Higher education dropouts, access to credit, and labor market outcomes: Evidence from Chile *

Tomás Rau
P. Universidad Católica de Chile

Eugenio Rojas
Dirección de Presupuestos
Ministerio de Hacienda de Chile

Sergio Urzúa
University of Maryland,
IZA and NBER

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Abstract

In this paper we estimate a structural model of sequential decision of higher education and dropout to evaluate the impact of short-term credit constraint on dropouts. In particular, we analyze the impact on dropouts of the State Guaranteed Credit program (CAE) the most important funding program for higher education in Chile. The model allows for heterogeneity in observable and unobservable individual characteristics (Heckman et al. 2006) and controls for selectivity. Our data combine different sources of information, including individual data from standardized tests scores (PSU), higher education enrollment and unemployment insurance system (UI) data. The results show the important role of the abilities of individuals on educational choice. Individuals with higher ability tend to enroll in universities and not to drop out (sorting on ability). We show that household income and access to credit influence the probability of dropping out. Specifically, the results suggest that CAE has a positive impact on reducing the dropouts from higher education, where the program reduces the first year dropout rate in 15.5% for those enrolled in a university and a 24% for enrolled in a Center or Technical Formation (CFT) and Professional Institute (IP). We also found that the CAE is more effective in reducing the probability of dropping out for low-skill individuals from low-income families. However, our results show that CAE beneficiaries have lower wages than those who are not beneficiaries (even after controlling for characteristics, ability and selectivity bias). We attribute this to a incentive problems in the design of CAE which may lead to higher education institutions to reduce the quality of education. The evidence then calls to revise the design of CAE.

Keywords: Education, Dropouts, Credit Constraints.

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1 Introduction

Although credit constraints have been reported to be a determinant of college dropout decision, the difficulty in identifying constrained students have lead to the implementation of indirect empirical approaches in the related literature (Heckman, Lochner and Taber (1998),Card (1995), Lang (1993), Cameron and Heckman (1998, 2001), Carneiro and Heckman (2005), Kane (1996), and Keane and Wolpin (2001)). Moreover, the empirical evidence on the effects of credit constraints on dropout decision is mixed and there is no clarity on the importance of them as pointed out by Kane (2005).

Even direct approaches exploiting rich panel data, such as Stinebrickner y Stinebrickner (2009), suggests that further research is needed to understand how low income students decide to wether to remain in the school or not.

This article contributes in the college dropout literature analyzing the impact of credit constraints on the decision of dropping out from Higher Education Institutions (HEI) using a rich panel data from the Chilean school system.[1] Using a unique database we estimate a structural model of sequential schooling decisions, where it allows the presence of unobserved heterogeneity (Heckman, Stixrud and Urzúa, 2006), that is interpreted as a combinations of cognitive and noncognitive skills. This is the first model in the context of higher education which integrate selectivity (with flexible functional forms that relax the usual normality assumptions), unobservable skills, and individual characteristics to study the determinants of dropouts.

In particular, we focus on the impact of the State Guaranteed Credit program (CAE) on the college dropout decision. Our interest in this program is due to its large impact on the access to the higher education system. As reported in Tables 2 and 3, between 2006 and 2010 the allocation of CAE loans have quadrupled, passing from a 10% of the total student aids in 2006 to 43% of these aids on 2010.

We also analyze the impact of CAE loans on labor market outputs. The potential impact of this loan program is related to one characteristics of its design, giving economic incentives to HEI in order to reduce dropout rates. This may have consequences in some labor market outcomes, such as wage, due to it effects on accumulation of labor market experience. Thus, we estimate the sequential schooling choice model with a wage model for the same individuals since we are able to match administrative records form the unemployment insurance (UI) system with our enrollment data.

The empirical strategy we use in this paper considers the existence of unobserved factors that influence the dropout decision which may bias the estimates of the impact of CAE on dropouts (Dynarski, 2002, Stinebrickner y Stinebrickner 2007, 2009). Hence, there may be sorting in ability, which implies that other factors than monetary costs (for instance, effort) could be affecting the dropout decision.[2] This could be

[1] We consider dropout from higher education in the first year

[2] Tiebout sorting in ability means that there is self-selection in the decisions where ability is a determinant factor, such as

explained by, what Carneiro y Heckman (2002) calls, the long-run constraints. These constraints are related to characteristics that remain in the long-run, such as ability. On the other hand, short-run constraints are those related to funding. We evaluate the importance of both: short and long run constraint in the probability of dropping out.

We find that there is sorting in ability in such a way that more skilled students enroll in universitites and have a lower dropout rate after first year.[3] We find also that the CAE reduces the dropout rate after the first year in 15,5% and 24% for universities and CFT-IP respectively, controlling for ability. Also, results show that short and long run constraints are binding. Although CAE has positive effects on dropout from higher education, it may have some negative effects. We find that students with CAE have lower wages even after adjusting for ability. This may reflect serious issues in the mechanism design of the incentives to HEI with students with CAE.

Previous studies analyzing the determinants of the dropout decision for the Chilean case includes Gonález and Uribe (2002), Microdatos (2008) and Meller (2010) finding that vocational issues, familiar problems, and economic reasons as the most important determinants of dropping out of college.

The organization of this paper is the following. Section 2 analyzes the institutions and the chilean system. In section 3 we present the model of sequential decisions with unobserved heterogeneity and section 4 describes the unique database and some descriptive statistics. In section 5 we present the estimation results and an analysis of sorting in ability. In section **??** we compute some treatments effects such as the effect of the CAE on dropping out from higher education after the first year and the effect of the CAE on wages. In section 7 we conclude.

2 The Chilean Institutions

The education reform implemented in the 80s creates incentives to private agents to participate in the education system. This permits the incorporation of a large number and type of private HEI, including Universities, Professional Institutes (IP) and Technical Training Centers (CFT) .[4] Between 1984 and 2010, enrollment in higher education institutions have quadrupled, as shown in Figure 1. This growth was strongly influenced by the universities, as shown in Figure 2.[5] We can see an important break in the trend of enrollment in the early 90's, when the effects of the educational reform seems to be larger (Meller, 2010).

Even though the Increasing access to HEI has contributed to an important goal of public policy in Chile,

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the case of dropout or study

[3]We consider two types of HEI: universities and non-universitites (CFT and IP).

[4]The CFT are institutions that are allowed to grant technical degrees and IP are permitted to grant technical and professional degrees, including bachelor, master and doctoral degrees.

[5]According to Meller (2010) the number of universities increased from 10 in 1981 to 60 in 2009

this has not translated into an increased participation of all sectors of society, and the access has been quite uneven (Espinoza et al. 2006). That is why since 2006 it has been provided an increased financial support, consisting of grants and loans, for vulnerable students. Figure 3 shows the total number of financial aids that have been awarded to undergraduate students between 1989 and 2009, considering scholarships and loans.

In 2006, the Ministry of Education of Chile (MINEDUC) started implementing a new system of credits, the state-guaranteed credit (CAE), in which the Chilean government becomes the guarantor of higher education students (who meet certain requirements to be detailed later). Given that the type of asset that the student is taking is intangible, financial institutions have little incentive to lend to vulnerable students since they have no financial assets that could act as a guarantee for failure to pay. It is here where the State, as guarantor, is involved.

The CAE is an instrument that has increased its relative importance in recent years. Figure 4 shows the substantial increase of student aids coverage from 2006 on. This increase coincides with implementation of the CAE, whose annual allocation statistics are presented in Table 2. Additionally, Table 3 shows the ratio of CAE over all student aids per year. We observe a substantial growth of this ratio from 2006 to 2010 (it went from 10% to approximately 43%), which shows that the CAE is a key instrument of financing higher education.

In addition to increased coverage as described before, a second purpose would be fulfilling the CAE is to allow credit to lighten restrictions during the study of individuals, which would reduce the high dropout rates in higher education (which presented in table 1), a result that both national and international literature supports (Gonzalez and Uribe, 2002, Meller, 2010, Goldrick-Rab et al. 2009, etc.). At the aggregate level, we can see that the EAC has not had a decisive impact on dropout rates, as described in Figure 5. However, it is important to note that the previous year is done at the aggregate level and lacks precision, analysis that will be corrected later in this article.

Regarding the formalities of application process to the CAE, the applicants must meet certain requirements. Among these are to be Chilean, get above 475 points at the University Selection Test (PSU), maintain satisfactory academic performance, have not graduated from any HEI, not having dropped out more than one time from higher education, have a socio-economic environment that justifies the allocation of CAE and certify that there is an actual link between a HEI and them (certificate of registry or letter of acceptance).[6,7] Additionally, the loans are granted through the financial institutions (typically banks). The Chilean gov-

[6]The University Selection Test (PSU) is a standardized test to access to the Chilean higher education system. It assesses, by separate tests, language and communication skills, mathematics (these two are mandatory), science and history and social sciences (at least one of these must be chosen).

[7]In case a student is applying for a CFT or IP it is required optionally to the PSU minimum, a GPA greater than or equal to 5.3 in high school. The Chilean scale ranges from 1.0 to 7.0 being a 4.0 the minimum passing grade.

ernment auction packages of students' applications (these packages are as homogeneous as possible to make them equally attractive to banks) and some institutions win this auction, after making appropriate bids. After the bidding process and its final allocation, the financing institutions provide the resources to students.

Once assigned the CAE, the beneficiary must meet different types of requirements, which depend on the stage of study it is found. If the beneficiary is studying and dropped out from the HEI, the mechanism begins to operate is the guarantee for academic dropout.[8] This warranty is granted by the HEI (which can be at most 90% of the principal plus interest) and operates as long as the individual is studying. If a student drops out, the HEI must respond with the guarantee to the financial institutions. In the event that the guarantee of the HEI is less than 90% of capital (plus interest) is the government who has to cover the additional amount (to get to the 90%). In Table 4 we present the percentage of the Academic Dropout Guarantee that HEI and the government have to cover.

The HEI, even when the student is on the verge of graduating, always cover a significant percentage of the loan (plus interest) awarded to the student. If a student dropped out, the financial institution may require payment of the guarantee .[9] After this, the HEI will continue the collection process (and may agree the process with the financial institution, if desired) as the debt acquired by the student is not prescribed.

An important factor to considered is that the collection process to a student who has not graduate from the HEI my be very complicated, and expensive to the HEI. This can be more evident if the student does not have a guarantee. The design of CAE creates incentives to reduce dropout rates. To the extent that these incentives imply lower academic standards, the mechanism design can impact the quality of education.[10] Our results suggest that this is indeed the case.

In cases where the beneficiaries have graduated from higher education another collection mechanism operate, the "state guarantee". If the graduate can not meet the quotas for the CAE (in where there is a grace period of 18 months after graduation), financial institutions may start legal proceedings aimed at rescuing the debt. If this is not possible, the institutions have the right to require to the Chilean state the warranty for these credits, which corresponds to 90% of the amount due, including interest capitalized.

[8] A dropout is defined formally as an unjustified interruption of the studies for at least 12 consecutive months.

[9] This is once you have met certain requirements, such as the exhaustion of judicial collection agencies.

[10] The easiest to teach courses or have lower failure rates, for example, are mechanisms that HEI can use to prevent desertion. These measures have a direct effect on the quality of education students receive.

3 A simple structural model for dropout decision with unobserved heterogeneity

The final level of education achieved by each individual is the conclusion of a sequence of decisions influenced by the institutions of the educational system. It is important to consider the fact that individual's decisions are conditional on a set of feasible alternatives for her. Furthermore, the choices made also depends on her skills and/or preferences, so that the final observed results (sequences of decisions), do not allow proper comparisons between individuals .

In this section we model the decision of dropping out from the higher education as the ending result of a sequence of decisions, which are influenced by observable and unobservable components. Even after controlling for potential endogeneity in decision making, selectivity, and observable characteristics we may have observationally equivalent individuals responding differently to the same stimulus. The reason for this may be explained by the presence of unobserved heterogeneity in endowments, as is seen in Hansen, Heckman and Mullen (2004), Heckman, Stixrud and Urzúa (2006), Urzua (2008) and Rau, Sanchez and Urzúa (2011). These endowments are a combination of cognitive and noncognitive unobservable skills, which can vary among individuals and that determines their schooling decisions. The structure modeled in this paper considers the presence of unobserved heterogeneity in addition to considering the presence of endogeneity and selection in the decisions of students.

The timing of the decisions considered in this paper is as follows: Once rendered the University Selection Test (PSU) students can apply for the CAE and then they can enroll in Technical Training Centres (CFT), Professional Institutes (IP) or in universities.[11]

The conditions, as explained above, to be eligible for the CAE are that there must be a verifiable link between the student and the higher education institution (registration, acceptance letter, for example) and, of course, others such as socio-economic requirements. After that, the credit is assigned (or not) and eventually they may choose to complete first year or dropout from the corresponding HEI.

3.1 The Model

We model a tree of sequential binary decisions, which is based on structural choice models closely related to Rau, Sánchez and Urzúa (2011). Following Hansen, Heckman and Mullen (2004) we model the decisions as follow

Consider a choice node j (for instance, applied or not to the CAE). Let $V_{id(j)}$ the indirect utility individual

[11] For purposes of this paper we consider two groups of institutions: universities and non universities. This second group considers the CFT and IP.

i obtain when choosing alternative d with $d \in \{0, 1\}$, belonging to an alternative set in node j:

$$V_{id(j)} = \mathbf{Z}_{id(j)} \delta_{d(j)} + \mu_{id(j)} \tag{1}$$

where $\mathbf{Z}_{id(j)}$ is a vector of observed characteristics that affects individual's schooling decision and $\mu_{id(j)}$ is an error term. All this conditional in being at node j. [12]

Let $D_{id(j)}$ be a binary variable defined as follow

$$D_{id(j)} = \begin{cases} 1 & \text{if} \quad V_{id(j)} \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

The previous expression implies that individual i chooses the schooling path that maximizes her utility, conditional on her characteristics.[13] Thus, we observe sequences of decisions in terminal nodes, noted as $\mathbf{D}_l$, with $l = 1, 2, \ldots, L$.[14] In Figure 6 we show the tree of sequential decisions, in which $L = 6$ in our model.

