Quality of Students' Course Selections and (Late) College Dropout

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Abstract

I develop *coherence*, a novel measure for the quality of students' course selections, to explain the high rate of costly *late* college dropout. I find that coherence is an effective predictor for degree completion, especially in the freshman year, when semester credit hours offer little predictive power. Low coherence, both in earlier and later years of college, predicts dropouts and, especially, late dropouts. I provide causal validation for this finding leveraging the staggered introduction of DegreeWorks, a web-based advising tool. The introduction of DegreeWorks improves students' coherence and subsequently leads to a reduction in dropout rates, providing evidence that course selection quality is a policy-actionable mechanism driving degree completion.

1 Introduction

While the overall college graduation rate in the US is indeed low (64% college students graduate within 6 years of matriculation), what is perhaps more disturbing is that many students drop out of college when they are close to the finish line. Using administrative data from the State of Texas, I calculate that while average dropout rates are the highest for freshmen (20%), dropout rates remain significant for later years of enrollment — 10% for sophomores, 8% for juniors, and 11% for seniors. Moreover, these late college dropouts are not unique to unprepared students in non-selective institutions — a recent study reports that even highly qualified college students in a highly selective institution drop out after more than three years in college at a non-trivial frequency (Cohodes, Ho, and Robles, 2022). Back of the envelope calculation suggests that simply shifting the junior-year

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and senior-year dropouts to dropping out during the sophomore year could save more than $10 billion in tuition and foregone earnings each year.[1]

Why do students dropout so close to the finish line and can this be prevented? Existing factors in the literature are shown to be effective at forecasting dropout — financial aid (Dynarski, 2003), instructor and institutional match (Hoffman and Oreopoulos, 2009), GPA, and semester credit hours (SCH) (Stinebrickner and Stinebrickner, 2012). However, these factors are also salient and observable to students, making them less effective as early warning signs for late dropout. Students can observe and quickly react to a lack of financial aid and poor academic performance in early years, and would not wait till later years to dropout. In this paper, I argue that low quality course selection provides the missing early warning sign. In addition to *how many* courses students take, *what* they take also matters. Moreover, in contrast to the other factors mentioned, the quality of course selection is a latent, late-revealed signal. A student may maintain a high GPA and accumulate SCH while taking the wrong courses. This structural debt can fly under the radar for years, especially when academic advising is lacking. This planning inefficiency only becomes fully apparent and observable through degree audits which happen late in college. As a result, the quality of course selection provides a distinct mechanism where early decisions can manifest as late college dropout, providing a unique opportunity for early policy interventions.

However, the importance of students' course selections is understudied because it is difficult to quantify in a parsimonious way. A significant challenge to measuring the quality of students' course selections comes from the fact that a *good* course schedule looks different for students from different majors, different institutions, and different cohorts. I overcome this dimensionality challenge and develop the coherence measure in the following two steps. First, I empirically identify the degree-required courses for each institution $\times$ major $\times$ cohort cell by examining the transcripts of students who have successfully attained a degree. Second, I define and calculate the coherence of a student's course selections as the share of degree-required courses that the student has completed in the student's major. Following this definition, a student gains coherence when the student makes course selections that are coherent to the degree plan, in the sense that they are logical and contribute to degree completion. This coherence measure can be easily calculated in any setting where students' transcripts are available.

Equipped with the coherence measure, I demonstrate its effectiveness in predicting degree completion and in explaining *late* college dropout. Coherence provides significant incremental predictive power for degree completion above and beyond SCH. This result is particularly pronounced when measured in the freshmen year, demonstrating its effectiveness as an early signal for degree comple-

[1] Applying the attrition rates found in the Texas data to the nearly 1 million freshmen entering public 4-year universities every year nationwide (National Student Clearing House, 2022), one can estimate that 60,000 juniors, and 70,000 seniors drop out each year. The average annual cost of attendance for a full-time, in-state, student in a US public university is around $27,000 (NCES, 2023), and the median annual earnings for an individual with some college but no degree is around $45,000 (NCES, 2023), implying that delaying dropout by one year incurs an additional cost of $72,000 to the society as a whole. I then multiply $72,000 by the 60,000 juniors, multiply $144,000 by the 70,000 seniors, and add the costs to arrive at the estimate. This calculation assumes that the cost of attendance reflects the direct cost for students and the public combined, and assumes that students who drop out have the same earnings potential regardless of the number of years enrolled.

tion. In addition, I find that coherence has a strong contemporaneous *and* lagging effect on students' dropout rates. A one standard deviation drop in freshmen coherence predicts a 1.4 percentage points (pp) higher freshmen dropout rate as well as 0.7, 1.0, and 1.7 pp higher sophomore, junior, and senior dropout rates. In comparison, credit accumulation and GPA have strong contemporaneous but no lagging effects on dropout rates. Furthermore, I show that coherence is uniquely powerful as an early signal of student-major fit. Major-specific coherence in the freshmen year strongly predicts a students' eventual major choice and major-specific degree completion.

To study how policies can improve the quality of students' course selection, I evaluate the impact of recent, staggered, introduction of a web-based advising tool, DegreeWorks (DW), in Texas public universities. Using an event study design that allows for dynamic treatment effects (de Chaisemartin and D'Haultfoeuille, 2023), I find that the web-based advising tool significantly improved students' coherence by 1.4 pp., or 20% of a standard deviation. This result is encouraging because it demonstrates that the quality of course selections can be improved substantially through relatively cheap interventions that do not require significant human capital investment.

Using the event study design as the first stage, I use instrumental variable (IV) regressions to estimate the causal effects of coherence on students' dropout rates. Critically, I demonstrate that the DegreeWorks shocks primarily affects coherence while leaving GPA and SCH unchanged, confirming that the causal mechanism is through course selection quality. The IV estimates confirm the findings of the OLS estimates, and validate that higher quality course selections, both in earlier and later years of college, causally reduces dropout and especially late dropout.

This paper contributes to the literature in the following four aspects. First, this paper contributes to the literature studying factors that help explain and predict students' degree completion. Previous works in this literature have shown the impact of several important factors, including instructor characteristics, GPA, credit accumulation, and financial aid available (Dynarski, 2003; Hoffman and Oreopoulos, 2009; Scott-Clayton, 2011a; Fairlie et al, 2014; Stinebrickner and Stinebrickner, 2014; Castleman and Long, 2016; Goodman et al, 2017; Denning et al, 2022). To the best of my knowledge, this paper provides the first quantitative evidence that the quality of course selections is also an important factor in predicting degree completion. I develop a novel measure, coherence, for the quality of students' course selections and demonstrate that coherence provides significant power as an early signal for degree completion, above and beyond SCH. In addition, most previous works in this literature have abstracted away from the timing of dropout and do not distinguish between dropouts in the first few years of college and the significantly costlier late dropouts. This paper pays special attention to the timing of dropout and demonstrates how the quality of students' course selections is uniquely effective for explaining late dropouts.

Second, this paper speaks to the literature on the importance of college advising and student support services. Previous works have found that high-quality student advising and coaching are critical for student success (Bettinger and Baker, 2014; Bahr, 2008; Ehrenberg and Webber, 2010; Scott-Clayton, 2011b; Clotfelter et al, 2018; Barr and Castleman, 2025). Scott-Clayton (2011b) describes that "finding a path to degree completion is the equivalent of navigating a shapeless river

on a dark night." This paper contributes to this literature in three ways. First, the coherence measure provides a simple way to quantify the "shape of the river" and can help institutions and policy makers systematically monitor students' progress towards degree completion. Second, the coherence measure provides a way to quantify the quality of course selection, which is arguably one of the most important dimensions of academic advising. Third, the event study analysis on DW provides direct evidence that web-based advising tools can be highly effective in supporting academic advising (Arteaga et al, 2022).

Third, this paper is related to the literature studying students' fields of study (Hastings et al, 2013; Kirkeboen et al, 2016; Bleemer and Mehta, 2022; Andrews et al, 2024). Since the coherence measure is major-specific, a student's coherence in a major can be taken as a one-dimensional summary of the student's course-taking towards a degree in the major. This paper demonstrates that a student's coherence in a major, even in freshmen year, is a strong predictor of the student's choice of major. A student's coherence in a major can therefore be used as a powerful tool to identify the relevant student population when studying the impact of fields of study on student outcomes (Altonji and Zhu, 2025).

Fourth, this paper makes a data contribution to the broad literature using structural models to study students' school choices (Keane and Wolpin, 1997; Arcidiacono, 2004; Johnson, 2013). Structural works on school choices require the specification of students' non-pecuniary preferences for fields and schooling. Without a convenient measure for students' preferences, prior structural works often make strong assumptions on students' idiosyncratic preferences. Conditioning on students' course selection could significantly relax the assumptions needed on idiosyncratic preferences. However, it is computationally difficult to model students' course selections given their large dimension. As a solution, the coherence measure is a parsimonious summary of course selections, can be calculated easily, and can be incorporated into models as a state variable alongside GPA and credit accumulation (Zhu, 2024).

The remainder of the paper proceeds as follows: Section 2 introduces the Texas administrative data, defines the coherence measure, and explains how the coherence measure is calculated. I also discuss several descriptive exercises used to validate the measure. Section 3 demonstrates the effectiveness of coherence as an early predictor for degree completion and choice of major. Section 4 presents results on the relationship between coherence and dropout rates. Section 5 evaluates the impact of the introduction of DW on coherence using an event study design, and validates the causal relationship between coherence and dropout rates using IV regressions. Finally, Section 6 concludes, discusses use cases of the coherence measure beyond the scope of this paper, and provides directions for future research.

