RELATIONSHIP BETWEEN MODALITY AND ACADEMIC ACHIEVEMENT: MULTILEVEL ANALYSIS OF ENADE IN ACCOUNTING

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ABSTRACT

Despite not being a recent mode, distance education is still viewed with suspicion by part of the academic community. With its expansion, there is a concern to ensure quality, according to MEC (Ministry of Education). To address it, the teaching evaluation system relies, among others, on the National Student Performance Examination - ENADE. This study sought to identify if there was a relationship between teaching mode and students' performance in Accounting Sciences, in the 2012, 2015, and 2018 exams. The foundations of the Education Production Function (EPF) supported the discussions. ENADE microdata were the main data source and the Linear Hierarchical Method (LHM) was used for empirical tests. For 2012, it was not possible to prove an effect of the teaching mode on performance, while for 2015 and 2018 there was, on average, a higher performance of face-to-face teaching. However, in the joint analysis, the results were inconclusive. This study fills the gaps found in investigations on education type and performance in Accounting, when studying this relationship from the perspective of EPF, through LHM, which enables contextual analysis, as education data are typically hierarchical. In addition, it innovates by contributing to understanding the institution's influence and the impacts that socioeconomic characteristics have on students' achievement. From the perspective of the hybrid model, the findings are relevant for analyzing if the mode's behavior is related to other variables, through potential interactions.

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Keywords: Higher Education Expansion. Distance Education. Educational Assessment. Linear Hierarchical Method. Academic Performance.

RELAÇÃO ENTRE MODALIDADE DE ENSINO E DESEMPENHO ACADÊMICO: ANÁLISE MULTINÍVEL DO ENADE EM CIÊNCIAS CONTÁBEIS.

RESUMO

Apesar de não ser modalidade recente, o EaD ainda é visto com desconfiança por parte da comunidade acadêmica. Com a expansão, há a preocupação em garantir a qualidade, nos critérios do MEC. Para isso, o sistema de avaliação do ensino conta, entre outros, com o ENADE. Este estudo buscou identificar se há relação entre a modalidade de ensino e o desempenho em Ciências Contábeis, no ENADE 2012, 2015 e 2018. Os fundamentos da Função de Produção Educacional (FPE) subsidiaram as discussões. Os microdados do ENADE foram a principal fonte de dados e recorreu-se ao Método Hierárquico Linear (MHL) para testes empíricos. Em 2012, não foi possível afirmar que houve efeito da modalidade no desempenho; enquanto 2015 e 2018 indicam, em média, desempenho superior do presencial. Na análise conjunta, no entanto, os resultados são inconclusivos para a modalidade. Este estudo cobre lacunas encontradas nas investigações sobre modalidade e desempenho em Contabilidade, ao estudar essa relação sob a ótica da FPE, através do MHL, que possibilita a análise contextual, já que os dados educacionais são tipicamente hierarquizados. Ademais, inova ao contribuir para a compreensão da influência da instituição e os impactos que as características socioeconômicas exercem sobre o desempenho. Com a perspectiva do modelo híbrido, os achados são relevantes para analisar se o comportamento da modalidade é relacionado a outras variáveis, através de interações possíveis.

Palavras-Chave: Expansão do Ensino Superior. Ensino à Distância. Avaliação Educacional. Método Hierárquico Linear. Desempenho Acadêmico.

1 INTRODUCTION

Distance education has consolidated as an alternative for higher education, especially since 2005, when its numbers increased (Luzzi, 2007). The Accounting Sciences course is one of the most demanded, in number of Distance Education (DE) enrollments (Inep, 2018). In 2006, there were 349 DE courses in Brazil, with 813,550 vacancies, of which 11 were in Accounting, with 14,369 vacancies (Inep, 2006). And in 2017, there were 2,108 courses and 4,042,488 vacancies, 78 of them in Accounting, with 164,963 vacancies (Inep, 2018).

But the expansion of vacancies and enrollments does not always mean quality education, according to the patterns established by the State (MEC, 2018). There are financial, structural, human, and logical limitations that affect the development of distance education in Brazil. The problems range from lack of investments, poor qualification, and deficiency in technological support (Niskier, 2009), to high dropout rates (Silva et al., 2020).

As part of the advances in the search for quality education, the National System for the Assessment of Higher Education (SINAES) was created in 2004; in addition to evaluating structural and pedagogical characteristics of Higher Education Institutions (HEIs), it assesses student performance and socioeconomic variables. SINAES includes the National Student Performance Examination (ENADE), comprising content questions and a survey of the institutional and student profile. The average performance in the exam, in the Accounting Sciences course - at both modes -, is historically below 40%, a result that highlights the need to investigate performance-related factors.

Given the scenario of accelerated growth of the DE mode and the criticisms found in the literature (Niskier, 2009), regarding the low performance of students and the implementation of evaluation systems for higher education in the country (Andrade, 2011; Ferreira, 2015), this study intended to answer the following question: *is there a relationship between teaching mode and student performance in the Accounting Sciences course, for the ENADE editions of 2012, 2015, and 2018?*

The use of the Hierarchical Linear Method (HLM) for the empirical tests showed that, in isolation, the impact of the mode should be interpreted cautiously, not being possible to state, in general terms, that it affects academic performance. By applying HLM, which takes into account the context of the data (educational data do not have independent observations), this research advances the empirical literature by revealing that socioeconomic, family, and individual variables affect the mode's size of impact on performance.

Hence, this research has the potential to extend discussions in the economic, political, and management spheres, since DE is considered an important instrument for democratizing education. The results of the study can assist in decision-making, regarding resource targeting to educational public policies, as the identification of factors that contribute to student performance can support the efficient allocation of resources, in addition to being useful for professors and educational managers, especially after the 2020 COVID pandemic, and the adoption of hybrid models.

2 THEORETICAL FRAMEWORK

2.1 The Education Production Function (EPF)

For a long time, scholars discussed that the production function was not applicable to education, under the argument that firms managed their inputs to maximize profits, based on the efficiency of their use; and this was not done by educational institutions, due to their non-profit nature (Blaug, 1975; Ramos, 2015).

Hanushek (1979) was a pioneer in identifying that the concepts of the production function were clearly appropriate to the field of education, provided there were some adaptions. Today, we know that "although there are significant differences between the production function of education in relation to other sectors, its application within schools and the educational system, as processes of knowledge production, is possible" (Santos, 2012, p. 26). In addition, other academics have advanced the discussion on education as a service managed by individuals seeking a return on invested capital (Giroux, 2014).

The models of educational production function have undergone changes over time, according to Hanushek and Woessmann (2011), and confirmed by Santos (2012). There is a statistical model of EPF usually employed in the literature on the topic:

$$T_i = \alpha_0 + \alpha_1 F_i + \alpha_2 P_i + \alpha_3 R_i + \alpha_4 I_i + \alpha_5 A_i + \varepsilon \tag{2.1}$$

where T are the results of the educational production process (usually obtained from standardized tests), F are students' personal characteristics and background, in addition to family background, P is the peer effect, R stands for school resources, and I represents the institutional specificities of the school and the educational system as a whole. Finally, A shows students' individual abilities.

