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Credit Loss, Institutional Retention, and Postsecondary Persistence Among Vertical Transfer Students

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Abstract

Although community colleges have served as a gateway to universities for millions of students—disproportionately so for students from populations historically underrepresented in higher education—prior research has demonstrated that the majority of vertical transfer students lose at least some of their pretransfer credits. However, researchers examining how credit loss relates to subsequent college outcomes have been hindered by data limitations. For this study, we drew from the literature on *academic momentum* and examined the relationship between credit loss, institutional retention, and postsecondary persistence. Our use of novel administrative data from Texas enabled us to disentangle *major credit loss* from *general credit loss* and study the contribution of each credit loss type to posttransfer outcomes. Our analyses show that both forms of credit loss are inversely related to institutional retention, but the relationships between credit loss and postsecondary persistence are far less consistent. We found evidence suggesting that *major credit loss* is more strongly related to both retention and persistence than *general credit loss*. We did not find evidence that the relationship between credit loss and posttransfer outcomes is moderated by students' race/ethnicity, economic status, or gender, and we found only limited evidence of moderation by major.

Keywords: Community colleges, universities, transfer, vertical transfer, credit loss, retention, persistence

Introduction

Despite the long-standing centrality of vertical transfer in the American higher education system, navigating transfer is challenging for many students (Rosenbaum et al., 2007; Schudde et al., 2021). Fewer than one-third of beginning community college students transfer to a 4-year college within six years (NSCRC, 2024b). Those who do transfer often lose credits. By some estimates, more than two-thirds of transfer students lose pretransfer credits, and nearly 40% lose all their credits (Simone, 2014). On average, the students who did not transfer any credits had accumulated 26.6 credits at their prior institution, meaning they lost roughly a year of college coursework. The widespread loss of credits among transfer students raises obvious concerns about excess credit accumulation and lost time and money (Fink et al., 2018; Xu et al., 2018). As low-income students and students of color are disproportionately likely to begin their postsecondary journey at a community college, credit loss has clear equity implications (Jain et al., 2011).

Despite growing evidence of the scope of credit loss and its correlates, evidence linking credit loss and university outcomes is lacking (GAO, 2017; Giani, 2019; Giani et al., 2024; Monaghan & Attewell, 2015; Simone, 2014). We identified four critical gaps in the literature. First, studies have produced conflicting conclusions regarding whether credit loss relates to bachelor's degree completion, and no studies have examined whether credit loss relates to more proximal outcomes like retention and persistence (Monaghan & Attewell, 2015; Spencer, 2022). Second, limited research has examined the functional form of the relationship between credit loss and university outcomes or factors that may moderate this relationship, such as race/ethnicity, socioeconomic status, gender, and majors. Third, prior estimates of the relationship between credit loss and university outcomes may have been biased by researchers' inability to account for institutions. Fourth, most studies have examined *general credit loss* (GCL) rather than *major credit loss* (MCL) (e.g. Monaghan & Attewell, 2015; Spencer, 2022). The latter relates to credits that are accepted as credit by the receiving institution but do not apply to the student's major. Although MCL has been identified in qualitative research (Kadlec & Gupta, 2014) and researchers have recently begun to measure it (Giani et al., 2024), researchers have yet to measure MCL or examine its relationship with university outcomes.

This study is designed to address these gaps using newly collected credit loss data from Texas linked with other student, course, and institutional data contained in Texas's statewide longitudinal data system known as the Texas Education Research Center (TERC). Examining the universe of students who transferred from a public 2-year to a public 4-year institution during the 2020–21 and 2021–22 academic years, we were able to measure total credit loss (TCL), GCL, and MCL and examine how all three measures of credit loss relate to institutional retention and postsecondary persistence. We estimated how both forms of credit loss relate to institutional retention and postsecondary persistence. We controlled for both sending and receiving institutional fixed effects to account for the possibility that credit loss and university outcomes are correlated across institutions, thereby limiting an important source of potential bias in prior research. Our sample size also enabled us to examine heterogeneity in the relationship between credit loss and university outcomes across demographic groups and majors.

Our results show that credit loss is meaningfully related to institutional retention. Students who lose 15 credits are up to ten percentage points less likely to be retained at the same institution than those who lost no credits during transfer. Our findings also suggest MCL is more strongly related to retention than GCL. While we find that credit loss is inversely related to short-term postsecondary persistence, the relationship with long-term persistence declines to insignificance. Taken together, these results suggest that credit loss may deter institutional retention without stymying postsecondary persistence altogether, potentially contributing to subsequent transfers. We find no compelling evidence that the relationship between credit loss and university outcomes varies across demographic groups, and modest variation in this relationship across majors. Overall, our study provides novel evidence of how credit loss may slow students' academic momentum, particularly at the original transfer destination.

The Scope of Credit Loss

Historically, researchers examined excess credit accumulation among transfer students as a proxy for credit loss. Cullinane (2014) used statewide administrative data in Texas and calculated that baccalaureate recipients who began at a community college attempted 150 college-level credits compared to 142 for native 4-year students. Xu et al. (2016) reached similar conclusions using data from Virginia, estimating that 2-year entrants who earned a bachelor's degree earned 10 more credits than observably similar native 4-year students. Fink et al. (2018) compared the excess credits attempted by 2-year and 4-year entrants in two states and estimated that 2-year entrants attempted 8–9 additional credits. Although this research suggests that vertical transfer students lose about 10 credits during transfer, other explanations are possible. For example, transfer students may be more likely to take additional elective courses at the 4-year institution, change their majors, or repeat courses to improve their GPA, potentially causing excess credit accumulation even without credit loss. Critically, research on excess credit accumulation must focus on baccalaureate recipients, which is problematic given that students may stopout of higher education *because of credit loss*.

In the past decade, postsecondary transcript data collected as part of the National Center for Education Statistics (NCES) Beginning Postsecondary Students (BPS) survey has enabled researchers to more directly measure credit loss for a nationally representative sample of beginning college students. In his 2014 analysis of BPS data, Simone estimated that two-thirds of first-time transfer students lose some credits, and nearly 40% lose all credits. Analyses of the same data source led to similar estimates (GAO, 2017; Monaghan & Attewell, 2015) and revealed the extent to which credit loss varies across transfer pathways. For example, the GAO (2017) report showed that credit loss was least prevalent among students who traversed the traditional vertical transfer path from public 2-year to public 4-year colleges but was more widespread among students taking less traditional transfer pathways.

Although the BPS transcript data facilitated a more direct measurement of credit loss rather than relying on excess credit accumulation, these estimates remain a rough proxy for credit loss. As Fink et al. (2018) and Kadlec and Gupta (2014) highlighted, courses may technically be accepted by an institution for credit even if they do not apply toward the student's major and facilitate progress-to-degree. Transfer students in Kadlec and Gupta's qualitative study described the elective category as an "academic graveyard" where transfer credits get buried. Although the importance of *major credit loss* (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 been able to systematically measure MCL and distinguish it from what we refer to as *general credit loss* (GCL), or courses that the institution does not accept for credit at all. As is discussed further below, research examining how credit loss shapes subsequent university outcomes has been able to measure GCL only by using the BPS data, raising questions about the robustness of those findings.

Conceptual Framework: Academic Momentum, Credit Loss, and University Outcomes

We drew upon the theoretical framework of *academic momentum* to conceptualize the relationship between credit loss and university outcomes. Traditionally, academic momentum was conceptualized as a student's rate of course-taking and credit accumulation in the first one or two semesters of college (Adelman, 1999, 2006). The theory suggests that faster rates of credit accumulation initially correspond to more rapid long-term progress-to-degree, which in turn increases the likelihood of baccalaureate attainment and decreases time-to-degree. Studies have found that students who attempt a greater number of credits in the first semester complete more credits in subsequent semesters than their peers who have lower initial course loads, which supports a key hypothesis of academic momentum (Attewell et al., 2012). This theory has been extended to the study of specific academic pathways, leading to frameworks such as “STEM momentum” and empirical studies supporting this mechanism (Chan & Wang, 2018; Fink et al., 2024; Wang et al., 2015; Zhang, 2022).

This theory has also been applied to vertical transfer and, specifically, the phenomenon of credit loss (Monaghan & Attewell, 2015). Within this framework, credit loss can be understood as a key *counter-momentum friction* (Wang, 2017) that reduces students’ academic momentum. Indeed, it is difficult to logically dispute that credit loss requires students to attempt additional courses posttransfer and delays progress toward a bachelor’s degree. At least one study examining the relationship between credit loss and baccalaureate attainment found that credit loss was inversely related to vertical transfer students odds of baccalaureate attainment, congruent with this theory (Monaghan & Attewell, 2015).

However, exactly how credit loss contributes to academic momentum remains underexplored, and a number of questions remain unaddressed. First, the academic momentum framework might suggest that each additional course or credit students lose during transfer increases “friction” and decreases momentum, but whether credit loss is linearly related to university outcomes or takes on another relationship is unknown. Second, although credit loss inevitably requires students to take additional courses posttransfer, it is unclear whether this friction is severe enough to disrupt students’ baccalaureate ambitions altogether or simply slows students’ academic progress. Although Monaghan and Attewell (2015) found an inverse relationship between credit loss and baccalaureate attainment, Spencer (2022) found no relationship between these variables using the same BPS dataset. Third, it is unknown whether MCL and GCL might differentially affect university outcomes. It is possible that GCL is a more severe friction and is more strongly related to retention and persistence, whereas MCL might incline students to switch majors (to ones where more of their credits applied to the degree) without necessarily decreasing their likelihood of retention at the university. Fourth, researchers have yet to examine key potential moderators of the relationship between credit loss and university outcomes. For example, low-income students or those from racial/ethnic groups historically marginalized from higher education may be more susceptible to the friction induced by credit loss, and credit loss may be more consequential in majors that have rigid degree plans and course sequences.

Methods

Research Questions

We asked the following research questions:

1. Which students experience credit loss upon vertical transfer and what type of credit loss—GCL vs. MCL—do they primarily experience?
2. How do total credit loss and credit loss types relate to institutional retention and postsecondary persistence?
3. To what extent does the relationship between credit loss and retention and persistence vary across demographic groups and majors?

Data

We leveraged statewide longitudinal data from the Texas Education Research Center (ERC), a clearinghouse at the University of Texas at Austin that maintains K–12 records from the Texas Education Agency (TEA), postsecondary information from Texas Higher Education Coordinating Board (THECB), and labor market outcomes from Texas Workforce Commission (TWC). Data usage follows a standard application and approval process by an advisory board on quarterly basis.[1]

We relied on THECB data, which covers all students enrolled in any Texas postsecondary institution. The data include student demographics; institutional enrollment information and degrees 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 courses denied for transfer and the institution's reported reason for credit denial. To be included in the transfer report, transfer students must: (a) be first-time vertical

[1] For more information, see https://texaserc.utexas.edu/.

transfer students transitioning from a public 2-year institution to a public 4-year institution in Texas; (b) have lost at least one credit-bearing lower-division course listed in the *Academic Course Guide Manual*, a list of approved academic lower-division courses offered by public 2-year colleges in the state; 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). We relied on the first available transfer report data from Fall 2020 up through the latest available report, from Spring 2022.