2 Data and the Construction of the Coherence Measure

2.1 The Texas Administrative Data

This paper uses a large administrative data from Texas, which links post-secondary education

data from the Texas Higher Education Coordination Board (THECB), to K-12 data from the Texas Education Agency (TEA), and to labor-market data from the Texas Workforce Commission (TWC). This allows researchers to observe an individual's progression from high school, to college, and to the labor market, so long as the individual remains in Texas.

The TEA data provides enrollment records, demographic backgrounds, course completion, graduation records, and attendance records for all Texas public high school students since 1993. The TEA data also includes students' performance in the state-wide standardized exams required for high school graduation. The THECB data provides information on all college students enrolled in Texas public higher education institutions since 1992.[2] The Texas public higher education system is composed of 38 four-year colleges and 50 public community colleges, and is the second largest in the US (after California) in terms of number of enrollments. The THECB data contains records of students' demographic background, enrollment, course selections and course grades, degree attainment, as well as financial aid and student loan. The availability of transcript level data started in the 2011-2012 academic year. Since the calculation of students' coherence requires their transcript information, I restrict my main analysis to students who started college in or after the 2011-2012 academic year. Since the calculation of students' coherence also requires a significant number of students from their entering cohort to have attained a degree, I further restrict my main analysis to students who started college in or before the 2018-2019 academic year.

2.2 Coherence Measure: Definition

I develop the coherence measure to quantify the quality of students' course selections. In this paper, high-quality course selection is defined as one that is logical and contributes to a student's degree completion. Following this definition, the coherence measure is designed to capture a student's progress towards completing degree-required courseworks and is defined as the share of required courses that the student has completed. Formally,

$$\text{coherence}_{it}^{m} = \begin{cases} \frac{h_{it}^{m}}{n^{m}} & \text{if } h_{it}^{m} < n^{m} \\ 1 & \text{if } h_{it}^{m} \geq n^{m} \end{cases} \tag{1}$$

where c_{it}^{m} denotes the coherence of student i at time t in major m, h_{it}^{m} denotes the number of credits in required courses for major m that student i has completed by time t, and n^{m} denotes the total number of credits in required courses for major m. By definition, the coherence measure is a measure between 0 and 1, where having a coherence of 1 simply means the student has completed all required courseworks in major m.

The overall coherence of student i is then defined as the student's coherence in the declared major m^{*} if m^{*} is declared. If the student has not yet declared a major, the student's coherence is defined as the highest coherence among all majors:

[2]While the data has information on students from both public and private institutions, I restrict my analysis to students in public institutions since critical information including transcript records are not available for private colleges.

$$\text{coherence}_{it} = \begin{cases} \text{coherence}_{it}^{m^*} & \text{if } m^* \text{ declared} \\ \max_{m \in M} \ \text{coherence}_{it}^{m} & \text{if } m^* \text{ not declared} \end{cases} \tag{2}$$

2.2.1 An Alternative Definition of Coherence

There are several alternative definitions for the quality of students' course selections that could make sense under different settings. It is therefore valuable to discuss two notable alternative definitions and why this paper uses the definition described in equations (1) and (2).

First, the coherence measure can be anchored to any educational objectives. For example, the breadth and flexibility of college course selections is a key feature of the US college education. In section 6, I discuss multiple ways the coherence measure in this paper can be adapted and extended to study different dimensions of the quality of students' course selections. I anchor the definition of coherence in this paper to degree completion for two reasons. First, drop out is the specific, highly costly, student outcome this paper is aiming to explain. Second, degree completion is one of the most important educational objectives that are universal across institutions. In addition, as will be explained in the next paragraphs, the coherence measure in this paper does not penalize breadth of curriculum, as long as it does not negatively impact degree completion.

Second, another sensible alternative to equation (1) is to define coherence as the share of credits a student has taken that fulfills the degree requirements of a major.[3] Instead of equation (1), coherence would be defined as:

$$\text{coherence}_{it}^{m} = \frac{h_{it}^{m}}{h_{it}}$$

where h_{it}^{m}, again, is the number of credits student i has taken by semester t that fulfill the degree requirements of major m. h_{it} is the total number of credits student i has taken by semester t. The most salient difference of this alternative definition is that it separates the "speed" of credit accumulation from the "quality" of credit accumulation. In particular, with the original definition of coherence, taking more credits will never decrease a student's coherence. In contrast, under this alternative definition, coherence could decrease if a student takes courses that deviate from her degree plan.

In this paper, I define coherence following equations (1) and (2) for three reasons. First, in all analyses that follows, we control for the total number of credits accumulated, which helps isolate the effect of "quality" from "speed". Moreover, in most imaginable settings where coherence can be calculated, the total number of credits accumulated would also be available. Second, the alternative definition would penalize students who take extra exploratory classes outside of major. In the current definition, although exploratory classes do not contribute to coherence, they do not slow students down either. The latter seems the more appropriate definition. Third, the current definition of coherence provides an intuitive and universal target — students and advisers should work towards

[3] I thank an anonymous referee for suggesting this alternative definition.

accumulating a coherence of one, which signals the completion of all degree-required courses. In comparison, the first alternative definition would yield different targets for students in different majors. For example, engineering majors would have a higher target coherence than history majors, because engineering curriculum often includes significantly more required courses. Regardless, as will be mentioned in section 4, I perform the main regressions with this alternative definition and show that the main patterns hold qualitatively. If anything, the current definition performs better.

2.3 Coherence Measure: Measurement

The observation of students' transcript level data makes measuring coherence possible. However, a significant challenge in measuring coherence remains: the more than 80 colleges and dozens of college majors create thousands of institution × major pairs that each have a distinct set of required courses. In addition, degree requirements and course labeling have potentially changed over time. Manually coding the degree requirements for students is therefore close to impossible and prone to severe human error. To solve this challenge, I empirically identify the major requirements using the following procedure. First, I identify the population of students who attain degree from institution J in major M in cohort T, $S_{J,M,T}$. Second, I identify the courses that more than 90% of $S_{J,M,T}$ took, and label these courses as the set of required courses, $C^R_{J,M,T}$. Third, I identify courses that more than 30% of $S_{J,M,T}$ took, and label these courses as the set of elective courses, $C^E_{J,M,T}$. Fourth, I count the number of elective courses that students in $S_{J,M,T}$ took and take the 30th percentile value of that distribution, $n^E_{J,M,T}$. The tuple $\{C^R_{J,M,T}, C^E_{J,M,T}, n^E_{J,M,T}\}$ then characterizes the degree requirement of degree J from school M in cohort T. In particular, students need to complete all courses in the set $C^R_{J,M,T}$, and at least $n^E_{J,M,T}$ courses in the set $C^E_{J,M,T}$.

Indeed, the 90%, 30%, and 30th percentile thresholds are arbitrary. However, the coherence measure is stable to the threshold choices. As I will show later, the main results do not qualitatively change when the thresholds are adjusted to be 95%, 50%, and 50th percentile (strict) or 70%, 20%, and 20th percentile (lax).

2.4 Mechanical Validation and Summary Statistics

2.4.1 Validation of Measure

I present evidence that this empirical procedure captures students' degree requirement with significant accuracy. To examine the accuracy of the empirical procedure for identifying degree requirements, I compare the required courses identified by the procedure and the actual required courses listed on institutions' websites for a random set of institution × major pairs.[4] Appendix Table A.1 shows the accuracy rates of the 16 institution × major pairs I tested. For each pair I audited, more than or close to 90% of empirically identified degree requirements were found on the

[4]The 2019 entering cohort was used for this procedure.

official degree plan, except for UT Austin x Economics (74%). The reason behind the relatively low accuracy is because many UT Austin economics majors enroll in business-related courses that are not necessarily required by the economics major.

Next, if a student's coherence is computed correctly, a student with coherence of one has completed all degree required courses. As a result, we should observe a strong mechanical relationship between a coherence of one and degree completion. In Table 1.1, I compare the accuracy of predicting the graduation of a four-year college student when using SCH accumulated, GPA, coherence, and various combinations of the three measures. I find that while students' credits accumulated strongly predict four-year college graduation, the prediction is not perfect — 92% of students who have at least 120 SCH graduates within a year. Once coherence is also taken into account, however, the prediction improves significantly — more than 96% of students who have at least 120 SCH and coherence of 1 receives a bachelor's degree within a year. The prediction increases further to 98% when also restricting to students with a GPA greater than 2.5.

Repeating the same exercise on community college students (reported in Table 1.2), I find that taking into account coherence improves predictive power of associate's degree completion by around 15%. The overall predictive power of this exercise is considerably weaker than in four-year colleges, because many students choose to transfer to a four-year college before attaining an associate's degree.

2.4.2 Summary Statistics on Coherence

Table 2 presents summary statistics for coherence gain per semester. Panel A shows that coherence gain decelerates monotonically from freshmen year (0.18 per semester) to senior year (0.10 per semester). The statistics imply that the average student completes all degree required courses after the first semester of senior year. Panel B reports coherence gain across student characteristics. The results show that first generation college students and economically disadvantaged students gain less coherence per semester. This suggest parental resources, both pecuniary and non-pecuniary, can serve as substitutes to academic advising. Notice, however, that the differences are small compared to the standard deviation. Panel C compares coherence gain between STEM and non-STEM majors. The results show that STEM majors accumulate coherence at a substantially slower pace. This reflects the fact that STEM majors typically have more degree required courses, which takes longer to complete.

