily from quantitatively trained researchers. For example, in the areas of corporate governance and sustainability, De Villiers (et al., 2022) emphasize that understanding qualitative data is necessary to gain appropriate insight into how organizations are managed and future directions on research are needed to answer key questions on environmental, social, and governance (ESG) and executive compensation packages. Kaczynski (et al., 2014) and Salmona (et al., 2015) suggest that to engage in qualitative financial research in a credible, high-quality manner, academics should design modeling that is more "fluid rather than linear" in design and should not compromise formality and credibility in presenting results. Parungao (et al., 2022) describes the importance of exploring qualitative data, particularly in the area of mergers and acquisitions. Qualitative data are also playing a role in assessing personal finance education (Shappell, et al., 2018), artificial intelligence in financial services (Bhatia, et al., 2021) and financial performance (Chou et al., 2018) and corporate bankruptcy (Lahmiri, et al., 2019). And when examining the relationship between ESG and financial performance, greater emphasis is being placed on finding better qualitative techniques to assess categorical data (Liu, et al., 2022).

Specifically, with respect to education, guidelines for conducting data analyses in quantitative education studies are common but often underemphasize four important methodological components, one of which is the proper level of measurement of the dependent variable (Abulela & Harwell, 2020). In light of this, while AACSB recognizes the importance of business statistics and analytics in business education and has taken measures to include it within its accreditation standards, it also recognizes that graduating business students with competencies in business analytics and quantitative methods must be a priority for universities (Clayton & Clopton, 2019), AACSB aligns its standards in partnership with the needs of small businesses and large corporations. As part of those standards, it highlights what some call technology agility, or "evidenced-based" decision making along with the ability to solve problems using technology (AACSB, 2018; AACSB 2020); however, there may be a mismatch between what employers' demand from and what business schools provide for their undergraduate students specifically (Woodside, 2020). This movement for greater coverage of statistical tools and techniques, data management, data analytics, and information technology throughout the business curriculum has impacted what business faculty teach (Mills et al., 2022). Given the enormity of the focus on data analytics within undergraduate business curricula, academics have raised concerns about what topics in statistics, econometrics, financial analytics, and other quantitative methods courses are being omitted to make room to help foster technical agility in new graduates (Mills, et al., 2022).

A part of the issue is the "tug of war" between how to balance the coverage of statistics and technological applications at the undergraduate level, particularly for students who aspire to careers in less technical business areas. How much time should be dedicated to interpreting values based upon statistic rules, scrutinizing values, and applications using the latest software packages? Business statistics and analytics are related but distinct fields. While business statistics involves the collection, analysis, interpretation, and presentation of data with statistical methods, business analytics highlights the use of data, predictive modeling, and fact-based management to drive decision-making and action. A business analyst's toolkit often consists of the use of statistical models, such as regression analysis and time series analysis to make predictions and identify patterns in the data. The knowledge of statistics is paramount to understanding how to develop an analytic framework. This typically begins with a good grounding in descriptive statistics, such as the mean, median, mode, and standard deviation to summarize data as well as inferential statistics (hypothesis testing and regression analysis) to make predictions and draw conclusions. Solid business statistics fundamentals are more crucial in an emerging area of Artificial Intelligence (AI). While AI algorithms can make it easier to identify patterns in data and quickly automate data analysis and modeling, it is important to critically assess the limitations and assumptions inherent in AI algorithms and have a good grounding in statistical concepts. In higher education, understanding the data type becomes the foundation for determining what statistical procedure to use or what model to employ. Knowing the correct data type allows for the individual charged with analysis to select the best technique possible for that analysis.

However, in a crowded business curriculum (Pan, 2018), modeling techniques that allow for ordinal dependent variables and categorical and nonparametric data (Cassel, 2018; Brusco, 2022) are often deemphasized in favor of including another software application to analyze data. Many business statistics and analytics textbooks do cover ordinal data; however, the coverage and specificity of its techniques depend upon the university and the curriculum. Evidence may suggest that business statistics education underemphasizes the importance of proper levels of measurement, specifically for dependent variables. Some researchers (e.g., Maker and Rubin, 2018; Williamson et al. 2020) suggest that statistics courses can focus heavily on inferential statistical techniques such as hypothesis testing and regression, without giving sufficient attention to underlying assumptions and requirements for these techniques. Linking the type of data – nominal, ordinal, interval, ratio – to the appropriate type of model and statistical test is pivotal for understanding a variety of business applications when assumptions of traditional tests are violated or when a sample size is small. Yet, its coverage is sometimes regulated to a second statistics or analytics course at best (Mine & Ellison, 2021). Some may argue that statistics education does not do enough to understand the implications of using inappropriate inferential techniques for a given level of measurement. As an example, using a t-test to compare means for an ordinal variable, when a nonparametric test would be more appropriate, can lead to incorrect conclusions and a lack of statistical power. Perhaps a more pragmatic approach is to consider how business statistics and quantitative methods courses can be employed to amplify the needs of undergraduate students, their potential employers, and the business community. Courses in business statistics and analytics can be viewed as those servicing a “hidden curriculum” because it teaches unintended lessons or values that are conveyed to students through the structure and content of the course and the problems it addresses (Sebastianelli, 2018). This hidden curriculum includes skills such as critical thinking, problem-solving, and data analysis as well as values such as the importance of accuracy, objectivity, and ethical decision-making.