Equation (2.1) applies to students currently at school, and due to the common limitation of available databases, structurally and temporally, this model is widely used, resulting in cross-sectional analyses. This study relied on this model for surveying inputs and their analysis and, for this purpose, the ENADE score was the measure used to assess EPF output.

2.2 The Growth of DE: Debates and Perspectives

The share of DE in total enrollments has increased in recent years, reducing the gap between modes. In the Accounting Sciences course, the search for DE mode also increased, starting in 2005, and it is one of the courses with the highest number of registrations. The number of DE enrollments increased almost tenfold between 2005 and 2010, and grew almost 300% between 2010 and 2019. On the other hand, the face-to-face mode began to lose students as of 2015, reaching a very small difference between the two modes in 2019, according to the Higher Education Census (CES), for the period 1995-2019.

However, there are factors that deserve attention, such as the pedagogical model. Currently, "a distance learning course is no longer a one-way correspondence course, where books and other texts are sent by mail and the student is expected to already know how to study and learn" (Nunes, 2009, p. 2). Failures like this can contribute to increase dropout, as well as other elements: balancing work and study; dissatisfaction with the teaching staff, materials, or pedagogical project; mandatory face-to-face meetings; financial problems; administrative category of the HEI; and school background (Alves et al., 2014; Sousa & Maciel, 2016; Silva et al., 2020).

Gatti (2002, p. 143) argues that for DE programs that provide certifications (such as undergraduate), it is necessary to develop, from the conception, a serious and interactive work for clarifying pedagogical issues, an appropriate curriculum, necessary knowledge and competencies, and all materials and support for the development: "the program cannot be a leap in the dark for participants".

Despite the challenges still to overcome, it is unthinkable to close our eyes to DE consolidation. Data show a constant growth, and there is no evidence pointing to the setback of the mode (Alves et al., 2014).

The COVID pandemic scenario, which began in 2020, despite revealing deficiencies in the distance system, also nurtured hope for improvements and new ways of doing education. It showed not only the fragility of the DE system, but the urgency to finally establish and improve it, through qualification, investment in physical and logical resources, as we see in countries where this mode is stronger, with positive results in performance evaluation (Zhao et al., 2005; Means et al., 2010; Means et al., 2013).

We highlight that remote teaching during the pandemic was not DE, but emergency teaching; it was disruptive, but showed the need to strengthen the system. Regarding potential links between the pandemic and the purpose of this research, the Accounting Sciences course participated in ENADE 2022, and many students who faced this scenario took the exam.

2.3 Performance Assessment in Higher Education

Performance involves the dimension of action and assessment, and is expressed by scores and concepts (Ferreira, 2015). Academic performance is the product of various inputs. "This result is presented individually, and its changes are related to the quality and quantity of inputs. These can be factors inherent to the person, to the context, and to the school" (Santos, 2012, p. 19).

School evaluation comprises academic assessment, as part of pedagogical activities, and institutional assessment. However, Brito (2008) already argued that, unlike teachers' attitudes, the use of evaluations by public policy managers was undue, without focusing on the development of students or the community, but motivated by economic or political interests, and evaluation results were used for resource reallocations. Caetano et al. (2015) confirm that author's criticisms. The consequence of this reality is that HEIs with worse results will have insufficient resources to improve their activities.

It is important to identify and understand the factors related to performance, in order to achieve a real evaluation. Luckesi (2005) criticized the education system for not evaluating, but examining; and one justification for this criticism was considering only the final performance, ignoring the path taken by the student.

Later, although recognizing that little had changed in institutional assessment, Andrade (2012) highlighted the position occupied by the debate on quality in higher education in the agenda of educational policies, especially due to the expansion of HEIs, which resulted in different models of teaching and training. The author showed the advances resulting from ENADE’s creation, one of the mechanisms that make up SINAES and forms the evaluation triad that shows the mode of operation and the quality of higher education courses and institutions in Brazil.

2.4 Acadeic Performance in Teaching Modes, Empirical Literature and Hypothesis Development

Results on mode and performance in the international literature are inconclusive: (i) 70% of null differences between modes, in the pioneering work of Thomas Russel (1999), who addressed 350 studies, from 1928 to 1997; (ii) 70% of results in which DE students outperformed those of the traditional mode, according to Shachar and Neumann (2010), who analyzed studies (only experiments and quasi-experiments) from a 20-year period (1990-2009), with 20,800 students.

Means et al. (2010) highlight the blend method[4]. Stanford researchers established criteria for selecting 45 robust empirical studies and observed that online students achieved slightly better results than those of the traditional mode, and this difference was higher in the blend mode. Most international studies that compare teaching modes have agreed that the blend method is the most effective, due to its hybrid characteristic and adequate dosage of human and technological resources (Zhao et al., 2005; Means et al., 2013).

In Brazil, Moran (2019), through a statistical comparison, identified that the performance of DE students, in seven of the thirteen areas of undergraduate courses where it was possible to compare, at 2005 and 2006 ENADE tests, was higher than that of students in face-to-face courses.

In addition, we sought empirical studies addressing academic performance. Not all of them examined mode effects, but their results were important for the selection and analysis of control variables.

Figlio, Rush and Yin (2010) analyzed the difference between means in a discipline, and found no significant difference, but next revealed superior online performance from robustness tests. Silva (2013) did the same analysis in Brazil, and could not reject the hypothesis of equality of means. Batista et al. (2014) also analyzed the difference between means in the Northeast region of Brazil, and found a better performance of DE in the 2009 and 2012 ENADE editions.

Santos (2012) and Ferreira (2015) used EPF and HLM to identify determinants of performance at ENADE, and found a list that we fully used in this research. Rodrigues et al. (2016) also used HLM and found the same factors. Miranda et al. (2015), through meta-analysis, surveyed the determining factors in the international literature, which we considered in this study, provided they were available at the ENADE database. The sources for selecting variables are detailed in Appendix I.

Caetano et al. (2015) and Klug et al. (2018) analyzed the 2009 and 2015 ENADE, respectively, through simple and multiple regressions, using the Ordinary Least Squares Method (OLS). They found higher and statistically significant performance for face-to-face teaching. However, they did not consider the control indications from previous literature. The statistics literature considers OLS inappropriate for contextual data (Raudenbush & Bryk, 2002; Goldstein, 2011; Rabe-Hesketh & Skrondal, 2012; Snijders & Bosker, 2012; Fávero & Belfiore, 2017; Finch, Bolin & Kelley, 2019).

This study fills the gaps of previous research by adding to the Brazilian literature the investigation of the relationship between teaching mode and

[4] A combination of teaching modes, using the strengths of both

academic performance, under the EPF approach, using HLM for hypothesis testing. In addition, it proposes a comparative analysis of the last three editions of ENADE, as a subsidy for educational managers, other researchers, and the government. Based on the results on the evolution of distance learning, considerations regarding the structure of the Brazilian system, and empirical literature, we raised the following research hypothesis:

H1: There is a relationship between teaching mode and the average performance of Accounting students at ENADE, in the years 2012, 2015 and 2018.

