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Is there a grade penalty for high school track and college degree mismatches? Evidence from the University of the Philippines

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Abstract

This study examines the consequences of college students pursuing degree programs that do not align with the tracks and strands they selected in senior high school. We utilize a unique dataset that links admissions and enrollment records from the University of the Philippines Diliman to investigate whether this mismatch affects students' academic performance. Using propensity score matching, we do not find evidence of a grade penalty for most degree programs. However, we estimate a significant grade penalty specifically for mismatch in science and engineering programs, where a strong background in the Science, Technology, Engineering, and Mathematics (STEM) strand is expected and in fact necessary for academic performance; i.e., students who did not come from the STEM strand tend to perform worse. These findings suggest that the choice of a SHS strand may matter in some fields more than others, raising important questions about how SHS tracks are offered and how college admissions policies take high school backgrounds into account.

Keywords: college performance, K to 12, mismatch, grade penalty, propensity score matching

JEL codes: I21, I23, I28, J24

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1. Introduction

The K-12 Basic Education reform in the Philippines introduced a sweeping overhaul of the Philippines' education system, extending basic education from a 10-year cycle to 13 years with the addition of a mandatory Kindergarten and two Senior High School (SHS) years. Implemented starting in 2012 and fully rolled out by 2016, the reform restructured the curriculum across all levels to align with international standards, promote college and career readiness, and offer SHS students specialized tracks in Academic, Technical-Vocational-Livelihood, Sports, and Arts and Design. This shift was unprecedented in scale, affecting millions of students, tens of thousands of teachers, and requiring massive investments in infrastructure, curriculum development, and teacher retraining. It also redefined the transition from high school to tertiary education or employment, fundamentally altering the pathways and expectations for Filipino youth.

By adding two years of Senior High School (Grades 11 and 12), the reform aimed to decongest the old 10-year curriculum and provide time for deeper learning and specialization through academic tracks aligned with prospective college courses. These included strands such as Science, Technology, Engineering, and Mathematics (STEM); Accountancy, Business, and Management (ABM); Humanities and Social Sciences (HUMSS); and General Academic, designed to match the prerequisites and rigor of various college programs. One goal of this reform was to improve the readiness of students choosing to pursue either higher education or technical-vocational education. For those going to college, K-12 education was intended to equip graduates with the foundational knowledge, skills, and habits necessary to succeed in a more demanding academic environment. The reform was also designed to reduce the need for remedial courses in universities, lower first-year college attrition, and shorten the time students need to adjust to higher education expectations. In essence, K-12 sought to bridge the gap between basic education and tertiary education, ensuring that students entered college not only with more years of schooling but also with more relevant and targeted preparation.

However, to this day, no empirical evidence exists to suggest that K-12 made college-bound students more ready for tertiary education. A major hurdle is that many degree programs do not strictly screen applicants based on the tracks and strands they took in Senior High School. For instance, students from the HUMSS strand have been observed enrolling in science-intensive programs, such as engineering or biology, despite lacking the foundational math and science subjects—such as calculus, chemistry, or physics—that are crucial for success in these fields. Conversely, students from the STEM strand sometimes pursue degrees in the humanities or social sciences, where they may struggle with philosophical reasoning, literature analysis, or extensive writing, which were not emphasized in their SHS training. Graduates of the Technical-Vocational-Livelihood (TVL) strand, whose curriculum is designed for employment or entrepreneurship, occasionally enter professional programs like nursing or accountancy without the academic foundation required in subjects such as algebra, biology, or English. Despite these track-to-degree misalignments, most universities admit students based on entrance exams or predictive grades, without strictly screening for SHS tracks or strands. This results in cohorts with widely varying levels of preparedness, pushing colleges to provide remedial instruction that the K-12 reform was supposed to make unnecessary.

In this paper, we use a new administrative dataset from the University of the Philippines Diliman that links students' anonymized admissions records—including their Senior High School (SHS) track and strand, high school type, and University Predictive Grade (UPG) or admissions score—with their college grades and degree programs. The dataset allows us to examine whether students who enroll in degree programs that do not align with their SHS strand perform differently from those whose academic paths are more closely aligned. We apply propensity score matching (PSM) to address selection bias and ensure comparability between students with and without strand-program mismatches. This method enables us to estimate the effect of mismatch on student grades while controlling for key student characteristics. Our findings show that, overall, mismatched students do not perform significantly worse than their matched peers. However, in science and engineering programs—where foundational knowledge in math and science is more critical—we observe a statistically significant "mismatch penalty" among students who did not come from the STEM strand.

This paper contributes to a slim literature on educational pathways and college readiness in several ways. First, it provides the first empirical assessments of the impact of SHS strand-program alignment on college academic performance in the Philippine context. This topic has remained underexplored despite the scale of the K-12 reform. By applying a quasi-experimental method to rich administrative data, this study also extends beyond descriptive accounts and contributes to the international evidence on how the alignment between secondary preparation and college programs affects student performance (Long, Conger, & Iatarola, 2012; Dougherty, 2018). Finally, the results have practical implications for both basic and higher education policy. They underscore the need for stronger curricular articulation between senior high school (SHS) and tertiary education, particularly in science and engineering fields, where prior preparation in mathematics and science is essential. This study offers new evidence on the consequences of curricular misalignment and contributes a Philippine case to global discussions on postsecondary readiness and equity.