In light of a business school’s strategic plan, business statistics/analytics courses serve as a prerequisite for other programs such as finance, economics, accounting, and supply chain management. The intersection of business statistics and analytics courses with “mission critical” objectives – social justice, sustainability, diversity, equity, and inclusion (DEI) – is often overlooked within the research (Ross & Shelton, 2019). Specifically, AACSB’s mission towards sustainability could be supported by greater connectivity of sustainability goals and objectives within statistical courses in an effort to train the future business researchers in mission critical areas. For example, ESG ratings, as a measure of sustainability, are subjective and employing quantitative analysis for these ratings could lead to incorrect analysis or bias (Kotsantonis & Serafeim, 2019). As business schools’ curriculum become more crowded, it becomes challenging to develop a curriculum for business and economics students without a background in mathematics or computer programming to do the program justice (Pan, 2018).

With that said, before moving forward, it is important to establish data classification and misapplication of data techniques affect different types of statistical tests.

DATA CLASSIFICATION

Standard business statistics curricula cover the four main types of data classifications: nominal, ordinal, interval, and ratio. Generally covered in the first two chapters of a textbook (such as Anderson, et al., 2020), business statistics and analytics curricula outline each type of data classification as well as its different properties and implications for choosing the appropriate statistical model. For example, nominal data consists of categories or labels without any inherent order or ranking. Examples include gender (male, female) and geographic regions (North, South, East, West). Analyzing nominal data typically involves frequency counts, proportions, and chi-square testing. Interval data, however, lacks a true zero point but distances between values are identifiable and equal. Common examples of interval data include temperature measured in Celsius or Fahrenheit and analyzing interval data usually includes parametric testing, such as t-tests, ANOVA, or linear regression. Ratio data has identifiable equal intervals between values and a meaningful zero point and examples include income, weight, and sales volume. Analyzing ratio data can include a wide range of statistical models, including parametric tests like t-tests and ANOVA, as well as regression analysis. Most textbooks are replete with examples on modeling techniques for ratio data and leave ordinal data analysis to supplemental chapters located online or a second course, at best.

Analyzing ordinal data often involves using non-parametric tests and techniques, such as the Mann-Whitney U test or Kruskal-Wallis test. If such tests are eliminated from or not emphasized in an overcrowded business curriculum, the next generation of business researchers are left with an incomplete toolkit for analyzing statistics, limiting their ability to select the most appropriate tests and perhaps leading to the use of the mean average for a qualitative variable. Tests like Mann-Whitney and Kruskal-Wallis are important because they focus on the positioning of the categories rather than assuming equal intervals between them, which distinguishes the test from those with numerical data. In the context of business, ordinal data is encountered when measuring variables such as credit ratings, risk levels, or investment preferences. It refers to a type of data that is categorial in nature with a natural ordering or hierarchy. Characterized by the ability to rank or order categories based on criteria, the intervals between the categories may be difficult to define. Hence, analyzing ordinal data often involves the use of non-parametric statistical tests and techniques, such as the Mann-Whitney U test, the Kruskal-Wallis test, and categorical (ordinal) regression.

MANN-WHITNEY TEST: FINANCIAL LITERACY SURVEY DATA

This section provides a financial example which can be used to help train future business researchers in nonparametric testing, allowing them to handle real-world business scenarios where parametric assumptions do not hold. The Mann-Whitney U test, also known as the Wilcoxon rank-sum test, is a non-parametrical statistical test used to compare the distributions of two independent groups. It is used when the data do not meet the assumptions required for parametric tests, such as the assumption of normality. The Mann-Whitney U test is particularly suitable for analyzing ordinal or continuous variables especially when the samples are small, the data have outliers, or the distributions are skewed. It focuses on the ranks of the observations between two groups rather than the actual values. One application of utilizing a large business dataset to illustrate the use of the Mann-Whitney U test is via the Consumer Financial Protection Bureau’s Financial Well-Being Survey (CFPB, 2017). Containing 217 variables in the dataset, the CFPB represents merged variable data from the American Community Survey as well as panel and additional survey data as constructed by the CFPB.