Institutions report denying credits related to one of the five THECB outlined factors: (a) credits were outside the student's major at the time of matriculation; (b) grades were below the institution's/program's minimum grade requirement; (c) the course was repeated and only one instance could be transferred; (d) the student had exceeded the maximum number of 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. We used instances of the first category to create our measure of major credit loss. These credits transfer but do not apply to the program of study, compelling the student to take additional hours toward their chosen program and potentially contributing to excess credit accrual (Cullinane, 2014). We capture credits denied for the remaining four reasons under our measure of general credit loss. These categories, particularly falling outside institutions' grade requirements and exceeding their maximum transferrable hours, offer wiggle room for institutions to tailor transfer conditions to their standards while creating uncertainty for students and advisors given that transfer information is not always posted or current on university websites (Schudde et al., 2018).

Sample

We drew our sample from the population of first-time vertical transfer students who moved from a public 2-year to a public 4-year institution during the fall or spring semesters of the 2020–21 and 2021–22 academic years. We restricted the sample to students who began at a community college between 2010–11 and 2020–21. Course-level data were not collected by THECB before 2010–11, and students who began college after 2020–21 were unlikely to have transferred in the semesters included on the available credit loss reports. We removed a small number of students who were listed on the credit loss report but whose enrollment records showed they had attended multiple institutions. Our full sample for descriptive analyses of credit loss is n = 28,969 students. A very small fraction of students (n = 35, 0.1%) had missing data for one or more covariates and were excluded from the statistical models, for a final inferential analysis sample of n = 28,934. In models of later outcomes, such as retention and persistence into the fourth term or the second year, the sample was further restricted to earlier cohorts, given that we were unable to observe longer-term outcomes for students who transferred later. Table A1 in the Appendix includes the descriptive characteristics of our sample, including the percentage of students who lost credits and the average number of credits students lost at the time of transfer. Tables A2 and A3 in the Appendix provide the number of students and descriptive characteristics of our key credit loss variables for the community colleges and public universities in our sample, respectively.

Dependent Variables

We examined both institutional retention and postsecondary persistence as dependent variables. *Institutional retention* is defined as students being enrolled at the same institution, as determined by students having the same institutional FICE code in a given term as the FICE code of the institution they originally transferred to. In contrast, *postsecondary persistence* is defined as student enrollment at any postsecondary institution in the state, regardless of whether they remained enrolled at the original 4-year receiving institution. For both retention and persistence, we examined semester-to-semester and year-to-year outcomes. For semester outcomes, we treated students as having experienced the outcome if they were enrolled in a given long semester (Fall and Spring), whether or not they remained continuously enrolled. For example, a student who stopped out in their second term but reenrolled in their third term would still be considered to have experienced the outcome (retention or persistence) in their third term. For yearly outcomes, students were treated as having experienced the outcome if they were retained/persisted throughout all semesters of the academic year. First-year retention represented the student being enrolled in both long semesters after transfer, including during their initial semester of transfer, whereas second-year retention represented the student being enrolled in both long semesters in the following year.

Independent Variables

We have three primary independent variables of interest that capture credit loss among transfer students. The first, *total credit loss* (TCL), represents the total number of academic credits (referred to as "semester credit hours" in Texas) that students lost at the time of transfer. We explored the possibility of a nonlinear relationship between total credit loss and our outcomes in two ways. First, we added a squared term of total credit loss in some models. The inclusion of the squared term changed the interpretation of the total credit loss main effect, and the coefficient of the squared term was difficult to interpret. We therefore graphed the relationship between total credit loss and our outcomes for models that included the squared term. Second, we converted total credit loss to a categorical variable. The categories for this variable were (a) no credits lost, (b) 1–6 credits lost, (c) 7–12 credits lost, (d) 13–18 credits lost, (e) 19–24 credits lost, (f) 25–30 credits lost, and (g) more than 30 credits lost. Because college courses typically confer three credits, the categories corresponded to increments of roughly two courses. Because the results from these two modeling approaches were similar, we focus on the models with the quadratic credit loss variables when examining nonlinear relationships for brevity. We include results of models with the categorical variables in the Appendix (Tables A6-A8).

In addition to TCL, *major credit loss* (MCL) captures the sum of credits that the student was able to transfer but did not apply to the student's major, whereas *general credit loss* (GCL) is the sum of all other credits that did not transfer for other reasons. As with the TCL variable, we fit different models with only the continuous versions of these variables, with the quadratic terms added, and with the continuous and quadratic terms replaced by categorical versions of the credit loss type variables. Again, we focused on the models with the continuous and quadratic terms but included the results of the models with categorical credit loss type variables in the Appendix.

We included covariates in the model that are aligned with our academic momentum conceptual framework and with common predictors of student retention and persistence (Clovis & Chang, 2021; Attewell et al., 2012; Spencer, 2022). We grouped the covariates into four primary blocks: demographic characteristics, pretransfer academic characteristics, major, and institutions. The demographic controls included age, race/ethnicity, gender, and low-income status. Age was defined as a continuous variable. 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 ethnically Hispanic/Latino. We created a single race/ethnicity variable where students identifying as Hispanic/Latino were defined as one group and all other racial groups were non-Hispanic/Latino. For our analysis, we further classified the latter under Asian, Black, White, and Other, a category that includes multiple groups with small sample sizes. Students report gender as a binary variable: male or female. Low-income status is a dichotomous indicator used by colleges (and provided in the student enrollment data) to identify economically disadvantaged students, captured through multiple measures such as falling below the annual federal poverty line or Pell Grant eligibility.

Pretransfer academic characteristics are measured using the number of credits completed before transfer and pretransfer GPA, which are indicative of pretransfer academic progress. We constructed pretransfer credits and GPA from the transcript data capturing courses, associated credit hours, and grades the student completed at a 2-year institution before transferring to the 4-year institution. We also included cohort fixed effects to indicate the year students began college, which could influence their retention and persistence. Major area of concentration was organized into 13 broad bins following Baker (2018) and Jenkins et al. (2017), based on the 2-digit Classification of Instructional Programs (CIP) code at the university as reported in the transfer term.

Finally, we included institutional fixed effects for both the sending and receiving institutions (i.e., 2-year colleges and university destinations) to control for potential endogeneity arising from correlations between credit loss, university outcomes, and university characteristics (Calcagno et al., 2008; Titus, 2004). Our estimates can therefore be interpreted as the relationship between credit loss measures and retention or persistence, controlling for the community college students transferred from and the university they transferred to.

Analytic Approach

We used linear probability models (LPM) to estimate the relationship between credit loss and retention/persistence. LPMs apply ordinary least squares (OLS) regression to a dichotomous outcome. Although logistic regression models can be used when the outcome is dichotomous, LPMs are appropriate when the outcome is not rare (e.g., 20%–80% of the sample experiences the outcome), as is the case for both retention and persistence as shown in Table A1 (Hellevik, 2009). LPMs also have the added benefit of being easier to interpret, as they produce coefficients that are interpreted as changes in the predicted probability of the outcome occurring for a one-unit change in the independent variable. In our case, this enabled us to interpret changes in the probability of either retention or persistence for each additional credit lost (or across ranges of credit loss for the categorical variable). Our statistical equation can be defined as:

$$\boldsymbol{y_{ijk} = \beta_0 + \beta_1 CL_i + \beta_2 Demog_i + \beta_3 Acad_i + \beta_4 Major_i + \gamma_j + \delta_k + \varepsilon_{ijk}}$$

where $\boldsymbol{y_{ijk}}$ is the outcome for student *i* transferring from 2-year institution *j* to 4-year institution *k*. $\boldsymbol{CL_i}$ represents the credit loss experienced by student *i*, $\boldsymbol{Demog_i}$ represents the vector of demographic controls discussed above, $\boldsymbol{Acad_i}$ includes pretransfer academic characteristics and cohort year, and $\boldsymbol{Major_i}$ indicates the major the student declared at the time of transfer. The models also include institutional fixed effects for the sending 2-year college indicated by $\boldsymbol{\gamma_j}$ and the receiving 4-year institution indicated by $\boldsymbol{\delta_k}$. The residual term $\boldsymbol{\varepsilon_{ijk}}$ represents the deviation of the student's outcome from their prediction after accounting for all variables included in the model and institutional fixed effects. We clustered standard errors at the 4-year institution level.

We initially took a model-building approach, adding related variables to the model in blocks and examining changes in the point estimate and standard errors of the credit loss variable(s) to determine how sensitive our estimates are to model controls. Overall, our estimates changed little, regardless of whether credit loss was the only variable included in the model or the model controlled for all covariates and institutional fixed effects. We therefore focused on the results from the full models that included all relevant controls. Table A4 provides a high-level overview of which covariates were added to each model during this model-building process, and Table A5 provides results for the full models.

To examine whether the relationship between credit loss and retention/persistence varies across demographic groups and majors (RQ #3), we added interaction terms to the models. An example of the equation for these models may be described as:

$$\boldsymbol{y_{ijk} = \beta_0 + \beta_1 CL_i + \beta_2 Demog_i + \beta_3 Acad_i + \beta_4 Major_i + \beta_5 CL_i * Demog_i}$$
$$\boldsymbol{+ \gamma_j + \delta_k + \varepsilon_{ijk}}$$

where all other terms are identical to those defined above, apart from the interaction term. The coefficient $\boldsymbol{\beta_5}$ represents the interaction between our credit loss variable(s) and a demographic characteristic (race, low-income status, or gender) or major (we run the model separately to test the interaction for each variable of interest). If this coefficient is significant, it suggests that the relationship between credit loss and retention/persistence varies across demographic or major groups included in the interaction. We tested interaction terms one at a time for ease of interpretation. We examined the interactions between credit loss and race/ethnicity, gender, and whether students are low-income. In addition, we replaced the credit loss by demographic variable interaction with an interaction term between credit loss and major group in order to examine whether the relationship between credit loss and retention or persistence varies across majors.

Results

Who Experiences Credit Loss and What Types Are Most Prevalent?

Given the novelty of our data, our first research question focused on describing which vertical transfer students experienced credit loss and, among all vertical transfer students, the magnitude and types of credit loss experienced. Table 1 presents descriptive statistics of credit loss disaggregated by demographic populations. Among all vertical transfer students in our sample, 83% of students lost any credits. The average number of total credits lost was 7.0, with 3.3 credits lost to GCL and 3.7 to MCL. Because students in the sample had earned roughly 50 credits before transfer, students lost 14% of their pretransfer credits on average. There was modest variation in total credits lost across demographic groups. For example, 71% of Asian students experienced credit loss with an average of 6.0 credits, compared with 85% of Hispanic/Latino students who lost an average of 7.3 credits. Among Black and White students, 83% and 81% lost any credits with averages of 6.7 and 6.9 credits, respectively. Among economically disadvantaged students, 82% lost any credits, with an average of 6.8 credits lost, in comparison with 83% of non-disadvantaged students with an average of 7.2 credits. Roughly 85% of female students lost any credits, compared with 80% of male students, and the two groups' average credits lost were 7.3 and 6.6, respectively. All demographic groups experienced more GCL than MCL on average, but the means of the two variables were quite similar for all groups.

