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# Toward a Comprehensive Model Predicting Credit Loss in Vertical Transfer

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## Author Note

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**Abstract**

A growing body of research has documented extensive credit loss among transfer students. However, the field lacks theoretically driven and empirically supported frameworks that can guide credit loss research and reforms. We develop and then test a comprehensive framework designed to address this gap using novel administrative credit loss data from Texas. Our results demonstrate how the likelihood of credit loss varies across course characteristics, majors, pretransfer academics, student characteristics, and sending and receiving institutions. Additionally, we are able to disentangle general credit loss from major credit loss and examine how they vary across institutions, majors, and the combination of both. The extensive variation in credit loss among universities in particular underscores the need for future research and reform.

## Introduction

Whether community colleges serve as an efficient and effective pathway to the baccalaureate hinges on their ability to support the transfer of students and credits to universities. The majority of beginning community college students intend to transfer to a university (Community College Center for Student Engagement, 2017). Of the one-third who do successfully transfer (National Student Clearinghouse, 2024), a large percentage lose at least some credits they earned at the community college. Simone's (2014) national estimates using data from the National Center for Education Statistics Beginning Postsecondary Students Longitudinal Study (BPS) suggest two-thirds of transfer students lose at least some credits, and 40% lose all of them. The threat of credit loss has led to state reforms aimed at mitigating it. Common course numbering, core curricula, fields of study, statewide articulation agreements, and guaranteed transfer associate degrees are examples of statewide strategies for reducing the loss of credits among transfer students and, by extension, improving the efficiency and effectiveness of vertical transfer (Education Commission of the States [ECS], 2022).

However, research on the effectiveness of these strategies is mixed. Although some studies suggest that policies such as statewide articulation agreements or core curriculum promote the transfer of students and/or credits (Anderson et al., 2006; Boatman & Soliz, 2018; Spencer, 2021), others have found limited effects of statewide policies on these outcomes (Gross & Goldhaber, 2009; LaSota & Zumeta, 2016; Roksa & Keith, 2008). In turn, researchers and reformers have increasingly highlighted the role of institutional policies, practices, and culture in shaping the transfer of students and credits across institutions.

Although there is theoretical justification for emphasizing the role of institutions in shaping the transfer of students and credits, the primary causes of credit loss generally and the role of institutions in mitigating or exacerbating credit loss specifically remain insufficiently explored. There are five primary gaps in the literature. First, course-level data on credit loss is rarely collected by states, limiting research on credit loss overall. Second, no research on credit loss has examined or sufficiently controlled for the pretransfer courses students completed, despite their obvious bearing on credit loss. Third, quantitative research on credit loss has been able to assess only *general credit loss* (GCL), where credits fail to transfer between institutions at all, despite the known issue of *major credit loss* (MCL), where credits transfer but do not apply to the student's major (Giani et al., 2024; Kadlec & Gupta, 2014). Fourth, conceptual frameworks have not been developed specifically to guide the study of credit loss. Fifth, limited research has examined the extent to which credit loss varies across institutions, particularly when controlling for factors that influence credit loss that may be articulated in a conceptual framework.

This study addresses these gaps by using novel administrative data capturing credit loss. Beginning in 2020, the Texas Higher Education Coordinating Board (THECB) began collecting student-by-course-level data on every credit that was lost by students who transferred from community colleges to public universities in the state. This data allows us to examine the relationship between course characteristics and credit loss and to more properly control for pretransfer courses in our analyses. In addition, this data indicates the reason credits were lost, enabling us to disentangle MCL from GCL. After reviewing the literature on student transfer, we developed and then tested a novel conceptual framework by applying it to Texas's statewide credit loss data. Thus, we can produce some of the first estimates of how credit loss varies across institutions, controlling for a range of factors theorized to relate to credit loss.

This paper is outlined as follows. We first review the extant literature on credit loss and describe the methods used to measure credit loss. We then offer a novel conceptual framework that can be used to examine the predictors of credit loss, where we identify seven key factors (and interactions between them) theorized to shape credit loss: (a) course characteristics, (b) major pathways and programs of study, (c) pretransfer academics, (d) student characteristics, (e) sending institution policies and practices, (f) receiving institution policies and practices, and (g) state and system policy. We then describe our methods for examining credit loss, applying this conceptual framework to analyses of total, major, and general credit loss using Texas administrative data. Our results provide novel evidence of the extent to which factors in our conceptual framework predict credit loss and how credit loss varies across institutions. We conclude by discussing how these results can both stimulate future research on the causes and consequences of credit loss and inform the development of new institutional policies, practices, and strategies designed to minimize the loss of credit for transfer students.

## Prior Literature on Credit Loss

Historically, limited access to detailed data about credit transferability hindered the direct measurement of credit loss. As a proxy, researchers examined excess credit accumulation among baccalaureate recipients, typically comparing vertical transfers with “native” students who began at a 4-year institution. Using Texas state administrative data, Cullinane (2014) found that baccalaureate recipients who began at a community college attempted, on average, 150 degree-bearing credits (i.e., not developmental education), compared with 142 credits among native 4-year students—at least two fewer courses. Estimates from other states reached similar conclusions, illustrating that 2-year college entrants accrued between 8 and 10 more excess credits than similar 4-year college entrants (Fink et al., 2018; Xu et al., 2016).

Although extant research suggests that vertical transfer students lose about 2–3 courses worth of credits during transfer, other explanations are possible. For example, transfer students may take additional elective courses at their transfer destination, change their majors, or repeat courses to improve their GPA to facilitate transfer into a more selective major, all of which could contribute to excess credit accumulation without credit loss (Liu et al., 2021; Schudde et al., 2023). Perhaps the most important limitation of research that relies on excess credit accumulation as a proxy for credit loss is its focus on baccalaureate recipients, a restriction that is necessary to calculate excess credits. Students who never earn a degree are excluded from these calculations, which is problematic because credit loss *may deter students from baccalaureate attainment.* Given the low rates of bachelor's degree completion among vertical transfer students, excess credit accumulation among baccalaureate recipients may not be a strong proxy for credit loss.

In the past decade, postsecondary transcript data collected as part of the BPS survey and some state administrative data have allowed researchers measure credit loss more directly (Government Accountability Office [GAO], 2017; Giani, 2019; Monaghan & Attewell, 2015; Simone, 2014). However, these estimates remain a rough proxy for credit loss. Some courses may be accepted by an institution for credit but do not apply toward the student's major or facilitate progress toward a degree (Fink et al., 2018; Kadlec & Gupta, 2014). Although the importance of MCL has been underscored in prior research, to our knowledge, the extant literature using BPS data (GAO, 2017; Monaghan & Attewell, 2015; Simone, 2014) or state administrative data (Giani, 2019) has not systematically measured MCL or distinguished between MCL and GCL, which refers to courses that the institution does not accept for credit upon transfer.

Given these data limitations and the associated challenges with operationalizing credit loss, research on the predictors of credit loss is sparse. To our knowledge, Richardson's (2023) recent dissertation on credit loss among engineering transfer students at one university is the only study, apart from Giani's (2019) analysis of administrative data from Hawaii and North Carolina, that has statistically examined predictors of credit loss.

## Credit Loss Conceptual Framework

The dearth of research on the correlates of credit loss has hindered the field's development of conceptual frameworks. Therefore, we developed a novel conceptual framework synthesizing extant literature on factors that influence transfer student outcomes, such as the likelihood of transfer, persistence and attainment of transfer students, and degree efficiency (e.g., excess credit accumulation and time-to-degree). Specifically, we identified seven key factors and described the mechanisms through which they may contribute to credit loss (or credit transferability): (a) course characteristics, (b) major pathways and programs of study, (c) pretransfer academics, (d) student characteristics, (e) sending institution policies and practices, (f) receiving institution policies and practices, and (g) state and system policy. The sections below elaborate on each component of our conceptual framework, which informs our analytic models.

### Course Characteristics

First, whether a credit can transfer depends on the characteristics of the course being considered. Although this seems obvious, there are a variety of ways to measure course characteristics, and different approaches affect our ability to predict credit transfer and to estimate institutional influence on credit applicability. College courses are often divided into three categories: academic, technical/workforce, and noncredit or personal enrichment (D'Amico et al., 2017; Xu & Ran, 2020). Academic courses are those in academic subjects that are offered by both 2-year and 4-year institutions, such as English, mathematics, and the sciences. Technical/workforce courses are those aligned with what has historically been referred to as vocational education, career and technical education, or workforce programs offered at community and technical colleges. Although these courses can confer college credit, in general, that credit is applicable only to the program of study at the community or technical college level, given that public universities seldom have programs in these technical fields. Noncredit courses include a variety of courses that tend to be offered to students for personal enrichment, most often taken by adult learners outside of a credit-bearing program (Xu & Ran, 2020). Generally speaking, academic courses are designed to be transferrable, technical courses are occasionally transferrable (though typically toward an applied baccalaureate), and noncredit courses are nontransferable (Kuneyl, 2022).

Within the category of academic courses designed for transfer, the characteristics of a course may influence its transferability. There are two particularly salient components of course characteristics: the content of the course and its method of delivery. The former can be understood at different levels of granularity. At the coarsest level, courses can be categorized into broad subjects such as Business, Humanities and Liberal Arts, and STEM (science, technology, engineering, and mathematics). These categories align loosely with different colleges typically found on university campuses (Bastedo, 2011). A more refined categorization identifies the specific subject of the course (e.g., engineering, English, chemistry), typically identified by course prefixes (e.g., ENGR, ENGL, CHEM). The most precise measurement of course content is the specific course completed, typically identified by combining a course prefix with a course number (e.g., ENGL 302, CHEM 408). We hypothesized that using more granular measures of course content would improve the accuracy of our predictions.

In addition to proxies for course content, the method of the course's delivery could influence its transferability. Courses can be offered in-person, online, or in a hybrid modality (Huntington-Klein et al., 2017; Jaggars, 2014; Xu & Jaggars, 2011). Perceived differences in the quality of online/hybrid vs. in-person courses may influence university decisions about whether to accept courses for transfer (Xu & Jaggars, 2014). Courses can also be taken in-residence by enrolled students or through dual-credit or dual-enrollment courses taken by high school students (An & Taylor, 2019). As with course modality, stakeholders' perceptions that dual-credit courses are "less rigorous" could lead to their denial for transfer credit (Duncheon & Relles, 2020). Finally, although not a course delivery characteristic per se, we note that in states with a transferable core, courses that are part of that core should be more likely to transfer.

**Majors and Programs of Study**

Credit loss is likely to vary across the majors or programs of study students transfer into, particularly in states or higher education systems without policies that mandate credit transferability in specific major pathways. Indeed, excess credit rates among transfer students vary across majors (Cullinane, 2014). Many transfer students report that their pretransfer credits do not apply credits to their chosen major at their destination university (Kadlec & Gupta, 2014; Hodara et al., 2016), the phenomenon of MCL noted previously and elaborated upon below.

There are three primary reasons we would hypothesize for variation in credit loss across majors. The first relates to university governance. Academic departments are primarily responsible for developing majors and determining the curricular requirements that comprise them. Although central university administrations have long shaped curricular requirements

(Bastedo, 2011) and state-level policies such as core curricula and guaranteed transfer associate degrees may constrain departmental autonomy over majors, faculty within departments remain powerful influencers of program requirements and credit transferability (O'Neil, 2011; Schmidtlein & Berdahl, 2011; Schudde et al., 2021). More selective majors may be restricted to transfer students who completed aligned prerequisite courses, and transfer students may be forced to enroll in a major other than what they intended, which could contribute to credit loss (Musoba et al., 2018).

