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Team-based learning and student performance in undergraduate economics: Evidence from a quasi-experimental study

Chiara Strozzi[1], Giuseppe Caruso[2]

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[1] Department of Economics Marco Biagi, University of Modena and Reggio Emilia, Italy and RECent
Email: chiara.strozzi@unimore.it
[2] Fondazione UniverMantova, Italy
Email: giuseppe.caruso@unimn.it

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Team-based learning and student performance in undergraduate economics: Evidence from a quasi-experimental study

Chiara Strozzi* and Giuseppe Caruso†

Abstract

This paper examines the effects of introducing Team-Based Learning (TBL) on academic outcomes in undergraduate economics. We study an instructional change at a large Italian public university, where one programme integrated TBL alongside standard lectures in a core second-year course, while a parallel programme maintained traditional lecture-based instruction throughout. Using administrative records tracking student careers from 2009 to 2025, we estimate a difference-in-differences model and find that exposure to TBL is associated with improvements in student performance across a broad set of outcomes, both in the short and in the medium run. Treated students accumulate more second-year ECTS credits and achieve higher average exam grades, with these gains persisting over time and translating into higher final degree grades and an increased probability of graduation. Positive effects are observed across multiple student subgroups, while evidence from the treated course indicates higher pass rates at early exam attempts and examination sessions.

Keywords: Team-Based Learning; higher education; economics; difference-in-differences; student performance

1. Introduction

Improving student engagement and academic achievement remains a central challenge for higher education systems worldwide. Despite the substantial expansion of access to tertiary education, universities continue to face persistent problems of delayed graduation and high dropout rates, as completion rates in many OECD countries remain modest and a large share of students do not graduate within the nominal duration of their programmes (OECD, 2025). These challenges are particularly salient in economics and related social sciences, where instruction has historically relied heavily on traditional lecture-based methods and comparative evidence indicates that more interactive approaches are associated with superior learning outcomes (Becker and Watts, 1996; Emerson and Taylor, 2004).

A large body of research documents positive associations between active learning approaches and student outcomes in higher education, including improved exam performance and higher levels of engagement. Evidence from large-scale reviews shows that replacing or supplementing traditional lectures with active learning improves exam performance and reduces failure rates (Freeman et al., 2014; Schneider and Preckel, 2017), while other studies emphasise that these effects extend beyond cognitive outcomes to engagement, persistence, and course completion (Theobald et al., 2020). Meta-analyses confirm sizeable effects also in the humanities and social sciences, including economics and other quantitatively oriented disciplines (Kozanitis and Nenciovici, 2023).

* University of Modena and Reggio Emilia, Department of Economics "Marco Biagi", 41121 Modena, Italy. chiara.strozzi@unimore.it.
† Fondazione UniverMantova, 46100 Mantua, Italy. giuseppe.caruso@unimn.it.

Within the broad set of active learning practices, collaborative and team-based approaches play a central role, as they directly target key mechanisms underlying student engagement, including peer accountability, social interaction, and repeated opportunities for feedback through group-based problem solving. In line with this perspective, research on cooperative learning and collaborative group work (CGW) shows that structured peer interaction can enhance conceptual understanding, student motivation, and the development of transferable skills (Prince, 2004; Kyndt et al., 2013). At the same time, the effectiveness of collaborative and team-based learning critically depends on implementation features such as team composition, task design, assessment alignment, and psychological safety within groups (Schmulian and Coetzee, 2019; You, 2024).

In this context, Team-Based Learning (TBL) has emerged as a prominent instructional strategy that institutionalizes collaborative learning through a structured sequence of individual preparation, team-based problem-solving, and immediate feedback, sustaining engagement throughout the course rather than relying on sporadic active-learning interventions.[1] This highly structured design also facilitates scalability, enabling TBL to preserve key benefits of small-group learning even in large university courses.

Empirical evidence on the impact of TBL in university settings reports positive effects on short-term academic performance and engagement. Early studies, concentrated in health and professional education, document improvements in test scores, perceived learning, and satisfaction relative to lecture-based formats (Haidet et al., 2012; Parmelee et al., 2012). Further evidence suggests that instructional practices incorporating teamwork, frequent assessment, and problem-solving activities are associated with improved performance in core courses and more favourable assessment outcomes (Emerson and Taylor, 2004; Hoyt and McGoldrick, 2012).

Subsequent contributions extend this evidence to economics and business education. Odell (2018), analysing a multi-semester transition from lectures to TBL in a Principles of Macroeconomics course, finds higher grades, improved performance on concept assessments, and increased self-reported engagement. Related evidence from economics education shows that structured combinations of TBL, flipped classroom elements, and frequent testing can significantly improve performance, particularly by strengthening continuous study incentives and exam preparedness (Bravo et al., 2019; Abío et al., 2019). Similarly, Cagliesi and Ghanei (2022) report positive associations between active and team-based instructional practices and exam outcomes in economics courses.

A smaller but growing literature applies more rigorous empirical designs to study team-based and collaborative learning. Using quasi-experimental and experimental approaches, these studies show that structured teamwork and peer interaction are associated with higher academic performance when exploiting within-course variation across cohorts or semesters, particularly when group composition and incentives are carefully designed (Swanson et al., 2019; Bravo et al., 2019; Abío et al., 2019). Evidence from field experiments in higher education further supports these findings, indicating that team-based production can improve individual performance even when collaboration is not explicitly framed as TBL (Lo Prete, Macrì, and Rania, 2021).

Recent research highlights that grades alone provide an incomplete measure of student success. From an economics of education perspective, outcomes such as credit accumulation, exam timing, retention, and time to degree are central determinants of educational attainment and subsequent labour-market returns (Bound, Lovenheim, and Turner, 2012; Garibaldi et al., 2012). In this context, active and collaborative pedagogies may influence these margins by shaping students' study behaviour, reducing procrastination, and fostering continuous engagement throughout the academic term. Evidence shows that timely and informative feedback affects academic achievement and effort provision (Bandiera et al., 2015), while peer-based learning environments are associated with higher course completion, greater credit accumulation, and improved student retention (Carson et al., 2025; Ramsey et al., 2025).

Although the existing literature suggests that TBL and related collaborative instructional practices are associated with improvements in student performance and engagement, important methodological limitations remain. Many studies rely on small samples, single-course interventions, short observation windows, or non-experimental designs that limit causal inference. While informative, these approaches lack parallel control groups, long observation windows, or controls for cohort composition, thus limiting causal interpretation (Sisk, 2011; Haidet et al., 2014; Burgess et al., 2017).

This paper addresses these gaps and provides new evidence on the impacts of Team-Based Learning on both short- and medium-term student outcomes, focusing on academic achievement, study engagement, and degree-related outcomes. More specifically, we study the introduction of TBL in undergraduate economics education at a large Italian public university and assess how student outcomes change following its adoption, both over time and relative to a comparable lecture-based course. Using rich administrative data on students' academic careers, we analyse this instructional change through a difference-in-differences approach within a quasi-experimental framework. Our results indicate that the introduction of Team-Based Learning is associated with sustained improvements in academic performance and progression, with heterogeneity estimates indicating particularly strong gains for less-prepared students.

The remainder of the paper is organised as follows. Section 2 describes the institutional setting and the TBL implementation. Section 3 introduces the data. Section 4 outlines the empirical strategy. Section 5 presents the results. Section 6 discusses the findings and their implications. Section 7 concludes.

2. Quasi-experimental setting and TBL implementation

Our quasi-experimental design exploits the introduction of Team-Based Learning (TBL) in a core undergraduate economics course at a large Italian public university. Since course assignment is determined by degree programme, students cannot self-select into instructional formats, thus generating exogenous variation in TBL exposure.

We distinguish between two types of courses: a *switching course* and a *lecture-based course*. The switching course adopts Team-Based Learning (TBL) alongside standard lectures, while the lecture-based course relies exclusively on traditional lectures. Prior to the reform, the switching course relied exclusively on a traditional lecture-based format.

The switching course under study is "Introduction to Macroeconomics", a compulsory second-year course in the Bachelor's degree programme in Economics and Finance (CLEF) at the Department of Economics of the University of Modena and Reggio Emilia (UNIMORE). The course is offered annually to large cohorts of undergraduate students, carries 9 ECTS credits, is delivered over a single semester, and does not impose mandatory attendance requirements.