Why illustrate financial literacy data? Financially literate individuals tend to make more informed consumer decisions. Undergraduate students who understand financial concepts and practices are more likely to make responsible purchasing decisions, manage debt effectively, and avoid predatory financial products or traps. The CFPB survey database presents a wealth of information that could be employed as a classroom exercise to help future business researchers use the Mann Whitney test, highlight non-parametric testing, and deemphasize the construction of a mean average for survey-based data.

Studying survey data helps business researchers develop important skills such as questionnaire design, data collection methods, sampling techniques, and data cleaning in addition to underscoring non-quantitative regression techniques to examine the data. While the CFPB survey is highly vetted, the answers to many of the questions on this survey are self-reported by the respondent. Self-reported data relies heavily on the respondents’ subjective experiences and perceptions. Different individual respondents may interpret and respond to the questions in this survey differently, leading to variability in responses. Applying a reputable survey within a business statistics course can equip students with the essential tools for understanding survey limitations and evaluating results.

In this application, the variable of interest is the following CFPB survey question: How would you assess your overall financial knowledge (Knowledge) and this question is ranked on a scale of 1 (very low) to 7 (very high). The survey provides demographic data, including gender. Hence, if a researcher is interested in determining whether there is a difference in the way males or females answer this question, the Mann-Whitney U test can be performed with the following null and alternative hypotheses developed:

Ho: *There is no difference in overall financial knowledge assessment based upon gender.*

Ha: *There is a significant difference in the perception of financial knowledge based upon gender.*

Appendix 1 presents the descriptive statistics, frequency distributions, and the results of the Mann Whitney U test to help assess whether an individual's perception of financial knowledge is based upon gender. Table 1A and Table 1B present the descriptive statistics for the variable of interest, knowledge, and the Mann-Whitney results based upon gender (where male =1 and female=2). After eliminating 50 respondents who elected not to answer this question on the survey, several conclusions can be drawn. First, descriptive statistics reveal similar median and modal scores regarding their assessment on their overall financial knowledge regardless of gender (median = 5.00). The arithmetic mean and traditional regression based upon this mean would be inappropriate to examine whether gender impacts financial knowledge.

Second, the percentage frequency distributions suggest that a greater percentage of males assessed themselves as possessing a high financial knowledge (a 6 or 7 score) in comparison to females. Third, a greater percentage of females assessed themselves as possessing lower financial knowledge (a 1 or 2 score) in comparison to males. Lastly, the Mann Whitney U test pooled the financial knowledge scores from both males and females. The calculated p-value provided in Table 1C (.001) suggests that the null hypothesis is rejected. Hence, it appears that there is a statistically significant difference in the perception of financial knowledge, based upon gender. Because the Mann-Whitney U test does not assume any specific data distribution, it is a robust alternative to parametric tests like the independent t-test when the data violates parametric assumptions, or if the data is ordinal in nature.

KRUSKAL-WALLIS: FINANCIAL LITERACY SURVEY DATA

In the previous example, the Mann Whitney test presents one type of non-parametric test used to assess survey data, such as the one from the CFPB. To provide future business researchers with more breadth in testing qualitative data, the Kruskal-Wallis test could also be employed. This test is a non-parametric test used to determine whether there are significant differences among two or more independent groups in terms of their ordinal or continuous dependent variable. Often viewed as an extension of the Mann-Whitney U test, Kruskal-Wallis tests make fewer assumptions and is based ranking the data values across several groups, not being limited to just two. It is likely that students will encounter such a scenario where the data is not isolated to just two groups. For the purposes of illustration, assume that knowledge is still the dependent, qualitative variable, based upon a seven-point Likert scale where 1=low, perceived financial knowledge and 7 = high, perceived financial knowledge. The Kruskal-Wallis test will now group the dependent variable by gender and income. Table 2A in Appendix 2 provides the descriptive statistical breakdown of the average financial knowledge score by gender, as grouped by income category. The CFPB subdivided income by nine categories (see Table 2B) with the lowest category being less than $20,000 and the highest category being greater than $150,000. The same CFPB Financial Well-Being database, the Kruskal-Wallis test can be performed with the following null and alternative hypotheses developed:

Ho: *There is no difference in perceived financial knowledge scores among groups*

Ha: *There is at least one group that differs significantly from the other groups*

Appendix 2 presents the descriptive statistics, frequency distributions, and the results of the Kruskal-Wallis test to help assess whether an individual's perception of financial knowledge is based upon gender, as grouped by income. Table 2A and Table 2B present the descriptive statistics for the variable of interest, knowledge, and the Kruskal-Wallis results based upon gender (where male =1 and female=2). Several conclusions can be drawn. First, descriptive statistics reveal similar median and modal scores regarding income levels (median = 6.00), which equates to respondents reporting earnings between $60,000 to $74,999 a year. Second, the percentage frequency distributions reveal that females who reported earnings between $40,000 to $49,999 also potentially reported lower financial knowledge scores. The same may be true for males in that same category. Third, a greater percentage of females assessed themselves as possessing higher financial knowledge scores within the reported income category of $100,000 to $149,999. Lastly, the Kruskal-Wallis test combined the data of financial knowledge scores based upon income groupings established in the survey. The calculated p-values provided in Table 2C (.001) suggest that the null hypotheses are rejected. Hence, it appears that there is a statistically significant difference in the perception of financial knowledge, based upon gender and income.