Second, some transfer pathways are more commonly traversed than others, and research suggests that pathways with higher transfer rates may be more likely to be the target of reform aimed at facilitating credit transfer. Hodara et al.'s (2017) analyses of credit mobility policies discussed how the City University of New York system, the University of California system, and state administrators in Washington State implemented transfer policy reforms specifying pre-major coursework for transfer students in the hopes of mitigating credit loss. In each case, state and/or system leaders targeted their most popular majors. In addition, majors with higher transfer rates result in greater opportunities (and needs) for universities and academic departments to determine the applicability of pretransfer coursework to major requirements.

Third, majors vary in terms of the rigidity vs. flexibility of the courses that comprise the program of study (Heileman et al., 2018; Jarratt et al., 2024; Kizilcec et al., 2023). This variation can be analyzed both in the design of majors and in the empirical paths students traverse through them. Heileman et al. (2018) discussed the *structural complexity* of majors, indicated by characteristics such as long, sequential chains of prerequisite courses; gateway courses early in a major; and bottleneck courses that must be passed before advancing into certain upper-division courses. Kizilcec et al. (2023) and Jarratt et al. (2024) analyzed the timing and sequence of coursetaking between majors to examine similarity in the curricular pathways traversed by students in the same major described as *path homogeneity*. Although we are not aware of studies linking the rigidity vs. flexibility of majors to credit loss, some researchers (Baker, 2016; Baker et al., 2023) have found that more structured pathways at the community college level may promote transfer and university completion rates. However, majors with greater path homogeneity at the university level could also relate to higher levels of credit loss.

**Pretransfer Academics**

Students' pretransfer academic experiences may shape their risk of credit loss. Apart from the specific courses students completed prior to transfer, the three most salient pretransfer academic characteristics are students' academic performance, their total pretransfer credits, and the credentials they earned before transfer. In regard to academic performance, both individual course grades and overall pretransfer GPA may influence credit loss. Receiving institutions may set grade standards for credit transfer that are higher than the grade needed to pass the course and receive credit, implying that these courses may transfer as passed credit but not count toward specific degree requirements (Bicak et al., 2023). Students' pretransfer GPA may influence which universities and majors they are admitted to (Bleemer & Mehta, 2022). Students with lower pretransfer GPAs may therefore have to enroll in institutions or majors that were not their first choice. If their pretransfer coursetaking was informed by their intended destination institution and major, this could result in students enrolling in institutions and majors where they are more likely to experience credit loss.

The number of credits students earn before transfer may also influence their risk of credit loss. In general, community colleges do not offer many upper division courses that students complete in their junior and senior year of a baccalaureate program. If students earn large numbers of credits before transfer (e.g., > 60), the likelihood that they are completing courses that will not transfer or apply to major requirements increases. Indeed, Giani (2019) found that students with 76–90 or 91–105 credits had more than twice the odds of experiencing any credit loss than students who completed 1–15 credits, and these two groups lost 17 and 27 more credits on average, respectively, than students in the 1–15 credit group. However, Giani (2019) also found that students with 16–30 and 31–45 credits had lower estimated odds of any credit loss than those in the 1–15 credit group, suggesting the possibility of a nonlinear relationship between pretransfer credits and credit loss.

Whether students earn credentials before transfer may also relate to the magnitude of credit loss they experience. As discussed further below, the most common policy in this vein relates to the guaranteed transfer of associate degrees. Typically, the 35 states with such policies guarantee that students who complete an associate degree prior to transfer must be able to transfer and apply all of the courses in the associate degree, enter into the university with junior standing, and be exempt from any additional lower-division course requirements (ECS, 2022). Therefore, we would assume that students in such states who completed an eligible associate degree, took no additional pretransfer courses, and transferred to a university should experience no credit loss. Even in states without statewide policies, universities and community colleges may establish similar policies that provide the same guarantees to students who earn eligible associate degrees prior to transfer. In contrast, other sub-baccalaureate credentials, such as certificates conferred by community colleges, tend not to be included in transfer guarantees and are therefore unlikely to shield students from credit loss. Students may also earn “procedural” credentials that signify their completion of certain milestones, such as completing the state’s core curriculum, which may mitigate their risk of credit loss.

**Student Characteristics**

Although research on how credit loss varies across student populations is limited, theoretical frameworks and empirical findings suggest the possibility of inequalities in credit transfer across racial/ethnic, socioeconomic, gender, and age groups. There are persistent demographic inequities in the likelihood of vertical transfer among community college entrants. Black and Latino students are less likely to transfer than White and Asian students, a phenomenon described as the "racial transfer gap" (Chase et al., 2012; Crisp & Nuñez, 2014; Wood et al., 2011). Low-SES students, as measured by factors such as Pell eligibility and parental education, transfer at lower rates than higher-SES students (Dougherty & Kienzl, 2006; Dowd & Melguizo, 2008; Wood et al., 2011). Although some studies suggest no relationship between gender and the likelihood of vertical transfer (Wood et al., 2011), women tend to be more likely to complete bachelor's degrees among vertical transfer students (Wang, 2009). If women tend to navigate the transfer process more successfully than men, they may also have lower odds of credit loss. Research also suggests that older students may be more likely to face challenges in navigating transfer (Ishitani, 2008; Rosenberg, 2016).

Lanaan et al. (2010) advanced the framework of *transfer student capital* to move beyond the historical focus on the "transfer shock" experienced by vertical transfer students and to highlight how the knowledge, experience, and connections students develop pretransfer may help them navigate the transfer. Although researchers have not established an empirical link between transfer student capital and credit loss, Lanaan et al. (2010) hypothesized that transfer student capital comprised knowledge of topics such as "understanding credit-transfer agreements between colleges" (p. 177). This may include an understanding that credit transfer and applicability decisions can be revised at the discretion of university faculty and students can appeal credit denial decisions. Research has shown that students rely heavily on family and peers in developing transfer student capital, and sociodemographic inequalities may exist in students' access to this information in their personal networks (Jabbar et al., 2020; Maliszewski Lukszo & Hayes, 2020). Racial/ethnic and socioeconomic inequalities in transfer student capital may therefore translate into racial/ethnic and socioeconomic inequalities in credit loss.

**Sending Institutions**

Credit loss rates vary considerably across types of sending institutions. As the GAO (2017) report detailed, students who transferred from a private for-profit institution to a public institution lost 94% of their credits on average, compared with 37% for students who transferred between public institutions. Disaggregating by institutional control and sector reveals even starker differences. Students transferring from a 2-year private for-profit to a 2-year public school lost 97% of their credits, compared with 22% for students who took the traditional vertical transfer route from a 2-year public to a 4-year public institution. Largely, credit loss rates are inversely related to how often students traverse that transfer path. It is unsurprising that 2-year public to 4-year public transfers experience the least credit loss given the long-standing role community colleges have played in facilitating vertical transfer (Kisker et al., 2023). In contrast, only 1% of all transfer students transferred between a 2-year private for-profit and a 2-year public college—perhaps why those transfer students lose 97% of their credits on average.

Although the GAO (2017) study documented considerable variation in credit loss rates across types of sending institutions, it did not examine variation in credit loss between sending institutions of the same type. Yet some community college practices may exacerbate credit loss. For example, a common practice of community colleges is to encourage students to focus on completing their general education requirements before choosing a major to maximize flexibility

(Bailey et al., 2015; Grubb, 2006). Fink et al.'s (2018) analysis of excess credit accumulation showed that community college students who took large numbers of entry-level courses (100- or 200-level) accumulated more excess credits. They concluded that this practice may be "bad advice" if it results in students attempting lower-division courses that are misaligned with their eventual major. Community colleges have also been critiqued for their "cafeteria model" of program and course offerings, which may provide students with a bewildering array of pathways to pursue that prevent them from making informed decisions about the courses most aligned with their intended programs of study (Bailey et al., 2015).

In contrast, the "guided pathways" movement contends that a variety of community college practices may promote transfer student outcomes and mitigate credit loss (Bailey et al., 2015). These practices include early advising to help students choose a major and create a plan for their coursework, creating "program plans" or default sequences of courses aligned with those majors, limiting the number of choices and course substitutions in these default plans, and developing "meta-majors" for students who are undecided about which program they'd like to pursue. These reforms are designed to help students choose a pathway more quickly and confidently and to minimize deviations from those plans that may contribute to credit loss (Jenkins & Cho, 2013).

Credit loss may also vary across sending institutions because of the absence or presence of articulation agreements and transfer partnerships between sending and receiving institutions (Jenkins et al., 2014; Shulock & Moore, 2014). In their examination of highly effective transfer partnerships, Fink and Jenkins (2017) identified the creation of "clear programmatic pathways with aligned high-quality instruction" in combination with "tailored transfer advising" as some of the key practices of these highly effective partnerships. Although state policy may guarantee that courses in the core curriculum transfer and apply across all public institutions, whether courses apply to specific major requirements at the receiving institution may depend on the existence of a formal partnership with the community college.

**Receiving Institutions**

Even for similar students who transfer from the same institution with identical pretransfer academic characteristics, the institution they transfer to predicts their likelihood and magnitude of credit loss (Giani, 2019). This may be due to the presence or absence of articulation agreements with the sending institution (as discussed above), as well as statewide policy that governs credit transferability (discussed below) that may differentially impact universities. However, receiving institutions may also vary in their rates of credit loss among transfer students because of how they implement state policy, the institutional transfer policies and practices they employ outside of statewide mandates, and the institution's transfer culture.

University faculty and administrators exert "disproportionate influence" over how transfer policy and practice gets enacted (Schudde et al., 2021; Schudde & Jabbar, 2024). Schudde et al. (2021) documented how university faculty councils severely limited the development and implementation of statewide policy that would have mandated the transfer and applicability of credits within specific *fields of study*, arguing that the policy would threaten "the authority and responsibility of higher education faculty to design curriculum" (p. 71). Other studies have also highlighted how universities have attempted to stymie state policies that would limit their institutional autonomy over how credits transfer and apply to specific majors (Logue, 2018; Senie, 2016). Even in the presence of statewide policies, universities may vary in how they implement them.

Given these dynamics in the transfer field, scholars have argued for the importance of developing *transfer receptive culture* at universities, particularly to promote equity in transfer students' outcomes. Transfer receptive culture comprises university strategies such as the prioritization of transfer students in undergraduate admissions, outreach and information dissemination to prospective transfer students, and the dedication of resources and supports at the university designed to facilitate transfer student success (Jain et al., 2011). The extent to which universities are willing to partner with community colleges to develop transfer pathways is a key ingredient in highly effective transfer partnerships (Fink & Jenkins, 2017). However, universities perceived as the most selective—those focused on "prestige maximization"—often hold the most power to thwart efforts to facilitate credit transferability (Schudde et al., 2021; Winston, 1999). Thus, whereas some university stakeholders may seek to subvert statewide transfer mandates and stymie the transfer and applicability of pretransfer credits, transfer-receptive cultures at others may promote the transfer of both students and credits from community colleges to universities.

**State and System Policy**

Although the present study is focused on the role of institutions within a single state, states have also adopted policies designed to facilitate the transfer of credits between institutions and programs. They vary in their prescriptiveness and granularity, and the lack of detailed credit loss data historically collected by states and federal data collections has hindered research on which policies might effectively mitigate credit loss. Nevertheless, the influence of institutions on credit loss may be constrained or enabled by the state policies that govern higher education.

State coordinating or governing boards may adopt a transferable core of lower-division courses, and 38 states have done so (ECS, 2022). States vary in their approach to the transferable core. In some states, students must complete the entire core to ensure all courses in the core will transfer, whereas in other states, any course completed in the core curriculum will transfer, regardless of whether students completed the core. States also vary in whether they allow institutions to require additional general studies courses beyond the requirements of the core curriculum. For example, Alabama requires institutions to do so, whereas in California a student's completion of the core curriculum means they are "deemed to have completed all lower division general education requirements" (Cal Educ. Code § 66720).