The lecture-based course is the parallel "Introduction to Macroeconomics" course in the Bachelor's degree programme in Economics and International Marketing (CLEMI) in the same department. The two courses share the same institutional context, duration, ECTS credits, syllabus, textbook, and examination format (written exam). They are taught in the first semester and at the same stage of the undergraduate degree programmes (second year). While the courses are taught by different instructors, our empirical analysis accounts for time-invariant course-specific heterogeneity through the inclusion of course fixed effects.

This institutional setting gives rise to a quasi-experimental framework that we exploit to identify the effects of Team-Based Learning. Treatment and control are defined at the course-year level. Treated observations are those from the switching course in the post-TBL period, while control observations consist of (i) pre-intervention observations from the switching course and (ii) all observations from the lecture-based course throughout the entire period.

The TBL intervention was implemented across six academic years (2017/18, 2018/19, 2019/20, 2021/22, 2022/23, 2023/24)[2], with five to six TBL sessions per semester**.** Although participation in TBL sessions was formally voluntary, the integration of TBL activities into the regular course structure resulted in participation rates above 95% among students enrolled in the switching course after the reform.[3]

Each TBL session followed the standard sequence described in the literature and combined pre-class preparation, individual and team readiness assurance activities, in-class application exercises, targeted mini-lectures, and peer evaluation (Michaelsen, Knight, and Fink, 2002). All TBL activities were delivered through the university's learning management platform (Moodle), which supported the organisation and administration of in-class activities in a large-enrolment setting.

The TBL teams were formed on the basis of the information collected through a pre-course questionnaire administered via the university's learning management system. The survey captured data on demographic characteristics (i.e., age and sex), prior educational attainment, work experience, academic performance indicators, and whether or not the participant had prior experience with collaborative learning environments. Based upon these responses, the Group Rumbler (GRumbler) algorithm, developed at Harvard Business School, was employed to allocate students to teams of 5 to 7 members with the objective of maximising within-team heterogeneity, consistent with TBL best practices (Michaelsen and Sweet, 2008).

3. Data

Our empirical analysis leverages a comprehensive administrative dataset provided by the University of Modena and Reggio Emilia (UNIMORE). The data cover the full population of undergraduate students enrolled in the two parallel Bachelor's degree programmes in economics - Economics and Finance (CLEF) and Economics and International Marketing (CLEMI) - over the period from October 2009 to February 2025.

The dataset includes student registry records (demographic characteristics and enrolment histories), examination transcripts (ECTS credits earned and grades obtained), results from the national entry test (TOLC-E[4]), tuition-fee brackets (used as a proxy for household income), indicators of regional mobility (i.e. whether students have legal residence outside the university city), and participation in Erasmus exchange programmes. All information is linked through a unique student identifier, allowing for a longitudinal reconstruction of academic trajectories from enrolment to graduation.

We distinguish between short-term and medium-term outcomes. Short-term outcomes (i.e. student outcomes up to one year after course completion) are second-year ECTS credits and second-year average exam score. Medium-term outcomes (i.e. student outcomes at graduation) are time to degree, degree grade, and graduation probability.

The set of control variables includes sex, entry test scores (TOLC-E), high-school type and final grade, first-year ECTS credits, socio-economic status (proxied by tuition-fee brackets), off-region student status, and Erasmus mobility.

Table A1 in Appendix reports the summary statistics for our full sample of students, distinguishing between treated and control students. Prior to treatment, students enrolled in the switching and the lecture-based courses display very similar observable characteristics. Entry test scores (TOLC-E), high-school final grades, and first-year ECTS credits are comparable across groups, as is the distribution of secondary-school backgrounds. Socio-economic characteristics, proxied by tuition-fee brackets, as well as indicators of student geographic mobility and participation in Erasmus exchange programmes, are also broadly balanced. Differences in academic outcomes become visible only after exposure to TBL: in particular, treated students accumulate more ECTS credits in the second year (56.0 versus 49.7) and achieve higher average exam grades (25.3 versus 24.2).

Table A2 reports summary statistics for the subsample of students who completed the degree during the sample period. Treated and control students remain highly comparable in terms of pre-treatment characteristics, including TOLC-E scores, high-school grades, and first-year ECTS credits. At graduation, students exposed to TBL exhibit higher average degree grades and shorter time to degree. Average final grades are about three points higher among treated students (100.1 versus 97.3), while time to degree is shorter by approximately two months (40.8 versus 43.0).

Overall, the close alignment between the switching and lecture-based courses prior to the introduction of TBL, combined with their parallel curricular pathways and shared institutional environment, provides a suitable setting for assessing the effects of the instructional change. The introduction of TBL in the switching course represents the only systematic difference between the two courses during the observation period, forming the basis for the difference-in-differences (DiD) framework developed in the next section.

4. Empirical strategy and identification

The quasi-experimental design described in Section 2 provides the basis for our identification strategy, which exploits a discrete instructional change at the course level: one course transitions from a traditional lecture-based format to Team-Based Learning (*switching course*), while a parallel course continues to be taught exclusively through standard lectures (*lecture-based course*).

Building on this institutional setting, we implement a difference-in-differences (DiD) design that combines both *within-course* and *across-course* variation. Before the introduction of TBL, the switching course serves as its own pre-intervention baseline. After the introduction, identification relies on comparing changes within the switching course to contemporaneous changes in the lecture-based course, which never adopted TBL and therefore captures the counterfactual trajectory of outcomes in the absence of the instructional innovation. Formally, treatment status is defined by the interaction between enrolment in the switching course and exposure to post-reform cohorts.

The empirical analysis is grounded in the potential-outcomes framework (Rubin, 1974; Imbens and Rubin, 2015), which formalises causal inference in terms of potential outcomes and counterfactual comparisons. For each student i, we define two potential outcomes: $Y_i(1)$, corresponding to exposure to TBL, and $Y_i(0)$ corresponding to instruction under the traditional lecture-based format. The primary causal estimand is the average treatment effect on the treated (ATT), capturing the average change in academic outcomes for students exposed to TBL relative to how these outcomes would have evolved under traditional instruction, defined as:

$$ATT = E[Y_i(1) - Y_i(0) \mid treated_i = 1] \quad [1]$$

Since only one of these potential outcomes can be observed for each student, causal identification requires isolating variation that approximates a counterfactual comparison. In our context, such variation is generated by the differential timing of the instructional change across two otherwise comparable courses.

Our baseline empirical specification is:

$$Y_i = \beta * treated_i + \gamma * X_i + \alpha_c + \alpha_t + \varepsilon_i \qquad [2]$$

where Y_i denotes academic outcomes, including second-year ECTS credits, second-year average exam scores[5], graduation probability, degree grade, and time to degree; X_i includes a set of pre-treatment individual characteristics including sex, enrolment test score (TOLC-E), high-school final grade, first-year ECTS credits and type of upper secondary school; α_c are course fixed effects capturing time-invariant differences between courses; α_t are cohort fixed effects capturing shocks common to all students in a given enrolment year.

We then estimate an extended specification that augments the baseline model by incorporating additional dimensions related to students' socio-economic background and mobility:

$$Y_i = \beta * treated_i + \gamma * X_i + \delta * Z_i + \alpha_c + \alpha_t + \varepsilon_i \qquad [3]$$

where Z_i includes indicators for Erasmus participation, off-region enrolment status, and tuition-fee bracket effects. These variables are added to capture residual heterogeneity related to mobility and family economic background that may influence academic progression.

Identification does not rely on the inclusion of these additional controls. Rather, the extended specification is intended to improve precision and assess the robustness of the estimated treatment effects. The magnitude and statistical significance of the estimated coefficient β remain highly stable across the baseline and extended model.

The validity of the DiD approach hinges on the parallel trends assumption, namely that, absent the introduction of TBL, outcomes in the switching and lecture-based courses would have followed similar trajectories over time (Angrist and Pischke, 2009). This assumption is supported by the data. First, pre-intervention trends in first-year ECTS credits evolve nearly identically across the two courses (Figure A1). Second, pre-treatment regressions reveal no systematic association between course affiliation and academic performance before the introduction of TBL (Table A3). Third, distributional evidence shows no signs of differential sorting across courses prior to treatment (Figure A2).

