Bayudan-Dacuycuy, Connie

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Hazard and incidence of exits of ever-enrolled college-age students

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Hazard and Incidence of Exits of Ever-Enrolled College-Age Students

Connie G. Bayudan-Dacuycuy

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CONTACT US:
RESEARCH INFORMATION DEPARTMENT
Philippine Institute for Development Studies

18th Floor, Three Cyberpod Centris - North Tower
EDSA corner Quezon Avenue, Quezon City, Philippines

https://www.pids.gov.ph
publications@pids.gov.ph
(+632) 8877-4000

Hazard and Incidence of Exits of Ever-Enrolled College-Age Students

Connie G. Bayudan-Dacuycuy

PHILIPPINE INSTITUTE FOR DEVELOPMENT STUDIES

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Abstract

Using survival analysis, this paper investigates student- and household-level factors that affect the hazard and incidence of exits of college-age students who have ever been enrolled in college. The paper has limitations since it focuses only on school attendance, the closest available indicator of enrollment patterns and, thus, attrition. Despite this, results offer insights into the covariates affecting the hazard and incidence of exits. The paper 1) provides some directions to address the issue arising from individual- and household-level vulnerabilities and 2) suggests ways to improve the data needed to reflect the success and performance of the HEI ecosystem accurately.

Keywords: hazard and incidence of exits, attrition

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Hazard and Incidence of Exits of Ever-Enrolled College-Age Students

***Connie G. Bayudan-Dacuycuy*[1]**

1. Introduction

The enrollment patterns of college students are important considerations for policies and interventions aimed at addressing challenges in retention and attrition in the tertiary education sector. Retention refers to the continuation of students in the subsequent year until graduation (Mason and Matas 2015; Manyanga et al. 2017). Meanwhile, attrition is often associated with the "diminution in numbers due to low student retention" (Hagedorn 2005). Retention (and thus attrition) is closely related to persistence, which is commonly understood as whether or not the student is still attending at some points after the enrollment/initial period (Bahr 2009; Leppel 2002; Titus 2004)[2].

While widely recognized as key indicators of the success of students and higher education institutions (HEI), statistics on attrition and retention are relatively scarce. This is partly due to some challenges in operationalizing the definition, including the lack of data that captures the dynamic nature of school attendance and the complexity of school progression. For example, dropping out, while easily understood as premature exits, requires a nuanced understanding of various factors to estimate dropout rates correctly. Earlier studies argue that departures should only be included in dropout metrics if students leave without achieving their educational goals (Tinto, 1987; Bean, 1990). Depending on opportunities and circumstances, goals can also change during a student's academic journey. Failing to account for these details can lead to an overestimation of dropout and attrition rates.

Given this backdrop and the limited data on hand, this paper focuses on school attendance, the closest available indicator of enrollment patterns that can shed light on the determinants of attrition. Leveraging survival analysis and using the 2019 Annual Poverty Indicator Survey,

[1] Senior Research Fellow, Philippine Institute for Development Studies. The author gratefully acknowledges the able research assistance of Ms. Anna Rita P. Vargas and Ms. Paola Ellaine D. Luzon.

[2] Other enrollment patterns like enrollment inconsistency (the frequency or incidence of absence from college), enrollment intensity (whether the load in an academic year is full or not), course completion rate (the courses passed relative to the courses failed/withdrawn), and delay (the cumulative number of attempted credits from first enrollment), although not as extensively studied as persistence, are also important in analyzing attrition and retention (see Bahr (2019) and the references reviewed therein).

the paper focuses on household- and student-level factors and analyzes the hazard and incidence of exits among samples who have ever been enrolled in college. The paper provides some insights to address school exits arising from individual- and household-level vulnerabilities and suggests ways to improve the data needed to reflect the success and performance of the HEI ecosystem accurately.