[Table 1]

Our results show greater variation in credit loss across majors than across demographic groups. For example, 73% of students transferring into Business lost any credits, and these students had the lowest mean total credit loss of 5.6. In contrast, 99% of students majoring in Industrial, Manufacturing, and Construction majors (which was also the least common major group) lost credits at the highest rate in the sample, with an average of 7.9 credits lost. Although this major group had the highest credit loss rate, other fields had higher averages of credit loss. Health, Engineering and Related, and Natural Science were the only three major groups that lost more than eight credits on average, with means of TCL of 8.6, 8.4, and 8.3, respectively. Although students generally lost more credits because of GCL than MCL, this was not true for all majors. Students who majored in Education and Social Services; Engineering and Related; and Industrial, Manufacturing, and Construction all lost more credits because of MCL than because of GCL, with the last group losing more than twice as many credits from MCL than GCL on average (5.54 vs. 2.39).

How Does Credit Loss Relate to Retention and Persistence?

To address our second research question, we examined the relationship between total credit loss (TCL) and both retention and persistence using linear probability models. We then disaggregated total credit loss into MCL and GCL to further understand the relationship between credit loss type and transfer students' university outcomes. Table 2 presents regression results from linear probability models for both sets of outcomes (retention in any institution vs. persistence in higher education) and for both sets of credit loss measures. Panel A presents results for *TCL* and Panel B for *MCL* and *GCL*, entered as separate independent variables. Results in the top-left quadrant of Panel A illustrate the correlation, even given a host of statistical controls and institutional fixed effects, between TCL and retention. As the results show, TCL is significantly and negatively related to institutional retention in every semester after transfer (second, third, and fourth) and in annual retention (remaining enrolled for the full academic year) in Year 1 and Year 2 after transfer. The estimates range from a -0.2- to a -0.4-percentage-point (pp) change in the probability of retention for each credit loss, depending on the retention outcome. Put differently, a student who lost 10 credits at the time of transfer is 4pp (i.e., 10 × 0.4) less likely to still be enrolled in the same institution by the third or fourth semester after transfer.

[Table 2]

In contrast, the relationship between TCL and persistence is both smaller initially and declines to non-significance across outcomes. Each credit lost is associated with a 0.1pp decrease in the probability of second-semester postsecondary persistence and a 0.2pp decrease in first-year persistence—both statistically significant estimates. However, the point estimate is 0.0 and non-significant for all other persistence outcomes. When TCL is parameterized as a continuous variable, we find no evidence that it is related to longer-term postsecondary persistence rates. Taken in tandem, these results suggest that TCL may be more strongly related to institutional retention than postsecondary persistence and may not be related to longer-term persistence.

Panel B of Table 2 examines whether the two different types of credit loss students experience—MCL and GCL—offer additional insights into how credit loss predicts student outcomes. The leftmost columns in Panel B include the estimates of MCL and GCL on student retention. We find that both MCL and GCL are negatively and significantly related to all retention outcomes, and their point estimates are roughly of the same magnitude. However, the point estimates for MCL are larger than those for GCL in every model of retention outcomes. Each additional credit lost via MCL is associated with a 0.3-0.5pp decrease in the likelihood of retention, whereas the estimates are 0.2-0.4pp for GCL. Interestingly, whereas the estimated relationship between TCL and retention through Year 2 was smaller than the estimate of Year 1 retention, in the models that replace TCL with the MCL and GCL variables, credit loss is more strongly related to retention through Year 2 than through Year 1.

The results in the rightmost columns of Panel B similarly show quite different relationships between MCL and GCL and our outcomes of persistence. GCL is not significantly related to any of the persistence outcomes. MCL appears to be associated with a decreased likelihood that students will persist through their second and third terms and their first year posttransfer, but is not significantly related to fourth-term persistence or persistence through Year 2. Thus, whereas the estimates of MCL and GCL on retention suggest that the relationship between credit loss and retention may grow over time, the models of persistence suggest that MCL (but not GCL) predicts short-term but not long-term persistence.

The previous regression models presented in Table 2 assume credit loss has a linear association with retention and persistence. To further explore this assumption, we fitted separate models to the same outcome variables and added a squared credit loss term for each credit loss measure of interest (i.e., total credit loss in our first models, and then the disaggregated measures of credit loss type in the subsequent models). We began with the models examining the relationship between TCL and retention, for which we found that both the main effect and the squared term for TCL were statistically significantly related to every retention outcome. To demonstrate these nonlinear relationships, we visualized the results in Figure 1 for ease of interpretation. Note that the scale of the *y*-axis varies across outcomes and graphs because the baseline rates of retention vary across terms and years. The relationships between TCL and the different retention outcomes included in Figure 1 are quite similar. TCL is more steeply related to declines in retention initially before the decline tapers off, usually at about 24 credits. Across outcomes, students who lost 15 total credits during transfer are 6–10pp less likely to be retained than students who lost no credits, but the difference in retention between students who lost 15 and 30 credits is negligible (roughly 1–3pp). The results from the models of retention with the categorical version of the TCL variable in the top panel of Table A6 in the Appendix suggest a similar pattern. Even losing only 1–6 credits was associated with up to a 15pp decline in second-year retention, but the differences in estimated retention across ranges of credit loss were often modest.

[Figure 1]

Figure 2 fits the same models, including both the TCL main effect and the squared term, to the persistence outcomes. Once again, the relationship between TCL and persistence differs markedly from the patterns observed for retention. In the models of second-semester and first-year persistence, both the main effects and the squared terms of TCL are significant. However, students who lost 15 credits during transfer were only 3–4pp less likely to persist than students who lost no credits, compared with the 6–10pp differences between these credit loss groups in the models of retention. We also found that neither the main effect nor the squared TCL term was significantly related to any of the other persistence outcomes, visualized by the relatively flat lines and large confidence intervals in the graphs from those models. Including the squared TCL term did not change our previous conclusion that TCL does not appear to predict longer-term persistence. The results of the models of persistence with the categorical TCL variable in the bottom panel of Table A5 also suggest minimal relationship between TCL and longer-term persistence outcomes.

[Figure 2]

We also examined the possibility of non-linear relationships between the disaggregated credit loss measures—MCL and GCL—and student outcomes. Figure 3 visualizes how MCL and GCL related to institutional retention outcomes when squared terms for both credit loss variables were added to the models. In this instance, the inclusion of the squared terms reveals potentially meaningful differences between MCL and GCL in their relationships with retention. For all retention outcomes, increases in MCL and GCL corresponded to roughly similar declines in retention initially. However, whereas GCL tended to have a curvilinear relationship with retention, the relationship between MCL and retention was far more linear. For example, students who lost 15 or 30 credits because of GCL had roughly similar predicted probabilities of second-year retention, whereas students who lost 30 credits because of MCL were roughly 7pp less likely to be retained through the second year than students who lost 15 credits. Additionally, whereas the squared term for the GCL variable was statistically significant at the $p < .001$ level in every model, suggesting a nonlinear relationship between GCL and retention, the squared term for MCL was non-significant in three of the models of retention outcomes. This pattern is reflected in Figure 3, which shows a curvilinear relationship between GCL and retention in every graph but a more linear relationship between MCL and retention for some of the outcomes, as well as in Table A6 of the

Appendix that includes categorical versions of the MCL and GCL variables in the models of retention outcomes. The results therefore provide stronger evidence of a nonlinear relationship with retention for GCL than for MCL.

[Figure 3]

Figure 4 visualizes the relationships between credit loss types and persistence from models that include squared terms for MCL and GCL. Once again, we found little relationship between GCL and persistence, similar to the results from the models without the squared terms in the bottom-right quadrant of Table 3. We also found quite different relationships between GCL and MCL. GCL had essentially no relationship with persistence, whereas MCL was significantly related to the probability of persistence in some outcomes. However, we found that credit loss is significantly related to second-term and first-year persistence but that neither MCL nor GCL was significantly related to the three longer-term persistence outcomes, even when the squared terms in the model were included.

[Figure 4]

Does the Relationship Between Credit Loss and Retention Vary Across Demographic Groups or Majors?

Descriptively, credit loss rates vary across demographic groups and majors (see Table 1). In the next analyses, we returned to using statistical models that contained the continuous TCL variable and examined whether the relationship between TCL and retention varied across demographic groups (Figure 5) and majors (Figure 6). Because of the modest relationships between credit loss and persistence found in the previous analyses, we only examined interactions for the outcome of institutional retention. We also focused exclusively on first-year retention, as the results were similar for the other constructions of the retention outcome.

Figure 5 combines the results of three separate models into a single figure, each of which includes one of the demographic interactions (race/ethnicity, economic status, and gender). We found limited evidence that the relationship between TCL and first-year retention varied across racial/ethnic groups, economic groups, or males and females, and even less evidence that TCL disproportionately impacted students from populations historically marginalized from higher education. Indeed, the point estimates for the race/ethnicity by TCL interaction suggest that if race/ethnicity moderates the relationship between TCL and first-year retention at all (which the results provide limited evidence of), the pattern is the inverse of historical racial/ethnic inequities in college outcomes. TCL was less negatively associated with first-year retention for Black and Hispanic/Latino students than for White students. In contrast, TCL was more negatively associated with first-year retention for Asian students than for White students. However, all of these TCL by race/ethnicity interaction estimates were nonsignificant. We also found that the point estimate for low-income students was less negative than the estimate for non-low-income students, though this interaction was also non-significant. The relationship between TCL and first-year retention was nearly identical for male and female students. Overall, we found limited evidence that student demographics moderated the relationship between TCL and retention.

[Figure 5]

In Figure 6, the model interacts the TCL variable with the indicator of the category of the major the student had declared at the time of transfer. The reference group was Humanities and Liberal Arts, which is the major group with the largest number of students and the smallest estimated relationship between TCL and first-year retention. The results show that the relationship between TCL and first-year retention was significantly different for certain major groups than for Humanities and Liberal Arts. Specifically, losing credits was more negatively related to institutional retention for students declaring a major in Education and Social Services or Health. None of the other estimates reached the threshold of statistical significance.

[Figure 6]

Discussion

If community colleges are to serve as an efficient path to the baccalaureate, they, universities, and state governing bodies must facilitate the transfer of students and credits. Unfortunately, credit loss is widespread (GAO, 2017; Giani, 2019; Monaghan & Attewell, 2015; Simone, 2014). The loss of credits at the time of transfer is a potential source of "friction" that can slow academic momentum (Attewell et al., 2012; Monaghan & Attewell, 2015; Wang et al., 2017). However, whether credit loss simply delays time-to-degree or diverts students from a baccalaureate pathway altogether is a key question, and researchers have reached conflicting conclusions regarding whether credit loss relates to university outcomes at all (Monaghan & Attewell, 2015; Spencer, 2022).

In this study, we used some of the first statewide data on credit loss for vertical transfer students. By linking these credit loss data with information on students' demographic and academic backgrounds as well as their subsequent higher education outcomes, we produced novel evidence of the relationship between credit loss and students' pathways to the baccalaureate. The detailed credit loss data collected in Texas allowed us to separately examine MCL and GCL, an important contribution given that nearly all quantitative research on credit loss has been able to measure only GCL (GAO, 2017; Giani, 2019; Monaghan & Attewell, 2015; Simone, 2014) despite reports of widespread MCL (Hodara et al., 2017; Kadlec & Gupta, 2014). The administrative data also enabled us to control for the sending and the receiving institutions to more accurately disentangle the potential confounding relationships between credit loss, institutional characteristics, and university outcomes.