In appendix B, I formalize these patterns using regressions controlling for student and institutional characteristics. I find that student characteristics such as high school test scores and parental resources are significant predictors for coherence accumulation. Institutional ranking also matters — controlling for students' application and admission sets, students in higher-ranked institutions accumulate coherence faster.

3 Predictive Power of Coherence

3.1 Early Signal for Degree Completion

The results reported in Table 1.1 validates a mechanical connection between a coherence of one and degree completion. However, for policy makers and practitioners, early signals are much more valuable as they enable early interventions that can help students persist. A priori, it is unclear how effective early coherence is as a predictor for degree completion — a freshmen who explores out-of-major courses could refocus and get back on track in later years.

I examine the predictive power of coherence with the following two steps. First, I run logistics regressions with degree attainment as the dependent variable, and coherence as the explanatory. For each $Y \in \{1, 2, 3, 4\}$,

$$\text{logit}(\text{BA}_i) = \beta_0 + \beta_1 \text{coherence}_{it}^{Y} + v_{it}$$

where $\text{coherence}_{it}^{Y}$ is the coherence of student i while she is in academic standing Y. For each regression, I restrict the sample to individuals who reach academic standing Y. Second, I compute the area under curve (AUC) measure according to the logistic model. The AUC measure the accuracy of the logistic model in predicting the degree completion of student i. An AUC of 0.5 indicates a random guess, while an AUC of 1.0 indicates a perfect prediction. For comparison, I perform the same exercise using SCH as the explanatory variable and using both coherence and SCH as explanatory variables.

Table 3 presents the results of the above exercise. The results from the freshmen year demonstrates the potential of coherence as an early signal. In freshmen year, coherence is a significantly more effective predictor for degree completion compared to SCH, which is effectively uninformative (0.60 vs. 0.49). The AUC of the combined model with both SCH and coherence has an AUC of 0.63.

Additionally, the results show that, across all academic standings, coherence is on par with the predictive power of SCH, and the combination of coherence and SCH is consistently superior to a model with only SCH. The above results confirm that coherence captures crucial component of course selection that is distinct from the traditional measure of SCH, especially at the early stages of college.

3.2 Major-Specific Degree Outcomes and Choice of Major

In Table 4, I report results when replacing the dependent variable as degree attainment in major m, BA_i^m, and replacing coherence with the major-specific coherence, $\text{coherence}_{it}^{m}$. I focus on freshmen year and perform the exercise for the three most populous undergraduate majors, business, psychology, and mechanical engineering. table 4.1 restricts the sample to students who entered college majoring in m, while table 4.2 restricts the sample to students who have not declared major m.

The results show that SCH alone do not help predict degree completion in specific majors.

The AUCs are consistently around 0.5. In contrast, coherence in major m is an effective predictor of degree completion for both freshmen who declared and have not declared major m, with AUCs ranging from 0.60 to 0.78. The AUCs of the combined models range from 0.62 to 0.86 for mechanical engineering. This implies that major-specific coherence is a highly effective tracking tool to detect structural deviations from major-specific plans. This also validates coherence as a powerful early signal of student-major fit.

Finally, comparing across the results for different majors, the patterns suggest that coherence is particularly effective for "structured" programs, such as engineering and business, which have prescriptive degree plans. For these majors, deviation from degree plans, even at an early stage, is predictive of failure to complete the degrees. For example, for freshmen who declared mechanical engineering as their major, coherence in mechanical engineering and SCH combined yield an AUC of 0.71, while a model with SCH only is as good as a random guess (AUC=0.5). For freshmen who did not declare mechanical engineering as their major, coherence in mechanical engineering and SCH combined yield an AUC of 0.86.

4 Coherence and (Late) Dropout

I formalize the descriptive patterns and predictive results from previous sections by examining how coherence accumulation impacts students' dropout rates at different stages in college. As highlighted earlier, special attention is given to examining the costly late dropouts. The timing of the relationship is critical. If poor course selection is hard to detect, low coherence in early years creates a "structural debt" that does not affect dropout immediately but becomes due in later years, leading to late dropout. On the contrary, if poor course selection is easily observable, it would act similar to immediate signals such as GPA and credit accumulation, and would predict same-period dropout but not late dropout.

4.1 Empirical Specifications

For student i enrolled in institution j, our main outcome of interest is DropOut_{it}, which is an indicator variable for whether the student dropped out during year t. The baseline OLS regression is:

$$\text{DropOut}_{it} = \beta_0 + \beta_{coh}\text{coherence}_{it} + \beta_{sch}\text{credit}_{it} + \beta_{gpa}\text{gpa}_{it} + \beta_x X_{it} + \beta_s S_j + \beta_m M_{it} + \epsilon_{it} \quad (3)$$

where coherence_{it}, credit_{it}, and gpa_{it} are the coherence gained, number of credits accumulated, and GPA for student i during year t. Since we control for credit_{it} in all regressions, we can interpret the coefficient β_{coh} as the correlation between the *quality* of credit accumulation on drop out rates,

controlling for the *speed* of credit accumulation. This specification ensures that the results are robust to the concern discussed in section 2.2.1. The regression also controls for a vector of student observables X_{it}, which includes student's high school standardized test score, gender, ethnicity, parental income, parental education, and part-time enrollment status. It also controls for student's school of enrollment S_j, and major enrolled, M_{it}. For the analyses, I restrict to students who are not transfer students from other two-year or four-year colleges.[5]

In addition to the contemporaneous effects of coherence on dropout rates, I am also interested in examining whether coherence gains in the earlier years of college enrollment might have lagging effects on dropout rates. While credits accumulated and GPA are clearly displayed on transcripts after each semester, coherence is typically not displayed and harder to observe for students. Students may not find out about their freshmen coherence accumulation until they try to enroll in an advanced level course that requires multiple prerequisite, when they meet with an academic advisor in later semesters, or when they apply for a degree in their senior year. If this is the case, earlier coherence accumulation could fly under the radar and affect later years' dropout decisions. For this purpose, I extend equation (3) to include lags of coherence, SCH, and GPA. Denote a student's academic standing as $Y \in \{1, 2, 3, 4\}$, where 1, 2, 3, and 4 represent freshmen, sophomore, junior, and senior, respectively. Then:

$$\text{DropOut}_i^Y = \beta_0 + \sum_{t=1}^{Y} \beta_{coh}^{tY} \text{coherence}_i^t + \sum_{t=1}^{Y} \beta_{sch}^{tY} \text{credit}_i^t + \sum_{t=1}^{Y} \beta_{gpa}^{tY} \text{gpa}_i^t + \beta_x X_i + \beta_s S_j + \beta_m M_i + \epsilon_i \quad (4)$$

where coherence_i^t,credit_i^t, and gpa_i^t are the coherence gained, number of credits accumulated, and GPA for student i during enrollment year t. β_{coh}^{tY}, β_{sch}^{tY}, and β_{gpa}^{tY} are the effects of coherence gained, number of credits accumulated, and GPA in year-t on the dropout rates in year-Y.

4.2 Empirical Results — Effects of Coherence on Dropout Rates

I present the results of regressions following specification of equation (4). The results are presented in columns (1) - (4) of Table 5, and show results separately for students in their freshmen, sophomore, junior, and senior years. Since coherence, SCH, and GPA have different scales, the coefficients are translated to represent the impact of a one standard deviation increase in each of the three factors. Two patterns emerge when examining the contemporaneous effects (in the diagonal cells). First, increases in all three factors are correlated with a decrease in the likelihood of dropping out in the current semester. Second, GPA appears to have the strongest contemporaneous correlation with dropout (ranging from 5 pp to 21 pp), followed by SCH (ranging from 0.3 pp to 4.0 pp), and then coherence (ranging from 0.9 pp to 2.1 pp).

[5]This is because the coherence measure is institution-specific and incorporating courses transferred from other institutions complicates the problem significantly due to uncertainty in transferrability of credits. I leave this aspect of calculating coherence to future works.

Most importantly, the results on the lagged measures (in the upper right quadrant) help explain the late dropout puzzle. Among the three factors, only coherence appears to have a persistent lagging effect on later years' dropout rates. Conditional on reaching junior or senior status, freshmen and sophomore coherence accumulations have as much, if not stronger, correlation with junior and senior dropout decisions compared to coherence accumulations in the later years. In contrast, freshmen and sophomore credit accumulation and GPA have no meaningful lagging effects on later drop out decisions. For example, holding junior and senior year coherence gain fixed, one standard deviation increases in freshmen and sophomore coherence gains are both correlated with a 1 pp decrease in senior year dropout rate, which is equivalent to 10% of all senior year dropout. This aligns with the hypothesis that poor early course selections often remain invisible until later years of college, leading to late dropouts.[6]

In addition to the average correlation of coherence on dropouts, three heterogeneity results are reported in Table 6. First, I find that the lagging effects of coherence are more significant for economically disadvantaged students. For example, a one standard deviation improvement in freshmen coherence predicts a 1.0 pp decrease in both junior and senior year dropout rates for the average student. For economically disadvantaged students, the numbers are 1.8 pp and 2.0 pp, respectively. This heterogeneity result suggests that students with less parental resources have a harder time recovering from poor course selections early in college. Second, we find similar but less significant results for first-gen students. The differences between first-gen students and average students are mainly in their junior dropout rates. Third, I find that the lagging effects of coherence on late dropouts are generally more significant for STEM majors. For STEM majors, one standard deviation improvements in freshmen and sophomore coherence predicts a 2.0 pp and 1.8 pp decrease in junior dropout rates. The effects on senior dropout rates are similar to the average student. This is consistent with the fact that STEM majors, especially engineering majors, have highly structured degree plans with more required courses and more courses with specific prerequisites. In these unforgiving majors, a deviation from the optimal course selections in the first two years precludes enrollment in upper-level courses and on-time graduation, forcing a costly dropout decisions during the junior year.

