Engineering Educators Bringing the World Together
2025 ASEE Annual Conference & Exposition
Palais des congrès de Montréal, Montréal, QC • June 22–25, 2025
Paper ID #48878

The Hidden Costs of Complexity: Using Causal Inference and Double Machine Learning to Uncover Important Relationships in Higher Education Data Sets

Melika Akbarsharifi, The University of Arizona

Melika Akbarsharifi is a PhD candidate in Software Engineering at the University of Arizona, studying under Professor Gregory L. Heileman. Her research at the Curricular Analytics Lab focuses on developing advanced computational methods and machine learning approaches to optimize educational pathways and student success.

Ahmad Slim

Dr. Slim received his B.E. and M.S degrees in Electrical and Computer Engineering from the Lebanese American University in 2008 and 2011, respectively. In 2016, he received his PhD degree in Computer Engineering from the University of New Mexico where he worked as a research assistant professor for three years after graduation. In 2020, Dr. Slim joined the Mechanical Engineering Education Research Center at Purdue University as a Postdoctoral Research Fellow. His main interests involve educational data mining, machine learning and curricular analytics. He published several papers on methodologies that support inferences in STEM education, student success and other educational practices that advance education outcomes.

Prof. Gregory L. Heileman, The University of Arizona

Gregory (Greg) L. Heileman currently serves as the Associate Vice Provost for Academic Administration and Professor of Electrical and Computer Engineering at the University of Arizona, where he is responsible for facilitating collaboration across campus t

Roxana Akbarsharifi, The University of Arizona

Roxana Akbarsharifi is a PhD student in Software Engineering at the University of Arizona. Her research focuses on educational analytics and developing tools to improve student outcomes and support academic success. Her research interests include software engineering, data analytics, and data visualization, with an emphasis on applying these technologies to solve educational challenges and enable data-driven decision making in higher education.

Kristina A Manasil, The University of Arizona

Kristi Manasil is a second-year PhD student in the College of Information Science at the University of Arizona. She received her bachelor's degree in Computer Science from the University of Arizona. Her areas of focus are data visualization, machine learning, learning analytics and educational data mining.

The Hidden Costs of Complexity: Using Causal Inference and Double Machine Learning to Uncover Important Relationships in Higher Education Data Sets

Melika Akbarsharifi, Ahmad Slim, Gregory L. Heileman,
Roxana Akbarsharifi, Kristi Manasil

{ahslim@arizona.edu, heileman@arizona.edu, akbarsharifi@arizona.edu,
roxanaa@arizona.edu, kmanasil@arizona.edu}

The University of Arizona

Abstract

Graduation rates are critical performance metrics for higher education institutions, reflecting student success and the effectiveness of educational programs. Among various factors, the complexity of university curricula, measured by prerequisite course sequences, total credit requirements, and course flexibility within degree programs, significantly influences outcomes such as timely graduation and retention rates. Previous studies analyzing these effects often lack a unified framework to address how factors such as gender, academic preparation, and socioeconomic background shape these relationships.

Using data from 26 U.S. universities funded by the Ascendium Foundation, this study employs a multifaceted causal inference framework to evaluate the impact of curricular complexity on graduation rates. Our methodology combines Hierarchical Linear Models (HLM) to account for the nested structure of students within universities, Generalized Propensity Scores (GPS) to adjust for confounders, and Double Machine Learning (DML) within GPS-stratified quintiles to provide robust causal estimates. Furthermore, we construct and refine a causal network using the Peter-Clark (PC) Algorithm and the Bayesian Information Criterion (BIC) score, with sensitivity analysis to ensure robustness.

Our results reveal a significant negative causal relationship between curricular complexity and four-year graduation rates, with an effect of -3.88% per unit increase in complexity. Sensitivity analysis supports the robustness of this relationship, showing a consistent effect of -3.76% when accounting for unobserved confounders. Introducing a hidden node representing socioeconomic status in our causal network further strengthens these findings, showing minimal change in the

estimated effect even when accounting for potential unobserved factors.
These findings suggest that complex curricula create barriers to completing the degree in time, underscoring the need for educational strategies that balance academic rigor with accessibility. This study provides a foundation for evidence-based policy reforms that aim to improve student success through optimized curricular design.

keywords: curricular complexity, causal inference, student success, graduation rates, educational data mining