3 METHODOLOGY

This was a descriptive study (De Vaus, 2001), as it registered, analyzed, and interpreted Inep's [Anísio Teixeira National Institute for Educational Studies and Research] data, regarding the 2012, 2015 and 2018 editions of ENADE, the Preliminary Course Concept (CPC), in the same years, as well as data from the Higher Education Census (CES), between 1995 and 2019. The approach is quantitative-qualitative, because, in addition to using statistical tools, we investigated the phenomenon of DE expansion, considering its evolution, context, and society. Regarding technical procedures, we used literature search, documentary analysis, and statistical analysis. The software used for cleaning and analyzing databases and for statistical tests were Excel©, R, and SPSS©.

3.1 Population and Sample

The population consists of students of Accounting Sciences courses in Brazil, and their corresponding HEIs. The sample gathers students who were *present* and had *valid tests* at ENADE, in 2012, 2015, and 2018, and their HEIs.

With the help of SPSS© software, data were "cleaned", excluding students who possibly "boycotted" the test or returned the blank test, for different reasons; or, still, who had their results invalidated by the body that applied the test. This identification was possible by following the specific codes for each situation, available at the data dictionary.

Other "cleaning" criteria were adopted: students who did not report income or reported "no income" were excluded, otherwise these cases could be interpreted as "zero income", an impossible fact, according to the economic literature; even if the individual/family does not have its own income, it receives assistance from some source, for subsistence (Blaug, 1975, Ramos, 2015). Likewise, students who did not inform their gender were excluded. Exclusions of cases of unreported income and gender were 2% of the observations in 2012, 0.3% in 2015, and 0.4% in 2018, which did not compromise the sample consistency.

Finally, we treated missing values. In HLM estimation, the software recognizes and treats the missing, and shows the number of observations considered in each estimation, signaling that the treatment took place. However, to carry out the comparison tests between the models, in order to identify the one with the best fit, the existence of missing values in the database is a problem; that is why we treated them even before the first estimations.

Thus, our initial sample consisted of 57,248 students and 747 HEIs in 2012, 65,483 students and 821 HEIs in 2015, and 62,475 students and 855 HEIs in 2018. The final sample had 45,252 students and 710 HEIs in 2012, 54,813 students and 817 HEIs in 2015, and 52,560 and 836 HEIs in 2018, representing 79.05%, 83.71%, and 84.13% of the initial sample, respectively.

In addition to the initial treatment at the databases, some variables in the ENADE and CPC microdata were reconfigured. The manipulation of ENADE data was necessary because there were variables that had non-numerical response patterns or many response options. For the CPC data, the manipulation was done to obtain the average values of the standardized scores per institution, since these are variables whose distribution in the database is by course. Although few, there are cases of institutions with more than one Accounting course, and calculating the average score was essential for statistical procedures.

3.2 Variable Description

The dependent variable is the student's overall ENADE score (NG), and the independent variable is the teaching mode (MOD). The dependent, independent, and control variables were selected according to Table 4, in Appendix I, which shows the papers supporting each choice. In EPF study, there is no exhaustive list of variables that affect student performance, since several variables may not have been identified and measured (Hanushek, 1968; Santos, 2012; Moreira, 2013; Ferreira 2015; Alves & Candido, 2017).

The choice of control variables was based on the literature, according to the research design. Hence, there are variables that, cumulatively or not: 1) contribute to achieve the research goal; 2) were tested in relevant empirical papers; and 3) are available for extraction in the databases used.

Therefore, the chosen variables followed the logic of the constructs identified by Santos (2012) and Ferreira (2015), comprising faculty-level variables at the institution level. Due to the contextual factor present in the statistical method used, a different strategy would result in a three-level model, which was not the purpose of this article. In addition, the variables related to faculty (qualifications and work regime) are standardized scores assigned to HEIs, which enable the aggregate use and do not compromise the results.

3.3 Hierarchical Linear Models (HLM)

According to Cruz (2010), hierarchical modeling emerged as a technical solution for cases where observations are grouped, and the pioneer area in this respect was education, through the proposal of Aitkin and Longford (1986). Raudenbush and Bryk (2002) highlight that education research is maybe the best example of hierarchical structures.

HLM is indicated when observations are nested, because, in these cases, the assumption of independence of error terms, required in traditional regression methods (such as OLS), is not respected. It is not coherent to imagine the independence of error terms when there is a clear interference from higher levels on the factors that influence a given behavior (Fávero & Belfiore, 2017).

Considering nesting for regression analyses provides more consistent estimations of coefficients, and leads to interpretations more appropriate to reality (Finch et al., 2019). By adopting HLM, it is possible to separate the role of each actor in the hierarchical context, due to the decomposition of the error variance at the various levels. Therefore, we know the reality more precisely, and intervene more efficiently (Cruz, 2010).

3.3.1 Empirical tests and models for hypothesis tests

The empirical tests were done using the R software, package *lme4*[5] and other necessary packages, with HLM estimations through the Maximum Likelihood (MV) method. For hypothesis testing and exploratory model analysis, MV should be adopted, since the validity of likelihood statistics is compromised in the presence of the Restricted Maximum Likelihood (REML) (Goldstein, 2011, p. 41-42).

Analyses using HLM start with the estimation of the null model, where there is no insertion of explanatory variables, only the response variable and the random effects of the levels. The One-Way ANOVA with Random Effects model "provides useful preliminary information on how much of result variation lies within and between schools, and on the reliability of the sample average for each school as an estimate of its true population average" (Raudenbush & Bryk, 2002, p. 69).

From the null model, we obtained the variance decomposition of the two levels of analysis: students and HEIs. $\tau00$ and $\sigma2$, shown in Table 3, are, respectively, the inter-group variability and the intra-group variability. With these data, it was possible to calculate the Intra-class Correlation Coefficient (ICC)[6], which measures the proportion of variance that is due to variability between the groups (Raudenbush & Bryk, 2002, p. 24).

After estimating the null model, the explanatory variables for each level were inserted. There is a divergence in the literature as to the order of the levels to consider in the next estimations. We chose the order of insertion from level 1 variables, following the logic observed in Snijders and Bosker (2012), Fávero and Belfiore (2017) and Finch et al. (2019).

We emphasize that the criteria for deciding the number of models for estimation also met the intention to observe the behavior that each estimation exerted on the residual variance. This means that, in addition to the best degree of fit, we also sought to understand data behavior at each estimation.

3.3.2 Models' degree of fit

There is no stepwise procedure for estimations in HLM (Goldstein, 2011, p. 33). The literature recommends that this should be done by the researcher, including the variables, one by one, and observing the characteristics of the model after their insertion, such as the proportion of variance explained and analyses of the model's improvement or not, from the new variable. Or start with the most complete model and reduce it, as this would avoid the occurrence of masked non-significance, where a variable is excluded for not being significant, but could be, if controlled by another variable. This paper has gone both ways.

[5] More information on the package at: https://cran.r-project.org/web/packages/lme4/lme4.pdf
[6] Goldstein (2011, p. 19) adopts the terms variance partition coefficient (VPC) or intra-school correlation, by recognizing the potential confusion that the expression "intra-class correlation", commonly used in genetic research, would cause in education studies.