Across all the results, four findings appear to be most critical for understanding the mechanisms that link credit loss with subsequent university outcomes. First, credit loss tends to be more strongly related to institutional retention than postsecondary persistence. Indeed, credit loss—total, major, and general—was significantly related to institutional retention in nearly every statistical model, whereas the relationships between credit loss and postsecondary persistence outcomes were far less consistent.

Second, the relationship between credit loss and retention waxes across time, whereas the relationship with persistence wanes. In nearly all models, credit loss was more strongly related to third-term, fourth-term, and second-year retention than to the earlier outcomes of second-term and first-year retention. In contrast, credit loss was often significantly related to second-term and first-year persistence but unrelated to longer-term persistence outcomes. One possible conclusion that can be drawn by combining these patterns is that the more credits students lose when transferring to an institution, the less likely they are to remain at that institution, but credit loss does not necessarily deter them from persisting in higher education overall. The only way for these patterns to emerge is if vertical transfer students are engaging in subsequent transfers (Andrews et al., 2014; NSCRC, 2024a). The more credits students lose during their first transfer, the more likely they may be to transfer again. The relatively short time frame of the study period makes it difficult to draw definitive conclusions about how credit loss relates to subsequent transfers. We return to this limitation and its implications for future research in the final section of the paper.

Third, the relationship between credit loss and retention is likely nonlinear. These patterns are most clearly represented in the figures visualizing the relationship between credit loss and retention from models that include a squared credit loss term. However, they are also evidenced in the models that include categorical versions of the credit loss variables included in the Appendix. Those results also suggest that even low levels of credit loss can at times be significantly related to large declines in the probability that students will be retained at the institution they transferred to. The results also suggest that high levels of credit loss may be less deleterious than low levels of credit loss. This finding is perhaps the most unexpected. Although this result may be a statistical anomaly, one hypothesis congruent with this finding is that students are engaged in a sunk cost fallacy wherein losing large numbers of credits (and the money paid to complete the courses) makes them feel even more obligated to complete their degree to preclude letting that time investment go to waste, which mitigates the relationship between high credit loss and retention. Additional research is needed to support this finding and investigate the mechanisms that may explain it.

Fourth, although MCL is somewhat less common than GCL, it appears to be even more strongly related to institutional retention than GCL. This finding is also congruent with the potential mechanism of students' likelihood of engaging in subsequent transfers rising as their MCL does. Specifically, if students are unable to transfer large numbers of credits to the major they intend to pursue, they may be more likely to transfer to another institution (or even to return to the institution they transferred from), because they believe those credits will both transfer and apply to their major.

Limitations and Future Research

Although this study provides some of the most robust evidence of the relationship between credit loss and posttransfer college outcomes to date, we faced limitations in the study that we hope can facilitate a discussion about future research and reform efforts. Perhaps most importantly, our results are relatively short term. We did not examine subsequent transfer patterns after the initial vertical transfer students experienced, baccalaureate attainment, time-to-degree, semester credit hour accumulation, the total costs of college, or economic outcomes such as debt-to-income ratio. The fact that Texas just began collecting this data in 2020 prevented us from examining outcomes beyond 2023, and some students in our sample could be observed for at most only one year after their initial transfer (Spring 2022 transfers, specifically). However, credit loss is hypothesized to relate to all these outcomes, and future research must continue to examine how credit loss shapes baccalaureate attainment, time-to-degree, and the value students derive from their higher education journeys, particularly given evidence of an inverse relationship between credit loss and baccalaureate attainment (Monaghan & Attewell, 2015).

Our study also provides limited evidence regarding potential inequities in the relationship between credit loss and higher education outcomes. It may be the case that the relationship between credit loss and retention or baccalaureate attainment does not meaningfully vary across racial/ethnic, socioeconomic, or gender groups. However, because historically marginalized students are more likely to begin their college careers at a community college, have higher rates of credit loss, and tend to have lower rates of baccalaureate attainment, we argue that future research that contributes to theories about the intersections between credit loss, students' backgrounds and identities, and university outcomes and empirically examines these relationships is warranted.

Finally, further research is needed to facilitate an understanding of the mechanisms whereby credit loss shapes college outcomes. In particular, although some qualitative research has examined the experiences of transfer students and their perceptions of credit loss (Hodara et al., 2017; Kadlec & Gupta, 2014), further inquiry into how students learn about the credits they have lost, how they interpret the causes and consequences of credit loss, and how credit loss changes their perceptions of the costs and benefits of higher education could further inform practice and policy. Additionally, research that explores the institutional mechanisms, policies, and practices by which both community colleges and universities help students understand course transferability—and particularly university strategies for "softening the blow" of credit loss—would offer a fruitful line of inquiry.

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Tables and Figures

Table 1

Vertical Transfer Students: Student Characteristics and Magnitude of Credit Loss

	N	Any CL %	Total CL Mean	General CL Mean	Major CL Mean
Gender					
Male	11,096	80%	6.62	3.10	3.52
Female	17,873	85%	7.27	3.45	3.82
Race/Ethnicity					
Asian (Non-Hispanic)	1,645	71%	6.03	2.13	3.90
Black (Non-Hispanic)	2,838	83%	6.65	2.61	4.03
Hispanic/Latino	13,979	85%	7.26	3.38	3.88
White (Non-Hispanic)	9,053	81%	6.93	3.67	3.26
Other	1,454	83%	7.10	3.19	3.91
Low-Income Status					
Yes	12,249	82%	6.83	3.12	3.71
No	16,720	83%	7.16	3.46	3.70
Major Area of Concentration					
Business	5,307	73%	5.63	2.53	3.10
Communication Studies	884	85%	5.98	2.82	3.16
Education and Social Services	3,555	82%	6.40	3.27	3.14
Engineering and related	2,071	84%	8.35	4.28	4.07
Health	3,218	91%	8.60	3.70	4.90
Humanities and Liberal Arts	3,202	79%	6.78	3.26	3.52
Industrial, Manufacturing and Construction	459	99%	7.93	5.54	2.39
Literature, Linguistics, and Fine Arts	1,562	80%	6.45	2.93	3.52
Math and Computer Science	1665	84%	7.56	3.12	4.44
Natural Science	2359	87%	8.30	4.11	4.19
Service Oriented	1293	88%	7.45	3.69	3.76
Social and Behavioral Science	3394	86%	6.86	3.12	3.74
Total	28,969	83%	7.02	3.32	3.70

Notes. The table shows descriptive statistics for various credit loss measures by demographic categories and major area of concentration. *N* in the second column represents the subsample size. The percentages in third column represent the proportion within each subsample experiencing any credit loss (e.g., 80% of male transfer students experience some credit loss), followed by the means for their total, general, and major credit loss. The bottom row (“Total”) reports descriptive statistics for the full sample. 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.

Table 2

Linear Probability Models: Credit Loss and Student Outcomes, by Semester and Year

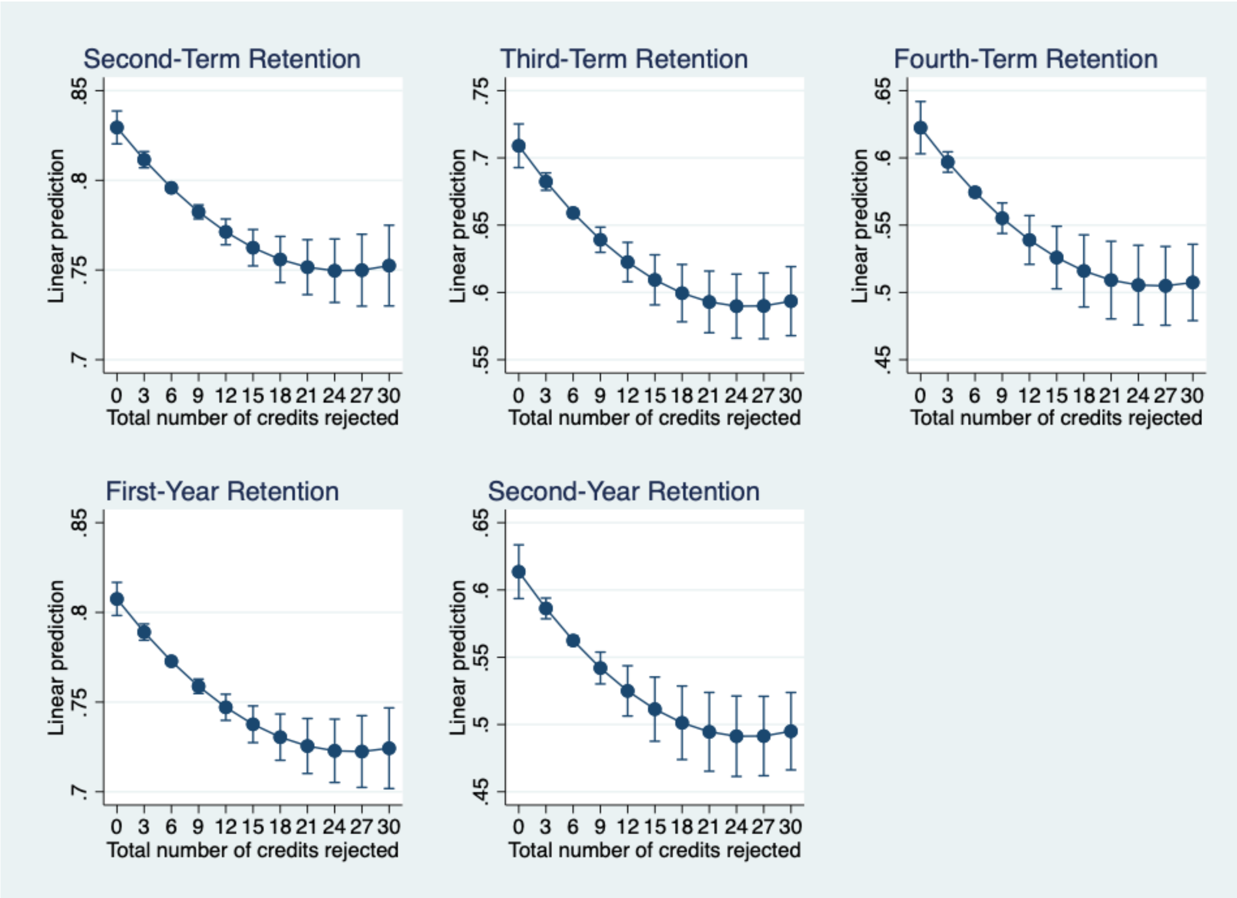
Panel A.	Retention (Any Institution)					Persistence (Transfer Destination)				
Key Variable	Second Term	Third Term	Fourth Term	First Year	Second Year	Second Term	Third Term	Fourth Term	First Year	Second Year
Total Credit Loss	-0.003***	-0.004***	-0.004***	-0.003***	-0.002***	-0.001***	-0.000	-0.000	-0.002***	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
R^2	0.066	0.131	0.127	0.068	0.126	0.039	0.061	0.080	0.049	0.090
Panel B.										
Major Credit Loss	-0.003***	-0.004***	-0.005***	-0.003***	-0.005***	-0.002***	-0.001*	-0.001	-0.003***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
General Credit Loss	-0.002**	-0.004***	-0.003*	-0.002**	-0.003*	-0.000	0.001	0.000	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.066	0.131	0.127	0.068	0.131	0.053	0.065	0.087	0.063	0.097
N	28,934	25,549	14,372	28,934	14,372	28,934	25,549	14,372	28,934	14,372