1. Introduction

Graduation rates are a key measure of the effectiveness of higher education institutions, reflecting both student success and program performance. Understanding factors affecting graduation rates is critical in the U.S., where student outcomes influence institutional funding and reputation. Among these factors, curricular complexity has emerged as a significant determinant of student success. Overly complex curricula may hinder timely graduation by increasing students' academic burden, affecting their performance and retention rates. Conversely, a well-structured curriculum that balances rigor and manageability can enhance student success by providing a clear path to degree completion. Previous studies suggest that while curricular complexity can enrich the educational experience, it can also lead to higher dropout rates and a prolonged time to graduation if not properly managed [1, 2]. This study aims to rigorously estimate the causal effect of curricular complexity[1] on four-year graduation rates across 26 U.S. universities. Extending our previous work that identified initial links between curricular complexity and graduation rates[4], this study introduces a more advanced methodological framework that incorporates multiple causal inference techniques to address specific challenges in analyzing educational data. To achieve this goal, we employ HLM to account for the multilevel nature of our data. This approach enables us to model how both individual characteristics and university-level factors influence student outcomes. Next, we use GPS to create balanced comparison groups across different levels of curricular complexity while adjusting for key confounding variables, including gender, ethnicity, first-generation status, and academic preparation. Building on these foundations, we stratify our data into quintiles based on GPS values and apply DML within each stratum to estimate the causal effect of curricular complexity on four-year graduation rates. To validate and refine our findings, we construct a causal network using the PC Algorithm incorporating domain expertise to better understand the interconnected relationships between student demographics, socioeconomic factors, and academic results. The optimal adjusted network is selected using the BIC score, and sensitivity analysis is conducted to evaluate the robustness of our results against potential unmeasured confounding factors.

[1]For a detailed explanation of how curricular complexity is calculated in this study, please refer to "Curricular Analytics: A Framework for Quantifying the Impact of Curricular Reforms and Pedagogical Innovations" by Heileman et al. [3]

1.1 Research Questions and Hypotheses

This study addresses two primary research questions:

1. What is the causal effect of curricular complexity on four-year graduation rates?
2. How do different levels of curricular complexity influence student outcomes across university settings?

Based on prior literature and our preliminary analyses, we hypothesize that increased curricular complexity will demonstrate a significant negative relationship with four-year graduation rates, with effects varying across institutional contexts and student populations.

2. Data Description

This section describes the dataset used to analyze the impact of curricular complexity on four-year graduation rates.

2.1 Data Sources and Key Variables

The dataset comes from 26 diverse public universities across the U.S., collected between 2000 and 2022 as part of an Ascendium Foundation research project. Each institution provided anonymized student-level data, including demographic information, academic performance metrics, and curricular complexity measures. Table 2.1 summarizes the participating universities and the number of programs and students contributed by each institution.

University	Number of Programs	Number of Students
University of Arizona	175	47410
Colorado State University	114	34471
Florida International University	105	22205
Florida State University	223	50006
George Mason University	96	23670
Georgia State University	68	15581
Kansas State University	162	32748
Michigan State University	83	17058
New Mexico State University	90	12965
Rutgers University-Newark	45	6657
Temple University	219	37275
University of California, Davis	120	44044
University of Central Florida	127	51619
University of California, Irvine	100	69150
University of California, Riverside	123	35816
University of Illinois at Chicago	123	22119
University of North Carolina at Charlotte	109	23730
University of New Mexico	126	21471
University of South Florida	158	37632
University of Texas at Arlington	88	16311
University of Texas at Dallas	72	17833
University of Texas at El Paso	96	15905
University of Texas at San Antonio	152	24097
University of Texas at Tyler	53	2534
University of Toledo	167	16656
Washington State University	91	26717

Table 2.1: List of Universities with Number of Programs and Students

The dataset includes the following key variables:

1. **GradIn4:** A binary variable indicating whether a student graduated within four years.
2. **DP_CC:** Curricular complexity. This variable is continuous and reflects the academic burden of a student's coursework.
3. **Sex:** A binary variable indicating the student's gender.
4. **Ethnicity:** A binary variable indicating Hispanic ethnicity.
5. **PellAward:** A binary variable for Pell Grant receipt.
6. **FirstGen:** A binary variable indicating first generation college status.
7. **HSGPA:** A continuous variable representing high school GPA.

8. **T1_CIP_CAP to T10_CIP_CAP:** Categorical variables capturing the CIP codes for each year a student is enrolled.

2.2 Data Preprocessing

Data preprocessing was conducted to ensure the quality and integrity of the dataset through three systematic steps. First, data cleaning involved eliminating duplicates, resolving inconsistencies in categorical variables, and standardizing field formats for uniformity. Second, missing data were addressed using Multiple Imputation [5], while substantial missingness was managed via listwise deletion to maintain data reliability. Lastly, continuous variables were normalized to a mean of zero and a standard deviation of one, ensuring uniform scaling and accurate interpretation across analyses.

2.3 Multilevel Structure of the Data

Given the nested data within universities, a multilevel modeling approach was employed:

- **Within-University Analysis**: Each university's data were analyzed separately to estimate the GPS and causal effect of curricular complexity on graduation rates.
- **Between-University Analysis**: A hierarchical linear model estimated the GPS across all universities, accounting for the nested data structure and institutional differences.

3. Methodology

This section details the methodologies and statistical techniques employed to estimate the causal effect of curricular complexity on four-year graduation rates. The methodologies include GPS, HLM, Stratification, DML, the PC Algorithm for causal network construction, and sensitivity analysis. Each technique was chosen for its unique ability to handle specific challenges in causal inference.

