Loans for Higher Education: Does the Dream Come True?*

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Abstract

This paper analyzes the impact of student loans for higher education on dropout decisions and future earnings. We posit a structural model of sequential schooling decisions which is estimated using rich administrative data from Chile. We allow for heterogeneity in both observed and unobserved variables. In our model, individuals can choose among institutions offering different type of degrees. Our empirical strategy benefits from a major reform implemented in Chile. In 2006, the government introduced the State Guaranteed Loan (SGL), a new higher education loan system. The new program shares some similarities with the Stafford Loans in the US. The SGL is, to date, the most important funding program for higher education in Chile.

Our results show that it reduces the probability of dropping out from tertiary education. Specifically, the program reduces the first year dropout rate by 12.4% for students enrolled in five-year colleges and 66% for those enrolled in institutions offering two- or four-year degrees. We also find SGL is more effective in reducing the probability of dropping out for low-skilled individuals from low-income families. Our results also show that SGLS beneficiaries have lower wages than those who are not beneficiaries (even after controlling for individual characteristics, and quality measures of higher education institutions). We attribute this to an incentive problem in the design of SGL, which may lead to higher education institutions reducing educational quality of education.

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JEL Classification: C31, D14, I22, I23, I28.

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1 Introduction

This paper investigates the short and long term impacts of loans for higher education. From an economic perspective, loans alleviate short term financial constraints preventing students from accessing tertiary education. Once the student is enrolled, the anticipation of the contracted obligation should motive him to enhance higher levels of efforts, implying a lower probability of dropping out, and eventually, a better performance on the labor market. This explains why many countries have adopted or incentivized systems of student loans. However, the logic critically depends on the mechanism design behind the loan system. We empirically document how an imperfect design can lead to unexpected consequences.

Although short term credit constraints have been reported to be a determinant of the college dropout decision, the evidence shows minor effects the difficulty in identifying credit constrained students have led to the implementation of indirect empirical approaches showing minor effects (**?????**). Moreover, there is some evidence on the potential negative effects of college subsidies on dropout rates. **?** develop an overlapping generation model and simulate different policy experiments. They show that increasing college subsidies increase aggregate college enrollment rate (especially for poorest families) but increase the aggregate college dropout rate.

Even direct approaches that identify constrained students, such as **?** who asked students if they would borrow more at a fair interest rate if offered, suggest that "while credit constraints likely play an important role in the drop-out decisions of some students, the large majority of attrition of students from low income families should be primarily attributed to reasons other than credit constraints."

This article contributes to the literature by analyzing the impact of credit constraints on the decision of dropping out from Higher Education Institutions (HEI) using rich panel data from the Chilean higher education system.[1] Using a unique database that allows us to identify credit constrained students, we estimate a structural model of sequential schooling decisions, allowing for the presence of unobserved heterogeneity (**?**) that is interpreted as a combination of cognitive and noncognitive skills. This is the first model in the context of higher education which integrates selectivity (with flexible functional forms that relax the usual normality assumptions), unobservable skills, and individual characteristics to study the determinants of dropouts.

We focus on the impact of the State Guaranteed Credit program (CAE) on the college dropout decision.[2] This credit shares some similarities with the Federal Guaranteed Loan (Stafford Loan) in the US, in the sense that it guarantees repayment to the lender if a student defaults. Our interest in this program is due to its large impact on access to the higher education system and due to the fact that we are able to identify

[1] We consider higher education dropouts in the first year.
[2] CAE stands for *Crdito con Aval del Estado*.

credit constrained student. As reported in Tables 2 and 3, between 2006 and 2010 the allocation of CAE loans have quadrupled, going from a 10% of the total student aids in 2006 to 43% of aid in 2010.

The related literature for the Chilean case evaluates the effects of credit programs on enrollment and the dropout decision for a subpopulation of students. **?** analyzes the effect of two loan programs (CAE and a different program for a reduced set of public universities) on enrollment and dropout rates finding a significant negative effect. He exploits the discontinuity in the assignment rule and estimates a local average treatment effect for a very specific neighborhood of students: those around the minimum qualifying score in the University Selection Test (PSU). He finds a significant effect on enrollment and dropout rates after the first and second year.[3]

We also analyze the impact of the CAE on labor market outputs, which is one important contribution of this paper. The potential impact of this loan program is related to some characteristics of its design. In particular, it gives economic incentives to HEI to reduce dropout rates. This may have consequences in labor market outcomes, such as wages, due to its effects on the quality of accumulated human capital. Thus, we estimate the sequential schooling choice model with a wage model for the same individuals since we are able to match administrative records from 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 the CAE on dropping out (**???**). Hence, there may be sorting in ability, which implies that other factors than monetary costs (e.g. effort) could be affecting the dropout decision.[4] This could be explained by what **?** calls the long-run constraints. These constraints are related to long-run characteristics such as ability unlike short-run constraints such as funding. This paper evaluates the importance of both on the probability of dropping out.

We find that there is sorting in ability such that higher skilled students enroll in universities and have a lower dropout rate after the first year.[5] We also find that the CAE reduces the dropout rate after the first year by 12.4% for universities and and 66% for CFT-IP, after controlling for ability. Also, our results show that both short and long run constraints are binding.

Our results also suggest that although the CAE has positive effects on dropout rates, it may have some negative effects. Specifically, we find that students with CAE have lower wages even after adjusting for individual characteristics, quality measures of higher education institutions, ability and selectivity bias. This may reflect serious issues in the mechanism design of the incentives that the CAE gives to HEI.

The following is the organization of the paper. Section 2 analyzes the institutions and the Chilean

[3]Other studies analyzing the determinants of the dropout decision for the Chilean case includes **?**, **?** and **?** finding that vocational issues, familiar problems, and economic reasons as the most important determinants of dropping out of college.

[4]Tiebout sorting in ability means that there is self-selection in the decisions where ability is a determinant factor, such as the case of higher education dropouts.

