



## IMPACT OF STATISTICAL SOFTWARE APPLICATION IN TEACHING ECONOMETRICS ON STUDENTS' LEARNING ACHIEVEMENTS

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### Abstract

*This paper examines the impact of using statistical software packages in teaching econometrics at the undergraduate level on the Students' learning achievements. The study explores the strong pedagogical advantages of using statistical software packages in improving the teaching and learning of econometrics at the undergraduate level. A model was developed to investigate the benefit of using the software packages on the student's learning achievements. Linear models, together with parameter constancy tests, were applied. The result suggests that attendance in the econometrics class with software application positively impacts the student's learning achievements in the year four econometrics course. However, it was evident that the student's learning achievement before attending the class, proxied by Cumulative Grade Point Average (CGPA), is the primary determinant of the student's learning achievements in the course. The study concludes that attendance in software-aided econometrics classes significantly improves students' learning achievements and has implications for attendance policy in such university courses.*

### 1. Introduction

This study examines the impact of statistical software applications in teaching econometrics on students' learning achievements. With the global improvement in the information and communication technology (ICT) sector in the last three decades, personal computers have become more accessible to students. The use of statistical software packages has gradually been introduced into the teaching of quantitative economic analysis courses over the last few decades with the development of personal

computers. The teaching and learning of econometrics, which is hitherto very difficult, seem to have been significantly simplified using statistical software packages.

According to Greene (2015), the econometricians' tools and methods have transformed over time, increasingly evolving from an initial emphasis on single and multiple equation linear models to the recent use of a wide variety of nonlinear techniques in addition to the traditional linear regression models. The statistical software have evolved

correspondingly, becoming more complex and flexible in the process.

Using the econometric and statistical software packages also aids in improving the learning achievement of students. Student learning achievement is “the outcome of learning, typically measured by classroom grades, classroom assessments, and external achievement tests” (Gajda *et al.*, 2017, p. 271). According to Wang *et al.* (2022), student learning achievement has to do with how well individual students have mastered the learning content.

Some studies suggest other factors, like teaching quality, are essential for students learning achievements (Teig *et al.*, 2018). Lecturers may use technology and software to deliver instructional content more effectively, aiding the dissemination of information and understanding of complex materials (Shah & Barkas, 2018).

On the other hand, lecturers’ technology and software use may support lower self-efficacy students by producing additional content and designing engaging learning activities. Self-efficacy reflects the amount of effort employed and the individual’s judgment of their abilities to achieve designated outcomes. Students’ self-efficacy is also essential and critical to improving student engagement. According to Manwaring *et al.* (2017), students’ self-efficacy, such as considering themselves doing excellent work in classes and having the confidence that they can understand the most complex material in classrooms, may influence their levels of engagement.

Thus, this study aims to examine whether using statistical software may interact with students’ self-efficacy and influence their level of engagement and learning achievements.

## 2. Literature review

Rattaphon and Namporn (2019) suggest that the growing body of literature concerning the effectiveness of teaching methods in economics provides an empirical approach to explain and

examine the theory quantitatively. Rattaphon and Namporn (2019) showed that over 80% of the students agree that working on empirical exercises using statistical software during an experiment enhanced their general understanding of quantitative and statistical techniques and their ability to carry out statistical analysis.

The advances in computing and econometrics nowadays have improved the econometrics processes as a principal research methodology in economics (Johnson *et al.*, 2012). The econometrics and general analytical skills to examine causal relationships and forecasting are essential in the labour market (Angrist & Pischke, 2017). According to Conaway *et al.* (2018), a survey conducted in the United States in 2016 showed that about 63% of employers hunt for job candidates with analytical and quantitative skills. The demand for employees with such skills is undoubtedly rising as data accessibility has tremendously increased over the years (Conaway *et al.*, 2018).

Now that data are increasingly available and cheaper, the knowledge of quantitative techniques to analyse and interpret data using statistical tools is in high demand in the labour market (Carter *et al.*, 2017). Therefore, econometrics is now part of the core curriculum in undergraduate and postgraduate economics programmes worldwide. Hence most economics programmes require students to take econometrics (see Siegfried & Walstad, 2014; McGoldrick, 2008).