As robustness check, I reconstruct Table 5 using several alternative measures of coherence mentioned in section 2.2.1. Specifically, I adjust the arbitrary thresholds for identifying degree requirements to be laxer and stricter (Table A2), and define coherence as the share of courses taken that satisfy degree requirements (Table A3). Across all alternative specifications, the main qualitative

[6] I repeat the regressions from equation (4) on community college students, and the results are presented in Table A4. Given community colleges' dual purpose of providing associate degrees and facilitating transfer to four-year colleges, I define dropout as leaving college without either transferring or an associate degree. The results in columns (1) - (2) suggest that coherence is negatively correlated with the likelihood of dropping out, although the correlations are weaker than those of SCH and GPA. Columns (3) - (8) break out the correlation with dropout into correlations with associate degree attainment, transfer to four-year colleges, and bachelor's degree attainment. The results suggest that, while coherence accumulation is not correlated with the likelihood of associate degree attainment, it has a large positive correlation with the likelihood to transfer to a four-year college and the likelihood of attaining a bachelor's degree. This partly reflects the fact that, among community college students who transfer to four-year colleges, 57% transfer without attaining an associate degree.

pattern holds — early coherence, unlike GPA and SCH, has a strong lagging effect on late dropout.

It should be noted that these results are based on OLS and therefore subject to endogeneity concerns. Despite the rich set of control variables available, it is likely that coherence accumulation is correlated with unobservable student characteristics that also contribute to degree completion. The direction of the bias is unclear. On the one hand, students who excel in planning ahead of time are more likely to make more coherent course selections and are also less likely to drop out. On the other hand, students who explore a broad range of fields in early years may be more intellectually curious, a characteristic likely correlated with lower likelihood of dropping out. In the next section, I introduce IV estimates leveraging the staggered introduction of DegreeWorks to estimate the causal effects of coherence on dropout rates. The IV estimates local average treatment effect (LATE) for student compliant with the DegreeWorks nudge. These are students who rely on advising tools to understand degree requirements. This marginal population likely benefits more from coherent course selections and, arguably, is also the population of interest for policy interventions targeting course selections.

5 Effect of DW on Coherence and Causal Validation of OLS Results

Can policies help improve the quality of students' course selections? Academic advising is perhaps the most common way institutions help students make course selections that are coherent with their degree plan. However, improving academic advising is potentially costly, since it may involve hiring additional advisers or demanding faculty to spend more time on advising. As explained in the next sub-section, DW provides a promising solution to improve academic advising at relatively low cost. I evaluate whether the implementation of DW in Texas public universities improved the quality of students' course selection. In addition, I take the introduction of DW as an exogenous shock to students' coherence and use IV methods to validate the main results from Section 4.

5.1 Institutional Backgrounds on DW

DegreeWorks (DW), is an online degree audit tool that allows students and their academic advisers to monitor students' progress towards degree completion and plan future academic course works. DW has two main functionalities. The first function is degree audit — DW automatically matches a student's transcript with the student's degree plan and calculates the student's progress towards degree completion. In doing so, DW effectively makes coherence visible to the students. The second function is "what-if" analyses — DW allows students to input hypothetical course selections for future semesters and calculate the resulting progress towards degree completion. While institutions highlight that DW is not a substitute for academic advisers, it does replicate many of their roles and allows students to be more informed when choosing courses. Moreover, DW, like other web-based tools, are easier to access than academic advisers since it does not require making an appointment.

DW is available for more than one third of the 38 public four-year institutions in Texas. Table 7 provides a list of Texas public 4-year institutions that have DW implemented, and the years in which they implemented DW. I leverage the staggered implementations of DW to study the effectiveness of DW in improving the quality of students' course selections. In addition, I use the staggered implementations as sources of exogenous variations for students' coherence to identify the causal effects of coherence on dropouts. The main variations for identification will come from the five institutions that implemented DW during the main sample observation window of 2012-2019. These institutions are UT San Antonio, Tarleton State University, Angelo State University, Midwestern State University, and Prairie View A&M University.[7] Combined, these five institutions enroll around 10% of all public university students in Texas.

5.2 Event Study Design and IV Method

A parallel trends assumption is needed — I assume that the trends of student outcomes for the universities that introduced DW would have been the same as those that did not if DW was not introduced. I follow de Chaisemartin and D'Haultfoeuille (2023), and estimate the treatment effects of DW on students' coherence accumulation using a heterogeneity-robust event-study design. The dynamic TWFE regression is as follows:

$$\text{coherence}_{ijt} = \gamma_0 + \gamma_1 X_{ijt} + \lambda_j + \delta_t + \sum_{l=-2}^{-1} \mu_l D_{jt}^l + \sum_{l=1}^{4} \mu_l \text{D}_{jt}^l + \nu_{ijt} \tag{5}$$

where λ_j is the institution FE and δ_t is the year FE. D_{jt}^l is a dummy variable that takes the value one if DW was introduced $l+1$ after period t in institution j. Under parallel trends, the vector of coefficients μ provides unbiased estimates for the treatment effects of DW for students in the corresponding treatment year.

Next, I leverage the staggered introduction of DW as a source of exogenous shift in students' coherence. I estimate equation (3) using 2SLS, where coherence is instrumented with D_{jt}^l. For equation (4), I interact D_{jt}^l with student's cohort as instruments. The intuition is that if a student entered college in 2013 and the college implemented DW in 2014, then the student's sophomore coherence is affected while the student's freshmen coherence is not. For a student who entered the same college in 2014, both freshmen and sophomore coherences are affected. It is important to note that there is a dynamic sample selection issue when estimating equation (4) with 2SLS. For example, the effect of coherence on freshmen dropout rate will lead to endogenous sample selection when examining the dropout rate of sophomores. There is no clear way to address this issue. However, notice that the dynamic selection issue will likely underestimate, rather than overestimate the effect. If DW improves freshmen coherence and leads to less freshmen dropout, the students

[7] Texas A&M - Texarkana, Texas A&M - San Antonio, Texas Tech, and UT - Rio Grande Valley implemented DW in the 2011-2012 academic year, but since I do not observe any pre-treatment periods for these schools, they would not contribute to identification.

who are nudged into the sophomore sample would likely be lower ability students who would have otherwise dropped out. This endogenous sample selection would likely harm sophomore dropout rates and underestimate the reduced form. Estimating equation (3) with 2SLS is not subject to this concern.

The exclusion restriction for the IV method is that DW only affects dropout through students' course selection. I provide two pieces of evidence to support the assumption. First, I report pre-trends for both coherence and dropout to see if the timing of DW introduction was endogenous. Second, I estimate placebo effects, where the dependent variable of equation (5) is replaced with gpa_{ijt} and credit_{ijt}.

5.3 Event Study and IV Results

The estimates of the dynamic treatment effects of DW on coherence are reported in Figure 1. The result shows significant improvement in coherence after the introduction of DW. The average increase in coherence gain per semester is 0.014, which is 20% of one standard deviation. The effect seems to persist over time. Figure 1 also shows no differential pre-trends, suggesting that the parallel pre-trends assumption holds. The p-value for the test for differential pre-trends is 0.49. Figure 2 reports the dynamic treatment effects of DW on dropout rates. The result shows significant decrease in dropout after the introduction of DW by half a percentage point. The p-value for the test for differential pre-trends is 0.75. The effect magnify over time, reaching around one percentage point by year 3 post introduction. The delayed ramification of the full treatment effect is consistent with coherence having a lagged impact on dropout.

Figure 3 show the placebo treatment effects of DW introduction on GPA and SCH. The results show that there is no meaningful change in these two intermediate outcomes following the introduction of DW. These results alleviate the concerns that DW affect student outcomes through channels other than course selection, and supports the exclusion restriction for the IV strategy.

Table 8 compares the OLS and IV estimates of equation (3). The OLS estimate shows that, on average, a one standard deviation improvement in coherence is associated with a 1.3 pp decrease in contemporaneous dropout rate. The IV estimate show that a one standard deviation increase in coherence decreases dropout rate by 1.9 pp, though the standard errors are larger. The F statistics for the first stage instrument is 395.3.

The difference in magnitude is consistent with the IV approach estimating a LATE for the compliers — students who rely on advising tools to understand their degree requirements. These students likely possess lower baseline information or planning ability compared to "always-takers" who navigate the curriculum successfully with or without DW. It is reasonable to expect that the returns to improved coherence are larger for this marginal student population.