2. Review of literature

The consequences of high school readiness on subsequent performance in higher education have been the subject of many studies. Long, Conger, and Iatarola (2012) examine the impact of rigorous high school course-taking on academic and postsecondary outcomes using propensity score matching on administrative data from Florida. They find that taking Level-3 courses (e.g., honors, AP) significantly improves 10th-grade test scores, graduation rates, and college enrollment, with the largest gains from the first rigorous course taken. Effects are especially pronounced for disadvantaged students, suggesting that access to rigorous coursework can help reduce educational inequalities. Meanwhile, Dougherty (2018) investigates whether students who take Career and Technical Education (CTE) courses in high school perform better academically and in the labor market. Using data from Arkansas and a difference-in-differences design, the study finds that CTE participation improves high school graduation rates, increases employment and earnings after high school, and does not negatively affect college enrollment. The benefits are particularly strong for lower-achieving students, suggesting that CTE can be a viable pathway to both academic and labor market success.

There are fundamental differences in the pre-tertiary tracks in the US and the Philippines. In the Philippines, the K-12 Basic Education Reform of 2012 established tracks and strands for senior high school students to help them prepare for the rigors of higher education or technical-vocational education. To this day, however, there are limited studies on the effectiveness of this policy on academic performance, let alone labor market outcomes. This is a major concern (and policy interest) because there remains a strong demand for college education in the Philippines, and there are also concerns among employers that K-12 graduates are not adequately prepared to enter the labor market. Orbeta et al. (2018) examine the perceptions of Grade 12 students and human resource (HR) officers regarding the K-12 reform, with a focus on the alignment between Senior High School training and labor market needs. Based on survey and focus group data, they find that while Senior High School students generally value work readiness, most still prefer pursuing college. Employers, meanwhile, are skeptical of hiring SHS graduates directly, citing concerns about maturity and skills. The study highlights the limited labor market impact of SHS and raises questions about the effectiveness of its tracks in preparing students for employment.

If most K-12 graduates still prefer going to college, there ought to be interest in the way that K-12 prepares its graduates for the rigors of higher education. Of particular concern is track-to-degree mismatch, which can manifest in many ways. For instance, a student who completed the Accountancy, Business, and Management (ABM) strand in SHS may pursue a BS Civil Engineering degree in college. However, without a strong foundation in advanced math and science—typically covered in the STEM strand—they may struggle with calculus, physics, and engineering courses. Similarly, a student from the Humanities and Social Sciences (HUMSS) strand might enroll in BS Biology, where laboratory skills and intensive scientific training expected of STEM strand students can put them at a disadvantage. In contrast, students from the TVL (Technical-Vocational-Livelihood) track who transition to academic degree programs, such as a BA in Communication, may lack exposure to research writing, theoretical frameworks, or other college-preparatory skills. To date, no empirical study investigates the impact of track-to-degree mismatch in the Philippine context—a gap that this paper fills.

3. Analytical framework

This study is anchored on the premise that the alignment—or lack thereof—between a student's Senior High School (SHS) track and their chosen college degree program affects their academic performance, particularly in the early years of tertiary education. To explain this relationship, we draw on Conley's (2008) expanded framework of college readiness, which proposes a multidimensional understanding of what it means to be prepared for postsecondary education. He defines college readiness not solely in terms of eligibility or high school graduation but as the degree to which students are equipped to succeed in credit-bearing, college-level courses without remediation. He identifies four interconnected dimensions:

1. Key cognitive strategies – Analytical reasoning, problem-solving, precision, and argumentation.
2. Key content knowledge – Mastery of subject-specific concepts and frameworks foundational to college coursework.
3. Academic behaviors – Self-regulation, time management, study skills, and academic persistence.
4. Contextual skills and college knowledge – Understanding of institutional norms, navigation of college systems, and engagement with the academic culture.

These dimensions interact in shaping students' transitions from high school to college. Students entering a degree program that aligns with their SHS strand are more likely to be adequately prepared across all four dimensions. For instance, STEM strand students who proceed to engineering or science degrees benefit from prior exposure to mathematical and scientific thinking; similarly, HUMSS strand students entering social science or communication-related programs may be more familiar with discursive writing and critical analysis.

In contrast, mismatched students—those whose SHS preparation does not correspond to their chosen college field—may face deficits in foundational knowledge and discipline-specific academic habits. These gaps can undermine their capacity to perform well in demanding first-year coursework, especially in programs with high cognitive and content expectations. The likelihood of academic struggle may be further compounded by underdeveloped self-regulation skills or unfamiliarity with the expectations of college academic culture.

We extend this framework by distinguishing between types of mismatch, as reflected in the dataset:

1. Weak Mismatch: The student did not take the ideal SHS strand for their current degree program.
2. Strong Mismatch: The student took the strand deemed least relevant to their current program.
3. STEM Overshoot/Undershoot: Students may gain or lose performance advantages based on whether they took STEM despite not needing it, or failed to take STEM when it was essential.