For Snijders and Bosker (2012), in hierarchical models the isolated analysis of variables' significance, to decide whether to keep or exclude them from the model, is not necessarily the best way, given its nesting characteristic. The criterion for inserting new variables in the EPF structure was based on the literature. The steps for analysis originated in the recommendation of Snijders and Bosker (2012, ch. 6), by using the *multilevel step-up strategy*, according to Fávero and Belfiore (2017).

To measure the models' degree of fit, we adopted some criteria. Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Deviance and logLik measures were observed comparatively between the estimates. The analysis was done from the most frugal model to the most complete one. While AIC, BIC and Deviance indices meet the criterion that the smaller they are, the better fitted to the data the model is, the logLik index will be higher as the model is better fitted.

The *full Model* was the best fit for the three years of analysis, due to the result of AIC, BIC, logLik and Deviance measures, shown in R's Anova test. The final notation of the selected model is presented below

$$\begin{aligned} NG_{ij} = \gamma_{00} &+ \gamma_{10}MOD_{ij} + \gamma_{20}d\_not_{ij} + \gamma_{30}c\_idade_{ij} + \gamma_{40}d\_sexf_{ij} + \gamma_{50}d\_etnia_{ij} + \gamma_{60}dedicH_{ij} \\ &+ \gamma_{70}livros_{ij} + \gamma_{80}d\_ecivil_{ij} + \gamma_{90}renda_{ij} + \gamma_{100}Md\_afirm_{ij} + \gamma_{110}d\_bolsa_{ij} \\ &+ \gamma_{120}escpub_{ij} + \gamma_{130}d\_moraso_{ij} + \gamma_{01}cat\_adm_j + \gamma_{02}org\_acad_j + \gamma_{03}regiao\_curso_j \\ &+ \gamma_{04}np\_infra_j + \gamma_{05}np\_me_j + \gamma_{06}np\_dr_j + \gamma_{07}np\_rt_j + \gamma_{08}idade\_M_j + \gamma_{09}renda\_IES_j \\ &+ u_{0j} + \varepsilon_{ij} \end{aligned}$$

4 RESULTS PRESENTATION AND DISCUSSION

4.1 Descriptive Statistics

The descriptive statistics presented in Table 1 helps to understand the characteristics of the dependent variable, enabling to identify patterns or peculiarities of each of the databases used, for the years 2012, 2015, and 2018.

Table 1

Descriptive Analysis of the Dependent Variable (NG)

Genera Score	2012	2015	2018
Minimum	0	0	1.1
1st Quartile	25.4	31.3	27.8
Median	33.8	39.9	35.7
3rd Quartile	43.3	49.3	44.6
Maximum	85.6	94.4	90.1

NG: General Score
Source: The authors.

Teaching mode (MOD) is the independent variable of this study; despite the considerable advance in the number of enrollments in Distance Education, the percentage of respondents is still about 20% of the total number of students examined, as shown in Table 2. From 2015 onwards, there was an increase in the participation of DE in ENADE, overcoming the 2012 data by about 70%, when it accounted for just 13% of those examined; however, the scenario is still not balanced.

Table 2

Independent Variable (MOD)

MODALIDADE	2012	2015	2018
Face-to-face	87%	78%	76%
Distance Education	13%	22%	24%

Source: The authors.

4.2 Teaching Mode and Academic Performance

Table 3 shows the estimates of the null model and the best-fit model, with the estimates of the variable MOD for all years. Discussions regarding control variables are addressed for comparison with previous findings, although their results are not shown[7].

Table 3

Estimation of hierarchical models 2012, 2015 and 2018

		Null Model				Full Model			
Fixed Effects		**Coef**	**SE**	**t**	**Sig**	**Coef**	**SE**	**t**	**Sig**
Intercept	2012	35,03	0,18	200,00	***	27,99	2,23	12,54	***
	2015	41,33	0,19	221,80	***	30,97	2,08	14,87	***
	2018	36,91	0,18	207,10	***	28,10	1,87	15,04	***
MOD	2012					0,40	0,41	0,98	
	2015					3,22	0,32	9,91	***
	2018					1,83	0,26	7,05	***
Random Effects		**Var**	**SD**			**Var**	**SD**		
ID_IES - τ_{00} (u_{0j})	2012	17,43	4,18			11,68	3,42		
	2015	23,68	4,87			11,46	3,39		
	2018	21,07	4,59			10,28	3,21		
Residual - σ^2 (e_{ij})	2012	151,21	12,30			146,12	12,09		
	2015	143,42	11,98			136,19	11,67		
	2018	134,51	11,60			127,72	11,30		
ICC (ρ)	2012	10,34%				7,40%			
	2015	14,17%				7,76%			
	2018	13,54%				7,45%			
AIC e BIC	2012	356814.5		356840.7		355134		355474	
	2015	429421.3		429448.1		426224.4		426571.9	
	2018	408350.4		408377.1		405286.5		405632.4	
Loglik e Deviance	2012	-178404.3		356808.5		-177528		355056	
	2015	-214707.7		429415.3		-213073.2		426146.4	
	2018	-204172.2		408344.4		-202604.3		405208.5	
Nº of students and HEIs	2012	45252		710		45252		710	
	2015	54813		817		54813		817	
	2018	52560		836		52560		836	
Significance level:		(***) 0,001	(**) 0,01	(*) 0,05	(.) 0,1	( ) Not significant			

Source: The authors.

The estimated coefficient should be considered within each HEI, and not for all students examined. In this case, the estimation should be read as the average

[7] To access all descriptive statistics and complete estimations: https://github.com/dados-artigos/Dados_artigos/blob/main/Estima%C3%A7%C3%A3o_H1_Artigo.docx

difference between the groups of students linked to DE and to face-to-face teaching, in a given school J.

When estimating the *Null_Model*, we calculated ICC (ρ), which measures the proportion of variance that is due to inter-group variability (Raudenbush & Bryk, 2002, p. 24). The results were 10.34%, 14.17%, and 13.54%, respectively, for 2012, 2015, and 2018. These values showed that estimation by traditional multiple regression was not suitable. The statistics literature indicates that an ICC of 5% or above is sufficient for applying HLM.

In the *Full_Model*, the results of the variable MOD were not significant in 2012, in any model. In 2015 and 2018, the positive and significant coefficient at 99.99% indicates that students attending the face-to-face mode had, on average, higher performance than DE students. The size of the coefficient fell by half between 2015 and 2018, which raises the possibility of testing the random effects on the slope, allowing to investigate the existence of variability in the mode impact; in other words, it is possible that some institutions had a better performance of DE between 2015 and 2018.

The 2012 results do not provide evidence to reject the null hypothesis of no relationship between mode and performance, while in 2015 and 2018 the null hypothesis was rejected, at 5% significance, thus accepting H1. However, in a joint analysis of the three periods, the findings showed inconclusive results. Caetano et al. (2015) and Klug et al. (2018), who investigated the years 2009 and 2015, respectively, showed superior performance of the face-to-face mode; however, these studies used traditional multiple regression for the hypothesis tests, a method not suitable for this type of data. Our paper differs from previous ones by revealing that caution is needed for interpreting the influence of the teaching mode, and care must be taken in generalizing results.

As for the control variables of student level[8], their behavior confirmed the findings of Santos (2012), Ferreira (2015), and Rodrigues et al. (2016). Miranda et al. (2013) mentioned the divergences found in the international literature for the variables representing gender and civil status, thus making a conclusive analysis impossible. Personal characteristics such as age, level of reading, and dedication to studies are significant for academic performance.