Notes. This table presents regression coefficients with standard errors in parentheses for the key variable of interest capturing credit loss. Each column represents a separate LPM run for each outcome, where all regressions include institutional fixed effects (for sending and receiving institutions) and the following statistical controls: age, race, gender, major area of concentration, cohort indicating year of first-time in college, credits completed before transfer, and pretransfer GPA. Panel A presents results for models run using total credit loss as the key independent variable. Panel B presents results for models that disaggregate credit loss into two key independent variables: major credit loss and general credit loss.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 1

Visualization of Nonlinear Relationship Between Total Credit Loss and Retention

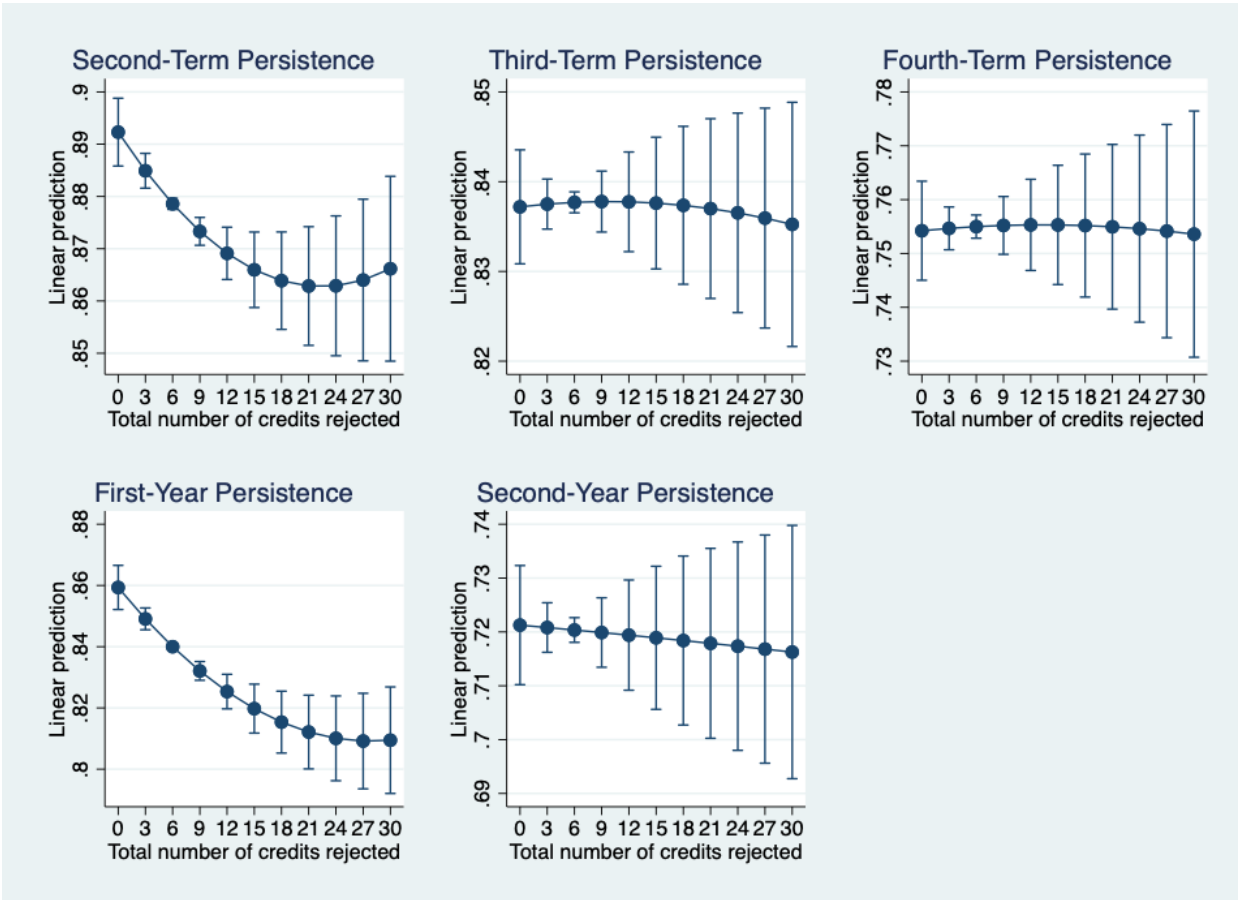


This figure plots the predicted probabilities and 95% confidence intervals for term and year retention at various values of credit loss from linear probability models. All models include institutional fixed effects (for sending and receiving institutions) and the following statistical controls: age, race, gender, major area of concentration, cohort, credits completed before transfer, and pretransfer GPA in addition to the linear and quadratic total credit loss variables. *Y*-axis scales are allowed to vary across subgraphs, as the lower limits vary substantially.

Data source: THECB transfer report data, linked with demographic measures from enrollment data and course schedules.

Figure 2

Visualization of Nonlinear Relationship Between Total Credit Loss and Persistence

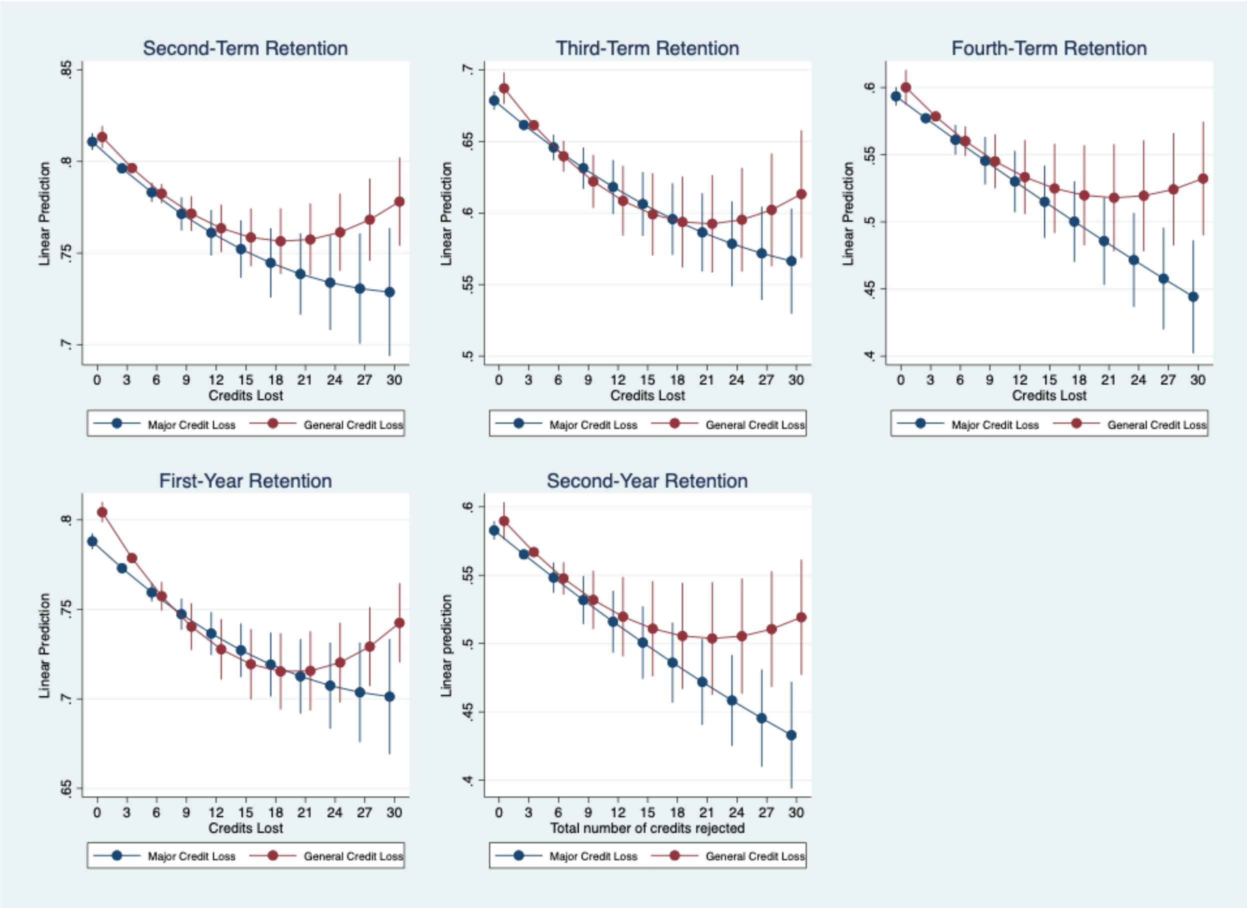


This figure plots the predicted probabilities and 95% confidence intervals for term and year persistence at various values of credit loss from linear probability models. All models include institutional fixed effects (for sending and receiving institutions) and the following statistical controls: age, race, gender, major area of concentration, cohort, credits completed before transfer, and pretransfer GPA in addition to the linear and quadratic total credit loss variables. *Y*-axis scales are allowed to vary, as the lower limits vary substantially.

Data source: THECB transfer report data, linked with demographic measures from enrollment data and course schedules.

Figure 3

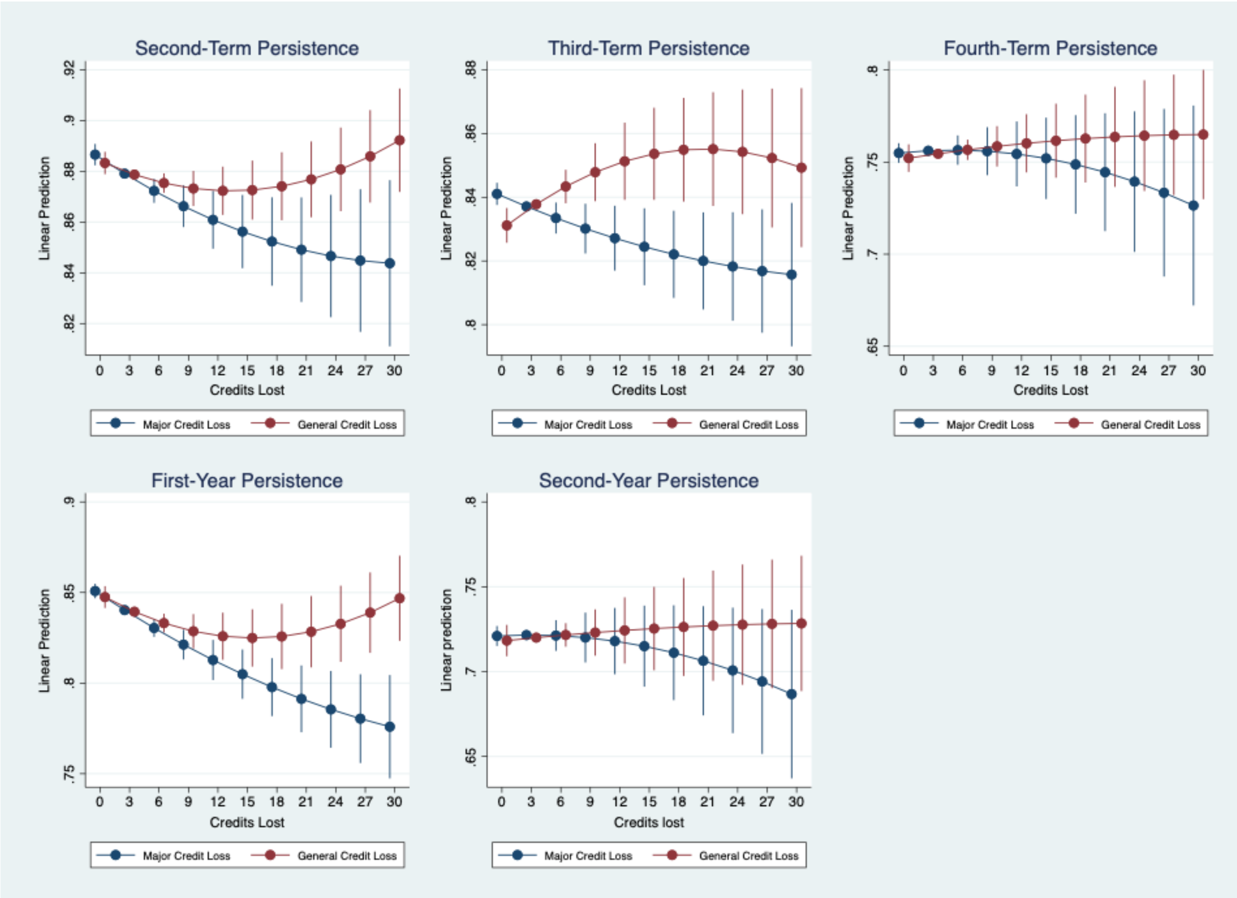
Linear Probability Models of Retention and Credit Loss Types With Squared Terms, by Semester



