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Research on Policy Evaluation Based on a Dual Machine Learning Model: Taking the Impact of the "Double Reduction" Policy on Students' Academic Performance as an Example

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Abstract: The "Double Reduction" policy is a major reform in China's basic education field, and the impact assessment of this change on students' academic performance is the core basis for strategy optimization. Previous evaluation methods were prone to selection bias and confounding variables, compromising the authenticity of results. This study employs panel data from students at School A (2020–2022) as a sample, treating the "Double Reduction" policy as a quasi-natural experiment. By applying a dual machine learning model to control for confounding variables such as individual student characteristics, family background, and school resources, it precisely identifies the causal relationship between the policy and academic outcomes. The study finds that the strategy has the characteristics of "overall improvement and structural improvement" in students' academic performance, the average score of core subjects is increased, and the dispersion degree is reduced, the improvement effect on students with medium academic level is the most outstanding, and the influence on excellent students and students with learning difficulties is relatively moderate. Research demonstrates that the dual machine learning model effectively addresses endogeneity issues, providing robust methodological support for educational strategy evaluation. The "Double Reduction" policy enhances academic quality and efficiency through optimized learning environments.
Keyword: Dual machine learning; Policy evaluation; "Double Reduction" policy; Academic outcomes; Causal identification

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1. Foreword

The strategy changes during the basic teaching period are related to the quality of talent training and educational equity. The "double reduction" strategy focuses on reducing students' homework and off-campus training burden, directly targeting the difficulties such as "involution" in basic teaching, and promoting the change of the educational environment. The precise evaluation of its effect on students' academic performance is the key to test the effect of the strategy and to optimize and adjust it. However, strategy evaluation is often influenced by selection bias and confounding variables, making it difficult for previous methods to draw reliable conclusions [1]. The dual machine learning model can effectively separate the interference of the mixed variables, providing a new way to solve the endogeneity problem.

2. Study design and methods

2.1. Research thought, research idea, and research approach

This study employs the implementation of the "Double Reduction" policy as a quasi-natural experiment, constructing a comparative analysis framework spanning "pre-policy implementation" and "post-policy implementation." Using student panel data from School A during the 2020–2021 academic year (pre-policy) and 2021–2022 academic year (post-policy), the study identifies policy implementation status as the core explanatory variable (treatment variable), with students' scores in core subjects (Chinese, Mathematics, and Foreign Languages) and their score dispersion as the dependent variables (academic performance indicators). By employing a dual machine learning model, the study first applies machine learning algorithms to model the relationships between treatment variables, confounding variables, and dependent variables. This enables the elimination of confounding variables' interference, allowing precise calculation of the net effect of the "Double Reduction" policy on students' academic performance. Furthermore, students are categorized into three tiers (excellent, average, and struggling) based on their academic achievement, facilitating a deeper analysis of the heterogeneous characteristics of the policy's impact [2].

2.2. Specification of variables

The core explanatory variable incorporates the implementation status of the "Double Reduction" policy (T), coded as 0 for the pre-policy period (2020-2021 academic year) and 1 for the post-policy period (2021–2022 academic year). The dependent variable focuses on student academic outcomes, with two key indicators selected: First, the average scores in core subjects (Chinese, Mathematics, and English, Score), which reflect overall academic performance; second, the standard deviation (SD) of these scores, calculated as the standard deviation of Chinese, Mathematics, and English grades to measure academic equity. The confounding variables follow a dual logic of "affecting policy implementation environment-influencing academic outcomes", comprising three categories: First, individual student characteristics including gender (Gender), grade (Grade), and study habits (StudyHabits, assessed through classroom focus and homework quality); second, family background variables such as parents' education level (ParEdu, highest parental education grade) and family income (FamilyIncome, categorized by school-based financial aid levels); third, school resource variables covering class size (ClassSize) and teachers' experience (TeacherExp).