2. Definition, methodology, and data sources

Two popular models explain retention: Student Integration Model (pioneered by (Tinto 1975)) and Student Attrition Model (pioneered by (Bean 1980)). The former expounds on the roles of abilities and social integration (e.g., networks, engagements, interactions). The latter articulates the roles of personal (e.g., attitudes, beliefs), environmental (e.g., family approval, friends, support), and HEI-level (e.g., quality of instructions, courses taken) factors. Efforts to harmonize the two models find that environmental factors influence the students' socialization and academic experiences (Cabrera et al. 1983).

While theoretical models have been well-developed and studies on retention, persistence, and attrition abound in developed economies, analyzing these outcomes requires longitudinal data at both the individual and higher education institution (HEI) levels. Such detailed datasets are not available in the Philippines, although there are national surveys that collect household and member data that can facilitate the analysis of some enrollment patterns. One such dataset is the Annual Poverty Indicator Survey (APIS). The paper uses the 2019 APIS, leveraging information on the highest grade completed (HGC), current grade enrolled in, and personal and household data to set up time-to-event data. These data, as the name suggests, are data pairs consisting of whether the event has occurred and the time that elapsed when the event has occurred. These are used for survival analysis and are popular in medical research (i.e., remission or death after cancer treatment, relapse after rehabilitation). Survival analysis can also be applied in social science research (i.e., divorce after marriage, labor market re-entry after childbirth, promotion after permanency). It should be noted that the event is not necessarily a failure (such as death) but can be a success, such as in the case of promotion or labor market re-entry.

Two important aspects in modeling survival data are censoring and non-normality. While estimators like the Tobit estimator can also account for censoring, these regression models

assume that the error terms are normally distributed. Time-to-event data are more likely to be right-skewed (i.e., Many samples survive for a shorter period.). A tobit regression model is also appropriate for continuous dependent variables. In the current research, the elapsed time is discrete.

Censoring, or when subjects are lost to follow-up (e.g., refused, withdrawn) or the event has not occurred by the end of the study period (Austin 2016), can be either uninformative or informative. Uninformative censoring assumes that subjects who are no longer being followed have the same risk of experiencing an event as those who have yet to experience the event. The hazard function describing the instantaneous occurrence of an event in at-risk subjects is $h(t) = \lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t \mid T \geq t)}{\Delta t}$ where T is the time to failure from an event, and t is time. This is interpreted as the "instantaneous rate of occurrence of the event in subjects who are still at risk of the event" (Austin 2016). Cox proportional hazard regression model, $h(t) = h_0(t)\exp(\beta x)$, is used to model this scenario. x and β are vectors of explanatory variables and their corresponding coefficients. $h_0(t)$ is the baseline hazard or the hazard at time t for all $x_n = 0$, which is unspecified and allowed to vary over time. The hazard ratio estimates have the following interpretation:

$$\frac{h(t)}{h_0(t)} = \begin{cases} > 1, x_1 \text{ has a bigger hazard vs } x_0, \text{shorter median time to experience the event} \\ < 1, x_1 \text{ has a lower hazard vs } x_0, \text{longer median time to experience the event} \end{cases}$$

Another strand of literature recognizes that censoring is informative. Key to the narrative is the presence of competing risk, or the "event whose occurrence precludes the occurrence of the primary event of interest" (Austin 2016). For example, death due to accidents or any other causes can be considered a competing risk in a study on the time to death due to heart disease (Austin 2016). In the context of enrollment patterns among 17-21-year-olds in the 2019 APIS data, samples that are attending, not attending, and having graduated account for 21%, 7%, and 72% of the sample, respectively. Further disaggregation indicates that 0.37% of the 1355 19-year-olds, 24% of the 1296 20-year-olds, and 56% of the 1448 21-year-olds have already graduated. On the one hand, removing these samples may result in the loss of valuable information for the current research. On the other hand, relegating the samples that graduated to the catchall censored data assumes that the hazard of departure for those currently attending and those who have graduated is the same.