This figure plots the predicted probabilities and 95% confidence intervals for term and year retention at various values of major and general credit loss from linear probability models. All models include institutional fixed effects (for sending and for receiving institutions) and the following statistical controls: age, race, gender, major area of concentration, cohort, credits completed before transfer, and pretransfer GPA in addition to the linear and quadratic credit loss type variables. *Y*-axis scales are allowed to vary, as the lower limits vary substantially.
Data source: THECB transfer report data, linked with demographic measures from enrollment data and course schedules.

Figure 4

Linear Probability Models of Persistence and Credit Loss Types with Squared Terms, by Semester

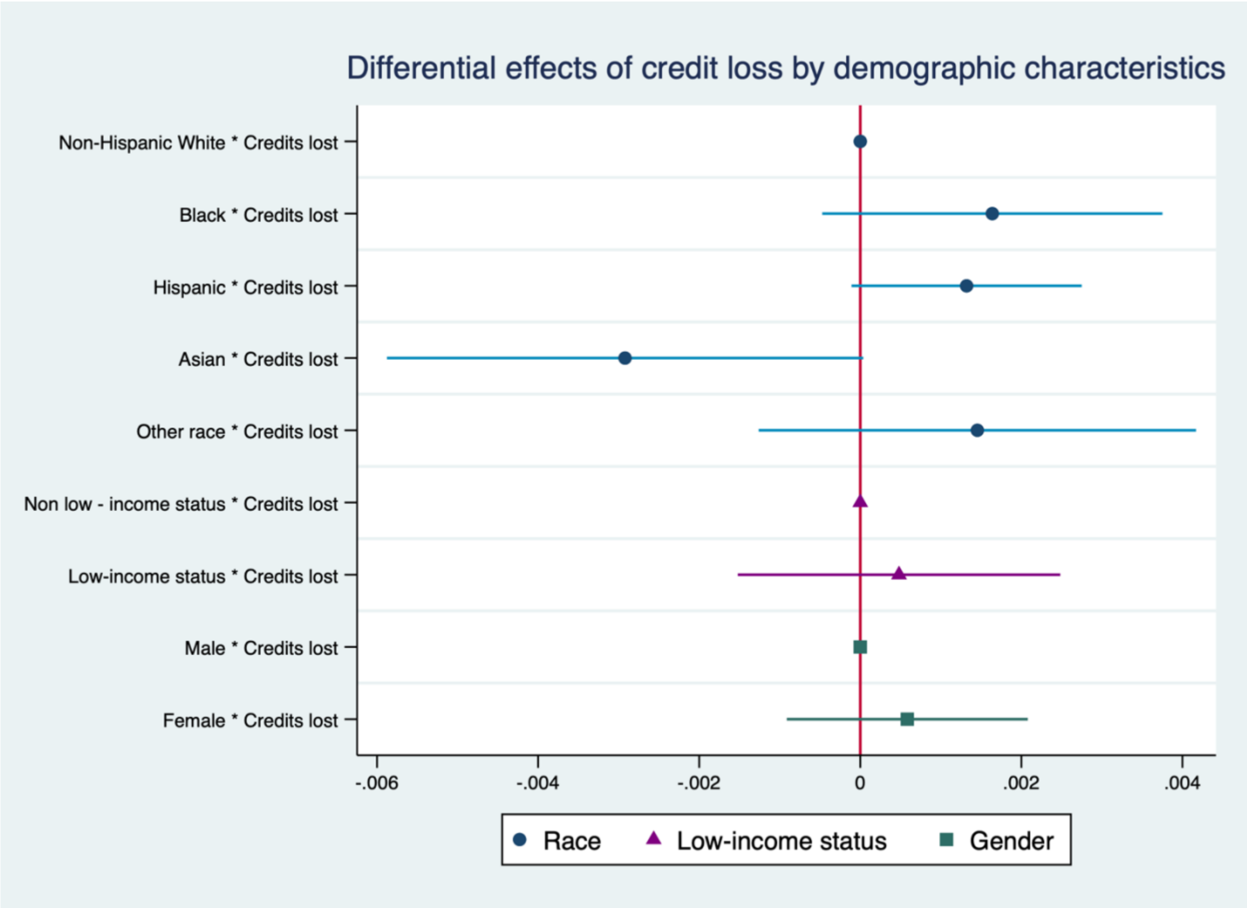


This figure plots the predicted probabilities and 95% confidence intervals for term and year persistence at various values of major and general credit loss from linear probability models. All models include institutional fixed effects (for sending and for receiving institutions) and the following statistical controls: age, race, gender, major area of concentration, cohort, credits completed before transfer, and pretransfer GPA in addition to the linear and quadratic credit loss type variables. *Y*-axis scales are allowed to vary, as the lower limits vary substantially.

Data source: THECB transfer report data, linked with demographic measures from enrollment data and course schedules.

Figure 5

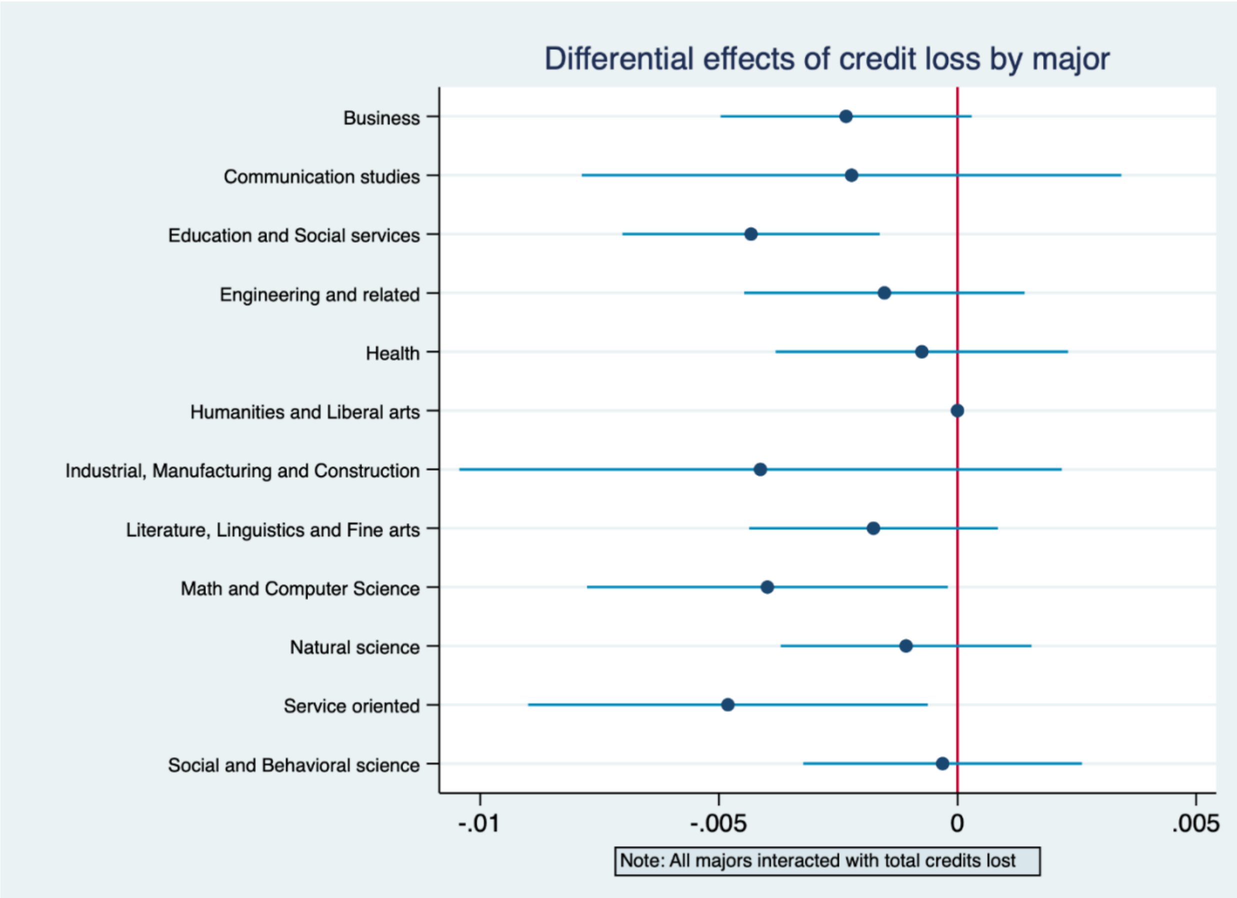
Relationship Between Total Credit Loss and First-Year Retention, by Demographic Group



This figure plots the 95% confidence intervals for first-year retention by demographic categories. All models include institutional fixed effects (for sending and for receiving institutions) and the following statistical controls: age, race, gender, major area of concentration, cohort, credits completed before transfer, and pretransfer GPA in addition to the total credit loss by demographic variable interactions. Data source: THECB transfer report data, linked with demographic measures from enrollment data and course schedules.

Figure 6

Relationship Between Total Credit Loss and First-Year Retention, by Major



This figure plots the 95% confidence intervals for first-year retention by major area of concentration. All models include institutional fixed effects (for sending and for receiving institutions) and the following statistical controls: age, race, gender, major area of concentration, cohort, credits completed before transfer, and pretransfer GPA in addition to the total credit loss by major area interaction.
Data source: THECB transfer report data, linked with demographic measures from enrollment data and course schedules.