The most stringent state course transferability policy is the guaranteed transfer associate degree. Whereas the transferable core curriculum generally includes 30–45 credits, associate degrees typically include 60 credits. In states with guaranteed transfer associate degrees, students who complete such a degree before transferring typically have all 60 credits transfer and apply to the baccalaureate program, transfer in as juniors, and are required to complete only the remaining 60 credits (with some exceptions) to complete their bachelor's degree. According to ECS (2022), 35 states have adopted statewide guaranteed transfer of associate degrees.

Despite the widespread presence of state policies designed to facilitate credit transfer, research on their effectiveness is mixed or absent (Anderson et al., 2006; Boatman & Soliz, 2018; Gross & Goldhaber, 2009; LaSota & Zumeta, 2016; Roksa & Keith, 2008; Spencer, 2021). To our knowledge, only Lasota and Zumeta (2016) analyzed the relationship between common course numbering and transfer probability. They found some significant relationships between this policy and transfer for particular subgroups but no relationship for the entire population of beginning community college students. Research suggests a positive relationship between core curricula and degree attainment, though results are mixed regarding whether the accrual of core credits decreases time to a bachelor's degree (Boatman & Soliz, 2018; Schudde et al., 2023). Research on California's associate degrees for transfer suggests the policy dramatically increased associate degrees awarded in affected disciplines, transfer rates, and baccalaureate attainment (Baker, 2016; Baker et al., 2023). However, the increase in baccalaureate attainment was driven entirely by increased transfer rates, rather than by the increased likelihood of earning a bachelor's conditional upon transfer, suggesting the policy may not have improved credit transferability. Overall, although studies suggest the importance of statewide policies for facilitating transfer student success, research has yet to identify statewide policies that reliably reduce the number or percentage of credits students lose during transfer.

### The Interaction of Factors That Shape Credit Loss

The components of the conceptual framework outlined above were described in terms of their independent influence on credit loss. However, these factors do not operate in isolation—they exist in a complex higher education ecosystem, and credit transferability is also shaped by the interplay of different components of the conceptual framework. For example, whether courses are accepted for transfer depends on the combination of the major students are transferring into, the university's degree plan for the major, and articulation agreements/partnerships between community colleges and universities covering that pathway. In the present study, we explore several of these interactions below. However, because these interactions across components of the conceptual framework are myriad, we could not fully test all possible interactions for this study. We encourage further research on these interactions.

## Research Questions

In this study, we examined predictors of credit loss, and specifically how and why credit loss is influenced by courses, majors, pretransfer academics, student characteristics, and sending and receiving institutions. We asked two key research questions:

1. How do course characteristics, pretransfer academics, student characteristics, majors, sending institutions, and receiving institutions relate to credit loss?
2. To what extent does institutional variation in credit loss depend on the major students are transferring into and the type of credit loss students experience?

## Methods

To address the research questions, we leveraged statewide longitudinal data from the Texas Education Research Center (TERC), including newly available data on credit loss among community college transfer students. We used both descriptive and inferential statistical analyses to understand predictors of credit loss.

### State Context

Colleges and universities in Texas are overseen by the THECB, which ensures the implementation of policies passed by the Texas Legislature and develops its own policies to supplement state legislation. However, individual community college and university campuses are governed by systems that often exert greater influence over academic policy at institutions within the system. All public community colleges offer academic courses aligned with THECB's *Academic Course Guide Manual* (ACGM) and use common course numbering, ensuring the transferability of courses across institutions. Public universities are not required to use common course numbering but must indicate how their courses align with other institutions' through the Texas Common Course Numbering System (TCCNS). Texas is one of 38 states that has adopted a fully transferrable core curriculum (Texas Administrative Code, Title 19 § 4.28), and institutions choose the courses that comprise their core curriculum. Texas has also adopted a policy called *field of study curriculum* (FOS), which delineates courses students can take in a field of study beyond the core curriculum courses and that must fully transfer between institutions. However, FOS do not exist in all majors, and institutions have resisted the implementation of FOS requirements (Schudde et al., 2021).

**Data and Sample**

The TERC, a clearinghouse at the University of Texas at Austin, maintains K–12 records from the Texas Education Agency, postsecondary information from THECB, and labor market outcomes from Texas Workforce Commission. Accessing the data requires research to submit a proposal to the ERC Advisory Board, which meets quarterly to review proposals and approve or deny researchers' use of ERC data for proposed studies.

We relied on THECB data, which includes all students enrolled in any Texas postsecondary institution. The data included student demographics, institutional enrollment information, degrees and credentials awarded, and transcript measures such as course enrollment and completion, associated credit hours, and grades. Our analysis hinged on the newly collected transfer report data obtained from public universities. The transfer report lists ACGM courses denied for transfer and the institution's reported reason. To be included in the transfer report, transfer students must: (a) be first-time vertical transfer students transitioning from a public 2-year institution to a 4-year institution in Texas; (b) have lost at least one credit-bearing lower-division course listed in the ACGM (i.e., students experiencing zero credit loss are not included in the transfer report), and (c) maintain the same major from the time of transfer application until the official census date of university enrollment (the 12th class day for long semesters). This means that many transfer students who are admitted under a different major or as undeclared would not be included in the report, which is a limitation of the new transfer report. We relied on the first available transfer report data from Fall 2020 up through the latest available report in Spring 2022.

The transfer report data's inclusion of the reason for credit denial offers advantages over other data traditionally used in studying credit loss and transfer outcomes, as we could better understand the type of credit loss students experienced. Institutions report denying credits for one of the five THECB outlined reasons: (a) credits outside the student's major at the time of matriculation, (b) grades below institution's/program's minimum grade requirement, (c) the course was repeated and only one instance could be transferred, (d) exceeded maximum transferable hours (based on institutional preference but there is a state maximum of 66 credit hours for transfer), or (e) any reason other than the four mentioned.

Our analytic sample was drawn from the population of students who started college at a Texas public community college between 2010 and 2020 and transferred to a public university for the first time between Fall 2020 and Spring 2022—this was the window of available data from the transfer report. College transcript data from before 2010–11 are not available, requiring us to delimit the sample to students who started after 2010. The transfer report included only students who completed at least one academic credit-bearing course before transferring, because only academic courses were eligible for inclusion in the report (technical and workforce credits are unable to transfer to public universities toward an academic bachelor's degree by law in Texas). Our analytic sample included $n$ = 28,969 transfer students. Because our analyses were at the course level, our sample included all academic courses taken by these students before transfer, totaling $k$ = 495,512 course records for an average of roughly 17 courses taken per student prior to transfer. A small fraction of these course records were dropped in our analyses because of missing data (1,151 course records, or 0.2%).

**Variable Construction**

We used the transfer report's measures of course credits lost and reason codes to create three course-level outcomes: any credit loss, major credit loss, and general credit loss. *Any credit loss* was a dichotomous variable (1 = lost, 0 = not lost) indicating whether a course failed to transfer or apply for any reason. *Major credit loss* (MCL) was a dichotomous variable (1 = not applied, 0 = applied) indicating that a course transferred to the institution but did not apply to the major the student declared at the time of transfer, the first credit loss denial reason discussed above. *General credit loss* (GCL) was a dichotomous variable (1 = lost, 0 = not lost) indicating that a course could not be transferred to the institution at all, combining the other four credit denial reasons.

Our independent variables were aligned with our proposed conceptual framework of credit loss. The first set of key factors in our framework was course characteristics, which we accounted for using several measures. The THECB data included variables that indicated the delivery characteristics of each college-level course, such as the course's instructional type, its instructional mode, and whether it was offered as dual-credit. Additionally, we included an indicator of whether the course was part of the institution's core curriculum. We controlled for these course characteristics in all models.

We described the content of the course in four ways. First, we referred to the coarsest grouping as *broad course subject*, which placed all course subjects into one of eight groups: (a) Business; (b) Education; (c) Humanities, Liberal Arts, and General Studies; (d) Health; (e) Industry, Agriculture, Manufacturing, and Construction; (f) Service Oriented; (g) Social and Behavioral Sciences; and (h) STEM. Second, we also captured *specific course subject* using the subject of the course aligned with the ACGM, which describes all lower-division academic courses that may be offered by all public postsecondary institutions in Texas. Each course subject receives a four-letter prefix (e.g., GOVT for Government). Third, *unique course* combined the four-letter course prefix with the four-digit course number (e.g., GOVT 2306), indicating the exact course taken. Fourth, we created *course-by-major pairs* by combining unique courses with the major students transferred into at the university. We defined majors by four-digit Classification of Instructional Program (CIP) codes. As discussed in the Online Supplementary Materials, we fit a series of logistic regression models with these different controls for course content. The results of these models showed that controlling for unique courses resulted in improved model fit compared to controlling for course subjects (broad or specific), but adding course-by-major pairs to the model worsened adjusted $R^2$. We therefore controlled for unique courses in our models.

Student demographic characteristics included age, race/ethnicity, gender, and low-income status. Age was defined as a continuous variable, and we also included a quadratic term for age to explore the possibility of nonlinear relationships between age and credit loss. The THECB provides race/ethnicity information categorized following U.S. census reporting format, where students self-report their racial identity from the options American Indian/Native American, Asian, Black, Native Hawaiian/Pacific Islander, White, or Multiracial and report whether they are Hispanic/Latino. We created a single race/ethnicity variable where students identifying as Hispanic/Latino were defined as one group and all others were deemed non-Hispanic/Latino. For our analysis, we further classified the latter under Asian, Black, White, and Other. The last category combined American Indian/Native American, Native Hawaiian/Pacific Islander, and Multiracial given the small number of students in each of these categories. Students reported gender as a binary variable: male or female. Low-income status was a dichotomous indicator that captured multiple measures, such as falling below the annual federal poverty line or Pell grant eligibility.

We measured pretransfer academic characteristics using the number of credits completed prior to transfer, pretransfer GPA, pretransfer credentials, and variables related to students' temporal pathways through higher education. We categorized pretransfer credits into bins of 15 credits that roughly corresponded to semesters of coursework for full-time students. These bins were: (a) 1–15 credits, (b) 16–30, (c) 31–45, (d) 46–60 (the modal case and reference group in the statistical models), (e) 61–75, (f) 76–90, and (g) More than 90 credits. Pretransfer GPA was a continuous variable measured on a 0.00–4.00 scale. We constructed the pretransfer credits and the GPA variables from the transcript data capturing courses, associated credit hours, and grade the student completed at the community college before transferring to the university. Pretransfer credentials included whether the student earned an associate degree prior to transfer as well as indicators for whether students completed the institution's core curriculum or a FOS pathway. We also controlled for the year students began in higher education (from 2010 through 2021) because that may have influenced the degree plans they could transfer into at the university; the semester a course was taken because that could influence its transferability; and the semester the student transferred from the community college to the university to account for temporal changes in university policy and practice that may have influenced credit loss.

We accounted for major in two ways. As discussed above, in one model we created course-by-major pairs using four-digit CIP codes and included those fixed effects in the model. However, the large number of these pairs limited the interpretability of the estimates. To provide actionable evidence regarding how majors influence credit loss, we created a variable indicating major area of concentration where two-digit CIP codes of the major students declared at the university are organized into 13 broad bins following Baker (2018) and Jenkins et al. (2017).

Finally, we included fixed effects for sending and receiving institutions in most models, apart from models where universities are treated as a random effect (discussed below). Although understanding how characteristics of institutions influence credit loss is important, our relatively small sample of institutions (54 community colleges and 35 universities) limited the feasibility of controlling for institutional covariates. For example, the selectivity of universities may be correlated with credit loss, but the number of Texas universities in different selectivity tiers is too small to have sufficient statistical power for us to examine this relationship. We discuss the implications of this limitation after presenting our results. Because all colleges in our sample were in Texas, they were all subject to the same state transfer policies, which is the final component of our conceptual framework. We therefore did not examine in this study how state policies influence credit transferability. Table OSM1 in the Online Supplementary Materials contains the names, descriptions, means, and SDs of all variables used in the study. Table OSM2 presents descriptive characteristics of credit loss by student characteristics.