Finally, after observing the sequences of optimal schooling decisions we observe two outcomes: dropping out (or not) from higher education and wages for dropouts and no dropouts. The equation modeling the dropout decision is

$$\Lambda_i^{\mathbf{D}_l} = \begin{cases} 1 & \text{if} \quad V_{i\mathbf{D}_l} \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

where the dropout decision depends on the node in which individual i is. On the other hand, the wage equation is given by:

$$W_{i\Lambda}^{\mathbf{D}_l} = \alpha_{\Lambda}^{\mathbf{D}_l} \mathbf{M}_{i\Lambda}^{\mathbf{D}_l} + \nu_{i\Lambda}^{\mathbf{D}_l} \tag{4}$$

Where $W_{i\Lambda}^{\mathbf{D}_l}$ corresponds to the log wages associated to the choice Λ in node $\mathbf{D}_l$ for individual i, $\mathbf{M}_{i\Lambda}^{\mathbf{D}_l}$ is a vector containing observed characteristics determining wages for individual i in case of choosing Λ in the same node and $\nu_{i\Lambda}^{\mathbf{D}_l}$ is an error term.

[12] In particular, we consider five nodes: the first one is the decision of applying to the CAE, the second and third considers the decision of enrolling into a university or CFT/IP conditional on having applied or not to the CAE. The fourth and fifth nodes considers the allocation of CAE conditional in that individuals enroll in an university or CFT/IP and apply to the CAE.

[13] We assume that indirect utility of unchosen alternatives is negative.

[14] For instance, $\mathbf{D}_1$ is the sequence for students that applied to the CAE, enrolled in an university, and got the CAE.

Then, the observed outcome vector is given by the dropout decision and the associated wage, denoted as

$$\mathbf{Y}^{\mathbf{D}_l} = [\Lambda^{\mathbf{D}_l} \quad W_{\Lambda}^{\mathbf{D}_l}] \quad l = 1, \ldots, L \tag{5}$$

It is important to mention that the model allows that all error terms ($\nu_{\Lambda}^{\mathbf{D}_l}$) are correlated. Thus, schooling decision are correlated with the outcomes, which implies that self-selection is based on unobservables.

The model assumes the presence of unobserved heterogeneity, which is denoted as f and we call *factor*. This factor represents individual's ability and has an important role in the decisions in each node since it allows us to control for selectivity and endogeneity. Additionally, it is possible to estimate counterfactual outcomes and obtain treatment effects as we show in section **??**. Imposing some structure for the factor will allow us to identify the effect of ability in the sequential choices. Thus, the structure is as follow

$$\mu_{id(j)} = \eta_{d(j)} f_i - \varepsilon_{id(j)} \tag{6}$$

$$\nu_{i\Lambda}^{\mathbf{D}_l} = \psi_{\Lambda}^{\mathbf{D}_l} f_i + \xi_{i\Lambda}^{\mathbf{D}_l} \tag{7}$$

where ε and ξ are error terms of the corresponding equations. We assume that $\varepsilon_d \perp\!\!\!\perp \xi_\Lambda \perp\!\!\!\perp f$.

Following Carneiro, Hansen, and Heckman (2003) and Heckman, Stixrud, and Urzua (2006), we posit a linear measurement system to identify the distribution of the unobserved endowments f. We supplement the model described above with a set of linear equations linking measured ability with observed characteristics and unobserved endowments. This allows us to interpret the unobserved factor f as a combination of different abilities (cognitive and non-cognitive). In particular, we observe University Selection Test (PSU) and the GPA from high school and we call them just "test score".[15] The equations describing these scores are

$$T_{ik} = \mathbf{X}_{ik}\gamma_k + \lambda_{ik} \quad k = 1, 2, 3 \tag{8}$$

Where T_{ik} is a test score k of individual i, $\mathbf{X}_{ik}$ is a vector containing observed characteristics (such as socioeconomic characteristics, parents' education, type of school attended, among others) and λ_{ik} is an error term associated to test k for individual i.[16]

In the same way we proceed before, we impose a factor structure for error terms in the test score equations

$$\lambda_{ik} = \omega_k f_i + \theta_{ik} \quad k = 1, 2, 3 \tag{9}$$

[15]Then we consider three measures: the GPA from high school, language and math PSU scores.

[16]Hansen, Heckman y Mullen (2004) shows that the minimum number of measurements to achieve identification is three which is our case.

where θ is an error term. We assume that $\varepsilon_d \perp\!\!\!\perp \theta_k \perp\!\!\!\perp \xi_\Lambda \perp\!\!\!\perp f$ and that the measurement system permits to identify the distribution of unobserved abilities. We can use equations (8) and (9) to express the test score equations as follow

$$T_{ik} = \mathbf{X}_{ik}\gamma_k + \omega_k f_i + \theta_{ik} \quad k = 1, 2, 3$$

Similarly, we can use equations (6) and (7) to express equations (1) and (4) as follow

$$\begin{aligned} V_{id(j)} &= \mathbf{Z}_{id(j)}\delta_{d(j)} + \eta_{d(j)} f_i - \varepsilon_{id(j)} \\ W_{i\Lambda}^{\mathbf{D}_l} &= \alpha_\Lambda^{\mathbf{D}_l}\mathbf{M}_{i\Lambda}^{\mathbf{D}_l} + \psi_\Lambda^{\mathbf{D}_l} f_i + \xi_{i\Lambda}^{\mathbf{D}_l} \end{aligned}$$

Assuming that $\varepsilon_{id(j)} \sim \mathcal{N}(0, 1)$, from equation (2) we have a probit model for choice d. Conditioning on the factor we have

$$\begin{aligned} \Pr\left(D_{id(j)} = 1 | \mathbf{Z}_{id(j)}, f_i, D_{id(j-1)}\right) &= \Pr\left(V_{id(j)} \geq 0 | \mathbf{Z}_{id(j)}, f_i, D_{id(j-1)}\right) && (10) \\ &= \Phi\left(\mathbf{Z}_{id(j)}\delta_{d(j)} + \eta_{d(j)} f_i\right) && (11) \end{aligned}$$

Where $D_{id(j-1)}$ are the previous decisions taken by individual i (if there is a previous decision). Consequently, we can express the probability of a particular schooling sequence $\mathbf{D}_l$ for individual i, given the observed characteristics and the factor f, in the following way

$$\prod_{d \in H_i} \left[\Pr\left(D_{id(j)} = 1 | \mathbf{Z}_{id(j)}, f_i, D_{id(j-1)}\right)\right]^{D_{id(j)}} \left[\Pr\left(D_{id(j)} = 0 | \mathbf{Z}_{id(j)}, f_i, D_{id(j-1)}\right)\right]^{1-D_{id(j)}} \tag{12}$$

Where H_i is the set of nodes visited by individual i. The structural model depends on observed variables and the unobserved factor. Given this structure, we can use an identification structure similar to those used by Hansen, Heckman y Mullen (2004) and Kotlarski (1967). With this, we are able to identify the distribution of the factor and the parameters of the model.

3.2 Implementing the Model

In the model, we have optimal schooling decisions, individual's characteristics, an outcome vector and its determinants , test scores and its determinants ($\mathbf{D}_l$, $\mathbf{Z}$, $\mathbf{Y}$, $\mathbf{M}$, $\mathbf{T}$ y $\mathbf{X}$, respectively). As it was described, the timing of the decisions is the following: an individual i decide to apply to CAE, then she takes the PSU and decide if enrolling in an university or in a CFT/IP, finally she decides wether dropping out or not after the first year. We observed wages after the schooling sequence.

The model allows the existence of endogeneity in the decisions since choices in each node depends on unobserved characteristics which may be correlated to some characteristics. The independence assumption between the error terms and the factor, conditioning in unobserved ability, is crucial since it allows us to write the likelihood function in the following way

$$L(\mathbf{T}, \mathbf{D}, \mathbf{Y}|\mathbf{X}, \mathbf{Z}, \mathbf{M}) = \prod_{i=1}^{N} \int f(\mathbf{T}_i, \mathbf{D}_i, \mathbf{Y}_i|\mathbf{X}_i, \mathbf{Z}_i, \mathbf{M}_i, f) dF(f) df$$

In which we integrate respect the density of the factor, because it is unobserved. We assume a *mixture* of normal distributions for the distribution of the factor to give flexibility to its shape allowing for asymmetries and multi modalities

$$f \sim \rho_1 \mathcal{N}(\tau_1, \sigma_1^2) + \rho_2 \mathcal{N}(\tau_2, \sigma_2^2) + \rho_3 \mathcal{N}(\tau_3, \sigma_3^2)$$

It is important to mention that this mixture structure for the distribution of the factor does not implies normality a-priori. Given the numeric complexity in maximizing the likelihood introduced by the integral, we estimate the model by *Markov Chain Monte Carlo* (MCMC).

A final comment related to the factor is that given that there is no intrinsic scale for ability it is necessary to normalize the mean of factor so it is 0 and normalize the parameter accompanying the factor of the math test score to 1. We also normalize the test scores so they have zero mean and standard deviation equal to one and permit the presence of correlation among the error terms.

4 Data

The data used in this paper comes from different sources of information.[17] To identify dropouts and no dropouts after the first year we use administrative enrollment data from SIES for years 2006 and 2007. We focus only on individuals enrolled in a HEI in 2006 for two reasons. First, we are able to merge this data with unemployment insurance (UI) data so we can observe wages in 2011, which can be unfeasible if we consider individuals enrolled in 2007 because a large fraction of them is not in the labor market in 2011. Second, in 2006 the CAE was mistakenly assigned to individuals from all quintiles of the income distribution and this does not happened in 2007. [18] The advantage of this, is that we will be able to estimate different

[17]The data were provided by the Dirección de Presupuestos del Ministerio de Hacienda de Chile in virtue of the agreement between Subsecretaría de Hacienda, Dirección de Presupuestos and the Servicio de Información de Educación Superior (SIES) from Ministerio de Educación (MINEDUC) de Chile, letter of agreement and confidentiality N 2011.

[18]The misallocation of the loans was due to a computational mistake which assignned the CAE to individuals of the fourth and fifth quintiles. Political pressure led to an increase in the number of loans assigning them to students in the lowest three

parameters of interest to individuals from all quintiles of the income distribution.

The enrollment data was merged with administrative records from the University Selection Test (PSU) undertaken in 2005. It added information on test scores, but also socioeconomic characteristics and family background. Additionally, administrative data from the CAE permits the identification of applicants to the CAE and those who obtain the credit in 2006. The number of observations of the merged data base is 31481 observations.[19]

Tables 5 and 6 show some descriptive statistics separated by decision node and choice. The variables included are Male, age (in 2007), a dummy for scholarship during the first year, geographic zone dummies for North and South, family income dummies in CLP with base category the interval 0 to $278.000.

We include also dummies for parents' schooling with base category less than 8 years of schooling. We add dummies for funding characteristics of (graduating) school: public and private-voucher dummies, length of the program, and test scores (math and language) and high school GPA.

Last, we also consider dummies for educational categories according to MINEDUC definition: Administration and Commerce is the base.

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5 Results

In Table 7 we present the estimation of the parameters of intermediate decision nodesD_1, D_2, D_3, D_4 y D_5. We can appreciate that relative to women, men have a lower probability of applying to CAE, enrolling in an university, and obtaining the credit. On the other hand, older applicants tend to enroll more in universities and, conditional on this, they have a higher probability of obtaining the CAE.

The geographic zone dummies tell us that people in South apply more to CAE than those in the North, relative to inhabitants of the Central part of the country. Northern applicants enroll more in universities relative to those in the Center. Once enrolled in an university, people from the North and South have a lower probability of obtaining the CAE.

The larger the number of people in the household, the lower the probability of receiving the credit for those enrolled in any HEI. Additionally, students from high income families tends to not apply to the CAE and to enroll in universities. Regarding to income, we can see that for those enrolled in universities the probability of obtaining the CAE increases with family income. This is mainly due to misallocation of credits occurred in 2006 in which they were assigned to high income family by mistake, and then to low

quintiles. For details see Ingresa (2010).

[19] These 31481 observations include only individuals with no missing values. We did not used imputation methods to increase the number of observations.

income families decreasing the level of focalization of the resources (Ingresa, 2010).

Having attended to a public or private-voucher increases the probability of applying to the CAE and decreases the probability of enrolling in an university. However, conditional on being enrolled in an university, students from public and private-voucher schools have a lower probability of obtaining the CAE

Finally, we see the importance of ability (measure by the factor) in the schooling decisions. Applicants with higher ability apply more to CAE and enroll with higher probability in universities. Also, high ability applicants have a larger probability of receiving the CAE. This is interesting since the credit should not be assigned by academic merit or ability, except the minimum passing score (475 in PSU test score).

Table 8 presents the estimation of the decision of dropping out from a HEI.[20] In some nodes, we have that men have a higher probability of dropping out, relative to women. In three nodes ($\mathbf{D}_2, \mathbf{D}_4, \mathbf{D}_5$) older students have a higher probability of dropping out too. On the other hand, geographic region dummies do not play a role on explaining dropout decision from HEI, except for students who did not apply to the CAE and enrolled in a CFT/IP. In that case, people in the North show a higher probability of dropping out from a CFT/IP.