Conditional on all caveats discussed in Section 5.2, I use the IV method to estimate equation (4) with the interaction of students' cohort and the introduction of DW as exogenous instruments. The results are reported in Table A5, and show similar qualitative patterns as the OLS results

— freshmen coherence has strong negative contemporaneous and lagged effects on dropout. The coefficient estimates are similar but larger for the IV estimates and less precise. I interpret the magnitude of these point estimates with caution given the larger standard errors, but note that the qualitative patterns support the causal connection between coherence and late dropout.

6 Conclusions and Directions for Future Research

In this paper, I formalize the widely accepted idea that, in addition to the number of courses taken, students' course selections also matter. I do so by defining and constructing a novel measure, coherence, which quantifies the alignment between students' course selections and their degree requirements. I demonstrate that the coherence measure provides significant predictive power for degree completion above and beyond the traditional SCH measure. This advantage is particularly pronounced in the freshmen year, when SCH fail to distinguish between successful graduates and dropout. Combined with the fact that coherence can be calculated easily with transcript information, coherence can be used by policy makers and practitioners as an effective early signal for students' likelihood of degree completion.

Crucially, the coherence measure offers a solution to the puzzle of costly late college dropouts. I find that slow coherence accumulation in earlier years of college significantly increases the likelihood of dropout in junior and senior years. This lagging effect is not present for GPA and credit accumulation. Unlike failing courses and receiving a low GPA, taking the wrong courses is harder to detect. As a result, many students may not realize they have low coherence accumulation until they take advanced courses that require prerequisites or when they go through degree audits, leading to late dropouts. The results from the staggered implementation of DW confirm that this mechanism is causal and policy-actionable. The introduction of the web-based advising tool led to significant improvements in coherence and a reduction in dropout rates. This implies that simple interventions targeting planning transparency can mitigate the structural risks from late dropouts.

Beyond the policy implications on degree completion examined in this paper, the coherence measure offers a methodological contribution to several active research areas. Below, I offer several potential directions for future research to leverage the coherence measure as a tool. First, by collapsing the high dimensional vector of course selections into a single parsimonious measure, the coherence measure is useful as a state variable alongside traditional factors (e.g., GPA and credit accumulation) in structural models of educational choices and outcomes. The major-specific coherence measure could also be used as a substitute or complement to major-specific course credits for structural models on students' choice of majors. Second, and relatedly, the major-specific coherence measure could be used as a tool for empirical research examining the effects of fields of studies. The ability of the major-specific coherence measure to predict the intended major of freshmen makes it a helpful tool to identify the relevant student population when studying the effects of a specific major. In an ongoing project (Altonji and Zhu, 2025), we use students' coherence in business and

engineering to improve the statistical power of our GPA cutoff instruments.

As the first paper to consider the measurement of the quality of students' course selections, this paper leaves open several avenues to apply and extend the coherence measure to different settings. First, the coherence measure can be generalized to settings beyond degree completion. The required course set can be anchored to any educational objectives, allowing researchers to use coherence as a measure of the alignment of student's course taking to a broad set of goals. Examples include pre-med or pre-law programs in four-year colleges, career and technical programs in community colleges, and even college readiness in high school. The empirical approach to identify suggested courses is particularly helpful in cases where course requirements are ambiguous or poorly documented. Second, this paper leaves the issue of the sequence of course-taking open. It is well known among academic advisers that some courses, such as calculus and introduction to microeconomics, should be completed early in college because they serve as prerequisites for required courses in many different majors. Identifying these courses and quantifying the importance of correct sequencing of courses is an important topic for future study.

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Tables and Figures

Table 1.1: Predictive power of coherence at the limit — 4-yr colleges

	Probability of Attaining Bachelor's Degree This Year			
	92%	96%	96%	98%
Semester Credit Hours $\geq$ 120	✓		✓	✓
Coherence $\geq$ 0.95		✓	✓	✓
GPA$\geq$ 2.5				✓

Notes: This table presents the predictive power of different factors for four-year college graduation at the limit — when the factors are at the level required for degree completion. The first column presents the share of students with more than or equal to 120 semester credit hours who graduates within a year of the observed semester. The second column presents the share of students with a coherence of at least 0.95 who graduates within a year of the observed semester (note that a coherence of 1 indicates completion of all degree required courses). The third column presents the share of students with more than or equal to 120 semester credit hours and a coherence of at least 0.95 that graduates within a year of the observed semester. The fourth column presents the share of students with more than or equal to 120 semester credit hours, a GPA of at least 2.5, and a coherence of 0.95 that graduate within a year of the observed semester.

Table 1.2: Predictive power of coherence at the limit — community colleges

	Probability of Attaining Bachelor's Degree This Year			
	41%	13%	53%	61%
Semester Credit Hours $\geq$ 60	✓		✓	✓
GPA $\geq$ 2.0		✓	✓	✓
Coherence = 1				✓

Notes: This table presents the predictive power of different factors for community college graduation at the limit. The first column presents the share of students with more than or equal to 60 semester credit hours who graduates within a year of the observed semester. The second column presents the share of students with a coherence of 1 who graduates within a year of the observed semester (note that a coherence of 1 indicates completion of all degree required courses). The third column presents the share of students with more than or equal to 60 semester credit hours and a coherence of at least 0.95 that graduates within a year of the observed semester. The fourth column presents the share of students with more than or equal to 60 semester credit hours, a GPA of at least 2.0, and a coherence of 1 that graduate within a year of the observed semester.

Table 2: Summary Statistics for Coherence

Sub-Sample	Coherence per Semester	
	Mean (1)	Std. Dev. (2)
Panel A: By Academic Standings		
Freshman	0.180	0.116
Sophomore	0.150	0.093
Junior	0.130	0.077
Senior	0.100	0.063
Panel B: By Background Characteristics		
First Generation	0.141	0.095
Not First Generation	0.148	0.100
Economically Disadvantaged	0.138	0.093
Not Economically Disadvantaged	0.150	0.101
Panel C: By Field of Study		
STEM	0.128	0.076
Non-STEM	0.158	0.110

Note: this table reports the average coherence gain per semester separately by academic standings (panel A), students' socioeconomic background (panel B), and field of study (panel C).

Table 3: AUC from Logistics Model on Degree Completion

	AUC from Logit Models for BA Attainment (AUC = 0.5: random guess; AUC = 1.0: perfect prediction)		
Model	Hours Only	Coherence Only	Hours + Coherence
Freshman	0.49	0.60	0.63
Sophomore	0.60	0.56	0.64
Junior	0.65	0.60	0.71
Senior	0.65	0.66	0.74

Note: this table presents the area under curve (AUC) of logit models for bachelor's degree attainment. Rows 1-4 present models that predict degree completion for freshmen, sophomore, junior, and seniors. The first column represents models with only semester credit hours as explanatory variable. The second column represents models with only coherence as explanatory variable. The third column represents models with both as explanatory variables. An AUC of 0.5 equivalent to a random guess, while an AUC of 1.0 indicates a perfect prediction.

Table 4: AUC from Logistics Model on Major-Specific Degree Completion

Freshmen - Major Declared	**AUC from Logit Models for BA Attainment in Major** m (AUC = 0.5: random guess; AUC = 1.0: perfect prediction)		
Model	Hours Only	Coherence in Major m	Hours + Coherence in Major m
Business	0.53	0.60	0.62
Psychology	0.52	0.63	0.66
Mechanical Engineering	0.50	0.63	0.71

(a) Freshmen Entering in Major

Freshmen - Major Declared	**AUC from Logit Models for BA Attainment in Major** m (AUC = 0.5: random guess; AUC = 1.0: perfect prediction)		
Model	Hours Only	Coherence in Major m	Hours + Coherence in Major m
Business	0.50	0.69	0.74
Psychology	0.51	0.60	0.63
Mechanical Engineering	0.56	0.78	0.86

(b) Freshmen Entering not Declared in Major

Note: this table presents the area under curve (AUC) of logit models for bachelor's degree attainment in specific major m. The models in both panels predict bachelor's degree attainment in m for freshmen. Panel 1 present models for students who declared major m entering college. Panel 2 present models for students who did not declare major m entering college. For each panel, the rows 1-3 present models for business, psychology, and mechanical engineering majors, respectively. Models in the first column use semester credit hours as the explanatory variable. Models in the second column use the major-specific coherence in major m as explanatory variable. This is the share of degree required courses for major m that a student has completed. An AUC of 0.5 equivalent to a random guess, while an AUC of 1.0 indicates a perfect prediction.