Thus, the competing risk model appears appropriate in the current context. In this case, the subdistribution hazard function describing the instantaneous occurrence of an event in at-risk subjects is given by $h_k(t) = \lim_{\Delta t \to 0} \frac{P(\, t < T \leq t+\Delta t\,,\ \ D = k \mid T > t \text{ or } (T \leq t \text{ and not event} \neq k)}{\Delta t}$ where k is the event type and T and t are as defined above (Stata 2018). This is interpreted as the "instantaneous risk of failure from event k in subjects who have yet to experience the event" (Austin 2016). The hazard model, in this case, is given by $h_k(t) = h_{0,\mathrm{k}}(t)\exp(\beta x)$. The model also assumes proportional hazard, and the interpretation of the subdistribution hazard ratio follows the interpretation of the hazard ratio, except that it considers the impact of covariates in the presence of competing events.

The current research investigates the exits of college-age students who have ever been enrolled in college. Time is equal to the HGC if the sample is no longer attending school and equal to the current grade if the sample is still attending school. Constructing the time information in this manner has limitations, as exits are not accurately recorded (i.e., ideally, they should be in months, not years). However, academic performance requires discrete steps to be accomplished in sequences to attain an academic level. This means that a specific age is expected to have earned a certain academic level once enrolled in college. Limiting the samples to 17-21-year-olds who have ever been enrolled in college (i.e., those with at least college HGC or currently enrolled in college) can partly mitigate inaccuracies in the time data.

Second, the paper cannot account for the role of intended goals in school attendance. In the context of student departure, earlier studies argue that departures do not necessarily indicate failure unless the students' educational goals have not been achieved (Tinto, 1987; Bean, 1990). These studies recognize that students leave school because they have already attained their intended goals. There is no way to account for this issue, and it is thus a subject of the ways forward below.

The main explanatory variables of interest include welfare status and government support. Welfare status is generated using the household's data on asset ownership (car, washing machine, stove, refrigerator, personal computer, and television) and dwelling attributes (presence of electricity, subscription to video streaming, concrete roof, and toilet inside the house). The tetrachoric correlation coefficients of these binary variables are computed and used

as inputs to factor analysis, a technique that reduces the dimensionality of the data. The overall Kaiser-Meyer-Olkin[3] measure of sampling adequacy is around 0.92, indicating that the data contain similar information warranting a factor analysis. Rotation after the factor analysis indicates that there is one factor with loading greater than one. Thus, one factor is predicted, with the welfare indicator constructed as equal to one for the 4th and 5th quantiles of the factor (representing non-poor) and zero otherwise[4].

Government support is generated from the Universal Access to Quality Tertiary Education (UAQTE) information, which equals one if receipt of free tuition fees (FTF) or tertiary education subsidy (TES) is reported and zero otherwise. The hazard and subdistribution hazard ratio estimates using the overall UAQTE and its two programs (FTF and TES) are presented. Other explanatory variables include personal characteristics (e.g., marital status), household-level attributes (e.g., the presence of high school students in the household and household head attributes such as educational attainment, age, and marital status), and other variables (e.g., dummy indicators for relationship to the household head).

3. Discussion of results

While the model with competing risk is the main model of interest, the model without competing risk is presented for comparison (Table 1). Table 1A in the Appendix indicates that the specifications in the model with competing risks satisfy the proportionality hazards assumption. The comparison indicates that the signs of the estimates are robust in both models. Focusing on the model with competing risk, results indicate the following:

1. Welfare status and gender do not significantly affect the hazard of exits (hazard hereafter). However, being single decreases the hazard by 84%.
2. Being a beneficiary of the UAQTE program decreases the hazard by 70%. Broken down by the UAQTE program, relative to non-recipients, beneficiaries of FTF and TES have 68% and 79% lower hazards, respectively.
3. The household head's attributes have significant effects on the hazards as well. Students in households headed by at least college units decrease the hazard by 33%.

[3] The Kaiser-Meyer-Olkin statistic, a measure of sampling adequacy (Kaiser, 1970), summarizes how small the partial correlations are relative to the original correlations. Variables that share common factor/s have small partial correlations and a statistic close to one.

[4] Welfare status using the deciles of the income per capita is also constructed and used in alternative specifications. Results are relatively similar to the results using the indicator derived from asset ownership and household attributes.

