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DETERMINANTS IN UNIVERSITY DESERTION AND GRADUATION: AN APPLICATION USING DURATION MODELS[1,2]

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1. Introduction

National universities in Argentina have implemented an unrestricted entrance system from the time of their inception, with the exception of the period between 1977 and 1982. Students are not subject to entrance examinations or limited enrollments, and they do not pay tuition or fees for college courses.

In part, this has led to a considerable increase in the demand for higher education across the years, particularly since the restoration of democracy in 1983. This increase has not been accompanied by similar increments in the number of graduates. For example, in 1973, the National University of Rosario (NUR) enrolled 21,000 new students, while the number of graduates exceeded 2,300. By 1999, there were 67,000 new students, but the number of graduates remained close to 2,500. Similar numbers were observed in the rest of the universities across the country[4].

This reflects the existence of two clear phenomena. On the one hand, the group of graduates is reduced in relation to the number of beginners, revealing that a large portion of the beginning group eventually drops out.

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[4] The detailed data for all Argentine universities and for each separate university can be found online, in the Statistical Annuals of the Department of Education.

On the other hand, as is clearly reflected in various investigations (Pagura, Quaglino, Iturbide, 2000; Porto and Di Gresia, 2001) within the group that does graduate, there is a large percentage of students who prolong their stay at the university beyond the time-frames established by the study plans.

Some authors, such as Manski (1989), argue that desertion is not necessarily bad, since the actual fact of having begun university studies allows the person to gain information about adapting to university training. Additionally, it would be reasonable to say that initiating studies adds knowledge that might be of some economic value, at least during the two years that the student attended the university.

Beyond this discussion, however, it is interesting to analyze how long it takes for the individual to make the decision to drop out or to graduate, and, above all, to determine which factors influence that decision. It is particularly important to consider whether the probability of dropping out or graduating remains the same during the length of the student's academic path.

In Argentina, there are very few investigations that attempt to give answers to these problems. The analysis and resolution of questions such as these are important for universities as well as for the government, who currently provides financial resources to support higher education. Being able to identify the years of greatest drop-out risk will facilitate the design of policies that prevent desertion and lead to an efficient administration of these scarce resources. It would be even more interesting to determine, for example, whether the risk of desertion is significantly greater for a beginning student whose parents have low educational levels and relatively low incomes, versus students in higher socio-economic positions. Measuring this difference would provide a first step for further analysis on higher education outcomes.

This study contributes to such an effort by proposing two main objectives. The first is the incorporation of the time factor into the analysis - when is it more likely that a student will drop out or graduate from university? The second objective is to identify the socioeconomic characteristics and personal factors that are most related to the duration and risk of each event.

In order to reach these objectives, the method known as duration analysis will be applied to a cohort of students who began the program of Public Accountant at NUR in 1991. This method allows us to examine the events of desertion (and graduation) using the available information on the duration of such events - which is incomplete in most cases, since the period of observation is not infinite.

The data, supplied by the School of Economic Sciences and Statistics of the NUR, includes personal characteristics, socioeconomic conditions of the students, and the academic performance from the time of entrance until graduation, desertion and continuance of studies.

This study differs from previous ones in that the majority of them examine whether the event (of desertion or graduation) occurs in a certain moment in time. The technique applied here allows us to see the event as a process in time, evaluating which students are most likely to abandon or graduate, taking into account how long they have been studying. Additionally, the event of finalization of studies is modeled by making the distinction between a culmination due to desertion or due to the completion of the university degree (model of multiple kinds of events).

The rest of the study is structured as follows. Section II presents the methodology used and justifies its selection. Section III describes the available data and section IV analyzes the results. The last section summarizes the conclusions and opens doors for future investigations.

2. Duration Models

Modelization

This section presents the model to be estimated and justifies its selection. Rather than specifying the structural form of the model, a reduced form is presented[5]. We begin by assuming a homogenous population, and then we introduce a model of multiple kinds of events with

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[5] For an exhaustive analysis of the models' derivations see Cox, 1972; Lancaster, 1979; Kalbfleisch and Prentice, 1980; Cox and Oakes, 1984; Heckman and Singer, 1984; Klein and Moeschberger, 1997.

observed heterogeneity. Finally, we present a model that allows for the existence of unobservable heterogeneity.

Homogenous population

A first step is to determine whether the probability of an event taking place in a moment in time (conditional on it not happening before) is constant, growing, or decreasing in time. Detecting the years of greatest risk of desertion is of interest not only to the effects of this investigation, but also for the design of policies that will prevent desertion.

A particularly important function that describes this behavior is what is called the hazard function, which represents a sequence of conditional probabilities, *λ(t)=Pr(to drop out at the moment t since he/she studied until t-1)*. If *T* is defined as a discrete, non-negative random variable, representing the duration of studies, *T* can take values $0 \leq t0 < t1 < t2 < t3...$ This variable will refer to the time that a student remains active[6] at the university and will also include information about the reasons for finishing studies *i*. The latter could have two different causes: graduating (obtaining the degree within the period of observation) or dropping out (not attending any classes during the school year or not attempting to regularize). The probability function associated with the discrete random variable *T* is (1):

$$f(t_i) = P(T = t_i) \qquad i = 0,1,2,... \tag{1}$$

If it is important to know the probability of T being greater or equal than a value t, then the survival function is given by (2):

$$S(t) = \sum_{j \mid t_j \geq t} f(t_j) \tag{2}$$

[6] An active student is defined as a person who attends (whether or not the course is passed) or attempts to regularize at least one class per year.

and expresses the probability that the duration of the event be $T \geq t$. If there is no censure, the estimation of this function is simply to count how many students reached the moment *tj* in relation to the total.

As previously stated, a particularly important function is the hazard function[7] in *tj* which is defined as:

$$\lambda_j = P(T = t_j | T \geq t_j) = \frac{f(t_j)}{S(t_j)} \qquad j = 0,1,2,... \tag{3}$$

and expresses the probability that an individual will end up in *tj* being that he/she survived until *tj*.

Heterogeneous population

A second step is to investigate whether the risk λ that an event will occur differs systematically among individuals. In other words, we seek to identify the explanatory variables for the observed heterogeneity[8] in the hazard function. For example, if the risk of desertion is under examination, the relevant question will be: which characteristics distinguish the students with a high risk of desertion from those students with a low risk of desertion?