Regarding to family background we have that, the larger the number of people in the household, the higher the probability of dropping out, and the higher the family income the lower the probability of dropping out from a HEI. If the student attended a public or private-voucher school increases the probability of dropping out from a HEI. This is particularly relevant for those enrolled in universities and who did not apply to CAE. Having received a scholarship decreases significantly the probability of dropping out after the first year, in all terminal nodes.

The influence of the education categories on the dropping out decision show mixed results. We have that Arts and Architecture are associated with a higher probability of dropping out, conditional on being enrolled in an university and not receiving the CAE. While those enrolled in Science have a higher probability of dropping out, students enrolled in a CFT/IP in Social Sciences who did not apply to the credit exhibit a higher probability as well. For people enrolled in Law, there is no relationship with dropping out decision except for those who did not apply to the CAE. This probability is lower for students in Education with no credit (applicants and no applicants) and higher for those in Humanities. Health and Agriculture show no relationship and for those in IT, we see a positve relationship with dropping out conditional on not applying to the CAE and being enrolled in an university.

Finally, we can see that the length of the career increases the probability of dropping out and that ability (measured by the factor) is negatively correlated with dropping out of a HEI. It is important to mention that,

[20] There are some nodes with few number of observations that make us to choose more parsimonious specifications to achieve convergence

apart from learning about the effect of ability on decisions, it allows to obtain estimations of the structural parameters purged of endogeneity due to ability.

Table 9 presents the results for the wage equations.[21] We can see that men have higher wages than women. Wages increase with age and with being enrolled in a career in Administration and Commerce. The length of the career is negatively related with wages, which can be related to the fact that those enrolled in longer careers have been less time in the labor market. Last, we see that ability is strongly related with wages in those who did not drop out after the first year.

Now we analyze the results for the test score equations. In Table 10 we can see that male performs better than women in math and worst in language. It can be observed that older people performs better in PSU but have lower GPA form high school. Living in the North decreases the three scores measures and those form the south perform better in language and have higher GPA from high school, relative to those living in the center of the country.

The number of people in the household is negatively correlated with PSU scores and NEM, while the contrary occurs with family income. Having attended a public or private-voucher school is negatively associated with all three scores. We can see that parent's education affects positively PSU scores but is negatively correlated with high school GPA. Last, we observe that ability os strongly positively correlated with the three test scores measures. This suggests that the factor is strongly related with cognitive abilities.

5.1 Goodness of fit

We compute goodness of fit statistics of the structural model. Specifically we compute χ^2 tests to contrast estimated and actual proportions.[22] We first implemented simple hypothesis test through decision nodes. In Table 11 we can see the results.

In particular, we can see the p-values of each single null hypothesis of equality between model and actual data. It can be appreciated that all the single hypothesis tests are rejected at a 1% level, which means that our structural model performs well, at least predicting the averages.

A more conservative goodness of fit test is to test the joint null hypothesis of equality between model and actual proportions. We can see the p-value of the joint hypothesis in Table 12. There is no evidence to reject the null of joint equality between the predictions of the model and the actual data.

[21] For those who dropped out in the first year we did not included characteristics of the career they attended.

[22] Since we have the structural parameters, we can simulate an economy with one million observations. The null hypothesis is that $Model = Actual$.

5.2 The role of ability in the sequential decisions

In this subsection we analyze in detail the central role of ability in individual choices according to our structural model. In particular, we study if there is *sorting* in ability and it relationship with schooling decisions. In order to do so, we use the estimated structural parameters of our model to simulate the distribution of the ability *factor*.[23]

Figure 7 show us the unconditional distribution of the factor and the estimated parameters of the mixture of normals that generate it. We can see the non-normality of the distribution which validates our mixture model.[24]

Now, we show the distribution of the ability for those who applied to the CAE relative to those who did not apply. We observe that CAE applicants are more able than those who did not apply. There is first order stochastic dominance.

The distribution of ability by type of HEI is presented in Figure 9. We see that more there is positive sorting regarding to ability and university enrollment: more able students enroll in universities instead of CFT/IP. This is consistent with what we found in Table 7 where the ability factor is a strong predictor of the decision of enrolling in an university.

Figure 10 presents the distribution of the ability factor according to having obtained the CAE or not, conditional on having applied to this loan. We can see that, either for those enrolled in an University or a CFT/IP, more able students have a higher probability of getting the CAE but this sorting is stronger in those enrolled in a CFT/IP. This agrees with Table 7 as well since the ability factor has a greater impact in the probability of obtaining the CAE for those enrolled in a CFT/IP.

Finally, in Figure 11 we observe sorting in the decision of dropping out of a HEI. We see that less able students have a higher probability of dropping out, even after controlling for observable variables such as family income among others. This result holds through decision nodes, independent of having applied to the CAE or not, having received the CAE, and havind enrolled in an university or a CFT/IP. These results agree with those found in Table 8 where the ability factor is consistently negative in the dropping out decision.[25]

6 Treatment effects

In this section we estimate the causal effect of having the CAE on the probability of dropping out of a HEI after the first year. We estimate also, the effect of having the CAE on wages, five years after enrolled in the

[23] The simulation considers one million observations

[24] We performed a normality test and reject the null hypothesis of normality.

[25] We performed stochastic dominance analysis for all comparisons finding first order dominance in all pairwise comparisons mentioned.

HEI.

[FOOTNOTE, NO SE ENTIENDE]

6.1 On the effects of CAE on dropout decision

We estimate the causal impact of CAE on the probability of dropping out of a HEI, separating by type of institution: University or CFT/IP. It is important to mention that such a kind of estimation is likely yo suffer from endogeneity/selectivity issues (Dynarski, 2002, Acuña, Makovec y Mizala, 2010). However, in this paper we control for these issues, modeling the decision process in each node with our structural model. This will allow us to estimate counterfactual scenarios, and to compute treatment effects of interest.

In section 2 we present Figure 5, which shows that there was no apparent change in dropouts rates before and after the introduction of the CAE in 2006. [ESTA FIGURA NO ME GUSTA MUCHO, NO SE SI PONER UNA TABLA EN SU LUGAR][26] However, a correct exercise would be such that analyze the effect of the CAE on dropouts rate, relative to those with no CAE, controlling for observable variables and ability.

A first approach is to compute the unconditional impact of CAE on the dropping out of a HEI after the first year.[27] Thus, we estimate the following treatment parameters

$$\Upsilon^{\text{CAE}}_{D_4=1} = \int E(\Lambda^{\mathbf{D}_1} - \Lambda^{\mathbf{D}_2} | D_4 = 1, f = \zeta) dF_{f|D_4=1}(\zeta) \tag{13}$$

$$\Upsilon^{\text{CAE}}_{D_5=1} = \int E(\Lambda^{\mathbf{D}_3} - \Lambda^{\mathbf{D}_4} | D_5 = 1, f = \zeta) dF_{f|D_5=1}(\zeta) \tag{14}$$

where $\Upsilon^{\text{CAE}}_{D_4=1}$ is the treatment parameter that accounts for the effect of CAE on the probability of dropping out of an university and $\Upsilon^{\text{CAE}}_{D_5=1}$ is the treatment parameter associated to the effect of CAE on the probability of dropping out of a CFT/IP.[28] These treatment parameters are estimated using those from the structural model, which permit us to estimate the counterfactual for each individual and then average over the distribution of the factor. Thus, our estimates controls for endogeneity and selectivity.

In Table 13 we present our estimates for the treatment parameters. We observe that the impact of the CAE on the probability of dropping out of a HEI are statistically significant (we reject the null hypothesis $\Upsilon^{\text{CAE}}_{D_j=1} = 0 \quad j = 4, 5$ at 1% level) and heterogeneous. For those enrolled in an university the CAE reduces the probability in 3.1 percentage points that corresponds to a reduction of 15.5% of the dropout rate for

[26] We see that through decision nodes there is significant differences. In particular, for those enrolled in an university the CAE reduces the dropout probability in 5.2 percentage points and in 10.7 for those enrolled in a CFT/IP. These are unadjusted measures.

[27] This effect is unconditional, thus it does not control for observable variables, such as income, and integrates over the density of the ability factor.

[28] In the decision tree presented in Figure 6, these parameters answer the question: what would have been the dropout rates for those in $\mathbf{D}_2$ and $\mathbf{D}_4$ should they have been obtained the CAE respectively.

students enrolled in universities. For students enrolled in a CFT/IP, we have a higher impact about 8.2 percentage points corresponding to a decrease of 24% of the dropout rate.[29] These results are lower than the uncorrected rates obtained dividing the number of dropouts over the total number of enrolled in each HEI. For instance, the difference in dropout rates between those with and without CAE is 5.2 and 10.7 percentage points for students enrolled in universities and CFT/IP respectively. This is important to remark since it shows the importance of controlling for endogeneity, self-selection, and unobservable ability when estimating the impact of the CAE on dropout rates.

A more detailed analysis requires to condition in other type of variables apart from type of HEI. In order to see if the impact of CAE on the probability of dropping out after the first year varies through income level or factor quintiles we estimate the following treatment parameters

$$\tilde{\Upsilon}^{\text{CAE}}_{D_4=1} = \int E(\Lambda^{\mathbf{D}_1} - \Lambda^{\mathbf{D}_2} | D_4 = 1, X = x, f = \zeta) dF_{f|D_4=1, X=x}(\zeta) \tag{15}$$

$$\tilde{\Upsilon}^{\text{CAE}}_{D_5=1} = \int E(\Lambda^{\mathbf{D}_3} - \Lambda^{\mathbf{D}_4} | D_5 = 1, X = x, f = \zeta) dF_{f|D_5=1, X=x}(\zeta) \tag{16}$$

Where the vector X includes family income categories, quintiles of (ability) factor, and quintiles of PSU scores.[30] The factor quintiles represent a a mixed of cognitive and non cognitive unobservable abilities and the PSU quintiles are a proxy of cognitive ability. The income categories considered are three due to the reduced number of observations in the higher tail of the income distribution in our sample.[31]

In Table 14 we present the effect of CAE on dropout rates for those enrolled in an university and applied to the CAE by income category and factor quintile. Similarly, in Table 15 we present the same effect but instead of factor quintile we consider PSU score. It is important to remark that students enrolled in universities from low income families benefits more in terms of reduction in dropout rates. When factor quintiles are considered there is no clear pattern. Except when we condition on both: income category and quintile of the factor (or PSU score). We observe, that less able students from income categories 1 and 3 benefits more than those from income category 2, we do not have a clear interpretation of this finding [ALGO DEBERIAMOS DECIR ACA....]

Similarly, Tables 16 and 17 show the effect of CAE on dropout rates for those enrolled in a CFT/IP by income category and factor (PSU score) quintile. There are three interesting results in these Tables. First, student from low income families benefits more in terms of reduction of the dropout rates, as in the previous

[29] Alternatively, we can see that in our sample, due to CAE there is 890 less dropouts in universities and 2578 less dropouts in CFT/IP's after the first year.

[30] Quintiles of PSU scores are calculated over the average PSU score.

[31] The income categories are in Chilean pesos being from \$0 to \$278,000 (1), from \$278,000 to \$834,000 (2), and from \$834,000 on (3).

analysis. Second, students with lower level of ability benefits significantly more than those in the higher tail of the factor distribution. Third, when we condition on both: income and factor (PSU score) we find that students from low income families with lower levels of ability benefits more in terms of reduction of dropout rates.

In Figure 12 we summarize the previous results. We plot the impact of the CAE on dropout rateds in percentage points over income category and factor (PSU scores) quintiles for type of HEI.

The results suggest that short run constraints, those related to income, are binding in the Chilean case. Additionally, there is evidence of active long term constraints as well. These constraints are related to ability and our results shows a significantly higher reductions of dropout rates due to CAE for those with lower level of abilities enrolled in CFT/IP institutions. These reductions are even higher for students with low level of ability and from low income families. This finding may shed light on the use of resources if focalization is desired.

6.2 Credit access and wages

We now estimate the impact of the CAE on wages. The design of this program may lead to higher education institutions to decrease dropout rates for those with CAE. This is due to the fact that higher education institutions are responsible for the credit during the period in which beneficiaries are enrolled. Thus, higher education institutions have the incentives to ensure their graduation.[32] Although the Chilean higher education system does not have an information system to measure the quality of its graduates, we can use information about the performance of the individuals in the labor market as a proxy of quality. In this context, we use the results of wage equations to identify differences in quality among those individuals receiving CAE and those individuals who do not receive CAE, if they exist.