These distinctions serve as operational proxies for the degree of preparedness mismatch and are expected to correlate with differential academic outcomes. Specifically, we hypothesize that students experiencing a weak mismatch may exhibit minor performance penalties due to partial misalignment in content or skills. Meanwhile, strong mismatches are more likely to result in substantial academic underperformance due to deeper misalignments across multiple readiness domains. Moreover, students lacking a STEM background for STEM-intensive degrees—known as STEM undershoots—will perform significantly worse due to cognitive and content gaps. Conversely, STEM overshoots—students taking STEM courses for non-STEM degrees—may perform better than their peers due to the general rigor and transferability of STEM preparation skills.

In sum, Conley's framework provides the conceptual scaffolding to interpret mismatch not merely as a categorical variable but as an indicator of multidimensional readiness gaps. By linking the degree of alignment to the four readiness domains, we gain a better understanding of why mismatches matter and under what conditions their effects are most pronounced.

5. Data and empirical strategy

A. Data

We use anonymized student registration data from the University of the Philippines Diliman, the flagship university of the University of the Philippines System. Specifically, we analyze data for cohorts of students admitted during Academic Year 2020-2021 and 2021-2022, and this is the first dataset from UP Diliman that contains information about students' Senior High School tracks and strands. Specifically, we have data on 2,671 students from the 2020-2021 academic year and 2,419 students from the 2021-2022 academic year. Table 1 shows a breakdown of the observations in the various academic years in the sample period. Note that the vast majority of students (97-98%) take the academic track, while 67-80% of those students take the STEM strand. Meanwhile, nearly three-quarters of those who took the academic track underwent the STEM strand. Note that the vast majority of UP students are admitted partially based on their performance in the UP College Admission Test (UPCAT), which includes sections on science and math.

Table 3.1. Breakdown of observations by SHS track, strand, and year of admission in UP Diliman

Track	Strand	2020	2021	Total
	No strand	10	3	13
	ABM	281	442	723
Academic	HUMMS	182	260	442
	STEM	2,062	1,607	3,669
	General	51	69	120

TLE/TVE	Home economics	1	2	3
	Industrial arts	-	-	-
	ICT	4	9	13
Arts & design	Design	10	21	31
Not indicated or from foreign school	N/A	70	6	76
Total		2,671	2,419	5,090

Note: This table shows the frequency of SHS tracks and strands taken by UP Diliman students by their year of admission.

We broadly define mismatch as a discrepancy between a student's senior high school track and strand and the track and strand that is ideal for their degree program. We consider two basic types of mismatch: weak and strong. "Weak mismatch" occurs when a student did not take the prescribed strand corresponding to their degree program. For instance, if an engineering student failed to take up the STEM strand, there is a weak mismatch. "Strong mismatch," meanwhile, occurs when a student takes up the least prescribed strand corresponding to their degree program (i.e., the one that is deemed to have the least value-added to their current degree program). For instance, if an arts student took up the STEM strand, which is considered to have the least value-added to an arts degree compared to the Arts and Design strand, then there is a substantial mismatch. Appendix 1 shows the assignment of most-preferred and least-preferred tracks for all the UP Diliman degree programs in the sample dataset. These assignments were done by the authors based on the degree program descriptions, select interviews with UP Diliman administrators, and our judgment. Our analysis yields 1,340 instances of weak mismatch (26.8% of the total sample) and only 187 instances of strong mismatch (2.4%). Because of this, we consider a weak but not strong mismatch in the analysis.

Another indication of mismatch is a student's shifting into another degree program at some point in their college life. In our sample, we observe that nearly 18% of students shifted to another degree program. The definition of weak mismatch is not clear-cut in the case of shiftees; for instance, the recommended strand for BS Economics students may not necessarily be ABM, because they initially took another degree program. As a result, we also conduct the analysis exclusively for non-shiftees.

Finally, for our purposes, another possibly important type of mismatch centers on taking the STEM strand in Senior High School. In our sample, we note that 3,669 or nearly 74% of our sample students took the STEM strand, which can be considered the most challenging strand and best equips students for the analytical rigor of tertiary education. We posit that pursuing STEM may result in a grade "bonus" for those pursuing degree programs that do not require it; we refer to this as a STEM "overshoot." On the opposite side, not taking up STEM may end up in a grade "penalty" for those taking up degree programs that require it; we call this a STEM "undershoot." We consider this critical mismatch typology in the analysis. Table 3.2 summarizes the extent of mismatch based on these varying definitions, while Table 3.3 shows the SHS strands and colleges of those with STEM undershoot mismatch (i.e., the 220 students who are in STEM-intensive degree programs but did not take up STEM in SHS). Even if one filters out those who shifted degree programs, the students in the sample with STEM undershoot mismatch were 191.

Table 3.2. Extent of mismatch using varying definitions

	Weak mismatch	Strong mismatch	Shiftee mismatch	STEM undershoot mismatch	STEM overshoot mismatch
Mismatch	1,340	187	883	220	749
Match	3,660	4,883	4,117	4,780	4,251
Total	5,000	5,000	5,000	5,000	5,000

Table 3.3. Breakdown of SHS strands and colleges of students with STEM undershoot mismatch

	College					
	Arch	CHE	CS	Engg	Stat	Total
ABM	8	3	36	47	51	145
Arts and Design	0	3	0	1	0	4
GAS	3	5	13	14	6	41

HUMSS	0	3	7	6	5	21
TLE/TVE	0	0	0	9	0	9
Total	11	14	56	77	62	220

B. Empirical strategy

To estimate the causal effect of strand-program mismatch on college academic performance and address selection bias arising from non-random assignment to mismatch status, we use propensity score matching or PSM (Rosenbaum and Rubin 1983). Students who enroll in degree programs misaligned with their SHS track or strand may differ systematically from those whose SHS preparation matches their college program. These differences—such as academic ability, school quality, and family income—can confound naive comparisons of academic performance between the two groups.