3.1 Generalized Propensity Scores (GPS)

GPS is a widely used method in observational studies to mitigate selection bias by balancing groups based on observed covariates. Unlike traditional propensity scores designed for binary treatments, GPS is specifically tailored for continuous treatments, representing the conditional probability of receiving a particular treatment level given a set of observed covariates [6].
In this study, GPS was calculated for each student using the covariates: sex, ethnicity, Pell Award status, first-generation status, and high school GPA. The treatment variable was defined as Curricular Complexity. The following model specification was used to estimate the GPS:

$$GPS(T) = P(T_i = t|X_i) \tag{1}$$

In this equation, T_i represents the treatment received by student i, and X_i is the vector of covariates for student i.

The primary objective of calculating GPS was to adjust for confounding variables, enabling the creation of comparable groups of students based on their likelihood of experiencing varying levels of curricular complexity. This adjustment is essential for minimizing selection bias and ensuring that the groups are equitably matched, thereby enhancing the validity of subsequent analyses.

3.2 Hierarchical Linear Models (HLM)

HLM, also known as multilevel modeling, is employed to account for the nested structure of the data, with students nested within universities. This two-level hierarchical structure allows HLM to estimate effects at both the student and the university level, capturing variability within and between universities [7].

HLM model includes random intercepts for universities to capture university-level effects. The model is specified as follows:

$$Y_{ij} = \beta_0 + \beta_1 \text{DP\_CC}_{ij} + \beta_2 X_{ij} + u_j + \epsilon_{ij} \tag{2}$$

In this equation, Y_{ij} represents the outcome for student i in university j. The term DP_CC_{ij} denotes the treatment, which is curricular complexity. The vector X_{ij} comprises the covariates for student i in university j. The term u_j is the random intercept for university j, and ϵ_{ij} represents the student-level error term.

3.3 Stratification and Quintile Analysis

Stratification, or subclassification, divides data into homogeneous groups (strata) based on the GPS to reduce bias caused by confounding variables [8]. For this study, GPS was calculated for each student using covariates such as sex, ethnicity, Pell Award status, first-generation status, and high school GPA. Students were then grouped into five quintiles based on their GPS values, with each quintile representing approximately 20% of the sample.

Within each quintile, treatment effects were estimated using DML to evaluate the impact of curricular complexity on four-year graduation rates. This approach ensures that treatment and control groups are comparable within each stratum, mitigating the effects of confounding variables. By creating balanced comparison groups, stratification enhances the robustness and reliability of causal inferences.

3.4 Double Machine Learning (DML)

DML is a robust method for estimating causal effects in high-dimensional data, effectively controlling for confounders by leveraging machine learning to model relationships between covariates and both the treatment and outcome variables [9].

In this study, DML was applied using logistic regression for the outcome variable (four-year graduation rates) and linear regression for the treatment variable (curricular complexity). The models were specified as follows:

$$Y_i = g(T_i, X_i) + \epsilon_i \tag{3}$$

$$T_i = m(X_i) + \nu_i \tag{4}$$

Here, Y_i denotes the outcome (four-year graduation), T_i is the treatment (curricular complexity), and X_i represents covariates such as sex, ethnicity, Pell Award status, first-generation status, and high school GPA. The functions g and m model the relationships for the outcome and treatment, respectively, while ϵ_i and ν_i are error terms. Residuals were calculated for both models, and in the final step, the residuals from the outcome model were regressed on those from the treatment model to estimate the causal effect.
DML was employed within each GPS quintile to estimate the causal effect of curricular complexity on four-year graduation rates. By harnessing machine learning techniques to account for high-dimensional covariates, this approach provided robust and reliable causal estimates.

3.5 Peter-Clark (PC) Algorithm and Causal Network Construction

The PC algorithm, a constraint-based method for causal discovery, identifies the structure of a causal network by testing conditional independencies among variables [10]. The PC algorithm was applied to construct an initial causal network from observed variables, which a domain expert subsequently refined to incorporate domain knowledge. The Bayesian Information Criterion (BIC) was used to evaluate and compare network structures, balancing model fit and complexity to identify the most parsimonious model. The causal network visually represents variable relationships, helping to identify potential confounders and direct causal effects.

3.6 Sensitivity Analysis

Sensitivity analysis assesses the robustness of the estimated causal effects to potential violations of the assumptions. This step is crucial to ensure that the results are sufficiently sensitive to unmeasured confounding or model specification [11].
Sensitivity analysis was conducted by varying the model specifications and examining the impact on the estimated causal effects. Different sets of covariates and alternative models were tested to evaluate the stability of the results. The primary purpose of sensitivity analysis is to determine the reliability of the findings and assess the potential impact of unmeasured confounders on the causal estimates.