[5]We consider two types of HEI: universities and then a category consisting of Centers of Technical Formation (CFT) and Professional Institutes (IP).

system. In section 3 we present the model of sequential decisions with unobserved heterogeneity and section 4 describes the database and presents descriptive statistics. In section 5 we present the estimation results and an analysis of sorting in ability. In section 6 we compute some treatments effects such as the effect of the CAE on dropping out 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 1980s created incentives for private agents to participate in the Chilean education system. This permitted the incorporation of a large number and types of private HEI, including universities, Professional Institutes (IP) and Centers of Technical Formation (CFT).[6] Between 1984 and 2010, enrollment in higher education institutions quadrupled, as shown in Figure 1. This growth was strongly influenced by the universities, as shown in Figure 2.[7] We can see an important break in the trend of enrollment in the early 1990s, when the effects of the educational reform seems to be larger (**?**).

Even though the increasing access to HEI has contributed to increased enrollment, an important goal of public policy in Chile, this has not translated into increased participation in all sectors of society, and the access has been quite uneven (**?**). 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 amount of financial aid that has been awarded to undergraduate students between 1989 and 2009.

In 2006, the Ministry of Education of Chile (MINEDUC) started implementing a new system of credits, the state-guaranteed credit (CAE), where the Chilean government is the guarantor. Given that the student is acquiring an intangible asset (human capital), financial institutions have few incentives to lend to vulnerable students, thus necessitating Chile as guarantor.

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

In addition to increased coverage as described before, a second purpose of the CAE is to allow students to not have to work/worry about their tuition, which would reduce the high dropout rates in higher education (which presented in Table 1), which is supported by national and international literature (**???**). At an

[6] The CFT are institutions that are allowed to grant technical degrees and IP are permitted to grant technical and professional degrees that not require a bachelor's degree.

[7] According to **?** the number of universities increased from 10 in 1981 to 60 in 2009.

aggregate level, we can see that the CAE has not had a decisive impact on dropout rates, as described in Table 5. However, it is important to note that this is an aggregate level and thus lacks precision. This analysis will be made more precise later in this article.

Regarding the formalities of the application process to the CAE, the applicants must meet certain requirements. Among these are to be Chilean, get above 475 points on the University Selection Test (PSU), maintain a satisfactory academic performance, have not graduated from any HEI or dropped out more than once from a higher education institution, have a socio-economic environment that justifies the allocation of CAE, and certify that they are enrolled at a HEI (certificate of registry or letter of acceptance).[8][9] The loans are granted through the financial institutions (typically banks). The Chilean government auction packages of students' loans (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 loans to the students.

Once assigned the CAE, the beneficiary must meet many requirements, which depend on the stage of study. If the beneficiary is studying and dropped out from the HEI, the mechanism that begins to operate is the "guarantee for academic dropout".[10] This guarantee is granted by the HEI (which can be at most 90% of the principal plus interest) and operates as long as the individual is in the HEI. If a student drops out, the HEI must reimburse the lending institution. In the event that the HEI guarantee is less than 90% of the capital (plus interest), the government 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 cover.

The HEI, even when the student is on the verge of graduating, always covers 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.[11] The HEI will continue the collection process with the financial institution as the debt acquired by the student is not longer enforceable.

An important factor to be considered is that the collection process for a student who has not graduated may be very complicated and expensive, especially if the student does not have a guarantee. The design of the CAE creates incentives for the HEIs to reduce dropout rates. To the extent that these incentives imply lower academic standards, the mechanism design can impact the quality of education.[12] Our results suggest that this is indeed the case.

[8]The University Selection Test (*Prueba de Selección Universitaria*, PSU) is a standardized test needed to access the Chilean higher education system. It assesses, by separate tests, language and communication skills, mathematics, social sciences and history, and science. Math and language are required and students must take one of the last two.

[9]In case a student is applying for a CFT or IP it is allowed 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.

[10]A dropout is defined formally as an unjustified schooling interruption for at least 12 consecutive months.

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

[12]Easier courses or lower failure rates, for example, are mechanisms that HEI can use to prevent dropouts. These measures have a direct effect on the quality of education.

In cases where the beneficiaries have graduated another collection mechanism operates, the "state guarantee". If the graduate cannot meet the quotas for repaying the CAE (with a grace period of 18 months after graduation), financial institutions may start legal proceedings. If this is not possible, the institutions have the right to require to Chile to pay the guarantee, which corresponds to 90% of the amount due including capitalized interests.

3 A Simple Structural Model for Dropout Decisions with Unobserved Heterogeneity

The highest level of education achieved by each individual is the conclusion of a sequence of decisions determined 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. Furthermore, the choices made also depend 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 as the final 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 **?**, **?**, **?**, and **?**. These endowments are a combination of cognitive and noncognitive unobservable skills, which can vary among individuals and determine 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: before taking the University Selection Test (PSU), students can apply for the CAE and then, after learning the test results, they can enroll in Centers of Technical Formation (CFT), Professional Institutes (IP) or in universities.[13]

The conditions, as explained above, for being eligible for the CAE are that there must be proof of admission (registration or an acceptance letter, for example) and others such as socioeconomic requirements. After that, the credit is assigned (or not) and eventually they may choose to complete the first year or dropout from the corresponding HEI.

[13] For purposes of this paper we consider two groups of institutions: universities and non universities, the CFT-IP.

3.1 The Model

We model a tree of sequential binary decisions, which is based on structural choice models closely related to **?**. Following **?** we model the decisions as follows.

Consider a choice node j (for instance, applied or not to the CAE). Let $V_{id(j)}$ the indirect utility individual 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 is conditional in being at node j.[14]

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.[15] Thus, we observe sequences of decisions in terminal nodes, noted as $\mathbf{D}_l$, with $l = 1, 2, \ldots, L$.[16] In Figure 5 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 non 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:

[14] In particular, we consider five nodes: the first one is the decision to apply to 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 consider the allocation of the CAE conditional in that individuals enroll in a university or CFT/IP and apply to the CAE.