While the simple results from the Mann Whitney and Kruskal Wallis tests suggest that a respondent's self-reported financial knowledge score is influenced by gender and income, the results should be treated with care. Respondents may provide inaccurate or misleading information about annual salary data. They may also overstate or understate income for a variety of reasons. Researchers should be cautious as to how a respondent responded to a question regarding income. Without clarity, a respondent might have assumed that salary included more than the base and may include bonus, commission, additional retirement benefits, and perhaps stock options. Before approaching any interpretation of salary data, researchers should acknowledge the limitations and biases within self-reported salary information in addition to the overall hesitancy by respondents to answer demographic information as a whole.

ORDINAL REGRESSION: CREDIT RATINGS AND SUSTAINABILITY DATA

In this section, non-survey data reflecting credit ratings and ESG ratings are collected to highlight a simple modeling technique which quantifies qualitative data. Ordinal regression is another statistical technique that is used to analyze the relationship between an ordinal dependent variable and one or more independent ordinal variables. Osborne (2015) suggests that ordinal logistic regression is useful in analyzing ordinal categorical data because it produces a single set of regression coefficients to estimate relationships between independent and dependent variables. It also provides proportional odds which allow researchers to assess the likelihood of a specific event occurring. In finance, ordinal regression can be applied to a variety of applications, such as credit rating analysis, risk assessment, and market analysis. Ordinal data is characterized by the ability to rank or order the categories based on a certain criterion; however, the intervals between categories may not be equal or easily measurable. The classic example is survey data, where individual respondents are asked to rate their level of satisfaction with a product or service using the following options: excellent, good, fair, or poor. These options can then be assigned numerical values but the difference between each category is not necessarily equal or quantifiable. In finance and economics, ordinal data is commonly encountered when measuring variables such as consumer sentiment, credit ratings, risk levels or ESG scores (Hirk et al., 2019; Zanin, 2022).

For example, in credit scoring, FICO scores can be considered a form of ordinal data. FICO scores are used by lenders to rank the creditworthiness of potential borrowers based on their credit history. The scores are ranked on an ordinal scale from 300 to 850, with higher scores indicating better creditworthiness. Scores are subsequently categorized by groups on a scale of "poor" to "exceptional" as an example. This allows lenders to make informed decisions about whether to approve or deny credit applications and to set interest rates and loan terms based on the level of credit risk.

Similarly, ESG scores can also be considered a form of ordinal data in that it provides a vehicle to rank companies based upon their environmental and social impact, as well as their governance practice. A company or entity with a higher ESG score is considered to have better ESG performance than a company with a lower score.

To illustrate ordinal regression, the research question and statistical analysis presented in Appendix 3 attempts to predict a state's credit score based upon several independent variables, one of which is the ordinal ESG score, adjusted personal income, population size, and location. Table 3A in Appendix 3 provides variable descriptions and sources from which data were collected. Data was collected from 50

U.S. states. As provided in Table 3A, the dependent variable "FICO" is an ordered, categorical variable indicating the Equifax credit score of a state, coded as 5=exceptional, 4=very good, 3=good, 2=fair, and 1=poor.

Independent variables for prediction include ESG scores representing a similar ordinal scaling as credit scores. It is important to note that ESG scores were collected from the United States Sustainable Development Report (2021) which is the first worldwide study assessing where countries and U.S. states rank on progress in achieving the United Nation's Sustainable Development Goals by 2030. Given the importance of sustainability initiatives to AACSB and its business school consortium, including ESG analysis within the context of business statistics is critical for helping train future business researchers. Additional variables include a breakdown of U.S. states ethnicity, race, and gender composition; however, those variables did not pass robustness checks and were eliminated from the final model.

Using SPSS, an ordinal regression is performed. FICO credit scores are the dependent variable with the remaining independent variables treated as covariates (Osborne, 2015). Tests for goodness of fit are provided. In addition, a test of parallel lines is included to validate the proportional odds assumptions. Table 3B in Appendix 3 provides a case processing report, outlining the proportion of cases at each level of the dependent variable, state FICO scores. Roughly 62% of the cases have attained a credit score of "very good" whereas only 2% of states received a "poor" ranking.