The observed heterogeneity is introduced into the model considering P explanatory variables *zp* with *p*= 1, 2,3, ..., *P* which characterize the members of a population. For example, *z1* represents the gender, *z2* the education of the mother, etc. We then have a vector *Zij=[z1ij, z2ij, ..., zPij]* in which each element of the vector represents the characteristic *p* for the individual *i* in the moment *j*.

In order to include the effect of this vector of characteristics in the duration and risk of an event, the alternatives of modelization that are most

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[7] A definition assuming continous time is: $\lambda(t) = \lim \frac{\Pr(t \leq T < t+h \geq t)}{h}$ when *h* tends to 0; known in economy as the opposite of Mill's Ratio.

[8] It refers to the fact that the information is available to the researcher.

common are the Accelerated Failure Time Model (AFTM) or the Proportional Hazard Model (PHM)[9].

In the proportional hazard model proposed by Cox (1972), the effect of vector Z*ij* takes place in a multiplicative manner over the hazard function by means of a factor which does not depend upon the time of duration.

This model implies three assumptions. A first assumption makes reference to the inexistence of unobserved heterogeneity, since all heterogeneity present among the individuals is gathered in the explanatory variables. The second assumption is of proportionality, and the third, of linearity.

There are several advantages of the PHM model over the AFTM. First, the interpretation of PHM is simpler and indicates the effect of the variable over the risk of an event occurring (for example, to drop out or graduate). Second, both the treatment to incorporate explanatory variables which are changing through time, as well as the issue of multiple kinds of events for finalization, are easier under the PHM model. One last advantage, and perhaps the most important, is the possibility of estimating the effects of the explanatory variables over the hazard without the need to specify a parametric function for the baseline hazard rate.

If the data is supposed to be generated by a continuous time model - proportional hazard - but is observed only in discrete intervals of time $(t_i - 1, t_i)$, or, alternatively, it may be assumed that the duration is intrinsically discrete. Prentice and Gloeckler (PG) (1978) have demonstrated that the corresponding hazard function in discrete time is given by (4):

$$\lambda_j(z_{ij}) = 1 - \exp\left\{ - e^{\left[(\beta_1 z_{1iJ} + \beta_2 z_{2iJ} + \ldots\ldots\beta_p z_{piJ}) + \lambda\ (t)\right]} \right\}$$

(4)

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[9] The basic difference between these two modelization alternatives is the way of introducing the effects in the explanatory variables. In other words, in the case of AFTM, the effect of the explanatory variables happens directly over the time of duration, while in the PH model, the effect is over the hazard function.

Where $\lambda_j(z_{ij})$ are the hazard rates in discrete time for the person i at each interval of duration of $j = 1, ...,t$. The main difference with the continuous model is the interpretation of the hazard function. In the discrete case, it is the conditional probability, while the continuous case makes reference to the instantaneous hazard rate. Each element of vector Z_{ij} represents a characteristic for the individual i at the moment j, and the vector of coefficients β (parameters to estimate) is identical to vector β of the proportional hazard model initially presented. Finally, $\lambda(t)$ is the function (of baseline hazard rate) that describes the duration and can be estimated non-parametrically[10].

This last modelization PG[11] is applied in this paper. This decision is based on two basic arguments.

On the one hand, it is considered to be conceptually more accurate, given the kind of data available. For the event under consideration (especially, desertion), the exact moment in which the decision is made is unknown, it is only known that it occurs within a given interval of time.

On the other hand, the discrete model offers several advantages in the interpretation and verification of the assumptions. By allowing for the incorporation of the binary variables associated with the different moments in time - the parameters of the baseline hazard rate - the discrete modelization provides a direct estimate of said baseline function, from which the survival base function can be constructed and the mean durations can be measured for the different subgroups of individuals in terms of their socio-economic characteristics. Another advantage is the possibility of easily identifying the assumption of proportionality in the model. Note that in each case, the assumption of proportionality is less restrictive than in the continuous case, since the effects only have to be proportional in the intervals and not during each instant of time.

[10] The main advantage of not assuming a functional form a priori for the baseline hazard function is to eliminate the possibility of estimating the β in an inconsistent way by incorrect specification of the baseline function.

[11] Also known as complementary log-log: $\log(-\log(1-\lambda_j) = \{[(\beta_1 z_{1i} + \beta_2 z_{2i} + ...\beta_p z_{pi}) + \lambda(t)]\}$

With regards to the assumption of the inexistence of unobservable heterogeneity, Meyer (1990) suggests the introduction in the model of the possibility of the existence of unobservable heterogeneity among individuals in the manner stated in (5):

$$\lambda_j(z_{ij}) = 1 - exp\left\{-e^{\left[(\beta_1 z_{1i} + \beta_2 z_{2i} + \dots\dots\beta_p z_{pi}) + \lambda(t) + log(e)\right]}\right\} \tag{5}$$

The difference between this model (5) and the previous one (4) is the incorporation of a new term that summarizes the unobservable heterogeneity, represented by *e*: a random variable with Gamma[12] distribution (with mean one and $Var = \sigma^2$). This random variable summarizes the impact of a group of factors that affect the risk of the event taking place but are not observed in a direct manner, be it because they are intrinsically unobservable, or because the data is unavailable. Other interpretations include possible mistakes in the measurement of data. (Lancaster, 1990).

Due to the potential fragility of the models that incorporate unobservable heterogeneity (Jenkins, 1995), both models will be estimated. These models are estimated using the maximum-likelihood method and non-parametric techniques in order to obtain the baseline hazard rate[13].

Defining a censure indicator $c_i = 1$ if the duration of the person i is observed completely and $c_i = 0$ if the duration is censured, the function of log-likelihood for (5) is (6):

$$\sum_{i=1}^{N} \log\left[(1 - c_i)A_i + c_i B_i\right] \tag{6}$$

[12] The selection of the distribution is not important when the baseline hazard function is estimates non-parametrically (Meyer, 1990).

[13] The discrete models have an advantage (as compared to the continuous models) of being easy to estimate, even when including the explanatory variables changing in time. See Jenkins S. (1995).

where:

$$A_i = \left[1 + \sum_{j=1}^{t_i} \left\{ \exp\left(I_{ij} + \ln(Var) \right) \right\} \right]^{-\frac{1}{Var}} \tag{7}$$

$$B_i = \left[1 + \sum_{j=1}^{t_i - 1} \left\{ \exp\left(I_{ij} + \ln(Var) \right) \right\} \right]^{-\frac{1}{Var}} - A_i \ , \quad \text{if} \quad t_i > 1 \tag{8}$$

$$B_i = 1 - A_i \, , \qquad \text{if } t_i = 1 \tag{9}$$

where:

$$I_{ij} = \left\lfloor (\beta_1 z_{1i} + \beta_2 z_{2i} + \dots\dots\beta_p z_{pi}) + \lambda(t) \right\rfloor \tag{10}$$

The log-likelihood function for (4)[14] is the limit case when the $Var \to 0$

3. Data

Although the analysis presented here can be applied to any university, for the purpose of implementation, the data used belonged to a cohort[15] of students who began the program of Public Accountant at the School of Economy and Statistics at the National University of Rosario in 1991.