**Statistical Modeling**

We used logistic regression models to estimate the influence of courses, majors, student demographic characteristics, pretransfer academics, community colleges, and universities on credit loss. We begin with the following model:

$$\mathbf{log}\left[\frac{\boldsymbol{p_{ijklmt}}}{\mathbf{1}-\boldsymbol{p_{ijklmt}}}\right] = \boldsymbol{\beta_{0ijklmt}} + \boldsymbol{\beta_1 Course_i} + \boldsymbol{\beta_2 Demog_k} + \boldsymbol{\beta_3 Acad_k}$$

$$+\boldsymbol{\alpha_i} + \boldsymbol{\gamma_j} + \boldsymbol{\delta_l} + \boldsymbol{\theta_m} + \boldsymbol{\tau_t} + \boldsymbol{\varepsilon_{ijklmt}}$$

where the outcome is the log-odds of credit loss for course *i* applied to major *j* for student *k* who transferred from community college *l* to university *m* in time *t*. In all models, the $\boldsymbol{Demog_{klmt}}$

term represents a vector of student-level demographic characteristics (age, race/ethnicity, gender, income), and $\boldsymbol{Acad_{klmt}}$ represents a vector of pretransfer academic characteristics (pretransfer credits earned, pretransfer GPA, pretransfer credentials) that may influence credit loss. The $\boldsymbol{\alpha_i}$, $\boldsymbol{\gamma_j}$, $\boldsymbol{\delta_l}$, and $\boldsymbol{\theta_m}$ terms represent course, major, community college, and university fixed effects. The $\boldsymbol{\tau_t}$ term represents a vector of temporal fixed effects for the year in which students began college, the semester in which they completed the specific course, and the semester in which students transferred to a university to account for variation in credit loss over time. The model includes a course-level residual clustered at the university level.

We addressed our first research question regarding how key factors from our conceptual framework influence credit loss by fitting the model to any credit loss. In addition to discussing the estimates for course covariates, majors, pretransfer academic, and students' demographic characteristics, we visualized the fixed-effect estimates (in the form of odds ratios) for both community colleges and universities. These analyses provided evidence regarding which components of our conceptual framework relate to the likelihood of credit loss and the extent of variation across institutions in credit loss after accounting for all other variables in the models.

We used two different approaches to address our second research question regarding how the influence of institutions on credit loss varies across types of credit loss (any, major, and general) and specific major pathways. First, we fit the same model to the outcomes of MCL and GCL. Because the estimates for course and student covariates were similar across these different credit loss outcomes, we focused on how the estimated influence of institutions varied depending on the type of credit loss being analyzed. To further quantify the amount of variation across universities in credit loss types, and to capture that variation across specific major pathways, we fit separate multilevel logistic regression models for subgroups of students with different major pathways (Guo & Zhao, 2000) to different combinations of the credit loss outcomes. The estimating equation can be described in the two-level framework thus:

$$\log\left[\frac{p_{iklmt}}{1-p_{iklmt}}\right] = \beta_{0iklmt} + \beta_1 Course_i + \beta_2 Demog_k + \beta_3 Acad_k$$

$$+ \alpha_i + \delta_l + \tau_t + \varepsilon_{ijklmt}$$

$$\beta_{0iklmt} = \beta_{0iklt} + u_m$$

There were two key differences between the previous modeling approach and this one. First, we removed the university fixed effects from the previous model ($\boldsymbol{\theta}_{mt}$) and now treated universities as a random effect, with each university's intercept ($\boldsymbol{\beta}_{0iklmt}$) being a combination of the grand mean intercept ($\boldsymbol{\beta}_{0iklt}$) and that university's deviation from the grand mean ($\boldsymbol{u}_m$). Second, we removed majors from the model previously indicated by the subscript *j* because we fit separate models on different samples of students based on their broad major area of concentration. We used the level-2 random effect to calculate the pseudo-ICCs, which can be interpreted as the amount of residual variation in the outcome that is explained by universities after accounting for all other covariates and fixed effects in the model.

**Limitations**

Before presenting our results, we note limitations of the study that readers should bear in mind. First, although THECB validates the credit loss data institutions submit on the credit loss report, it is difficult to assess the reliability of these data currently, given their relative novelty. Institutions may have an incentive to underreport the magnitude of credit loss students experience, which would imply our results are likely a conservative estimate of credit loss. Second, the sample was restricted to first-time vertical transfer students from a public community college to a public university who did not change their major between applying for transfer and enrolling at the university (according to the requirements of the credit loss report).

This was likely the sample of transfer students with the lowest risk of credit loss; students completing reverse or lateral transfers, those transferring from or to private institutions, and those required to change their major after transfer likely experience even greater credit loss (GAO, 2017). We caution against overgeneralizing our results to the full population of transfer students. Third, we could not test all theorized relationships stemming from our conceptual framework, such as the influence of transfer student capital (because we did not have measures of this capital available in the state data), the role of state policy (given that all the institutions in our sample were governed by the same policies), or all possible interactions between components of our framework (because those combinations are myriad). Finally, we emphasize that our results are correlational and do not support causal claims regarding factors that increase or decrease students' risk of credit loss.

## Results

### Which Components of the Conceptual Framework Relate to Any Credit Loss?

Table 1 presents the full results from the logistic regression model that includes the unique course fixed effects. Because the outcome variable was whether the credit was lost, odds ratios greater than 1 represent an increased likelihood of credit loss, whereas odds ratios less than 1 represent a decreased likelihood of credit loss. Fixed effects for the year students began college, the semester in which they completed the specific course, the semester they transferred to a university, the community colleges they transferred from, and the universities they transferred to are included in the statistical models but excluded from the table for brevity. The community college and university fixed effects are visualized in Figure 1. The sections below discuss our findings, organized by the component of the conceptual framework that each variable was aligned with.

[Table 1]

***Course Characteristics***

As discussed above, credit loss varies meaningfully across courses. The model controlling for unique courses demonstrated the best model fit. Even when controlling for the specific courses students attempted to transfer, characteristics of the courses were significantly related to the likelihood that they would be transferred. Whether a course was designated as part of the receiving institution's core curriculum was inversely related to the likelihood that the course would be lost. Courses taken as distance education or hybrid courses were less likely to be transferred. Dual-credit courses were also significantly more likely to be lost, whereas courses with other types of instruction were less likely to be lost than courses taken in-residence.

***Student Demographic Characteristics***

Overall, students' demographic characteristics were not meaningfully related to credit loss, even though some estimates of demographic characteristics were found to be statistically significant. Age at the time of transfer was not significantly related to credit loss, both for the age main effect and the quadratic term (used to explore a potential nonlinear relationship between age and credit loss). Although Black and Hispanic students exhibited odds ratios lower than one, they were not statistically significantly less likely to experience credit loss than White students (0.97, $p = 0.10$ and 0.98, $p < 0.1$, respectively). Female students were estimated to be significantly more likely to experience credit loss than male students, but the odds ratio (1.05, $p < 0.01$) suggested a minimal difference. Similarly, low-income students were found to be significantly less likely to experience credit loss than non-low-income students, but had nearly equivalent odds of credit loss (0.97, $p < 0.01$). Overall, there is limited evidence that students' demographic characteristics relate to the likelihood of credit loss controlling for all other variables in the model.

### *Pretransfer Academics*

In contrast, many of students' pretransfer academic characteristics appeared to be substantively and statistically significantly related to credit loss. Pretransfer GPA was found to be highly significant, and each 1-point increase in GPA on a 4-point scale corresponded with a 23% reduction in the odds of credit loss. Completing the core curriculum or an associate degree before transfer was related to a significantly higher risk of credit loss, whereas completing a FOS pathway was related to lower odds of credit loss. The number of credits students completed before transfer was also found to significantly relate to credit loss, but in the opposite direction, as we predicted. In general, the more credits a student had earned prior to transfer, the less likely the student was to lose credits. Students who completed 1–15 credits prior to transfer had roughly 2.5 times the odds of experiencing credit loss for a particular course of students who earned 45–60 credits prior to transfer (the modal case and reference group in the statistical model).

### *Majors*

Although the model with the course-by-major pairs demonstrated worse fit than the model with unique courses, we still found meaningful variation across major groups in the likelihood that students experienced credit loss, even when controlling for the specific courses students completed. Students who transferred into majors in Education and Social Services were the only group with lower odds of credit loss (0.91) than students who transferred into Business, which was the modal major and served as the reference group in the statistical model. In contrast, students transferring into a wide variety of major groups had significantly higher odds of credit loss than Business majors. The highest odds were for students majoring in Engineering and Related fields (1.60), Math and Computer Science (1.37), and Natural Science (1.26), although students transferring into Health (1.19), Humanities and Liberal Arts (1.09), Industrial, Manufacturing, and Construction (1.22), and Service Oriented (1.14) majors also had significantly higher odds of credit loss than Business students.

### *Community Colleges*

To better visualize the relationship between community colleges and students' likelihood of credit loss, Figure 1 (left panel) displays the odds ratio estimates for each community college in the sample. The reference group was Lone Star Community College because it had the largest number of vertical transfer students in the sample. Coincidentally, it also had the second lowest odds of credit loss, which is why most community college fixed-effect estimates were statistically significantly different—and larger—than the odds for credit loss at Lone Star Community College. Figure 1 highlights considerable variation across community colleges in terms of students' likelihood of losing credits, with two of the community colleges having odds ratio estimates greater than 3.0 compared with the reference group. In other words, after controlling for all other variables in the model, transferring from Panolo College or Frank Phillips College resulted in three times higher odds of losing course credit than transferring from Lone Star Community College.

### *Universities*

A similar pattern emerged from our analysis of university fixed effects, presented in Figure 1 (right panel). The reference group was University of Houston, which had the largest number of vertical transfer students among universities in the sample. In this case, some universities had significantly lower odds of credit loss than the reference institution, so that students transferring into an institution such as West Texas A&M University had half the odds of experiencing credit loss of those going to the University of Houston. In contrast, other universities, like Texas A&M at Galveston and Texas A&M–Kingsville, had 3.0–3.5 times higher odds of credit loss than the reference institution—all significant differences at the $p < 0.01$ level. Taken together, the maximum odds ratio estimates across the community college and university fixed effects were roughly equivalent, but there were several universities with lower odds of credit loss than the reference university but no community colleges with significantly lower odds than the reference community college. These results suggest that there is greater variation in credit loss across universities than across community colleges, at least when the outcome is any credit loss.

[Figure 1]

**How Did the Influence of Institutions Vary Across Types of Credit Loss and Majors?**

The previous analyses highlighted considerable variation across both community colleges and universities in any credit loss. To further explore how institutions may shape credit loss, we took two approaches. First, we fit the same models as above but to the outcomes of MCL (where the course might transfer to the institution but be unable to apply to the student's major) and GCL (where the course does not transfer to the university) to examine whether institutions matter more for certain types of credit loss. Second, we fit separate models of all three credit loss variables to subsamples of students based on their major area of concentration. This enabled us to examine whether there were certain major pathways where there was greater variation across institutions in the magnitude of credit loss students experience, and how that institutional variation within majors might have depended on the type of credit loss. Because many of the estimates of covariates were similar regardless of the outcome or sample, we focus our discussion on institutional variation in credit loss.

Figure 2 visualizes odds ratios for the fixed effects of community colleges (left panel) and universities (right panel) from models of MCL. Although the degree of institutional variation in any credit loss was roughly similar for community colleges and universities, a fundamentally different pattern appeared when examining MCL. For this outcome, variation across community colleges was more modest. Roughly half the community colleges were not significantly different from the reference college in terms of the odds of MCL, and the range of estimates was compressed. Only one community college—Panola College—exhibited odds of MCL that were at least twice the odds of the reference group, and only a handful of institutions had significantly lower odds. In contrast, the range of fixed effects for universities presented in Figure 2 was extreme. The institutions with the highest rates of MCL had 120–130 times the odds of the reference group, and all but two of the universities had significantly higher odds of credit loss than that reference institution. Although the reference university was chosen because of its sample size rather than its MCL rate, a small fraction (< 0.1%) of all courses lost at University of Houston were due to MCL, contributing to the substantial odds ratio estimates. Nevertheless, variation across universities in MCL was extensive, whereas the variation across community colleges was minimal.