4. Results And Discussion

This section presents the results of our analysis, focusing on the impact of curricular complexity on four-year graduation rates. The analysis is divided into three components: (1) results from the HLM used to compute the GPS, (2) outcomes of the DML method on stratified data, and (3) the distribution of critical covariates across GPS quintiles. This structured approach ensures a comprehensive and robust understanding of how curricular complexity affects graduation rates.

4.1 Hierarchical Linear Models (HLM) Results

The HLM takes into account the variability across 26 universities and includes both fixed effects (common across all universities) and random effects (specific to each university). The model specification was as follows:

Fixed Effects Formula: `DP_CC ∼ Sex + PellAward + FirstGen + Ethnicity + HSGPA_standard`
This formula includes the main predictors: Sex, Ethnicity, Pell Award, First Generation status, and high school GPA).
Random Effects Formula: `∼ 1 + Sex + PellAward + FirstGen + Ethnicity + HSGPA_standard | Uni`
This formula accounts for the variability in these predictors across different universities.

The mixed effects model results shown in Table 4.1 reveal significant relationships between curricular complexity and the covariates:

Table 4.1: Hierarchical Linear Model Regression Results

	Coef.	Std. Err.	z	P> |z|	[0.025	0.975]
Intercept	0.283	0.089	3.180	0.001	0.108	0.457
Sex	-0.293	0.063	-4.651	0.000	-0.416	-0.169
PellAward	-0.044	0.012	-3.720	0.000	-0.068	-0.021
FirstGen	-0.040	0.007	-5.431	0.000	-0.054	-0.025
Ethnicity	-0.048	0.018	-2.653	0.008	-0.083	-0.012
HSGPA_standard	0.166	0.013	12.670	0.000	0.140	0.191
Group Var	0.197	0.063				
Group x Sex Cov	-0.052	0.033				
Sex Var	0.099	0.031				
Group x PellAward Cov	-0.012	0.007				
Sex x PellAward Cov	-0.003	0.005				
PellAward Var	0.003	0.001				
Group x FirstGen Cov	-0.006	0.004				
Sex x FirstGen Cov	0.005	0.003				
PellAward x FirstGen Cov	0.000	0.001				
FirstGen Var	0.001	0.000				
Group x Ethnicity Cov	-0.006	0.009				
Sex x Ethnicity Cov	0.007	0.007				
PellAward x Ethnicity Cov	-0.001	0.001				
FirstGen x Ethnicity Cov	0.001	0.001				
Ethnicity Var	0.007	0.002				
Group x HSGPA_standard Cov	0.019	0.008				
Sex x HSGPA_standard Cov	-0.005	0.005				
PellAward x HSGPA_standard Cov	-0.002	0.001				
FirstGen x HSGPA_standard Cov	-0.001	0.001				
Ethnicity x HSGPA_standard Cov	-0.001	0.001				
HSGPA_standard Var	0.004	0.001				

The analysis identifies key factors influencing curricular complexity. The baseline curricular complexity, represented by the intercept, is 0.283 units when all other predictors are zero. Female students have a significantly lower curricular complexity by 0.293 units. Receiving a Pell Grant and being a first-generation student are associated with decreases of 0.044 and 0.040 units, respectively, while Hispanic students exhibit a 0.048 unit decrease. Additionally, each unit increase in standardized high school GPA corresponds to a 0.166 unit increase in curricular complexity.

The random effects component captures variability across universities. Group variance, measured at 0.197, reflects differences in curricular complexity among the 26 universities. Higher group variance suggests greater disparity in curricular complexity across institutions.

Interactions between university groups and covariates reveal how effects vary by institution. For example, the group × sex covariance is -0.052, indicating that the impact of gender differs across universities. Similarly, the group × Pell Award covariance is -0.012, reflecting variability in how receiving a Pell Grant influences curricular complexity. Interactions involving first-generation status, ethnicity, and high school GPA further illustrate this heterogeneity.

These findings highlight the variability in how student characteristics influence curricular complexity across universities, emphasizing the importance of considering institutional context in the analysis.

4.2 Stratification into Quintiles and Double Machine Learning (DML) Analysis

After computing the GPS, the data was stratified into quintiles to create balanced groups for causal inference. DML method was applied within each quintile to estimate the causal effect of curricular complexity on four-year graduation rates. Table 4.2 summarizes the results, including the Average Treatment Effect (ATE), p-values, intervention effects, and counterfactual effects.