There was access to the data regarding the socio-economic characteristics of the students, gathered from the forms of the Unified Registration System (URS), and to data regarding the classes that were taken (whether they had been passed or not) and are in position to continue their studies regularized, with the grade received and the exam dates[16]. This

[14] The log-likelihood function for model 1 is the same as the log-likelihood for a general lineal model of the complementary, binomial log-log link family. See Allison (1982).

[15] A cohort is defined in this study as the group of students who enroll in a university program during a specific year.

[16] It is important to clarify that re-enrollment is mandatory in order to be able to sit for an exam during the school year.

data is of interest in order to trace the academic path of the students and detect their condition as drop-outs, graduates, or continuing students.

According to the enrollment records at the university, the total number of persons who signed up to begin their major reached 1423. Of this group, there are 23 students who did not complete their registration forms and did not attend or sit for exams in any course, hence they are not considered part of the group we will be studying. For the remaining 1400 individuals, we conducted an academic follow-up from March of 1991 to May of 2001. Due to the fact that of this total, 24 students had their registration cancelled either for bad behavior or for a serious misdeed (for example, cheating in an exam), they are also excluded from the group under study, thus leaving a group of 1376 students.

In table 1 we observe the distribution of the joined frequency of the academic situation and the duration of studies for the 1991 cohort. For each year, we compute the number of students who drop out, continue, or graduate. Here, we must make two important clarifications.

We define as a "drop-out" a student who, during a school period of one full year, did not attempt to sit for any exams or attend any courses, regardless of passing them. In other words, the student was passive during that year without engaging in any academic activity. Some investigations call this behavior first drop-out, since there is no way of knowing whether the student will resume studies after the observation period, or change majors.

The students grouped under the "continuing" label are those who in May of 2001 were still active at the university and had not made the decision to drop-out or graduate. Graduates are the students who, having met all the academic requirements, have passed the total course load and have obtained their diploma or degree. As can be observed in table 1, this last group is very small. Of the total 1376 students who began their studies in 1991, after over 10 years, only 240 students have graduated (17,44%); since 920 students (66.86%) have dropped out and 216 (15.70%) are still continuing their studies[17].

[17] In the initial group of Actives, there were 58 students who, although re-enrolled in 2001, had their last academic activity between year 3 and 5 (depending on each case). Thus, this

Each cell in this table contains the absolute frequency, the relative frequency, the percentage in relation to the row and the percentage in relation to the column, organized according to the academic situation and year of observation.

This table reveals that:

1. The largest desertion takes place during the first years. As the third row indicates, of the group that dropped out, 32.39% did it during the first year. This percentage drops to 19.24% in the second year and again in the remaining years.

2. The largest percentages of graduates are those in the seventh and eighth years. We can see then a “delay” in the finalization of studies according to the theoretical study plan of five years is observed. Practically all graduates stay at university longer than the theoretical length of the program. Only 5.83% of graduates finish in curricular time.

3. In the sixth year, the percentage of students who graduate is approximately the same as the percentage of students who drop out, both in relation to the total of beginning students.

Apart from the data previously discussed, the socioeconomic characteristics for each student are also available. These refer to: variables that indicate education and previous orientation received by the student (such as type of secondary school attended, degree obtained, whether another university major was previously attempted); demographic and personal variables of the student (gender, age, marital status, type and place of residence); variables that indicate work situations and variables related to the characteristics of the parents of the students (occupational category and parent´s education). A detailed description of each of these variables included in the model and their summarized statistics (table 2) are presented in the Descriptive Annex.

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subgroup is considered to have dropped out. I thank A. Castaña, Dean of the School of Economic Sciences and Statistics at the National University of Rosario for providing this data, and also Engineer Aldo Gimbatti, Vice-President of the National University of Rosario, and C. Guarnieri and the Alumni Department staff.

4. Empirical Results

Two different models are estimated for each of the event of interest (drop out and graduation). A first discrete hazard model proposed by Prentice and Gloecker (1978) (Model 1), and a second model proposed by Meyer (1990), which includes unobservable heterogeneity among individuals (Model 2)[18].

Both models use the total of 1376 students[19]. Since we have multiple kinds of events that are mutually exclusive, they are estimated separately as if there was only one cause. On the one hand, we analyze the group of deserters considering the graduates and those who continue as censured. On the other hand, as we study other factors related to the greater chance of graduation, the data of deserters and those who continue are the ones that are censored.

4.1 Factors related to the risk of desertion

The results of the estimations are reported in table 3[20]. When the estimated coefficient is positive, it indicates that the variable positively affects the conditional probability of desertion. Expressed in relative risk, e^{β} indicates how much riskier the group is in relation to the base category, when everything else remains constant. The "effect" of a variable over the hazard function is proportional and does not change in time.

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[18] The estimation is done using the Stata 6.0 program. Jenkins programmed the pgmhaz command to estimate both models. Model 1 is estimated by MV using the command glm. Model 2 is estimated using the command m1 deriv0, beginning with an initial value beta estimated in model 1. See STB-39 for more details.

[19] Note that the number of total observations that appear in the desertion model is 7281 and 3132 for graduation, since in the makeup of the base, this represents the sum for all students of the total of periods of observation at risk.

[20] Table 4 presents the results of the non-parametric results of the coefficients of the baseline hazard functions. As the theory suggests, when taking into account the unobservable heterogeneity, the baseline function can change its slope in relation to the model that does not incorporate unobservable heterogeneity (see Jenkins, 2000). A possible extension which escapes the goals of this study, is to test whether the discrete model applied here is consistent with a continuous model of Weibull, which specifies the baseline function (see Narandranathan, W. Stewart, M. (1993) for an application of this case). This would allow affirmations to be made about the baseline hazard function.

The P value of the likelihood ratio test is zero, indicating that the model with unobservable heterogeneity is statistically significant. We must take into consideration that this test is not a rule of decision between Model 1 and Model 2 since they are not nested models, and it only reflects whether the unobservable heterogeneity is significantly different from zero.