Table 5: Effects of Lagging and Current Coherence, Credits, and GPA on Dropout

	Freshmen Dropout (1)	Sophomore Dropout (2)	Junior Dropout (3)	Senior Dropout (4)
Coherence - Freshmen	-0.021	-0.008	-0.010	-0.010
	(0.002)	(0.002)	(0.002)	(0.001)
Coherence - Sophomore	-	-0.010	-0.010	-0.010
		(0.002)	(0.001)	(0.001)
Coherence - Junior	-	-	-0.017	-0.011
			(0.002)	(0.001)
Coherence - Senior	-	-	-	-0.009
				(0.002)
Semester Credit Hours - Freshmen	-0.037	0.000	0.003	0.003
	(0.001)	(0.001)	(0.001)	(0.001)
Semester Credit Hours - Sophomore	-	-0.040	0.005	0.002
		(0.002)	(0.001)	(0.001)
Semester Credit Hours - Junior	-	-	-0.037	-0.003
			(0.002)	(0.001)
Semester Credit Hours - Senior	-	-	-	-0.003
				(0.001)
GPA - Freshmen	-0.210	0.015	0.013	0.007
	(0.001)	(0.002)	(0.002)	(0.002)
GPA - Sophomore	-	-0.101	0.004	0.003
		(0.002)	(0.002)	(0.001)
GPA - Junior	-	-	-0.068	-0.011
			(0.002)	(0.002)
GPA - Senior	-	-	-	-0.051
				(0.002)
N	81294	65507	61376	58309

Notes: This table presents the results of OLS regressions in the form of equation (4). Columns (1) — (4) present results for freshmen, sophomore, junior, and senior years respectively. Each regression restricts to the sample of students who reach the corresponding year. The dependent variable is an indicator for whether the student drops out during that year. The main explanatory variables are the coherence accumulated, semester credit hours accumulated, and GPA in the corresponding year and the preceding years. The main explanatory variables are scaled to their standard deviations in each year. So the coefficients should be interpreted as the effect of a one standard deviation increase in each variable on dropout rate. Standard errors are clustered at school level.

Table 6: Effects of Lagging and Current Coherence on Dropout — Heterogeneity Results

	Freshmen Dropout	**Sophomore Dropout**	**Junior Dropout**	**Senior Dropout**
	(1)	(2)	(3)	(4)
Panel A: First Generation College Students				
Coherence - Freshmen	-0.029	-0.013	-0.012	-0.009
	(0.003)	(0.003)	(0.003)	(0.003)
Coherence - Sophomore	–	-0.019	-0.016	-0.009
		(0.003)	(0.003)	(0.003)
Coherence - Junior	–	–	-0.017	-0.009
			(0.003)	(0.002)
Coherence - Senior	–	–	–	-0.011
				(0.003)
Panel B: Economically Disadvantaged				
Coherence - Freshmen	-0.033	-0.008	-0.018	-0.020
	(0.003)	(0.003)	(0.004)	(0.003)
Coherence - Sophomore	–	-0.015	-0.017	-0.019
		(0.003)	(0.003)	(0.003)
Coherence - Junior	–	–	-0.024	-0.016
			(0.004)	(0.003)
Coherence - Senior	–	–	–	-0.014
				(0.003)
Panel C: STEM Majors				
Coherence - Freshmen	-0.041	-0.022	-0.020	-0.007
	(0.003)	(0.003)	(0.003)	(0.002)
Coherence - Sophomore	–	-0.020	-0.018	-0.011
		(0.003)	(0.003)	(0.002)
Coherence - Junior	–	–	-0.019	-0.010
			(0.003)	(0.002)
Coherence - Senior	–	–	–	-0.016
				(0.003)

Notes: This table presents the results of OLS regressions that estimate equation (4) for the subsamples of students who (a) is a first-generation college student; or (b) declared a STEM major in the year of interest. Columns (1) — (4) present result for freshmen, sophomore, junior, and senior years respectively. Each regression restricts to the sample of students who reach the corresponding year. The dependent variable is an indicator for whether the student drops out during that year. The main explanatory variables are the coherence accumulated in the corresponding year and the preceding years, scaled to its standard deviations. The regression also controls for current and lagging semester credit hours and GPA. Standard errors are clustered at school level.

Table 7: Institutions with DegreeWorks and Year of Implementation

Institution	Academic Year Implemented DW
Texas A&M - Commerce	2010-2011
Texas A&M - Corpus Christi	2010-2011
Sam Houston University	2011-2012
Texas A&M - Kingsville	2011-2012
Texas State University	2011-2012
Texas A&M - Texarkana	2011-2012
Texas A&M - San Antonio	2011-2012
Texas Tech University	2011-2012
UT - Rio Grande Valley	2011-2012
UT - San Antonio	**2014-2015**
Prairie View A&M University	**2014-2015**
Tarleton State University	**2015-2016**
Angelo State University	**2016-2017**
Midwestern State University	**2016-2017**

Notes: this table presents the list of Texas public 4-year institutions that have implemented DegreeWorks, as well as the academic year when the tool was implemented. The information on the year implemented were acquired from the institutions' registrar's office if not directly found on their websites. The five institutions that are the main source of exogenous variation in the event study are highlighted in bold.

Table 8: Comparison between OLS and IV - Concurrent Coherence

	Dropout Rate	
	OLS	IV
	(1)	(2)
Coherence	-0.013	-0.019
	(0.000)	(0.011)
Semester Credit Hours	-0.017	-0.011
	(0.000)	(0.002)
GPA	-0.081	-0.053
	(0.001)	(0.002)
F Score		395.3
N	562,274	562,274

Notes: this table presents the results of OLS regressions that estimate equation (3) — column 1 — and IV regressions that estimate equation (3) using introduction of DW as instrument for coherence — column 2. The dependent variable is an indicator for whether the student drops out. The main explanatory variables are the coherence accumulated in the corresponding year. The regression also controls for current semester credit hours and GPA. All specifications control for basic controls, including gender, ethnicity, high school standardized test scores, and parental income. Standard errors are clustered at school level.

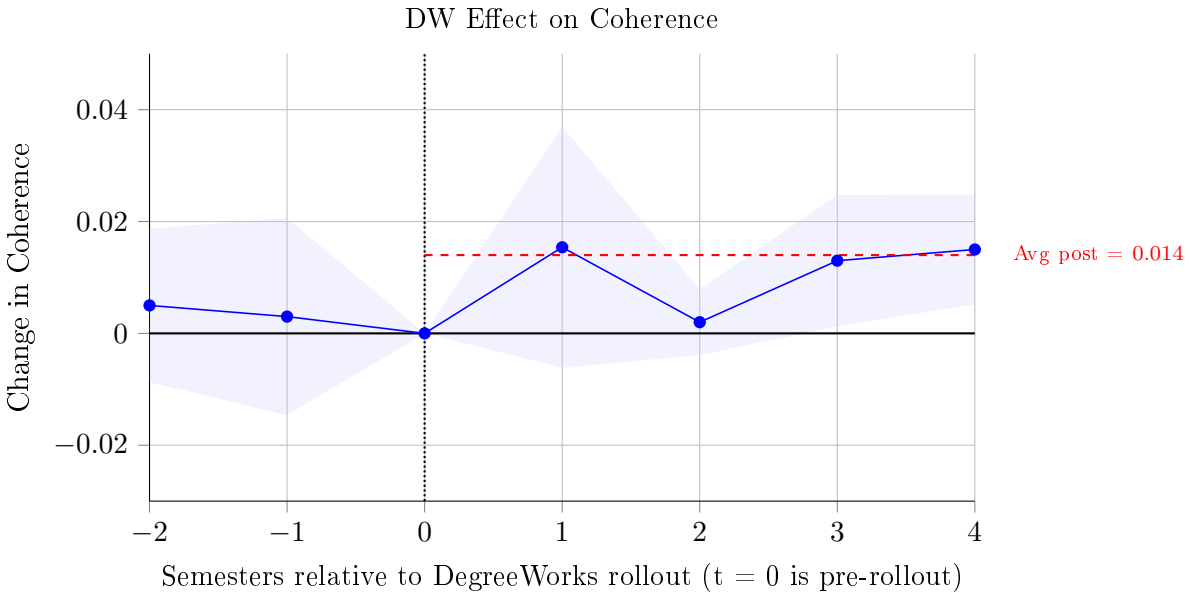


Figure 1: Treatment Effect of DW on Coherence

Note: this figure presents the estimated treatment effects of the introduction of DW on coherence, relative to the last period before treatment (T=0). The estimates are on the full sample of students and use dynamic TWFE (equation (8)) following de Chaisemartin and D'Haultfoeuille (2023). 95% confidence intervals are shown in wicks. The estimation controls for basic controls, including gender, ethnicity, high school standardized test scores, and parental income, as well as GPA, semester credit hours, and academic standing. Standard errors are clustered at school level.