2.3. Dual machine learning model construction

The dual machine learning model operates through two fitting steps to achieve consistent causal effect estimation, with the specific construction process as follows:

The first step is to fit the relationships between the treatment variables and the dependent variables, as well as the confounding variables. Using the Lasso regression algorithm (which is particularly effective for screening and fitting high-dimensional variables), two predictive models were constructed: the first model predicts the treatment variable T based on the confounding variable X to obtain the predicted value T; the second model predicts the explained variable Y (Score/SD) based on the confounding variable X to obtain the predicted value Y. The Lasso algorithm compresses the coefficients of irrelevant variables through penalty terms, effectively addressing multicollinearity issues in high-dimensional confounding variables, thereby improving the precision of the fit [3].

The second step involves estimating the net effect of the policy. By plugging the predicted values T and Y from the first step into the simplified regression model, we construct an estimation equation for the causal effect using the residual term: $Y-Y=\alpha+\beta(T-T)+\varepsilon$. Here, β represents the average treatment effect (ATE) of the "Double Reduction" policy on academic outcomes, α is the constant term, and ε denotes the random error term. This process eliminates confounding variables' interference on T and Y, enabling β to accurately reflect the net impact of policy implementation on academic performance. This approach effectively avoids endogeneity issues in traditional regression models caused by omitted confounders or fitting biases.

3. Empirical results and analysis

3.1. Descriptive statistical analysis

Table 1 presents the descriptive statistics of key variables. Regarding academic performance metrics, the policy implementation resulted in a 4.89% improvement in students' average scores for Chinese, Mathematics, and English, rising from 78.32 to 82.15. Meanwhile, the standard deviation (SD) decreased from 11.26 to 8.73, reflecting a 22.47% reduction. These findings indicate that the "Double Reduction" policy has not only enhanced overall academic achievement but also improved its distributional equity. From the perspective of confounding variables, the sample demonstrates a relatively balanced distribution of gender and grade levels. Parents predominantly hold bachelor's degrees or higher (58.3% of respondents), and class sizes are mostly concentrated in the 40–50 student range. This sample structure aligns well with the typical characteristics of schools in the basic education stage, providing a solid data foundation for subsequent empirical analysis.

Table 1. Descriptive statistics of core variables

Variable name	Observed value	Before policy implementation (mean ± SD)	After policy implementation (mean ± standard deviation)
Average scores in Chinese, Mathematics, and English (Score)	1246	78.32±11.26	82.15±8.73
score dispersion (SD)	1246	11.26±3.42	8.73±2.15
Gender (Male=1)	1246	0.52±0.50	0.51±0.50
Parental education level (ParEdu, bachelor's degree or above = 1)	1246	0.57±0.50	0.59±0.49
Class Size	1246	45.32±3.15	44.86±2.98

3.2. The overall effect of policies on academic performance

Table 2 presents the overall policy impact estimated by the dual machine learning model. Regarding the Average Treatment Effect (ATE), the "Double Reduction" policy significantly improved students' average scores in Chinese, Mathematics, and English by 3.72 points (t-value=5.89 at the 1% level), demonstrating a substantial improvement in core subjects. This validates the policy's overall enhancement of academic outcomes. In terms of score dispersion, the policy had a significant negative impact coefficient of-2.45 (t-value=-4.63 at the 1% level), indicating a 2.45-point reduction in academic performance standard deviation and a marked improvement in score equilibrium.

To validate the model's effectiveness, we compare the estimation results of the dual machine learning model with those of the traditional OLS regression model. The OLS regression failed to adequately account for the confounding variables, yielding a performance improvement coefficient of 2.15, which is lower than the 3.72 coefficient from the dual machine learning model. Moreover, the significance level was merely 10%, indicating that the traditional model underestimated the positive policy effects due to endogeneity issues. This comparison confirms the advantages of the dual machine learning model in handling confounding variables and addressing endogeneity issues, with its estimation results demonstrating greater reliability.