Although the coefficients for Model 2 are larger in magnitude, the direction of the effects does not vary from one model to the other and the coefficients that are significant in one model are significant in the other as well. That the estimated coefficients are greater in absolute value might be due to the fact that when we do not take into account the unobservable heterogeneity, this induces to an over-estimation of the hazard rate and diminishes the magnitude of the impact of the explanatory variables. (Jenkins, 2000).

The first group of explanatory variables refers to the education and previous orientation of the individual before beginning university studies. When controlling for unobservable heterogeneity (Model 2), the variables related to the type of secondary school attended by the student are significant to explain the differences in the risk of desertion. The results indicate that graduates from national schools[21] are four times more likely to drop out than graduates from schools that are dependant upon the university, given that everything else remains constant. This may reflect that there is a difference in the quality of previous education. A lesser preparation at the secondary level may force the student to make a much greater personal effort during the first period at the university.

In many cases, this can lead the student to abandon higher studies. It is important to point out that schools depending on the University are free of charge but not without restrictions, since a selective entrance exam is required.

Finishing secondary school and starting university studies immediately reduces the conditional probability of desertion in relation to someone who waited for some time between the finalization of secondary studies and the initiation of higher studies.

[21] The national schools to which reference is made were those running during the 80’s, since they do not formally exist in the 90’s.

Some studies such as Spady (1970) and Tinto (1975) conclude that those who have already attended university at some point have a lesser risk of desertion in relation to the group that begins university studies for the first time (beginners), simply because the first group has already adjusted to the university level. However, according to the results obtained here, setting a level of confidence of 95%, there are no significant differences in the risk of dropping out among those who began and abandoned another degree and beginners. The same conclusions are obtained for those who continue or finish another degree, given that everything else remains constant.

The variables that indicate whether the beginner received a vocational orientation previous to beginning a degree are also not significant in explaining the conditional probability of desertion[22].

Equally, given that everything else remains constant, a student who attended a national secondary school and chose humanistic orientation , in relation to another student who chose commercial orientation (and began a degree in Public Accountant) does not differ significantly in the risk of desertion.

The results indicate that the demographic and personal characteristics of the student are all significant to the 1% (except male, significant at 10%) to explain the differences in the conditional probabilities of desertion. Being male has a positive effect on the increased risk of dropping out; it is estimated that the risk for a male is 1.36 greater than it is for the female. The literature also points to this result, attributing it to cultural factors or to the fact that the male is less perseverant than the woman in continuing the degree. Something similar occurs with singles, in relation to those who are married, widowed, or separated. Two opposite effects may be interacting here. On one hand, it would be expected that a single person would have less family responsibilities and more time to study, controlling for all other variables. This effect would reduce the risk of desertion for singles. However, there is also the effect of “cost of time opportunity”, hypothetically less for those who are single than for those who are married,

[22] The baseline category against which the coefficients must be analyzed is “not having received any vocational orientation.”

that would increase the risk of desertion. This latter effect would be the dominating one.

Students who live with their families have a greater risk of desertion than students who live independently. The same result is observed in Rosario students, in relation to students who come from another city or town. Those who come from other localities have sunk costs (rent, moving expenses, adjustment) at the beginning of a degree course which are virtually non-existent for those who are already from the city.

Lastly, it is interesting to inquire whether older beginning students are more likely to abandon than younger students, given that the first group might face a more significant time restriction. In fact, the proportional change in the hazard function that results in the increase of one year in the age of the individual who goes into university is positive. The age squared variable captures the non-lineal relationship in the U shape, inverted between the linear index and the age.

As expected, beginning university studies while simultaneously working leads to a greater risk of desertion (3.4 times greater) in relation to those who begin their studies without the responsibility of working. These last students are supposed to assign their total time between study or leisure. However, given that everything else remains constant, working during the last year diminishes the conditional probability of desertion in relation to a student who does not work.

The last group of variables related to the characteristics of the parents reflects in part the family environment in which the student finds him/herself. For the group of indicative variables of the last occupation held by the father, the base category selected is worker or employee. The signs of the coefficients which accompany these variables are, in all cases, negative (although not all significant). If the student's father is a boss, director, or high executive, his or her risk of abandoning studies is 26.7% less in relation to an individual who has a working or employed father. A similar case happens with the students with parents who are self-employed. Both coefficients are significant when fixing a level of significance of 1% and 5% respectively.

Another point of interest is to analyze how important education is to the parents in the decision to not conclude higher studies. According to the results of this study the lesser the education level of the parents, the greater the risk of desertion for the students. An explanation is that the more formal education the parents have incorporated, the more value they will place on more years of study. A student with a parent who has only an incomplete primary education or has no formal education, has a risk of desertion that is 2.7 times greater than a student in the base category (parents with completed superior studies). All coefficients have an effect on the hazard rate -significant at 5% and 10%-, except middle-high education of the mother. It is important to point out that the lack of statistical significance in this last case might be due to a high correlation with the education of the father, meaning, due to a problem of high multicolineality.

Additionally, the education of the parents is also a proxy of the main income of the home, and hence, it may affect the probability of desertion through the budget restrains of the family[23].

In Moscoloni N., Conti O., Tuttolomondo I., Meinardi, B. (1990), applying different research techniques and using an alternative data base, similar results were obtained. The two groups of students with the greatest risk of desertion possess the following characteristics: they work and have working parents with only a primary level education, and for students who live in Rosario, who work and have employed parents who reached only a primary education.

4.2 Factors related to graduation

The theoretical duration of the degree under analysis is five years. However, students who do not drop out, prolong their studies. This section focuses on one question: given the length of time that the student has been studying, which factors favor the successful finalization of university

[23] Proportionality was assumed throughout this study. In other words, the effect of a change in the explanatory variable over the hazard is independent from the interval of time in which it is measured. This assumption is much less restrictive in the discrete model than in the continuous model, in which proportionality had to take place “at each moment in time.” The assumption was verified by introducing interactions among the binary variables for each interval with the explanatory variables and they were insignificant.

studies? The studies by Cameron and Heckman (2001), and Cameron and Taber (2004) applying other techniques suggest that the factors such as "family environment" play a central role in the determination of the decisions to finalize educational levels. The results of this study support this evidence. According to the estimated models for the group of graduates[24] (see table 5), the level of education reached by the parents influences significantly the probability of graduation. A student whose father did not finish primary studies (or without instruction) has a 70% lesser chance of graduating than a student with a professional parent. For the remaining educational categories and observing Model 1, the coefficients are all significant at 1% and 5% (except mid-high education of the father which is significant at 10% and low education of the mother, which is not significant).