To further assess the plausibility of our identifying assumptions, we implement placebo difference-in-differences tests using only pre-intervention cohorts. Specifically, we artificially assign a treatment date to cohorts observed entirely before the introduction of TBL and estimate DiD specifications analogous to the baseline model. Under the null hypothesis of parallel trends, placebo treatment effects should be indistinguishable from zero. Consistent with this prediction, placebo estimates are small and statistically insignificant (Table A4), providing additional support for the chosen identification strategy.

5. Results

This section presents the empirical findings on the impact of TBL on academic outcomes, following the temporal structure of students' academic trajectories. We first examine short-run outcomes observed during the second year of university courses and then turn to medium-run outcomes measured at graduation. This distinction allows us to assess whether early improvements in academic performance persist over time and translate into stronger degree-level outcomes.

5.1 Short-term effects of TBL on student outcomes

We focus first on the short-run effects of TBL on academic outcomes measured at the end of the second year of study, namely total ECTS credits earned and the average exam grade. These indicators capture complementary dimensions of academic performance: progress through the curriculum and achievement in assessed coursework. Table 1 reports estimates of the short-term (i.e. 2nd year) average treatment effect on the treated (ATT).

Table 1. Short-term effects of TBL on student outcomes (ATT)

Variables	2nd year ECTS credits		2nd year average exam score	
	Baseline model	Full model	Baseline model	Full model
TBL	6.455*** (1.189)	6.801*** (1.152)	0.893*** (0.189)	0.943*** (0.176)
Female	-0.043 (0.552)	-0.223 (0.566)	-0.162* (0.090)	-0.179* (0.091)
High school final grade	0.185*** (0.016)	0.185*** (0.014)	0.081*** (0.004)	0.081*** (0.004)
Enrolment test score (TOLC-E)	-0.084** (0.032)	-0.091** (0.032)	0.016 (0.009)	0.015 (0.010)
1st year ECTS credits	0.570*** (0.030)	0.558*** (0.030)	0.062*** (0.002)	0.061*** (0.003)
Erasmus mobility	-	2.562*** (0.346)	-	0.429*** (0.120)
Off-region student	-	-1.029 (0.607)	-	-0.083 (0.105)
Constant	1.946 (2.223)	3.092 (2.357)	13.892*** (0.593)	13.932*** (0.617)
Tuition-fee bracket FE	No	Yes	No	Yes
High-school type FE	Yes	Yes	Yes	Yes
Program and cohort FE	Yes	Yes	Yes	Yes
Observations	4,320	4,320	4,320	4,320
Adj. R^2	0.296	0.299	0.371	0.375

*Notes: All models include enrolment-cohort fixed effects. Standard errors are clustered at the enrolment cohort level. *** p<0.01, ** p<0.05, * p<0.1.*
Source: UNIMORE administrative microdata.

Exposure to TBL is associated with a sizable and precisely estimated increase in second-year credit accumulation. In the baseline specification, TBL increases total ECTS accumulation by 6.46 credits ($p < 0.01$). The estimated effect rises slightly to 6.80 credits once additional controls are included (full model).

The effect on average exam grade is similarly pronounced. TBL increases the second-year average exam grade by 0.89 points in the baseline model and by 0.94 points in the fully controlled specification. Relative to a mean of approximately 24.3 and a standard deviation of about 2.7 on the 30-point grading scale[6], this represents an improvement of roughly one-third of a standard deviation. The estimate implies an upward shift in the grade distribution among treated students.

The estimated coefficients on control variables reported in Table 1 are consistent with well-established patterns in higher education. First-year ECTS credits are a strong predictor of both second-year credit accumulation and exam grades, reflecting persistence in academic performance over time. High-school final grades also retain explanatory power. By contrast, once early university performance is controlled for, the TOLC-E has a limited and often statistically insignificant association with second-year outcomes.

Taken together, the short-term results indicate that the introduction of TBL is associated with meaningful improvements in student performance. TBL enhances both the pace of progress through the curriculum and the quality of academic outcomes during a pivotal phase of the degree programme. These results anticipate the medium-run effects examined in the next paragraph.

5.2 Medium-term effects of TBL on student outcomes

We examine whether the short-term outcomes associated with TBL persist and translate into improvements in medium-term (i.e. graduation) academic outcomes. Table 2 reports estimated effects on degree grade and time to degree for students who graduate over the sample period, while Figure 1 presents corresponding estimates for graduation probability.

Exposure to TBL is associated with higher student performance at graduation. In the full specification, the estimated effect on the final degree grade is 2.15 points ($p < 0.01$). Relative to the distribution of graduation grades, this corresponds to an increase of about 2% of the mean and to a shift of about half a standard deviation, indicating a non-negligible improvement in academic achievement at graduation.

TBL also affects the timing of degree completion. Students exposed to TBL graduate, on average, about 0.75 months earlier than comparable students in the lecture-based course ($p < 0.05$), pointing to a modest but systematic reduction in time to degree.

Table 2. Medium-term effects of TBL on student outcomes (ATT)

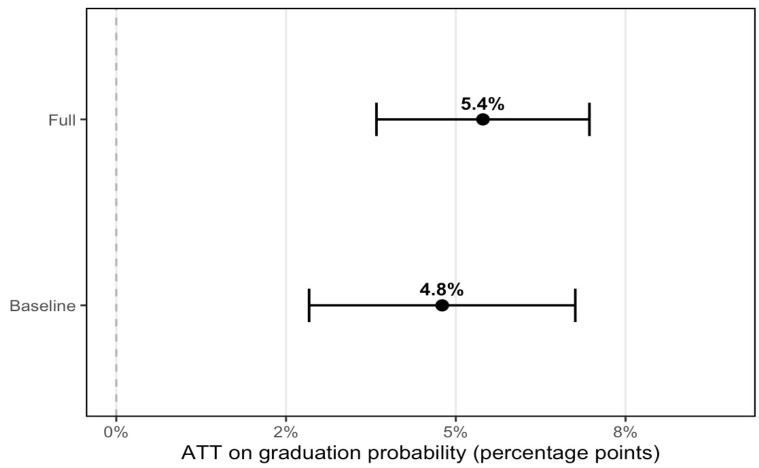
Variables	Degree grade		Time to degree (in months)	
	Baseline model	Full model	Baseline model	Full model
TBL	1.845*** (0.370)	2.154*** (0.363)	-0.464 (0.279)	-0.746** (0.292)
Female	-0.551** (0.248)	-0.666** (0.244)	-0.352 (0.225)	-0.159 (0.227)
High school final grade	0.311*** (0.015)	0.313*** (0.016)	-0.108*** (0.020)	-0.108*** (0.019)
Enrolment test score (TOLC-E)	0.054 (0.037)	0.043 (0.038)	0.033 (0.033)	0.034 (0.033)

1st year ECTS credits	0.236*** (0.037)	0.228*** (0.038)	-0.374*** (0.042)	-0.365*** (0.040)
Erasmus mobility	-	2.136*** (0.328)	-	-1.707*** (0.472)
Off-region student	-	-0.804*** (0.242)	-	0.964* (0.487)
Constant	62.779*** (2.181)	63.108*** (2.123)	72.090*** (4.114)	70.365*** (3.822)
Tuition-fee bracket FE	No	Yes	No	Yes
High-school type FE	Yes	Yes	Yes	Yes
Program and cohort FE	Yes	Yes	Yes	Yes
Observation	3,449	3,449	3,449	3,449
Adj. R^2	0.457	0.468	0.297	0.303

*Notes: All models include enrolment-cohort fixed effects. Standard errors are clustered at the enrolment cohort level. *** p<0.01, ** p<0.05, * p<0.1.*
Source: UNIMORE administrative microdata.

These results indicate that the improvements observed in the second year are not transitory but extend to later stages of the degree programme. The largest medium-run effect concerns graduation probability.

Figure 1. Medium-term effects of TBL on graduation probability (ATT)



Notes: The figure reports difference-in-differences estimates of the average treatment effect on the treated (ATT) on graduation probability. Horizontal bars denote 95% confidence intervals. Standard errors are clustered at the enrolment-cohort level.
Source: UNIMORE administrative microdata.