Let $D_i = 1$ indicate that the student i is in a mismatched program, and $D_i = 0$ otherwise, with varying definitions of mismatch as described in the previous section. Let $Y_i(1)$ and $Y_i(0)$ denote the potential outcomes for a student i under mismatch and non-mismatch, respectively. The estimators of interest are the average treatment effect (ATE) and the average treatment effect on the treated (ATT):

$$ATE = E[Y_i(1) - Y_i(0)]. \quad (1)$$

$$ATT = E[Y_i(1) - Y_i^0 | D_i = 1] \quad (2)$$

Since we do not observe both potential outcomes for each student, we estimate the ATE using nearest-neighbor matching on the propensity score, defined as:

$$p(X_i) = \Pr\,(D_i = 1|X_i). \tag{2}$$

We estimate the propensity score $\hat{p}(X_i)$ via logistic regression:

$$\Pr(D_i = 1|X_i) = \hat{p}(X_i) = \frac{\exp\,(X_i'\beta)}{1+\exp\,(X_i'\beta)}. \tag{3}$$

and we use the estimated propensity score to produce the sample versions of the estimators above:

$$ATE = \frac{1}{N}\sum_{i=1}^{N} Y_i \frac{D_i - \hat{p}(X_i)}{\hat{p}(X_i)(1-\hat{p}(X_i))} \tag{4}$$

$$ATT = \frac{1}{N}\sum_{i=1}^{N} Y_i \frac{D_i - \hat{p}(X_i)}{1-\hat{p}(X_i)}. \tag{5}$$

In all our specifications, covariate vector X_i includes a categorical variable on high school type (e.g., public, private, science high school); the decile of the student's University Predicted Grade (UPG) or the admissions score that contains information about students' high school average grades and UPCAT performance; the student's household income category (self-reported at the point of admission), the student's final college and degree program, the year of their admission, and their K-12 track and strand. Table 3.4 shows the descriptive statistics.

We implement nearest-neighbor matching with three neighbors and without replacement, using the Stata -teffects psmatch- command, where the outcome variable is the student's grade-weighted average. Specifically, we look at two types of grades: their grade weighted average in their 1st year and their 2nd year. We expect that if there are any grade penalties, they will manifest more in the 2nd year when students typically take up major subjects (in their first year, they spend much of their time on general electives like English or Philippine history).

Propensity score matching relies on the conditional independence assumption (CIA)—that conditional on the covariates X_i, assignment to mismatch is as good as random, and the common support assumption, ensuring sufficient overlap in the distribution of propensity scores between the treated and control groups. We verify covariate balance and overlap in the results below.

Table 3.4. Descriptive statistics by mismatch type (1st definition)

	Matched	Mismatch	Total
N	3,660 (73.2%)	1,340 (26.8%)	5,000 (100.0%)
1st year GWA	1.413 (0.291)	1.412 (0.256)	1.413 (0.282)
2nd year GWA	1.690 (0.535)	1.569 (0.481)	1.658 (0.524)
High school type			
Private	1,857 (50.7%)	863 (64.4%)	2,720 (54.4%)
Public	390 (10.7%)	139 (10.4%)	529 (10.6%)
Science	1,207 (33.0%)	243 (18.1%)	1,450 (29.0%)
State university	127 (3.5%)	41 (3.1%)	168 (3.4%)
UP high school	71 (1.9%)	46 (3.4%)	117 (2.3%)
Foreign & others	8 (0.2%)	8 (0.6%)	16 (0.3%)
UPG quantile (1=best, 10=lowest)			
1	409 (11.2%)	91 (6.8%)	500 (10.0%)
2	416 (11.4%)	84 (6.3%)	500 (10.0%)
3	387 (10.6%)	113 (8.4%)	500 (10.0%)
4	384 (10.5%)	116 (8.7%)	500 (10.0%)
5	389 (10.6%)	111 (8.3%)	500 (10.0%)
6	368 (10.1%)	132 (9.9%)	500 (10.0%)
7	346 (9.5%)	154 (11.5%)	500 (10.0%)
8	349 (9.5%)	151 (11.3%)	500 (10.0%)
9	310 (8.5%)	190 (14.2%)	500 (10.0%)
10	302 (8.3%)	198 (14.8%)	500 (10.0%)
Annual income category			
No data	124 (3.4%)	34 (2.5%)	158 (3.2%)
P100,000 and below	212 (5.8%)	67 (5.0%)	279 (5.6%)
P101,000 to P200,000	436 (11.9%)	164 (12.2%)	600 (12.0%)