Most lecturers, on the other hand, observed that students usually see econometrics courses as hard and “unpleasant” hence getting students involved and motivated to learn and acquire econometric knowledge and skills is difficult (Angrist & Pischke, 2017). Studies in different countries show that many economics and undergraduate business students do not have robust mathematical training. Hence, they often hate econometrics; they see them as complex (Cook *et al.*, 2019). Moreover, because of a lack

of personal interest or lack of training. Hence, attaining statistical and econometric knowledge and competencies is challenging for most students (Cladera *et al.*, 2021; Cook *et al.*, 2019).

Many studies observed the presence of a crisis of numeracy in higher education all over the world. Gibbs (2010) states that many university students in the United Kingdom need essential mathematical and statistical skills and are resistant to acquiring them. Cook *et al.* (2019) stated that they display low confidence and anxiety about econometrics. Cook *et al.* (2019) added that social science students find it particularly evident. Moreso, Berger *et al.* (2020) observed that the problem plays out in secondary education. A declining number of students chose mathematics and science subjects in Australia, despite the increasing need for science and mathematics skills.

Quantitative anxiety usually starts in secondary school and goes up to university. Quantitative anxiety is the fear associated with dealing with numbers. Quantitative anxiety is among the factors that affect one's analytical performance (Tsui & Mazzocco, 2007). In our Economics departments, where most of the courses entail quantitative components, it is a likely problem for students' learning and academic performance.

Pan and Tang (2005) show that factors causing quantitative anxiety, among others, include mathematics phobia, the speed of instruction, and the lecturer's approach. They found that using a multidimensional instructional technique is one of the valuable strategies to ease learners' anxiety. Quantitative anxiety does not show one's ability to carry out a task; however, it can hamper one's ability to effectively learn and apply skills (Freiberg, 2005). It is rather damaging in an economics career where decisions are often data-driven. It is a severe concern for students' future carrier and the economy.

In this situation, teaching methods are necessary to make students happy learning econometrics. The students' poor attitudes towards the courses can negatively impact the learning process (Comas *et al.*, 2017). Hence, there is a need to find tools to change the students' attitudes towards econometrics.

Auerbach *et al.* (2018) recommend developing the application of computer technology in teaching econometrics and statistical courses as a viable solution to the problems encountered in teaching econometrics and statistical courses. The abundance of cheap computer technology nowadays can help lecturers and students conduct quantitative analytical tasks easily and intuitively. The applications will demonstrate the significance of quantitative analysis in real-world situations to the student. Auerbach *et al.* (2018) also suggest active learning strategies which involve students in identifying vital topics that entail quantitative analysis will help them identify essential concepts appropriate for the analysis.

### 3. Methodology

#### 3.1. Data

This study uses tests and examination performance evaluations of the students. The evaluation is on the students taught using different statistical software. The evaluation assesses students' learning achievements after using the software. The student's academic learning achievements in the post-training were assessed to examine the impact of the software application in teaching the econometrics course using their class attendance.

Following Westerman *et al.* (2011) and Sund and Bignoux (2018), we specify the model used to gauge the impact on students' learning achievements. It is a linear model together with parameter constancy tests. We start by reviewing the variables to be used in the specifications. The simple function model of student learning achievement is as follows:

$$ECS4i = f(CGPA3i, ATDi, DERi, SGi) \quad 1$$

Table 1 below describes the type of variables (continuous or categorical/dummy) in the model.

Table 1: Description of Variables

Name	Description	Type
$ECS4i$	Student's 400-level Econometrics Course Score (percentage)	Continuous
$CGPA3i$	Student's 300 Level Cumulative Grade Point Average	Continuous
$ATDi$	Student's Percentage of Econometrics class attendance	Continuous
$DERi$	$DERi = 1$ if the entry route was UTME (53 students); $DERi = 0$ if the entry route was Direct (5 students);	Categorical: dichotomous dummy variable
$SGi$	$SGi = 1$ if the Student is Male (48 students); $SGi = 0$ if the Student is Female (10 students);	Categorical: dichotomous dummy variable

The categorical variable  $DERi$ , denoting the degree entry route for students, has two groupings: UTME and Direct. The  $DERi$  is included as the students' self-efficacy improves with the number of previous programmes the student undertakes and level of maturity and age. Most students who joined the degree through UTME are often young and naïve and have no post-secondary education. In contrast, those that joined the degree through the Direct route are more mature and older as they have attained some post-secondary education. Hence the dummy variable  $DERi$  is included to see if that has some influence on the student learning achievement. The variables take 1 for UTME and 0 for Direct.

