Academic Momentum and Undergraduate Student Attrition: Comparative Analysis in US and Russian Universities

OLGA KONDRATJEVA, ELENA V. GORBUNOVA, AND JOSHUA D. HAWLEY

Student attrition in postsecondary education is a significant public policy problem. Nations invest substantial resources in college systems, and when students leave, this investment is lost. To understand the factors that influence student attrition in US and Russian public universities, we use the perspective of academic momentum, defined empirically as measures representing student enrollment and study progress. Using a discrete-time event history analysis of samples of eight US and two Russian universities, we provide support for the central claims of the academic momentum theory that undergraduate students who progress through college more rapidly have a lower likelihood of attrition. However, a more detailed analysis reveals variability in the relationship between several academic momentum measures and student attrition, depending on a university's selectivity and the student's chosen academic field and gender.

Introduction

College noncompletion has long-term implications for both students and nation-states. College dropouts, on average, earn less over their lifetime, achieve lower occupational success than college graduates (Tinto 1987), and experience long-term psychological distress, self-esteem issues, and loss of social opportunities (Pascarella and Terenzini 1991). On the national level, individual losses translate into slower economic growth and lower human capital (DesJardins et al. 1999). The fact that students enter university and do

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not graduate is strongly affected by cultural and institutional factors. Among students entering higher education, 43 percent in the US and 22 percent in Russia leave university without completing a degree (OECD 2010).[1]

In Russia, high student attrition is interpreted as a sign of institutional selectivity and a higher quality of educational process. In elite universities, some instructors purposely design strict grading requirements because they indicate high standards within the academic culture (Gruzdev et al. 2013). The system is relatively unforgiving to academically struggling students, and noncompletion is viewed as a part of the natural selection process (Gruzdev et al. 2013). Russian policy makers pay relatively little attention to university noncompletion because the postsecondary education enrollment and attainment rates are high (OECD 2012), and attrition is relatively low. Nonetheless, as Russia modernizes its economy and reforms the financing system of higher education, student attrition is expected to attract more national attention. The issues of student attrition and deteriorating academic preparation of incoming students have already become more relevant to non-elite universities in economically depressed regions that are struggling with decreased government funding.

In contrast, the US higher education system has consistently paid attention to the issue of student attrition. Student attrition can reflect concerns about institutional reputation and adequacy of funding in public higher education institutions. It is also relevant to the long-term prosperity of the economy. Shortfalls in high-skill specialists, particularly in the STEM disciplines, have been projected for the US (Carnevale et al. 2010). As state governments exercise substantial control over higher education systems, some states have already shifted toward performance-based funding that is tied to student outcomes, such as course and degree completion (National Conference of State Legislatures 2013).

This article is an empirical comparative study of student attrition in the contexts of the US and Russia. To understand the factors that influence student attrition, we apply a theoretical concept of academic momentum that focuses on the speed with which students progress early in their undergraduate studies. We address the following research questions: How is academic momentum associated with student attrition in US and Russian public universities? Does this association differ for universities with different selectivity levels in their admission policies, and does it differ across academic fields and gender? By comparing universities in the US and Russia, we explore the research questions on the continuum of institutional arrangements related to voluntary/nonvoluntary student attrition.

[1] This statistic refers to theory-based tertiary-type A programs, which prepare students for high-skilled occupations and advanced research programs. Full-time programs last for three years at least, although the typical length of the program is four or more years.

This comparative analysis focuses on two of the largest public higher education systems (UNESCO Institute for Statistics 2009) that represent different institutions. US universities represent a highly flexible and open education system that enables easy changes of educational and career trajectories (Arnett 2004). Curricula in the majority of US universities allow students to manipulate the speed at which they proceed through undergraduate studies. In contrast, the Russian higher education system is characterized by curriculum rigidity, fixed transitions from college to employment, and inflexibility in changing careers or educational paths. The timing and content of the curriculum are predetermined by the dean's office and apply to nearly all incoming students within the same discipline. There is little room for academic experimentation during the first year and limited opportunities for transfer between academic programs and institutions (Kuzminov and Yudkevich 2007). The nature of the attrition process also differs: in the US a student is typically the subject of the process (i.e., students decide to leave the university), while in Russia a student is mostly the object (i.e., the system forces students to attrite from the institution).

Despite these differences, the higher education systems in these two countries share commonalities in their historical and institutional processes,[2] and over time, the two systems are becoming more similar in terms of availability and flexibility of academic choices. Russia's efforts to modernize its higher education system have introduced more flexibility in educational processes. For example, correctional courses that are similar to remedial courses in the US are already offered in some Russian universities. Many Russian universities have also adopted the two-level "Bachelor-Master" system and the European Credit Transfer System, and by 2020, all universities are required to shift to a more individualized curriculum with greater emphasis on independent student work (State Program of Russian Federation 2013).

To ensure validity comparing different higher education systems, we focus on homogeneous student groups in the two countries. We limit our analysis to full-time, first-time traditional-age undergraduate students enrolled in the main campus of a public university with selective admissions policies. These students are likely to be similar in terms of linearity of the transition from high school to college, commitment to university degree, and developmental characteristics. We also stratify our sample by university selectivity, academic discipline, and gender for a more valid comparison of student subgroups in the two countries.

Our research makes several contributions to the comparative higher education literature. First, we operationalize and test the academic momentum model outside the US context. This expands previous empirical work, which has tested the concept of academic momentum in the US (except Martin et al.

[2] Broadly speaking, education began as an elite system in both nations and evolved to mass higher education systems, providing both vocational and academic degrees and having close ties with industry.

2013), and contributes to comprehensive theory development to explain student attrition in the cross-national environment. Second, our research advances institutional research on student attrition. Using up-to-date data, we apply a conceptual model that focuses not only on intrinsic student characteristics that are beyond the direct influence of external stakeholders, but also on curriculum and coursework that can be manipulated by policy makers and university officials. This makes the proposed study relevant to both countries as they undergo demographic and economic changes accompanied by shifts in the public education system. The analysis is particularly timely for Russian universities, which lack sound evidence on the factors influencing student attrition. Finally, from a practical standpoint, comparative analysis facilitates cross-national learning by contrasting outcomes achieved by diverse higher education systems and identifying their strengths and weaknesses.

The next sections introduce the theoretical concept of academic momentum, present our analysis, and report the findings. This study uses data from administrative records of eight public universities in the US and two public universities in Russia, and applies the event history method. Our findings indicate that, in general, the speed at which students progress through their studies is associated with a lower attrition probability in both countries. This association varies by selectivity in admissions, gender, and academic disciplines.

Theoretical Framework

One of the earliest, most comprehensive discussions on student dropout in the postsecondary education system was initiated by Vincent Tinto (1975), who suggested that a student's academic and social integration in the college environment is important for explaining undergraduate student persistence and attrition. Tinto's model has been extended by the researcher himself, as well as other scholars (Cabrera et al. 1993; Berger and Braxton 1998). Besides Tinto's integration model, the topic of college attrition was addressed from different theoretical perspectives, including psychology (Astin 1984; Bean and Eaton 2001–2), economics (Becker 1964), institutional frameworks (Bean 1983; Titus 2006), and developmental theory (Arnett 2004).