[Figure 2]

Figure 3 presents the fixed effects from the models of GCL for community colleges (left panel) and universities (right panel). Although the numeric ranges of the odds ratio estimates are quite different for the present figures of GCL than for the previous figures of MCL, the key findings are similar. Overall, Figure 3 suggests that the variation in GCL across community colleges was minimal. The majority of institutions did not differ significantly in terms of the likelihood that students would experience GCL, and all of the odds ratios range from 0.5 to 1.5. In contrast, most universities' fixed effects were significantly different from those of the reference group, but for GCL the odds ratios were nearly all less than 1—quite different from what we observed for MCL, where they were nearly all greater than 1. Overall, these analyses highlight wide variation across universities not only in students' likelihood of losing credits but also in whether institutions rejected credits for general reasons or failed to apply transferred credits toward students' majors.

[Figure 3]

Our final analyses fit a series of logistic regression models, each of which is a combination of one of the three credit loss outcomes (any credit loss, MCL, GCL) and a major area of concentration. The covariates and fixed effects are the same as the previous models, but in this instance, we fit multilevel logit models to the outcomes and treated course records as being nested within universities, which we treated as the Level-2 random effect. This enabled us to estimate the pseudo-ICC for each model, which can be interpreted as the amount of variation across universities for that type of credit loss in that major pathway.

The pseudo-ICCs from these models are presented in Table 2. These estimates can be interpreted as the amount of unexplained variation in credit loss accounted for by the level-2 variable—in this case, universities. Because the models are not "empty" (i.e., they include covariates), the value of the ICC in a given model is of less importance than the relative magnitude of the ICCs across models for our purpose of identifying where there is greatest variation across universities in credit loss. Three key findings emerged from this analysis. First, as suggested from the previous analyses, there was far greater variation across universities in both MCL and GCL than for any credit loss. Second, the pseudo-ICC estimates for MCL were far larger than those for GCL. Third, there was considerable variation across major groups in terms of the influence of institutions on credit loss, and the ranking of majors in terms of these pseudo-ICCs is fairly consistent across types of credit loss. For example, the two major groups with the most variation across universities in any credit loss were Business and Engineering and Related majors, which were also the two major groups with the highest pseudo-ICCs for the outcomes of MCL and GCL. Literature, Linguistics, and Fine Arts had the second-lowest pseudo-ICC for any credit loss and the lowest for GCL, although its estimate for MCL was closer to the average. Overall, the results suggest that the extent to which the likelihood of credit loss varies across universities depends both on the type of credit loss being examined and the major pathway students are traversing.

[Table 2]

## Discussion

In the past decade, research has begun to illuminate the extent to which students lose credits during the transfer process (GAO, 2017; Monaghan & Attewell, 2015; Simone, 2014), factors that relate to the loss of credits (Giani, 2019), and how credit loss shapes subsequent college outcomes (Giani et al., 2024; Monaghan & Attewell, 2015; Spencer, 2022). However, data limitations have hampered researchers' ability to accurately measure credit loss—particularly the phenomenon of MCL (Hodara et al., 2017; Kadlec & Gupta, 2014). Additionally, the extant literature lacked conceptual frameworks that explicated credit loss mechanisms.

To address these limitations, we proposed and tested a novel conceptual framework drawing upon prior research and theory related to student transfer. We hypothesized seven key factors that may relate to credit loss: (a) course characteristics, (b) major pathways and programs of study, (c) pretransfer academics, (d) student characteristics, (e) sending institution policies and practices, (f) receiving institution policies and practices, and (g) state and system policies and practices pretransfer. Although our empirical analyses were unable to test all components of this framework given data limitations (e.g., a lack of measures on transfer student capital) and the sample we drew upon (e.g., a single-state sample with no variation in state policy), we were otherwise able to build comprehensive models aligned with the conceptual framework. The framework itself can also guide future research on credit loss using different data sources.

Overall, our empirical results support our hypotheses that components of the conceptual framework relate to credit loss, with one exception. We found that the estimated likelihood of credit loss did not vary meaningfully across demographic groups, despite prior evidence of inequities in vertical transfer (Chase et al., 2012; Crisp & Nuñez, 2014; Dougherty & Kienzl, 2006; Dowd, 2007; Wood et al., 2011). Some caveats should be borne in mind, however. First, our focal sample comprised vertical transfer students who are therefore positively selected (i.e., they navigated the transfer process)—not to mention that it focused on students who maintained their major across institutions and therefore likely differed from the analytic samples in prior research. Even within this positively selected group of vertical transfer students, we caution against interpreting the results as evidence of equity in credit transfer. For example, students from historically marginalized backgrounds may be more likely to enroll in courses, majors, or institutions with higher rates of credit loss, which would mean that inequalities in credit transfer across demographic groups may exist but would not be apparent using models controlling for courses, majors, and institutions. We encourage future researchers to examine potential inequities in credit loss.

Apart from this exception, we found that all other components of the framework related to credit loss. Our results underscore the importance of accounting for unique courses students completed, given the variation in credit loss across unique courses in the same subject. Course characteristics also influenced their transferability, at times in unexpected ways. We found that courses taken in online/hybrid formats were more likely to be denied credit than in-person courses, and those taken as dual-credit were more likely to be denied than in-residence courses. We are not aware of state or institutional policies that relate to how course modality or delivery may influence credit loss—both state policy and articulation agreements typically stipulate that identical courses should receive identical credit transferability decisions, regardless of the modality or delivery of the course. Future research should examine how stakeholders' perceptions of nontraditional course delivery formats—for example, perceptions of "rigor"—influence decisions to accept transfer credits (Duncheon & Relles, 2020; Xu & Jaggars, 2014).

Even controlling for the courses students completed, students' likelihood of credit loss (and the extent to which institutions influence credit loss) depends on their major pathways. In the present study, we primarily analyzed broad major areas and found that many of the STEM pathways—specifically Engineering (and related fields), Mathematics, and Natural Science—tended to have the highest rates of credit loss. More research is needed to examine what components of majors mitigate or exacerbate credit loss. Categorizing majors based on their rigidity vs. flexibility aligns with how transfer-relevant personnel at colleges and universities describe credit transfer processes (Schudde et al., 2024). For that reason, examining "path homogeneity" among students traversing majors may be a promising line of future inquiry on credit loss (Heileman et al., 2018; Jarratt et al., 2024; Kizilcec et al., 2023).

Students' pretransfer academic characteristics also shape their risk of credit loss, but some of the estimated relationships were in the opposite direction of what we hypothesized. Students with higher GPAs and those who completed a FOS pathway prior to transfer had lower odds of credit loss. However, completing fewer credits (1–15), the core curriculum, or an associate degree were associated with higher odds of credit loss. We hypothesize that completing an associate degree may minimize the risk of credit loss in states with guaranteed associate degrees for transfer, unlike Texas (ECS, 2022). Still, it is unclear why students who completed fewer credits or the core curriculum have higher odds of credit loss. Recent evidence on the link between core credit accrual and degree attainment among transfer students suggests that core credits are positively linked to student success only up to the 42-credit limit, where many students "overaccrue" core courses (Schudde et al., 2023).

Perhaps the most important contribution of this study is novel evidence of the extensive variation across institutions in credit loss. Research on the effects of state policy on transfer student outcomes is decidedly mixed (Anderson et al., 2006; Baker, 2016; Baker et al., 2023; Boatman & Soliz, 2018; Gross & Goldhaber, 2009; LaSota & Zumeta, 2016; Roksa & Keith, 2008; Spencer, 2021). This finding has contributed to the growing emphasis on reforming institutional policy and practice in efforts to improve the transfer and baccalaureate completion rates of community college students, with emphasis on community colleges (Bailey et al., 2015). These reform efforts are warranted, but our results suggest that credit loss is more heavily influenced by universities than by community colleges, particularly regarding specific types of credit loss. Because universities may exert much influence in stymying well-intentioned transfer reforms (Schudde et al., 2021), understanding how universities' policies, practices, and institutional cultures contribute to credit loss—both overall and within specific major pathways—is a critical area for future research.