Table 3C contains the -2-log likelihood for an intercept only model as well as the full model with all variables included. The chi-square test indicates that there is significant improvement in the fit of the final model with all variables included over the baseline model. The p-value of 0.00 suggests ordinal regression is a good fit for credit scores and its subsequent predictors.

Table 3D presents the standard pseudo R-square values which proxy R-square statistics from ordinary least square (OLS) regression models. The Cox and Snell R-square, Nagelkerke R-square, and McFadden's R-square have slightly nuanced calculations, formulas, and interpretations. While Osborne (2015) suggests that pseudo R-square values be interpreted with care, all three indicators can be used to evaluate the fit of the regression model and determine the amount of variance explained.

Table 3E presents the regression coefficients and significance tests for each independent variable in the model. Ordinal regression provides researchers with an opportunity to interpret the predicted change in log odds of being in a higher category. Osborne (2017) states that threshold estimates in the table are treated as intercepts. After reviewing the parameter estimates, the following conclusions may be drawn.

First, there are several significant positive predictors within this model. For example, ESG scores are a significant positive predictor of FICO scores at the state level, with a p-value of 0.001. For every one unit increase on ESG scores, there is a predicted increase of .44 in the log odds of a state being in a higher credit score category. Thus, a state with higher ESG scores is more likely to have higher FICO scores.

Second, the locational variable for the Midwest and personal income (per capita) are significant at the 0.05 level of significance. It appears that credit scores are roughly two points higher for those living in the Midwest. In addition, the estimate on per capita personal income suggests that the log odds of having a higher state FICO score was only negligibly higher (.001) for those states with higher per capital personal income.

Third, several variables were marginally significant at the .10 level of significance. This included state tax collections per capita (p-value = .093) and monthly rent of a two-bedroom apartment (p-value = .096). The number of businesses filing for bankruptcy did not impact state's credit scores in this model.

The assumption of proportional odds is a key assumption in ordinal regression. It primarily states that the relationship between the independent variables and the cumulative odds of being in a particular category remains constant across all levels or categories of the ordinal dependent variable. In other words, it assumes that the effect of the independent variable (such as ESG scores) on the odds of being in a higher category versus a lower category is the same regardless of the specified cutoffs between categories. SPSS's test of parallel lines helps provide a check to assess the validity and reliability of the model's results and interpretations. What is important to note is that when the test of parallel lines is not significant, the mean assumption of ordinal regression is satisfied. Table 3F yields a significance level of p=.705; hence, the assumptions of ordinal regression are met. Researchers can conclude that there is a positive proportional odds relationship between ESG scores and credit scores at the state level.

CONCLUSION

Business curricula at AACSB institutions should prepare students for careers and give them a toolkit for tackling issues which are important to businesses, consumers, and the environment. By deemphasizing the quantification of qualitative variables in modeling techniques, business administrators are graduating students with a limited understanding of data and an overemphasis on quantitative modeling techniques, including the arithmetic mean as the appropriate measure of the representative average score. Within a crowded curriculum, if non-parametric testing is eliminated from the curriculum at the undergraduate level, future researchers may be entering a field with a limited understanding of data. First, non-parametric testing offers alternative approaches to hypothesis testing and allows researchers to handle real-world business scenarios, specifically when studying survey data and sustainability data. Non-parametric testing is becoming more advanced due to the wealth of data that can now be collected via artificial intelligence and cloud computing. Reinforcing techniques for treating ordinal data require researchers to think critically and may provide new researchers with a more complete toolkit for assessing data.

If business students can grasp Mann-Whitney, Kruskal-Wallis, and ordinal regression, future extensions into graduate education could include employing tests such as Somers' D, which measures the strength and direction of the relationship between ordinal variables. It could also include Jonckheere-Terpstra testing which assesses ordered groups or conditions to evaluate systematic differences across groups. Both of these tests generally are not covered within undergraduate business statistics or analytics courses.

While statistics and analytics are sometimes used as overlapping terms, there are distinct differences. Statistics is the foundation for analyzing data. Emphasizing data collection, organization, analyses, interpretation, and data presentation, statistics operates as a branch of mathematics to draw conclusions about a population based upon a sample. The sample statistic most relevant is often the arithmetic mean (Anderson et al., 2020). However, analytics acts as an extension, building upon statistics to incorporate techniques such as machine learning, predictive modeling, and simulation to identify patterns and make evidence-based decisions. If the mean is mis-specified because the data are ordinal in nature, the consequences can be far reaching and severe. In the case of ESG ratings for this study, using an arithmetic mean as opposed to reporting proportional odds, could potential impact a state's rating. ESG scores were used here to evaluate a state's sustainability performance in alignment with environmental and social values. If mis-specified through a quantitative model, a state's true ESG practices could be misrepresented. This could affect the state's reputation, perception by stakeholders, and relationships with customers, investors, and even regulators. A misspecification as an input into a model can distort the output of financial models, leading to incorrect valuation or cost of capital calculations.