The theory of academic momentum (Adelman 1999, 2006) proposes another way to explain student attrition. Academic momentum is defined as an accumulation of academic resources over time and a pace of student progression through high school and college, especially during the early years of college. A student's family background, socioeconomic status, and intrinsic characteristics are most critical for explaining academic and psychological development in the early years of life and high school. Subsequent high school curriculum decisions and academic performance determine immediate college choices and first-year progression in college. In turn, these choices and pace of progression shape the future academic advancement: moving quicker and achieving higher academic momentum early in college increase the like-

lihood of attaining a degree. Adelman (1999, 2006) identifies several indicators of academic momentum, such as intensity of high school curriculum, delayed college entry, amount of college coursework, first-year grades, changes in grades, taking remedial courses, part-time enrollment, continuous enrollment, and summer-term enrollment, most of which are statistically associated with degree completion.

Attewell et al. (2012) test the causal effect of the four measures of academic momentum on degree completion in US four-year colleges: delayed college enrollment, part-time attendance in the first semester, enrollment in a high number of credits in the first semester, and taking summer classes after the freshman year. Their findings generally support the central claims of the academic momentum theory. The authors theorize that academic momentum relates to degree attainment through several mechanisms. First, higher academic momentum helps students integrate into academic life and develop commitment to a particular institution. Second, students with higher academic momentum develop psychological skills and behaviors that are important for persistence, such as feelings of accomplishment, competence, and self-confidence. Finally, external factors, such as financial aid or combining college with employment, influence academic momentum and subsequent student attrition.

Martin et al. (2013) provide support for the positive effects of several academic momentum measures, such as high school achievement, ongoing university achievement, and delayed enrollment, on subsequent academic performance in university. The positive effect of delayed enrollment contradicts prior literature (Attewell et al. 2012; Attewell and Jang 2013) but is consistent with the authors' supposition that delayed enrollment can increase academic momentum if during the gap year a student undertakes activities that contribute to holistic knowledge and experience-based learning.

For several decades Tinto's student integration model has been a dominant theoretical framework to conceptualize the attrition process, but its application to comparative analyses has been limited. One of the limitations of Tinto's theory is its focus on mostly voluntary attrition. In Russian universities, student attrition is frequently the result of a disciplinary punishment for violation of academic or nonacademic rules (Gruzdev et al. 2013) and is therefore not voluntary. The advantage of the theoretical perspective of academic momentum is that it does not differentiate between voluntary and nonvoluntary student attrition, but focuses on the influence of institutional conditions and student efforts.

Empirical Method

We apply the event history method to study the relationship between academic momentum and student attrition, using the Kaplan-Meier estimator for our descriptive analyses and the discrete-time event history method for

regression analyses. The Kaplan-Meier estimator is a nonparametric model that estimates the probability of student attrition as the function of time. We use this estimator to produce graphical representations of the probability of student attrition, and to compare the survivor functions across different student subpopulations.

We use the discrete-time event history method to estimate the linear relationship between academic momentum indicators and the probability of student attrition. This method measures duration until event occurrence, takes into account censoring of events, and controls for time-varying explanatory variables and time intervals; these characteristics make the technique superior to other statistical procedures (Allison 1984; Singer and Willet 2003). The discrete-time event history model for student i and time j is estimated for each country using a logistic regression model:

$$\text{logit } h(t_{ij}) = \alpha + \boldsymbol{A_i}\beta + \boldsymbol{A_{ij}}\gamma + \boldsymbol{X_i}\theta + \boldsymbol{X_{ij}}\pi + \boldsymbol{D_j}\varphi + \varepsilon_{ij},$$

where the dependent variable is a dichotomous variable signifying student attrition, $\boldsymbol{A_i}$ and $\boldsymbol{A_{ij}}$ are vectors of time-invariant and time-varying academic momentum measures, respectively, $\boldsymbol{X_i}$ and $\boldsymbol{X_{ij}}$ are vectors of time-invariant and time-varying explanatory variables, respectively, $\boldsymbol{D_j}$ are dummy variables for time intervals capturing time dependency, and ε_{ij} is an error term.

A methodological difficulty arises when we construct a consistent measure of time for US institutions that operate under either semester or quarter terms. Time intervals for these academic terms are distinct—a winter academic term is absent under the semester system and academic terms vary in length—which complicates the comparison of student attrition across different academic systems. While most of the prior research dealt with aggregated yearly data (DesJardins et al. 1999, 2002), we attempt to capture the process of student attrition with more precision. We make the time intervals identical across different academic systems by transforming the data set from student-quarter and student-semester formats to a student-bimonth format. Therefore, depending on the academic system, a semester (4.5 months) is split into nine bimonthly periods, and a quarter (3 months) is split into six bimonthly periods. In Russia, student attrition corresponds to academic quarters. Thus, in the regression above, $\boldsymbol{D}$ is a series of discrete-time indicators for bimonthly periods in the US and academic quarters in Russia.

Data and Sampling

Data from the US come from eight public institutions in the state of Ohio, accessed through the Ohio Higher Education system. Ohio is the seventh largest US state by population, with one of the country's best known state university systems. The longitudinal data set includes student-level adminis-

trative records on demographics, enrollment, coursework, academic progress, and financial aid of students enrolled in Ohio public colleges and universities.[3] The student-level data are supplemented with the regional-level information from the Census Bureau's American Community Survey. The longitudinal data from Russia come from the administrative records of two public universities. One university is highly selective, located in Russia's capital, and specializes in socioeconomic disciplines. The other university is of medium selectivity, situated in a large regional city, and specializes in STEM disciplines. The data from these two universities contain student-level records on enrollment, academic progress, financial aid, and high school information.

Both data sources contain high-quality administrative records for all students enrolled during the given time period, allowing for a detailed investigation of student behavior over the course of study. Moreover, the data are not self-reported but are obtained through university records, thus reducing measurement errors.

For comparability, we restrict our analysis to samples of traditional students. The Russian sample is limited to full-time, first-time traditional-age (16–24 years old) undergraduate students who enrolled in the fall of 2009 in the main campus of two universities. The US sample includes full-time, first-time undergraduate students of traditional age (18–24 years old) who enrolled in an Ohio four-year public university (main campus) with selective admission policies in the fall of 2007. Student behavior is tracked for a period of 2.5 years since the first enrollment.

For a deeper cross-national comparison, we also split universities into subgroups according to their selectivity level, as attrition trends may be more similar within the same university type. Eight US universities are grouped into three categories according to their ACT test scores and undergraduate student graduation rates: two highly selective, two medium selective, and four least selective universities. The 75th percentiles of the composite ACT scores are 28–29, 26–27, and 23–24 for highly, medium, and least selective universities, respectively. The six-year graduation rates for the 2007 cohort of undergraduate students are 81–83, 58–67, and 32–54 percent for highly, medium, and least selective universities, respectively (National Center for Educational Statistics 2007, 2013). The two Russian universities in our sample represent high and medium selectivity levels in terms of academic preparation of high school students: the average Unified State Examination scores for students receiving government education subsidies are 79 and 63 (out of 100), and for students without a government subsidy, the average scores are 72 and 55, respectively.[4]

[3] Data from Ohio were obtained under the terms of The Ohio State University IRB procedure.
[4] Authors' calculations.