4. Students in certain households are at a disadvantage. Relative to their counterparts, those in households headed by the elderly and widowed/separated have higher hazards at 45% and around 33%, respectively.

Table 1: Estimates of the hazard and subhazard of not attending

	Without competing risk model: Hazard			With competing risk model: Subhazard		
	Government support programs					
	UAQTE	FTF	TES	UAQTE	FTF	TES
Poor	1.03	1.02	1.01	0.94	0.93	0.92
	[0.11]	[0.11]	[0.11]	[0.10]	[0.10]	[0.10]
Recipient of gov support programs	0.25***	0.28***	0.18***	0.30***	0.32***	0.21***
	[0.06]	[0.07]	[0.11]	[0.07]	[0.08]	[0.12]
Male	0.91	0.9	0.92	0.85	0.85	0.86
	[0.10]	[0.10]	[0.10]	[0.09]	[0.09]	[0.09]
Single	0.20***	0.20***	0.20***	0.16***	0.16***	0.16***
	[0.03]	[0.03]	[0.03]	[0.02]	[0.02]	[0.02]
HH HGC: At least college	0.62***	0.63***	0.64***	0.67**	0.68**	0.69**
	[0.10]	[0.10]	[0.10]	[0.10]	[0.11]	[0.11]
HH age: At least 60 years old	1.33*	1.34**	1.33*	1.45***	1.45***	1.46***
	[0.20]	[0.20]	[0.20]	[0.21]	[0.21]	[0.21]
HH marital status: Separated/Widowed	1.36**	1.37**	1.36**	1.33**	1.34**	1.32**
	[0.20]	[0.20]	[0.20]	[0.19]	[0.19]	[0.19]

Source: Author's computation using 2019, 2020, and 2022 APIS.
Notes: */**/*** significant at 10/5/1% level. Figures in brackets are standard errors.
UAQTE: Universal quality tertiary education. FTF: Free tuition fee. TES: Tertiary education subsidy.
Figures are generated using *stcox* (without competing risk model) and *stcrreg* (with competing risk model) in Stata. Other explanatory variables include the presence of high school students in the household and dummy indicators for relationship to the household head.

The cumulative incidence of exits (incidence hereafter) for select covariates is presented in Table 2. Results indicate the following:

1. Students who are not beneficiaries of the UAQTE programs have a higher incidence. In the third year, the incidence for non-recipients, regardless of welfare status, is 6%, four percentage points higher than for UAQTE beneficiaries.
2. The incidence for non-single is substantially higher than their single counterparts. In the second year (fourth year), the incidence for the former is 19% (28%), 16 (23) percentage points higher than for the latter.
3. Covariates related to household head attributes also have differential effects on the incidence, although the effects are not as big as the impact of the student's marital status. The incidence for students in households headed by the elderly and separated/widowed is higher than for students in households headed by non-

separated/widowed and non-senior adults. In the second (fourth) year, the incidence for students in elderly-headed households is 5% (7%). For those in separated or widowed-headed households, the incidence is 4% (7%).

Table 2: Cumulative incidence of not attending school by covariates

Time	Non-poor, UAQTE non-recipient	Non-poor, UAQTE recipient	Poor, UAQTE non-recipient	Poor, UAQTE recipient
2	0.04	0.01	0.04	0.01
3	0.06	0.02	0.06	0.02
4	0.07	0.02	0.06	0.02
Time	Not single	Single	HH marital status: Not separated	HH marital status: Separated/Widowed
2	0.19	0.03	0.03	0.04
3	0.25	0.04	0.05	0.06
4	0.28	0.05	0.05	0.07
Time	HH HGC: Less than college	HH HGC: At least a college degree	HH age: Less than 60	HH age: 60 years and above
2	0.04	0.03	0.03	0.05
3	0.05	0.04	0.05	0.06
4	0.06	0.04	0.05	0.07

Source: Author's computation using 2019 APIS.
Note: Figures are generated by linear interpolation after *stcrreg* and *stcurve* in Stata. The cumulative incidence function is evaluated at 1) specified values of each covariate (welfare status, UAQTE recipient indicator, marital status, and household head's marital status, education, and age) and 2) overall means of the rest of the explanatory variables.