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

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

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

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.

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 decisions are correlated with the outcomes, which implies that self-selection is based on unobservables factors. 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 6. Imposing some structure for the factor allows us to identify the effect of ability in the sequential choices. Thus, the structure is as follows:

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

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

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

Following **?** and **?**, 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 scores".[17] The equations describing these scores are

[17] Then we consider three measures: high school GPA, language and mathematics PSU scores.

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

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.[18]

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

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

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 allows 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). Con-

[18] **?** shows that three is the minimum number of measurements to achieve identification, which is our case.

sequently, 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 **?** and **?**. 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, and test scores and their determinants ($\mathbf{D}_l$, $\mathbf{Z}$, $\mathbf{Y}$, $\mathbf{M}$, $\mathbf{T}$ and $\mathbf{X}$, respectively). As it was described, the timing of the decisions is the following: an individual i decides to apply to CAE, then she takes the PSU, decides to enroll in an university or in a CFT/IP, and finally she decides whether to drop out or not after the first year. We observe 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 to 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.[19] To identify 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. This could be unfeasible if we consider individuals enrolled in 2007 because a large fraction of them would not necessarily be 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.[20] Thus, we will be able to estimate different parameters of interest to individuals from all quintiles of the income distribution using this mistake.

The enrollment data was merged with administrative records from the University Selection Test (PSU) undertaken in 2005. It added information on test scores, as well as socioeconomic characteristics and family background. Additionally, administrative data from the CAE permitted the identification of CAE applicants and those who obtained the credit in 2006. The number of observations of the merged database is 31481.[21]

Tables 6 and 7 show some descriptive statistics separated by decision node and choice. The variables included are a gender dummy (where female is the baseline), age (in 2006), geographic zone dummies for North and South, family size, and family income dummies in Chilean pesos with the base category of 0 to $278.000.

We also include dummies for parents' schooling years with base category of less than 8 years of schooling. We add dummies for funding characteristics of (graduating) school: public and private-voucher dummies (where graduating from private school is the base category), a dummy for scholarship during the first year, and dummies for educational categories of the higher education program the student is enrolled in, according

[19] 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.

[20] The misallocation of the loans was due to a computational mistake that assigned the CAE to individuals in the fourth and fifth quintiles. Political pressure led to an increase in the number of loans assigned to students in the lowest three quintiles. For details see **?**.

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

to the MINEDUC definition (the educational category of Administration and Commerce is the base). We also consider the length of the program measured in number of semesters, years of accreditation of the higher education institutions (as a measure of HEI quality), and test scores (mathematics and language) along with high school GPA.

5 Results

In Table 8 we present the estimation of the parameters of intermediate decision nodes D_1, D_2, D_3, D_4, and D_5. Note that men have a lower probability of applying to CAE, enrolling in a university, and obtaining the credit. On the other hand, older applicants tend to enroll more in universities and, conditional on this, 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 from the center. Once enrolled in a university, people from the north and south have a lower probability of obtaining the CAE.

The more people in the household, the lower the probability of receiving the credit for those enrolled in any HEI. Additionally, students from high-income families tend to enroll in universities and not apply to CAE. Regarding 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 the misallocation of credits that occurred in 2006 (Ingresa, 2010).

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

Finally, we see the importance of ability (measured by the factor) in schooling and financing decisions. Individuals with higher ability apply more to CAE and are more likely to enroll in universities. Also, high ability applicants have a higher probability of receiving the CAE. This is interesting since the credit should not be assigned by academic merit or ability, except for the minimum passing score.[22]

Table 9 presents the estimation of the decision of dropping out.[23] In some nodes, men have a higher probability of dropping out. In three nodes ($\mathbf{D}_2, \mathbf{D}_4, \mathbf{D}_5$) older students have a higher probability of dropping out. On the other hand, geographic region dummies do not play a role on explaining dropout decisions, except for students who did not apply to the CAE and enrolled in a CFT/IP. In that case, people in the north show

[22] 475 in PSU test score or a GPA of 5.3 for the case of CFT and IP.

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

a higher probability of dropping out.

Regarding to family background we have that, students from larger households have a higher probability of dropping out, and the higher the family income, the lower the probability of dropping out. Attending 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 significantly decreases the probability of dropping out after the first year in most terminal nodes.

Education categories have mixed impacts on the probability of the dropping out. We have that Arts and Architecture are associated with a higher probability of dropping out, conditional on being enrolled in a university and not receiving the CAE. While those enrolled in programs related to Basic Sciences have a higher probability of dropping out. Social Sciences and Agriculture programs do not exhibit any particular effect on the probability of dropping out. For people enrolled in Law, there is no relationship with dropping out decision except for those who did not apply to the CAE and enrolled in a university. This probability is lower for students in Education with no credit (applicants and no applicants) and higher for those in Humanities. We see that the Health category reduces the probability of dropping out for individuals enrolled in a CFT/IP who did not apply to the CAE. On the other hand, those enrolled in the Technology educational category are more likely to drop out conditional on not applying to the CAE and being enrolled in a university.

Finally, we can see that career length increases the probability of dropping out while the years of accreditation of the HEI reduce this probability for those enrolled in a CFT/IP and did not obtain the CAE. We also see that ability (measured by the factor) is negatively correlated with dropping out. It is important to mention that, 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 10 presents the results for the wage equations.[24] We can see that men have higher wages than women. Wages increase with age and, in general, with being enrolled in a career in of the Administration and Commerce area. The career length is negatively related with wages, which can be related to the fact that those enrolled in longer careers have spent less time in the labor market while the HEI years of accreditation do not have a clear effect on wages. Last, we see that ability is strongly related with wages for those who did not drop out after the first year.

Now we analyze the results for the test score equations. In Table 11 we can see that men perform better than women in mathematics and worst in language. It can be observed that older people perform better in the PSU but have lower high school GPAs. Living in the north decreases the three scores measures and those from the south perform better in language and have higher high school GPAs compared to those living

[24]We did not include characteristics of career they attended for those who dropped out in the first year.

in the center of the country.