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## Tables and Figures

**Table 1**

*Final Logistic Regression Model of Any Credit Loss*

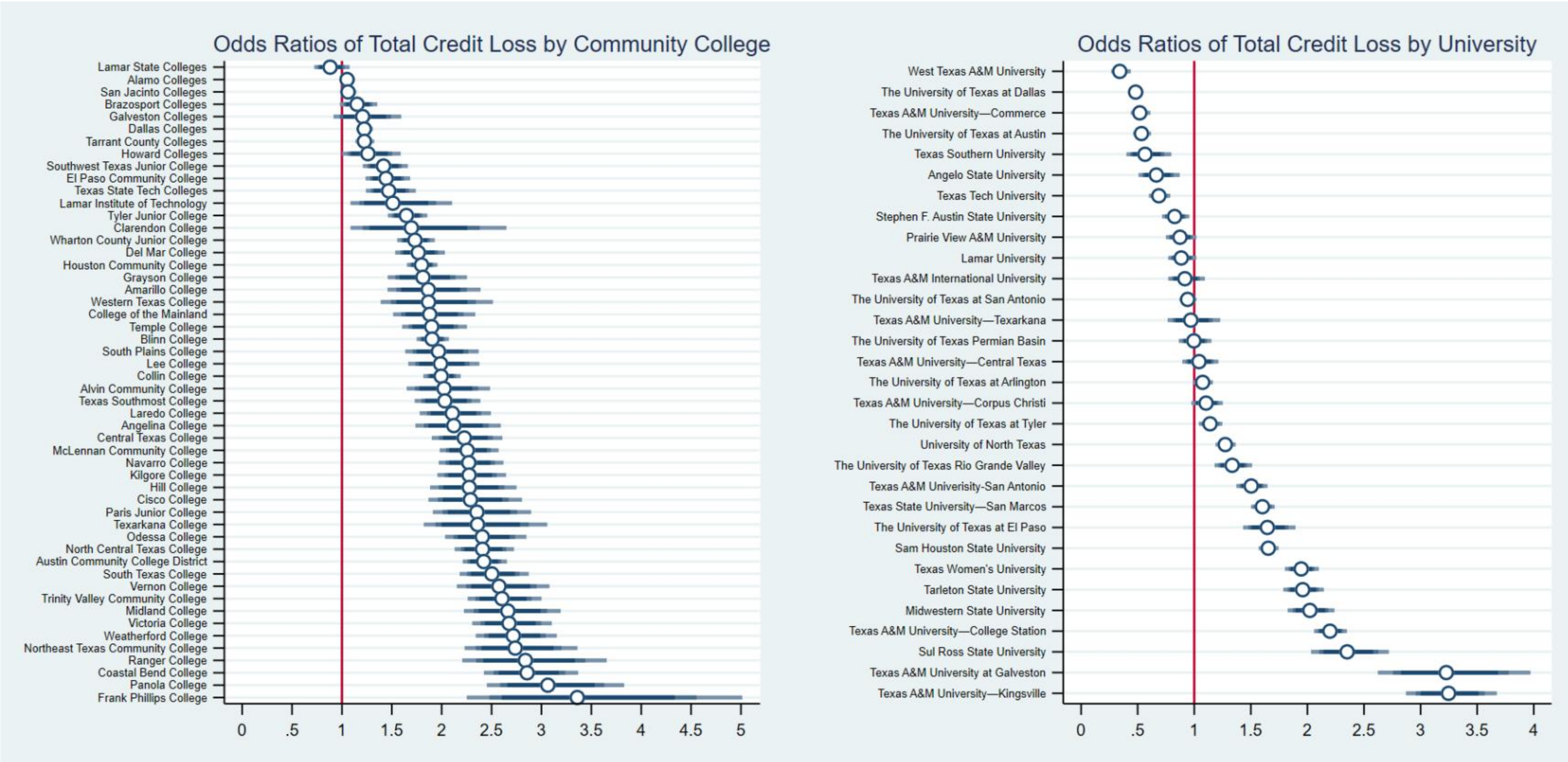
| **Any Credit loss** | ***OR*** | ***SE*** | ***z*** | ***p*-value** | **95% CI** | |
|---|---|---|---|---|---|---|
| Core Course | 0.71 | 0.01 | -21.69 | 0.00 | 0.69 | 0.73 |
| *Instructional Mode (In-person)* | | | | | | |
| Distance education | 1.22 | 0.01 | 16.53 | 0.00 | 1.19 | 1.25 |
| Hybrid | 1.17 | 0.03 | 6.85 | 0.00 | 1.12 | 1.23 |
| *Instructional Type (In-residence)* | | | | | | |
| Other types | 0.90 | 0.02 | -6.41 | 0.00 | 0.87 | 0.93 |
| Dual-Credit (Not) | 1.18 | 0.03 | 7.05 | 0.00 | 1.13 | 1.23 |
| Age | 1.00 | 0.01 | 0.30 | 0.77 | 0.99 | 1.01 |
| Age-squared | 1.00 | 0.00 | -0.27 | 0.79 | 1.00 | 1.00 |
| *Race/Ethnicity (White)* | | | | | | |
| Black, non-Hispanic | 0.97 | 0.02 | -1.65 | 0.10 | 0.94 | 1.01 |
| Hispanic | 0.98 | 0.01 | -1.94 | 0.05 | 0.96 | 1.00 |
| Asian, non-Hispanic | 0.99 | 0.02 | -0.41 | 0.68 | 0.95 | 1.03 |
| Other, non-Hispanic | 1.00 | 0.02 | 0.19 | 0.85 | 0.96 | 1.05 |
| Female | 1.04 | 0.01 | 4.18 | 0.00 | 1.02 | 1.06 |
| Low-income | 0.97 | 0.01 | -3.12 | 0.00 | 0.95 | 0.99 |
| Pre-transfer GPA | 0.77 | 0.01 | -33.82 | 0.00 | 0.76 | 0.78 |
| Core Complete | 1.09 | 0.01 | 7.40 | 0.00 | 1.06 | 1.11 |
| FOS Complete | 0.88 | 0.02 | -6.61 | 0.00 | 0.84 | 0.91 |
| Associate Degree | 1.07 | 0.01 | 5.91 | 0.00 | 1.05 | 1.09 |
| *Pretransfer Credits (45–60)* | | | | | | |
| 1–15 | 2.50 | 0.10 | 21.97 | 0.00 | 2.31 | 2.72 |
| 16–30 | 1.61 | 0.03 | 23.43 | 0.00 | 1.54 | 1.67 |
| 31–45 | 1.29 | 0.02 | 18.43 | 0.00 | 1.25 | 1.32 |
| 61–75 | 0.85 | 0.01 | -14.43 | 0.00 | 0.83 | 0.87 |
| 76–90 | 0.93 | 0.02 | -4.00 | 0.00 | 0.90 | 0.96 |
| More than 90 | 0.97 | 0.03 | -1.06 | 0.29 | 0.91 | 1.03 |
| *Major Group (Business)* | | | | | | |
| Communication Studies | 1.02 | 0.03 | 0.77 | 0.44 | 0.97 | 1.08 |
| Education and Social Services | 0.91 | 0.02 | -4.93 | 0.00 | 0.88 | 0.95 |
| Engineering and related | 1.62 | 0.04 | 22.44 | 0.00 | 1.56 | 1.69 |
| Health | 1.19 | 0.02 | 8.81 | 0.00 | 1.15 | 1.24 |
| Humanities and Liberal Arts | 1.09 | 0.02 | 4.59 | 0.00 | 1.05 | 1.13 |
| Industrial, Manufacturing and Construction | 1.25 | 0.05 | 6.10 | 0.00 | 1.16 | 1.34 |

| **Any Credit loss** | ***OR*** | ***SE*** | ***z*** | ***p*-value** | **95% CI** | |
|---|---|---|---|---|---|---|
| Literature, Linguistics and Fine Arts | 0.99 | 0.02 | -0.29 | 0.77 | 0.95 | 1.04 |
| Math and Computer Science | 1.36 | 0.03 | 13.68 | 0.00 | 1.30 | 1.42 |
| Natural Science | 1.28 | 0.02 | 12.67 | 0.00 | 1.23 | 1.33 |
| Service oriented | 1.16 | 0.03 | 6.12 | 0.00 | 1.11 | 1.22 |
| Social and Behavioral Science | 1.01 | 0.02 | 0.40 | 0.69 | 0.97 | 1.04 |
| *n* | | | 482,931 | | | |
| Pseudo $R^2$ | | | 0.105 | | | |

*Notes.* The table displays Odds Ratios (*OR*), standard errors (*SE*s), *z*-stats, *p*-values, and 95% confidence intervals from a logistic regression model predicting the dichotomous outcome of whether a course was unable to transfer or apply to the student's declared major at the receiving institution. The analytic sample consists of the population of students who transferred from a public community college to a public university in Texas between Fall 2020 and Spring 2022. The model also includes fixed effects for courses (course subject-number pairs), the year students first enrolled in higher education, the semester in which the course was taken, the semester students transferred to the receiving institution, community colleges, and universities.

**Figure 1**

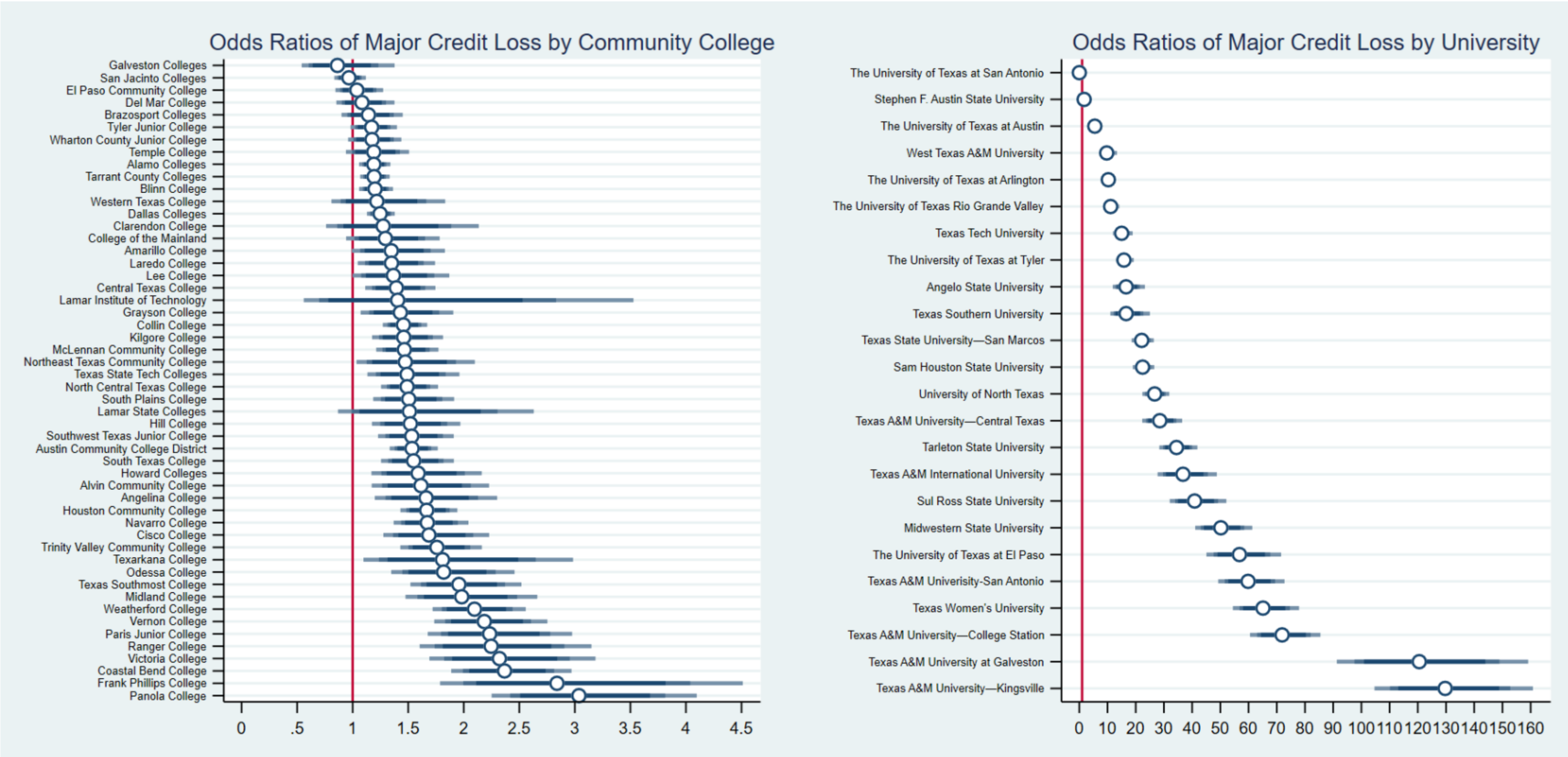
*Odds Ratios of Any Credit Loss by Institution*




*Notes.* The figure displays odds ratios of the community college (left graph) and university (right graph) fixed effects from the logistic regression model of any credit loss presented in Table 1. The analytic sample is the population of students who transferred from a public community college to a public university in Texas between Fall 2020 and Spring 2022. The model also includes fixed effects for courses (course subject-number pairs), the year students first enrolled in higher education, the semester in which the course was taken, the semester students transferred to the receiving institution, community colleges, and universities. Lone Star Community College and University of Houston were selected as the community college and university reference groups, respectively, because they had the largest number of vertical transfer students in the sample.