To estimate the impact of CAE on wages, we must recognize that this may have an effect on two decisions the student faces. First, the prospective student decides whether or not the apply CAE. This does not only determine the type of financing that will eventually have access, but also the type of institution where she will be studying. This second instance is defined by obtaining credit (conditional on the application). Hence, we can define two pairs of treatment effects, depending on the HEI where the individual is enrolled:

[32] Table 4 shows the guarantee that HEI should pay while students are enrolled. As can be appreciated, this guarantee decreases along the study period and disappears after graduation. Potential incentives to prevent defection might arise between these institutions that could be reflected in the quality of education they provide to their students (eg, easier courses or low failure rates)

$$\Delta^{\text{CAE}}_{\mathbf{D}_1,\mathbf{D}_2} = \int E(W^{\mathbf{D}_1}_{\Lambda=0} - W^{\mathbf{D}_2}_{\Lambda=0}|\mathbf{D}_1 = 1, \Lambda^{\mathbf{D}_1} = 0, \zeta)dF_{f|\mathbf{D}_1=1,\Lambda^{\mathbf{D}_1}=0}(\zeta) \tag{17}$$

$$\Delta^{\text{CAE}}_{\mathbf{D}_3,\mathbf{D}_4} = \int E(W^{\mathbf{D}_3}_{\Lambda=0} - W^{\mathbf{D}_4}_{\Lambda=0}|\mathbf{D}_3 = 1, \Lambda^{\mathbf{D}_3} = 0, \zeta)dF_{f|\mathbf{D}_3=1,\Lambda^{\mathbf{D}_3}=0}(\zeta) \tag{18}$$

y

$$\Delta^{\text{CAE}}_{\mathbf{D}_1,\mathbf{D}_5} = \int E(W^{\mathbf{D}_1}_{\Lambda=0} - W^{\mathbf{D}_5}_{\Lambda=0}|\mathbf{D}_1 = 1, \Lambda^{\mathbf{D}_1} = 0, \zeta)dF_{f|\mathbf{D}_1=1,\Lambda^{\mathbf{D}_1}=0}(\zeta) \tag{19}$$

$$\Delta^{\text{CAE}}_{\mathbf{D}_3,\mathbf{D}_6} = \int E(W^{\mathbf{D}_3}_{\Lambda=0} - W^{\mathbf{D}_6}_{\Lambda=0}|\mathbf{D}_3 = 1, \Lambda^{\mathbf{D}_3} = 0, \zeta)dF_{f|\mathbf{D}_3=1,\Lambda^{\mathbf{D}_3}=0}(\zeta) \tag{20}$$

It is important to remark that the parameters described above are conditional on the fact that the student applies to the CAE, enroll in a particular HEI, get the CAE and does not dropout in the first year.

Hence, the first pair of parameters identify the effect of CAE on wages of those that applied to CAE and did not dropout.[33] The second pair of parameters identify the impact of getting the CAE vs. having not even applied to the CAE.[34]

In Table 18 we present the results of the estimation. We can see that for those enrolled in an university, the impact of getting the CAE on wages is -2%. For those enrolled in a CFT/IP, the impact of CAE on wages is -2,9%. These results are different from uncorrected comparisons. While for those in universities the uncorrected wage gap is -3.4% for those in CFT/IP the wage gap is 2.1%. This suggests that selectivity bias and/or endogeneity issues affects these measures and supports the necessity of pursuing methods that controls for these issues.

For treatment effects $\Delta^{\text{CAE}}_{\mathbf{D}_1,\mathbf{D}_5}$ and $\Delta^{\text{CAE}}_{\mathbf{D}_3,\mathbf{D}_6}$, the decreases are larger. Individuals enrolled in universities with CAE shows a reduction of 12,9% in their wages in comparison with those enrolled in universities who did not apple to CAE. For those in CFT/IP, the wage gap is 6.9% among those with CAE and those who did not apply to CAE. These results are statistically significant at 1% level. [35], [36]

The results show that after controling for self-selection and endogeneity in the decisions, individuals that study with CAE, in the first year, have lower wages five years after in the labor market in comparison to

[33] According to Figure 6 this is equivalent to compare wages of those in node $\mathbf{D}_1$ who did not drop out, with wages of people at node $\mathbf{D}_2$ that did not drop out. For those in a CFT/IP, this is equivalent to compare wages of people at node $\mathbf{D}_3$ and did not drop out, with those from individuals at node $\mathbf{D}_4$ and did not drop either.

[34] According to Figure 6 this is equivalent to compare wages of those in node $\mathbf{D}_1$ who did not drop out with those from people at node $\mathbf{D}_5$ and did not drop out either. For those enrolled in a CFT/IP this is equivalent to compare wages of individuals at node $\mathbf{D}_3$ and did not drop out with those of node $\mathbf{D}_6$ and did not drop out as well.

[35] To compute the significance we perform difference in mean tests for the estimated parameters.

[36] Similarly, uncorrected measures shows a wage gap of -12,9% for those enrolled in universities and -0.2% for those in CFT/IP. This suggests that endogeneity and selectivity bias is present, especially for those in CFT/IP.

those that study without CAE.

6.2.1 Understanding the wage gap

According to the results, we have that CAE reduces the probability of dropping out of a HEI. Thus, comparing dropouts wages with those of non dropouts needs a labor market experience adjustment. This is due to dropouts may have more labor market experience than non dropouts.

In Tables 19 and 20 we show the cumulative average number of pension contributions between 2007 and 2010 for individuals enrolled in universities and CFT/IP. We can see that for university enrollees we fail to reject the null hypothesis of equality of pension contributions between CAE and no CAE recipients in most of the years. On the other hand, for CFT/IP enrollees the number of pension contributions is larger for those who did not obtain the CAE. The difference is 4.5 contributions and seems to not account for the wage gap. For instance, according to Sapelli (2009) the average annual return to experience is 2.4%, hence this could explain a 0.9% of wage gap but we observe a wage gap of almost -3% between CAE recipients and those who did not obtain the CAE.

One plausible hypothesis to understand this wage gap, in addition to labor market experience, is that the incentive for HEI to retain CAE students may decrease the retention requirements for students with the credit. As we explained before, HEI are responsible for the credit during the period in which beneficiaries are enrolled. Thus, higher education institutions have the incentives to ensure their graduation. This may be affecting the quality of the average CAE graduates that reflects in their wages in the labor market. Thus, it may be relevant to revise the design of this credit since the increasing number of beneficiaries that could be affected.

7 Conclusions

The relationship between access to credit and dropout from higher education decision is an important topic in the literature and several approaches have been implemented to estimate it. However, the evidence is mixed and there is no clarity on the importance of credit constraint on dropout decision as pointed out by Kane (2005).

In this paper we analyze the determinants of the dropout from HEI decision in the first year using a unique database with includes information of type of higher education institution, credit access, and labor market outcomes. We estimate a estructural model of sequential schooling decisions that allows us to control for endogeneity, self-selection, and unobservable heterogeneity. We estimate the causal effect of *Crédito con Aval del Estado (CAE)* on the probability of dropping out from a HEI, and the effect of getting the CAE for non dropouts on wages.

The results suggest that there is sorting in ability having that more able students enroll in universities and dropout less. There is heterogeneity in the results of the effect of CAE on dropout decisions. We find also that the CAE reduces the dropout rate after the first year in 15,5% and 24% for universities and CFT-IP respectively, controlling for ability.

We compute also the impact of CAE for different levels of family income and ability. This allow us to investigate if there are short run (related to income) and long run (related to ability) constraints as defined Carneiro and Heckman (2002).We find significantly higher impact on dropout rate for students with low level of ability from poorer families.

Although CAE has positive effects on dropout from higher education, it may have some negative effects. We find that students with CAE have lower wages even after adjusting for ability. This may reflect serious issues in the mechanism design of the incentives to HEI with students with CAE.

In this paper we present evidence of the impact of credit access on dropout rates. The evidence shows that the CAE is a good instrument. However, the results about the impact of CAE on wages shows that the beneficiaries of this credit will be harmed by getting lower wages in the labor market than their peers who did not receive the CAE, even after controlling for selection bias, endogeneity, and unobserved heterogeneity. These results question the design of this instrument and call for a urgent revision since its incentives to reduce dropouts via lowering retention requirements and, thus, reducing the quality standards.

Tablas

Table 1: Average Dropout Rates by HEI Type

	University	IP	CFT
First Year	20.0%	35.3%	33.1%
Second Year	30.8%	52.0%	47.2%
Third Year	38.0%	60.2%	51.9%
Fourth Year	46.4%	63.2%	53.3%
Fifth Year	48.5%		

Source: Consejo Nacional de Educación.
Cohorts from 2004 to 2009 are considered.
IP stands for *Institutos Profesionales* and CFT for *Centros de Formación Técnica*.

Table 2: CAE Assignment by Year

Year	2006	2007	2008	2009	2010
Assignment	21,251	35,035	42,696	69,901	91,202

Source: SIES/MINEDUC.

Table 3: Share of Student Aids that the CAE Represents

Year	2006	2007	2008	2009	2010
Share	10.0%	19.8%	27.5%	36.2%	42.9%

Source: Authors' elaboration based on SIES/MINEDUC.

Table 4: Academic Dropout Guarantee

Year of Studies	1st	2nd	3rd and on		
HEI	90%	70%	60%	60%	60%
Government	0%	20%	30%	30%	30%

Source: SIES/MINEDUC.

Table 5: Summary Statistics by Choices D_1, D_2, D_3, D_4 y D_5.

	D_1		D_2		D_3		D_4		D_5	
Variable	Apply	Don't Apply	University	CFT/IP	University	CFT/IP	CAE	No CAE	CAE	No CAE
Gender	0.489	0.522	0.471	0.532	0.492	0.556	0.453	0.478	0.462	0.573
	(0.500)	(0.500)	(0.499)	(0.499)	(0.500)	(0.497)	(0.498)	(0.500)	(0.499)	(0.495)
Age	18.738	18.724	18.775	18.651	18.754	18.690	18.830	18.756	18.644	18.655
	(1.839)	(1.805)	(1.898)	(1.688)	(1.875)	(1.717)	(1.964)	(1.874)	(1.704)	(1.679)
North	0.116	0.150	0.125	0.096	0.169	0.128	0.060	0.148	0.088	0.102
	(0.320)	(0.357)	(0.330)	(0.295)	(0.375)	(0.334)	(0.237)	(0.355)	(0.283)	(0.302)
South	0.231	0.176	0.241	0.207	0.186	0.165	0.128	0.281	0.203	0.209
	(0.421)	(0.381)	(0.428)	(0.405)	(0.389)	(0.371)	(0.334)	(0.450)	(0.403)	(0.406)
Size of Familiar Group	4.799	4.900	4.800	4.796	4.937	4.857	4.711	4.832	4.753	4.822
	(1.504)	(1.540)	(1.497)	(1.52)	(1.558)	(1.517)	(1.500)	(1.494)	(1.443)	(1.564)
Household Income 278-834 (Thousands of Pesos)	0.631	0.492	0.596	0.714	0.404	0.597	0.484	0.636	0.710	0.716
	(0.483)	(0.500)	(0.491)	(0.452)	(0.491)	(0.491)	(0.500)	(0.481)	(0.454)	(0.451)
Household Income 834-1.400 (Thousands of Pesos)	0.334	0.370	0.362	0.266	0.396	0.338	0.433	0.337	0.269	0.265
	(0.472)	(0.483)	(0.481)	(0.442)	(0.489)	(0.473)	(0.496)	(0.473)	(0.444)	(0.441)
Household Income 1.400-1.950 (Thousands of Pesos)	0.028	0.075	0.034	0.017	0.103	0.043	0.064	0.023	0.017	0.016
	(0.166)	(0.264)	(0.180)	(0.128)	(0.304)	(0.203)	(0.244)	(0.149)	(0.129)	(0.127)
Household Income 1.950 and More (Thousands of Pesos)	0.005	0.025	0.006	0.002	0.038	0.010	0.015	0.003	0.002	0.001
	(0.070)	(0.157)	(0.079)	(0.041)	(0.192)	(0.097)	(0.123)	(0.056)	(0.048)	(0.037)
Father's Education: 8-12 Years	0.250	0.221	0.231	0.294	0.173	0.277	0.193	0.244	0.295	0.293
	(0.433)	(0.415)	(0.421)	(0.455)	(0.379)	(0.448)	(0.395)	(0.430)	(0.456)	(0.455)
Father's Education: 12 Years	0.381	0.370	0.383	0.375	0.354	0.389	0.366	0.390	0.359	0.385
	(0.486)	(0.483)	(0.486)	(0.484)	(0.478)	(0.488)	(0.482)	(0.488)	(0.480)	(0.487)
Father's Education: More than 12 Years	0.267	0.322	0.294	0.205	0.406	0.222	0.370	0.267	0.221	0.195
	(0.443)	(0.467)	(0.456)	(0.404)	(0.491)	(0.416)	(0.483)	(0.442)	(0.415)	(0.396)
Mother's Education: 8-12 Years	0.268	0.255	0.256	0.297	0.212	0.306	0.219	0.269	0.299	0.296
	(0.443)	(0.436)	(0.436)	(0.457)	(0.409)	(0.461)	(0.414)	(0.443)	(0.458)	(0.456)
Mother's Education: 12 Years	0.413	0.388	0.410	0.420	0.378	0.400	0.390	0.418	0.423	0.418
	(0.492)	(0.487)	(0.492)	(0.494)	(0.485)	(0.490)	(0.488)	(0.493)	(0.494)	(0.493)
Mother's Education: More than 12 Years	0.223	0.272	0.249	0.161	0.346	0.185	0.329	0.221	0.162	0.161
	(0.416)	(0.445)	(0.433)	(0.368)	(0.476)	(0.389)	(0.470)	(0.415)	(0.368)	(0.367)
Public School	0.471	0.403	0.457	0.505	0.352	0.463	0.366	0.489	0.504	0.506
	(0.499)	(0.491)	(0.498)	(0.500)	(0.478)	(0.499)	(0.482)	(0.500)	(0.500)	(0.500)
Private-Voucher School	0.485	0.472	0.491	0.471	0.467	0.479	0.543	0.473	0.470	0.471
	(0.500)	(0.499)	(0.500)	(0.499)	(0.499)	(0.500)	(0.498)	(0.499)	(0.499)	(0.499)

Note: Standard errors in parentheses.

Table 6: Summary Statistics by Choices D_1, D_2, D_3, D_4 y D_5 (Continuation).