The number of people in the household is negatively correlated with PSU scores and GPA and the opposite occurs for family income. Having attended a public or private-voucher school is negatively associated with all three scores. We can see that parent's education positively affects PSU scores but is negatively correlated with high school GPA. Last, we observe that ability is 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.[25] We first implement a simple hypothesis test through decision nodes. In Table 12 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 most of the single hypothesis tests cannot be rejected at a 1% level, which means that our structural model performs well at least in 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 13. There is no evidence to reject the null of joint equality between the predictions of the model and the actual data.

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 its 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*.[26]

Figure 6 shows 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.[27]

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

The distribution of ability by type of HEI is presented in Figure 8. We see that there is positive sorting

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

[26] The simulation considers one million observations

[27] Additionally, we performed a normality test and reject the null hypothesis of normality.

(regarding to ability) in university enrollment: more able students enroll in universities instead of CFT/IP. This is consistent with what we found in Table 8, where the ability factor is a strong predictor of the decision of enrolling in a university.

Figure 9 presents the distribution of the ability factor according to having obtained the CAE or not, conditional on having applied. We can see that, either for those enrolled in a university or a CFT/IP, more able students have a higher probability of getting the CAE but this sorting is stronger for those enrolled in a CFT/IP. This agrees with Table 8 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 10 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, having received the CAE, and having enrolled in a university or a CFT/IP. These results coincide with those found in Table 9, where the ability factor is consistently negative in the dropping out decision.[28]

6 Treatment Effects

In this section we estimate the causal effect of having the CAE on the probability of dropping out after the first year. We also estimate the effect of having the CAE on wages five years after enrolling in a HEI for those who did not dropout (in the first year).

6.1 On the Effects of CAE on Dropout Decision

We estimate the causal impact of the CAE on the probability of dropping out of a HEI, separated by type of institution: university or CFT/IP. It is important to mention that this type of estimation is likely to suffer from endogeneity/selectivity issues (**??**). 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 presented Table 5, which shows that there was no apparent change in dropouts rates before and after the introduction of the CAE in 2006.[29] However, a correct exercise would be such that analyzes the effect of the CAE on dropout rates, relative to those without CAE, controlling for observable variables and ability.

[28] We performed stochastic dominance analysis for all comparisons finding first order dominance in all pair wise comparisons mentioned.

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

A first approach is to compute the unconditional impact of CAE on the dropping out of a HEI after the first year.[30] 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 a 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.[31] 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 14 we present our estimates for the treatment parameters. We observe that the impacts 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 a university the CAE reduces the probability by 1.6 percentage points that corresponds to a reduction of 12.4% in the dropout rate for students enrolled in this type of FEI. For students enrolled in a CFT/IP, we have a higher impact, close to 10.9 percentage points, corresponding to a decrease of 66% of the dropout rate.[32][33] These results differ from 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. Our results differ from those of **?** since he finds a decrease of 6 percentage points for students enrolled in universities corresponding to a decrease of 46.5% in the dropout rate instead of the 12.4% that we find. Certainly our estimates correspond to the average treatment effect and **?**' are local average treatment effects for a very specific population.

A more detailed analysis requires to conditioning in other type of variables besides 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

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

[31] In the decision tree presented in Figure 5, these parameters answer the question: what would have been the dropout rates for those in $\mathbf{D}_2$ and $\mathbf{D}_4$ if they had obtained the CAE respectively.

[32] For these calculations we consider the dropout rates of nodes $\mathbf{D}_2$ and $\mathbf{D}_4$ from Figure 5.

[33] Alternatively, we can see that in our sample, if individuals in nodes $\mathbf{D}_2$ and $\mathbf{D}_4$ (see Figure 5) received the CAE, there would 750 less dropouts in universities and 1443 less dropouts in CFT/IPs after the first year, respectively.

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

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

Where the vector X includes family income categories, quintiles of (ability) factor, and quintiles of PSU scores.[34] The factor quintiles represent a mixed of cognitive and noncognitive unobservable abilities and the PSU quintiles are a proxy of cognitive ability. Three income categories are considered due to the reduced number of observations in the higher tail of the income distribution in our sample.[35]

In Table 15 we present the effect of CAE on dropout rates for those enrolled in a university and applied to the CAE by income category and factor quintile. Similarly, in Table 16 we present the same effect but instead of factor quintile, we consider PSU score. It is important to note that students enrolled in universities from low-income families benefit more in reduction in dropout rates. When factor quintiles are considered, we see that individuals with lower factor benefit more. When we condition on both income category and quintile of the factor (or PSU score) we see that there is not a clear pattern. We also observe that less able students from income categories 1 and 3 benefit more than those from income category 2.

Similarly, Tables 17 and 18 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 benefit more in terms of reduction of dropout rates, as in the previous analysis. Second, students with lower level of ability benefit 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 benefit more in terms of reduction of dropout rates.

In Figure 11 we summarize the previous results. We plot the impact of the CAE on dropout rates in percentage points over income category and factor (PSU scores) quintiles for type of HEI.

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

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

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

6.2 Credit Access and Wages

We now estimate the impact of CAE on wages. The design of this program may lead to higher education institutions decreasing 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 an incentive to ensure graduation.[36] Although the Chilean higher education system does not have a method to measure the quality of its graduates, we can use information about the labor market performance of individuals 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, 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 to apply to the CAE. This does not only determine the type of financing that she will eventually have access to, but also the type of institution where she can study. 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:

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

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

and

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

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

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.[37] The second pair of parameters identify the impact of getting the CAE vs. having not

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

[37] According to Figure 5 this is equivalent when comparing wages of those in node $\mathbf{D}_1$ who did not drop out, with wages of those in node $\mathbf{D}_2$ who did not drop out. For those in a CFT/IP, this is equivalent to comparing wages of people at node $\mathbf{D}_3$ and did not drop out, with those from individuals at node $\mathbf{D}_4$ and also did not drop out.

even applied to the CAE.[38]

In Table 19 we present the results of the estimation. We can see that for those enrolled in a university, the impact of getting the CAE on wages is -1.8%. For those enrolled in a CFT/IP, the impact of CAE on wages is -4.8%. 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 13.2% 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 9.2%. These results are statistically significant at 1% level.[39][40]

The results show that after controlling for self-selection and endogeneity in the decisions, individuals with CAE in the first year, have lower wages five years after in the labor market in comparison to those that study without CAE.