Table 4.2: DML Results by Quintile

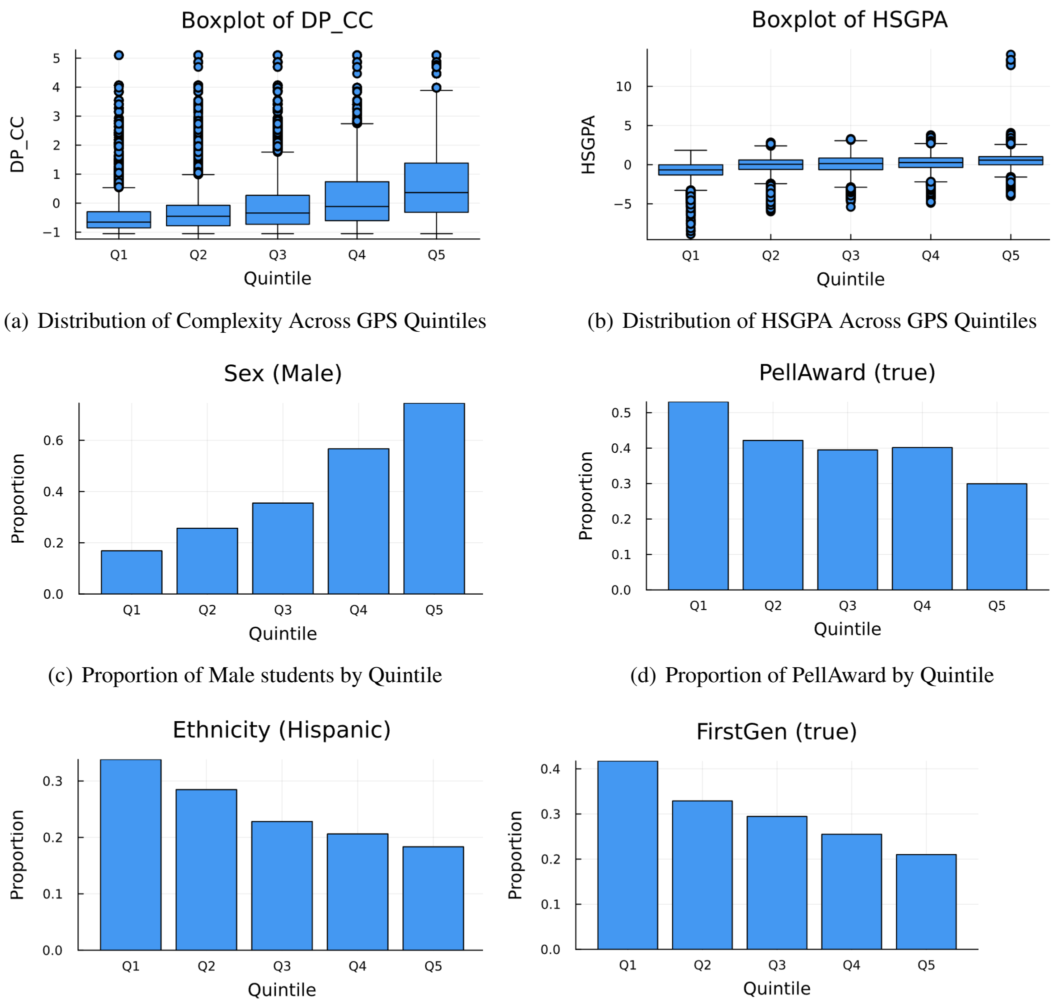
GPS Quintile	ATE	P-Values	Intervention Effect	Counterfactual Effect	Score
Q1	-0.053034	$7.412716 \times 10^{-116}$	-0.053034	-0.024892	0.206613
Q2	-0.054680	$1.838619 \times 10^{-178}$	-0.054680	-0.015371	0.198490
Q3	-0.034824	$7.639624 \times 10^{-120}$	-0.034824	-0.002554	0.200643
Q4	-0.026808	1.779450×10^{-87}	-0.026808	0.005007	0.221091
Q5	-0.023975	$1.107657 \times 10^{-100}$	-0.023975	0.015886	0.218602

These results indicate a consistently negative effect of increased curricular complexity on four-year graduation rates across all quintiles. The p-values confirm the statistical significance of these findings.

The impact of increasing curricular complexity by one unit ranges from -0.053034 in Q1 to -0.023975 in Q5. Setting curricular complexity to zero results in a positive shift, with the highest effect of 0.015886 in Q5, suggesting that reducing complexity could significantly improve graduation rates.

4.3 Distribution of Covariates Across Quintiles

The boxplots and bar charts shown in Figure 4.1 illustrate the distribution of curricular complexity, standardized high school GPA, and other covariates across GPS quintiles.



(a) Distribution of Complexity Across GPS Quintiles

(b) Distribution of HSGPA Across GPS Quintiles

(c) Proportion of Male students by Quintile

(d) Proportion of PellAward by Quintile

(e) Proportion of Hispanic students by Quintile

(f) Proportion of FirstGen students by Quintile

Figure 4.1: Distribution of Variables Across GPS Quintiles

Our hierarchical linear model reveals that women, Pell Grant recipients, first-generation students, and Hispanic students typically select programs with lower curricular complexity. The DML analysis shows that increased curricular complexity negatively impacts graduation rates across all quintiles, with the strongest effects in higher quintiles where complexity is most significant. Intervention and counterfactual analyses suggest that reducing curricular complexity could significantly improve graduation rates, particularly for underrepresented and disadvantaged students. These findings highlight the need for targeted curricular reforms that balance program quality with accessibility.