**Figure 2**

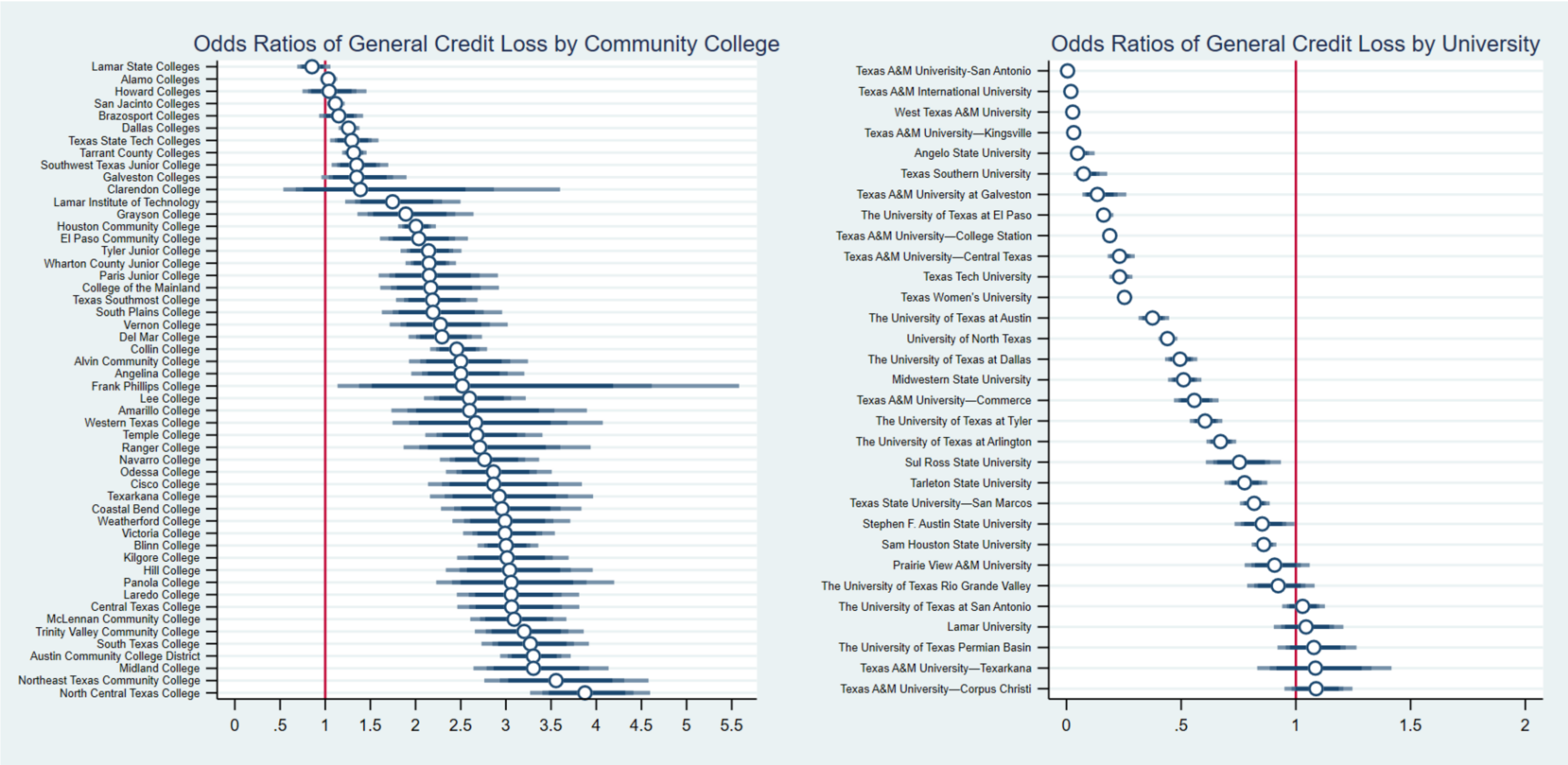
*Odds Ratios of Major Credit Loss by Institution*




*Notes.* The figure displays odds ratios of the community college (left graph) and university (right graph) fixed effects from the logistic regression model of major credit loss. The analytic sample is the population of students who transferred from a public community college to a public university in Texas between Fall 2020 and Spring 2022. The model also includes fixed effects for courses (course subject-number pairs), the year students first enrolled in higher education, the semester in which the course was taken, the semester students transferred to the receiving institution, community colleges, and universities. Lone Star Community College and University of Houston were selected as the community college and university reference groups, respectively, because they had the largest number of vertical transfer students in the sample.

**Figure 3**

*Odds Ratios of General Credit Loss by Institution*




*Notes.* The figure displays odds ratios of the community college (left graph) and university (right graph) fixed effects from the logistic regression model of general credit loss. The analytic sample is the population of students who transferred from a public community college to a public university in Texas between Fall 2020 and Spring 2022. The model also includes fixed effects for courses (course subject-number pairs), the year students first enrolled in higher education, the semester in which the course was taken, the semester students transferred to the receiving institution, community colleges, and universities. Lone Star Community College and University of Houston were selected as the community college and university reference groups, respectively, because they had the largest number of vertical transfer students in the sample.

**Table 2**

*Pseudo-ICCs From Multilevel Logit Models of Credit Loss Types by Major Group*

| Major Sample | Any Credit Loss | Major Credit Loss | General Credit Loss |
|---|---|---|---|
| Business | 0.160 | 0.808 | 0.436 |
| Communication Studies | 0.108 | 0.733 | 0.235 |
| Education and Social Services | 0.113 | 0.678 | 0.336 |
| Engineering and Related | 0.183 | 0.828 | 0.435 |
| Health | 0.101 | 0.751 | 0.265 |
| Humanities and Liberal Arts | 0.120 | 0.671 | 0.401 |
| Industrial, Manufacturing, and Construction | 0.109 | 0.588 | 0.298 |
| Literature, Linguistics, and Fine Arts | 0.099 | 0.711 | 0.195 |
| Math and Computer Science | 0.123 | 0.807 | 0.338 |
| Natural Science | 0.091 | 0.760 | 0.364 |
| Service Oriented | 0.083 | 0.704 | 0.292 |
| Social and Behavioral Science | 0.105 | 0.752 | 0.285 |

*Notes.* The table displays pseudo-ICCs from multilevel logit models where courses are nested in universities as the Level-2 variable. Each pseudo-ICC represents the amount of variation explained by universities in the type of credit loss included as the outcome variable once all other covariates and fixed effects were controlled for. The model includes the same covariates and fixed effects from the previous model of any credit loss, apart from removing the university fixed effects and replacing them with a level-2 university random effect that allows us to calculate the pseudo-ICCs. The analytic sample is the population of students who transferred from a public community college to a public university in Texas between Fall 2020 and Spring 2022.

## Online Supplementary Materials

**Table OSM1**

*Variable Descriptions and Descriptive Characteristics*

| Variable name | Description | Mean (*SD*) |
|---|---|---|
| *Demographics* | | |
| Age | Age of the student at initial enrollment; obtained from THECB enrollment data | 19.77 (4.90) |
| Female | Identified as female; drawn from THECB enrollment data, which contains a dichotomous measure of gender (male or female) | 0.62 (0.49) |
| *Race* | | |
| Non-Hispanic White | Identified as Non-Hispanic White in the first term of college | 0.30 (0.46) |
| Non-Hispanic Black | Identified as Black in the first term of college | 0.09 (0.27) |
| Hispanic/Latino | Identified as Hispanic/Latino in the first term of college | 0.51 (0.50) |
| Non-Hispanic Asian | Identified as Asian in the first term of college | 0.06 (0.23) |
| Other | Identified as another race, including Native Hawaiian or Other Pacific Islander, Native American and unknown | 0.05 (0.22) |
| Low-income status | Indicator for low-income status in the first term, drawn from THECB enrollment data | 0.44 (0.50) |
| *Major* | | |
| Business | Architecture, Business, Management, marketing and related | 0.19 (0.39) |
| Communication | Communication, Journalism, related technicians and support services, and Library science | 0.03 (0.17) |
| Education and Social Services | Education, Homeland security, Law enforcement, Firefighting, Protective services, Public administration, and Social services professions | 0.13 (0.33) |
| Engineering and related | Engineering, Engineering technologies and related | 0.07 (0.26) |
| Health | Health related knowledge and skills, Health professionals and related, Residency programs | 0.11 (0.31) |
| Humanities and Liberal Arts | Liberal arts/general studies, Multicultural/interdisciplinary, Philosophy and Religious studies, Theology and Religious vocations, History | 0.11 (0.31) |
| Industrial, manufacturing, and construction | Agriculture and related, Construction trades, Mechanic and repair technologies, Precision production, Transportation and material moving | 0.02 (0.12) |
| Literature, Linguistics, and Fine Arts | Foreign languages, literature and linguistics, English language, and literature, Visual and performing arts | 0.05 (0.23) |

| **Variable name** | **Description** | **Mean (*SD*)** |
|---|---|---|
| Math and Computer Science | Computer technologies, Information sciences, and support services, Mathematics and Statistics | 0.06 (0.23) |
| Natural Science | Natural resources and conservation, Biological and biomedical science, physical science, Science and technologies/technicians | 0.09 (0.28) |
| Service Oriented | Personal and culinary services, Military science, leadership and operational art, Military technologies and applied sciences, Parks, recreation and leisure studies | 0.04 (0.21) |
| Social and Behavioral Science | Area, ethnic, culture, gender and group studies, Human sciences, Legal professions and studies, Psychology, Social Sciences | 0.12 (0.32) |
| *Pretransfer information* | | |
| Total credits completed | Total credit hours completed with a passing grade in terms before vertical transfer | 56.36 (15.32) |
| Pretransfer GPA | Average GPA up to the transfer term | 2.10 (1.51) |
| *Credit loss variables* | | |
| Any credit loss (Course-level) | A dichotomous indicator of whether a course did not transfer for any reason | 0.14 (0.35) |
| Major credit loss (Course-level) | A dichotomous indicator of whether a course transferred to the institution but did not apply to the major the student declared at the time of transfer | 0.07 (0.25) |
| General credit loss (Course-level) | A dichotomous indicator of whether a course could not be transferred to the institution at all | 0.07 (0.26) |
| *Milestone completion* | | |
| Core complete | A dichotomous variable indicating if the student has completed all the core courses | 0.50 (0.50) |
| FOS complete | A dichotomous variable indicating if the student has completed field of study courses | 0.07 (0.26) |
| Associate degree | A dichotomous variable indicating if the student has completed associate degree | 0.53 (0.50) |
| *Course characteristics* | | |
| Core course | A dichotomous variable indicating if the course is listed as core | 0.75 (0.43) |

**Table OSM2**

*Descriptive Characteristics of Credit Loss Variables at the Student Level*

| | Full Sample | No Credit Loss | | Any Credit Loss | | Average Credit Loss | | |
|---|---|---|---|---|---|---|---|---|
| | ***N*(total)** | ***N*(none)** | **%** | ***N*(any)** | **%** | **TCL** | **MCL** | **GCL** |
| Gender | | | | | | | | |
| Male | 11,096 | 2,219 | 20% | 8,877 | 80% | 6.62 | 3.10 | 3.52 |
| Female | 17,873 | 2,681 | 15% | 15,192 | 85% | 7.27 | 3.45 | 3.82 |
| Race/Ethnicity | | | | | | | | |
| Asian (Non-Hispanic) | 1,645 | 477 | 29% | 1,168 | 71% | 6.03 | 2.13 | 3.90 |
| Black (Non-Hispanic) | 2,838 | 482 | 17% | 2,364 | 83% | 6.65 | 2.61 | 4.03 |
| Hispanic/Latino | 13,979 | 2,097 | 15% | 11,882 | 85% | 7.26 | 3.38 | 3.88 |
| White (Non-Hispanic) | 9,053 | 1,720 | 19% | 7,333 | 81% | 6.93 | 3.67 | 3.26 |
| Other | 1,454 | 247 | 17% | 1,207 | 83% | 7.10 | 3.19 | 3.91 |
| Low-Income Status | | | | | | | | |
| Yes | 12,249 | 2,205 | 18% | 10,044 | 82% | 6.83 | 3.12 | 3.71 |
| No | 16,720 | 2,842 | 17% | 13,878 | 83% | 7.16 | 3.46 | 3.70 |
| Major Area of Concentration | | | | | | | | |
| Business | 5,307 | 1,433 | 27% | 3,874 | 73% | 5.63 | 2.53 | 3.10 |
| Communication Studies | 884 | 133 | 15% | 751 | 85% | 5.98 | 2.82 | 3.16 |
| Education and Social Services | 3,555 | 640 | 18% | 2,389 | 82% | 6.40 | 3.27 | 3.14 |
| Engineering and related | 2,071 | 331 | 16% | 1,740 | 84% | 8.35 | 4.28 | 4.07 |
| Health | 3,218 | 290 | 9% | 2,928 | 91% | 8.60 | 3.70 | 4.90 |
| Humanities and Liberal Arts | 3,202 | 672 | 21% | 2,530 | 79% | 6.78 | 3.26 | 3.52 |
| Industrial, Manufacturing, Construction | 459 | 5 | 1% | 454 | 99% | 7.93 | 5.54 | 2.39 |
| Literature, Linguistics, Fine Arts | 1,562 | 312 | 20% | 1,250 | 80% | 6.45 | 2.93 | 3.52 |
| Math and Computer Science | 1665 | 266 | 16% | 1,399 | 84% | 7.56 | 3.12 | 4.44 |
| Natural Science | 2359 | 307 | 13% | 2,052 | 87% | 8.30 | 4.11 | 4.19 |
| Service Oriented | 1293 | 155 | 12% | 1,138 | 88% | 7.45 | 3.69 | 3.76 |
| Social and Behavioral Science | 3394 | 475 | 14% | 2,919 | 86% | 6.86 | 3.12 | 3.74 |
| Total | 28,969 | 4,925 | 17% | 24,044 | 83% | 7.02 | 3.32 | 3.70 |

*Notes.* The table shows student-level descriptive statistics for various credit loss measures by demographic categories and major area of concentration. *N* represents the subsample size; the bottom row reports descriptive statistics for the full sample. Within each analytic sample, the

percentages add up to 100% across the row. For the purpose of this table, *No Credit Loss* indicates that the student did not lose any of their pre-transfer credits for any reason, whereas *Any Credit Loss* indicates that the student lost at least one pre-transfer credit. These student-level variables were derived from the course-level variables defined in Table OSM1 and used as outcomes in our analyses. All numbers are rounded up to two digits after decimal, and percentages are rounded to the closest integers.
Data source: THECB transfer report data, linked with demographic measures from enrollment data.