The association between academic momentum and the likelihood of student attrition also may not be uniform across student's gender and academic fields, so we stratify our samples by gender and academic discipline during the first term. More specifically, students across different disciplines may differ in their academic preparation, motivational attitudes, and the course load. College pressures may differ by gender, as male students may have other commitments (e.g., military service) or may choose to drop out and enter the labor market before graduating. Female students may feel more internal pressure to persist, or conversely, may drop out due to unplanned pregnancy. Focusing on more homogenous student groups helps uncover differentials in the association of academic momentum and student attrition for different student subpopulations and improves the validity of between-country comparison.

Statistical Considerations

The problem of endogeneity, caused by simultaneity and omitted variables, challenges the ability to infer causality to the relationships that we estimate. Simultaneity arises because several academic momentum indicators are jointly determined with student attrition (Wooldridge 2009). For example, poor first-term academic performance increases the probability of student attrition in the first term, and early student attrition results in low first-term grades. To illustrate this endogeneity problem, consider a single academic momentum measure: academic performance as measured by first-term grades. The simultaneous equations model can be written as:

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 X_i + u_i \text{ and } x_i = \delta_0 + \delta_1 y_i + \delta_2 X_i + v_i,$$

where y_i is student attrition, x_i is first-term grades, X_i are other covariates, and u_i and v_i are the error terms. Solving the system of equations for x_i shows that the error term u_i is correlated with x_i, that is, that first-year academic performance is itself endogenous. While an instrumental variable approach could solve the simultaneity problem, finding an exogenous variable that meets all requirements for a valid instrument is impossible with the given data. An alternative solution is to emphasize the temporal nature of variables—that is, that the academic momentum indicators that occur prior to the beginning of the academic term are "predetermined," thus weakening the possibility that student attrition from a university has a causal effect on those indicators. For example, student attrition is unlikely to have a causal effect on high school performance, the initial choice of credit hours, or the initial enrollment in developmental courses.

Another estimation bias results from omitted variables. Academic momentum and student attrition depend on a number of observed and unobserved student characteristics, including employment, family obligations, socioeco-

nomic status, high school performance, motivation, and commitment.[5] Due to data limitations, we cannot account for these characteristics in the regression model. Theoretically, propensity score matching could alleviate the omitted variable problem by creating matched groups of similar students, but this estimation method matches only on observable characteristics, not on unobserved student characteristics. Implementing this statistical technique with a limited set of observable student characteristics available in the data would not improve our estimation strategy. The instrumental variable approach is also constrained by data availability.

Recognizing these limitations, we implement several strategies for a more rigorous and credible analysis. First, we limit our sample to traditional students, which helps reduce the likelihood that some unobserved characteristics will influence our results. Second, we include as many time-variant and time-invariant student characteristics as possible, and add institution and time fixed effects. For the US estimates, we include regional-level variables as proxies for student socioeconomic status, such as the percentage of the population with bachelor's degree or higher and the unemployment level in the region of a student's residence. Third, stratifying the sample by university selectivity, gender, and academic discipline allows us to make comparisons for homogeneous student groups. Despite implementing these empirical strategies, data limitations preclude rigorous causal inference. Therefore, the emphasis of this study is to investigate the association between academic momentum and student attrition.

Variables

Student attrition is a dichotomous variable equal to unity if a student attrited from the first university of enrollment, and zero otherwise. In Russian universities, student attrition is registered in university administrative records with a precise date and includes cases of students withdrawing completely from higher education, transferring to another university, or withdrawing but later reenrolling in the same university. In US universities, the exact date of student attrition is not documented. We consider that US students attrite if they are not enrolled in the initial institution for more than a year and one academic term without having graduated. The time of student attrition is defined as the last term of enrollment in the initial institution. Student withdrawals, transfers, and longer-term stop-outs are treated identically in the US model.

In the US, we operationalize academic momentum following Adelman (1999, 2006) and Attewell et al. (2012). In Russia, given the rigidity of the

[5] Tinto (1975); Bean (1983); Cabrera et al. (1993); Adelman (1999, 2006); Goldrick-Rab et al. (2007).

higher education system, the empirical analysis contains fewer academic momentum measures. Most academic momentum measures refer to the first academic term, where a term represents academic quarters or semesters in the US (depending on the university) and academic semesters in Russia. Conceptual and operational definitions of academic momentum are provided in table 1. As such, higher academic momentum in the US is measured by on-time enrollment, higher number of credits attempted in the first term, no developmental courses in the first term, reporting the major at the time of enrollment, higher first-term GPA, and improvement in grades over time. In Russia, higher academic momentum is measured by on-time enrollment, no failure of courses in the first term, and improvement in grades over time.[6]

We also control for individual-level characteristics, such as student demographics, living arrangements, academic fields in the first term, and financial assistance. Receipt of financial assistance is registered for every term in US universities and for the first academic term in Russia's universities; financial assistance in Russia is assigned based on student enrollment scores and remains fairly constant during the study period. We also add a measure of high school academic performance in the Russian model. University and time fixed effects are included in the estimates for both countries. Regional-level proxies for missing student-level SES are added in the US model.

We investigate multicollinearity among academic momentum measures using the variance inflation factor (VIF). The VIF values do not exceed 10, corroborating that multicollinearity is not an issue (Baum 2006). Table 2 describes weighted sample means of the outcome variable, academic momentum variables, and selected covariates across clusters of universities. In the US, students in more selective universities generally exhibit higher academic momentum in the first term, expressed as a lower share of students who delayed college enrollment, fewer students enrolled in remedial courses, and a higher share of students who took a heavier credit load, showed better academic performance, and reported their major. In contrast, in Russia, the relationship between higher academic momentum and university selectivity is not as evident.

Results

This section describes the level and timing of student attrition, applying the Kaplan-Meier estimator, and explores the association between academic momentum and student attrition using an event history regression model. We use a log-rank test to compare the distributions of event occurrence be-

[6] In theory, since Russia moved to the two-tier education system in 2007, joining the Bologna process, the total number of attempted academic credits could be added. However, because the schedule remained fairly standardized and credit hours varied little during the observation period, this indicator is not included.

tween subgroups, and the Wald test to compare the coefficients between regression estimates. The descriptive analyses are conducted using the full sample and the sample stratified by university selectivity, gender, and academic disciplines,[7] but the regression analyses pertain only to students who have grades in the first two terms. To explore whether this model specification influences our findings, we compare a model that excludes students without the grades in the first term and a model that excludes students without the grades in the first two terms, where the estimation includes all measures of academic momentum except for changes in grades. The direction and significance of the coefficients on academic momentum measures remain unchanged, indicating robustness of our results to the specification.