Table 2. Overall policy impact effects estimated by the dual machine learning model

Explained variable, variable being explained	Dual Machine Learning Model (ATE)	t value	OLS regression model (coefficients)	t value
Average scores in Chinese, Mathematics, and English	3.72***	5.89	2.15*	1.86
Standard Deviation (SD)	-2.45***	-4.63	-1.32**	-2.31

3.3. Analysis of the heterogeneity of policy impact

Based on students' average scores in Chinese, mathematics, and English before the policy implementation, the sample was divided into three tiers: the top-tier group (≥85 points), the middle-tier group (60–85 points), and the underperforming group (below 60 points). A dual machine learning model was employed to estimate the policy's impact on each tier, with the results presented in **Table 3**.

The analysis of the estimation results reveals significant heterogeneity in policy effects: For students with average academic performance, the improvement effect is most pronounced, with an average score increase coefficient of 4.86, statistically significant at the 1% level. For high-achieving students, the coefficient rises to 1.92, remaining significant at the 5% level, though the improvement effect is relatively moderate. For students with learning difficulties, the coefficient reaches 2.35, remaining significant at the 10% level, with an effect intensity that falls between the high-achieving and average groups. The results show that the coefficient of standard deviation of the middle group is the largest (-3.12), and the excellent group and the difficult group are -1.56 and -1.89, respectively, which indicates that the double reduction policy has the most outstanding effect on the improvement of academic balance of the middle level students.

Table 3. Heterogeneity analysis of policy impact

Academic level	Average Grade improvement coefficient	t value	Coefficient of dispersion of achievement	t value
Excellent Group	1.92**	2.45	-1.56**	-2.23
Intermediate group	4.86***	6.12	-3.12***	-5.01
Difficult group	2.35*	1.78	-1.89**	-2.41

4. Debate

The empirical analysis based on a dual machine learning model demonstrates that the "Double Reduction" policy has achieved "overall improvement and structural optimization" in students' academic performance, which aligns closely with the core objectives of the policy design. By reducing academic workload, the policy mitigates students' fatigue caused by excessive rote training, thereby enhancing learning efficiency. Through standardized off-campus training measures, it curbs unhealthy practices like "advanced learning" and "cutthroat competition", fostering a fairer learning environment. This approach drives comprehensive improvement and balanced progress in academic performance. This achievement refutes the one-sided view that "reducing academic burden will lead to a decline in scores", and validates the practical value of the "Double Reduction" policy in improving academic quality and efficiency through the optimization of the learning ecosystem [3].

The heterogeneity of policy impact provides key guidance for subsequent policy optimization. Students with average academic performance are the primary beneficiaries of the policy, while those facing learning difficulties show relatively limited improvement. This highlights the need for further stratified measures in implementing the "Double Reduction" policy: For academically challenged students, personalized tutoring and study method guidance should be strengthened to address foundational learning gaps, building on the foundation of reduced academic pressure. For high-achieving students, measures like offering extended courses and innovative practical activities can meet their individual development needs and further unlock their learning potential.

From the methodological perspective, the dual machine learning model leverages the high-dimensional variable processing capability of the Lasso algorithm to effectively isolate the interference caused by mixed variables across multiple dimensions, such as individual students, families, and schools. This approach resolves the endogeneity issues inherent in traditional policy evaluation processes, yielding more reliable estimation results compared to Ordinary Least Squares (OLS) regression. This shows that the dual machine learning model has broad application prospects in the field of education policy evaluation, especially suitable for the evaluation scenarios with complex policy influencing factors and a large number of mixed variables, which provides a useful reference for the methodological innovation of education policy evaluation.

5. Conclusion

The "Double Reduction" policy has exerted a significant positive impact on students' academic performance, not only driving an overall improvement in the average scores of core subjects such as Chinese, Mathematics, and English, but also reducing the dispersion of academic achievements, thereby achieving the goal of structural optimization in academic outcomes. The effect of the policy is heterogeneous; the effect on the students with the middle academic level is the most significant, the effect on the students with the excellent and difficult academic level is relatively mild, and the effect on the improvement of the academic balance of the middle group is the most outstanding. The dual machine learning model can effectively solve the endogeneity problem in the process of policy evaluation, improve the accuracy of causal identification, and provide a more reliable methodological support for the evaluation of the effect of education policies.

Disclosure statement

The author declares no conflict of interest.

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