As shown in Figure 1, exposure to TBL increases the likelihood of graduating over the sample period by 4.8 percentage points in the baseline specification and by 5.4 percentage points in the full specification. The similarity of the estimates across specifications suggests that results are not sensitive to the inclusion of additional controls.

Overall, medium-run findings indicate that short-run gains associated with TBL persist over time and translate into higher completion rates and improved degree-level outcomes.

5.3 Heterogeneous short- and medium-term outcomes

To assess whether the effects of TBL vary across student groups, we estimate heterogeneous treatment effects along two dimensions: academic performance at entry and gender. Academic performance at entry is proxied by the score obtained in the national enrolment test (TOLC-E). Students are classified as lower-scoring or higher-scoring depending on whether their TOLC-E score lies below or above the sample median. Heterogeneous effects by sex are examined both separately and jointly with TOLC-E performance. Table 3 reports short- and medium-run average treatment effects on the treated across the full set of student outcomes.

Across all specifications, exposure to TBL is associated with positive effects for both lower-scoring and higher-scoring students, although the magnitude of the gains differs across groups. Among students with higher TOLC-E scores, TBL increases second-year ECTS credits by approximately 7.8 credits and raises second-year average exam grades by more than 1.3 points. These short-run gains are accompanied by improvements in medium-run outcomes, including higher final degree grades and an increase in graduation probability of about 5.8 percentage points.

Table 3. Short- and medium-term effects of TBL on student outcomes by sex and TOLC-E

TBL effect by	2nd year ECTS credits	2nd year average exam score	Degree grade	Time to degree (in months)	Graduation probability
TOLC-E (low)	5.621*** (1.578)	0.469* (0.251)	1.268* (0.694)	-0.992** (0.503)	0.041** (0.018)
TOLC-E (high)	7.774*** (1.149)	1.337*** (0.136)	2.957*** (0.376)	-0.524 (0.382)	0.058*** (0.016)
Male	7.108*** (1.133)	1.006*** (0.181)	2.363*** (0.348)	-0.746** (0.309)	0.056*** (0.008)
Female	6.141*** (1.475)	0.808*** (0.272)	1.744** (0.766)	-0.746 (0.515)	0.035*** (0.013)
Male x TOLC-E (low)	5.600*** (1.635)	0.439 (0.307)	1.355* (0.716)	-0.443 (0.626)	0.033* (0.017)
Female x TOLC-E (low)	5.875*** (1.742)	0.462 (0.335)	1.029 (1.163)	-1.693*** (0.672)	0.055** (0.026)
Male x TOLC-E (high)	8.101*** (1.080)	1.435*** (0.103)	3.170*** (0.361)	-1.065** (0.541)	0.085*** (0.013)
Female x TOLC-E (high)	6.210*** (1.631)	1.224*** (0.377)	2.740** (1.192)	0.490 (0.848)	0.001 (0.033)
Tuition-fee bracket FE	Yes	Yes	Yes	Yes	Yes
High-school type FE	Yes	Yes	Yes	Yes	Yes
Program and cohort FE	Yes	Yes	Yes	Yes	Yes
Observations	4,320	4,320	3,449	3,449	3,996

*Notes: Heterogeneity is analysed by sex and by enrolment test performance (TOLC-E), with lower- and higher-scoring students defined relative to the sample median. All models include the same pre-treatment controls as in the full specification, as well as course and enrolment-cohort fixed effects. Standard errors are clustered at the enrolment-cohort level. *** p<0.01, ** p<0.05, * p<0.1.*
Source: UNIMORE administrative microdata.

Positive effects are also observed among lower-scoring students. In this group, exposure to TBL increases second-year ECTS credits by more than 5.6 credits and raises second-year exam grades by approximately 0.5 points. Medium-run outcomes also improve: final degree grades increase, graduation probability rises by around 4 percentage points, and time to degree is reduced by approximately one month.

When heterogeneity is examined by sex, the results indicate broadly similar benefits for males and females. Both groups experience statistically significant gains in second-year ECTS credits, exam grades, degree grades, and graduation probability. Graduation probability increases by approximately 5.6 percentage points for males and by about 3.5 percentage points for females, with overlapping confidence intervals.

Additional heterogeneity emerges when sex and academic performance at entry are considered jointly. Among higher-scoring students, males display larger gains in second-year exam grades and final degree grades. Among lower-scoring students, relatively larger medium-run gains are observed for females, who experience a more pronounced reduction in time to degree (around 1.5 months) and a statistically significant increase in graduation probability of approximately 5 percentage points.

Overall, the heterogeneity analysis shows that the positive effects of TBL are shared across students with different baseline characteristics. Although effect sizes differ by sex and by initial academic performance, the estimated impacts are consistently positive across all subgroups, suggesting that TBL operates as a broadly inclusive pedagogical intervention.

5.4 Course-level behavioural effects

Beyond aggregate academic outcomes, we examine whether the introduction of TBL is associated with changes in exam-taking patterns within the switching course, where the instructional innovation was implemented. Focusing on exam outcomes at the course level allows us to consider dimensions of academic engagement that are not fully captured by cumulative performance measures.

We analyse exam success probabilities by attempt and by examination session, which provide us with information on the timing and regularity of assessment completion.

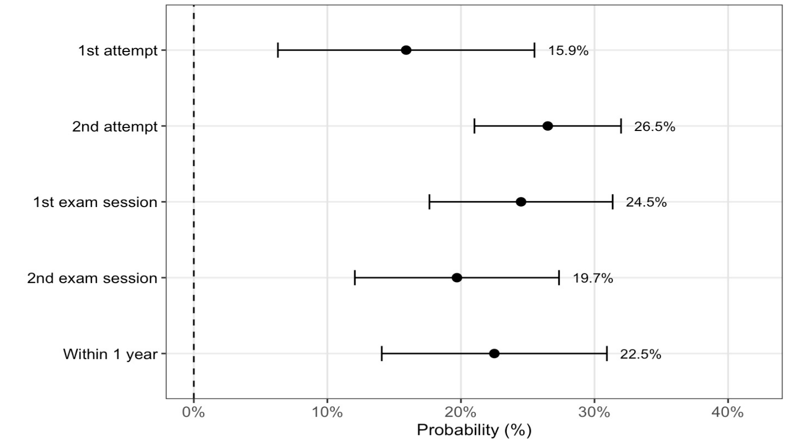
Exam timing and the number of attempts are outcomes defined at the course level rather than at the programme level. For this reason, the analysis is conducted on the switching course, while the lecture-based course supplies the counterfactual evolution necessary for causal identification in the difference-in-differences framework.

Figure 2 reports difference-in-differences estimates of the effect of TBL on exam passing probabilities along these margins. Relative to control students, treated students are estimated to be approximately 16 percentage points more likely to pass the exam at the first attempt and about 26 percentage points more likely to succeed by the second attempt. The probability of passing during the first examination session increases by roughly 24-25 percentage points, while success during the second session rises by about 20 percentage points. When considering a broader horizon, treated students are more than 22 percentage points more likely to pass the exam within one year.

These patterns indicate a marked shift in the timing of exam completion associated with the introduction of TBL.

Higher success rates at earlier attempts and sessions are consistent with the improvements in second-year ECTS accumulation and with the shorter time to degree documented in previous sections.

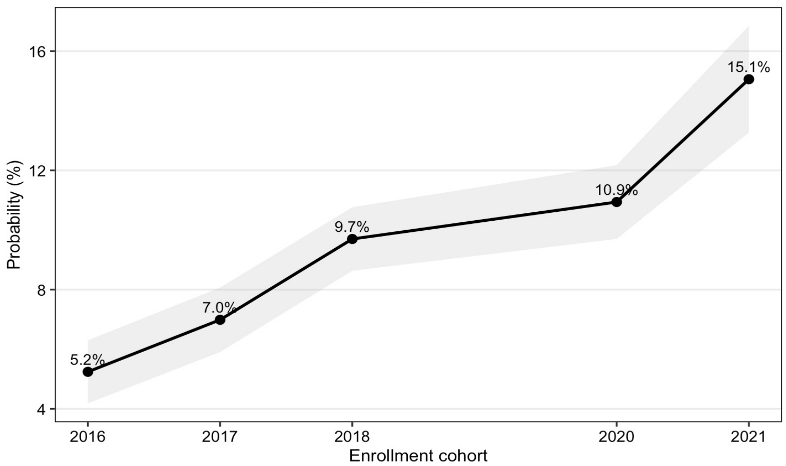
Figure 2. Exam passing rates by session and attempt - Switching course



Notes: The figure reports difference-in-differences estimates of the average treatment effect on the treated (ATT) on exam passing probabilities in the switching course. Outcomes refer to success by attempt, by examination session and are calculated within one year after course completion.
Source: UNIMORE administrative microdata.