Unlike in the case of desertion, the results now suggest that the unobservable heterogeneity is insignificant. It is preferred, thus, to carry out the analysis of the coefficients for Model 1 (supposing that there is no unobservable heterogeneity).

Given that everything else remains constant, for a student who is working (at least) during the last year of university attendance, the probability of graduation is 45% less than for a student who dedicates all of his or her time to studies. Moreover, the effect of beginning the degree while working is insignificant in the reduction of the probability of graduating.

There is a greater probability of graduating in the case of women and also for single students. However, entering university at a later age or residing with the family during school term, do not explain the differences in the chances of finishing the degree. Neither does receiving vocational orientation from an official or private entity (in relation to someone who received some type of orientation) seems to have an effect over the conditional probability of graduating. However, when vocational orientation was given by a professional, the student is 1.67 times more likely to successfully finish the career.

[24] And considering the information of drop-outs and continuing students as censured.

The coefficients which accompany the indicative, binary variables of the secondary school attended by the student are significant at 1% and 5% and have negative sign revealing that attending a secondary school which depends on the university favors the probability of graduating, in relation to each of the other secondary schools. Specifically, for a graduate from a national school, the conditional probability of graduating is 48.2% less than for a student who graduated from a secondary school which depended on the university.

Graduating from secondary school and beginning university the following year does not seem to contribute significantly to a greater conditional probability of successfully finishing university studies. It did constitute, however, an important factor when explaining the differences in the drop out hazard rates.

Finally, finishing another higher education program (before beginning this program) makes the student, given that everything else remains constant, have 4.46 times more chances to graduate than a student who begins a university career for the first time. Those who abandoned the career, however, have a probability that is 75.4% inferior as compared to the beginner.

The estimated models supposed discrete time. We should clarify that the shorter the time is between the successive re-examinations (for example, instead of observing dropouts once a year, doing it each semester) and greater is the number of intervals, the closer the results would get to those of a continual time model.

5. Conclusions

During the last decades, public universities in Argentina have experienced an increase in the number of enrolled students, and the majority extends its stay at the University to more than the theoretically established time frame. Both the desertion and the delay in graduation from public universities are clear phenomena and are socially well-known.

This study analyzes these issues and investigates the factors related to the probability of desertion or graduation for a student, conditioned to the length of time that the student has been at the university, thus focusing the process of finalizing studies from a more dynamic perspective than the previous studies.

The model used is one of discrete proportional hazard, proposed by Prentice and Gloeckler (1976). Without specifying any functional form a priori of the baseline hazard rate, the model proposed by Meyer (1990) is also estimated. This model - apart from the incorporation of the observable, explanatory variables - allows for the introduction of unobservable heterogeneity among individuals.

The empirical application is done for the cohort of students who entered the career of Public Accountant at the National University of Rosario in 1991. Once the data base is built, the follow-up is performed year to year for this cohort until May of 2001. When the recollection of data is complete, there are students in this group who are still continuing their university studies, thus the event of interest (desertion-graduation) is not observed in their cases; it is only known that they studied up until this point. This problem of censured data is addressed by the methodology applied in this paper.

The results indicate that factors related to the education of the parents and the type of secondary school attended by the students are important in the explanation of the differences of risk of desertion and the conditional probabilities of graduation. Independently from other characteristics, a student whose father has not completed primary studies (or who has no formal education) has a 70% smaller possibility of graduating than a student with a professional father. Controlling for unobservable heterogeneity, the risk of desertion is 2.86 times greater for the student whose mother has not completed primary studies in relation to a student whose mother completed superior studies. It was also proven that the risk of desertion is significantly less (26.7% less) for students whose fathers are bosses, directors, or high executives as compared with students whose parents are workers or employees. At the same time, given that all else remains constant, initiating the degree and working at the same time makes the student 3.4 times more likely to drop out. Gender also plays a significant part. It is estimated that the risk of desertion is 1.36 greater for the male than it is for the woman. The remaining demographic and personal characteristics (residence in Rosario, living with family, being single, and being older when beginning the career) also proved to be significant, positively affecting the conditional probability of desertion. Graduating from secondary school and immediately beginning university studies has been shown to be a relevant factor for the case of desertion, but has not been a factor that significantly increments the probability of graduation for a student. Lastly, a student who has already abandoned another degree in comparison with one who is starting university for the first time is less likely to graduate. Controlling for all other variables, the student who was working last time he/she re-enrolled at the university has a smaller probability of successfully finalizing the career than someone who was not working at that time.

Although the conclusions obtained through this study present only a first approximation to the phenomena of desertion and graduation and the influential factors, they are useful both at the university level – in order to implement entrance strategies and student follow-up, and to regulate the requirements for full-time students -, as well as at the level of designing educational policies that allow for the improvement of university educational systems – for example, those policies dealing with the financing of universities and students. The factors that play an important role in the increased conditional probabilities of graduation and in the diminished risk of desertion are intimately related with the family environment and must be a subject of concern for social policies and their relationship with university policies themselves.

There are several questions to keep in mind in future studies. If the information about changes in the socioeconomic situation of the students was to be stored, it would be interesting to include the effect that these “changing” explanatory variables would have over time. We have yet to make the information system more adequate in order to avoid the loss of this information. We could also introduce to the model a certain measure of performance of investigation mode, for example to understand why two students with equal performance make different decisions when finalizing their studies. If the data were available for the entire university it would be possible to also capture any differences according to each program.