	D_1		D_2		D_3		D_4		D_5	
Variable	Apply	Don't Apply	University	CFT/IP	University	CFT/IP	CAE	No CAE	CAE	No CAE
Scholarship	0.341	0.107	0.411	0.176	0.148	0.058	0.082	0.529	0.240	0.137
	(0.474)	(0.309)	(0.492)	(0.381)	(0.355)	(0.235)	(0.275)	(0.499)	(0.427)	(0.344)
Agricultural and Livestock	0.034	0.030	0.038	0.027	0.034	0.026	0.042	0.036	0.034	0.023
	(0.182)	(0.171)	(0.190)	(0.163)	(0.181)	(0.158)	(0.200)	(0.186)	(0.181)	(0.151)
Arts and Architecture	0.056	0.067	0.040	0.096	0.053	0.083	0.040	0.039	0.118	0.083
	(0.231)	(0.249)	(0.195)	(0.295)	(0.223)	(0.276)	(0.196)	(0.194)	(0.322)	(0.276)
Basic Sciences	0.021	0.015	0.030	0.001	0.026	0.001	0.036	0.027	-	0.001
	(0.143)	(0.120)	(0.169)	(0.024)	(0.160)	(0.035)	(0.186)	(0.163)	-	(0.030)
Social Sciences	0.116	0.111	0.136	0.070	0.159	0.056	0.184	0.118	0.071	0.070
	(0.320)	(0.315)	(0.342)	(0.256)	(0.365)	(0.229)	(0.388)	(0.323)	(0.257)	(0.255)
Law	0.069	0.084	0.056	0.097	0.078	0.091	0.064	0.054	0.127	0.080
	(0.253)	(0.277)	(0.231)	(0.296)	(0.268)	(0.288)	(0.245)	(0.225)	(0.333)	(0.271)
Education	0.217	0.161	0.287	0.053	0.244	0.063	0.199	0.318	0.041	0.060
	(0.412)	(0.368)	(0.452)	(0.224)	(0.430)	(0.243)	(0.399)	(0.466)	(0.198)	(0.238)
Humanities	0.018	0.014	0.023	0.004	0.023	0.003	0.029	0.021	0.001	0.006
	(0.132)	(0.117)	(0.151)	(0.065)	(0.149)	(0.058)	(0.168)	(0.145)	(0.028)	(0.080)
Health	0.119	0.105	0.117	0.124	0.104	0.106	0.198	0.088	0.125	0.123
	(0.324)	(0.307)	(0.322)	(0.329)	(0.305)	(0.308)	(0.399)	(0.284)	(0.331)	(0.329)
Technology	0.239	0.264	0.201	0.330	0.203	0.337	0.139	0.223	0.286	0.356
	(0.427)	(0.441)	(0.400)	(0.47)	(0.402)	(0.473)	(0.346)	(0.416)	(0.452)	(0.479)
Number of Semesters	8.360	7.707	9.243	6.278	9.058	6.111	9.345	9.207	6.499	6.147
	(2.130)	(2.271)	(1.638)	(1.651)	(1.797)	(1.653)	(1.615)	(1.645)	(1.564)	(1.688)
High School Grades	0.192	-0.114	0.330	-0.132	0.127	-0.398	0.311	0.337	0.171	-0.312
	(0.968)	(1.001)	(0.961)	(0.905)	(1.012)	(0.91)	(0.947)	(0.966)	(0.817)	(0.907)
Mathematics	0.184	-0.109	0.396	-0.315	0.267	-0.553	0.644	0.307	-0.174	-0.399
	(0.895)	(1.042)	(0.834)	(0.831)	(1.033)	(0.863)	(0.684)	(0.865)	(0.817)	(0.828)
Language	0.229	-0.135	0.449	-0.290	0.259	-0.601	0.759	0.338	-0.111	-0.396
	(0.892)	(1.035)	(0.826)	(0.825)	(1.000)	(0.869)	(0.695)	(0.841)	(0.784)	(0.831)
Number of Observations	11694	19787	8210	3484	10716	9071	2165	6045	1299	2185

Note: Standard errors in parentheses.

Table 7: Estimation Results for Choices D_1, D_2, D_3, D_4 y D_5.

	D_1	D_2	D_3	D_4	D_5
Constant	-0.310	-0.071	0.092	-0.822	0.144
	(0.092)	(0.182)	(0.124)	(0.187)	(0.311)
Gender	-0.079	-0.236	-0.221	-0.118	-0.316
	(0.016)	(0.029)	(0.022)	(0.032)	(0.045)
Age	-0.006	0.038	0.024	0.026	0.000
	(0.004)	(0.008)	(0.006)	(0.008)	(0.013)
North	-0.189	0.306	0.302	-0.693	-0.047
	(0.024)	(0.049)	(0.031)	(0.056)	(0.078)
South	0.136	0.334	0.238	-0.583	0.065
	(0.020)	(0.037)	(0.028)	(0.041)	(0.058)
Size of Familiar Group	-0.008	-0.006	-0.008	-0.028	-0.028
	(0.005)	(0.010)	(0.007)	(0.011)	(0.015)
Household Income 278-834 (Thousands of Pesos)	-0.193	0.351	0.366	0.256	0.098
	(0.017)	(0.033)	(0.024)	(0.035)	(0.052)
Household Income 834-1.400 (Thousands of Pesos)	-0.671	0.592	0.687	0.687	0.182
	(0.040)	(0.104)	(0.047)	(0.084)	(0.183)
Household Income 1.400-1.950 (Thousands of Pesos)	-0.983	0.935	0.918	1.034	0.484
	(0.081)	(0.270)	(0.088)	(0.182)	(0.574)
Household Income 1.950 and More (Thousands of Pesos)	-1.596	0.432	0.983	0.753	-0.033
	(0.100)	(0.341)	(0.078)	(0.319)	(0.544)
Public School	0.318	-0.450	-0.548	-0.365	-0.106
	(0.036)	(0.088)	(0.044)	(0.071)	(0.155)
Private-Voucher School	0.294	-0.347	-0.432	-0.226	-0.121
	(0.034)	(0.086)	(0.042)	(0.070)	(0.153)
Factor	0.541	1.125	0.867	0.435	0.601
	(0.012)	(0.030)	(0.019)	(0.034)	(0.048)

Note: Standard errors in parentheses.

Table 8: Estimation Results for Choices $\Lambda^{\mathbf{D}_1}$, $\Lambda^{\mathbf{D}_2}$, $\Lambda^{\mathbf{D}_3}$, $\Lambda^{\mathbf{D}_4}$, $\Lambda^{\mathbf{D}_5}$ y $\Lambda^{\mathbf{D}_6}$.

	$\Lambda^{\mathbf{D}_1}$	$\Lambda^{\mathbf{D}_2}$	$\Lambda^{\mathbf{D}_3}$	$\Lambda^{\mathbf{D}_4}$	$\Lambda^{\mathbf{D}_5}$	$\Lambda^{\mathbf{D}_6}$
Constant	-1.961	-3.284	-2.151	-3.404	-2.388	-1.614
	(0.468)	(0.283)	(0.985)	(0.492)	(0.204)	(0.228)
Gender	0.338	0.104	0.303	0.061	0.141	0.154
	(0.087)	(0.048)	(0.120)	(0.079)	(0.036)	(0.041)
Age	0.015	0.062	-0.034	0.077	0.023	-0.007
	(0.020)	(0.010)	(0.040)	(0.018)	(0.008)	(0.010)
North	0.204	0.087	0.250	0.110	0.037	0.204
	(0.169)	(0.061)	(0.189)	(0.111)	(0.045)	(0.049)
South	-0.033	-0.045	-0.014	-0.157	0.046	-0.087
	(0.129)	(0.053)	(0.158)	(0.089)	(0.044)	(0.046)
Size of Familiar Group	0.004	0.056	0.093	0.039	0.046	0.052
	(0.029)	(0.014)	(0.039)	(0.021)	(0.011)	(0.011)
Household Income 278-834 (Thousands of Pesos)	0.065	-0.234	-0.040	-0.219	-0.275	-0.317
	(0.089)	(0.050)	(0.138)	(0.083)	(0.038)	(0.038)
Household Income 834-1.400 (Thousands of Pesos)	-0.293	-0.387	-	-0.772	-0.409	-0.636
	(0.229)	(0.161)	-	(0.368)	(0.069)	(0.104)
Household Income 1.400-1.950 (Thousands of Pesos)	-0.192	-0.307	-	0.592	-0.410	-1.149
	(0.394)	(0.441)	-	(0.823)	(0.109)	(0.277)
Household Income 1.950 and More (Thousands of Pesos)	-	0.235	-	0.197	-0.556	-0.470
	-	(0.507)	-	(0.755)	(0.107)	(0.177)
Public School	0.332	0.430	0.552	0.683	0.394	0.353
	(0.187)	(0.137)	(0.536)	(0.294)	(0.068)	(0.090)
Private-Voucher School	0.231	0.290	0.502	0.411	0.250	0.229
	(0.180)	(0.138)	(0.538)	(0.294)	(0.062)	(0.089)
Scholarship	-	-0.345	-	-0.315	-0.202	-0.244
	-	(0.058)	-	(0.108)	(0.053)	(0.081)
Agricultural and Livestock	-	-0.032	-	0.137	0.158	-0.181
	-	(0.133)	-	(0.223)	(0.103)	(0.115)
Arts and Architecture	-	0.277	-	0.090	0.096	0.055
	-	(0.131)	-	(0.141)	(0.096)	(0.074)
Basic Sciences	-	0.535	-	-	0.343	-
	-	(0.144)	-	-	(0.118)	-
Social Sciences	-	-0.138	-	0.288	-0.117	0.181
	-	(0.104)	-	(0.149)	(0.078)	(0.078)
Law	-	0.024	-	0.052	0.215	0.141
	-	(0.121)	-	(0.144)	(0.079)	(0.065)
Education	-	-0.347	-	0.085	-0.169	0.027
	-	(0.091)	-	(0.155)	(0.068)	(0.073)
Humanities	-	0.293	-	-	0.205	-
	-	(0.148)	-	-	(0.116)	-
Health	-	-0.059	-	0.049	0.145	-0.111
	-	(0.107)	-	(0.125)	(0.078)	(0.066)
Technology	-	0.108	-	0.081	0.189	-0.035
	-	(0.094)	-	(0.104)	(0.071)	(0.050)
Number of Semesters	-	0.073	-	0.013	0.042	-0.012
	-	(0.014)	-	(0.022)	(0.010)	(0.011)
Factor	-0.497	-0.349	-0.482	-0.425	-0.366	-0.496
	(0.128)	(0.053)	(0.144)	(0.071)	(0.029)	(0.034)

Note: Standard errors in parentheses.

Table 9: Estimation Results for Wage Equations.

	$W^{\mathbf{D}_1}$		$W^{\mathbf{D}_2}$		$W^{\mathbf{D}_3}$		$W^{\mathbf{D}_4}$		$W^{\mathbf{D}_5}$		$W^{\mathbf{D}_6}$	
	$\Lambda^{\mathbf{D}_1}=1$	$\Lambda^{\mathbf{D}_1}=0$	$\Lambda^{\mathbf{D}_2}=1$	$\Lambda^{\mathbf{D}_2}=0$	$\Lambda^{\mathbf{D}_3}=1$	$\Lambda^{\mathbf{D}_3}=0$	$\Lambda^{\mathbf{D}_4}=1$	$\Lambda^{\mathbf{D}_4}=0$	$\Lambda^{\mathbf{D}_5}=1$	$\Lambda^{\mathbf{D}_5}=0$	$\Lambda^{\mathbf{D}_6}=1$	$\Lambda^{\mathbf{D}_6}=0$
Constant	11.763	12.564	11.367	12.786	14.418	12.470	12.698	12.538	11.540	12.729	12.145	12.210
	(0.546)	(0.245)	(0.241)	(0.142)	(1.522)	(0.242)	(0.355)	(0.209)	(0.184)	(0.111)	(0.179)	(0.094)
Gender	0.231	0.011	0.166	-0.003	0.163	0.021	0.208	0.024	0.159	0.027	0.278	0.044
	(0.126)	(0.045)	(0.057)	(0.025)	(0.195)	(0.046)	(0.074)	(0.038)	(0.041)	(0.020)	(0.037)	(0.019)
Age	0.018	0.037	0.046	0.022	-0.123	0.009	-0.018	0.006	0.037	0.022	0.008	0.024
	(0.028)	(0.010)	(0.012)	(0.007)	(0.084)	(0.012)	(0.019)	(0.011)	(0.010)	(0.005)	(0.009)	(0.005)
Agricultural and Livestock	-	-0.957	-	-0.333	-	-0.215	-	-0.059	-	-0.477	-	-0.256
	-	(0.13)	-	(0.073)	-	(0.118)	-	(0.114)	-	(0.060)	-	(0.049)
Arts and Architecture	-	-0.631	-	-0.470	-	-0.338	-	-0.247	-	-0.446	-	-0.190
	-	(0.126)	-	(0.071)	-	(0.076)	-	(0.069)	-	(0.051)	-	(0.033)
Basic Sciences	-	-0.931	-	-0.519	-	-	-	-	-	-0.579	-	-
	-	(0.134)	-	(0.087)	-	-	-	-	-	(0.064)	-	-
Social Sciences	-	-0.357	-	-0.174	-	-0.172	-	-0.203	-	-0.052	-	-0.140
	-	(0.091)	-	(0.055)	-	(0.090)	-	(0.075)	-	(0.041)	-	(0.037)
Law	-	-0.936	-	-0.291	-	-0.457	-	-0.274	-	-0.466	-	-0.321
	-	(0.115)	-	(0.068)	-	(0.073)	-	(0.070)	-	(0.047)	-	(0.030)
Education	-	-0.298	-	-0.044	-	-0.374	-	-0.026	-	-0.222	-	-0.200
	-	(0.089)	-	(0.048)	-	(0.113)	-	(0.080)	-	(0.037)	-	(0.036)
Humanities	-	-0.929	-	-0.392	-	-0.115	-	-	-	-0.450	-	-
	-	(0.142)	-	(0.093)	-	(0.721)	-	-	-	(0.068)	-	-
Health	-	-0.576	-	-0.148	-	-0.111	-	-0.184	-	-0.346	-	-0.172
	-	(0.092)	-	(0.060)	-	(0.074)	-	(0.060)	-	(0.044)	-	(0.028)
Technology	-	-0.457	-	-0.056	-	0.162	-	0.142	-	-0.206	-	0.082
	-	(0.095)	-	(0.049)	-	(0.060)	-	(0.048)	-	(0.040)	-	(0.023)
Number of Semesters	-	-0.068	-	-0.086	-	-0.001	-	-0.011	-	-0.056	-	-0.002
	-	(0.015)	-	(0.008)	-	(0.015)	-	(0.011)	-	(0.006)	-	(0.005)
Factor	0.100	0.240	0.000	0.129	0.013	0.119	0.239	0.198	0.002	0.127	0.111	0.159
	(0.172)	(0.055)	(0.052)	(0.024)	(0.239)	(0.048)	(0.072)	(0.034)	(0.033)	(0.016)	(0.037)	(0.014)

Note: Standard errors in parentheses.