6.2.1 Understanding the Wage Gap

According to the results, the CAE reduces the probability of dropping out after the first year. Thus, comparing the wages of those who did not dropout and received CAE versus those who did not obtain CAE, needs a labor market experience adjustment. This is due to the fact that the individuals who did not obtain the CAE have, according to the estimations in this section, a greater probability of dropping out in the future than those with the CAE.

In Tables 20 and 21 we show the cumulative average number of pension contributions between 2007 and 2010 for individuals enrolled in universities and CFT/IP. For university enrollees we fail to reject the null hypothesis of equality of pension contributions between CAE and non-CAE recipients for most years. On the other hand, for CFT/IP enrollees, the number of pension contributions is larger for those who did not obtain the CAE. This difference is 3.7 contributions and seems to not account for the wage gap. For instance, according to **?** the average annual return to experience is 2.4%, hence this could explain a 0.07% of wage gap but we observe a wage gap of at least -4.8% (depending on the treatment effect considered) between CAE recipients and non-recipients.

[38] According to Figure 5 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.

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

[40] 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.

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 explained before, HEI are responsible for the credit during the period in which beneficiaries are enrolled. Thus, higher education institutions have an incentive to ensure graduation. This may be affecting the quality of the average CAE graduates, which is reflected in wages. 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 dropping out from higher education is an important topic in the literature and several approaches have been implemented to estimate it. However, the evidence is mixed and there is not any clarity on the importance of credit constraints on dropout decision as pointed out by **?**.

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

Our results suggest that there is sorting in ability, where more able students enroll in universities and dropout less often. There is heterogeneity in the results of the effect of the CAE on dropout decisions. We find also that the CAE reduces the dropout rate after the first year by 12.4% for universities and 66% for CFT-IP, controlling for ability.

We also compute the impact of the CAE for different levels of family income and ability. This allows us to investigate if there are short-run (related to income) and long-run (related to ability) constraints, as defined by **?**. We find a significantly higher impact on dropout rates for students with low level of ability from poorer families.

Although the CAE has positive effects on dropout rates, it may have some negative effects. In particular, we find that students with CAE have lower wages even after adjusting for ability and HEI quality measures. This may reflect serious issues in the mechanism design of the incentives to HEI with students with CAE as these institutions benefit more from retaining students.

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 on the impact of CAE on wages shows that the beneficiaries of this credit will be harmed by getting lower wages, even after controlling for selection bias, endogeneity, and unobserved heterogeneity. These results question the design of this instrument and call for an urgent revision due to its incentives to reduce dropouts via lowering retention requirements and, thus, reducing the quality standards.

Tables

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 Educacin.
Cohorts from 2004 to 2009 are considered.
IP stands for *Institutos Profesionales* and CFT for *Centros de Formacin Tcnica*.

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	1^{st}	2^{nd}	3^{rd} and on		
HEI	90%	70%	60%	60%	60%
Government	0%	20%	30%	30%	30%

Source: SIES/MINEDUC.

Table 5: Average Dropout Rates by HEI Type

HEI Type	Dropout Rate	First Year	Second Year	Third Year	Fourth Year
University	Before 2006	20.0%	30.4%	37.4%	42.6%
	After 2006	19.9%	31.1%	38.5%	43.2%
IP	Before 2006	31.7%	47.9%	57.4%	61.7%
	After 2006	37.2%	54.7%	63.0%	66.2%
CFT	Before 2006	34.1%	47.5%	52.1%	52.6%
	After 2006	32.7%	46.9%	51.6%	54.7%

Source: Authors' Elaboration based on Consejo Nacional de Educacin.

Table 6: 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 8: 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	-0.311	-0.072	0.088	-0.834	0.127
	(0.095)	(0.189)	(0.127)	(0.187)	(0.310)
Gender	-0.079	-0.235	-0.222	-0.118	-0.320
	(0.015)	(0.031)	(0.021)	(0.032)	(0.045)
Age	-0.006	0.038	0.024	0.026	0.001
	(0.004)	(0.009)	(0.006)	(0.008)	(0.013)
North	-0.188	0.307	0.302	-0.695	-0.049
	(0.023)	(0.048)	(0.031)	(0.058)	(0.079)
South	0.136	0.336	0.235	-0.582	0.064
	(0.020)	(0.038)	(0.028)	(0.042)	(0.058)
Size of Familiar Group	-0.008	-0.006	-0.007	-0.027	-0.028
	(0.005)	(0.010)	(0.007)	(0.011)	(0.016)
Household Income 278-834 (Thousands of Pesos)	-0.193	0.351	0.365	0.257	0.099
	(0.017)	(0.034)	(0.024)	(0.034)	(0.054)
Household Income 834-1.400 (Thousands of Pesos)	-0.671	0.588	0.684	0.686	0.181
	(0.042)	(0.101)	(0.048)	(0.082)	(0.189)
Household Income 1.400-1.950 (Thousands of Pesos)	-0.976	0.915	0.922	1.032	0.474
	(0.082)	(0.265)	(0.092)	(0.188)	(0.531)
Household Income 1.950 and More (Thousands of Pesos)	-1.598	0.434	0.975	0.755	-0.050
	(0.101)	(0.330)	(0.078)	(0.328)	(0.556)
Public School	0.321	-0.450	-0.549	-0.368	-0.096
	(0.038)	(0.086)	(0.046)	(0.074)	(0.151)
Private-Voucher School	0.296	-0.347	-0.434	-0.224	-0.114
	(0.037)	(0.085)	(0.044)	(0.071)	(0.149)
Factor	0.540	1.123	0.867	0.435	0.599
	(0.013)	(0.031)	(0.017)	(0.034)	(0.048)

Note: Standard errors in parentheses.