The incidence for various profiles using the combination of covariates (students' UAQTE receipt and marital status and the attributes of their household heads) is presented in Table 3. Results are consistent with those in Table 2, including the relatively higher incidence for non-single than single students. For example, profile A has an incidence of 38% in the 3rd year, while profile E (which differs from profile A only in marital status) has an incidence of 7% only in the same year. A similar pattern can be observed when comparing other profiles (e.g., B vs. F, I vs. M).

The following additional observations are also noted:

1. The incidence is the highest for the profile with vulnerabilities, including being non-beneficiaries of government financial aid, non-single, and members of households headed by non-college, senior, and separated/widowed adults (profile B, baseline

profile). This profile has a 47% and 52% incidence in the third and fourth years, respectively.

2. Relative to the baseline profile, the incidence is lower for profiles headed by non-separated adults. Profile A (which differs from profile B only in the head's marital status) has a 38% incidence in the third year, nine percentage points lower than the baseline profile.
3. Relative to the baseline profile, the incidence is lower for profiles headed by college-educated adults. Profile D (which differs from profile B only in the head's educational attainment) has a 35% incidence in the third year, 12 percentage points lower than the baseline profile.
4. Relative to the baseline profile, the incidence is substantially lower for profiles where students are beneficiaries of government support programs (e.g., B vs. J). Profile J (which differs from profile B only in the receipt of government support programs) has a 17% incidence, 30 percentage points lower than the baseline profile.
5. Despite the reduction due to the receipt of government aid, the incidence among students in separated- or widowed-headed households remains relatively high when students are not single (e.g., I vs. J and K vs. L). Profile I (which differs from profile J only in the head's marital status) has a 13% incidence in the third year, four percentage points lower than profile J.
6. The lowest incidence is observed in students who are single and recipients of government support programs (M, N, O, and P). In these profiles, the attributes of the household heads do not substantially alter the incidence.

Table 3: Cumulative incidence of not attending school, various profiles

	Non-recipient and non-single	**Recipient and non-single**
Time	**A.** HH non-college, senior, and not separated	**I.** HH non-college, senior, and not separated
2	0.29	0.10
3	0.38	0.13
4	0.42	0.15
	B. HH non-college, senior, and separated	**J.** HH non-college, senior, and separated
2	0.37	0.13
3	0.47	0.17
4	0.52	0.20
	C. HH college, senior, and not separated	**K.** HH college, senior, and not separated
2	0.21	0.07
3	0.27	0.09
4	0.31	0.10

	Non-recipient and non-single	Recipient and non-single
	D. HH college, senior, and separated	**L.** HH college, senior, and separated
2	0.26	0.09
3	0.35	0.12
4	0.39	0.14
	Non-recipient and single	**Recipient and single**
	E. HH non-college, senior, and not separated	**M.** HH non-college, senior, and not separated
2	0.05	0.02
3	0.07	0.02
4	0.08	0.03
	F. HH non-college, senior, and separated	**N.** HH non-college, senior, and separated
2	0.07	0.02
3	0.10	0.03
4	0.11	0.03
	G. HH college, senior, and not separated	**O.** HH college, senior, and not separated
2	0.04	0.01
3	0.05	0.02
4	0.06	0.02
	H. HH college, senior, and separated	**P.** HH college, senior, and separated
2	0.05	0.01
3	0.07	0.02
4	0.08	0.02

Source: Author's computation using 2019 APIS.

Note: Figures are generated by linear interpolation after *stcrreg* and *stcurve* in Stata. The cumulative incidence function is evaluated at 1) specified values of welfare status, UAQTE recipient indicator, marital status, and household head's marital status, education, and age, and 2) overall means of the rest of the explanatory variables.