Table 10: Estimation Results for Test Score Equations.

	HSG	MATH	LANG
Constant	1.607	-0.038	-0.517
	(0.067)	(0.064)	(0.065)
Gender	-0.378	0.195	-0.133
	(0.011)	(0.011)	(0.011)
Age	-0.055	0.007	0.040
	(0.003)	(0.003)	(0.003)
North	-0.004	-0.133	-0.270
	(0.016)	(0.015)	(0.016)
South	0.043	0.029	-0.035
	(0.014)	(0.013)	(0.013)
Size of Familiar Group	-0.005	-0.016	-0.022
	(0.003)	(0.003)	(0.003)
Household Income 278-834 (Thousands of Pesos)	0.018	0.179	0.162
	(0.013)	(0.012)	(0.012)
Household Income 834-1.400 (Thousands of Pesos)	0.124	0.364	0.312
	(0.026)	(0.025)	(0.025)
Household Income 1.400-1.950 (Thousands of Pesos)	0.246	0.563	0.471
	(0.045)	(0.042)	(0.042)
Household Income 1.950 and More (Thousands)	0.338	0.668	0.514
	(0.039)	(0.039)	(0.039)
Public School	-0.117	-0.427	-0.398
	(0.024)	(0.023)	(0.022)
Private-Voucher School	-0.170	-0.379	-0.303
	(0.022)	(0.021)	(0.021)
Father's Education: 8-12 Years	-0.103	0.003	0.033
	(0.022)	(0.019)	(0.019)
Father's Education: 12 Years	-0.183	0.019	0.066
	(0.021)	(0.019)	(0.019)
Father's Education: More than 12 Years	-0.155	0.185	0.226
	(0.023)	(0.022)	(0.021)
Mother's Education: 8-12 Years	-0.127	0.022	0.020
	(0.021)	(0.019)	(0.019)
Mother's Education: 12 Years	-0.153	0.074	0.081
	(0.021)	(0.019)	(0.019)
Mother's Education: More than 12 Years	-0.124	0.203	0.232
	(0.024)	(0.021)	(0.021)
Factor	0.757	1.000	0.971
	(0.008)	(0.000)	(0.008)

Note: Standard errors in parentheses.

Table 11: Goodness of Fit - Model Choices.

	Actual	Model	P-Value
D_1	0.372	0.372	0.954
D_2	0.702	0.702	0.963
D_3	0.542	0.546	0.516
D_4	0.264	0.264	0.934
D_5	0.373	0.368	0.427
$\Lambda^{\mathbf{D}_1}$	0.072	0.071	0.823
$\Lambda^{\mathbf{D}_2}$	0.122	0.126	0.356
$\Lambda^{\mathbf{D}_3}$	0.058	0.061	0.268
$\Lambda^{\mathbf{D}_4}$	0.165	0.172	0.157
$\Lambda^{\mathbf{D}_5}$	0.122	0.117	0.240
$\Lambda^{\mathbf{D}_6}$	0.152	0.146	0.164

Table 12: Goodness of Fit - Joint Test.

P-Value	0.886

Table 13: Estimated Impact of the CAE on Dropout Rates.

$\Upsilon^{CAE}_{D_4=1}$	-0.031^{***}
$\Upsilon^{CAE}_{D_5=1}$	-0.082^{***}

Note: *** denotes statistical significance at 1%.

Table 14: Estimated Impact of the CAE on Dropout Rates Conditional on Income and Factor (University).

		Income Category			
		1	2	3	Unconditional
Factor Quintile	1	-0.037^{***}	0.026^{***}	-0.046^{***}	-0.013^{***}
	2	-0.055^{***}	-0.002	-0.040^{***}	-0.035^{***}
	3	-0.048^{***}	-0.013^{***}	-0.040^{***}	-0.035^{***}
	4	-0.049^{***}	-0.014^{***}	-0.032^{***}	-0.036^{***}
	5	-0.044^{***}	-0.015^{***}	-0.031^{***}	-0.033^{***}
	Unconditional	-0.047^{***}	-0.003^{**}	-0.038^{***}	-0.031^{***}

Note: ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively. Income categories are defined as follows: between 0 and 278.000 pesos (category 1), between 278.000 and 834.000 pesos (category 2) and 834.000 or more pesos (category 3).

Table 15: Estimated Impact of the CAE on Dropout Rates Conditional on Income and PSU (University).

		Income Category			
		1	2	3	Unconditional
PSU Quintile	1	-0.040^{***}	0.020^{***}	-0.032^{**}	-0.021^{***}
	2	-0.051^{***}	0.000	-0.033^{***}	-0.033^{***}
	3	-0.049^{***}	-0.004	-0.039^{***}	-0.033^{***}
	4	-0.050^{***}	-0.008^{***}	-0.050^{***}	-0.034^{***}
	5	-0.045^{***}	-0.016^{***}	-0.034^{***}	-0.032^{***}
	Unconditional	-0.047^{***}	-0.003^{**}	-0.038^{***}	-0.031^{***}

Note: ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively. Income categories are defined as follows: between 0 and 278.000 pesos (category 1), between 278.000 and 834.000 pesos (category 2) and 834.000 or more pesos (category 3).

Table 16: Estimated Impact of the CAE on Dropout Rates Conditional on Income and Factor (CFT/IP).

		Income Category			
		1	2	3	Unconditional
Factor Quintile	1	-0.129^{***}	-0.054^{***}	-0.016	-0.106^{***}
	2	-0.112^{***}	-0.059^{***}	-0.019	-0.095^{***}
	3	-0.099^{***}	-0.054^{***}	-0.027	-0.086^{***}
	4	-0.080^{***}	-0.044^{***}	-0.025	-0.070^{***}
	5	-0.058^{***}	-0.035^{***}	0.012	-0.051^{***}
	Unconditional	-0.095^{***}	-0.049^{***}	-0.015^{*}	-0.082^{***}

Note: ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively. Income categories are defined as follows: between 0 and 278.000 pesos (category 1), between 278.000 and 834.000 pesos (category 2) and 834.000 or more pesos (category 3).

Table 17: Estimated Impact of the CAE on Dropout Rates Conditional on Income and PSU (CFT/IP).

		Income Category			
		1	2	3	Unconditional
PSU Quintile	1	-0.120^{***}	-0.049^{***}	0.048	-0.103^{***}
	2	-0.109^{***}	-0.066^{***}	-0.023	-0.097^{***}
	3	-0.097^{***}	-0.048^{***}	-0.003	-0.083^{***}
	4	-0.082^{***}	-0.046^{***}	-0.023	-0.071^{***}
	5	-0.062^{***}	-0.041^{***}	-0.028^{*}	-0.055^{***}
	Unconditional	-0.095^{***}	-0.049^{***}	-0.015^{*}	-0.082^{***}

Note: ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively. Income categories are defined as follows: between 0 and 278.000 pesos (category 1), between 278.000 and 834.000 pesos (category 2) and 834.000 or more pesos (category 3).

Table 18: Estimation of the Impact of Having Attended a HEI with CAE on Wages

Parameter	Estimate
$\Delta^{\mathrm{CAE}}_{\mathbf{D}_1,\mathbf{D}_2}$	-0.020^{***}
$\Delta^{\mathrm{CAE}}_{\mathbf{D}_3,\mathbf{D}_4}$	-0.029^{***}
$\Delta^{\mathrm{CAE}}_{\mathbf{D}_1,\mathbf{D}_5}$	-0.129^{***}
$\Delta^{\mathrm{CAE}}_{\mathbf{D}_3,\mathbf{D}_6}$	-0.069^{***}

Note: *** denotes statistical significance at 1%.

Table 19: Number of Average Social Security Contributions for University Enrolled Students.

Year	CAE	No CAE	Same?
2007	2.66	2.75	Yes
2008	6.39	6.58	Yes
2009	10.68	11.14	Si
2010	15.94	17.03	No

Table 20: Number of Average Social Security Contributions for CFT/IP Enrolled Students.

Year	CAE	No CAE	Same?
2007	2.62	3.91	No
2008	6.6	9.29	No
2009	12.12	15.97	No
2010	19.25	23.75	No

Figures

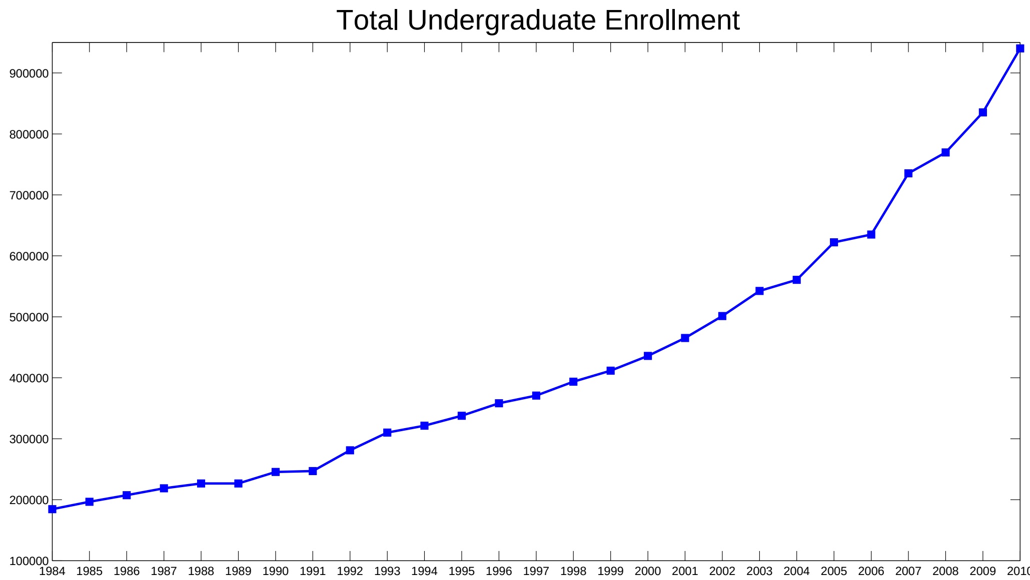


Figure 1: Total Undergraduate Enrollment. Source: SIES/MINEDUC.

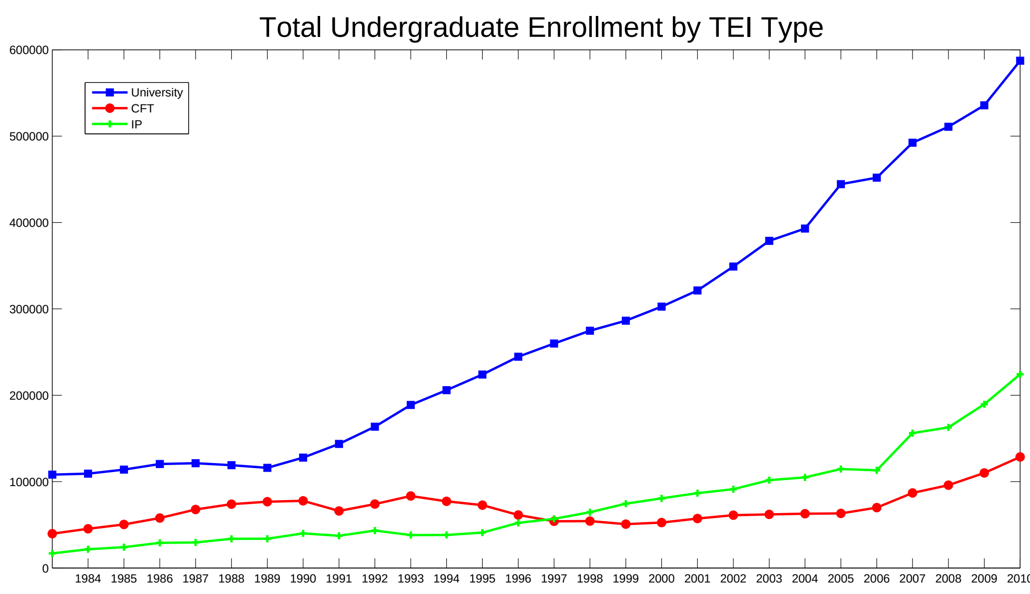


Figure 2: Total Undergraduate Enrollment by HEI Type. Source: SIES/MINEDUC.