The analysis in the Russian medium selective university is further limited because almost all students who attrited during the first two semesters (99 percent) do not have data on grades due to administrative reasons.[8] Dropping these students could potentially bias our estimates because, on average, students who attrite during the first year may also have lower academic momentum. To address this issue, our regression model excludes both attrited and nonattrited students in the first two semesters for the medium selective university. To test the robustness of such model specification, we compare the regression model that excludes only students without the grades in the first two semesters and the model that excludes all students during the same time period. The unchanged direction and significance levels of the coefficients imply that our findings remain robust.

For the US estimates, we explore two specifications of first-term GPA, measured as a series of dichotomous variables or as a series of ten continuous variables. Different specifications allow us to test how different GPA levels are associated with the likelihood of student attrition, and whether a one-point increase in GPA influences the likelihood of student attrition differently at different grade levels. We keep students with zero GPA: these are students who dropped or failed the classes in the first term. While the majority of these students eventually dropped out, some persisted (13 percent).

Differences by University Selectivity, Academic Field, and Gender

Table 3 provides the descriptive analysis of student attrition based on the Kaplan-Meier estimator. Survival and hazard rates are reported for each subsample. Survival rates describe the probability that a student will not attrite by

[7] In Russia's sample, we conduct the regression analysis by the academic discipline only for the medium selective university due to the small number of observations in the STEM field in the highly selective university.

[8] During the academic year of 2009–10, the medium selective university changed its record keeping system—transitioning from a paper-based to a computer-based data management system. During this transition, academic records on students who left the university before the summer of 2010 were not copied to the electronic system, because the university no longer needed to track their academic performance.

TABLE 1
CONCEPTUAL AND OPERATIONAL DEFINITIONS OF ACADEMIC MOMENTUM VARIABLES USED IN THE STUDY

Variable Name	Variable Definition	Operationalization in the US	Operationalization in Russia
Delayed university enrollment	This indicator describes whether a student has delayed college enrollment.	Equals 1 if graduation from high school occurred before 2007, and 0 otherwise.	Equals 1 if college enrollment was delayed by at least one year, and 0 otherwise.
Total number of attempted academic credits in the first term	The indicator is adopted from Attewell et al. (2012), who suggests that academic momentum should measure the course load students undertake rather than complete, because passing (or not passing) courses is an outcome of academic momentum rather than its characteristic.	The total number of attempted credits in the first term is split into three groups: [12–15), [15–17), [17, …).	
Enrollment in developmental courses in the first term	Developmental courses are designed to help under-prepared students succeed in college-level courses. Because these courses are not counted toward a degree, enrollment in developmental classes delays taking credit-bearing courses and can decelerate the academic progress in early undergraduate studies.	Equals 1 if a student took a developmental course in the first term, and 0 otherwise.	
Reporting major upon college entry	The US higher education system permits students to delay decision making about majors or enroll in the exploration and general studies programs. Without committing to a specific major, however, students may delay taking major-related courses, which could slow down their college progress and prolong their time to graduation.	Equals 1 if students decided to delay reporting the major or recorded liberal/general studies as the major in the first term, and 0 otherwise.	

First-term academic performance	The indicator represents academic performance in the first term. In the US, academic performance is expressed using the first-term GPA. In Russia, academic performance is approximated using course failures in the first term. In Russia's universities, most courses are compulsory, and voluntary course withdrawals are impossible. Failing a certain number of courses in one term—usually three or more courses—or failing reexaminations leads to immediate dismissal from a university.	Measured in two ways. First, the cumulative GPA recorded at the end of the first term is split into seven groups, reflecting the idea that attrition risk is not constant along the GPA range: GPA = 0, (0, 1.5), [1.5, 2), [2, 3), [3, 3.5), [3.5, 4]; no cumulative GPA reported in the first term. Second, the cumulative GPA recorded at the end of the first term is split into 10 bins within which the first-term GPA is continuous: [0, 1.5); [1.5, 2); [2, 2.25); [2.25, 2.5); [2.5, 2.75); [2.75, 3); [3, 3.25); [3.25, 3.5); [3.5, 3.75); [3.75, 4].	Expressed by a series of four dichotomous variables: 0 course failures, 1 course failure, 2 course failures, 3 or more course failures in the first term.
Changes in grades over time	The variable reflects whether a student's GPA improved, declined, or remained unchanged between the first and second terms. The role of academic performance during the freshman year is critical (Adelman 1999), and we attempt to capture this by including both first-term grades and trends in grades.	The changes in grades reflect shifts between the GPA groups between the first and second terms: GPA = 0, (0, 1.5), [1.5, 2), [2, 3), [3, 3.5), [3.5, 4]. The effective sample includes only students for whom GPA was reported.	The variable is defined identically as in the US model but using grade scores specific to Russia's higher education system between 2 and 5: [2; 3], (3; 3.5], (3.5; 4], (4; 4.5], (4.5; 5].

NOTE.—Academic term is represented by quarters or semesters (depending on the university) in the US, and by semesters in Russia.

TABLE 2
WEIGHTED SAMPLE MEANS FOR US AND RUSSIAN UNIVERSITIES

	US Public Universities (N = 25,339)			Russia's Public Universities (N = 6,553)	
	Highly Selective (N = 8,297)	Medium Selective (N = 6,712)	Least Selective (N = 10,330)	Highly Selective (N = 2,414)	Medium Selective (N = 4,139)
Variable	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Outcome variable:					
Departed from the institution of initial enrollment	.13 (.34)	.31 (.46)	.39 (.49)	.23 (.42)	.23 (.42)
Academic momentum indicators:					
Delayed enrollment in college	.01 (.09)	.02 (.15)	.04 (.2)	.07 (.25)	.04 (.2)
Took at least one developmental course (first term)	.02 (.15)	.05 (.21)	.38 (.48)		
Number of attempted credits (first term)	15.94 (.01)	15.74 (.02)	14.8 (.01)		
Number of failed courses (first term)				.47 (1.07)	.91 (1.16)
Cumulative GPA (first term)	3.09 (.01)	2.86 (.01)	2.58 (.01)		
Grades remained unchanged (between the first and second terms)	.67 (.47)	.61 (.49)	.56 (.5)	.57 (.5)	.3 (.46)
Grades improved (between the first and second terms)	.14 (.35)	.14 (.35)	.13 (.33)	.12 (.32)	.16 (.37)
Grades declined (between the first and second terms)	.17 (.37)	.18 (.39)	.19 (.39)	.27 (.45)	.3 (.46)
No information about grades in the first or second term	.02 (.16)	.06 (.25)	.12 (.33)	.04 (.19)	.23 (.42)
Reported STEM (first term)	.3 (.46)	.22 (.42)	.15 (.36)		
Reported non-STEM (first term)	.51 (.5)	.57 (.49)	.61 (.49)		
Unreported or reported liberal /general studies (first term)	.19 (.39)	.2 (.4)	.24 (.43)		
Enrolled in natural science, engineering and mathematics				.08 (.27)	.58 (.49)
Enrolled in humanities and social sciences				.38 (.49	.06 (.24)
Enrolled in economics and government				.54 (.5)	.31 (.46)
Demographic and academic characteristics:					
Age at the time of enrollment	18.4 (.52)	18.46 (.69)	18.49 (.75)	17 (.73)	17.1 (.76)
Female	.52 (.5)	.5 (.5)	.55 (.5)	.52 (.5)	.44 (.5)
White	.85 (.36)	.86 (.35)	.82 (.38)		
African American	.06 (.23)	.08 (.27)	.12 (.33)		
Attended a 4-year institution after attrition	.24 (.01)	.22 (.01)	.17 (.01)		
Attended a 2-year institution after attrition	.17 (.01)	.25 (.01)	.3 (.01)		

NOTE.—Descriptive statistics refer to fall 2007 in the US and fall 2009 in Russia, with exception of the attrition variable. All indicators but changes in grades refer to the first term of undergraduate studies. Statistical differences between means are significant at the .05 level except for following variables: grades improved between first and second terms, white, attended a 4-year institution after attrition (between highly and medium selective university clusters in the US); departed from the institution of initial enrollment (between highly and medium selective university in Russia).