Figure 3 complements this evidence by reporting graduation probabilities by enrolment cohort for students exposed to TBL in the switching course. Graduation probabilities increase across successive post-TBL cohorts, reaching approximately 15% within the sample period for the 2021 enrolment cohort. While graduation outcomes may reflect a combination of cohort-specific and institutional factors, the sustained increase over time in graduation probability is consistent with a cumulative association between earlier exam completion and subsequent degree completion.

Figure 3. Graduation probability by enrolment cohort - Switching course



*Notes: The figure reports graduation probabilities by enrolment cohort for students exposed to TBL in the switching course. Estimates are obtained from difference-in-differences specifications including course and enrolment-cohort fixed effects. Shaded areas denote 95% confidence intervals. *** p<0.01, ** p<0.05, * p<0.1.*
Source: UNIMORE administrative microdata.

5.5 Robustness checks and sensitivity analyses

This section summarises the results of robustness checks assessing the stability of the estimated effects of TBL. Full results are reported in the Appendix.

We first address the issue of inference with a limited number of enrolment cohorts. Since treatment varies at the course level within cohorts and outcomes may exhibit correlation among students from the same cohort, all baseline standard errors are clustered at the enrolment-cohort level. To account for the relatively small number of clusters, we complement standard inference with wild cluster bootstrap-t procedures as proposed by Cameron, Gelbach, and Miller (2008). The effect on time to degree is less precisely estimated under bootstrap inference, consistent with its smaller magnitude.

Second, we assess sensitivity to cohort-specific shocks through leave-one-cohort-out analyses. Table A6 reports estimates obtained by re-estimating the baseline difference-in-differences specification while excluding one enrolment cohort at a time. Across all exclusions, the estimated effects on second-year ECTS credits, exam grades, final degree grade, and graduation probability remain stable in sign and similar in magnitude across specifications. Excluding cohorts affected by the COVID-19 pandemic does not materially alter the results.

Third, we examine the correlation structure among covariates included in the empirical specifications. Correlations among controls are moderate and do not indicate problematic multicollinearity (Table A7).

Finally, we assess sensitivity to outliers by trimming the top and bottom 5% of the distributions of key academic variables. As reported in Table A8, the estimated short-run effect of TBL on second-year ECTS credits remains positive and statistically significant after trimming, indicating that the results are not driven by extreme observations.

Overall, these robustness checks indicate that the main findings are stable across alternative inference procedures, cohort compositions, and sample definitions.

6. Discussion

The results of our empirical analysis indicate that the adoption of TBL is associated with sustained improvements in students' academic trajectories, observed both in early academic outcomes and at graduation. Our findings are consistent with previous evidence indicating that active and collaborative learning approaches are linked to improvements in student outcomes in economics and related fields (Abío et al., 2019; Lo Prete, Macrì, and Rania, 2021; Cagliesi and Ghanei, 2022).

A key contribution of our study is to link course-level behavioural responses to programme-level academic outcomes. We show that higher success rates at early exam attempts and participation in early examination sessions are systematically related to greater credit accumulation and improved degree outcomes. This pattern suggests that instructional formats fostering regular study effort and timely assessment completion shape students' progression paths and, ultimately, degree completion.

The findings also shed light on the mechanisms through which TBL operates. Course-level evidence shows that TBL increases the likelihood of passing key exams at earlier attempts and sessions. This interpretation aligns with theoretical and empirical work emphasising the role of structured engagement, formative feedback, and peer interaction in shaping students' study organisation (Odell, 2018; Kozanitis and Nenciovici, 2023). In line with recent contributions, the benefits of active learning appear to extend beyond exam performance to include changes in assessment timing and participation (Schmulian and Coetzee, 2019; You, 2024).

The heterogeneity analysis further refines the interpretation of these effects. Students with higher enrolment test scores (TOLC-E) experience larger gains in grades, while students with lower scores benefit particularly in terms of progression-related outcomes, including time to degree and graduation probability. This suggests that TBL supports academic success across the performance distribution, with gains emerging along different outcome dimensions. Consistent with prior evidence, the effects are broadly similar across sex groups, indicating that team-based instructional formats do not generate systematic differences by sex in economics education (Cagliesi and Ghanei, 2022; McKay and Sridharan, 2024).

Finally, the gradual strengthening of estimated effects across successive cohorts points to an important implementation dimension. As instructors and students gain experience with the TBL format, its effectiveness appears to increase. The fact that cohorts affected by COVID-19 disruptions do not drive the results further supports the interpretation that the estimated effects reflect sustained changes in instructional practice rather than cohort-specific shocks. This interpretation is consistent with recent evidence highlighting how assessment and instructional practices can differentially shape student outcomes under changing institutional conditions (Canal and Child, 2025).

Overall, the evidence suggests that TBL represents an instructional approach with the potential to improve academic progression and performance in undergraduate economics. More broadly, the findings underline the importance of evaluating instructional reforms using longitudinal administrative data and quasi-experimental designs that capture both short-term and cumulative effects.

7. Conclusion

This paper examines the effects of introducing Team-Based Learning (TBL) on academic outcomes in undergraduate economics by exploiting an instructional reform at a large Italian public university, where one economics programme integrated TBL alongside standard lectures while a parallel programme continued with traditional lecture-based instruction. Using administrative data across multiple cohorts within a quasi-experimental research design,, our empirical analysis documents improvements in student outcomes both in the short and in the medium run and shows that these gains are broadly shared across different groups of students**.**

Our study contributes to the literature on active learning by demonstrating that instructional design can generate persistent effects on students' academic performance throughout the undergraduate trajectory. Unlike most existing studies, which focus on course-level outcomes - or rely on short-term evaluation windows (e.g., one semester or academic year), we track multiple student cohorts from enrolment to degree completion**.**. This longitudinal approach allows us to assess how active learning academic progression over time and across multiple outcomes, thereby providing - institutions with systematic evidence to inform the adoption of evidence-based instructional strategies aimed at improving student success.

Alongside these contributions, important limitations should be acknowledged.. First, the analysis focuses on a single institutional context and on one core course as the main - treatment, which may limit external validity. Second, while administrative data allow for a detailed reconstruction of academic trajectories and examination behaviour, they do not capture dimensions such as motivation, teamwork skills or post-graduation outcomes. Future research could extend this approach to other disciplines, institutions and outcome domains.

Overall, the evidence indicates that TBL represents a promising instructional approach for supporting student engagement and academic progression in mass undergraduate education. From an institutional perspective, these findings suggest that curriculum-integrated active learning can effectively address delayed progression and low degree completion rates, while remaining compatible with existing course structures and assessment frameworks.

Acknowledgements

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Notes

1. Building on earlier work on cooperative and collaborative learning, TBL was formalised by Michaelsen and colleagues as a highly structured instructional strategy combining individual accountability, stable teams, frequent low-stakes testing, and immediate feedback (Michaelsen, Knight, & Fink, 2002; Michaelsen & Sweet, 2008). Unlike loosely defined group work, TBL is characterised by a fixed instructional sequence-pre-class preparation, individual and team readiness assurance tests, application-focused problem solving, targeted mini-lectures and peer evaluation - that aims to align incentives, mitigate free-riding, and integrate teamwork directly into assessment.

2. The intervention was not conducted during the 2020/21 academic year due to the shift to remote teaching imposed by the COVID-19 pandemic. While TBL can be adapted for online delivery, in-person TBL sessions were deemed preferable to facilitate group collaboration and maintain consistency in implementation across cohorts.