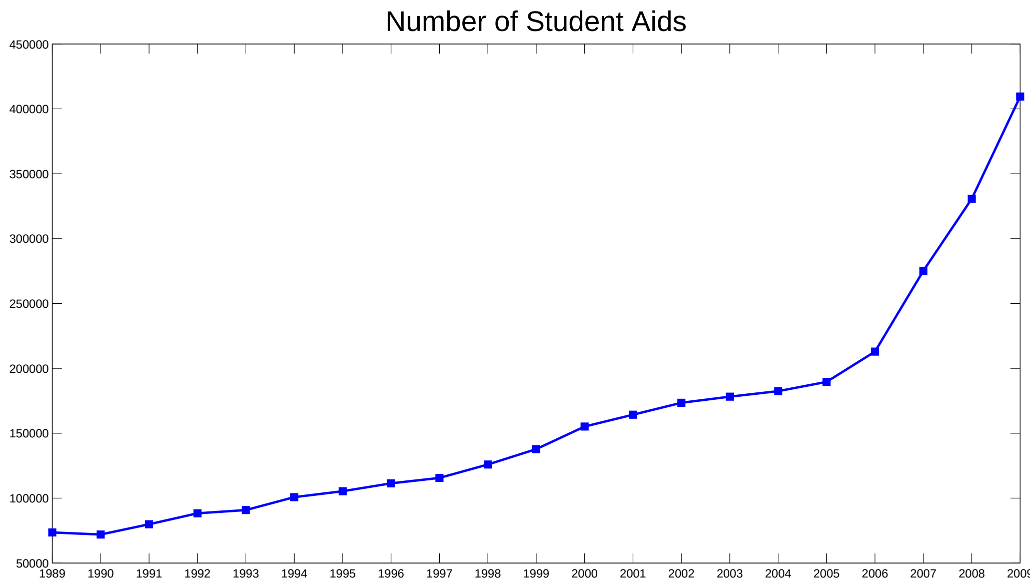


Figure 3: Number of Student Aids. Source: SIES/MINEDUC.

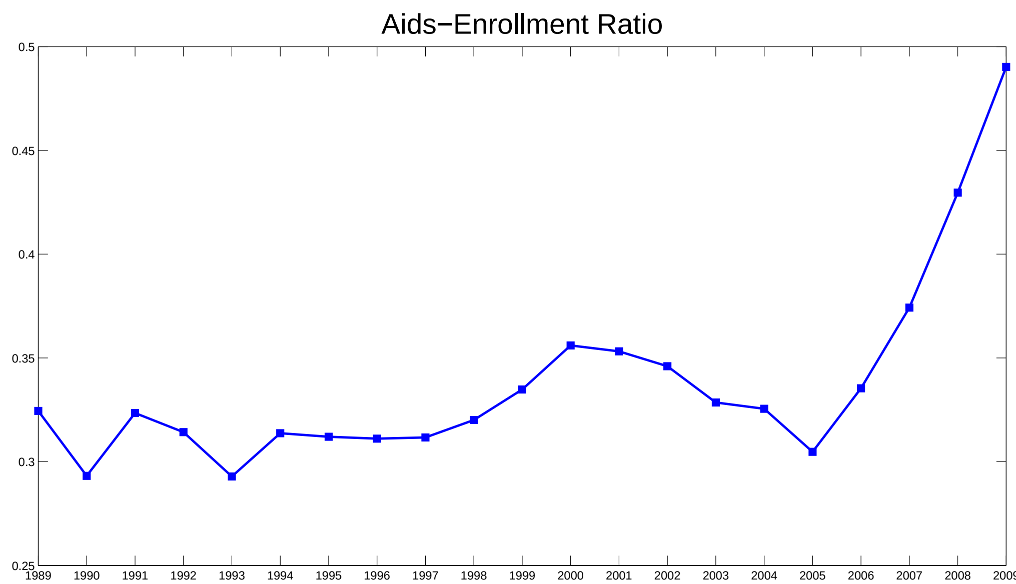


Figure 4: Aids-Enrollment Ratio. Source: Authors' Elaboration based on SIES/MINEDUC.

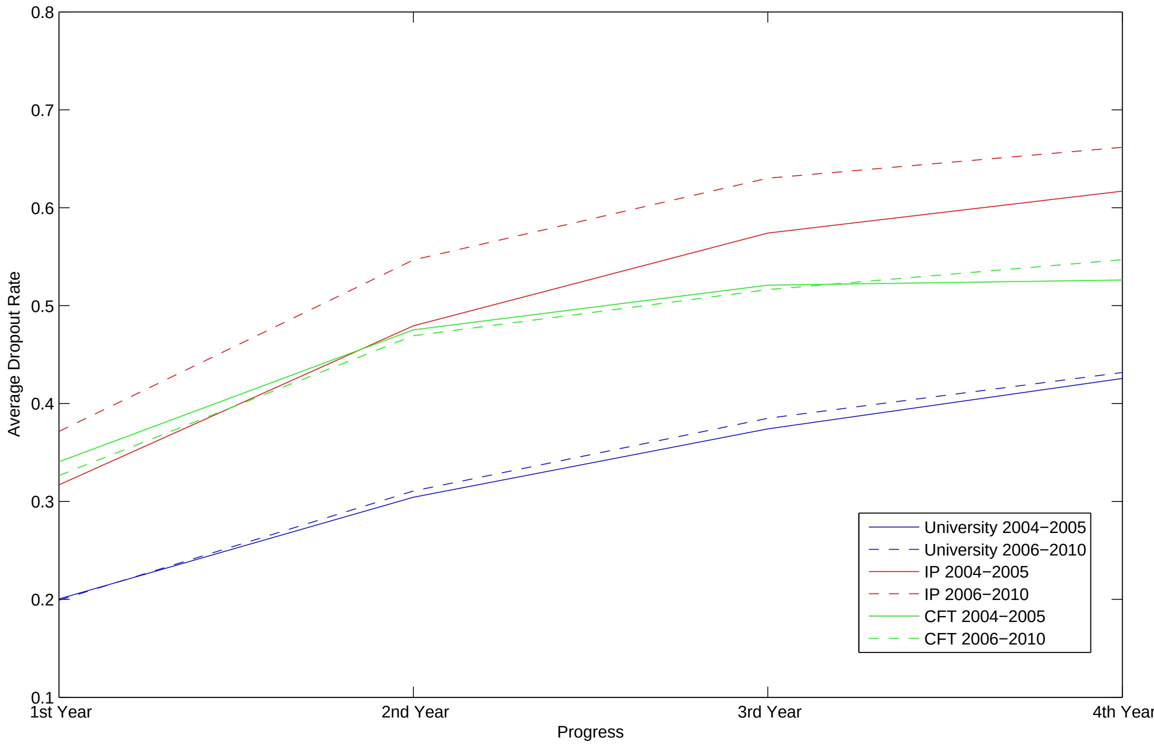


Figure 5: Average Dropout Rates by HEI Type. Source: Authors' Elaboration based on Consejo Nacional de Educación.

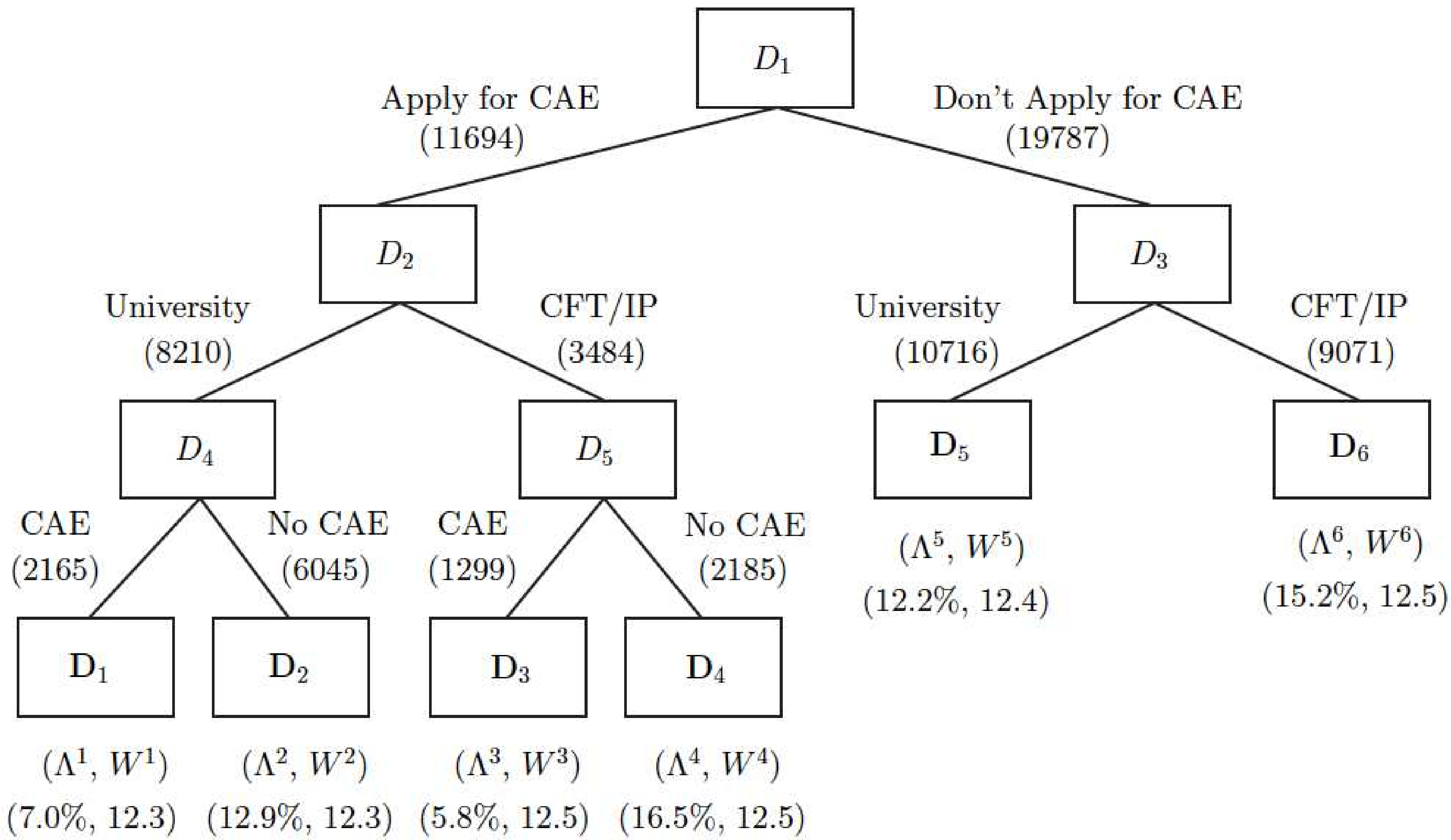


Figure 6: Decision Scheme. Number of Observations by Node, Average Dropout Rates and Average Natural Logarithm of Wages in parentheses.

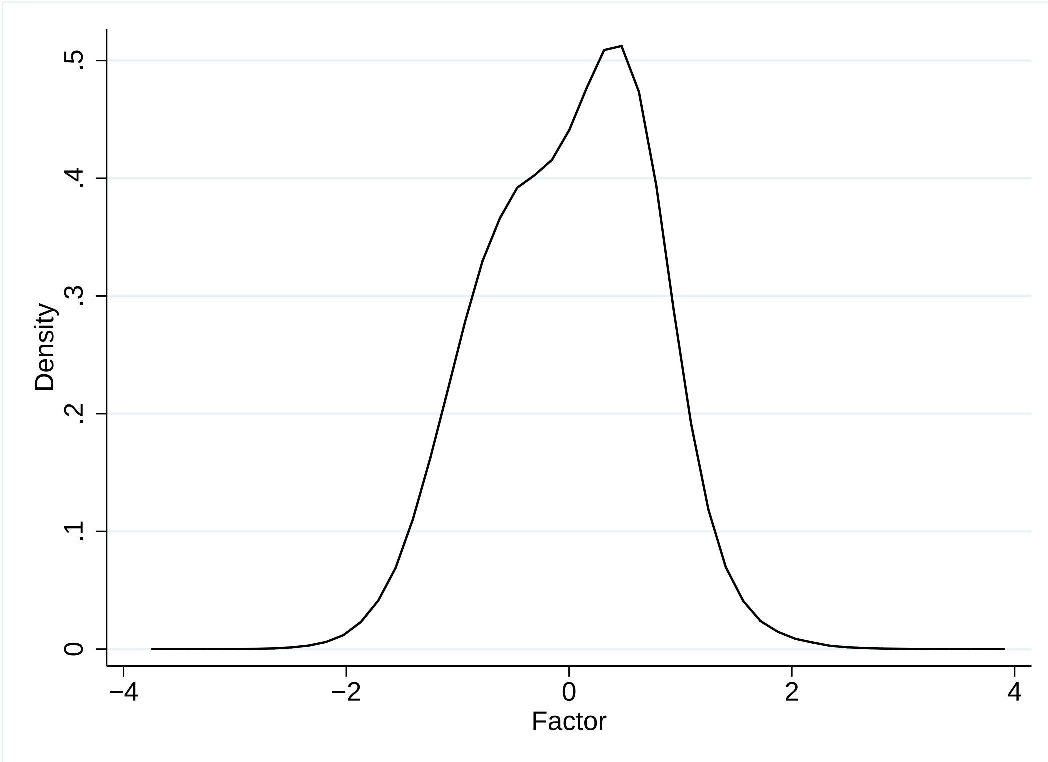


Figure 7: Unconditional Distribution of Factor.