P201,000 to P300,000	426 (11.6%)	151 (11.3%)	577 (11.5%)
P301,000 to P400,000	310 (8.5%)	103 (7.7%)	413 (8.3%)
P401,000 to P500,000	268 (7.3%)	104 (7.8%)	372 (7.4%)
P501,000 to P1 million	767 (21.0%)	289 (21.6%)	1,056 (21.1%)
P1 million and above	1,117 (30.5%)	428 (31.9%)	1,545 (30.9%)
Year of admission			
2020	1,982 (54.2%)	608 (45.4%)	2,590 (51.8%)
2021	1,678 (45.8%)	732 (54.6%)	2,410 (48.2%)
Final college			
AIT	3 (0.1%)	44 (3.3%)	47 (0.9%)
Arch	151 (4.1%)	11 (0.8%)	162 (3.2%)
CAL	53 (1.4%)	102 (7.6%)	155 (3.1%)
CFA	4 (0.1%)	31 (2.3%)	35 (0.7%)
CHE	184 (5.0%)	114 (8.5%)	298 (6.0%)
CHK	0 (0.0%)	43 (3.2%)	43 (0.9%)
CMC	73 (2.0%)	105 (7.8%)	178 (3.6%)
CMu	2 (0.1%)	1 (0.1%)	3 (0.1%)
CS	680 (18.6%)	56 (4.2%)	736 (14.7%)
CSSP	169 (4.6%)	355 (26.5%)	524 (10.5%)
CSWCD	15 (0.4%)	15 (1.1%)	30 (0.6%)
Educ	28 (0.8%)	69 (5.1%)	97 (1.9%)
Engg	1,781 (48.7%)	77 (5.7%)	1,858 (37.2%)
NCPAG	1 (0.0%)	61 (4.6%)	62 (1.2%)
SE	118 (3.2%)	95 (7.1%)	213 (4.3%)
SLIS	0 (0.0%)	17 (1.3%)	17 (0.3%)
Stat	151 (4.1%)	62 (4.6%)	213 (4.3%)
VSB	247 (6.7%)	82 (6.1%)	329 (6.6%)

Note: Includes shiftees and non-shiftees. Not shown: breakdown by final degree program.

6. Results

A. Main results

We begin with the propensity score matching estimates for all the students in the sample, with the mismatch defined as not taking the prescribed strand. Table 4.1 shows that when it comes to average 1st-year grades, there is no significant treatment effect (grade penalty) arising from weak mismatch. However, there is a small but statistically significant grade *bonus* for mismatch when it comes to average 2nd-year grades (recall that lower grades are better). Tables 4.2 and 4.3 show that differences in weighted means are minimal while all variance ratios are near one, indicating good covariate balance. This is further supported by the box and density plots in Figure 4.1.

Table 4.1. Propensity score matching estimates, dependent variable: average 1st year GWA and 2nd year GWA

		ATE		ATT	
		Nearest neighbor=1	Nearest neighbor=3	Nearest neighbor=1	Nearest neighbor=3
1st year GWA	Mismatch	0.016	0.001	0.026**	0.013
		(0.013)	(0.011)	(0.013)	(0.011)
	N	4712	4712	4712	4712
2nd year GWA	Mismatch	-0.051**	-0.068***	-0.040*	-0.036*
		(0.026)	(0.022)	(0.023)	(0.020)
	N	4373	4373	4373	4373

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Results are the same as NN=3 using caliper=0.1 and caliper=0.3.

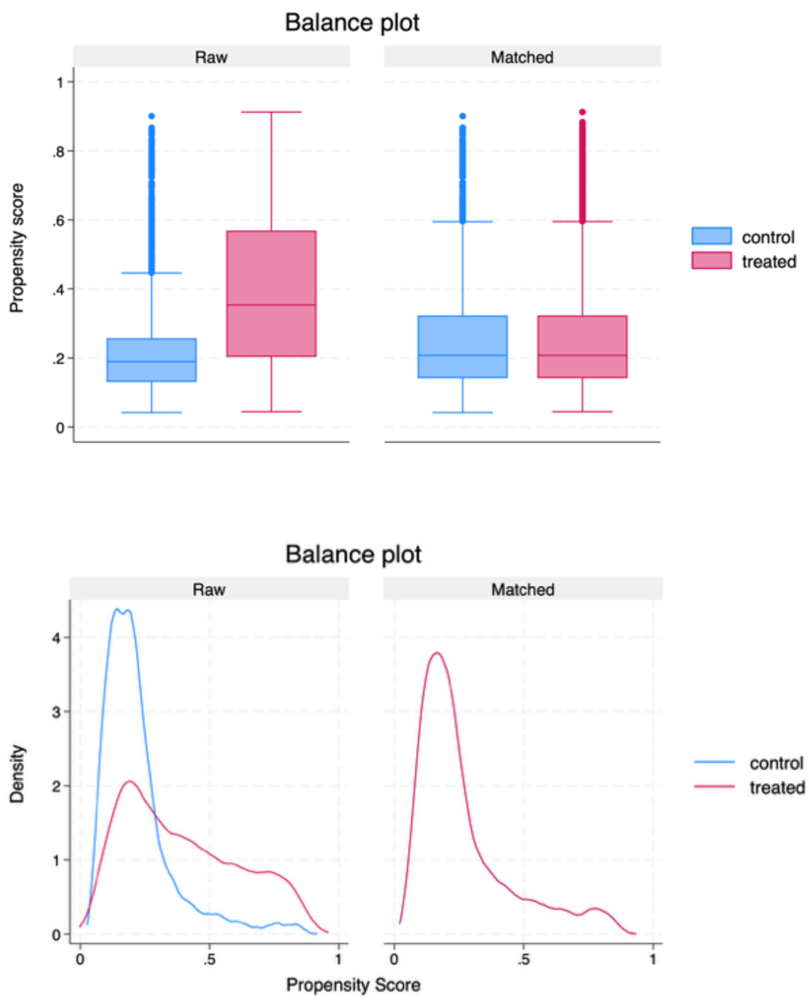
Table 4.2. Covariate balance summary: number of observations by group