3. This high compliance rate implies that treatment assignment is largely driven by course enrolment rather than individual take-up decisions, reducing concerns about individual-level self-selection and strengthening the credibility of the quasi-experimental design.

4. The TOLC-E is a standardized entry test used for admission to economics and related university programmes in Italy, introduced at the national level in the mid-2010s and administered by CISIA, an inter-university consortium responsible for the design and administration of admission and assessment tests used by Italian universities to evaluate foundational academic skills prior to enrolment. In this study, TOLC-E scores are used as an indicator of students’ pre-enrolment academic proficiency and preparedness for university courses in economics.

5. Average exam score corresponds to the student’s grade point average (GPA), computed on the Italian 30-point grading scale.

6. In the Italian university system, individual exam grades are recorded on a 30-point scale, where 18 is the minimum passing grade and 30 is the maximum. Outstanding performance may be awarded *30 e lode* (30 with honours). Final degree grades are expressed on a 110-point scale, with 66 as the minimum passing grade and 110 as the maximum, with the possibility of *lode* (honours).

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

The data that support the findings of this study (*UNIMORE administrative microdata)* are derived from confidential student administrative records provided by the University of Modena and Reggio Emilia. Due to data protection regulations and ethical restrictions, these data are not publicly available. Access may be granted upon reasonable request and subject to approval by the data-providing institution.

Ethics statement

The dataset used in this study combines anonymized student administrative records provided by the University of Modena and Reggio Emilia with one survey-based measure obtained from students in the TBL-treated course. This variable, collected via the university's e-learning platform (https://www.edunova.it/images/Informativa_Privacy_Dolly.pdf), captures students' willingness to participate in Team-Based Learning activities in the "Introduction to Macroeconomics" course of the Bachelor’s degree programme in Economics and Finance (*Corso di Laurea in Economia e Finanza* - CLEF) during the academic years in which the TBL was implemented. The combined dataset was pseudonymized by replacing student identifiers with randomly generated non-intrinsic codes. The correspondence table linking the codes to actual identities was stored separately in a secure, encrypted archive, accessible only to authorized personnel. Statistical analyses were conducted exclusively on pseudonymized data, and results are disseminated solely in aggregated form. Data processing was carried out in compliance with Articles 6(1)(e) and 89 of the EU General Data Protection Regulation (Regulation (EU) 2016/679, GDPR) and with the Guidelines of the Italian Data Protection Authority for the processing of personal data for scientific research purposes (Official Gazette No. 72/2021).

Use of AI disclosure

During the preparation of this manuscript, the authors used ChatGPT (GPT-5.2) to assist with language editing and improving clarity. All intellectual content, research design, and data analysis were conducted solely by the authors. All AI-generated suggestions were carefully reviewed, edited, and approved by the authors, who take full responsibility for the accuracy and integrity of the final work.

References

Abío, G., Alcañiz, M., Gómez-Puig, M., Rubert, G., Serrano, M., Stoyanova, A., and Vilalta-Bufí, M. 2019. "Retaking a course in economics: innovative teaching strategies to improve academic performance in groups of low-performing students." *Innovations in Education and Teaching International* 56 (2): 206-216. https://doi.org/10.1080/14703297.2017.1389289.

Angrist, J. D., and Pischke, J.-S. 2009. *Mostly harmless econometrics: an empiricist's companion*. Princeton, NJ: Princeton University Press.

Bandiera, O., Larcinese, V., and Rasul, I. 2015. "Blissful ignorance? Evidence from a natural experiment on the effect of individual feedback on performance." *Labour Economics* 34: 13-25. https://doi.org/10.1016/j.labeco.2015.02.002.

Becker, W. E., and Watts, M. 1996. "Chalk and talk: a national survey on teaching undergraduate economics." *American Economic Review* 86 (2): 448-453. https://www.jstor.org/stable/2118168.

Bound, J., Lovenheim, M. F., and Turner, S. 2012. "Increasing time to baccalaureate degree in the United States." *Education Finance and Policy* 7 (4): 375-424. https://doi.org/10.1162/EDFP_a_00074.

Burgess, A., Bleasel, J., Haq, I., Roberts, C., Garsia, R., Robertson, T., and Mellis, C. 2017. "Team-based learning (TBL) in the medical curriculum: better than PBL?" *BMC Medical Education* 17 (1): 243. https://doi.org/10.1186/s12909-017-1068-z.

Bravo, R., Catalán, S., and Pina, J. M. 2019. "Analysing teamwork in higher education: An empirical study on the antecedents and consequences of team cohesiveness." *Studies in Higher Education* 44 (7): 1153-1165. https://doi.org/10.1080/03075079.2017.1420049

Cagliesi, G., and Ghanei, M. 2022. "Team-based learning in economics: promoting group collaboration, diversity and inclusion." *The Journal of Economic Education* 53 (1): 11-30. https://doi.org/10.1080/00220485.2021.2004276.

Cameron, A. C., Gelbach, J. B., and Miller, D. L. 2008. "Bootstrap-based improvements for inference with clustered errors." *The Review of Economics and Statistics* 90 (3): 414-427. https://doi.org/10.1162/rest.90.3.414.

Canal, M. M., and Child, R. 2025. "Impact of the type of assessment on awarding gaps in bioscience undergraduate degrees." *Assessment & Evaluation in Higher Education*, Advance online publication: 1-14. https://doi.org/10.1080/02602938.2025.2500365.

Carson, K. S., González-Ramírez, J., Heinicke, C., Maier, M. H., Ruder, P. J., Simkins, S. P., Adams, H., Latham, J. M., and Malakar, C. L. 2025. "Results of a randomized evaluation of team-based learning exercises." *International Review of Economics Education* 49: 100316. https://doi.org/10.1016/j.iree.2025.100316.

Emerson, T. L., and Taylor, B. A. 2004. "Comparing student achievement across experimental and lecture-oriented sections of a principles of microeconomics course." *Southern Economic Journal* 70 (3): 672-693. https://doi.org/10.1002/j.2325-8012.2004.tb00596.x.

Freeman, S., Eddy, S. L., McDonough, M., Smith, M. K., Okoroafor, N., Jordt, H., and Wenderoth, M. P. 2014. "Active learning increases student performance in science, engineering, and mathematics." *Proceedings of the National Academy of Sciences* 111 (23): 8410-8415. https://doi.org/10.1073/pnas.1319030111.

Garibaldi, P., Giavazzi, F., Ichino, A., and Rettore, E. 2012. "College cost and time to complete a degree: Evidence from tuition discontinuities." *Review of Economics and Statistics* 94 (3): 699-711. https://doi.org/10.1162/REST_a_00195.

Haidet, P., Kubitz, K., and McCormack, W. T. 2014. "Analysis of the team-based learning literature: TBL comes of age." *Journal on Excellence in College Teaching* 25 (3-4): 303-333.

Hoyt, G. M., and McGoldrick, K. eds. 2012. *International handbook on teaching and learning economics*. Cheltenham: Edward Elgar Publishing.