4.4 Causal Network Construction and Analysis

We constructed a causal network using the PC algorithm to better understand the causal relationships among the variables and estimate the causal effect of curricular complexity on four-year graduation rates. Domain experts further refined the network to ensure its accuracy and relevance. Figure 4.2 shows the constructed causal network.

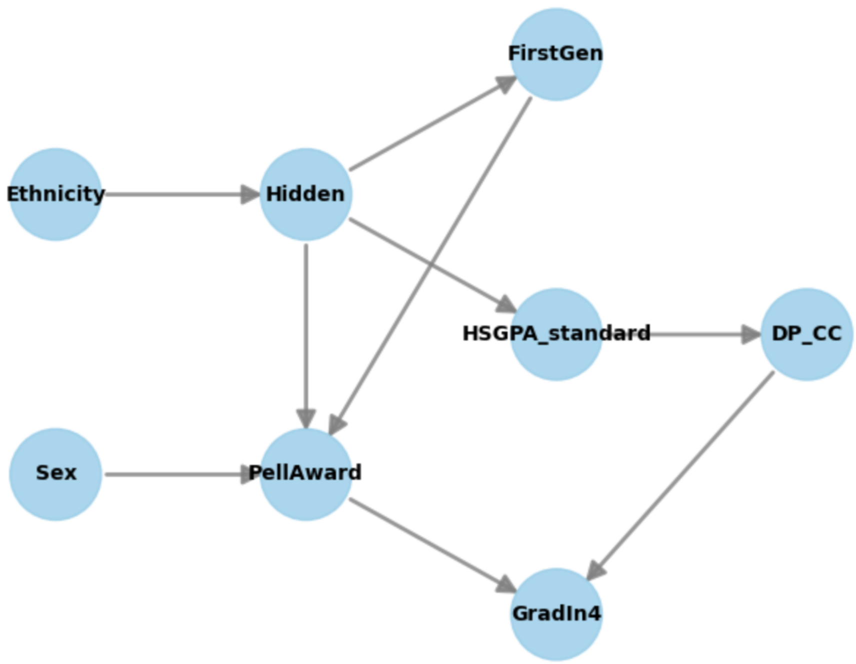


Figure 4.2: Causal Network Constructed using the PC Algorithm with Domain Expert Adjustment.

In this network, nodes represent variables, and directed edges (arrows) denote causal relationships between them. For instance, the directed edge from Ethnicity to the hidden node (socioeconomic status) indicates that Ethnicity causally influences socioeconomic status. Similarly, Sex affects the likelihood of receiving a Pell Award, while first-generation status impacts high school GPA, which, in turn, influences curricular complexity. Four-year graduation is influenced by the Pell Award and curricular complexity, illustrating the multifaceted pathways through which various factors contribute to graduation outcomes. This analysis highlights critical leverage points for targeted interventions to improve graduation outcomes.
Table 4.3 presents the BIC and K2 scores for the manually constructed causal network, which incorporates a hidden node representing students' socioeconomic status. This addition enhances the model's fit and underscores the robustness of the network.

Metric	**Value**
BIC Score	-237512027.2637457
K2 Score	-11159409.194497831
Estimated Causal Effect	-0.03879046
Sensitivity Analysis	
Refute: Add an Unobserved Common Cause	
Estimated effect	-0.03879046
New effect	-0.03762818

Table 4.3: BIC and K2 Scores for the Manually Constructed Network with a Hidden Node, and Sensitivity Analysis Results.

Including the hidden node significantly improves model performance, as evidenced by a lower BIC score (-237,512,027.26) and K2 score (-11,159,409.19) compared to the network without it. Sensitivity analysis reveals minimal change in the estimated causal effect of curricular complexity on four-year graduation rates, shifting slightly from -3.879% to -3.763% per unit increase, indicating resilience to unobserved confounding. The causal network estimates that a one-unit increase in curricular complexity reduces four-year graduation rates by approximately 3.879%. This negative relationship aligns with findings from the HLM and DML analyses across all 26 universities, reinforcing the link between increased complexity and lower graduation rates. Adding the hidden socioeconomic status node offers more profound insights into causal mechanisms, highlighting the critical role of addressing unobserved confounders. The robustness and reliability of these conclusions are validated through domain expert adjustments, BIC scores, and sensitivity analyses.

4.5 Case Studies: A Public Research University

This section delves into the analysis of curricular complexity and its impact on four-year graduation rates at a representative public research university.

4.5.1 Causal Effect Analysis

The analysis estimates the ATE of curricular complexity on four-year graduation rates using the DML approach within GPS-stratified quintiles. Table 4.4 presents the results, summarizing the ATE, p-values, intervention effects, and counterfactual effects.