To address these complexities and enhance interpretation of results in finance and economics, academics and researchers need to teach university students how to employ ordinal data analysis earlier within their university careers. Limiting data analytics to quantitative analysis, particularly ordinary least squares (OLS) regression will limit the skillset of the next generation of researchers at a time when many of the future relevant research questions will use less orthodox datasets.

REFERENCES

AACSB Association to Advance Collegiate Schools of Business International. (2020). *2020 Guiding principles and standards for business accreditation*. Retrieved from https://www.aacsb.edu/-/media/aacsb/docs/accreditation/business/standards-andtables/2020%20business%20accreditation%20standards.ashx?la=en&hash=E4B7D8348A6860B3AA9804567F02C68960281DA2

AACSB Association to Advance Collegiate Schools of Business. (2018). *Eligibility procedures and accreditation standards for business accreditation*. Retrieved from https://www.aacsb.edu

Abulela, M.A., & Harwell, M. (2020). Data analysis: Strengthening inferences in quantitative education studies conducted by novice researchers. *Educational Sciences: Theory & Practice*, *20*(1), 59–78.

Anderson, D.R., Sweeney, D.J., Williams, T.A., Camm, J.D., & Cochran, J.J. (2011). *Modern business statistics with Microsoft Excel*. Cengage Learning.

Aspers, P., & Corte, U. (2019). What is Qualitative in Qualitative Research. *Qualitative Sociology*, *42*, 139–160.

Bhatia, A., Chandani, A., Atiq, R., Mehta, M., & Divekar, R. (2021). Artificial intelligence in financial services: A qualitative research to discover robo-advisory services. *Qualitative Research in Financial Markets*, *13*(5), 632–654.

Brusco, M. (2022). Logistic regression via Excel spreadsheets: Mechanics, model selection, and relative predictor importance. *INFORMS Transactions on Education*, *23*(1), 1–11.

Cassell, C. (2018). "Pushed beyond my comfort zone:" MBA student experiences of conducting qualitative research. *Academy of Management Learning and Education*, *17*(2), 119–136.

Çetinkaya-Rundel, M., & Ellison, V. (2020). A fresh look at introductory data science. *Journal of Statistics and Data Science Education*, *29*(Sup1), S16–S26. DOI: 10.1080/10691898.2020.1804497

Chou, C.C., Chang, C.J., Chin, C.L., & Chiang, W.T. (2018). Measuring the consistency of quantitative and qualitative information in financial reports: A design science approach. *Journal of Emerging Technologies in Accounting*, *15*(2), 93–109.

Clayton, P.R., & Clopton, J. (2018). Business curriculum redesign: Integrating data analytics. *Journal of Education for Business*, *94*(1), 57–63.

Consumer Financial Protection Bureau (CFPB). (2017). *Financial well-being in America*. Retrieved from https://files.consumerfinance.gov/f/documents/201709_cfpb_financial-well-being-in-America.pdf?mod=article_inline

de Villiers, C., Farooq, M.B., & Molinari, M. (2021). Qualitative research interviews using online video technology – challenges and opportunities. *Meditari Accountancy Research*, *30*(6), 1764–1782.

Hirk, R., Hornik, K., & Vana, L. (2019). Multivariate ordinal regression models: An analysis of corporate credit ratings. *Statistical Methods and Applications*, *28*, 507–539.

Kaczynski, D., Salmona, M., & Smith, T. (2014). Qualitative research in finance. *Australian Journal of Management*, *39*(1), 127–135.

Kotsantonis, S., & Serafeim, G. (2019). Four things no one will tell you about ESG data. *Journal of Applied Corporate Finance*, *31*(2), 50–58.

Lahmiri, S., & Bekiros, S. (2019). Can machine learning approaches predict corporate bankruptcy? Evidence from a qualitative experimental design. *Quantitative Finance*, *19*(9), 1569–1577.

Makar, K., & Rubin, A. (2018). Learning about statistical inference. In *Springer International Handbooks of Education* (pp. 261–294).

Mills, R.J., Fadel, K.J., Olsen, T., Chudoba, K.M., & Dupin-Bryant, P.A. (2022). Examining Trends in Business Analytics Education From 2011 to 2020 in AACSB-Accredited Information Systems Programs. *Journal of Information Systems Education*, *33*(3), 232–244.

Osborne, J.W. (2015). *Best practices in logistic regression*. Los Angeles: Sage.

Osborne, J.W. (2017). *Regression & Linear Modeling: Best Practices and Modern Methods*. Thousand Oaks, CA: Sage.