Imbens, G. W., and Rubin, D. B. 2015. *Causal inference in statistics, social, and biomedical sciences*. Cambridge: Cambridge University Press.
Kyndt, E., Raes, E., Lismont, B., Timmers, F., Cascallar, E., and Dochy, F. 2013. "A meta-analysis of the effects of face-to-face cooperative learning." *Educational Research Review* 10: 133-149. https://doi.org/10.1016/j.edurev.2013.02.002.
Kozanitis, A., and Nenciovici, L. 2023. "Effect of active learning versus traditional lecturing on the learning achievement of college students in humanities and social sciences: a meta-analysis." *Higher Education* 86 (6): 1377-1394. https://doi.org/10.1007/s10734-022-00977-8.
Lo Prete, F., Macrì, E., and Rania, F. 2021. "Team production in a field experiment: study of aggregative versus individual cultural activities." *Higher Education* 81 (2): 345-365. https://doi.org/10.1007/s10734-022-00977-8.
McKay, J., and Sridharan, B. 2024. "Student perceptions of collaborative group work (CGW) in higher education." *Studies in Higher Education* 49 (2): 221-234. https://doi.org/10.1080/03075079.2023.2227677.
Michaelsen, L. K., Knight, A. B., and Fink, L. D. 2002. *Team-based learning: a transformative use of small groups in college teaching*. Sterling, VA: Stylus Publishing.
Michaelsen, L. K., and Sweet, M. 2008. "The essential elements of team-based learning." *New Directions for Teaching and Learning* 2008 (116): 7-27. https://doi.org/10.1002/tl.330.
Odell, K. E. 2018. "Team-based learning and student performance: preliminary evidence from a principle of macroeconomics classroom." *International Review of Economics Education* 29: 44-58. https://doi.org/10.1016/j.iree.2018.01.001.
OECD. 2025. *Education at a glance 2025: OECD indicators*. Paris: OECD Publishing. https://doi.org/10.1787/1c0d9c79-en.
Parmelee, D., Michaelsen, L. K., Cook, S., and Hudes, P. D. 2012. "Team-based learning: A practical guide: AMEE Guide No. 65." *Medical Teacher* 34 (5): e275-e287. https://doi.org/10.3109/0142159x.2012.651179.
Prince, M. 2004. "Does active learning work? A review of the research." *Journal of Engineering Education* 93 (3): 223-231. https://doi.org/10.1002/j.2168-9830.2004.tb00809.x.
Ramsey, L. R., Kling, T., and Yu, W. 2025. "STEM linked-course communities can increase student success: Results from a randomized controlled trial." *Research in Higher Education* 66 (4): Article 28. https://doi.org/10.1007/s11162-025-09846-6.
Rubin, D. B. 1974. "Estimating causal effects of treatments in randomized and nonrandomized studies." *Journal of Educational Psychology* 66 (5): 688-701. https://psycnet.apa.org/doi/10.1037/h0037350.
Schmulian, A., and Coetzee, S. A. 2019. "Students' experience of team assessment with immediate feedback in a large accounting class." *Assessment & Evaluation in Higher Education* 44 (4): 516-532. https://doi.org/10.1080/02602938.2018.1522295.
Schneider, M., and Preckel, F. 2017. "Variables associated with achievement in higher education: A systematic review of meta-analyses." *Psychological Bulletin* 143 (6): 565-600. https://psycnet.apa.org/doi/10.1037/bul0000098.
Sisk, R. J. 2011. "Team-based learning: systematic research review." *Journal of Nursing Education* 50 (12): 665-669. https://doi.org/10.3928/01484834-20111017-01.
Swanson, E., McCulley, L. V., Osman, D. J., Scammacca Lewis, N., and Solis, M. 2019. "The effect of team-based learning on content knowledge: A meta-analysis." *Active Learning in Higher Education* 20 (1): 39-50. https://doi.org/10.1177/1469787417731201.
Theobald, E. J., et al. 2020. "Active learning narrows achievement gaps for underrepresented students in undergraduate science, technology, engineering, and math." *Proceedings of the National Academy of Sciences* 117 (12): 6476-6483. https://doi.org/10.1073/pnas.1916903117.
You, J. W. 2024. "Relationship between team learning profiles and outcomes in team project-based learning: a cluster analysis." *Studies in Higher Education* 49 (1): 16-32. https://doi.org/10.1080/03075079.2023.2219298.

Appendix

Appendix A. Additional summary statistics and sample composition

Table A1. Summary statistics - full sample

Variables	All sample (N=4,320)		Treated (N=501)		Control (3,819)	
	Mean	Sd	Mean	Sd	Mean	Sd
2nd year ECTS credits	50.4	18.5	56.0	16.3	49.7	18.7
2nd year average exam score	24.3	2.7	25.3	2.9	24.2	2.7
Female	0.50	0.50	0.30	0.46	0.53	0.50
TOLC-E score	41.0	8.0	41.4	8.7	40.9	7.9
High school final grade	81.8	11.5	82.7	11.7	81.7	11.5
1st year ECTS credits	44.6	15.1	46.2	14.4	44.4	15.2
Scientific high school	0.32	0.47	0.34	0.47	0.32	0.47
Humanities high school	0.18	0.38	0.14	0.35	0.18	0.38
Technical school - economics	0.24	0.43	0.30	0.46	0.23	0.42
Technical school - technology	0.05	0.21	0.03	0.18	0.05	0.22
Vocational school	0.10	0.30	0.10	0.30	0.10	0.30
Other school	0.11	0.31	0.08	0.27	0.12	0.32
Erasmus mobility	0.22	0.41	0.12	0.32	0.23	0.42
Low tuition-fee bracket	0.16	0.36	0.19	0.39	0.15	0.36
Medium tuition-fee bracket	0.07	0.26	0.08	0.27	0.07	0.26
High tuition-fee bracket	0.77	0.42	0.74	0.44	0.78	0.42
Off-region student	0.17	0.38	0.20	0.40	0.17	0.37

Notes: The table reports means and standard deviations for the full sample used to analyse short-run outcomes. Treated students are enrolled in the switching course after the introduction of TBL. Control students include (i) students enrolled in the switching course before the introduction of TBL and (ii) students enrolled in the lecture-based course over the entire observation period.
Source: UNIMORE administrative microdata.

Table A2. Summary statistics - graduates sample

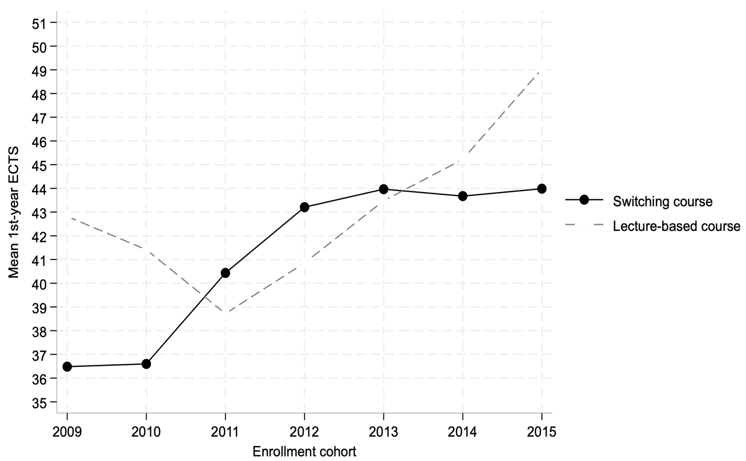
Variables	All sample (N=3,449)		Treated (N=376)		Control (3,073)	
	Mean	Sd	Mean	Sd	Mean	Sd
Degree grade	97.6	8.9	100.1	8.8	97.3	8.8
Time to degree (in months)	42.8	11.9	40.8	8.5	43.0	12.2
Female	0.52	0.50	0.31	0.46	0.54	0.50
TOLC-E score	40.9	7.9	41.1	8.9	40.9	7.7
High school final grade	82.3	11.4	83.0	11.6	82.2	11.3
1st year ECTS credits	46.7	14.1	47.7	13.9	46.6	14.1
2nd year ECTS credits	54.3	15.9	58.1	15.2	53.8	15.9
2nd year average exam score	24.6	2.6	25.5	2.8	24.5	2.5
Scientific high school	0.33	0.47	0.35	0.48	0.33	0.47
Humanities high school	0.18	0.38	0.14	0.35	0.18	0.39
Technical school - economics	0.23	0.42	0.30	0.46	0.22	0.41

Technical school - technology	0.05	0.22	0.02	0.14	0.05	0.23
Vocational school	0.09	0.29	0.09	0.28	0.10	0.29
Other school	0.12	0.32	0.11	0.31	0.12	0.33
Low tuition-fee bracket	0.15	0.35	0.16	0.37	0.15	0.35
Medium tuition-fee bracket	0.07	0.25	0.07	0.26	0.07	0.25
High tuition-fee bracket	0.78	0.41	0.77	0.42	0.79	0.41
Erasmus mobility	0.25	0.44	0.14	0.35	0.27	0.44
Off-region student	0.17	0.38	0.20	0.40	0.17	0.38

Notes: The table reports means and standard deviations for the subsample of students who completed the degree used to analyse medium-run outcomes. Treated students are enrolled in the switching course after the introduction of TBL. Control students include (i) students enrolled in the switching course before the introduction of TBL and (ii) students enrolled in the lecture-based course over the entire observation period.
Source: UNIMORE administrative microdata.