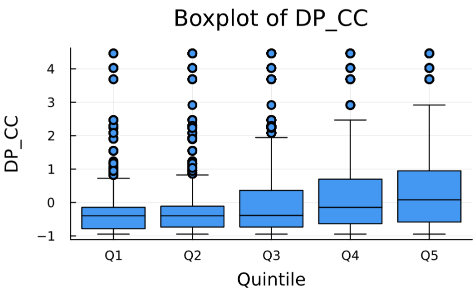
Table 4.4: DML Results for the University of Arizona by Quintile

GPS Quintile	ATE	P-Values	Intervention Effect	Counterfactual Effect	Score
Q1	-0.075196	8.677314e-10	-0.075196	-0.006672	0.225373
Q2	-0.070944	1.391074e-08	-0.070944	0.011943	0.236080
Q3	-0.103423	1.134560e-20	-0.103423	0.044749	0.222349
Q4	-0.141026	7.319481e-43	-0.141026	0.083339	0.207782
Q5	-0.215088	1.106193e-104	-0.215088	0.201597	0.186561
Average	**-0.121135**	-	**-0.121135**	**0.066991**	-

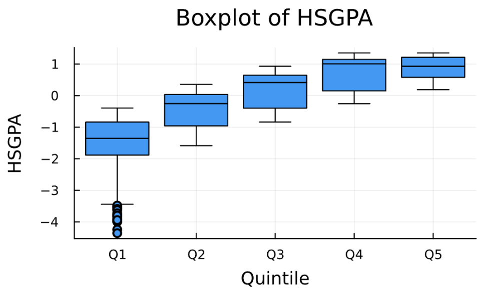
The ATE indicates that a one-unit increase in curricular complexity reduces graduation rates by 12.11%, with the most significant impact observed in quintile 5, which represents students with the highest probability of encountering complex curricula.

4.5.2 Distribution of Key Variables Across Quintiles

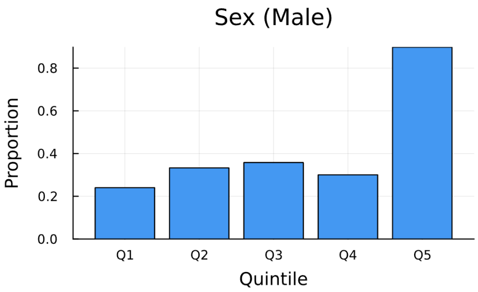
This subsection examines the distribution of curricular complexity, high school GPA, and demographic variables across GPS quintiles at the university. Figures 4.3 display these distributions.



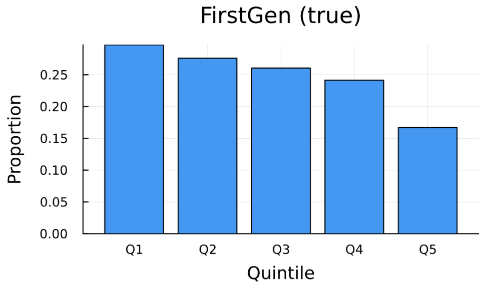
(a) Distribution of DP_CC Across GPS Quintiles



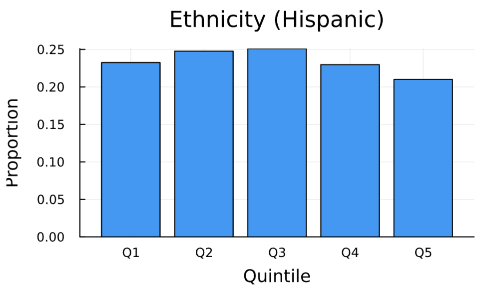
(b) Distribution of HSGPA Across GPS Quintiles



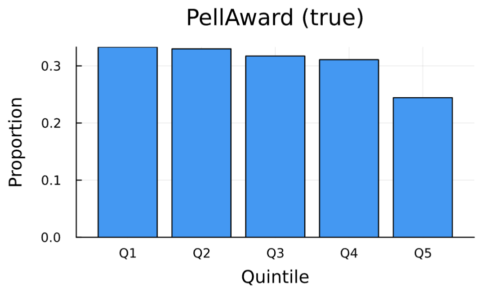
(c) Proportion of Sex (Male) by Quintile



(d) Proportion of FirstGen (True) by Quintile



(e) Proportion of Ethnicity (Hispanic) by Quintile



(f) Proportion of PellAward (True) by Quintile

Figure 4.3: Distributions and Proportions Across GPS Quintiles for AZ

The distribution of curricular complexity shows increasing medians and variances across higher GPS quintiles, indicating that students in these quintiles generally face more complex curricula (Figure 4.3(a)). Similarly, high school GPA distributions exhibit a clear upward trend, with higher quintiles associated with higher GPAs, reflecting greater academic preparedness (Figure 4.3(b)). The proportion of male students rises notably in higher quintiles, peaking in quintile 5 (Figure 4.3(c)). In contrast, first-generation students are more prevalent in lower quintiles, with their proportion declining as GPS quintiles increase (Figure 4.3(d)). Hispanic student proportions remain relatively stable across quintiles, showing only a slight decline in the higher ones (Figure 4.3(e)). Meanwhile, Pell Award recipients are most concentrated in quintile 1 and decrease steadily across higher quintiles, with the lowest proportion in quintile 5 (Figure 4.3(f)).