Table 7: 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	0.077	0.037	0.036	0.175	0.018	0.058	0.014	0.044	0.240	0.136
	(0.267)	(0.188)	(0.186)	(0.380)	(0.134)	(0.234)	(0.119)	(0.205)	(0.427)	(0.343)
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)
HEI Years of Accreditation	2.507	2.363	2.100	3.465	1.734	3.107	2.861	1.828	4.223	3.015
	(2.248)	(2.409)	(2.008)	(2.482)	(1.991)	(2.638)	(1.585)	(2.072)	(1.880)	(2.679)
GPA	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 9: 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	-2.042	-3.269	-2.220	-3.389	-2.363	-1.417
	(0.473)	(0.313)	(0.991)	(0.522)	(0.201)	(0.237)
Gender	0.340	0.119	0.305	0.094	0.142	0.177
	(0.084)	(0.047)	(0.122)	(0.080)	(0.035)	(0.040)
Age	0.015	0.059	-0.031	0.079	0.022	-0.011
	(0.021)	(0.010)	(0.041)	(0.019)	(0.008)	(0.010)
North	0.184	0.074	0.243	0.181	0.029	0.280
	(0.166)	(0.060)	(0.185)	(0.115)	(0.044)	(0.050)
South	-0.060	-0.097	-0.012	-0.122	0.030	-0.024
	(0.136)	(0.054)	(0.155)	(0.089)	(0.044)	(0.048)
Size of Familiar Group	0.002	0.055	0.094	0.035	0.046	0.047
	(0.029)	(0.014)	(0.037)	(0.021)	(0.010)	(0.011)
Household Income 278-834 (Thousands of Pesos)	0.047	-0.220	-0.040	-0.176	-0.261	-0.259
	(0.091)	(0.050)	(0.141)	(0.085)	(0.036)	(0.041)
Household Income 834-1.400 (Thousands of Pesos)	-0.325	-0.326	-	-0.707	-0.378	-0.517
	(0.229)	(0.166)	-	(0.378)	(0.068)	(0.108)
Household Income 1.400-1.950 (Thousands of Pesos)	-0.207	-0.250	-	0.653	-0.379	-1.021
	(0.376)	(0.434)	-	(0.769)	(0.105)	(0.300)
Household Income 1.950 and More (Thousands of Pesos)	-	0.319	-	0.236	-0.529	-0.354
	-	(0.526)	-	(0.730)	(0.110)	(0.184)
Public School	0.339	0.418	0.566	0.663	0.382	0.284
	(0.189)	(0.134)	(0.537)	(0.303)	(0.067)	(0.096)
Private-Voucher School	0.238	0.285	0.511	0.397	0.244	0.185
	(0.183)	(0.134)	(0.535)	(0.304)	(0.065)	(0.093)
Scholarship	-	-0.037	-	-0.268	-0.179	-0.214
	-	(0.129)	-	(0.112)	(0.143)	(0.080)
Agricultural and Livestock	-	-0.047	-	0.220	0.155	-0.152
	-	(0.14)	-	(0.223)	(0.104)	(0.115)
Arts and Architecture	-	0.278	-	0.086	0.082	0.044
	-	(0.125)	-	(0.149)	(0.097)	(0.073)
Basic Sciences	-	0.515	-	-	0.324	-
	-	(0.143)	-	-	(0.114)	-
Social Sciences	-	-0.108	-	0.156	-0.117	0.048
	-	(0.104)	-	(0.150)	(0.079)	(0.078)
Law	-	0.077	-	-0.042	0.213	0.032
	-	(0.118)	-	(0.145)	(0.083)	(0.065)
Education	-	-0.353	-	-0.081	-0.178	-0.13
	-	(0.093)	-	(0.155)	(0.072)	(0.072)
Humanities	-	0.289	-	-	0.188	-
	-	(0.154)	-	-	(0.125)	-
Health	-	0.026	-	0.015	0.157	-0.158
	-	(0.109)	-	(0.128)	(0.082)	(0.064)
Technology	-	0.071	-	0.153	0.167	0.037
	-	(0.094)	-	(0.106)	(0.075)	(0.053)
Number of Semesters	-	0.068	-	0.041	0.041	0.015
	-	(0.014)	-	(0.021)	(0.010)	(0.011)
HEI Years of Accreditation	0.041	-0.011	-	-0.085	-0.011	-0.093
	(0.030)	(0.012)	-	(0.014)	(0.010)	(0.007)
Factor	-0.531	-0.502	-0.475	-0.413	-0.387	-0.475
	(0.128)	(0.049)	(0.136)	(0.073)	(0.031)	(0.034)

Note: Standard errors in parentheses.