The other categorical variable  $SGi$  denotes the student's gender and has Male or Female. The variable takes 1 for females and 0 for males. The dummy variable  $SGi$  is also included to examine whether the student's gender has anything to do with the student's learning achievement.

The continuous variables are; the percentage of classes attended for the econometrics course (denoted  $ATDi$ ) and Cumulative Grade Points Average at level three denoted by  $CGPA3i$  which controls for the previous level of achievement in the course and captures factors such as the level of ability, knowledge and effort of each student just before starting the year four

(400 level) course. Sund and Bignoux (2018) emphasise the importance of controlling for other relevant factors of student learning achievements, such as  $CGPA3i$ , when considering the relationship between attendance and learning achievements.

However, econometrics and statistical courses are prevalent in most academic departments; the target population of this study were fourth-year (400 Level) undergraduate economics students on a core econometrics course at Yobe State University Damaturu, Nigeria. They had Mathematics, Statistics and Introductory Econometrics courses in their first, second and third year. The course comprises theoretical lectures, practical exercises, and tests and examinations to assess learning achievement. Overall, the motivation of the course is an application, with all the test and exam questions related to the field of economics. The lecture and exercise sessions involve solving work under the supervision and help of the lecturer to solve problems. Part of the test and examination is in writing, and part is with econometric software. The course content, among others, includes statistical inference, linear regression model, dummy variables, multicollinearity, specification errors, heteroscedasticity and autocorrelation.

The data is for 58 students of the year four econometrics course in the first semester of the

2020/21 academic session. Every student had 14 scheduled classes in the semester. There is a two-hour class every week in the semester. Students complete an econometric class test in the middle of the semester (constituting 30% of the course's

mark). The second was an exam (70%) taken at the end of the semester. The *ECS4i* is the weighted average exams and the test scores.

Table 2. Descriptive statistics for continuous variables	Variable	<i>ECS4i</i>	<i>CGPA3i</i>	<i>ATDi</i>
	Mean	56.707	3.220	77.463
	Median	58.000	3.230	78.571
	Maximum	72.000	4.810	100.000
	Minimum	30.000	1.510	28.571
	Std. Dev.	8.758	0.829	19.927
	Skewness	-0.605	-0.079	-0.793
	Observations	58	58	58

Table 2 reports descriptive statistics for the continuous variables. The mean value of *ECS4i* (57%) shows that the average score exceeds the pass mark of 45% for the course. Mean attendance is 77.46%, indicating that, on average, students attend just under 80% of the classes. The mean *CGPA3i* prior to the year four course is 3.220.

The maximum value of *ECS4i* (72%) is slightly higher than the minimum for the highest grade(A), 70% and above. The maximum value for attendance is 100%, indicating that some attended all the classes. At the same time, the maximum *CGPA3i* of the class is 4.810, which is in the first-class degree category.

The minimum value of *ECS4i* (30%) is 15 percentage points less than the pass mark of 45%. This indicates that some students did fail the course, not meeting a minimum grade of 45% hence will retake the course in the next academic session. The minimum value of *ATDi* (28.53%) shows that students that least attended the classes were around for only about 28.53% of the classes. At the same time, some students had a

*CGPA3i* of 1.510 before the class, which was narrowly above the 'repeating a class' threshold of 1.50.

The standard deviation of *ECS4i* (8.75%) indicates a greater variety of marks in the *ECS4i* assessment compared to the students' learning achievements in year one to three-level courses proxied by *CGPA3i*. The Standard deviation of *ATDi* (19.92%) also shows the variation in class attendance among the students.

The negative skewness shows that the tail on the left side of the distribution is longer or fatter than the tail on the right side, meaning that the mean and median of the *ECS4i*, *CGPA3i* and *ATDi* are less than the mode of the variables.

Table 3 shows the simple correlation coefficient matrix for the three continuous variables. The simple correlation coefficients suggest that *CGPA3i* has a high correlation of around 73% with *ECS4i* while *ATDi* has a slightly lower correlation of 63.8% with *ECS4i*. Hence, both *CGPA3i* and *ATDi* are likely to be significant determinants of *ECS4i*.