Pan, K., Blankley, A.I., Mazzei, M.J., Frownfelter-Lohrke, C., Marshall, J.B., & Carson, C.M. (2018). Surveying industry advisors to select data analytics topics for all business majors. *The International Journal of Management Education*, *16*(3), 483–492.
Parungao, M.E., Galido, A., Suazo, M.L., & Parungao, L.A. (2022). Exploring qualitative data as predictors for M&A: Empirical analysis of target firms' letters to shareholders. *Cogent Business & Management*, *9*(1). 2084970.
Ross, J., & Shelton, T. (2019). Supermarkets, highways, and natural gas production: Statistics and social justice. *Primus*, *29*(3–4), 328–344.
Salmona, M., Kaczynski, D., & Smith, T. (2015). Qualitative theory in finance: Theory into practice. *Australian Journal of Management*, *40*(3), 403–413.
Sebastianelli, R. (2018). Multiple student learning objectives in basic business statistics: Strategies, assessment, and recommendations. *Journal of Education for Business*, *93*(7), 341–352.
Shappell, E., Ahn, J., Ahmed, N., Harris, I., Park, Y.S., & Tekian, A. (2018). Personal Finance Education for Residents: A Qualitative Study of Resident Perspectives. *AEM Education and Training*, *2*(3), 195–203.
U.S. Sustainable Development Report. (2021). *United States Sustainable Development Report 2021*. Retrieved from https://www.sdgindex.org/reports/united-states-sustainable-development-report-2021/
Williamson, B., Bayne, S., & Shay, S. (2020). The datafication of teaching in Higher Education: Critical issues and perspectives. *Teaching in Higher Education*, *25*(4), 351–365.
Woodard, V., & Lee, H. (2021). How students use statistical computing in problem solving. *Journal of Statistics and Data Science Education*, *29*(sup1), S145–S156.
Zanin, L. (2022). Estimating the effects of ESG scores on corporate credit ratings using multivariate ordinal logit regression. *Empirical Economics*, *62*(6), 3087–3118.

APPENDIX 1

TABLE 1A
DESCRIPTIVE STATISTICS AND FREQUENCY DISTRIBUTIONS: PERCEIVED FINANCIAL KNOWLEDGE

Descriptive Statistics	Total	Males	Females
Valid	6333	3316	3017
Missing	50	31	19
Mean	4.7200	4.8577	4.5688
Median	5.0000	5.0000	5.0000
Mode	5.00	5.00	5.00
Skewness	-.626	-.649	-.614
Std. Error (Skew)	.031	.043	.045
Kurtosis	.961	1.020	.958
Std. Error (Kurtosis)	.062	.085	.089
Minimum	1.00	1.00	1.00
Maximum	7.00	7.00	7.00

TABLE 1B
DESCRIPTIVE STATISTICS BY GENDER: PERCEIVED FINANCIAL KNOWLEDGE

Knowledge (Males and Females)			Knowledge (Males)			Knowledge (Females)		
Knowledge	**Freq.**	**Percent**	**Knowledge**	**Freq.**	**Percent**	**Knowledge**	**Freq.**	**Percent**
1.00	124	1.9	1.00	49	1.5	1.00	75	2.5
2.00	153	2.4	2.00	71	2.1	2.00	82	2.7
3.00	528	8.3	3.00	228	6.8	3.00	300	9.9
4.00	1486	23.3	4.00	698	20.9	4.00	788	26.0
5.00	2644	41.4	5.00	1381	41.3	5.00	1263	41.6
6.00	1072	16.8	6.00	687	20.5	6.00	385	12.7
7.00	326	5.1	7.00	202	6.0	7.00	124	4.1
Total	6333	99.2	Total	3316	99.1	Total	3017	99.4
Missing	50	.8	Missing	31	.9	Missing	19	.6
Total	6383	100.0	Total	3347	100.0	Total	3036	100.0

TABLE 1C
MANN-WHITNEY U TEST RESULTS

Ranks of Knowledge by Gender				Mann-Whitney Test	
Gender	**N**	**Mean Rank**	**Sum of Ranks**	Mann-Whitney U	4286704.500
Male (1)	3316	3382.77	11217253.50	Wilcoxon W	8839357.500
Female (2)	3017	2929.85	8839357.50	Z statistic	-10.329
Total	6333			Asymp. Sig. (2-tailed)	<.001

APPENDIX 2

TABLE 2A
DESCRIPTIVE STATISTICS AND FREQUENCY DISTRIBUTIONS BY INCOME

Descriptive Statistics	Total	Males	Females
Valid	6383	3347	3036
Missing	0	0	0
Mean	5.51	5.77	5.23
Median	6.00	6.00	6.00
Mode	8.00	8.00	8.00
Skewness	-.347	-.846	-.194
Std. Error (Skew)	.031	.042	.044
Kurtosis	-1.226	-1.057	-1.342
Std. Error (Kurtosis)	.061	.085	.089
Minimum	1.00	1.00	1.00
Maximum	9.00	9.00	9.00