Appendix B. Identification checks and robustness analyses

Figure A1. Pre-treatment trends in first-year ECTS credits by enrolment cohort



Notes: The figure plots average first-year ECTS credits for treated and control students across pre-TBL enrolment cohorts (2009-2015). The parallel evolution of outcomes prior to the introduction of TBL provides graphical support for the parallel trends assumption.
Source: UNIMORE administrative microdata.

Table A3. Pre-treatment regression in first-year ECTS credits

Variables	1st year ECTS credits
Switching course	0.962 (1.061)
High school final grade	0.541*** (0.035)

Enrolment test score (TOLC-E)	0.261*** (0.037)
Female	-0.663 (0.377)
Constant	-16.537** (4.896)
Observations	1,991
Adj. R^2	0.237

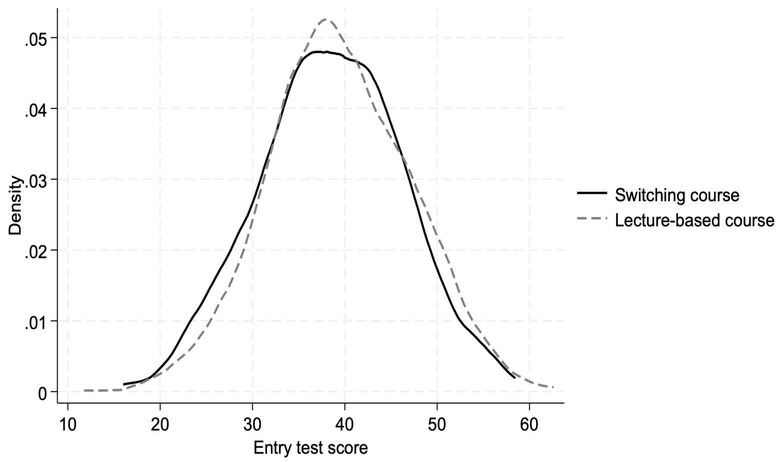
*Notes: The table reports estimates from regressions of first-year ECTS credits on course affiliation and pre-treatment characteristics, estimated on pre-TBL enrolment cohorts only. The specification is intended to assess whether systematic differences across courses are present prior to the introduction of TBL. *** p<0.01, ** p<0.05, * p<0.1.*
Source: UNIMORE administrative microdata.

Table A4. Placebo difference-in-differences test (pre-TBL cohorts)

Variables	1st year ECTS credits
Placebo DiD term (Switching course × Post 2013)	1.975 (1.663)
High school final grade	0.515*** (0.033)
Enrolment test score (TOLC-E)	0.239*** (0.043)
Female	-0.726 (0.456)
Constant	-13.796** (4.422)
Observations	1,991
Adj. R^2	0.256

*Notes: The placebo test assigns a fictitious treatment to pre-TBL cohorts only. The reported coefficient refers to the interaction between the switching course indicator and a post-placebo period (Post 2013) and captures the estimated placebo difference-in-differences (DiD) effect. *** p<0.01, ** p<0.05, * p<0.1.*
Source: UNIMORE administrative data.

Figure A2. Pre-treatment distribution of enrolment test scores (TOLC-E)



Notes: The figure reports kernel density estimates of TOLC-E enrolment test scores for pre-TBL enrolment cohorts (2009-2015). The similarity of the distributions across groups is consistent with the absence of differential sorting prior to the introduction of TBL.
Source: UNIMORE administrative microdata.

Table A5. Wild cluster bootstrap inference for main outcomes (999 replications)

Outcome	β	p-value CR	p-value WCB	95% CI WCB
2nd year ECTS credits	7.808	0.000	0.027	[3.447; 10.280]
2nd year average exam score	1.053	0.000	0.031	[0.359; 1.506]
Degree grade	2.325	0.001	0.046	[0.695; 3.884]
Time to degree (in months)	-1.020	0.053	0.204	[-1.993; 1.250]
Graduation probability	0.057	0.000	0.031	[0.009; 0.082]

Notes: The table reports wild cluster bootstrap-t inference following Cameron, Gelbach, and Miller (2008), based on 999 Rademacher replications. CR p-values refer to conventional cluster-robust inference, while wild cluster bootstrap (WCB) p-values and confidence intervals are obtained from the bootstrap procedure.
Source: UNIMORE administrative microdata.

Table A6. Leave-one-cohort-out sensitivity analysis

Excluded cohort	2nd year ECTS credits	2nd year average exam score	Degree grade	Graduation probability
2009	7.759***	1.044***	2.265***	0.057***
2010	7.728***	1.054***	2.329***	0.059***
2011	7.929***	1.061***	2.356***	0.057***

2012	7.745***	1.055***	2.341***	0.057***
2013	7.860***	1.072***	2.382***	0.058***
2014	7.800***	1.062***	2.326***	0.058***
2015	8.172***	1.110***	2.490***	0.061***
2016	8.707***	1.192***	2.434***	0.059***
2017	7.650***	0.989***	2.251***	0.053***
2018	7.353***	0.933***	1.815***	0.050***
2019	7.936***	1.062***	2.316***	0.057***
2020	7.938***	1.116***	2.538***	0.052***
2021	7.425***	1.030***	2.337***	0.054***
2022	7.264***	0.956***	2.325***	0.065***

Notes: Each row reports the estimated treatment effect obtained by re-estimating the baseline difference-in-differences specification while excluding one enrolment cohort at a time.
Source: UNIMORE administrative microdata.

Table A7. Correlation matrix of pre-treatment covariates

Variable	Female	Year of birth	High school final grade	TOLC-E score	1st year ECTS credits	Off-region student	Erasmus mobility	Tuition-fee bracket
Female	1.000 (.)	0.004 (0.769)	0.279 (0.000)	-0.005 (0.738)	0.097 (0.000)	-0.006 (0.712)	0.099 (0.000)	-0.087 (0.000)
Year of birth	0.004 (0.769)	1.000 (.)	0.213 (0.000)	0.278 (0.000)	0.196 (0.000)	0.110 (0.000)	0.008 (0.576)	-0.134 (0.000)
High school final grade	0.279 (0.000)	0.213 (0.000)	1.000 (.)	0.191 (0.000)	0.385 (0.000)	0.160 (0.000)	0.124 (0.000)	-0.102 (0.000)
TOLC-E score	-0.005 (0.738)	0.278 (0.000)	0.191 (0.000)	1.000 (.)	0.241 (0.000)	-0.006 (0.716)	0.101 (0.000)	0.054 (0.000)
1st year ECTS credits	0.097 (0.000)	0.196 (0.000)	0.385 (0.000)	0.241 (0.000)	1.000 (.)	0.093 (0.000)	0.207 (0.000)	-0.072 (0.000)
Off-region student	-0.006 (0.712)	0.110 (0.000)	0.160 (0.000)	-0.006 (0.716)	0.093 (0.000)	1.000 (.)	0.100 (0.000)	-0.186 (0.000)
Erasmus mobility	0.099 (0.000)	0.008 (0.576)	0.124 (0.000)	0.101 (0.000)	0.207 (0.000)	0.100 (0.000)	1.000 (.)	-0.025 (0.096)
Tuition-fee bracket	-0.087 (0.000)	-0.134 (0.000)	-0.102 (0.000)	0.054 (0.000)	-0.072 (0.000)	-0.186 (0.000)	-0.025 (0.096)	1.000 (.)

Notes: The table reports pairwise correlation coefficients between all pre-treatment covariates included in the main difference-in-differences specifications. P-values from two-sided tests of zero correlation are reported in parentheses.
Source: UNIMORE administrative microdata.

Table A8. Sensitivity to outlier trimming (5%)

Variables	2nd year ECTS credits - 5% trimmed sample
TBL	5.379*** (1.502)
High school final grade	0.140*** (0.017)
Enrolment test score (TOLC-E)	-0.064 (0.043)
Female	-0.165 (0.488)
Constant	6.730** (2.985)
Observations	3,456
Adj. R^2	0.285

*Notes: The sample excludes observations in the top and bottom 5 per cent of the distributions of TOLC-E scores, first-year ECTS credits, and second-year ECTS credits. Standard errors are reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.*
Source: UNIMORE administrative microdata.