		<i>ECS4i</i>	<i>CGPA3i</i>	<i>ATDi</i>
Table 3. Correlation matrix for continuous variables	<i>ECS4i</i>	1	0.7294	0.6386
	<i>CGPA3i</i>	0.7294	1	0.5234
	<i>ATDi</i>	0.6386	0.5234	1

### 3.2. Model

We estimate two sets of linear models: those without categorical dummy variables and those

with categorical dummy variables. The linear models without dummy variables are nested within the following equation:

$$ECS4_i = \beta_1 + \beta_2 CGPA3_i + \beta_3 ATDi + u_i \quad 2$$

Chow tests are employed to ascertain if the intercept and slope coefficients are different when the sample breaks into regimes according to the values of the dummy variables. For the degree entry route (DERi) set of categorical

variables, there are two regimes such that the sample split is specified by (3) and (4). The corresponding Chow test for  $H_0: \beta_{k1} = \beta_{k2}$ ,  $k = 1, 2, 3$  is denoted F(DERi).

$$ECS4_i = \beta_{11} + \beta_{21} CGPA3_i + \beta_{31} ATDi + u_{i1} \quad DER_i = 1 \quad 3$$

$$ECS4_i = \beta_{12} + \beta_{22} CGPA3_i + \beta_{32} ATDi + u_{i2} \quad DER_i = 0 \quad 4$$

For the student's gender (SGi) set of categorical variables, there are two regimes such that the sample split is specified by (5) and (6). The

corresponding Chow test for  $H_0: \beta_{k1} = \beta_{k2}$ ,  $k = 1, 2, 3$  is denoted F(SGi).

$$ECS4_i = \beta_{11} + \beta_{21} CGPA3_i + \beta_{31} ATDi + u_{i1} \quad SG_i = 1 \quad 5$$

$$ECS4_i = \beta_{12} + \beta_{22} CGPA3_i + \beta_{32} ATDi + u_{i2} \quad SG_i = 0 \quad 6$$

The linear models with dummy variables are nested in equation 7 below:

$$ECS4_i = \beta_1 + \beta_2 CGPA3_i + \beta_3 ATDi + \beta_4 DER_i + \beta_5 SG_i + u_i \quad 7$$

Chow tests are applied to determine whether intercept and slope coefficients are different when the sample is split into regimes according to the values of the dummy variables (using essentially the same split samples that are indicated by (3) to (7) above).

## 4. Results

In Table 4, we report the results of four estimated models. No model shows evident parameter change across the different degree entry routes [F(DERi)] or across students' gender groups [F(SGi)] based on Chow tests. The test is for changes in both slope and intercept in the models excluding dummy variables and for t-tests for intercept-only shifts in the models including

dummy variables. We fail to reject the null hypothesis of no significant improvement in the model when split based on the degree entry route as the F- value of 0.7075 is less than the critical value of 2.7826. For the students' gender, also we fail to reject the null hypothesis of no significant improvement in the models when splitted as the F- value of 0.2487 is less than the critical value of 2.7826. Therefore, there is no need to develop separate models for samples of students on different degree entry routes or by students' gender.

The results indicate no clear significant difference in student learning achievements due to degree entry route and gender. These inferences are based on Chow tests for parameter constancy of intercept and slopes in the linear specifications. Usually, the literature narrows testing for intercept-only shifts for the categorical variables by adding dummy variables. So, testing for both intercept and slope shifts is a more generic way of studying differences across the categorical variables than is usually considered in the literature.

Table 4: Models Estimation Results

	M1	M2	M3	M4
<i>C</i>	8.015*** (7.528)	36.43*** (7.017)	36.304*** (7.026)	36.404*** (6.981)
<i>ECS4i(-1)</i>	-0.183** (-2.081)	-0.191** (-2.390)	-0.192** (-2.412)	-0.190** (-2.375)
<i>CGPA3i</i>	41.491*** (8.656)	6.158*** (6.238)	5.851*** (5.775)	5.855*** (5.732)
<i>ATDi</i>		0.147*** (3.570)	0.158*** (3.772)	0.154*** (3.537)
<i>ERDi</i>			3.117 (1.240)	3.234 (1.268)
<i>SGFi</i>				0.777 (0.407)
<i>Adj_R2</i>	0.568	0.645	0.649	0.643
<i>SE</i>	5.740	5.202	5.176	5.218
<i>AIC</i>	6.384	6.203	6.209	6.241
<i>SIC</i>	6.491	6.347	6.388	6.456
<i>F(R2=0)</i>	37.883 [0.000]	34.998 [0.000]	26.899 [0.000]	21.207 [0.000]
<i>F(LIN)</i>	0.019 [0.984]	0.317 [0.575]	0.215 [0.644]	0.135 [0.714]
<i>F(HET)</i>	0.756 [0.585]	0.525 [0.848]	0.400 [0.961]	0.428 [0.968]