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Appendix

Table 1. Distribution of the joined frequency of the academic situation of the student and the duration of studies

Academic situation		Observation Period (Years*) Theoretical Duration 1	2	3	4	5	Remaining years of observation 6	7	8	9	10	11	Total
	Continue	0	0	0	0	0	0	0	0	0	29	187	**216**
		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.11	13.59	*15.70*
		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	13.43	86.57	100.00
		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	40.28	95.90	15.70
	Drop Out	298	177	107	81	77	42	39	40	41	12	6	**920**
		21.66	12.86	7.78	5.89	5.60	3.05	2.83	2.91	2.98	0.87	0.44	66.86
		32.39	19.24	11.63	8.80	8.37	4.57	4.24	4.35	4.46	1.30	0.65	100.00
		100.00	100.00	100.00	100.00	84.62	50.60	41.49	42.55	48.81	16.67	3.08	66.86
	Graduate					14	41	55	54	43	31	2	**240**
		0.00	0.00	0.00	0.00	1.02	2.98	4.00	3.92	3.13	2.25	0.15	17.44
		0.00	0.00	0.00	0.00	**5.83**	17.08	22.92	22.50	17.92	12.92	0.83	100.00
		0.00	0.00	0.00	0.00	15.38	49.40	58.51	57.45	51.19	43.06	1.03	17.44
	Total	298	177	107	81	91	83	94	94	84	72	195	**1376**
		21.66	12.86	7.78	5.89	6.61	6.03	6.83	6.83	6.10	5.23	14.17	100.00

*Years refers to the academic calendar.
The year 11 goes from March 31 to the end of May 2001 (last information available)
Source: Authour's calculations based on SUR I - FCEyE NUR

Description of the variables

In the models to estimate, the regressors (Z) are included as all available variables that affect the risk of desertion and graduation. These variables are divided in 4 groups:

1. Variables indicative of the previous education and orientation received by the student

Secondary School Degree Obtained		
Commercial (a)	=	1 if student obtained commercial degree
Magist. Others	=	1 if student obtained magister degree, farming technical degree, or others
National Bachelor	=	1 if student obtained a national bachelor's degree
Type of School Attended by Student		
Univ. Dep. Sch. (a)	=	1 if student attended a school that depended on a university
National Sch.	=	1 if student attended a National secondary school
Prov. Mun. Sch.	=	1 if student attended a provincial or municipal school
Priv. Rel. Sch.	=	1 if student attended a private religious school
Priv. Part. Sch.	=	1 if student attended a particular private school
Other Sch.	=	1 if student attended "other" schools (i.e. military school)
Vocational Orientation received before entering university		
Without V.O.	=	1 if student received no vocational orientation
Priv. V.O.	=	1 if student received vocational orientation from a private institution
Ofic. V.O.	=	1 if student received vocational orientation from an official institution
Prof. V.O.	=	1 if student received vocational orientation from a professional
Begins (a)	=	1 if it is the first time student begins university studies
Cont. An. Program	=	1 if student continues in another program, aside from this one
Fin. An. Program	=	1 if student finished another program before beginning this one
Aband. An. Program	=	1 if student abandoned a program before beginning this one
Grad. Sec. Sch.	=	1 if student graduated from secondary school and began university immediately

2. Demographic and personal variables of the student

Age	=	age when beginning university studies
Male	=	1 if student is male
Single	=	1 if student is single
Resides with family	=	1 if student resides with family
Rosario native	=	1 if student is from Rosario

3. Variables indicative of the working situation of the student **(c)**		
Working Sit. Beg.	=	1 if student works when beginning career
Working Sit. End.	=	1 if student works during the last year of university studies
4. Variables related to characteristics of the parents **(d)**		
Student's father		
Worker (a)	=	1 if the father is a blue collar worker or employee
Diseased Unknown	=	1 if the father is diseased or unknown
Manager	=	1 if the father is a technician or manager
Boss-Director-High Exec.	=	1 if the father is a boss, director, or high executive of a profitable organization
Owner	=	1 if the father is an owner
Self-employed	=	1 if the father is an account holder, or self-employeed
Maximum level of education reached by the father of the student		
Father's educ. Low	=	1 if father did not attend or finish primary school
Father's educ. Medium	=	1 if father finished primary school but not secondary school
Father's educ. Medium high	=	1 if father finished secondary studies and started but did not finish university studies
Father's educ. High	=	1 if father completed higher or university studies
Maximum level of education reached by the mother of the student (M). *(Same as father).*		

(a) / Base category

(b) / Of the group that has already abandoned another program, approx. 80% had abandoned the program of Systems Analyst at UTN.

(c) / Although it would be optimal to have year-to-year information regarding the job situation of the individual, given the restrictions on data that have been previously discussed, only these two moments in time are available.

(d) /This group of variables reflects the potential incomes of the students' families. It is expected that the higher the education of the parents, the higher their incomes will be.

The descriptive statistics for these variables are summarized in the following table.