For family income, the results confirm the findings of Santos (2012), Ferreira (2015), and Rodrigues et al. (2016): the higher the income, the better the average performance. Our study kept all 7 income categories considered by MEC/INEP, a strategy also adopted by Santos (2012), while Ferreira (2015) reconfigured the family income variable into a dichotomous dummy. The composition of family income is one of the factors that stands out among the impacts on academic performance. "Bourdieu (1977) concluded in his studies that the social origin of students translates into school inequalities" (Cruz, 2010, p. 4).

For the HEI level, there was disagreement with the findings for administrative category and academic organization. In this study, public institutions and universities are related to a higher average performance. Ramos (2015) argues that, among the possible explanations, the high competition for admission to

[8] To access the estimates of all control variables: https://github.com/dados-artigos/Dados_artigos/blob/main/Estima%C3%A7%C3%A3o_H1_Artigo.docx

public institutions may attract better prepared students. Santos (2012) did not find significance for the link with public HEIs in 2002, but found it in 2003 and 2006; the same occurred with the link to a University, but with a 10% significance in 2006. The author joined university centers and universities, different from our strategy, which considered only universities.

Ferreira (2015) also analyzed HEIs' administrative category and academic organization, and excluded the latter from her final model, as it was not significant at 5%; hence, there was no discussion on the findings. However, the *Full_Model* of our paper found significance for academic organization in 2012, the same period analyzed by that author, who adopted the strategy of joining universities and university centers. Academic organization explains part of the performance, due to the attributes that distinguish universities from colleges, for example. Issues such as institutional autonomy, greater dedication to research and extension, and professor training enable universities to offer a more complete qualification.

Caetano et al. (2015) worked with ENADE 2009 data, and analyzed administrative category and academic organization, finding t values over 20 times higher than ours, through traditional regression, thus confirming the criticism addressed in Cruz (2010) and Heck, Thomas and Tabata (2014). The study by Klug et al. (2018), also using traditional regression (OLS), found a lower result for students linked to public institutions, disagreeing with the literature; and, for academic organization, the coefficient was positive for the group of universities. The study does not discuss these findings.

The behavior of faculty-related variables, here assigned to the HEI level, was inconclusive. The standardized score of Masters loses predictive power in the presence of variables at students' level. The standardized score of PhDs brings a curious fact, since it presents a negative sign in 2012. This indicates that the higher the score for the presence of PhDs in the course, the lower the average performance of students at that HEI. These variables deserve further investigation, to analyze if PhD professors work in undergraduate courses, as analyzed data only consider the existence of a link between the PhD professor and the course.

The location of the course was addressed considering Brazil's five regions. This enabled a detailed analysis of the contribution of each region to the overall average, an innovation of our study. The strategy of analyzing the region as a categorical variable fills gaps found in the literature; most papers address the region only in descriptive statistics, showing lower performances in the North and Northeast Ferreira (2015) was the only one, among those surveyed, to study ENADE for Accounting Sciences and insert the region as a control variable, creating a dichotomous dummy, by separating the South and Southeast regions from the others, and finding significance for the positive coefficient at 5%. In this study, coefficients were significant at 5% in 2012, except for the Midwest region. The Southeast region coefficient was higher than the others, on average.

The inclusion of the variable renda_IES (income_HEI) followed literature recommendation for studies in education using HLM (Raudenbush & Bryk, 2002; Snijders & Bosker, 2012), since it was not considered in the selected papers. The result of the estimates for the influence of the average income reported by students, by HEI, on the relationship between mode and average performance indicates that, in a context of higher equality at the HEI, the performance of DE students tends to be higher, confirming the impact of the context on this relationship. The effect of the average age of HEI's students on average performance was negative at all years, and not significant in 2018. This means that the higher the average age of the students, the lower the average performance. Despite the statistical significance, the size of the coefficient was small, confirming the findings with the level 1 variable c_idade (c_age). Santos (2012) used average age by HEI in her analysis, and found no significance in any of the three years analyzed: Provão 2002 and 2003, and ENADE 2006 regions (Santos, 2012).

4.3 Variance Analysis and Estimates for the Full Model

The first analysis of the final model estimates is the result of ICC, which was 7.4% for 2012, 7.76% for 2015, and 7.45% for 2018. Compared to the values found in the null models of each year, shown in Table 3, there was a reduction in ICC of 28% in 2012, and of 45% in 2015 and 2018. This means that the percentage of variance that is due to the variability between the groups was partially explained by inserting the variables in the model. This ICC is called residual or conditioned.

As for the variance by level, compared to the *Null_Model*: for the year 2012, at the HEI level ($\tau 00$), there was a decrease from 17.43 to 11.68; at the student level ($\sigma 2$), it fell from 151.21 to 146.12. In 2015, $\tau 00$ decreased from 23.68 to 11.46, and $\sigma 2$ fell from 142.42 to 136.19, while in 2018, $\tau 00$ decreased from 21.07 to 10.28, and $\sigma 2$ fell from 134.51 to 127.72. The largest reduction was at the HEI level, which indicates that the model was able to capture, to a greater extent, the variability between groups, with a reduction higher than 30% in 2012, and 50% in 2015 and 2018. In models with two random effects, these reductions in variance are called explained variance (Raudenbush & Bryk, 2002; Rabe-Hesketh & Skrondal, 2012) or modeled variance (Snijders & Bosker, 2012).

From the results of the final model, we can infer that, based on the theory of Education Production Function, the estimation of the parameters, controlled by inputs at HEI level and at student level, reduced between 30% and 50% the unexplained variance at HEI level, and about 5% at student level. This result was expected, because, according to Santos (2012), the inclusion of inputs in EFP is very delicate and often generates insufficient results at student level, due to the failure in capturing innate skills that clearly interfere with the modeled fixed effects.

5 CONCLUSIONS

In order to identify if there is a relationship between teaching mode and academic performance, this study had as theoretical support the literature on education evaluation, the empirical literature on teaching modes, and the constructs of the Educational Production Function (EPF) model, adapted to contemporary data, extracted from ENADE and CPC 2012, 2015, and 2018 databases. Hypothesis tests used the Hierarchical Linear Method (HLM).

From the EPF model, in addition to the variable of interest, *MOD*, the input categories, both at level 1 (students) and level 2 (HEIs), found in the empirical literature or exploratory, were controlled. The results indicate that there was no relationship between teaching mode and the performance at ENADE in 2012, but the relationship was positive in 2015 and 2018, indicating that students linked to the face-to-face mode had a higher average performance. As the year 2012 did not present significance in any of the estimated models, in a joint analysis of the three periods, the results were inconclusive. If the mode did not present conclusive results in isolation, considering the three periods, possibly its behavior is related to other variables or interactions not tested.

The adoption of HLM for the empirical tests is the difference of this research, in relation to the empirical literature, especially in comparison with papers that used OLS in the analyses. HLM considers the context of educational data, which are hierarchical data by nature, and the main contributions regard highlighting the influence of socioeconomic, family, and individual factors on performance, being inappropriate to state that only the choice of mode can affect academic performance in standardized tests, such as ENADE.