TABLE 3
LIFE TABLE DESCRIBING STUDENT ATTRITION IN US AND RUSSIAN UNIVERSITIES DURING THE 2.5 YEAR OBSERVATION PERIOD

	US Universities								Russian Universities					
	Full Sample		Highly Selective		Medium Selective		Least Selective		Full Sample		Highly Selective		Medium Selective	
Term	SR[b]	HR[c]	SR	HR	SR	HR	SR	HR	SR	HR	SR	HR	SR	HR
First year AU	.934	.066	.979	.021	.945	.055	.892	.108	.99	.01	.987	.013	.991	.009
First year WI[a]	.921	.014	.971	.008	.905	.042	.892	0	.952	.038	.946	.041	.956	.036
First year SP	.809	.122	.923	.05	.803	.113	.722	.19	.916	.038	.917	.031	.916	.042
First year SM	.807	.003	.921	.002	.801	.004	.719	.004	.883	.036	.896	.023	.876	.043
Second year AU	.776	.039	.905	.018	.767	.042	.677	.058	.84	.049	.837	.066	.842	.039
Second year WI[2]	.769	.008	.9	.006	.749	.023	.677	0	.823	.021	.813	.029	.829	.016
Second year SP	.726	.056	.876	.026	.711	.051	.616	.091	.814	.011	.806	.009	.819	.012
Second year SM	.723	.004	.875	.002	.708	.004	.612	.006	.803	.013	.804	.003	.803	.019
Third year AU	**.718**	.008	**.869**	.006	**.695**	.019	**.611**	.001	**.77**	.041	**.768**	.044	**.771**	.04

NOTE.—The following term abbreviations are used: SR = survival rate, HR = hazard rate, AU = autumn term, WI = winter term, SP = spring term, SM = summer term.

[a] Universities in the least selective cluster operate under the semester system. The indicator of hazard rate for winter term is equal to 0, and the survival rate for the winter term is equal to the survival rate in the autumn term. Numbers in boldface refer to cumulative survival rates.

[b] Survival rate is the probability that individual *i* will not experience the event in the *j*th time period or in any earlier period.

[c] Hazard rate is the probability that individual *i* will experience the event in time period *j*, given that he or she did not experience it in any earlier time period.

a particular term. Hazard rates describe the probability of student attrition at a particular term, conditional that a student has remained enrolled until that term.

The cumulative attrition rate within the 2.5-year observation period varies between 13 and 39 percent for the highly and least selective clusters in the US, respectively, and is approximately 23 percent in both Russian universities (table 3). The life table indicates that the majority of attrited students in the US leave before the summer of the second year. The attrition risk peaks in the spring term of the first year, which includes students who left during the spring term and those who completed the spring term but dropped out after that. In Russia, although most students leave before the fall term of the second year, the highest attrition rate is observed in the fall term of the second year. The finding that attrition is most prevalent in the first year of study is consistent with the existing literature on experiences of first-year students in both countries (Bowen et al. 2009; Kolotova 2011).

The distribution of attrition risk differs by the university selectivity. In the highly selective university cluster in the US, the attrition pattern is smooth over time, whereas in less selective universities, there are more evident peaks in student attrition in the first year of study. Comparing academic choices after students attrite from the first institution of enrollment (table 2) reveals the following: a higher proportion of students from the highly selective cluster attend a four-year institution, while a higher proportion from the least selective cluster attend a two-year institution. In Russia, attrition rate in the

highly selective university peaks most in the fall of the second year, and in the medium selective university, the attrition rate is consistently smooth between the winter term of the first year and the fall term of the second year.

When stratifying the US sample by academic field, the lowest attrition rate is observed in STEM fields, while the highest attrition rate is among unreported/undecided students; these differences are statistically significant (fig. 1). By university selectivity, the differences in attrition rates across academic fields in highly selective universities are fairly small (overall attrition equals 12 percent in STEM fields, 13.5 percent in non-STEM fields, and 13.8 percent for unreported/undecided students). In comparison, in medium and least selective universities, the unreported/undecided students have much higher levels of attrition equal to 39.6 and 47.8 percent, respectively. Moreover, in medium selective universities, attrition in STEM (30.7 percent) is higher than in non-STEM (27.3 percent) fields, while in least selective universities, attrition is lower in STEM (32.4 percent) than in non-STEM (37 percent) fields. The opposite trend is noted in Russian universities (fig. 2), where students in STEM disciplines have a higher attrition risk than non-STEM students. These differences are statistically significant, and the difference is larger in the highly