Table 10: 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	11.776	12.513	11.359	12.799	14.313	12.431	12.702	12.551	11.532	12.744	12.157	12.195
	(0.532)	(0.251)	(0.237)	(0.142)	(1.539)	(0.244)	(0.353)	(0.206)	(0.186)	(0.105)	(0.180)	(0.096)
Gender	0.231	0.009	0.167	-0.005	0.156	0.018	0.211	0.022	0.157	0.025	0.276	0.041
	(0.120)	(0.043)	(0.058)	(0.025)	(0.197)	(0.047)	(0.076)	(0.040)	(0.042)	(0.020)	(0.038)	(0.018)
Age	0.018	0.038	0.046	0.022	-0.117	0.009	-0.019	0.005	0.038	0.022	0.008	0.025
	(0.027)	(0.011)	(0.012)	(0.006)	(0.085)	(0.012)	(0.019)	(0.010)	(0.010)	(0.005)	(0.009)	(0.005)
Agricultural and Livestock	-	-0.956	-	-0.326	-	-0.200	-	-0.075	-	-0.479	-	-0.257
	-	(0.131)	-	(0.074)	-	(0.122)	-	(0.118)	-	(0.061)	-	(0.050)
Arts and Architecture	-	-0.626	-	-0.477	-	-0.329	-	-0.245	-	-0.454	-	-0.188
	-	(0.127)	-	(0.078)	-	(0.075)	-	(0.071)	-	(0.052)	-	(0.031)
Basic Sciences	-	-0.931	-	-0.507	-	-	-	-	-	-0.578	-	-
	-	(0.134)	-	(0.088)	-	-	-	-	-	(0.064)	-	-
Social Sciences	-	-0.343	-	-0.182	-	-0.151	-	-0.186	-	-0.054	-	-0.124
	-	(0.092)	-	(0.054)	-	(0.092)	-	(0.078)	-	(0.043)	-	(0.039)
Law	-	-0.927	-	-0.319	-	-0.422	-	-0.253	-	-0.475	-	-0.302
	-	(0.116)	-	(0.068)	-	(0.080)	-	(0.072)	-	(0.047)	-	(0.029)
Education	-	-0.274	-	-0.062	-	-0.354	-	0.002	-	-0.228	-	-0.175
	-	(0.091)	-	(0.049)	-	(0.116)	-	(0.080)	-	(0.038)	-	(0.036)
Humanities	-	-0.922	-	-0.401	-	-0.087	-	-	-	-0.454	-	-
	-	(0.144)	-	(0.095)	-	(0.730)	-	-	-	(0.071)	-	-
Health	-	-0.563	-	-0.162	-	-0.099	-	-0.184	-	-0.353	-	-0.163
	-	(0.094)	-	(0.058)	-	(0.075)	-	(0.062)	-	(0.046)	-	(0.028)
Technology	-	-0.448	-	-0.067	-	0.169	-	0.132	-	-0.212	-	0.076
	-	(0.097)	-	(0.049)	-	(0.064)	-	(0.050)	-	(0.041)	-	(0.022)
Number of Semesters	-	-0.070	-	-0.083	-	-0.006	-	-0.015	-	-0.055	-	-0.006
	-	(0.015)	-	(0.008)	-	(0.016)	-	(0.011)	-	(0.006)	-	(0.005)
HEI Years of Accreditation	-	0.022	-	-0.014	-	0.015	-	0.011	-	-0.005	-	0.010
	-	(0.013)	-	(0.006)	-	(0.013)	-	(0.007)	-	(0.005)	-	(0.003)
Factor	0.095	0.224	-0.001	0.143	0.005	0.111	0.236	0.201	0.000	0.131	0.112	0.158
	(0.161)	(0.057)	(0.052)	(0.024)	(0.244)	(0.048)	(0.075)	(0.035)	(0.033)	(0.017)	(0.037)	(0.014)

Note: Standard errors in parentheses.

Table 11: Estimation Results for Test Score Equations.

	GPA	Mathematics	Language
Constant	1.605	-0.042	-0.521
	(0.070)	(0.065)	(0.064)
Gender	-0.378	0.196	-0.133
	(0.011)	(0.010)	(0.011)
Age	-0.055	0.007	0.041
	(0.003)	(0.003)	(0.003)
North	-0.004	-0.132	-0.269
	(0.016)	(0.015)	(0.015)
South	0.043	0.029	-0.035
	(0.014)	(0.013)	(0.013)
Size of Familiar Group	-0.005	-0.015	-0.022
	(0.004)	(0.004)	(0.003)
Household Income 278-834 (Thousands of Pesos)	0.018	0.178	0.162
	(0.013)	(0.012)	(0.012)
Household Income 834-1.400 (Thousands of Pesos)	0.123	0.364	0.311
	(0.027)	(0.025)	(0.026)
Household Income 1.400-1.950 (Thousands of Pesos)	0.246	0.565	0.470
	(0.044)	(0.043)	(0.041)
Household Income 1.950 and More (Thousands of Pesos)	0.339	0.669	0.515
	(0.040)	(0.039)	(0.040)
Public School	-0.116	-0.425	-0.397
	(0.024)	(0.024)	(0.024)
Private-Voucher School	-0.170	-0.378	-0.302
	(0.023)	(0.022)	(0.022)
Father's Education: 8-12 Years	-0.102	0.003	0.032
	(0.021)	(0.019)	(0.019)
Father's Education: 12 Years	-0.180	0.019	0.066
	(0.022)	(0.019)	(0.019)
Father's Education: More than 12 Years	-0.153	0.187	0.227
	(0.023)	(0.021)	(0.021)
Mother's Education: 8-12 Years	-0.127	0.022	0.020
	(0.020)	(0.018)	(0.019)
Mother's Education: 12 Years	-0.155	0.074	0.080
	(0.021)	(0.018)	(0.019)
Mother's Education: More than 12 Years	-0.125	0.203	0.232
	(0.023)	(0.021)	(0.021)
Factor	0.758	1.000	0.970
	(0.008)	(0.000)	(0.008)

Note: Standard errors in parentheses.

Table 12: Goodness of Fit - Model Choices.

	Actual	Model	P-Value
D_1	0.372	0.371	0.962
D_2	0.702	0.701	0.924
D_3	0.542	0.546	0.491
D_4	0.264	0.264	0.930
D_5	0.373	0.366	0.258
$\Lambda^{\mathbf{D}_1}$	0.072	0.070	0.962
$\Lambda^{\mathbf{D}_2}$	0.122	0.111	0.016
$\Lambda^{\mathbf{D}_3}$	0.058	0.059	0.728
$\Lambda^{\mathbf{D}_4}$	0.165	0.201	0.000
$\Lambda^{\mathbf{D}_5}$	0.122	0.118	0.267
$\Lambda^{\mathbf{D}_6}$	0.152	0.169	0.002

Table 13: Goodness of Fit - Joint Test.

P-Value	0.852

Table 14: Estimated Impact of the CAE on Dropout Rates.