The factors identified in this study can be explored in the educational system management, seeking to understand their influence on DE low performances. In addition, the results contribute to analyze the distance education scenario in Brazil, especially after the Covid-19 pandemic.

The need to develop remote academic activities revealed weaknesses in the DE structural system, already mentioned by Nunes (2009). Despite the differences between DE and the model applied during the pandemic, the same resources and methodologies of the distance mode were used in the remote model, showing problems of connection overload, pedagogical unpreparedness, inequality of access etc.

The evidence of the DE system's fragility in the country requires urgency to finally improve it, through investments in qualification, development of logical systems, physical structure for access, and pedagogical models. In addition, consistent policies for monitoring new courses are needed. It should be checked to what extent complying with the guidelines of the mode regulation is effective, regarding hiring policies and resource availability.

There are limitations in the study, due to frequent changes in the methodologies and metrics used by educational databases. This characteristic affects the development of research in this area. ENADE microdata, in the editions that assessed Accountancy Sciences courses, show changes in this respect, such as in survey questions and their inclusion/exclusion in each cycle. Reconfigurations were made to minimize the impact on results.

In addition, we cannot say that building questions was efficient to capture what was intended, both in the test body and in student's and coordination's questionnaires. Perhaps this has affected the number of missing values found. These scores are part of the criticisms directed at the exam, already addressed in this paper.

We suggest to study the DE scenario in Brazil, especially after the global pandemic of 2020. Due to inconclusive results, studies that enable the insertion of random effects in the slope of the mode variable may bring interesting results, since this procedure captures variability in the relationship between variables, by HEI. Likewise, it is worth investigating potential interactions between the variables, common in hierarchical modeling.

As for the socioeconomic aspect, it is worth investigating factors such as the relationship between being a scholarship student or having entered through affirmative policies and average performance, which, in this study, was positive in all estimates. Understanding the context of these students is critical for the analysis of national and local public policies.

REFERENCES

Alves, A. M., Araújo, E., Borali, H. L., Ferreira, P. V., & Souza, S. R. (2014). Educação a distância: aspectos positivos e análise a favor da modalidade. *Cadernos de Educação*, *13*(27), 188-199. http://dx.doi.org/10.15603/1679-8104/ce.v13n27p188-199

Alves, F., & Candido, O. (2017). O efeito da escola e os determinantes do rendimento escolar: uma análise dos resultados dos estudantes brasileiros nas últimas três edições do PISA. *Anais do 45° Encontro Nacional de Economia*, Natal, RN, Brasil.

Andrade, M. A. B. (2011). *As contribuições da avaliação dos cursos de graduação para a melhoria da qualidade da educação superior* [Tese de Doutorado]. Universidade Federal da Bahia, Salvador. http://www.repositorio.ufba.br/ri/handle/ri/9019

Andrade, M. A. B. (2012). A avaliação da educação superior: Uma breve análise no campo teórico-conceitual. *Revista Entre Ideias*, *1*(2), 27-45. https://doi.org/10.9771/2317-1219rf.v1i2.6379

Andriola, W. B. (2009). Fatores institucionais associados aos resultados do Exame Nacional de Desempenho Estudantil (ENADE): Estudo dos cursos de graduação da Universidade Federal do Ceará (UFC). *Revista Electrónica Iberoamericana sobre Calidad, Eficacia y Cambio em Educación*, *7*(1), 22-49. https://revistas.uam.es/reice/article/view/5421

Batista, A. B., Cruz, N. V. S., Andrade, C. M., & Bruni, A. L. (2014). Desempenho discente nos ENADEs 2009 e 2012 do curso de ciências contábeis do nordeste brasileiro: Uma análise comparativa entre o ensino à distância e o ensino presencial. *Anais do 21° Congresso Brasileiro de Custos*, Natal, RN.

Blaug, M. (1975). *Introdução à Economia da Educação* (L.V. Vallandro e V. A. Corrêa, trads.). Editora Globo.

Brasil. (2020). *Coronavírus Brasil*. https://covid.saude.gov.br/

Brito, M. R. F. (2008). O Sinaes e o ENADE: Da concepção à implantação. *Avaliação*, *13*(3), 841-850. https://doi.org/10.1590/S1414-40772008000300014

Caetano, C. C. R., Cardoso, T. A. O., Miranda, G. J., & Freitas, S. C. (2015). Desempenho no ENADE em ciências contábeis: Ensino à distância (EAD) versus presencial. *Revista Universo Contábil*, *11*(4), 147-165. https://doi.org/10.4270/ruc.2015436

Chen, C. C., Jones, K. T., & Moreland, K. A. (2013). Online accounting education versus in-class delivery: Does course level matter? *Issues in Accounting Education*, *28*(1), 1-16. http://dx.doi.org/10.2308/iace-50303

Ching, Y., & Hsu, Y. (2015). Online graduate students' preferences of discussion modality: does gender matter? *MERLOT Journal of Online Learning and Teaching*, *11*(1). https://jolt.merlot.org/vol11no1/Ching_0315.pdf

Cruz, C. C. M. S. (2010). *Modelos Multi-nível: Fundamentos e Aplicações* [Dissertação de Mestrado]. Universidade Aberta, Lisboa.

De Vaus, D. (2001). *Research Design in Social Research*. Sage Publications.

Fávero, L. P., & Belfiore, P. (2017). Manual de análise de dados: Estatística e modelagem multivariada com Excel®, SPSS® e Stata®. Elsevier.

Ferreira, M. A. (2015). *Determinantes do desempenho discente no ENADE em cursos de Ciências Contábeis* [Dissertação de Mestrado]. Universidade Federal de Uberlândia. https://repositorio.ufu.br/handle/123456789/12620

Figlio, D. N., Rush, M., & Yin, L. (2010). Is it live or is it internet? Experimental estimates of the effects of online instruction on student learning. *Journal of Labor Economics*, *31*(4), 763-784. https://doi.org/10.1086/669930

Finch, W. H., Bolin, J. E., & Kelley, K. (2019). *Multilevel modeling using R*. (2nd ed.). CRC Press.

Gatti, B. A. (2002). Avaliação educacional no Brasil: Pontuando uma história de ações. *EccoS Rev. Cient., UNINOVE*, *1*(4), 17-41. https://doi.org/10.5585/eccos.v4i1.291

Giroux, H. A. (2014). *Neoliberalism's war on higher education*. Haymarket Books.

Goldstein, H. (2011). *Multilevel Statistical Models* (4th ed.). John Wiley & Sons Ltd.

Hanushek, E. A. (1968). *The education of negroes and whites* [Doctoral Dissertation]. Massachusetts Institute of Technology.

Hanushek, E. A. (1979) Conceptual and empirical issues in the estimation of educational production functions. *The Journal of Human Resources*, *14*(3), 351-388. https://doi.org/10.2307/145575

Heck, R. H., Thomas, S. L., & Tabata, L. N. (2014). *Multilevel and Longitudinal Modeling with IBM SPSS* (2nd ed.). Routledge.

Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira [INEP]. *Sinopses Estatísticas da Educação Superior (1995-2019)*. http://portal.inep.gov.br/web/guest/sinopses-estatisticas-da-educacao-superior

Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira [INEP]. *Microdados ENADE (2012-2015)*. https://www.gov.br/inep/pt-br/acesso-a-informacao/dados-abertos/microdados/enade

Klug, Y. S., Machado, D. G., Menezes, G. R., & Lemos, V. S. (2018). Ensino superior em Contabilidade: Análise da influência da modalidade de ensino no desempenho discente conforme ENADE e CPC. *Proceedings of the 18th USP International Conference in Accounting*, São Paulo, BR.

Lemos, K. C. S., & Miranda, G. J. (2015). Alto e baixo desempenho no ENADE: Que variáveis explicam? *Revista Ambiente Contábil*, *7*(2), 101-118. https://periodicos.ufrn.br/ambiente/article/view/5579

Luckesi, C. C. (2005). Avaliação da aprendizagem: visão geral [Entrevista concedida a Paulo Camargo], *Conferência: Avaliação da Aprendizagem na Escola*, Sorocaba, SP.

Luzzi, D. A. (2007). *O papel da educação à distância na mudança de paradigma educativo: da visão dicotômica ao continuum educativo* [Doctoral Dissertation]. Universidade de São Paulo, São Paulo. https://doi.org/10.11606/T.48.2007.tde-09102007-090908

Means, B., Toyama, Y., Murphy, R., Baki, M., & Jones, K. (2010). *Evaluation of evidence-based practices in online learning: a meta-analysis and review of online learning studies*. U.S. Department of Education, Washington, D.C. https://www2.ed.gov/rschstat/eval/tech/evidence-based-practices/finalreport.pdf

Means, B., Toyama, Y., Murphy, R., & Baki, M. (2013). The effectiveness of online and blended learning: a meta-analysis of the empirical literature. *Teachers College Record*, *115*(3), 1-47. https://doi.org/10.1177/016146811311500307

Ministério da Educação (Brasil). (2018). *Apresentação*. Brasília, DF. http://portal.mec.gov.br/institucional.

Miranda, G. J., Lemos, K. C. S., Oliveira, A. S., & Ferreira, M. A. (2015). Determinantes do desempenho acadêmico na área de negócios. *Revista Meta: Avaliação*, *7*(20), 175-209. https://revistas.cesgranrio.org.br/index.php/metaavaliacao/article/view/264

Moran, J. M. (2009). Modelos e avaliação do ensino superior a distância no Brasil. *Revista ETD – Educação Temática Digital da Unicamp*, *10*(2). https://doi.org/10.20396/etd.v10i2.977

Moreira, A. M. A. (2010). Fatores institucionais e desempenho acadêmico no Enade: Um estudo sobre os cursos de biologia, engenharia civil, história e pedagogia [Doctoral Dissertation]. Universidade de Brasília, DF. https://repositorio.unb.br/handle/10482/8663

Moreira, K. S. G. (2013). *Determinantes do desempenho escolar no Rio Grande do Sul: uma análise a partir de modelos hierárquicos* [Master Thesis]. Pontifícia Universidade Católica do Rio Grande do Sul. https://hdl.handle.net/10923/5523

Niskier, A. (2009). Os aspectos culturais e a EAD. In F. M. Litto & M. M. M. Formiga (Orgs.), *Educação à distância: O estado da arte* (pp. 28-33). Pearson Education.

Nunes, I. B. (2009). A história da EAD no mundo. In F. M. Litto & M. M. M. Formiga (Orgs.), *Educação à distância: O estado da arte* (pp. 2-8). Pearson Education.

Ramos, C. A. (2015). *Introdução à Economia da Educação*. Alta Books.

Rabe-Hesketh, S., & Skrondal, A. (2012). *Multilevel and longitudinal using Stata* (3rd ed.). Stata Press.

Raudenbush, S., & Bryk, A. (2002). Hierarchical linear models: applications and data analysis methods (2nd ed.). Sage Publications.

Rodrigues, B. C. O., Resende, M. S., Miranda, G. J., & Pereira, J. M. (2016). Determinantes do desempenho acadêmico dos alunos dos cursos de Ciências Contábeis no ensino à distância. *Enfoque: Reflexão Contábil*, *35*(2), 139-153. https://doi.org/10.4025/enfoque.v35i2.30105

Russell, T. L. (1999). The no significant difference phenomenon: A comparative research annotated bibliography on technology for distance education: About the book. http://www.nosignificantdifference.org/about.asp

Santos, N. A. (2012). *Determinantes do desempenho acadêmico dos alunos dos cursos de ciências contábeis* [Doctoral Dissertation]. Universidade de São Paulo, São Paulo. https://doi.org/10.11606/T.12.2012.tde-11062012-164530

Shachar, M., & Neumann, Y. (2010). Twenty years of research on the academic performance differences between traditional and distance learning: Summative meta-analysis and trend examination. *MERLOT Journal of Online Learning and Teaching*. *6*(2), 318-334. https://jolt.merlot.org/vol6no2/shachar_0610.pdf

Silva, I. G. (2013). Avaliando o aprendizado à distância versus o presencial: A que distância a educação on-line se encontra do ensino presencial? *Revista FGV Online*, *3*(1), 1-15. https://bibliotecadigital.fgv.br/ojs/index.php/revfgvonline/article/view/19366/18562

Silva, I. J. A., Nasu, V. H., Leal, E. A., & Miranda, G. J. (2020). Fatores determinantes da evasão nos cursos de Ciências Contábeis no Brasil. *Revista GUAL*, *13*(1), 48-69. http://dx.doi.org/10.5007/1983-4535.2020v13n1p48

Snijders, T. A. B., & Bosker, R. J. (2012). Multilevel analysis: an introduction to basic and advanced multilevel modeling (2nd ed.). Sage Publications.

Sousa, A. S. Q., & Maciel, C. E. (2016). Expansão da educação superior: Permanência e evasão em cursos da Universidade Aberta do Brasil. *Educação em Revista*, *32*(4), 175-204. https://doi.org/10.1590/0102-4698161689

The R Foundation. *The R Project for Statistical Computing*. https://www.r-project.org/

Zhao, Y., Lei, J., Yan, B., Lai, C., & Tan, H. S. (2005). What makes the difference? A practical analysis of research on the effectiveness of distance education. *Teachers College Record*, *107*(8), 1836-1884. https://pdfs.semanticscholar.org/a1c7/938dd1c674ac58ec068197a108058b9af60e.pdf

APPENDIX I

Table 4

Variable description, literature background, and origin of collection.