**Course Content Measurement and Credit Loss**

In order to develop parsimonious statistical models of credit loss, we explored how credit loss varies across parameterizations of course content. We began by descriptively analyzing how credit loss varied across courses. Figure OSM1 visualizes the percentage of credits that were lost across four different parameterizations of course subject areas. The top-left panel uses broad course subjects as the grouping variable, the top-right panel uses specific course subjects, the bottom-left panel uses unique courses (course subject and number combinations), and the bottom-right panel uses course-by-major pairs. To improve the interpretability of the figures, we restricted the sample to the most common courses. As shown in the top-right panel of Figure 1, we found variation across broad course subjects in the likelihood that credits will be lost at the time of transfer. Courses in the subjects of Business and Humanities, Liberal Arts, and General Studies had the two lowest rates of credit loss, both under 10%. In contrast, courses in Education or Health both had credit loss rates between 20% and 25%. The remaining four broad course subjects all had moderate credit loss rates of between 10% and 15%.

The top-right panel visualizes credit loss by specific course subjects. We included only course subjects with at least 500 student enrollments in our sample to limit the number of course subjects displayed on the graph. As shown in that figure, the percentage of credits lost at the time of transfer varied from a high of 25% of credits for Education courses (EDUC) to roughly 5% of credits lost for Government (GOVT) courses. In general, course subjects that were included in the common core curriculum, such as Government, History (HIST), and English (ENGL), tended to have lower rates of credit loss, whereas the four course subjects with the highest credit loss rates were two types of languages (Spanish [SPAN] and American Sign Language [SGNL]) and two types of education courses (Early Childhood Education [TECA] and Education [EDUC]) typically outside of the core. However, some course subjects found widely in institutions' core curricula, such as Mathematics (MATH), Sociology (SOCI), and Psychology (PSYC), had moderate rates of credit loss.

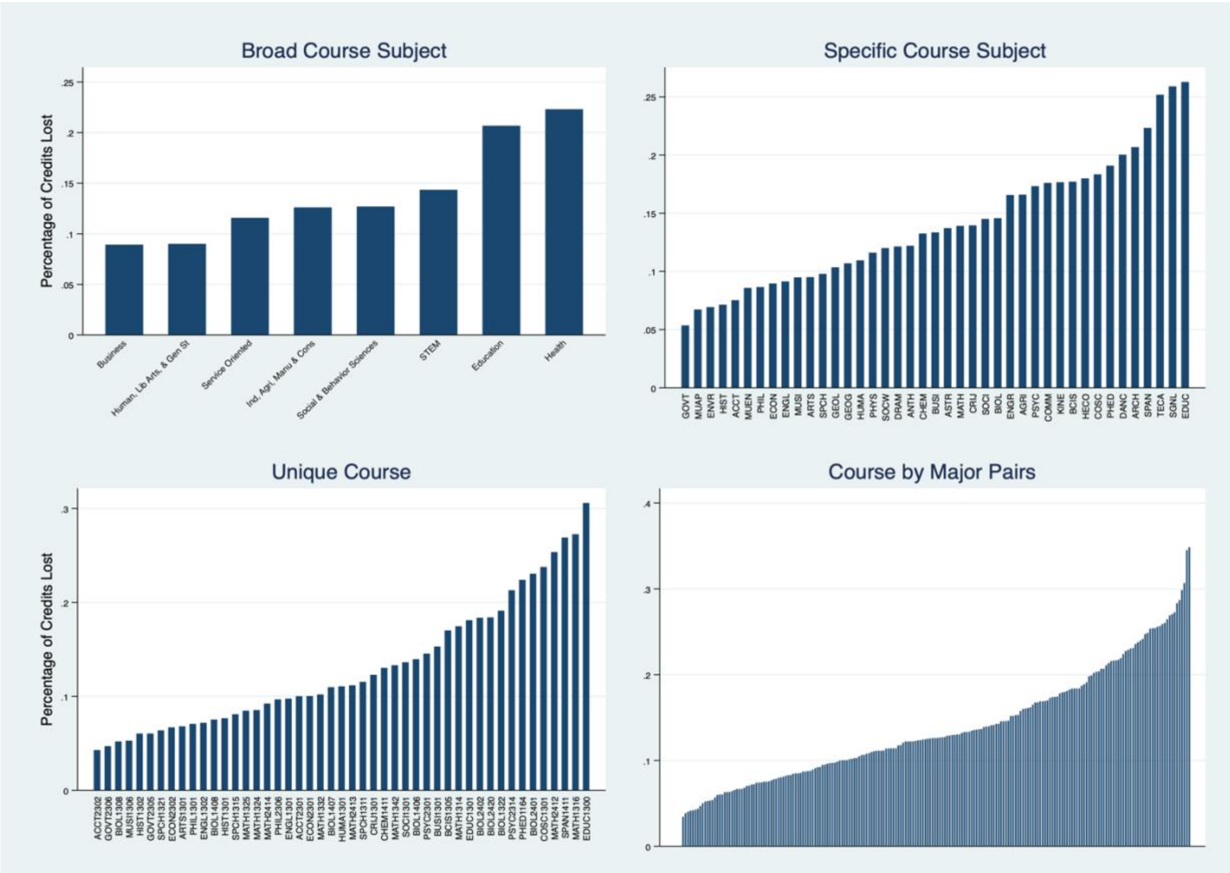
The bottom-left panel disaggregates the course grouping into the specific courses students completed, represented by the combination of the course subject and number. We note that this graph includes only courses where at least 2,500 students completed the course prior to transfer in order to ensure the courses are legible. This figure highlights how much variation existed across course numbers, even within the same course subject. For example, MATH 1325 (Calculus for Business), MATH 1324 (Math for Business), and MATH 2414 (Integral Calculus) all had credit loss rates below 10% and are in the bottom third of the distribution of credit loss, whereas MATH 2412 (Precalculus) and MATH 1316 (Trigonometry) had credit loss rates above 25% and were in the top five courses most likely to be lost at the time of transfer. Similarly, BIOL 1308 (Biology for Non-Science Majors) had the third lowest credit loss rate out of all courses in the sample, whereas BIOL 2401 (Human Anatomy & Physiology) had the sixth highest credit loss rate. This analysis suggests that aggregating to the course subject level may mask important variation in credit loss across course numbers in the same subject.

The bottom-right panel disaggregates further to examine course-by-major pairs, or unique courses taken by students transferring into a specific major. Because of the large number of course-by-number pairs, we exclude the labels and do not focus on the individual estimates. Rather, we highlight that although this figure provides additional granularity regarding the courses students were completing in specific major pathways, the overall range of credit loss (5%–30%) is roughly equivalent to the range in the previous figure of course numbers. For example, one course in the previous figure (EDUC 1300: Learning Frameworks—this is a student success-oriented course) had a credit loss rate of above 30%, whereas in this analysis only three course-by-major pairs exhibit credit loss rates of above 30%. Although examining course-by-major pairs provides greater granularity, it is unclear whether the additional granularity is worth the complexity, both in terms of the parsimony of the statistical models and in terms of producing interpretable estimates of how credit loss varied across courses.

To further test this assumption, we ran a series of logistic regression models that all controlled for the same covariates and fixed effects but varied the parameterization of courses. An overview of this modeling approach is provided in Appendix Table OSM3. The first model included only course delivery characteristics (e.g., dual-credit or not, hybrid or not), the second model included broad course subjects, the third model included unique course subjects, the fourth included unique courses (course subject and number pairs), and the fifth included the course-by-major pairs. We note that we removed the major group variable from the fifth model because the course-by-major pairs controlled for the specific major students transferred into, rendering the major group variable redundant. We also note that the logistic regression models drop groups where there is no variation in the outcome, such as course subjects or unique courses where zero students lost credits, resulting in the sample decreasing slightly (a maximum of 3% of cases lost in the final model) across models. As shown in the final row of the table, the adjusted pseudo-$R^2$ values indicate that model fit improves as the granularity of our parameterization of courses increases, until the final model of course-by-major pairs. These results suggest that controlling for unique courses produces a considerably more accurate model than controlling for course subjects alone, but accounting for course-by-major pairs decreases model fit. We therefore control for unique courses in our remaining analyses.

**Figure OSM1**

*Percentage of Credits Lost for Any Reason (Any Credit Loss) by TCCNS Course Subject*




*Notes.* The figures display the percentage of credits lost by course characteristics among the population of students who transferred from a public community college to a public university in Texas between Fall 2020 and Spring 2022. In the top left figure, each bar represents a broad course subject. In the top right figure, each bar represents a unique course subject aligned with Texas's *Academic Course Guide Manual* (ACGM). That figure includes only course subjects where at least 500 courses were completed by students in the sample prior to transfer. In the bottom left figure, each bar represents a unique course, identified by combining the course subject and number, aligned with the ACGM. That figure includes only courses where at least 2,500 courses were completed by students in the sample prior to transfer. In the bottom right figure, each bar represents a course by major pair, which is a course taken by students who declared a specific major at the time of transfer. Courses are identified by combining the course subject and number aligned with the ACGM, and majors are identified using 4-digit Classification of Instructional Program (CIP) codes. The figure includes only course by major pairs with at least 500 records in the sample. The actual course by major pairs are not indicated on the *x*-axis because of the large number of pairs.

**Table OSM3**

*Logistic Regression Models of Any Credit Loss With Varying Parameterizations of Courses*

| | Course Covariates Only | Broad Course Subjects | Specific Course Subjects | Course Numbers | Course by Major Pairs |
|---|---|---|---|---|---|
| Course Covariates | Yes | Yes | Yes | Yes | Yes |
| Student Demographics | Yes | Yes | Yes | Yes | Yes |
| Pretransfer Academics | Yes | Yes | Yes | Yes | Yes |
| Major Groups | Yes | Yes | Yes | Yes | No |
| Beginning Cohort FEs | Yes | Yes | Yes | Yes | Yes |
| Course Semester FEs | Yes | Yes | Yes | Yes | Yes |
| Semester of Transfer FEs | Yes | Yes | Yes | Yes | Yes |
| Sending Institution FEs | Yes | Yes | Yes | Yes | Yes |
| Receiving Institution FEs | Yes | Yes | Yes | Yes | Yes |
| *n* | 494,309 | 494,309 | 491,860 | 482,931 | 479,371 |
| Pseudo-ICC | 0.053 | 0.061 | 0.076 | 0.104 | 0.102 |

*Notes:* The table demonstrates our approach for examining how the parameterization of course content influences model fit. Each model included all blocks of covariates indicated by rows in the table, apart from the final model with removed the variable indicating major groups because the course-by-major pairs added to this model rendered the major group variable redundant.