Table 2. Descriptive Statistics

	Total Students				Continue				Dropped Out				Graduated			
	Median	Dev	Min	Max	Median	Dev	Min	Max	Median	Dev	Min	Max	Median	Dev	Min	Max
Age	19.331	3.745	16	50	18.231	1.979	17	34	19.945	4.305	16	50	17.967	1.230	17	30
Magist. Others	0.105	0.306	0	1	0.106	0.309	0	1	0.111	0.314	0	1	0.079	0.271	0	1
National Bachelor	0.148	0.355	0	1	0.167	0.374	0	1	0.151	0.358	0	1	0.117	0.322	0	1
Commercial	0.748	0.434	0	1	0.727	0.447	0	1	0.738	0.440	0	1	0.804	0.398	0	1
National Sch.	0.318	0.466	0	1	0.329	0.471	0	1	0.328	0.470	0	1	0.267	0.443	0	1
Prov. Mun. Sch.	0.148	0.355	0	1	0.111	0.315	0	1	0.171	0.376	0	1	0.096	0.295	0	1
Univ. Dep. Sch.	0.078	0.268	0	1	0.093	0.291	0	1	0.054	0.227	0	1	0.154	0.362	0	1
Priv. Rel. Sch.	0.335	0.472	0	1	0.352	0.479	0	1	0.335	0.472	0	1	0.321	0.468	0	1
Priv. Part. Sch.	0.108	0.311	0	1	0.111	0.315	0	1	0.096	0.294	0	1	0.154	0.362	0	1
Other Sch.	0.013	0.114	0	1	0.005	0.068	0	1	0.016	0.127	0	1	0.008	0.091	0	1
Grad. Sec. Sch.	0.709	0.454	0	1	0.884	0.321	0	1	0.614	0.487	0	1	0.917	0.277	0	1
Begins	0.868	0.338	0	1	0.917	0.277	0	1	0.835	0.372	0	1	0.954	0.210	0	1
Cont. An. Program	0.029	0.168	0	1	0.019	0.135	0	1	0.036	0.186	0	1	0.013	0.111	0	1
Fin. An. Program	0.025	0.155	0	1	0.005	0.068	0	1	0.032	0.175	0	1	0.017	0.128	0	1
Aband. An. Program	0.078	0.268	0	1	0.060	0.238	0	1	0.098	0.297	0	1	0.017	0.128	0	1
Without V.O.	0.793	0.405	0	1	0.796	0.404	0	1	0.800	0.400	0	1	0.763	0.426	0	1
Priv. V.O.	0.090	0.286	0	1	0.088	0.284	0	1	0.091	0.288	0	1	0.088	0.283	0	1
Ofic. V.O.	0.054	0.226	0	1	0.056	0.230	0	1	0.055	0.229	0	1	0.046	0.210	0	1
Prof. V.O.	0.063	0.243	0	1	0.060	0.238	0	1	0.053	0.225	0	1	0.104	0.306	0	1
Male	0.466	0.499	0	1	0.412	0.493	0	1	0.488	0.500	0	1	0.429	0.496	0	1
Single	0.891	0.312	0	1	0.843	0.365	0	1	0.893	0.309	0	1	0.925	0.264	0	1
Resides with family	0.775	0.417	0	1	0.741	0.439	0	1	0.792	0.406	0	1	0.742	0.439	0	1
Rosario native	0.792	0.406	0	1	0.778	0.417	0	1	0.804	0.397	0	1	0.758	0.429	0	1
Working Sit. Beg.	0.488	0.500	0	1	0.407	0.492	0	1	0.545	0.498	0	1	0.346	0.477	0	1
Working Sit. End.	0.645	0.479	0	1	0.713	0.453	0	1	0.649	0.478	0	1	0.571	0.496	0	1
Diseased/ Unknown	0.042	0.201	0	1	0.032	0.177	0	1	0.049	0.216	0	1	0.025	0.156	0	1
Manager	0.070	0.256	0	1	0.069	0.255	0	1	0.078	0.269	0	1	0.042	0.200	0	1
Boss-Director-High Exec.	0.175	0.380	0	1	0.218	0.414	0	1	0.153	0.360	0	1	0.221	0.416	0	1
Owner	0.164	0.370	0	1	0.167	0.374	0	1	0.153	0.360	0	1	0.200	0.401	0	1
Self-employed	0.236	0.425	0	1	0.227	0.420	0	1	0.227	0.419	0	1	0.279	0.450	0	1
Worker	0.313	0.464	0	1	0.287	0.453	0	1	0.339	0.474	0	1	0.233	0.424	0	1
Father's educ. Low	0.057	0.231	0	1	0.042	0.200	0	1	0.070	0.255	0	1	0.021	0.143	0	1
Father's educ. Medium	0.496	0.500	0	1	0.463	0.500	0	1	0.540	0.499	0	1	0.358	0.481	0	1
Father's educ. Medium high	0.304	0.460	0	1	0.329	0.471	0	1	0.287	0.453	0	1	0.346	0.477	0	1
Father's educ. High	0.143	0.350	0	1	0.167	0.374	0	1	0.103	0.304	0	1	0.275	0.447	0	1
Mother's educ. Low	0.070	0.256	0	1	0.023	0.151	0	1	0.091	0.288	0	1	0.033	0.180	0	1
Mother's educ. Medium	0.474	0.499	0	1	0.491	0.501	0	1	0.503	0.500	0	1	0.346	0.477	0	1
Mother's educ. Medium high	0.333	0.471	0	1	0.384	0.488	0	1	0.312	0.464	0	1	0.367	0.483	0	1
Mother's educ. High	0.123	0.328	0	1	0.102	0.303	0	1	0.093	0.291	0	1	0.254	0.436	0	1
Obs.	1376				216				920				240			

Table 3. Factors related to the Hazard Rate of Desertion

	Model 1				Model 2			
Variables	Coef.		Est. Error	Exp b	Coef.		Est. Err.	Exp b
Magist. Other	0.023		0.110	1.024	0.398		0.312	1.488
National Bachelor	-0.002		0.099	0.998	0.086		0.256	1.090
National Sch.	0.488	***	0.159	1.628	1.392	***	0.368	4.025
Prov. Mun. Sch.	0.665	***	0.173	1.946	1.571	***	0.402	4.813
Priv. Rel. Sch.	0.503	***	0.158	1.654	1.203	***	0.343	3.331
Priv. Rel. Sch.	0.421	**	0.180	1.524	1.240	***	0.399	3.457
Other Sch.	0.686	**	0.318	1.987	1.591	**	0.772	4.909
Grad. Sec. Sch.	-0.783	***	0.102	0.457	-2.092	***	0.360	0.123
Cont. An. Program	0.276		0.189	1.318	0.673		0.576	1.961
Fin. An. Program	-0.054		0.209	0.947	1.869	*	1.015	6.482
Aband. An. Program	-0.238	*	0.129	0.788	-0.327		0.382	0.721
Priv. V.O.	0.184		0.123	1.203	0.351		0.280	1.420
Ofic. V.O.	0.168		0.152	1.184	0.243		0.343	1.275
Prof. V.O.	-0.162		0.150	0.850	-0.282		0.331	0.754
Age	0.192	***	0.063	1.212	0.695	***	0.215	2.005
Age sq	-0.002	*	0.001	0.998	-0.008	**	0.004	0.991
Male	0.146	**	0.069	1.158	0.314	*	0.163	1.369
Single	0.524	***	0.125	1.690	1.340	***	0.344	3.822
Resides with family	0.23	***	0.087	1.264	0.728	***	0.217	2.071
Rosario native	0.345	***	0.088	1.413	0.753	***	0.221	2.124
Working Sit. Beg.	0.454	***	0.101	1.576	1.230	***	0.283	3.422
Working Sit. End.	-0.501	***	0.103	0.605	-1.418	***	0.304	0.242
Diseased/Unknown	-0.034		0.167	0.966	-0.070		0.467	0.932
Manager	-0.264	*	0.139	0.767	-0.159		0.322	0.853
Boss-Director-High Exec.	-0.254	**	0.108	0.775	-0.733	***	0.256	0.480
Owner	-0.1131		0.107	0.893	-0.179		0.243	0.836
Self-employed	-0.051		0.092	0.950	-0.521	**	0.229	0.594
Father's educ. Low	0.3785	**	0.189	1.460	1.000	*	0.514	2.721
Father's educ. Medium	0.4113	***	0.125	1.509	0.708	**	0.277	2.032
Father's educ. Medium high	0.2541	**	0.124	1.289	0.745	***	0.290	2.108
Mother's educ. Low	0.4609	***	0.177	1.586	1.053	**	0.453	2.868
Mother's educ. Medium	0.198		0.129	1.220	0.464	*	0.279	1.591
Mother's educ. Medium high	0.197		0.126	1.218	0.405		0.265	1.500
Gamma var exp(ln_varg)					2.944	***	0 .611	
Log Likelik.	-2435				-2378			
LR test (1) vs (2)					*113.31*			
Pr. Test Chi(1)					*0.000*			
Num. obser.	7281				7281			