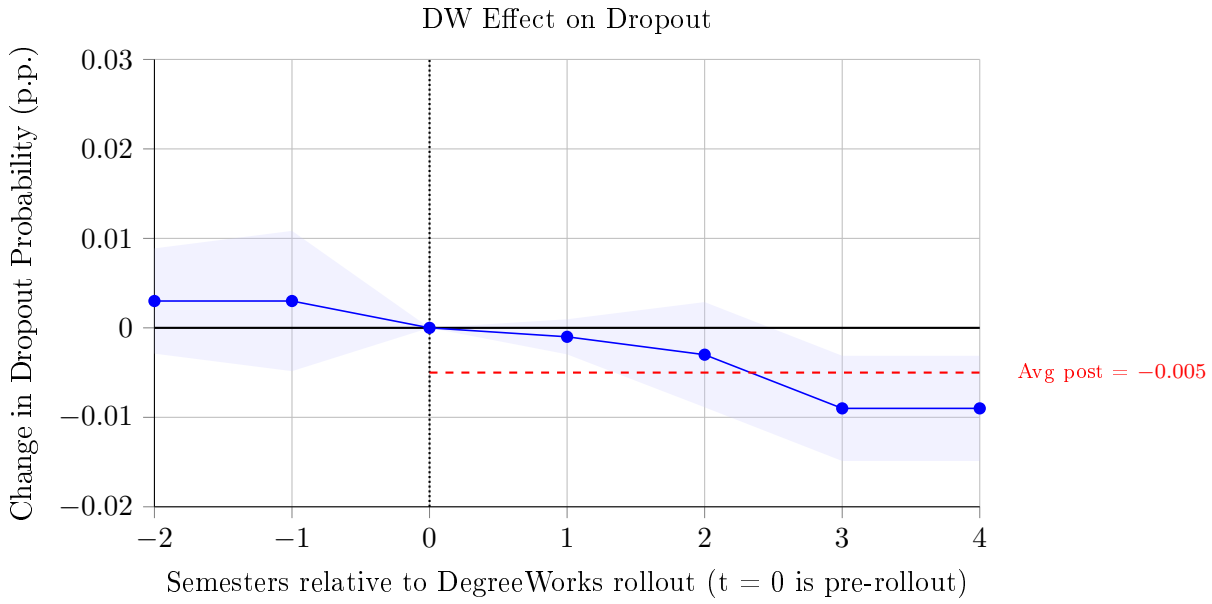
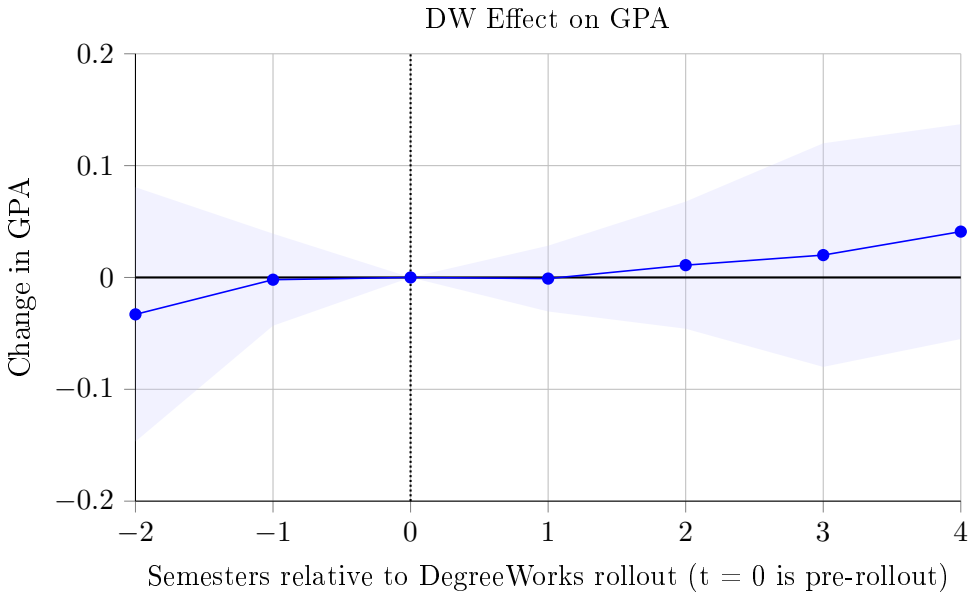
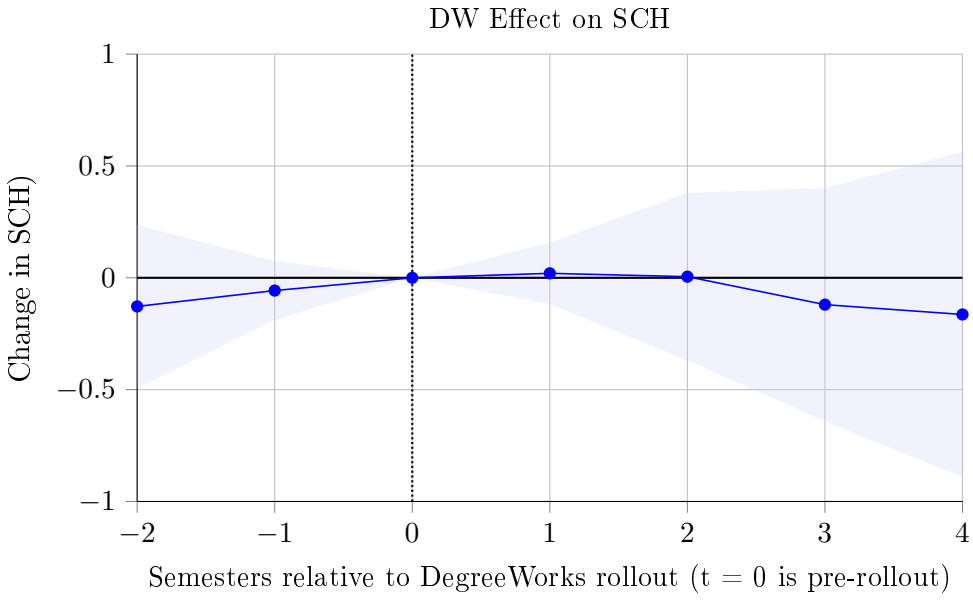


Figure 2: Treatment Effect of DW on Dropout

Note: this figure presents the estimated treatment effects of the introduction of DW on contemporaneous dropout rate, relative to the last period before treatment (T=0). The estimates are on the full sample of students and use dynamic TWFE (equation (8)) following de Chaisemartin and D'Haultfoeuille (2023). 95% confidence intervals are shown in wicks. The estimation controls for basic controls, including gender, ethnicity, high school standardized test scores, and parental income, as well as GPA, semester credit hours, and academic standing. Standard errors are clustered at school level.



(a) GPA



(b) SCH

Figure 3: Treatment Effect of DW on GPA and SCH

Note: this figure presents the estimated treatment effects of the introduction of DW on GPA (sub-figure a) and SCH (sub-figure b), relative to the last period before treatment (T=0). The estimates are on the full sample of students and use dynamic TWFE (equation (8)) following de Chaisemartin and D'Haultfoeuille (2023). 95% confidence intervals are shown in wicks. The estimation controls for basic controls, including gender, ethnicity, high school standardized test scores, and parental income, as well as GPA, semester credit hours, and academic standing. Standard errors are clustered at school level.

Appendix: Additional Tables and Figures

Table A.1: Accuracy of Audit of 16 Institution x Degree Pairs

Institution x Degree	**% in Catalog**
UT Austin x Business	88%
UT Austin x Biology	94%
UT Austin x Economics	74%
UT Austin x Communications	95%
U North Texas x Computer Science	100%
U North Texas x Biology	100%
UT Arlington x Business	88%
UT Arlington x Psychology	93%
Sam Houston State x Criminal Justice	98%
U Houston x Psychology	88%
UT Rio Grande Valley x Nursing	98%
UT San Antonio x Business	91%
UT El Paso x Mechanical Engineering	96%
Texas Tech x Biology	85%
UT Dallas x Computer Science	86%

Notes: This table presents the accuracy of the empirically identified degree requirements for 16 random institution x degree pairs. The audit focus on the degree requirements for the 2023 graduation cohort since I compare the empirically identified requirements to the current degree plans posted on the institutions' websites. The numbers presented here calculates the share of the empirically identified degree required courses that are found in the actual degree plans.

Table A2: Comparison between Alternative Thresholds - Concurrent and Lagged Coherence

	Freshmen Dropout	Sophomore Dropout	Junior Dropout	Senior Dropout
Main OLS				
1st Coherence	-0.021	-0.008	-0.010	-0.010
	(0.002)	(0.002)	(0.002)	(0.001)
2nd Coherence		-0.010	-0.010	-0.010
		(0.002)	(0.001)	(0.001)
3rd Coherence			-0.017	-0.011
			(0.002)	(0.001)
4th Coherence				-0.009
				(0.002)
N	81294	65507	61376	58309
OLS – Strict Coherence				
1st Coherence	0.001	-0.006	-0.004	-0.005
	(0.001)	(0.001)	(0.001)	(0.001)
2nd Coherence		-0.008	-0.004	-0.006
		(0.001)	(0.001)	(0.001)
3rd Coherence			-0.010	-0.007
			(0.001)	(0.001)
4th Coherence				-0.006
				(0.001)
N	81294	65507	61376	58309
OLS – Lax Coherence				
1st Coherence	-0.029	-0.011	-0.008	-0.005
	(0.001)	(0.001)	(0.001)	(0.001)
2nd Coherence		-0.015	-0.009	-0.008
		(0.001)	(0.001)	(0.001)
3rd Coherence			-0.020	-0.010
			(0.001)	(0.001)
4th Coherence				-0.013
				(0.001)
N	81294	65507	61376	58309

Note: This table presents the results of OLS regressions in the form of equation (4). Columns (1) — (4) present results for freshmen, sophomore, junior, and senior years respectively. Each regression restricts to the sample of students who reach the corresponding year. The dependent variable is an indicator for whether the student drops out during that year. The top panel uses the main coherence measure used. The middle panel uses a "strict" coherence measure, where the thresholds of share of graduates who have taken a course is 95% for required courses and 50% for elective courses. The bottom panel uses a "lax" coherence measure, where the thresholds are 70% and 20% instead. Standard errors are clustered at school level.