4. Ways forward

The paper investigates the attendance of college-age students who have ever been enrolled in college. It leverages the highest grade completed and current grade information to implement a time-to-event analysis within a competing risk framework. The paper recognizes the potential inaccuracies in the construction of the time variable. However, academic performance requires discrete steps to be accomplished in sequences to attain an academic level. This means that a specific age is expected to have earned a certain academic level once enrolled in college. Limiting the samples to 17-21-year-olds who have ever been enrolled in college can partly mitigate inaccuracies in the time data. This and other observations in data limitations are important points in the ways forward below.

Limitations in the data notwithstanding, the results offer some insights into the covariates affecting the risk and incidence of exits among students who have ever enrolled in college.

1. Non-single students and those in households headed by the elderly and separated/widowed adults have higher risks of exits. Meanwhile, beneficiaries of government aid and students in households with college-educated heads have lower hazards of exit.
2. Students with a vulnerable profile (non-recipient of government support, non-single, and members of households headed by non-college, senior, and separated/widowed adults) have the highest incidence. Relative to this baseline profile, the incidence is lower for students in households headed by college-educated and non-separated adults and even lower for students who are beneficiaries of government programs.
3. Despite the reduction resulting from government support programs, the incidence for students in separated/widowed-headed households remains high when students are not single.

Given the preceding discussion, the following ways forward can be considered:

Strengthen programs addressing teenage pregnancy. While teenage pregnancy is not a covariate in the estimation exercises conducted, the potential implications of the student's marital status resonate with the issues of teenage pregnancy. The 2022 National Demographic Household Survey indicates that the overall rate of teenage pregnancy declined from 8.6% in 2017 to 5.4% in 2022 (https://psa.gov.ph/content/teenage-pregnancy-declined-86-percent-2017-54-percent-2022). However, the percentage of 17-, 18-, and 19-year-olds who have ever been pregnant is higher than the national figure at 5.6%, 5.9%, and 13.3%, respectively.

Information is critical, and ensuring that teenagers obtain it from reliable sources is key. Thus, sex education, the content and appropriateness of which to be developed through in-depth consultation and collaboration with stakeholders (i.e., parents/associations, guidance counselors, child development experts, and teachers), can be integrated into the school curriculum.

Develop programs for teenage parents to help them become self-sufficient. Programs that can be considered include counseling services to determine their next course of action (i.e., college re-entry, shift to technical vocational education) and financial support for these plans. The

provision of the latter can be made conditional on achieving certain outcomes, such as delayed subsequent pregnancy and the utilization of reproductive, maternal, and natal care services.

Improve the targeting of financial aid beneficiaries. Given the government's limited resources, there is a need to ensure that financial support is given to those who need support. Earlier studies have called for improving the tertiary education subsidy prioritization scheme, although the focus remains on income- and welfare-based targeting. Bayudan-Dacuycuy et al. (2024), for example, suggest the integration of 4Ps information into the *Listahanan* database. Results of the present study indicate that the government's financial aid can mitigate the adverse effects of household-level vulnerabilities on the hazards and incidence of school departures. Thus, the household heads' age and civil status can be used as non-income criteria when improving the targeting scheme.

Mainstream the collection of vital information upon students' entries and exits. The path to educational outcomes is dynamic and involves exits and re-entries that can occur at various stages of the student's academic journey. These movements can be used to determine attrition, a leading success indicator of the overall tertiary education ecosystem and at the HEI and student levels. At the aggregate level, data on intentions and goals upon entry, as well as whether and how these intentions and goals have been achieved upon exit, are needed. Accounting for this information mitigates the overestimation of the underperformance of the tertiary education system. In addition, students may leave one HEI only to enter another HEI or shift to a technical vocational school. Thus, attrition at the HEI level will differ from the overall attrition level. Given this, the PhilSys number (national ID) should be collected, as it can facilitate the analysis of student mobility in the higher education and technical vocational ecosystems and aid in a more accurate estimation of success indicators at different levels.