The dependent variable is *ECS4i*, and the figures in parentheses below coefficients are estimated *t*-ratios. *Adj\_R2* = determination adjusted for degrees of freedom, *SE* = standard error, and (*R2* = 0) is the *F*-test for deleting all slope coefficients from the model. *AIC* = Akaike's information criterion, and *SIC* = Schwarz's information criterion. *F(Het)* = *F* version of White's test for heteroscedasticity (based on only squared regressors), *F(Lin)* = *F*-version of Ramsey's Reset test for non-linear functional form (based on the squared fitted value only). Probability values in squared brackets.

\*\*\*, \*\*, and \* denote significance 1%, 5% and 10% levels, respectively. Observations = 58.

The constant ( $C$ ) is included in the models to ensure that the model is unbiased. At the same time, the lagged dependent variable  $ECS4(-1)$  is included to reduce the occurrence of autocorrelation. In the first model (denoted M1), the three included variables (the constant  $C$ ,  $ECS4(-1)$  and  $CGPA3i$ ) are significant, and the model has 56.8% explanatory power according to the adjusted coefficient of determination ( $Adj\_R^2$ ).

In the second model (M2), all four included variables ( $C$ ,  $ECS4(-1)$ ,  $CGPA3i$  and  $ATDi$ ) are significant, and the model has 64.5% explanatory power. Therefore,  $ATDi$  is an essential determinant of  $ECS4i$  since attendance has a significant positive impact on  $ECS4i$  (a one percentage point increase in  $ATDi$  raises  $ECS4i$  by approximately 0.15%) and the inclusion of  $ATDi$  has significantly increased the explanatory power of the model relative to its exclusion.

The last two models (M3 and M4) add different combinations of dummy (intercept shift) variables to the second model (M2). These dummy variables are not significant in all cases, which proves our decision that it is unnecessary to develop separate models for students from different degree entry routes or by gender based on the Chow test.

The favoured specification is the second model (M2) that includes the four variables  $C$ ,  $ECS4(-1)$ ,  $CGPA3i$  and  $ATDi$  and has 64.5% explanatory power. Both  $CGPA3i$  and  $ATDi$  are positively and significantly correlated with  $ECS4i$ .

Overall, the result suggests that attendance in the econometrics class with econometric and statistical software applications shows a positive impact on the student's learning achievement in the year four econometrics course. However, it was evident that the student's ability and self-efficacy before attending the class (represented by  $CGPA3i$ ) is the primary determinant of the student's learning achievement. At the same time, the impact of attendance in the class is also significant.

Some studies like Bianchi, Lu, & Song (2022) and Bai *et al.* (2023) show that exposure to the computer-aided environment at lower school levels has a long-term impact on the student's learning achievements at higher levels. We believe the inclusion of the  $CGPA3i$  captures the students' ability before the attendance of the econometrics course class covers it, considering that the  $CGPA3i$  includes learning achievements in some computer courses as well at the lower level of the degree programme.

Attendance in software-aided econometrics classes significantly improves learning achievements, which has implications for attendance policy in such courses. While the mandatory at least 75% attendance to qualify for an exam has been in university policy, its implementation could have been taken more seriously. Such an attendance policy should be upheld, especially in courses that involve the practical application of the software. Sund & Bignoux (2018) suggest that having continuous in-class assessments throughout the course is an option to look into to encourage attendance.

## 5. Conclusion

The study examined the impact of using statistical software packages in teaching econometrics at the undergraduate level. The study determined the effect of attendance of the classes using statistical software packages in teaching econometrics and its influence on students' learning achievement.

A model was developed to investigate the benefit of using the software packages on the student's learning achievements. The study explores the strong pedagogical advantages of using the statistical software packages in improving the teaching and learning of econometrics at the undergraduate level.