Table A3: Comparison between Alternative Definitions - Concurrent and Lagged Coherence

	Freshmen Dropout	Sophomore Dropout	Junior Dropout	Senior Dropout
Main OLS				
1st Coherence	-0.021	-0.008	-0.010	-0.010
	(0.002)	(0.002)	(0.002)	(0.001)
2nd Coherence		-0.010	-0.010	-0.010
		(0.002)	(0.001)	(0.001)
3rd Coherence			-0.017	-0.011
			(0.002)	(0.001)
4th Coherence				-0.009
				(0.002)
N	81294	65507	61376	58309
OLS – Alternative Coherence				
1st Coherence	-0.038	0.002	-0.001	-0.006
	(0.001)	(0.002)	(0.001)	(0.001)
2nd Coherence		-0.022	-0.004	-0.002
		(0.001)	(0.002)	(0.001)
3rd Coherence			-0.014	-0.002
			(0.002)	(0.001)
4th Coherence				-0.004
				(0.002)
N	81294	65507	61376	58309

Note: This table presents the results of OLS regressions in the form of equation (4). Columns (1) — (4) present results for freshmen, sophomore, junior, and senior years respectively. Each regression restricts to the sample of students who reach the corresponding year. The dependent variable is an indicator for whether the student drops out during that year. The top panel uses the main coherence measure used. The bottom panel uses an alternative definition of coherence, which is the share of courses taken that satisfy degree requirements. Standard errors are clustered at school level.

Table A4: Effect of Coherence, Credits, and GPA on Persistence, Associate Degree Attainment, Transfer to 4-Yr College, and Bachelor's Degree Attainment for Community College Students

	Dropout		Associate Degree		Transfer to 4-Yr		Bachelor's Degree	
	1st Year	2nd Year	1st Year	2nd Year	1st Year	2nd Year	1st Year	2nd Year
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Coherence - 1st Year	-0.007	0.001	-0.000	-0.008	0.009	0.012	0.009	0.028
	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)
Coherence - 2nd Year		-0.006		-0.009		0.019		0.001
		(0.003)		(0.003)		(0.003)		(0.002)
Semester Credit Hours - 1st Year	-0.057	-0.035	0.041	0.011	0.043	0.035	0.024	0.011
	(0.003)	(0.003)	(0.000)	(0.005)	(0.003)	(0.005)	(0.000)	(0.003)
Semester Credit Hours - 2nd Year		-0.099		0.087		0.084		0.056
		(0.003)		(0.003)		(0.003)		(0.003)
GPA - 1st Year	-0.175	-0.008	0.110	0.015	0.132	0.003	0.074	0.019
	(0.001)	(0.004)	(0.001)	(0.006)	(0.001)	(0.004)	(0.001)	(0.004)
GPA - 2nd Year		-0.182		0.150		0.126		0.072
		(0.003)		(0.003)		(0.003)		(0.003)
N	108,833	27,657	108,833	27,657	108,833	27,657	108,833	27,657

Notes: This table presents the results of regressions in the form of equation (3). Columns (1) — (2) presents results for dropping out without transfer or Associate Degree. Columns (3) — (4) presents results for Associate Degree attainment. Columns (5) — (6) presents results for transferring to a four-year college. Columns (7) — (8) presents results for Bachelor's Degree attainment. Each regression restricts to the sample of students in community colleges who reach the corresponding year. The main explanatory variables are the coherence accumulated, semester credit hours accumulated, and GPA in the corresponding year. The main explanatory variables are scaled to their standard deviations in each year. Robust standard errors are reported in parentheses.

Table A.5: Comparison between OLS and IV - Concurrent and Lagged Coherence

	Dropout			
	Freshmen	**Sophomore**	**Junior**	**Senior**
Main OLS				
1st Coherence	-0.021	-0.008	-0.010	-0.010
	(0.002)	(0.002)	(0.002)	(0.001)
2nd Coherence		-0.010	-0.010	-0.010
		(0.002)	(0.001)	(0.001)
3rd Coherence			-0.017	-0.011
			(0.002)	(0.001)
4th Coherence				-0.009
				(0.002)
N	81294	65507	61376	58309
IV				
1st Coherence	-0.037	-0.000	-0.017	-0.025
	(0.007)	(0.008)	(0.011)	(0.014)
2nd Coherence		0.015	0.007	-0.008
		(0.010)	(0.011)	(0.015)
3rd Coherence			-0.010	-0.049
			(0.016)	(0.014)
4th Coherence				-0.025
				(0.013)
N	81294	65507	61376	58309

Note: This table presents the results of OLS regressions in the form of equation (4). Columns (1) — (4) present results for freshmen, sophomore, junior, and senior years respectively. Each regression restricts to the sample of students who reach the corresponding year. The dependent variable is an indicator for whether the student drops out during that year. All specifications control for basic controls, including gender, ethnicity, high school standardized test scores, and parental income. The top panel is the main OLS estimates reported in table 5. The bottom panel uses an IV strategy where the instruments are the interactions of the introductions of DW and students' entering cohort. Standard errors are clustered at school level.

Appendix B: Factors for Coherence Accumulation

Another goal of the empirical analysis is to understand factors that contribute to the production of coherence. The baseline regression is:

$$\text{Coherence}_{it} = \alpha_0 + \alpha_x X_{it} + \alpha_s S_j + \alpha_m M_{it} + \epsilon_{it} \tag{6}$$

where X_{it} includes gender, ethnicity, parental income, parental education, and high school test scores. Similar to previous specifications, S_j are fixed effects for institutions enrolled, and M_{it} are fixed effects for the major a student is enrolled in. To compare coherence production to the accumulation of semester credit hours, I also run regressions following equation (5), but with the dependent variable substituted with credits accumulated.

To examine whether quality of institution is related to coherence accumulation, I proxy quality with the US News and World Reports ranking of institutions, rank_j, and estimate:

$$\text{Coherence}_{it} = \alpha_0 + \alpha_x X_{it} + \alpha_r \text{rank}_j + \alpha_m M_{it} + \Omega_i + \epsilon_{it} \tag{7}$$

The ranking of institutions is most likely correlated with unobservable student characteristics. To control for selection issues, I follow Dale and Krueger's (2002) idea of addressing selection into specific institutions by controlling for the programs a student applied to and was admitted to. Ω_i includes a vector of indicators that specifies the institutions that student i applied to and were admitted to. Given the availability of data, Ω_i only considers students' application portfolio among Texas public four-year institutions.[8]

Results — Factors Effecting Coherence

I now turn to the results on factors that contribute to the production of coherence. First, I test for impact of individual-level factors, including parental income, first-generation college student status, and high school test scores. Second, I examine whether the quality of institution affects students' coherence accumulation.

To examine the impact of individual-level factors, I run regressions following equation (6). The estimates for freshmen, sophomores, juniors, and seniors are reported separately in Table B1. Students with higher high-school test scores accumulate coherence faster — a one decile increase in HS test score is associated with 0.4 pp, 0.3 pp, 0.3 pp, and 0.1 pp improvements in coherence accumulation each semester in freshmen, sophomore, junior, and senior years, respectively. Students with higher parental income also accumulate coherence faster — the effect of a three decile increase in parental income is roughly equivalent to that of a one decile increase in HS test score. First generation college students accumulate less coherence and the gap to students with college-educated

[8] Mountjoy and Hickman (2021) and Altonji and Zhu (2025) also use the Dale-Krueger approach on the Texas administrative data.

parents is roughly equivalent to the impact of a 5 percentile increase in HS test scores. These results suggest that parental resources, both monetary and non-monetary, may be substitutes to academic advising when it comes to the quality of course selections.

I run regressions that control for students' application / admission portfolios following equation (7). The results on the effect of four-year college ranking on coherence and credit accumulation are reported in Table B2. The results show that higher ranked institutions are better at helping students accumulate coherence faster. A drop in ranking by 100 (i.e., moving from a top 100 college to a top 200 college) reduces coherence accumulation by 0.4 pp, 0.2 pp, 0.1 pp, and 0.2 pp for freshmen, sophomores, juniors, and seniors, respectively. Compared to results in Table B1, this is similar to the effects of a one decile increase in high school test score or a 3 decile increase in parental income. In comparison, enrolling in lower ranking institutions actually increases the number of semester credit hours accumulated (bottom panel of Table B2). Notice that, since the standard deviation of coherence accumulation is around 10 pp, the impacts of the factors above are not large.

Table B1: Production Functions of Coherence

	Coherence			
	Freshmen	Sophomore	Junior	Senior
	(1)	(2)	(3)	(4)
HS Test Score Decile	0.0040	0.0030	0.0030	0.0014
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Parent Income Decile	0.0014	0.0011	0.0009	0.0004
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
First Gen	-0.0030	-0.0017	-0.0007	-0.0013
	(0.0001)	(0.0001)	(0.0001)	(0.0004)
N	181,146	140,131	133,962	155,491

Notes: This table presents the estimates for β from regressions in the form of equation (7). HS test score is the students' performance in the Texas standardized exams in high school. First Gen is an indicator for first generation college students.

Table B2: Ranking and Production of Coherence and Credits

	Coherence			
	Freshmen	Sophomore	Junior	Senior
+100 in Ranking	-0.0040	-0.0017	-0.0009	0.0015
	(0.0004)	(0.0005)	(0.0004)	(0.0002)
	Semester Credit Hours			
	Freshmen	Sophomore	Junior	Senior
+100 in Ranking	0.080	0.120	0.060	0.070
	(0.007)	(0.008)	(0.001)	(0.009)
N	435,440	381,605	372,127	465,656

Notes: This table presents the estimates for λ from regressions in the form of equation (8), controlling for students' application and admission portfolio. The top panel presents results for the production of coherence while the bottom panel presents results for the production of credit accumulation. Robust standard errors are reported in parentheses.