4.5.3 Analysis and Interpretation

The analysis for this public research university reveals that increased curricular complexity has a notable adverse impact on the four-year graduation rates, with the strongest effect observed in students within the highest GPS quintile. Despite being more academically prepared, these students face more significant challenges due to higher coursework complexity. Lower proportions of first-generation students and Pell Grant recipients in higher quintiles suggest these groups may have better resources but experience adverse effects. The consistent negative impact across all quintiles emphasizes the need to address curricular complexity in academic program design and support systems. This case highlights the unique challenges specific student groups face compared to trends across other institutions.

5. Discussion

This study investigated the causal relationship between curricular complexity and 4-year graduation rates across 26 universities using multiple analytical methods, including GPS, HLM, DML, and PC algorithm. The analysis revealed that demographic factors like sex, Pell Award status, first-generation status, and ethnicity negatively influenced curricular complexity, while high school GPA showed a positive correlation. Analysis of GPS quintiles and DML results consistently demonstrated that higher curricular complexity was associated with lower 4-year graduation rates, with effects varying across institutional contexts and student populations, showing adverse ATE across all quintiles. The causal network analysis, enhanced by including a hidden node representing socioeconomic status, estimated that increasing curricular complexity from 0 to 1 decreased the expected four-year graduation rate by approximately 0.039. This finding remained robust under sensitivity analysis, and a case study at a public research university further supported these overall trends at an institutional level.

6. Limitations and Future Research

While this study provides robust insights into the impact of curricular complexity on graduation rates, there are limitations to consider. The analysis is based on historical data, and future research should explore the long-term effects of interventions to reduce curricular complexity. Additionally, including socioeconomic status as a hidden variable in the causal network highlights the need for more comprehensive data collection on students' backgrounds and experiences. Future research should explore how additional factors, including extracurricular activities, work commitments, and mental health, influence graduation outcomes. A more holistic approach to understanding student success will enable universities to design more effective policies and support systems.

7. Conclusion

This study underscores the critical role of curricular complexity in influencing 4-year graduation rates. By employing advanced statistical and causal inference methods, the research provides compelling evidence that higher curricular complexity poses significant challenges to timely graduation. The findings highlight the need for strategic program design, targeted support for at-risk students, and ongoing monitoring to ensure student success. As universities strive for higher graduation rates and better student outcomes, understanding and addressing curricular complexity will remain a key priority.

References

[1] Stephen L. DesJardins et al. "A Temporal Investigation of Factors Related to Timely Degree Completion". In: *The Journal of Higher Education* (2002).

[2] Clifford Adelman. *The Toolbox Revisited: Paths to Degree Completion from High School Through College*. Washington, D.C.: U.S. Department of Education, 2006. URL: https://www2.ed.gov/rschstat/research/pubs/toolboxrevisit/toolbox.pdf.

[3] Gregory L. Heileman et al. "Curricular Analytics: A Framework for Quantifying the Impact of Curricular Reforms and Pedagogical Innovations". In: *arXiv preprint* arXiv:1811.09676 (2018). DOI: https://doi.org/10.48550/arXiv.1811.09676. URL: https://arxiv.org/abs/1811.09676.

[4] Ahmad Slim et al. "Causal Inference Networks: Unraveling the Complex Relationships Between Curriculum Complexity, Student Characteristics, and Performance in Higher Education". In: *2024 ASEE Annual Conference & Exposition*. 10.18260/1-2–48449. https://peer.asee.org/48449. Portland, Oregon: ASEE Conferences, June 2024.

[5] Melissa J Azur et al. "Multiple imputation by chained equations: what is it and how does it work?" In: *International Journal of Methods in Psychiatric Research* 20.1 (2011), pp. 40–49.

[6] Keisuke Hirano and Guido W. Imbens. "The Propensity Score with Continuous Treatments". In: *Applied Bayesian Modeling and Causal Inference from Incomplete-Data Perspectives* (2004). Ed. by Andrew Gelman and Xiao-Li Meng.

[7] Stephen W. Raudenbush and Anthony S. Bryk. *Hierarchical Linear Models: Applications and Data Analysis Methods*. 2nd. Thousand Oaks, CA: Sage Publications, 2002.

[8] Paul R. Rosenbaum and Donald B. Rubin. "Reducing Bias in Observational Studies Using Subclassification on the Propensity Score". In: *Journal of the American Statistical Association* 79.387 (1984), pp. 516–524.

[9] Victor Chernozhukov et al. "Double/debiased machine learning for treatment and structural parameters". In: *The Econometrics Journal* (2018).

[10] Peter Spirtes, Clark Glymour, and Richard Scheines. *Causation, Prediction, and Search*. 2nd. Cambridge, MA: MIT Press, 2000.

[11] Paul R. Rosenbaum. *Observational Studies*. 2nd. New York, NY: Springer, 2002.