TABLE 2B
DESCRIPTIVE STATISTICS BY INCOME

		Total		Males		Females	
Income	**Income**	**Freq.**	**Percent**	**Freq.**	**Percent**	**Freq.**	**Percent**
Less than $20,000	1.00	714	11.2	311	9.3	403	13.3
$20,000 to $29,999	2.00	506	7.9	224	6.7	282	9.3
$30,000 to $39,999	3.00	613	9.6	301	9.0	312	10.3
$40,000 to $49,999	4.00	467	7.3	236	7.1	231	7.6
$50,000 to $59,999	5.00	505	7.9	250	7.5	255	8.4
$60,000 to $74,999	6.00	650	10.2	357	10.7	293	9.7
$75,000 to $99,999	7.00	954	14.9	539	16.1	415	13.7
$100,000 to $149,999	8.00	1114	17.5	632	18.9	482	15.9
$150,000 or more	9.00	860	13.5	497	14.8	363	12.0
	Total	6383	100.0	3347	100.0	3036	100.0

TABLE 2C
KRUSKAL-WALLIS TEST RESULTS: RANKS AND TEST STATISTICS FOR FINANCIAL KNOWLEDGE*

		Males		Females			Males	Females
Income	**Income**	**N**	**Mean Rank**	**N**	**Mean Rank**	Kruskal-Wallis	285.578	93.186
Less than $20,000	1.00	306	1214.89	398	1314.80	df	8	8
$20,000 to $29,999	2.00	219	1271.66	282	1307.19	Asymp. Sig	<.001	<.001
$30,000 to $39,999	3.00	297	1360.63	310	1352.77			
$40,000 to $49,999	4.00	232	1588.11	226	1499.23			
$50,000 to $59,999	5.00	249	1557.83	254	1498.08			
$60,000 to $74,999	6.00	356	1639.47	293	1530.72			
$75,000 to $99,999	7.00	535	1708.37	412	1624.79			
$100,000 to $149,999	8.00	626	1846.17	480	1615.08			
$150,000 or more	7.00	496	2087.81	362	1737.25			

***Grouping Variable: Income and Gender**

APPENDIX 3

TABLE 3A
VARIABLE DESCRIPTION*

Variable	Description	Source
FICO	Credit score (1-5 scale)	Equifax
ESG	ESG score (0-100)	US Sustainable Development Report
PCPI	Adjusted personal income, per capita	Bureau of Economic Analysis
StateCollections	Tax collections, per capita	Kaiser Family Foundation
Rent2bed	Avg monthly rent for 2 bed apartments	World Population Review
Bankrupt	Business bankruptcy filings (thousands)	US Courts
Population	Population (thousands)	US Population Review
Midwest	Midwest = 1, 0 otherwise	US Census Bureau

***Years: 2021, 2020, 2019

TABLE 3B
CASE PROCESSING SUMMARY

FICO Ratings	FICO	N	Marginal Percentage
Poor	1.00	1	2.0%
Fair	2.00	3	6.0%
Good	3.00	9	18.0%
Very Good	4.00	31	62.0%
Exceptional	5.00	6	12.0%
	Total	50	100.0%

TABLE 3C
GOODNESS OF FIT AND PSEUDO R-SQUARE

Model	2 Log Likelihood	Chi-Square	df	Significance
Intercept only	110.652			
Final	56.842	53.810	7	0.00

TABLE 3D
PSEUDO R-SQUARE

Cox and Snell	.659
Nagelkerke	.740
McFadden	.486

TABLE 3E
PARAMETER ESTIMATES

	Estimate	Std. Error	Wald	Significance	Lower Bound	Upper Bound
Threshold [FICO =1.00]	19.236	5.772	11.108	.001	7.924	30.549
Threshold [FICO =2.00]	21.507	5.938	13.116	.001	9.868	33.146
Threshold [FICO =3.00]	24.845	6.370	15.215	.001	12.361	37.329
Threshold [FICO =4.00]	32.711	7.826	17.471	.001	17.373	48.050
ESG	.441	.115	15.663	.001	.215	.667
PCPI	.001	.0009	4.776	.029	.000	.001
StateCollections	.002	.000	.009	.093	-.001	.001
Rent2bed	-.004	.002	2.618	.096	-.008	.001
BankruptBus	-.003	.003	.638	.124	-.009	.004
Population	.005	.018	.068	.794	-.030	.040
Midwest	2.059	1.174	3.075	.050	-.242	4.360

TABLE 3F
TEST OF PARALLEL LINES

Model	2 Log Likelihood	Chi-Square	Df	Significance
Null Hypothesis	56.842			
General	39.742	17.100	21	.705