Appendix

Table A1

Demographic Characteristics of Sample

Variable name	Description	Mean (*SD*)
Demographics		
Age	Age of the student at initial enrollment; obtained from THECB enrollment data	19.97 (5.19)
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	0.31 (0.46)
Non-Hispanic Black	Identified as Black in the first term of college	0.10 (0.30)
Hispanic/Latino	Identified as Hispanic/Latino in the first term of college	0.48 (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	0.42 (0.49)
Major area of concentration at the 2-year institution		
Business	Architecture, Business, Management, marketing and related	0.18 (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 enforcements, Firefighting, Protective services, Public administration, and Social services professions	0.12 (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)
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	0.08 (0.27)

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	50.20 (18.03)
Pretransfer GPA	Average GPA up to the transfer term	3.14 (0.53)
Credit loss variables		
Any credit loss	A dichotomous indicator of whether students lost any credits at the time of transfer	0.83 (0.38)
Total credit loss	Total credit hours from pretransfer coursework denied at the 4-year institution (for any reason)	7.02 (7.17)
Major credit loss	Total credit hours from pretransfer coursework not applied to the major field of study	3.32 (5.84)
General credit loss	Credits lost due to below minimum grade, repetition, exceeded maximum credit transfer allowance and for reasons other than those mentioned	3.70 (5.26)
Retention variables		
Second-term retention	Indicator for remaining in the same institution in term following transfer term	0.80 (0.40)
Third-term retention	Indicator for remaining in the same institution in the third term including transfer term	0.66 (0.47)
Fourth-term retention	Indicator for remaining in the same institution in the fourth term including transfer term	0.58 (0.49)
First-year retention	Indicator for remaining in the same institution for 1 full year including transfer term	0.77 (0.42)
Second-year retention	Indicator for remaining in the same institution for 2 full years including transfer term	0.57 (0.50)
Persistence variables		
Second-term persistence	Indicator for remaining enrolled in any postsecondary institution in term following transfer term	0.88 (0.33)
Third-term persistence	Indicator for remaining enrolled in any postsecondary institution in the third term including transfer term	0.84 (0.37)
Fourth-term persistence	Indicator for remaining enrolled in any postsecondary institution in the fourth term including transfer term	0.75 (0.43)
First-year persistence	Indicator for remaining enrolled in any postsecondary institution for 1 full year including transfer term	0.84 (0.37)
Second-year persistence	Indicator for remaining enrolled in any postsecondary institution for 2 full years including transfer term	0.72 (0.45)

Table A2

Descriptive Characteristics of Credit Loss, by Community College

Community College	Obs.	Any CL	MCL	GCL	TCL
Alamo Colleges	2,686	0.96	4.05	4.42	8.47
Alvin Community College	110	0.80	2.74	3.77	6.51
Amarillo College	255	0.33	1.96	0.48	2.44
Angelina College	139	0.75	2.04	4.03	6.07
Austin Community College District	1,784	0.77	2.97	4.34	7.31
Blinn College	2,058	0.73	3.82	2.33	6.15
Brazosport College	106	0.96	4.94	4.92	9.87
Central Texas College	297	0.81	4.06	2.22	6.27
Cisco College	117	0.76	3.98	2.61	6.59
Clarendon College	28	0.50	2.29	0.71	3.00
Coastal Bend College	132	0.93	7.83	3.06	10.89
College of the Mainland	75	0.93	4.49	4.44	8.93
Collin College	1,528	0.68	3.27	2.35	5.62
Dallas Colleges	1,780	0.93	4.28	3.76	8.03
Del Mar College	391	0.77	2.13	4.18	6.32
El Paso Community College	1,999	0.87	5.34	1.00	6.35
Frank Phillips College	31	0.74	6.32	1.13	7.45
Galveston Colleges	53	0.75	2.53	3.45	5.98
Grayson College	90	0.68	3.44	2.32	5.77
Hill College	133	0.72	4.10	2.95	7.05
Houston Community College	2,008	0.74	1.30	4.10	5.40
Howard Colleges	88	0.70	3.86	2.47	6.33
Kilgore College	209	0.96	4.43	4.16	8.59
Lamar Institute of Technology	69	0.67	0.19	3.35	3.54
Lamar State Colleges	170	0.83	0.61	4.38	4.99
Laredo College	485	0.73	4.41	1.33	5.73
Lee College	145	0.82	1.90	4.73	6.63
Lone Star Colleges	3,592	0.91	2.51	5.07	7.58
McLennan Community College	359	0.88	3.76	4.00	7.76
Midland College	149	0.93	2.50	4.86	7.36
Navarro College	277	0.74	3.67	2.84	6.51
North Central Texas College	394	0.91	5.27	3.48	8.75
Northeast Texas Community College	102	0.97	2.29	6.24	8.53
Odessa College	254	0.83	1.41	5.50	6.90
Panola College	65	0.86	4.29	3.48	7.77
Paris Junior College	139	0.57	3.43	2.32	5.75
Ranger College	58	0.91	5.29	2.76	8.05
San Jacinto Colleges	786	0.77	1.83	4.73	6.55

South Plains College	211	0.55	3.22	1.41	4.63
South Texas College	1,240	0.86	2.40	5.89	8.28
Southwest Texas Junior College	349	0.93	4.67	2.85	7.52
Tarrant County Colleges	1,141	0.91	4.79	3.79	8.58
Temple College	190	0.76	3.74	2.73	6.47
Texarkana College	129	0.92	0.74	6.19	6.94
Texas Southmost College	410	0.82	2.26	4.03	6.30
Texas State Tech College	173	0.91	2.46	5.73	8.20
Trinity Valley Community College	231	0.92	3.66	4.42	8.08
Tyler Junior College	572	0.74	2.72	3.05	5.77
Vernon College	131	0.95	6.73	2.56	9.29
Victoria College	182	0.96	2.01	6.57	8.58
Weatherford College	206	0.88	5.39	2.83	8.22
Western Texas College	55	0.75	3.53	2.67	6.20
Wharton County Junior College	607	0.69	1.36	3.82	5.18

Notes. This table reports the number of vertical transfer students from each public community college in Texas between Fall 2020 and Spring 2022 and the mean credit loss across various measures for the sample of students transferring from that community college. Column three essentially reflects the probability of losing any credit while transferring out of each community college. All numbers are rounded up to two digits after decimal, and percentages are rounded to the closest integers.
Data Source: THECB transfer reports linked with course schedules.

Table A3

Descriptive Characteristics of Credit Loss, by Public University

Public University	Obs.	Any CL	MCL	GCL	TCL
Angelo State University	96	0.54	3.25	0.23	3.48
Lamar University	400	0.82	0.00	5.14	5.14
Midwestern State University	497	0.96	7.13	3.75	10.88
Prairie View A&M University	236	0.81	0.00	4.83	4.83
Sam Houston State University	2,609	0.95	3.85	4.51	8.36
Stephen F. Austin State University	314	0.67	0.29	3.86	4.15
Sul Ross State University	288	0.97	6.28	2.94	9.23
Tarleton State University	799	0.87	4.50	3.71	8.21
Texas A&M International University	391	0.71	5.37	0.13	5.50
Texas A&M University—San Antonio	923	1.00	9.56	0.01	9.58
Texas A&M University—Galveston	64	0.84	11.28	0.69	11.97
Texas A&M University—Central Texas	292	0.82	4.74	1.34	6.08
Texas A&M University—College Station	1,888	0.78	7.06	0.80	7.86
Texas A&M University—Commerce	310	0.69	0.00	3.23	3.23
Texas A&M University—Corpus Christi	426	0.80	0.00	5.45	5.45
Texas A&M University—Kingsville	215	0.85	14.31	0.16	14.47
Texas A&M University—Texarkana	158	0.95	0.00	7.00	7.00
Texas Southern University	62	0.32	2.63	0.40	3.03
Texas State University—San Marcos	2,111	0.83	3.26	4.62	7.89
Texas Tech University	510	0.50	2.05	1.11	3.15
Texas Women’s University	956	0.91	9.10	1.99	11.09
The University of Texas Permian Basin	363	0.90	0.00	6.26	6.26
The University of Texas Rio Grande Vall	1,661	0.88	1.96	5.74	7.70
The University of Texas at Arlington	1,147	0.79	1.76	5.43	7.19
The University of Texas at Austin	468	0.57	0.72	1.82	2.54
The University of Texas at Dallas	612	0.58	0.00	2.60	2.60
The University of Texas at El Paso	2,004	0.88	5.63	0.88	6.50
The University of Texas at San Antonio	1,664	0.91	0.01	7.13	7.14
The University of Texas at Tyler	816	0.87	3.09	4.13	7.22
University of Houston	2,497	0.77	0.07	5.69	5.77
University of Houston Downtown	1,073	0.70	0.11	3.66	3.77
University of Houston Victoria	542	0.95	0.95	7.42	8.37
University of North Texas	2,257	0.87	4.25	3.12	7.37
West Texas A&M University	297	0.34	2.04	0.15	2.19

Notes. This table reports the number of vertical transfer students each public university in Texas receives between Fall 2020 and Spring 2022 and the mean credit loss across various measures for the university. Column three reflects the probability of losing any credit at each of the universities. All numbers are rounded up to two digits after decimal, and percentages are rounded to the closest integers.
Source: THECB transfer reports linked with course schedules.

Table A4

Linear Probability Model-Building With Blocks of Variables

Variable	Model 1	Model 2	Model 3	Model 4
Credit loss measure*	Yes	Yes	Yes	Yes
Demographics	No	Yes	Yes	Yes
Major area of concentration	No	No	Yes	Yes
Pretransfer academics	No	No	Yes	Yes
Institutional fixed effects	No	No	No	Yes

* Models estimating the retention/persistence effects of any credit loss include only the total credits lost variable. Models classifying credit loss include both major and general credits lost.

Table A5

Linear Probability Models of First-Year Retention Using Blocks of Variables

	Model 1	Model 2	Model 3	Model 4
Total number of credits rejected	-0.003***	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.001)
Student's age in first term		-0.005***	-0.004***	-0.002***
		(0.000)	(0.000)	(0.000)
Asian (Non-Hispanic)		0.004	0.007	0.021*
		(0.011)	(0.011)	(0.008)
Black (Non-Hispanic)		-0.059***	-0.015	-0.012
		(0.009)	(0.009)	(0.008)
Hispanic/Latino		-0.031***	-0.019***	-0.009
		(0.006)	(0.006)	(0.005)
White (Non-Hispanic)		0.000	0.000	0.000
		(.)	(.)	(.)
Other		-0.027*	-0.015	-0.010
		(0.012)	(0.012)	(0.013)
Indicator for female in first term		-0.014**	-0.009	0.001
		(0.005)	(0.005)	(0.006)
Indicator for low-income status in first term		0.000	-0.006	0.000
		(0.005)	(0.005)	(0.006)
Business			-0.003	0.003
			(0.009)	(0.013)
Communication Studies			0.055***	0.031*
			(0.016)	(0.012)
Education and Social Services			0.028**	0.016
			(0.010)	(0.013)
Engineering and related			0.009	-0.015
			(0.012)	(0.014)
Health			-0.091***	-0.080***
			(0.010)	(0.022)
Humanities and Liberal Arts			0.000	0.000
			(.)	(.)
Industrial, Manufacturing and Construction			0.046*	0.018
			(0.021)	(0.020)
Literature, Linguistics, and Fine Arts			0.029*	0.018
			(0.013)	(0.009)
Math and Computer Science			-0.029*	-0.033
			(0.013)	(0.022)
Natural Science			-0.018	-0.032**
			(0.011)	(0.011)
Service oriented			0.015	0.011
			(0.014)	(0.015)
Social and Behavioral Science			0.009	0.015
			(0.010)	(0.015)
Average GPA before transfer			0.078***	0.072***