Constructs	Variable Name	Description/Measurement	Type	Level	Background	Database
Dependent						
	NG	Overall gross score at ENADE	Continuous, from 0 to 100	Students	Santos (2012); Miranda *et al.* (2015); Caetano *et al*. (2015); Ferreira (2015)	ENADE microdata
Independent						
F – personal characteristics	c_idade	Student age at the day of the test, centralized to the large average	Continuous	Students	Santos (2012); Miranda *et al.* (2013); Caetano *et al*. (2015); Ferreira (2015)	ENADE microdata
	d_sexf	1 = Gender F; 0 = Gender M	Dummy	Students	Santos (2012); Ching & Hsu (2015); Caetano *et al.* (2015); Ferreira (2015); Rodrigues *et al*. (2016)	ENADE microdata
	d_etnia	1 = White or Asian; 0 = Black, brown, indigenous	Dummy	Students	Santos (2012); Caetano *et al.* (2015); Ferreira (2015); Rodrigues *et al*. (2016)	ENADE microdata
	dedicH (hours)	Weekly dedication to study 0 = None, just attend classes. 1 = From one to three; 2 = From four to seven. 3 = From eight to twelve; 4 = More than twelve.	5 levels with order of magnitude	Students	Santos (2012); Ferreira (2015)	ENADE microdata
	Livros (books)	Books read/year, except course bibliography 0 = None 1 = 1 or 2 books; 2 = 3 to 5 books 3 = 6 to 8 books; 4 = More than 8 books	5 levels with order of magnitude	Students	Santos (2012); Ferreira (2015)	ENADE microdata
P – peer effect	d_ecivil (civil status)	1 = Single; 0 = Other	Dummy	Students	Santos (2012); Ferreira (2015)	ENADE microdata
F – Family and socioeconomic factors	Renda (Income)	0 = up to 1,5 SM; 1 = from 1,5 to 3 SM 2 = from 3 to 4,5 SM; 3 = from 4,5 to 6 SM 4 = from 6 to 10 SM; 5 = from 10 to 30 SM	7 levels with order of magnitude	Students Students Students	Santos (2012); Miranda *et al.* (2013); Ferreira (2015); Rodrigues *et al*. (2016)	ENADE microdata

		6 = above 30 SM		Students		
	d_afirm	Entered through affirmative actions 1= yes; 0= no	Dummy	Students	Santos (2012); Ferreira (2015)	ENADE microdata
	d_bolsa	Has a scholarship for tuition 1= yes; 0= no	Dummy	Students	Santos (2012); Ferreira (2015)	ENADE microdata
	d_moraso	Lives alone 1= yes; 0= no	Dummy	Students	Exploratory	ENADE microdata
	escpub	Public school student 1= yes; 0= no	Dummy	Students	Ferreira (2015)	ENADE microdata
I – peculiarities of the educational system	**MOD**	**1= Face-to-face mode; 0= DE**	**Dummy**	**Students**	**Figlio *et al*. (2010); Chen, Jones, & Moreland (2013); Silva (2013); Batista *et al*. (2014); Caetano *et al*. (2015); Klug *et al*. (2018)**	**ENADE Microdata**
	d_not	If an evening course 1= yes; 0= no	Dummy	Students	Santos (2012); Ferreira (2015)	ENADE microdata
	regiao_curso	1: North / 2: Northeast / 3: Southeast / 4: South / 5: Midwest	5 levels **without** order of magnitude	Students	Exploratory for levels	ENADE microdata
R – resources of courses / institutions	np_infra	Standardized average score for Infrastructure	Continuous	Institutions	Andriola (2009); Moreira (2010); Santos (2012); Ferreira (2015); Lemos & Miranda, 2015	CPC Database
	np_me	Standardized average score for Masters	Continuous	Institutions	Moreira (2010); Santos (2012); Ferreira (2015); Lemos & Miranda (2015)	CPC Database
	np_dr	Standardized average score for PhDs	Continuous	Institutions	Moreira (2010); Santos (2012); Ferreira (2015); Lemos & Miranda (2015)	CPC Database
	np_rt	Standardized average score for Professors' Work Regime	Continuous	Institutions	Santos (2012); Ferreira (2015)	CPC Database
P – Peer effects	idade_M	Simple average age informed by students, by HEI	Continuous	Institutions	Santos (2012)	ENADE microdata
	renda_IES	Simple average for family income informed by students, by HEI	Continuous	Institutions	Raudenbush & Bryk (2002); Santos (2012)	ENADE microdata
I - peculiarities of the educational system	cat_adm	1= Public; 0= Private	Dummy	Institutions	Santos (2012); Caetano *et al*. (2015); Ferreira (2015)	ENADE microdata
	org_acad	1= University; 0= Other	Dummy	Institutions	Santos (2012); Caetano *et al*. (2015); Ferreira (2015)	ENADE microdata

APPENDIX II

Table 5

Estimation of hierarchical models 2012, 2015, and 2018.

		Null Model				Model_1				Model_2				Full Model			
Fixed Effects		**Coef**	**SE**	**t**	**Sig**	**Coef**	**SE**	**t**	**Sig**	**Coef**	**SE**	**t**	**Sig**	**Coef**	**SE**	**t**	**Sig**
Intercept	2012	35.03	0.18	200.00	***	29.58	0.60	48.95	***	31.32	2.09	15.00	***	27.99	2.23	12.54	***
	2015	41.33	0.19	221.80	***	35.72	0.52	68.82	***	35.71	2.02	17.72	***	30.97	2.08	14.87	***
	2018	36.91	0.18	207.10	***	35.00	0.41	85.78	***	30.20	1.87	16.15	***	28.10	1.87	15.04	***
MOD	2012					0.36	0.41							0.40	0.41	0.98	
	2015					3.19	0.33	9.73	***					3.22	0.32	9.91	***
	2018					1.76	0.26	6.77	***					1.83	0.26	7.05	***
Random Effects		**Var**	**SD**			**Var**	**SD**			**Var**	**SD**			**Var**	**SD**		
ID_IES - τ_{00} (u_{0j})	2012	17.43	4.18			16.62	4.08			11.61	3.41			11.68	3.42		
	2015	23.68	4.87			19.82	4.45			11.93	3.45			11.46	3.39		
	2018	21.07	4.59			16.28	4.04			11.41	3.38			10.28	3.21		
Residual - σ^2 (e_{ij})	2012	151.21	12.30			146.10	12.09			151.23	12.30			146.12	12.09		
	2015	143.42	11.98			136.14	11.67			143.50	11.98			136.19	11.67		
	2018	134.51	11.60			127.68	11.30			134.58	11.60			127.72	11.30		
ICC (ρ)	2012	10.34%				10.21%				7.13%				7.40%			
	2015	14.17%				12.71%				7.68%				7.76%			
	2018	13.54%				11.31%				7.82%				7.45%			
AIC and BIC	2012	356814,5		356840,7		355298,2		355533,6		356622,0		356752,8		355134		355474	
	2015	429421,3		429448,1		426528,1		426768,7		429034,7		429168,4		426224.4		426571,9	
	2018	408350,4		408377,1		405522,1		405761,6		408016,5		408149,5		405286,5		405632,4	
Loglik and Deviance	2012	-178404,3		356808,5		-177622,1		355244,2		-178296,0		356592,0		-177528		355056	
	2015	-214707,7		429415,3		-213237,1		426474,1		-214502,4		429004,7		-213073,2		426146,4	
	2018	-204172,2		408344,4		-202734,0		405468,1		-203993,2		407986,5		-202604,3		405208,5	
N. of students and HEIs	2012	45252	710			45252	710			45252	710			45252	710		
	2015	54813	817			54813	817			54813	817			54813	817		
	2018	52560	836			52560	836			52560	836			52560	836		

Level of significance: (***) 0.001 (**) 0.01 (*) 0.05 ( ) 0.1 ( ) Not significant