The study follows Westerman *et al.* (2011) and Sund and Bignoux (2018) and specifies a model used to gauge the impact on student learning achievements. A linear model, together with parameter constancy tests, was used. The



model used student learning achievement proxied by 400-level econometric course examination and continuous assessment scores ( $ECS4_i$ ) as the dependent variable. At the same time, the students' 300 level CGPA ( $CGPA3_i$ ) and the econometrics class attendance ( $ATD_i$ ) are used as independent variables. Dummy variables for students' gender ( $SG_i$ ) and the students' degree entry route – direct entry or UTME ( $DER_i$ ) are included in the equation.

The result suggests that attendance in the econometrics class with econometric and statistical software applications positively impacts the student's learning achievements in the year four econometrics course. However, it was evident that the student's ability and self-efficacy before attending the class, proxied by Cumulative Grade Point Average (CGPA), is the primary determinant of the student's learning achievements in the course. The study found that attendance in software-aided econometrics classes significantly improves students' learning achievement and has implications for attendance policy in such courses in universities.

Hence, the study concludes that attendance in econometrics classes using statistical and econometrics software applications is essential in enhancing the students' learning achievement 'to develop the desired analytical skills required in the industry. As such, students' attendance in software applying econometrics class is essential.

The study, therefore, recommends that the universities should use ways of convincing students to attendance the econometrics classes applying softwares to improve learning achievements.

## References

- Angrist, J.D., & Pischke, J.S. (2017). Undergraduate Econometrics Instruction: Through Our Classes, Darkly. *Journal of Economic Perspectives*, 31(2), 125-144. <https://pubs.aeaweb.org/doi/pdfplus/10.1257/jep.31.2.125>
- Auerbach, A. J., Higgins M., Brickman, P. & Andrews, T. C. (2018). Teacher Knowledge for Active-Learning Instruction: Expert–Novice Comparison Reveals Differences. *CBE—Life Sciences Education*, 17(1). <https://doi.org/10.1187/cbe.17-07-0149>
- Bai, Y., Tang, B., Wang, B., Mo, D., Zhang, L., Rozelle, S., Auden, E., & Mandell, B. (2023). Impact of Online Computer Assisted Learning on Education: Experimental Evidence From Economically Vulnerable Areas of China. *Economics of Education Review*, 94(June). <https://www.sciencedirect.com/science/article/abs/pii/S0272775723000328>
- Berger, N., Mackenzie, E., Holmes, K., (2020). Positive Attitudes Towards Mathematics And Science Are Mutually Beneficial For Student Achievement: A Latent Profile Analysis Of TIMSS 2015. *Australian Educational Researcher*, 47(3), 409-444. <https://link.springer.com/article/10.1007/s13384-020-00379-8>
- Bianchi, N., Lu, Y., & Song, H. (2022). The effect of computer-assisted learning on students' long-term development. *Journal of Development Economics*, 158. <https://www.sciencedirect.com/science/article/abs/pii/S0304387822000761>
- Carter, J., Brown, M., Simpson, K., (2017). From the Classroom to the Workplace: How Social Sciences Students are Learning to do Data Analysis for Real. *Statistics Education Research Journal*, 16(1), 80-101. <https://iase-web.org/ojs/SERJ/article/view/218>
- Cladera, M., Rejon-Guardia, F., Vich-I-Martorell A., G., Juaneda, C., (2021). Evolution of Undergraduate Tourism Students' Attitudes Towards Statistics: Pre and Post Evaluation. *Journal of Teaching in Travel & Tourism*, 21(2), 120-141. <https://www.tandfonline.com/doi/abs/10.1080/15313220.2020.1828014>