	1st year GWA		2nd year GWA	
	Raw	Matched	Raw	Matched
Total obs.	4712	9424	4373	8746
Treated obs.	1257	4712	1165	4373
Control obs.	3455	4712	3208	4373

Table 4.3. Covariate balance summary: differences between raw and matched observations

		Standardized differences		Variance ratios	
		Raw	Matched	Raw	Matched
1st year GWA	High school type	-0.2059	-0.0727	1.0886	1.3450
	UPG decile	0.3652	0.0857	1.0114	1.0295
	Income category	0.0590	0.0274	0.9487	1.0013
	Degree program	-0.8445	0.0590	2.3782	1.2467
	Year of admission	0.1704	0.0986	0.9999	0.9974
2nd year GWA	High school type	-0.2057	-0.0183	1.0627	1.3949
	UPG decile	0.3725	0.1007	1.0140	1.0101
	Income category	0.0519	-0.0113	0.9498	1.0435
	Degree program	-0.8527	0.0422	2.3906	1.2357
	Year of admission	0.1720	0.0384	0.9949	0.9989

Figure 4.1. Balance analysis: box and density plots (using 1st year GWA as dependent variable)



Note: Covariates used are high school type, UPG decile, income category, final degree program, and year of UP admission.

B. Performance of non-shiftees

A possible reason for the observed grade reward in the second year is that the experiences of shiftees may differ from those of non-shiftees. We take note that 17-18% of students shifted in the sample period, and the mismatch experience for them may be different from those who never shifted. Table 4.5 shows the results restricted to only non-shiftees, and again we see an even more significant grade reward in terms of 2nd year GWA for those who are mismatched.

Table 4.5. Propensity score matching estimates for non-shiftees, dependent variable: average 1st year GWA and 2nd year GWA

		ATE		ATT	
		Nearest neighbor=1	Nearest neighbor=3	Nearest neighbor=1	Nearest neighbor=3
1st year GWA	Mismatch	-0.009	-0.014	-0.026*	-0.016
		(0.014)	(0.011)	(0.015)	(0.012)
	N	3863	3863	3863	3863
2nd year GWA	Mismatch	-0.114***	-0.105***	-0.098***	-0.096***
		(0.030)	(0.027)	(0.029)	(0.024)
	N	3576	3576	3576	3576

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Results are the same as NN=3 using caliper=0.1 and caliper=0.3.

C. STEM-based mismatch

Next, we consider STEM-based mismatch, examining STEM undershoot and overshoot as defined earlier. Table 4.6 shows that across specifications, there is a clear and significant grade penalty for those who experienced STEM overshoot, and a significant grade bonus for those with STEM undershoot. Table 4.7 shows that the signs are consistent with the 2nd year GWA, and the magnitudes are much greater, too. These results point to the singular importance of the STEM track in affecting the grade performance of UP Diliman students, regardless of the degree program they end up with.

Table 4.6. Propensity score matching estimates for STEM-based mismatch, dependent variable: average 1st year GWA

		ATE		ATT	
		Nearest neighbor=1	Nearest neighbor=3	Nearest neighbor=1	Nearest neighbor=3
1st year GWA	STEM undershoot	0.135***	0.116***	0.066**	0.077***
		(0.035)	(0.025)	(0.030)	(0.028)
	N	3863	3863	3863	3863
1st year GWA	STEM overshoot	-0.069***	-0.068***	-0.028	-0.037**
		(0.017)	(0.015)	(0.018)	(0.015)
	N	3863	3863	3863	3863

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Results are the same as NN=3 using caliper=0.1 and caliper=0.3.

Table 4.7. Propensity score matching estimates for STEM-based mismatch, dependent variable: average 2nd year GWA

		ATE		ATT	
		Nearest neighbor=1	Nearest neighbor=3	Nearest neighbor=1	Nearest neighbor=3
2nd year GWA	STEM undershoot	0.273***	0.243***	0.139**	0.199***
		(0.051)	(0.047)	(0.067)	(0.055)
	N	3576	3576	3576	3576
2nd year GWA	STEM overshoot	-0.168***	-0.216***	-0.080***	-0.139***
		(0.038)	(0.027)	(0.029)	(0.024)
	N	3576	3576	3576	3576

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Results are the same as NN=3 using caliper=0.1 and caliper=0.3.

To parse this important result, we conduct PSM by college using the same vector of covariates for the calculation of the propensity scores. We group together students from Science-oriented colleges (Engineering, Science, Home Economics, Statistics, and Architecture) and call them the Science cluster; the rest of the colleges are in the Others category.[3] In our sample, 2,880 students are in the Science cluster while 1,237 are in Others. When it comes to STEM undershooting, we take note that 191 non-shiftee students in the Science cluster took non-STEM strands; no one from the Others category experienced STEM undershooting (everyone took non-STEM tracks). Meanwhile, as for STEM overshooting, we take note that 484 students in Others took STEM, while 67 students in the Science cluster (all from the College of Home Economics) took non-STEM tracks.