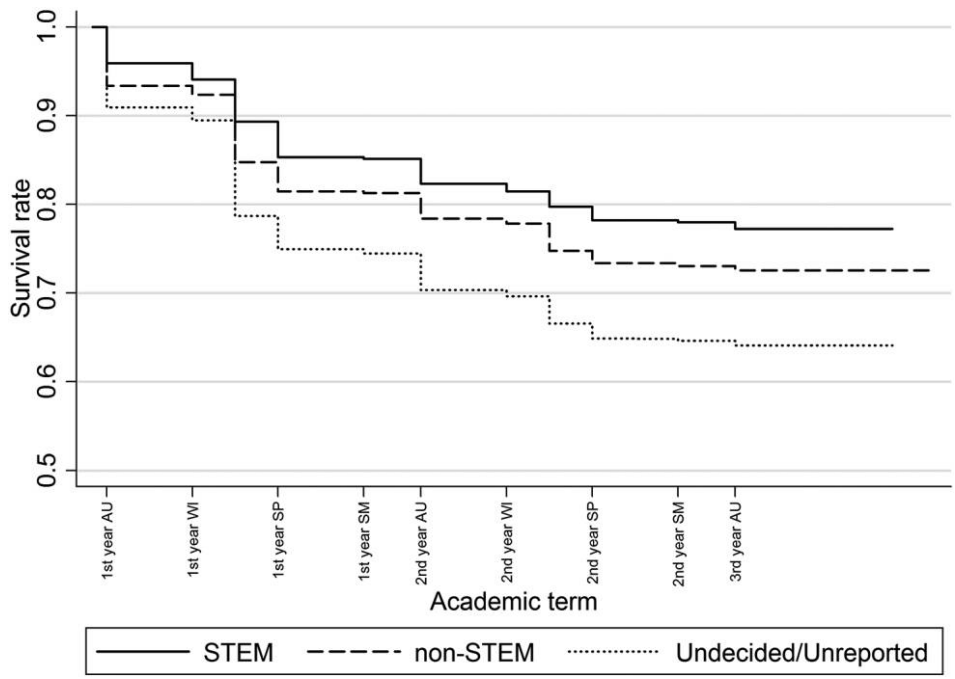

FIG. 1.—Kaplan-Meier estimates—stratifying by academic discipline in the US

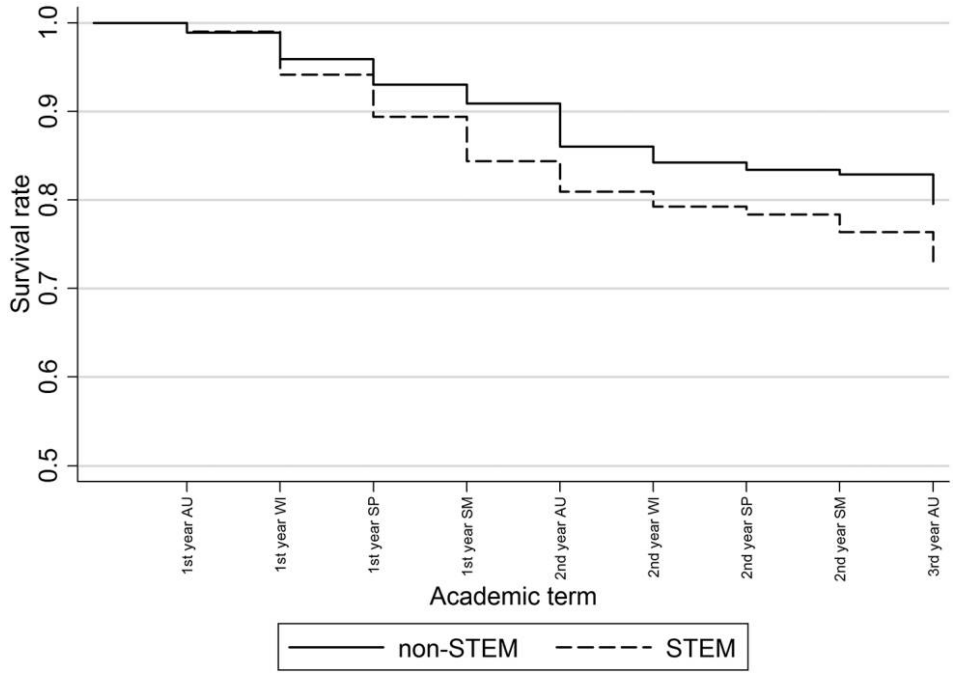

FIG. 2.—Kaplan-Meier estimates—stratifying by academic discipline in Russia

selective university. This result could be due to lower selectivity,[9] curriculum difficulty, and the lack of academic services for academically struggling students in engineering departments.

In terms of gender, survivor functions are not different between males and females in US universities, irrespective of selectivity cluster and study discipline. Despite this similarity, the association between academic momentum and attrition differs by gender in the regression models. Conversely, in Russian universities, attrition rates for males are significantly higher than for females, across the selectivity clusters and disciplines. Descriptive findings by university selectivity, academic discipline, and gender are available upon request.

Academic Momentum Indicators

The event history regression estimates, presented in tables 4 and 5, suggest that for the full sample, all academic momentum measures are statistically

[9] The results of admissions quality monitoring provide evidence for lower scores on the Unified State Examination among enrollees in most engineering programs in Russia (http://www.hse.ru/ege/stata#forth).

TABLE 4

EVENT HISTORY ANALYSIS ESTIMATES OF ACADEMIC MOMENTUM MEASURES ON STUDENT ATTRITION FROM THE FIRST INSTITUTION OF ENROLLMENT IN US UNIVERSITIES DURING THE 2.5 YEAR OBSERVATION PERIOD

		Selectivity of University			Gender		Academic Field		
Variable	Full sample	High	Medium	Low	Female	Male	STEM	Non-STEM	Unreported
	1.26**	2.56**	1.09	1.31**	1.13	1.43***	.88	1.29*	1.33*
Delayed enrollment in college[a]	(.12)	(.94)	(.22)	(.17)	(.16)	(.18)	(.25)	(.17)	(.22)
	1.17***	1.71***	1.82***	1.11**	1.12**	1.25***	1.78***	1.01	1.27***
Took at least one developmental course[b]	(.05)	(.35)	(.19)	(.05)	(.06)	(.08)	(.2)	(.05)	(.1)
	.92**	1.24*	.71***	.95	.86***	.98	.97	.89**	.92
Attempted credits [15, 17)[c]	(.03)	(.16)	(.05)	(.04)	(.04)	(.05)	(.08)	(.04)	(.06)
	.89**	1.19	.77***	.82**	.78***	1.04	.98	.85**	.95
Attempted credits [17, ...)[c]	(.05)	(.18)	(.06)	(.07)	(.06)	(.08)	(.11)	(.06)	(.12)
	8.38***	28.13***	14.51***	7.99***	5.53***	13.06***	8.47***	8.18***	9.88***
GPA (=0)[d]	(.82)	(9.55)	(3.74)	(1.01)	(.79)	(1.76)	(1.99)	(1.14)	(1.73)
	5.90***	8.80***	5.68***	6.39***	4.89***	7.20***	6.94***	5.53***	6.57***
GPA (0, 1.5)[d]	(.29)	(1.2)	(.57)	(.44)	(.35)	(.49)	(.82)	(.36)	(.64)
	2.58***	3.36***	2.81***	2.51***	2.34***	2.80***	3.32***	2.41***	2.50***
GPA [1.5, 2)[d]	(.13)	(.5)	(.28)	(.18)	(.17)	(.2)	(.37)	(.17)	(.26)
	.47***	.51***	.46***	.46***	.50***	.44***	.43***	.47***	.49***
GPA [3, 3.5)[d]	(.02)	(.05)	(.04)	(.03)	(.03)	(.03)	(.05)	(.03)	(.04)
	.31***	.24***	.36***	.32***	.33***	.29***	.27***	.30***	.36***
GPA [3.5, 4][d]	(.02)	(.03)	(.03)	(.03)	(.02)	(.03)	(.04)	(.02)	(.04)
	.19***	.19***	.20***	.16***	.22***	.15***	.15***	.21***	.17***
Grades improved over time[e]	(.01)	(.03)	(.02)	(.01)	(.02)	(.01)	(.02)	(.02)	(.02)
	1.18***	1.16	1.27***	1.14***	1.14***	1.23***			
No major reported[f]	(.04)	(.12)	(.08)	(.06)	(.06)	(.06)			
Number of observations	247,231	72,612	52,920	70,589	129,425	109,697	49,844	141,658	44,385
Akaike information criterion (AIC)	39,603	7,123	11,714	15,700	21,139	18,438	7,825	22,006	9,684

NOTE.—The table reports only coefficients on the measures of academic momentum reported as odds ratios, with standard errors reported in parentheses. The table with full coefficients can be provided upon request. Control variables: student's age at the time of enrollment, gender, race/ethnicity, student's housing arrangements during the first term, receipt of a need-based grant, a merit-based grant, a loan and work-study appointment during any given term, region-level characteristics (the percentage of population with bachelor's degree or higher and unemployment level) and university fixed effects. Models include dummies for bimonthly periods.