- Comas, C., Martins, J.A., Nascimento, M.M., & Estrada, A., (2017). Study of Attitudes Toward Statistics in Psychology Students. *Bolema*, 31(57), 479–496. <https://doi.org/10.1590/1980-4415v31n57a23>
- Conaway, B., Clark, C., Arias, J.J., & Folk, J., (2018). Integrating Econometrics: A Modern Undergraduate Economics Capstone Experience. *The Journal of Economic Education*, 49(3), 260–270. <https://www.tandfonline.com/doi/abs/10.1080/00220485.2018.1464986?journalCode=vece20>
- Cook, S., Watson, D., & Vougas, D., (2019). Solving The Quantitative Skills Gap: A Flexible Learning Call To Arms! *Higher Education Pedagogies*, 4(1) 17–31. <https://www.tandfonline.com/doi/full/10.1080/23752696.2018.1564880>
- Freiberg, M. (2005). Math - That Four-Letter Word! *Academic Exchange Quarterly*, 9(3), 7–11. <https://www.thefreelibrary.com/Math--that+four-letter+word!-a0138703652>
- Gajda, A., Karwowski, M. & Beghetto, R.A. (2017). Creativity and Academic Achievement: A Meta-Analysis. *Journal of Educational Psychology*, 109 (2), 269-299. <https://psycnet.apa.org/doi/10.1037/edu0000133>
- Gibbs, G.R., (2010). Mathematics and Statistics Skills in the Social Sciences. In: Marr, C.M., Grove, M.J. (Eds.), Responding to the Mathematics Problem: The Implementation of Institutional Support Mechanisms. Maths, Stats & OR Network, pp. 44–50 <http://eprints.hud.ac.uk/8879/>.
- Greene, W. H. (2015). Econometric Software. *International Encyclopedia of the Social & Behavioral Sciences* (Second Edition), 1-7. <https://doi.org/10.1016/B978-0-08-097086-8.71006-3>
- Johnson, B.K., Perry, J.J., Petkus, M., (2012). The Status of Econometrics in the Economics Major: A Survey. *The Journal of Economic Education*, 43(3), 315–324. <https://doi.org/10.1080/00220485.2012.686782>
- Manwaring, K. C., Larsen, R., Graham, C. R., Henrie, C. R., & Halverson, L. R. (2017). Investigating Student Engagement in Blended Learning Settings Using Experience Sampling and Structural Equation Modelling. *The Internet and Higher Education*, 35, 21–33. <https://doi.org/10.1016/j.iheduc.2017.06.002>
- McGoldrick, K., (2008). Writing Requirements and Economic Research Opportunities in the Undergraduate Curriculum: Results From A Survey of Departmental Practices. *The Journal of Economic Education*, 39(3), 287–296. <https://doi.org/10.3200/JECE.39.3.287-296>
- Pan, W., & Tang, M. (2005). Students' Perceptions on Factors of Statistics Anxiety and Instructional Strategies, *Journal of Instructional Psychology*, 32(3), 205-214. <https://psycnet.apa.org/record/2005-12870-004>
- Rattaphon, W. & Namporn, T. (2019). "Teaching Macroeconomics with Data: Materials for Enhancing Students' Quantitative Skills". *International Review of Economics Education*, 30. <https://doi.org/10.1016/j.iree.2018.11.001>
- Shah, R., & Barkas, L. (2018). Analysing The Impact of E-Learning Technology on Students' Engagement, Attendance and Performance. *Research in Learning Technology*, 26. <https://doi.org/10.25304/rlt.v26.2070>
- Siegfried, J.J., Walstad, W.B., 2014. Undergraduate Coursework in Economics: A Survey Perspective. *The Journal of Economic Education*, 45(2), 147–158. <https://doi.org/10.1080/00220485.2014.889965>

- Sund, K. J. and Bignoux, S. (2018). Can the performance effect be ignored in the attendance policy discussion? *Higher Education Quarterly*, 72(4), 360 – 374. <https://doi.org/10.1111/hequ.12172>
- Teig, N., Scherer, R., & Nilsen, T., (2018). More Isn't Always Better: The Curvilinear Relationship Between Inquiry-Based Teaching and Student Achievement in Science. *Learning and Instruction*, 56, 20-29. <https://doi.org/10.1016/j.learninstruc.2018.02.006>.
- Tsui, J.M., & Mazzocco, M.M. (2007). Effects Of Math Anxiety and Perfectionism on Timed Versus Untimed Math Testing in Mathematically Gifted Sixth Graders, *Roeper Review*. 29(2), 132-39. <https://doi.org/10.1080/02783190709554397>
- Wang, L.H., Chen, B., Hwang, G.J., Guan, J.Q., & Wang, Y.Q. (2022). Wang Effects of Digital Game-Based STEM Education on Students' Learning Achievement: A Meta-Analysis. *International Journal of STEM Education*, 9, 1–13. <https://doi.org/10.1186/s40594-022-00344-0>
- Westerman, J. W., Perez-Batres, L. A., Coffey, B. S. & Pouder, R. W. (2011). The relationship between undergraduate attendance and performance revisited: alignment of student and instructor goals. *Decision Sciences Journal of Innovative Education*, 9(1), 49 – 67. <https://doi.org/10.1111/j.1540-4609.2010.00294.x>