	Model 1	Model 2	Model 3	Model 4
			(0.005)	(0.006)
Credits earned before transfer			0.002***	0.002***
			(0.000)	(0.000)
2010			0.000	0.000
			(.)	(.)
2011			-0.012	-0.002
			(0.020)	(0.022)
2012			0.008	0.011
			(0.021)	(0.024)
2013			0.010	0.015
			(0.021)	(0.023)
2014			0.027	0.026
			(0.020)	(0.018)
2015			0.046*	0.045*
			(0.019)	(0.018)
2016			0.047*	0.043*
			(0.019)	(0.020)
2017			0.057**	0.050**
			(0.018)	(0.018)
2018			0.076***	0.066***
			(0.018)	(0.018)
2019			0.116***	0.098***
			(0.018)	(0.020)
2020			0.151***	0.134***
			(0.020)	(0.020)
Angelo State University				-0.037
				(0.053)
Lamar University				0.011
				(0.027)
Midwestern State University				-0.038
				(0.031)
Prairie View A&M University				-0.017
				(0.032)
Sam Houston State University				0.000
				(.)
Stephen F. Austin State University				-0.046
				(0.026)
Sul Ross State University				-0.177***
				(0.036)
Tarleton State University				-0.209***
				(0.043)
Texas A&M International University				-0.116***
				(0.026)
Texas A&M University–San Antonio				-0.265***
				(0.016)
Texas A&M University at Galveston				-0.021
				(0.056)

	Model 1	Model 2	Model 3	Model 4
Texas A&M University—Central Texas				-0.157***
				(0.040)
Texas A&M University—College Station				0.037**
				(0.011)
Texas A&M University—Commerce				-0.249***
				(0.039)
Texas A&M University—Corpus Christi				-0.104*
				(0.046)
Texas A&M University—Kingsville				-0.004
				(0.031)
Texas A&M University—Texarkana				-0.162**
				(0.048)
Texas Southern University				0.064
				(0.044)
Texas State University—San Marcos				0.007
				(0.012)
Texas Tech University				-0.102**
				(0.030)
Texas Women's University				-0.253***
				(0.030)
The University of Texas Permian Basin				-0.043
				(0.023)
The University of Texas Rio Grande Valley				-0.041
				(0.027)
The University of Texas at Arlington				-0.076**
				(0.028)
The University of Texas at Austin				0.020
				(0.017)
The University of Texas at Dallas				-0.105***
				(0.026)
The University of Texas at El Paso				-0.042
				(0.034)
The University of Texas at San Antonio				0.002
				(0.014)
The University of Texas at Tyler				-0.078***
				(0.020)
University of Houston				-0.091***
				(0.014)
University of Houston Downtown				-0.026
				(0.014)
University of Houston Victoria				-0.042
				(0.025)
University of North Texas				-0.015
				(0.017)
West Texas A&M University				-0.041
				(0.041)
Total number of credits rejected				

	Model 1	Model 2	Model 3	Model 4
Constant	0.798***	0.936***	0.493***	0.540***
	(0.003)	(0.011)	(0.026)	(0.029)
Demographic Controls	No	Yes	Yes	Yes
Institutional Fixed Effects	No	No	No	Yes
Observations	28,965	28,965	28,965	28,965
R^2	0.004	0.011	0.046	0.068

Table A6

Linear Probability Models of Retention and Persistence With Categorical TCL Variable

	Term retention			Year retention	
Total credit loss	Second term	Third term	Fourth term	First year	Second year
1–6	-0.066***	-0.144***	-0.135***	-0.065***	-0.147***
	(0.010)	(0.029)	(0.027)	(0.011)	(0.029)
7–12	-0.083***	-0.148***	-0.145***	-0.080***	-0.157***
	(0.012)	(0.026)	(0.030)	(0.011)	(0.031)
13–18	-0.098***	-0.164***	-0.157***	-0.097***	-0.165***
	(0.017)	(0.027)	(0.026)	(0.017)	(0.027)
19–24	-0.095***	-0.169***	-0.148***	-0.104***	-0.157***
	(0.017)	(0.030)	(0.034)	(0.018)	(0.034)
25–30	-0.068**	-0.114***	-0.119**	-0.079***	-0.122**
	(0.022)	(0.029)	(0.041)	(0.021)	(0.042)
30+	-0.098***	-0.173***	-0.169**	-0.105***	-0.173**
	(0.022)	(0.034)	(0.053)	(0.025)	(0.054)
Observations	28,934	25,549	14,372	28,934	14,372
R^2	0.069	0.141	0.134	0.070	0.140

	Term persistence			Year persistence	
Total credit loss	Second term	Third term	Fourth term	First year	Second year
1–6	-0.018*	0.024*	0.038***	-0.026*	0.038***
	(0.009)	(0.009)	(0.010)	(0.011)	(0.011)
7–12	-0.025**	0.023**	0.022*	-0.036**	0.025
	(0.009)	(0.008)	(0.011)	(0.010)	(0.013)
13–18	-0.042**	-0.000	0.020	-0.054***	0.010
	(0.013)	(0.010)	(0.014)	(0.014)	(0.018)
19–24	-0.026*	0.005	0.010	-0.051***	0.014
	(0.012)	(0.013)	(0.017)	(0.014)	(0.019)
25–30	-0.009	0.050	0.051	-0.046*	0.051
	(0.015)	(0.028)	(0.031)	(0.020)	(0.035)
30+	-0.031	0.018	0.036	-0.062**	0.034
	(0.019)	(0.017)	(0.027)	(0.021)	(0.030)
Observations	0.053	0.066	0.088	0.063	0.098
R^2	28,934	25,549	14,372	28,934	14,372

Notes. Table presents regression coefficients with standard errors in parentheses for the key variable of interest capturing credit loss. Each column represents a separate LPM run for each outcome, where all regressions include institutional fixed effects (for sending and for receiving institutions) and the following statistical controls: age, race, gender, major area of concentration, credits completed before transfer and pretransfer GPA.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Data source: THECB transfer report data, linked with demographic measures from enrollment data and course schedules.

Table A7

Linear Probability Models of Retention With Categorical MCL and GCL Variables

	Term Retention			Year Retention	
Credit loss	Second term	Third term	Fourth term	First year	Second year
Major credit loss					
1–6	-0.037***	-0.060***	-0.075***	-0.035***	-0.079***
	(0.006)	(0.016)	(0.018)	(0.006)	(0.017)
7–12	-0.055***	-0.079***	-0.075***	-0.054***	-0.083***
	(0.009)	(0.015)	(0.015)	(0.009)	(0.016)
13–18	-0.067***	-0.082***	-0.058*	-0.070***	-0.057*
	(0.015)	(0.018)	(0.025)	(0.015)	(0.024)
19–24	-0.065*	-0.095**	-0.155**	-0.073**	-0.158**
	(0.026)	(0.032)	(0.055)	(0.026)	(0.055)
25–30	-0.088**	-0.091**	-0.133*	-0.088**	-0.143*
	(0.030)	(0.034)	(0.062)	(0.031)	(0.062)
30+	-0.095**	-0.149***	-0.260***	-0.102**	-0.256***
	(0.035)	(0.037)	(0.063)	(0.031)	(0.063)
General credit loss					
1–6	-0.044***	-0.093***	-0.090***	-0.048***	-0.100***
	(0.008)	(0.020)	(0.021)	(0.008)	(0.021)
7–12	-0.051***	-0.083***	-0.075***	-0.058***	-0.081***
	(0.010)	(0.019)	(0.020)	(0.011)	(0.021)
13–18	-0.065***	-0.107***	-0.122***	-0.067***	-0.122***
	(0.015)	(0.020)	(0.027)	(0.014)	(0.030)
19–24	-0.047	-0.110**	-0.089**	-0.056*	-0.096***
	(0.025)	(0.035)	(0.029)	(0.024)	(0.027)
25–30	-0.037	-0.026	0.011	-0.070	0.016
	(0.031)	(0.043)	(0.045)	(0.039)	(0.044)
30+	0.005	-0.056	-0.023	0.012	-0.033
	(0.033)	(0.045)	(0.043)	(0.036)	(0.048)
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Observations	28,934	25,549	14,372	28,934	14,372
R^2	0.068	0.137	0.133	0.070	0.138

Notes. Table presents regression coefficients with standard errors in parentheses for the key variable of interest capturing credit loss. Each column represents a separate LPM run for each outcome, where all regressions include institutional fixed effects (for sending and for receiving institutions) and the following statistical controls: age, race, gender, major area of concentration, credits completed before transfer and pretransfer GPA.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Data source: THECB transfer report data, linked with demographic measures from enrollment data and course schedules.

Table A8

Linear Probability Models of Persistence With Categorical MCL and GCL Variables

	Term persistence			Year persistence	
Credit loss	Second term	Third term	Fourth term	First year	Second year
Major credit loss					
1–6	-0.008	0.004	0.013	-0.010	0.013
	(0.007)	(0.006)	(0.012)	(0.007)	(0.013)
7–12	-0.022**	-0.008	0.010	-0.030**	0.008
	(0.007)	(0.008)	(0.010)	(0.009)	(0.010)
13–18	-0.038*	-0.029*	0.006	-0.052***	-0.004
	(0.014)	(0.013)	(0.018)	(0.013)	(0.020)
19–24	-0.036	-0.008	-0.027	-0.059*	-0.022
	(0.023)	(0.019)	(0.044)	(0.024)	(0.044)
25–30	-0.042	0.007	-0.054	-0.071*	-0.039
	(0.022)	(0.028)	(0.054)	(0.032)	(0.052)
30+	-0.040	-0.024	-0.018	-0.096**	-0.041
	(0.037)	(0.020)	(0.050)	(0.034)	(0.048)
General credit loss					
1–6	-0.018**	0.021**	0.017*	-0.026**	0.012
	(0.006)	(0.008)	(0.007)	(0.008)	(0.007)
7–12	-0.015	0.030**	0.016	-0.029**	0.021
	(0.008)	(0.010)	(0.015)	(0.010)	(0.017)
13–18	-0.016	0.009	0.015	-0.025	-0.000
	(0.014)	(0.013)	(0.019)	(0.016)	(0.029)
19–24	-0.004	-0.002	-0.026	-0.013	-0.026
	(0.016)	(0.021)	(0.029)	(0.017)	(0.028)
25–30	0.018	0.041	0.086**	-0.016	0.086*
	(0.027)	(0.043)	(0.028)	(0.035)	(0.034)
30+	0.017	0.017	0.040	0.026	0.039
	(0.023)	(0.031)	(0.032)	(0.026)	(0.036)
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Observations	28,934	25,549	14,372	28,934	14,372
R^2	0.054	0.066	0.088	0.064	0.098

Notes. Table presents regression coefficients with standard errors in parentheses for the key variable of interest capturing credit loss. Each column represents a separate LPM run for each outcome, where all regressions include institutional fixed effects (for sending and for receiving institutions) and the following statistical controls: age, race, gender, major area of concentration, credits completed before transfer, and pretransfer GPA.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Data source: THECB transfer report data, linked with demographic measures from enrollment data and course schedules.