[a] No delay in college enrollment.

[b] Did not take any developmental courses.

[c] Attempted credits [12, 15).

[d] Cumulative GPA [2, 3).

[e] Grades declined between first and second terms.

[f] Reported a major.

* $P < .1$.

** $P < .05$.

*** $P < .01$.

TABLE 5
EVENT HISTORY ANALYSIS ESTIMATES OF ACADEMIC MOMENTUM MEASURES ON STUDENT ATTRITION FROM THE FIRST INSTITUTION OF ENROLLMENT IN RUSSIAN UNIVERSITIES DURING THE 2.5 YEAR OBSERVATION PERIOD

		Selectivity of University		Gender		Academic Field	
Variable	Full Sample	High	Medium	Female	Male	STEM	Non-STEM
Delayed enrollment in university[a]	1.61***	1.49*	2.18***	1.6*	1.61**	2.51***	1.37
	(.27)	(.33)	(.65)	(.43)	(.34)	(.86)	(.8)
Failed one course[b]	2.07***	1.86***	2.32***	1.9***	2.15***	2.16***	2.66***
	(.18)	(.23)	(.33)	(.27)	(.25)	(.41)	(.56)
Failed two courses[b]	3.41***	1.88***	4.48***	3.78***	3.28***	4.45***	4.75***
	(.37)	(.38)	(.66)	(.69)	(.44)	(.83)	(1.18)
Failed three or more courses[b]	6.44***	8.26***	6.04***	8.33***	6.02***	6.95***	3.44***
	(.78)	(1.47)	(1.07)	(1.9)	(.87)	(1.48)	(1.38)
Grades improved over time[c]	.37***	.24***	.48***	.27***	.44***	.53***	.47***
	(.05)	(.05)	(.08)	(.05)	(.07)	(.12)	(.13)
Number of observations	37,297	19,091	18,206	19,264	18,033	9,731	8,403
Akaike information criterion (AIC)	7,154	3,560	3,460	2,885	4,272	2,116.0	1,347.7

NOTE.—The table reports only coefficients on the measures of academic momentum reported as odds ratios, with standard errors reported in parentheses. The table with full coefficients can be provided upon the request. Control variables: student's age at the time of enrollment, gender, residency status combined with university housing during the first term, selected academic discipline at the time of enrollment, receipt of tuition subsidies from the government, award of the gold medal for academic performance in high school, and university fixed effects. Models include dummies for quarter periods.

[a] No delay in college enrollment.
[b] Did not fail any course in the first term.
[c] Grades declined between first and second terms.
* $P < .1$.
** $P < .05$.
*** $P < .01$.

significant ($P < .05$) and have the expected coefficient signs. These results provide strong support for a negative relationship between academic momentum and the risk of student attrition in both countries. However, this general result overlooks the variability of academic momentum across university selectivity, gender, and academic disciplines.

To address this limitation, we demonstrate how the association of academic momentum and student attrition varies across different student subpopulations. We further describe how this observed variability can be explained by both individual (endogenous) and institutional (exogenous) characteristics. Specifically, academic momentum is considered as the endogenous student characteristic determined by academic choices and other individual characteristics. The reasons for selecting a higher academic momentum may differ, as students vary by observable and unobservable individual characteristics, including the level of academic preparation, academic motivation, long-term commitment to the degree, academic aspirations, employment, and

socioeconomic status. At the same time, academic momentum is influenced by exogenous characteristics, such as institutional characteristics and academic discipline.

The rest of the section presents the findings from the descriptive event history analysis (stratified by university selectivity) and regression results that explore the association between academic momentum and the probability of student attrition for different student subpopulations.

First-Term Academic Performance and Grade Improvement between the First Two Terms

The descriptive event history analysis in the US shows that when GPA is equal to zero, student attrition in least selective universities is not statistically different from that in more selective universities. For higher GPA levels, survivor functions of student attrition differ between the highly selective university cluster and other two clusters, while there are fewer statistically significant differences between the medium and least selective clusters. In the regression models, for highly selective universities, the coefficients are higher in lower nonzero GPA ranges (between 0 and 1.5), lower in higher GPA ranges (between 3.5 and 4), as compared to medium and least selective universities. At zero GPA, student attrition is lower in least selective universities than in highly and medium selective universities. Coefficients remain lower in least selective universities compared to highly selective universities for GPA between 1.5 and 2. These statistically significant differences suggest that in more selective universities, students with lower GPA are more likely to attrite, while those with higher GPA are less likely to do so. Students with zero GPA from least selective universities are less likely to attrite compared to students in more selective institutions. By gender, male students with the lowest academic achievement (GPA between 0 and 2, including GPA = 0) have significantly higher probability of attrition than females with similar GPA. By academic discipline, at lower nonzero GPA levels of 0–2, STEM students attrite at a higher rate than non-STEM students, and at GPA between 1.5 and 2, STEM students also attrite more than unreported/undecided.

As an alternative specification, breaking down GPA into continuous variables, a one-point increase in GPA is associated with lower student attrition in the lower GPA ranges (between 0 and 2). For higher GPA (between 3.5 and 4), the coefficients are not statistically significant, except for least selective universities and unreported/undecided students (only between 3.5 and 3.75). Between GPA levels of 2 and 3, specifically in the ranges of 2–2.25 and 2.75–3, with several exceptions, a one-point increase in GPA is associated with lower student attrition. For GPA between 2.25 and 2.75, none of the coefficients are statistically significant. The joint distribution of persisting and attrited students by GPA illustrates that in this GPA interval, the proportion of persisting students begins to exceed the proportion of attrited students. Estimates from this analysis are available upon request.

In Russia, in the highly selective university, students with three or more course failures attrite at a higher rate than in the medium selective university. However, in the regression model with controls, this difference is not statistically significant. On the other hand, comparing regression coefficients reveals that students with two course failures in the medium selective university are more likely to attrite than those in the highly selective university.

Grade improvement is associated with lower attrition among male students compared with female students, and STEM students compared to non-STEM students, in the US sample. In the Russian sample, grade improvement is associated with lower attrition among female students compared to male students, and students in the highly selective university compared to the medium selective university.

Delayed College Enrollment

Descriptive results for both countries suggest that students with delayed enrollment attrite at higher rates than students who did not delay their enrollment. In less selective universities in both countries, attrition rates are statistically different between students with and without delayed enrollment from the very beginning of the study. In more selective universities, these differences become evident in later terms: in medium and highly selective universities in the US, statistically significant differences start from the summer term of the first and second year, respectively. In Russian highly selective universities, students who delayed enrollment face a higher attrition risk only from the winter term of the second year.