Table 4.8 shows that for students in the Science cluster who didn't take up STEM, there's a significant grade penalty in 1st year GWA across all specifications, and an even

[3] Note that this is a simplification, because, for example, not all degree programs in the Science cluster require STEM strictly; the same goes for those in Others.

stronger penalty in the 2nd year (although the result is not significant in one specification). Meanwhile, for students not in the Science cluster who took up STEM, there is a grade bonus, but only significant in one specification, and only in the 2nd year. The results show a clear disadvantage for students who should have taken up STEM but didn't, but no clear advantage for students who took up STEM even if not required. The results may differ at the level of different colleges, but we skip that analysis because the sample size diminishes significantly at the level of individual colleges.

Table 4.8. Propensity score matching estimates based on STEM mismatch

Mismatch in college	1st year GWA				2nd year GWA			
	ATE		ATT		ATE		ATT	
	NN=1	NN=3	NN=1	NN=3	NN=1	NN=3	NN=1	NN=3
STEM undershoot in Science cluster	0.088*** (0.029)	0.113*** (0.028)	0.065** (0.032)	0.066** (0.029)	0.202*** (0.064)	0.238*** (0.058)	0.125* (0.068)	0.087 (0.058)
N	2686	2686	2686	2686	2494	2494	2494	2494
STEM overshoot in non-Science cluster	-0.028 (0.017)	-0.019 (0.017)	-0.018 (0.024)	-0.024 (0.021)	-0.028 (0.026)	-0.053** (0.022)	-0.015 (0.036)	-0.046 (0.028)
N	1177	1177	1177	1177	1082	1082	1082	1082

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The science cluster includes Engineering, Science, Home Economics, Statistics, and Architecture. The rest of the colleges are in Others.

7. Discussion

Our key finding is that mismatched students—those whose senior high school (SHS) strand does not align with the recommended preparation for their degree program—do not perform worse, on average, than matched peers in terms of college grades in the 1st and 2nd years. In fact, for non-shiftees, we find a surprising grade "reward" in the second year, suggesting that mismatched students may either adapt well or select into courses where their existing skills still prove valuable.

However, this average finding conceals important heterogeneity. When we focus on STEM-based mismatches, we uncover substantial penalties and bonuses depending on alignment. Students who pursue science or engineering programs without coming from the STEM strand (i.e., "STEM undershoot") suffer significant grade penalties, particularly in the second year when students typically begin major coursework. This pattern persists across specifications and holds even when analysis is limited to students in science-related colleges. In contrast, students who take the STEM strand but pursue non-STEM degrees ("STEM overshoot") tend to benefit from a small but significant grade bonus, especially in their second year.

These asymmetric effects suggest that the STEM strand provides foundational knowledge and study habits that transfer well even to non-STEM degree programs. Conversely, students lacking the mathematical and scientific preparation embedded in the STEM curriculum are at a marked disadvantage when pursuing STEM-heavy programs. These findings align with international evidence showing that prior exposure to rigorous high school coursework significantly improves postsecondary outcomes (Long, Conger, and Iatarola 2012; Dougherty 2018) and underscore the importance of curricular alignment in educational pathways.

The fact that mismatch yields no observable penalty on average, yet leads to pronounced penalties in specific fields, suggests that track-strand alignment matters more in some disciplines than others. In UP Diliman, where the student population is highly selected, this could reflect the compensatory abilities of students who manage to succeed despite initial misalignment. But in less selective institutions, or in courses with steeper learning curves and fewer institutional supports, mismatch penalties could be larger and more widespread.

Our findings also highlight limitations in current higher education admissions practices. Despite the intention of the K-12 reform to streamline educational transitions, college admissions at UP—and likely elsewhere—continue to rely solely on entrance exam scores or predictive grades, without reference to students' SHS strand. This disconnect undermines the reform's objective of better preparing students for tertiary education and places the burden of curricular misalignment on individual students and academic units. In light of our findings, there is a strong case for integrating SHS strand information into admissions or advising systems, especially in science and engineering fields.

Finally, these results have broader implications for education policy. First, they underscore the urgent need to revisit how SHS strands are implemented, offered, and communicated. Second, they point to a need for stronger articulation between secondary and tertiary curricula. And third, they suggest that blanket assumptions about the efficacy of K-12 reforms—without empirical backing—may be misguided. The promise of K-12 depends not only on additional years of schooling but also on whether students are guided into appropriate and supportive academic pathways.

8. Conclusion

This paper provides one of the first empirical investigations into the academic consequences of strand-program mismatch under the Philippines' K-12 education system. Using detailed administrative data from UP Diliman and propensity score matching to address selection bias, we find that while mismatch does not lead to an average grade penalty, there are important exceptions. In particular, students who pursue science and engineering degrees without a STEM background face consistent and significant academic disadvantages. Meanwhile, students with STEM backgrounds enrolled in non-STEM programs tend to perform slightly better than their peers, suggesting that the STEM strand offers transferable academic advantages.

These findings point to the differentiated impact of mismatch depending on the field of study. The negative consequences of curricular misalignment are most severe in disciplines where foundational knowledge from SHS is essential, particularly in math- and science-intensive courses. Our results highlight both the potential and the limits of the K-12 reform. While additional years of high school have expanded academic pathways, the continued disconnect between SHS preparation and college program demands undermines the reform's goals of ensuring readiness and reducing attrition.