The estimated distribution, $f \sim \rho_1 \mathcal{N}(\tau_1, \sigma_1^2) + \rho_2 \mathcal{N}(\tau_2, \sigma_2^2) + \rho_3 \mathcal{N}(\tau_3, \sigma_3^2)$, is given by the following parameters:

$$\begin{aligned} \tau &= (-0.584 \quad 0.193 \quad 0.521) \\ \sigma^2 &= (3.489 \quad 1.662 \quad 6.799) \\ \rho &= (0.385 \quad 0.275 \quad 0.340) \end{aligned}$$

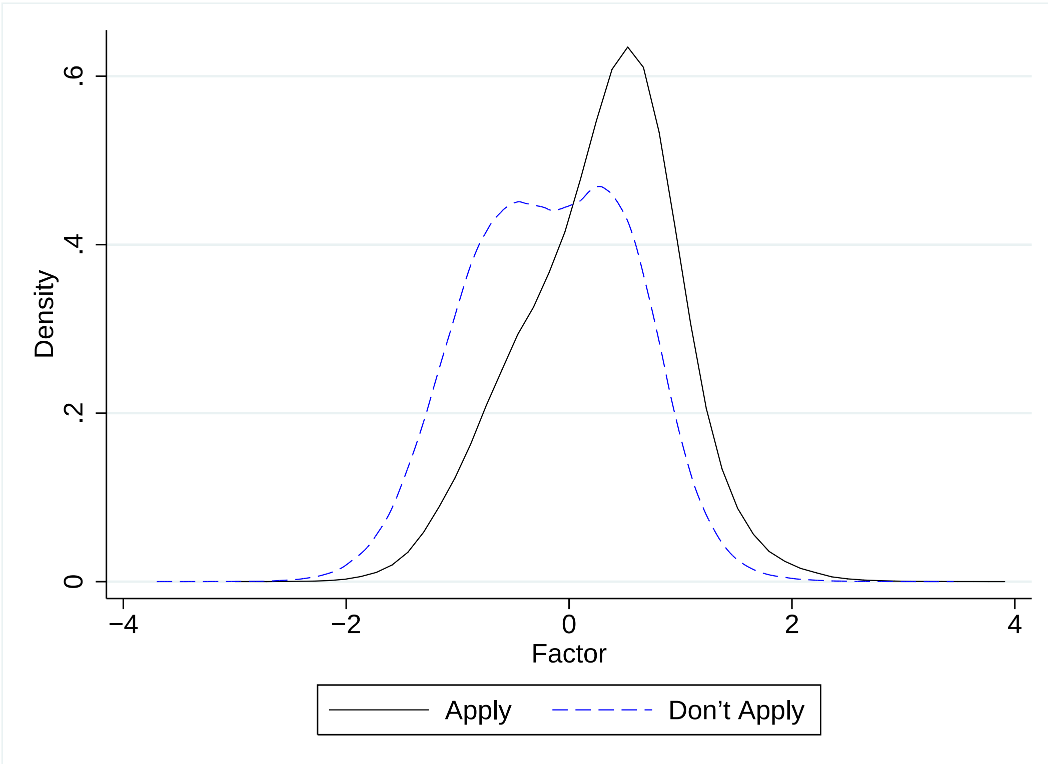
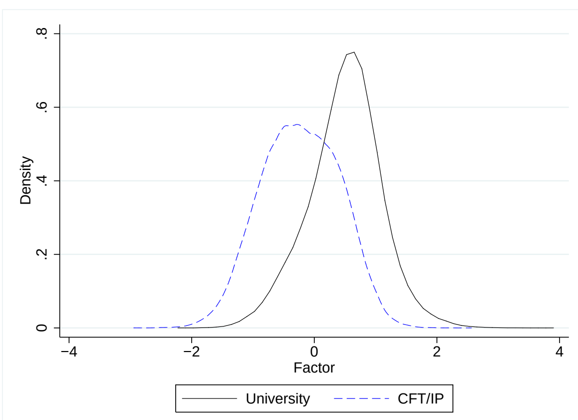
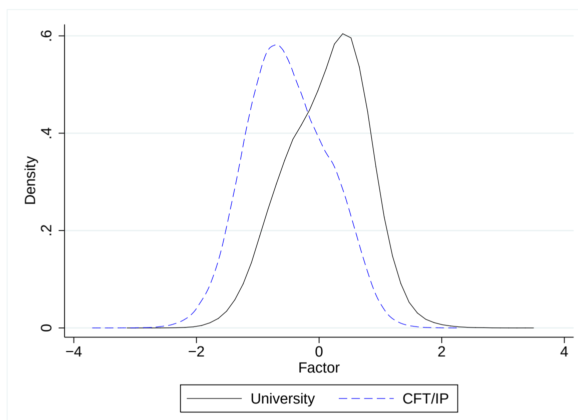


Figure 8: Distribution of Factor by CAE Application.

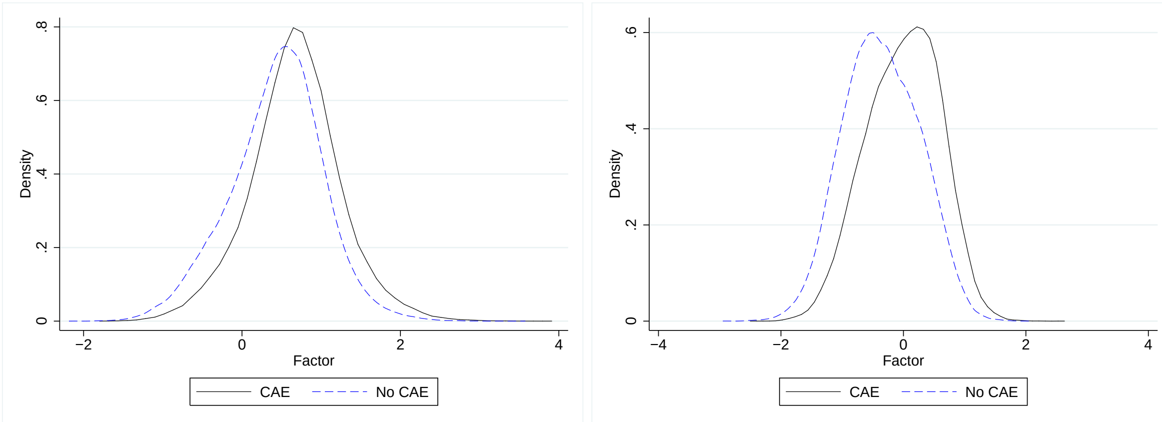


(a) Apply for CAE



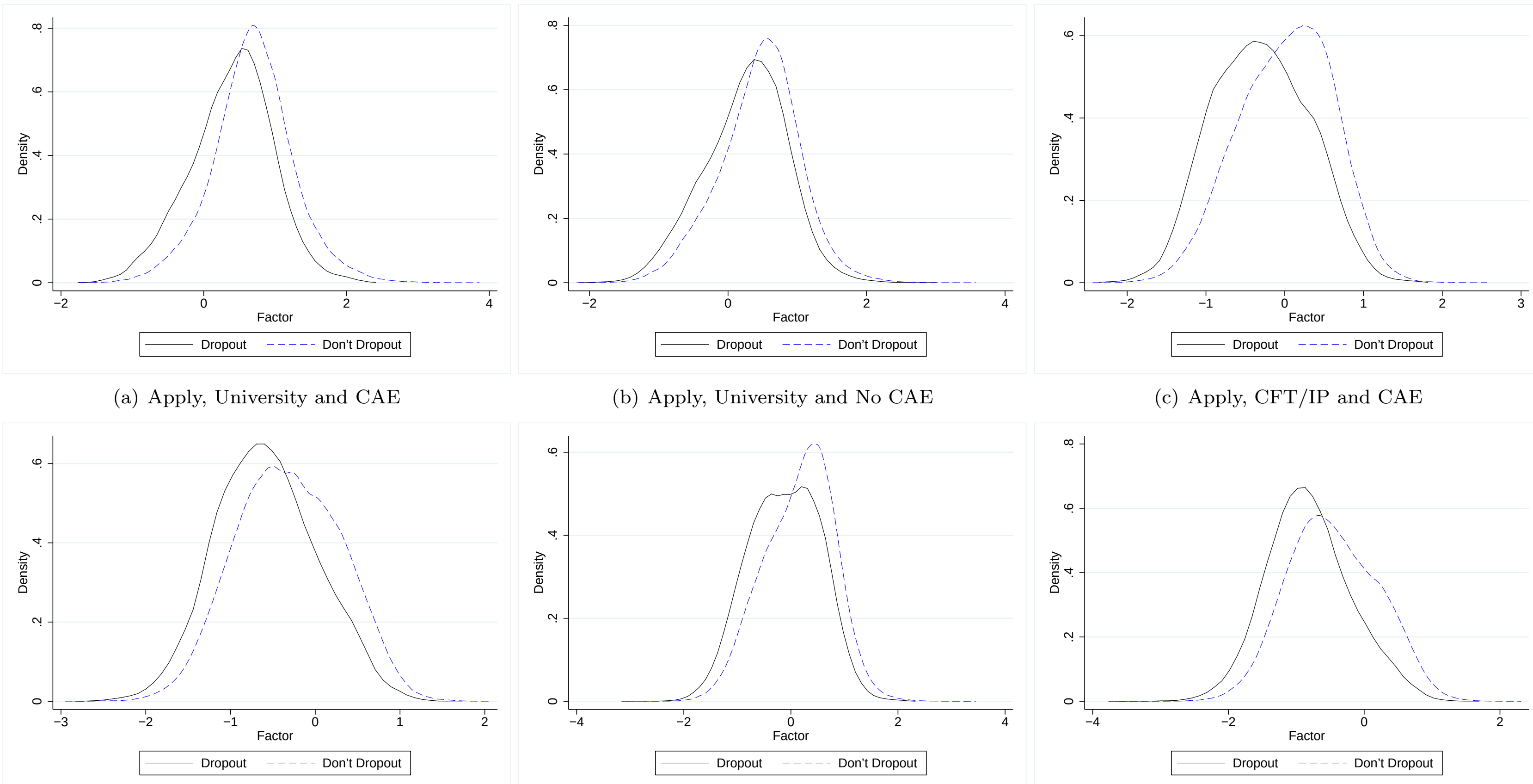
(b) Don't Apply for CAE

Figure 9: Distribution of Factor by HEI Type.



(a) University (b) CFT/IP

Figure 10: Distribution of Factor by CAE Assigment.



(a) Apply, University and CAE

(b) Apply, University and No CAE

(c) Apply, CFT/IP and CAE

(d) Apply, CFT/IP and No CAE

(e) Don't Apply and University

(f) Don't Apply and CFT/IP

Figure 11: Distribution of Factor by Dropout Decision.

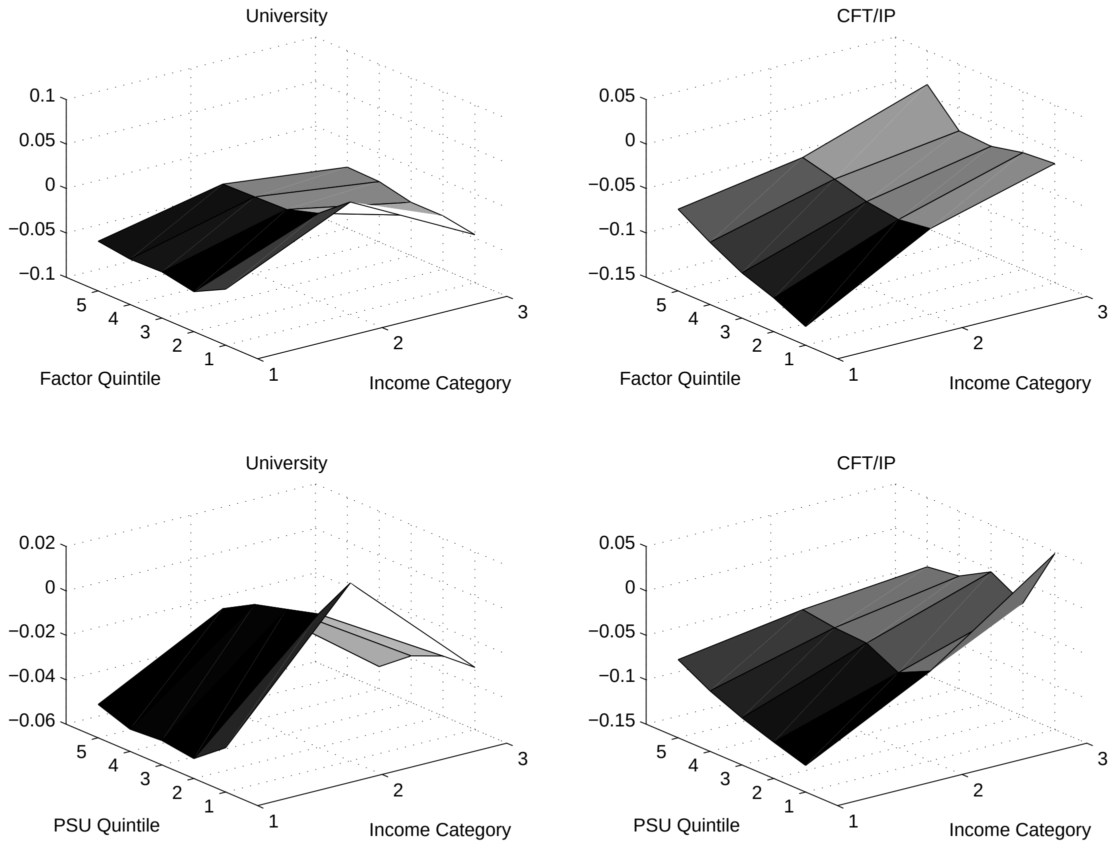


Figure 12: Impact of the CAE on Dropout Rates Conditional on Income and Skill Measures.