The positive association between delayed enrollment and higher student attrition is supported in the regression models. The coefficient on delayed enrollment is statistically significant in both Russian universities, and in highly and least selective universities in the US. The coefficient on delayed enrollment is higher for highly selective universities compared with medium and least selective universities. In the US, delayed university enrollment increases attrition for male students but not females. In Russia, a weakly significant relationship is observed for both genders. By academic discipline, the coefficient on delayed college enrollment is weakly significant for non-STEM and undecided/unreported students in the US, and strongly significant for STEM students in Russian universities.

Based on further analysis, on average, in least selective universities in both countries, students with delayed enrollment perform worse than students without delayed enrollment. In more selective universities, this difference is not statistically significant, suggesting perhaps that the characteristics of students who delay enrollment differ by the type of institution in which they enroll. This is consistent with prior research showing that attrition among students who delay college enrollment is contextual (Martin et al. 2013). Delayed college enrollment may positively influence academic experience if during

the gap year students undertake activities that enrich their knowledge and experience. Conversely, delayed enrollment due to family obligations and low level of academic preparation or life circumstances may adversely influence academic experience. We find that academic performance and attrition patterns of students who delay enrollment vary with institutional selectivity in both countries; different processes may underlie decisions to take a gap year, and these decisions differ by university selectivity.

Higher Credit Load in the First Term

The descriptive analyses suggest that students with different course loads in the first term attrite at similar rates in highly selective universities, and at different rates in medium and least selective universities. For example, in the latter universities, students with a lower course load (between 12 and 15 credits) attrite at higher rates than students who enroll in more credits. Regression results, however, are mixed. Taking more credit hours in the first term is associated with lower student attrition in the medium selective cluster (over 15 credit hours), the least selective cluster (over 17), and the most selective cluster (15–17). The decision to take a higher number of credits may reflect (observed and unobserved) student characteristics and institutional factors, such as studying under the quarter or semester system, or specific disciplinary requirements. Finally, taking over 15 credit hours is associated with lower attrition among female and non-STEM students. The estimates for male students, and STEM and unreported/undecided students, are not statistically significant.

Remedial Courses in the First Term

The descriptive analyses suggest that taking remedial courses in the first term increases attrition, but the size of this association differs across selectivity clusters and within those clusters. This finding is supported in all regression estimates, with one exception: the coefficient is not statistically significant among non-STEM students. Perhaps this is because students who take remedial courses lack academic preparation and tend to choose majors that fit their academic preparation levels. Moreover, STEM disciplines contain more academically challenging curriculum, while non-STEM disciplines tend to be less mathematically heavy.

Not Reporting Major in the First Term

The regression analyses indicate that students reporting a major in the first term attrite at rates similar to those of students not reporting in the highly selective cluster, but not in less selective universities. This finding may reflect the fact that reporting a major upon enrollment depends on university policy. Particularly, while selecting a major is an individual choice, universities influence the timing of reporting a major because they may have different

financial aid guidelines, academic policies, and availability of information about the majors. We also find that not reporting a major upon enrollment increases attrition for both genders.

Robustness Checks

For robustness checks, first, we estimate five nested event history models: (1) including only control variables without any academic momentum indicators, and adding (2) delayed enrollment, (3) enrollment in developmental courses, attempted credit hours and not reporting the major, only in the U.S. model, (4) first-term academic performance, and (5) grade improvement measures. Estimating model 1 separates the results without confounding them with the endogeneity of academic momentum. Models 2 and 3 describe how the academic momentum measures prior to the beginning of the academic term influence student attrition. As argued above, temporal precedence is one way of addressing the simultaneity problem in order to establish a causal link between academic momentum measures and student attrition. Finally, models 4 and 5 present a more complete set of measures of academic momentum.

The results from models 1–5 are similar to our original findings. Significance of the coefficients on academic momentum indicators remains stable as more variables are added in the model. The exception in the US is the coefficient on delayed enrollment that changes significance in highly selective universities and among female students, and the coefficient on credit hours that slightly changes significance in highly and least selective universities. In Russia, the coefficient on delayed enrollment becomes statistically significant for students in the highly selective university and female students as more variables are added in the model. Including grade improvement measures in model 5 does not considerably affect the significance levels of academic momentum. In fact, coefficient magnitudes for academic performance indicators are higher for the lowest GPA levels in the US, and having three or more course failures in Russia.

Second, following Attewell et al. (2012), we estimate a logistic regression model where the dependent variable signifies whether or not a student attrites within 2.5 years of study. This estimation focuses on overall student attrition, rather than attrition at different time periods. The estimates for academic momentum are generally similar to the results discussed above.

Estimation results of these alternative models show consistency and robustness for the original results, and are available upon request.

Discussion

This article contributes to the debate on the factors that determine student attrition in a cross-national context. Our analysis from eight US and

two Russian public universities supports the result in existing literature that higher academic momentum at the beginning of undergraduate studies is associated with a lower risk of student attrition, and that this association varies by university selectivity, gender, and academic discipline (Attewell et al. 2012; Attewell and Jang 2013). We show that both individual and institutional characteristics are also important for understanding differences in academic momentum. Academic momentum indicators can serve as the "early warning system" for later attrition, which can be of practical importance to university administrators. Although causal inference is greatly limited, our results point to indicators of early student progress, which are contingent on institutional factors, such as university selectivity and academic discipline requirements. A "one-size-fits-all" principle and failure to account for the variability in academic momentum through the implementation of standardized institutional policies may be ineffective across different types of students and institutions.

The academic momentum perspective has potential for a broader application in a cross-national context. Our analysis suggests that this concept is salient for higher education systems characterized by openness, flexibility, and student freedom to change their educational trajectories and design an individually tailored curriculum (as in the US). Its application is limited in countries with rigid and inflexible higher education systems, including Russia, but with more globalization and greater flexibility in higher education, the academic momentum perspective will likely have broader theoretical and practical applications there too. Taking into account that emerging adults value identity explorations in personal and professional lives (Arnett 2004), considerations for student choice and the related concept of academic momentum are expected to gain more prominence in the higher education literature.

Our study also has implications for institutional research and data management. The Russian data come from two public institutions. Securing collaboration from more universities was difficult due to data limitations in Russian universities and low interest in conducting institutional research. Russian policy makers and the academic community would benefit from the creation of a centralized data management system and a requirement that universities regularly submit academic data via a supervisory agency. Such a data management system could be used to conduct more comprehensive institutional research. Similarly, our analysis for the US is based on Ohio data despite the existence of similar databases in other states. Securing states' cooperation and combining data across the states would significantly improve research on student attrition, allowing explorations beyond a single state.

Future research on student attrition should focus on increasing the internal and external validity of their findings. Due to data limitations, our study does not appropriately account for unobserved student characteristics (e.g.,

student employment, SES, and high school background) that may be related to student attrition. While we use several empirical strategies to increase internal validity, we are reluctant to make causal claims. Additionally, student attrition as defined in this study cannot be generalized beyond attrition from the first institution of enrollment. We do not know whether students who drop out from the first institution leave higher education altogether and what other academic choices they may have adopted. Finally, future research might examine the factors that explain attrition of nontraditional students, although addressing this question would be even more data intensive.

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