To move forward, policy reforms must consider ways to strengthen the articulation between secondary and tertiary education. This may include integrating SHS strand information into college admissions and advising systems, re-evaluating how strands are assigned and accessed at the SHS level, and ensuring that students receive adequate support when transitioning into demanding college programs. By surfacing the uneven consequences of track-strand mismatch, this study offers critical insights into how the design and implementation of education pathways can better support student success in higher education.

Future research will do well to include more years and, if possible, more universities, especially since propensity score matching estimates ideally use large datasets. The experience of the University of the Philippines, an elite university, may also be different from the experience of other higher education institutions. It would be beneficial as well to investigate how junior high school students choose tracks and strands in the first place, and the factors that go into that choice (i.e., the endogeneity of strand choice in senior high school). Since students self-select into SHS strands based on unobserved traits such as motivation, parental support, or junior high school quality, our propensity score matching strategy—while accounting for observable covariates—may not fully eliminate selection bias. This is particularly relevant in interpreting the apparent grade advantages associated with STEM overshoots or the penalties from STEM undershoots. Future work employing alternative identification strategies, such as instrumental variables or regression discontinuity designs, could also genertate additional insights on the causal effect of strand-program alignment on college performance. Finally, an analysis of the labor market impact of high school-college mismatches may guide policymakers further on how to better guide the choice of tracks and strands early on.

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Appendix

Table A1. Mapping of UP Diliman degree program to prescribed strands

Degree program	Prescribed strand	Degree program	Prescribed strand
AA (Theatre)	Arts and Design	BA (TA: TM)	Arts and Design
AA (VisComm)	Arts and Design	BA BC	HUMSS
B EEd	HUMSS	BA BMAS	HUMSS
B EEd (EEd, K-3)	HUMSS	BA CommRes	HUMSS
B EEd (Lit Ed)	HUMSS	BA Fil	HUMSS
B EEd (Math)	HUMSS	BA Film	Arts and Design
B EEd (SH)	HUMSS	BA J	HUMSS
B EEd (SpEd)	HUMSS	BA PhilStud	HUMSS
B FA (ArtEd)	Arts and Design	BA-MA H (PolSci)	HUMSS
B FA (ArtHist)	Arts and Design	BS (Geog)	HUMSS
B FA (IndDes)	Arts and Design	BS (Psych)	HUMSS
B FA (Paint)	Arts and Design	BS (Stat)	STEM
B FA (VisComm)	Arts and Design	BS AppPhysics	STEM
B LArch	STEM	BS Arch	STEM
B LIS	GAS	BS BA	ABM
B M (Comp)	Arts and Design	BS BAA	ABM
B M (MuE)	Arts and Design	BS BE	ABM
B M (Musicology)	Arts and Design	BS Bio	STEM
B M (Voice)	Arts and Design	BS CD	HUMSS
B PA	GAS	BS CE	STEM
B PE	Sports	BS CN	STEM
B SEd	HUMSS	BS CS	STEM
B SEd (BioEd)	HUMSS	BS CT	STEM
B SEd (ChemEd)	HUMSS	BS ChE	STEM
B SEd (EngLangEd)	HUMSS	BS Chem	STEM
B SEd (FilLangEd)	HUMSS	BS CoE	STEM
B SEd (HE)	HUMSS	BS ECE	STEM
B SEd (MathEd)	HUMSS	BS EE	STEM
B SEd (PhysicsEd)	HUMSS	BS EM	STEM
B SEd (SS)	HUMSS	BS Econ	ABM
B SEd (SpEd)	HUMSS	BS FLCD	GAS
B SEd (VEd)	HUMSS	BS FT	STEM
B SS	Sports	BS GE	STEM
BA (Anthro)	HUMSS	BS Geol	STEM
BA (ArtStud)	Arts and Design	BS HE	GAS
BA (CL)	HUMSS	BS HRIM	ABM

BA (CL: EL)	HUMSS	BS ID	Arts and Design
BA (CL: PLE&ET)	HUMSS	BS IE	STEM
BA (CW)	HUMSS	BS MBB	STEM
BA (EL)	HUMSS	BS ME	STEM
BA (EngStud)	HUMSS	BS MatE	STEM
BA (EngStud: Lang)	HUMSS	BS Math	STEM
BA (EngStud: Lit)	HUMSS	BS MetE	STEM
BA (Hist)	HUMSS	BS Physics	STEM
BA (Ling)	HUMSS	BS SW	HUMSS
BA (MPF)	HUMSS	BS Tour	HUMSS
BA (Philo)	HUMSS	Cross Registrant (UPM)	
BA (PolSci)	HUMSS	Non-Major (Arch)	STEM
BA (Psych)	HUMSS	Non-Major (CBA)	ABM
BA (SC)	HUMSS	Non-Major (CMC)	HUMSS
BA (Socio)	HUMSS	Non-Major (CS)	STEM
BA (TA)	Arts and Design	Non-Major (Engg)	STEM
BA (TA: DD)	Arts and Design	Non-Major (SE)	ABM
BA (TA: P)	Arts and Design	Non-Major (Stat)	STEM