5. References

Austin, P., Lee, D., and Fine, J. (2016). Introduction to the Analysis of Survival Data in the Presence of Competing Risks: Statistical Primer for Cardiovascular Research. DOI: 10.1161/CIRCULATIONAHA.115.017719

Bahr, P. (2009). Educational Attainment as Process: Using Hierarchical Discrete-Time Event History Analysis to Model Rate, *Research in Higher Education* 50:691-714.

Bayudan-Dacuycuy, C., Orbeta, A., Vargas, AR, and Ortiz, MK. (2024). An Evaluation of the Tertiary Education Subsidy: Context, Input, Process, and Product. Philippine Institute for Development Studies Discussion Paper 2024-22. https://doi.org/10.62986/dp2024.22

Bean, J. P. (1980). Dropouts and Turnover: The Synthesis and Test of a Causal Model of Student Attrition. *Research in Higher Education* 12(2): 155-187.

Cabrera, A., Nora, A., and Castañeda, M. (1993). College Persistence: Structural Equations Modeling Test of an Integrated Model of Student Retention. *The Journal of Higher Education* 64(2):123-139.

Hagedorn, L. (2005). How to Define Retention: A New Look at an Old Problem. Paper sponsored by the Transfer and Retention of Urban Community College Students Project (TRUCCS) funded by the Lumina Foundation (Grant # 1415). https://files.eric.ed.gov/fulltext/ED493674.pdf

Kaiser, H.F. (1970). A Second Generation Little Jiffy. *Psychometrika* 35(4): 401-415.

Leppel, K. (2002). Similarities and Differences Between the College Persistence of Men and Women. *Review of Higher Education*, 25: 433-450.

Manyanga, F., Sithole, A., and Hanson, S. (2017). Comparison of Student Retention Models in Undergraduate Education From the Past Eight Decades. *Journal of Applied Learning in Higher Education* 7:29-41.

Mason, S. and Matas, C. P. (2015). Teacher Attrition and Retention Research in Australia: Towards a New Theoretical Framework. *Australian Journal of Teacher Education (Online)* 40(11), 45.

Stata manual (2018). https://www.stata.com/manuals/ststcrreg.pdf

Tinto, V. (1975). Dropout From Higher Education: A Theoretical Synthesis of Recent Research. *Review of Educational Research* 45:89-125.

Tinto, V. (1987). Leaving College: Rethinking the Causes and Cures of Student Attrition. Chicago: The University of Chicago Press.

Titus, M. A. (2004). An examination of the Influence of Institutional Context on Student Persistence at 4-year Colleges and Universities: A Multilevel Approach. *Research in Higher Education* 45:673-699.

Appendix

Table 1A: Check for the proportional hazard assumption in the competing risk model

	Government support program					
	UAQTE		FTF		TES	
	Estimate	Std error	Estimate	Std error	Estimate	Std error
Poor	-0.18	0.22	-0.18	0.22	-0.18	0.22
Government support program	-0.03	0.46	-0.09	0.49	0.34	1.21
Male	-0.35*	0.21	-0.35*	0.21	-0.34	0.21
Single	0.13	0.28	0.14	0.28	0.15	0.28
Presence of high school students in the household	-0.09	0.22	-0.09	0.22	-0.10	0.22
HH HGC: At least college	0.48	0.32	0.48	0.32	0.48	0.32
HH age: At least 60 years old	-0.49*	0.27	-0.49*	0.27	-0.51*	0.27
HH marital status: Separated/Widowed	-0.02	0.27	-0.02	0.27	-0.01	0.27
Wife/Spouse	0.47	0.87	0.47	0.87	0.50	0.87
Son/daughter	0.45	0.49	0.45	0.49	0.47	0.49
Son-in-law/Daughter-in-law	0.15	0.60	0.15	0.61	0.17	0.61
Grandson/Granddaughter	0.15	0.66	0.14	0.66	0.18	0.65
Other relatives	0.77	0.59	0.76	0.59	0.79	0.59

Source: Author's computation using 2019 APIS.
Notes: Test of the null hypothesis of proportional hazard. *significant at 10% level.
UAQTE: Universal quality tertiary education. FTF: Free tuition fee. TES: Tertiary education subsidy.