*** Significant at 1%, ** Significant at 5%, * Significant at 10%

Table 4. Coefficients of the Baseline Hazard Function

	Model 1				Model 2			
Years	Coef.	Est. Error	z	P>|z|	Coef.	Est. Error	z	P>|z|
1	-5.7351	0.8791	-6.5240	0.0000	-14.373	2.996	-4.798	0.000
2	-5.8378	0.8769	-6.6570	0.0000	-13.348	2.913	-4.582	0.000
3	-6.1053	0.8799	-6.9380	0.0000	-13.045	2.869	-4.546	0.000
4	-6.2154	0.8795	-7.0670	0.0000	-12.778	2.839	-4.500	0.000
5	-6.1253	0.8788	-6.9700	0.0000	-12.352	2.814	-4.389	0.000
6	-6.5904	0.8846	-7.4500	0.0000	-12.542	2.797	-4.484	0.000
7	-6.5085	0.8850	-7.3540	0.0000	-12.238	2.782	-4.399	0.000
8	-6.2741	0.8853	-7.0870	0.0000	-11.741	2.765	-4.246	0.000
9	-6.0002	0.8851	-6.7790	0.0000	-11.122	2.745	-4.052	0.000
10	-6.9894	0.9191	-7.6040	0.0000	-11.861	2.742	-4.326	0.000
11	-7.3772	0.9647	-7.6470	0.0000	-12.140	2.753	-4.411	0.000

Table 5. Factors related to the Conditional Probability of Graduation

	Model 1			Model 2		
Variables	Coef.	Est. Error	Exp β	Coef.	Est. Error	Exp β
Mag. Others	-0.063	0.259	0.938	-0.054	0.294	0.947
National Bachelor	-0.387 *	0.221	0.679	-0.436 *	0.261	0.647
National Sch.	-0.657 ***	0.230	0.518	-0.699 **	0.273	0.497
Prov. Mun. Sch.	-0.601 **	0.299	0.548	-0.626 *	0.348	0.535
Priv. Rel. Sch.	-0.670 ***	0.222	0.511	-0.719 ***	0.268	0.487
Priv. Part. Sch.	-0.074	0.248	0.929	0.002	0.326	1.003
Other Sch.	0.069	0.764	1.072	-0.064	0.942	0.938
Grad. Sec. Sch.	-0.242	0.329	0.785	-0.339	0.421	0.712
Cont. An. Program	0.715	0.594	2.045	0.835	0.756	2.306
Finish. An. Program	1.496 **	0.654	4.465	1.518 *	0.807	4.565
Aband. An. Program	-1.403 **	0.578	0.246	-1.590 **	0.707	0.204
Priv. V.O.	-0.203	0.250	0.816	-0.197	0.292	0.821
Ofic. V.O.	-0.074	0.320	0.928	-0.068	0.373	0.934
Prof. V.O.	0.512 **	0.228	1.670	0.631 **	0.322	1.880
Age	0.306	0.509	1.358	0.289	0.601	1.336
Age sq	-0.009	0.012	0.991	-0.009	0.014	0.990
Male	-0.347 **	0.144	0.706	-0.392 **	0.182	0.675
Single	0.616 **	0.266	1.852	0.729 **	0.357	2.074
Resides with amily	-0.271	0.167	0.762	-0.277	0.195	0.758
Rosario native	-0.310 *	0.170	0.733	-0.329	0.204	0.719
Working Sit. Beg.	0.087	0.171	1.091	0.040	0.210	1.041
Working Sit. End.	-0.585 ***	0.165	0.557	-0.632 ***	0.205	0.531
Diseased Unknown	0.222	0.444	1.249	0.243	0.503	1.275
Manager	-0.264	0.356	0.767	-0.287	0.400	0.750
Boss-High Executive	-0.005	0.203	0.995	-0.058	0.257	0.943
Owner	0.136	0.209	1.146	0.192	0.259	1.213
Self-employed	0.122	0.187	1.130	0.133	0.218	1.143
Father's educ. Low	-1.192 **	0.538	0.303	-1.287 **	0.614	0.276
Father's educ. Medium	-0.528 ***	0.194	0.590	-0.6323 **	0.282	0.531
Father's educ. Medium high	-0.353 *	0.182	0.703	-0.417 **	0.237	0.659
Mother's educ. Low	-0.078	0.437	0.924	-0.084	0.499	0.919
Mother's educ. Medium	-0.638 ***	0.199	0.528	-0.666 ***	0.242	0.514
Mother's educ. Medium high	-0.501 ***	0.180	0.606	-0.504 **	0.217	0.604
Gamma var exp(ln_varg)				0.5621	0.99	
Log Likelik.	-750.73			-749.87		
LR test (1) vs (2)				*0.41*		
Pr. Test Chi(1)				*0.52*		
Num. obser.	3132			3132		

*** Significant at 1%, ** Significant at 5%, * Significant at 10%

DETERMINANTS IN UNIVERSITY DESERTION AND GRADUATION: AN APPLICATION USING DURATION MODELS

PAULA GIOVAGNOLI

SUMMARY

JEL Classification: I-121, C-41

This study examines the issue of student departure from a public university. Non-parametric proportional hazard models are used to estimate the quantitative and qualitative effects of the students' personal and socioeconomic characteristics on the probability of their dropping out or graduating. Data include a cohort of students who started studying accounting at the National University of Rosario, Argentina, in 1991. The results are useful to evaluate and design public policies in the educational sector.

Keywords: university students, drop out and graduation, duration models.

RESUMEN

Clasificación JEL: I-121, C-41

Este trabajo investiga el problema de la deserción y graduación de los estudiantes universitarios. Se utilizan modelos de riesgo proporcional no paramétricos para estimar los efectos cualitativos y cuantitativos de factores personales y características socioeconómicas de los alumnos sobre las probabilidades condicionales de deserción y graduación. Se emplean datos de una cohorte de estudiantes de 1991 de la carrera de Contador Público de la Universidad Nacional de Rosario, Argentina. Los hallazgos son útiles para evaluar y diseñar políticas públicas en el sector de educación.

Palabras claves: estudiantes universitarios, deserción y graduación, modelos de duración.