$\Upsilon^{CAE}_{D_4=1}$	-0.016^{***}
$\Upsilon^{CAE}_{D_5=1}$	-0.109^{***}

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

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

		Income Category			
		1	2	3	Unconditional
	1	-0.048^{***}	0.019^{***}	-0.044^{***}	-0.022^{***}
Factor	2	-0.030^{***}	0.011^{***}	-0.035^{***}	-0.017^{***}
Quintile	3	-0.027^{***}	0.009^{***}	-0.029^{***}	-0.017^{***}
	4	-0.027^{***}	0.005^{**}	-0.028^{***}	-0.012^{***}
	5	-0.022^{***}	0.002	-0.019^{***}	-0.013^{***}
	Unconditional	-0.031^{***}	0.009^{**}	-0.031^{***}	-0.016^{***}

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 PSU (University).

		Income Category			
		1	2	3	Unconditional
Factor Quintile	1	-0.041^{***}	0.020^{***}	-0.045^{***}	-0.022^{***}
	2	-0.032^{***}	0.013^{***}	-0.034^{***}	-0.017^{***}
	3	-0.030^{***}	0.006^{**}	-0.036^{***}	-0.017^{***}
	4	-0.025^{***}	0.009^{***}	-0.027^{***}	-0.012^{***}
	5	-0.023^{***}	0.002	-0.027^{***}	-0.013^{***}
	Unconditional	-0.031^{***}	0.009^{***}	-0.031^{***}	-0.016^{***}

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 Factor (CFT/IP).

		Income Category			
		1	2	3	Unconditional
Factor Quintile	1	-0.164^{***}	-0.095^{***}	0.028	-0.142^{***}
	2	-0.138^{***}	-0.088^{***}	-0.016	-0.122^{***}
	3	-0.123^{***}	-0.077^{***}	-0.075^{***}	-0.110^{***}
	4	-0.106^{***}	-0.067^{***}	-0.025	-0.095^{***}
	5	-0.083^{***}	-0.065^{***}	-0.047^{***}	-0.078^{***}
	Unconditional	-0.122^{***}	-0.079^{***}	-0.026^{***}	-0.109^{***}

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

		Income Category			
		1	2	3	Unconditional
Factor Quintile	1	-0.151^{***}	-0.089^{***}	0.037	-0.142^{***}
	2	-0.138^{***}	-0.097^{***}	-0.021	-0.122^{***}
	3	-0.125^{***}	-0.085^{***}	-0.003	-0.110^{***}
	4	-0.106^{***}	-0.070^{***}	-0.025	-0.015^{***}
	5	-0.086^{***}	-0.062^{***}	-0.047^{***}	-0.061^{***}
	Unconditional	-0.122^{***}	-0.079^{***}	-0.026^{***}	-0.109^{***}

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

Parameter	Estimate
$\Delta^{\text{CAE}}_{\mathbf{D}_1,\mathbf{D}_2}$	-0.018^{***}
$\Delta^{\text{CAE}}_{\mathbf{D}_3,\mathbf{D}_4}$	-0.048^{***}
$\Delta^{\text{CAE}}_{\mathbf{D}_1,\mathbf{D}_5}$	-0.132^{***}
$\Delta^{\text{CAE}}_{\mathbf{D}_3,\mathbf{D}_6}$	-0.092^{***}

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

Table 20: Number of Average Pension Contributions for University Enrolled Students.

Year	CAE	No CAE	Same?
2007	2.53	2.31	No
2008	6.12	5.69	No
2009	10.28	9.84	Yes
2010	15.41	15.44	Yes

Note: Students who did not dropout in the first year are considered. Mean difference tests were computed.

Table 21: Number of Average Pension Contributions for CFT/IP Enrolled Students.

Year	CAE	No CAE	Same?
2007	2.51	3.46	No
2008	6.37	8.46	No
2009	11.79	14.91	No
2010	18.88	22.61	No

Note: Students who did not dropout in the first year are considered. Mean difference tests were computed.

Figures

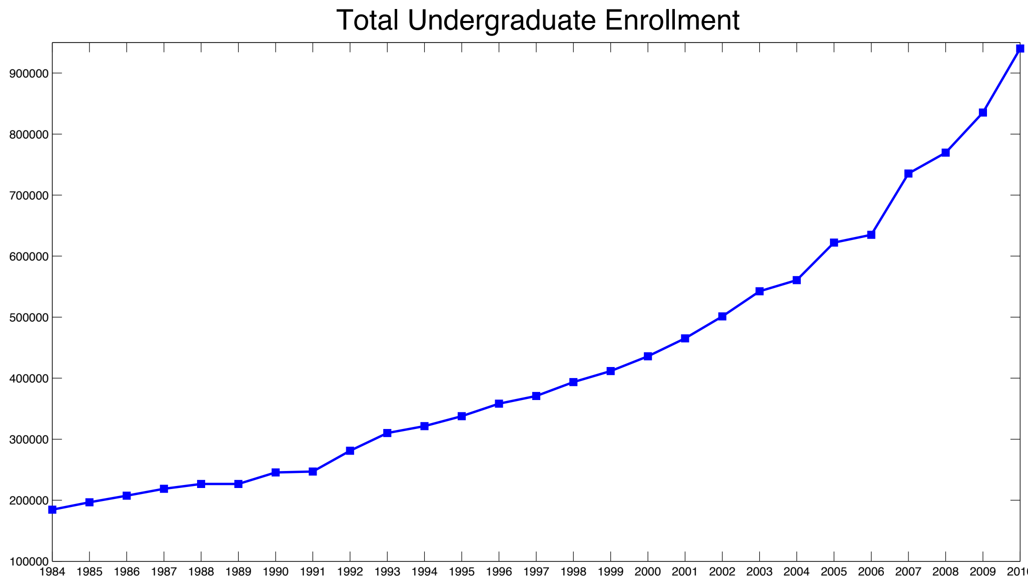


Figure 1: Total Undergraduate Enrollment. Source: SIES/MINEDUC.

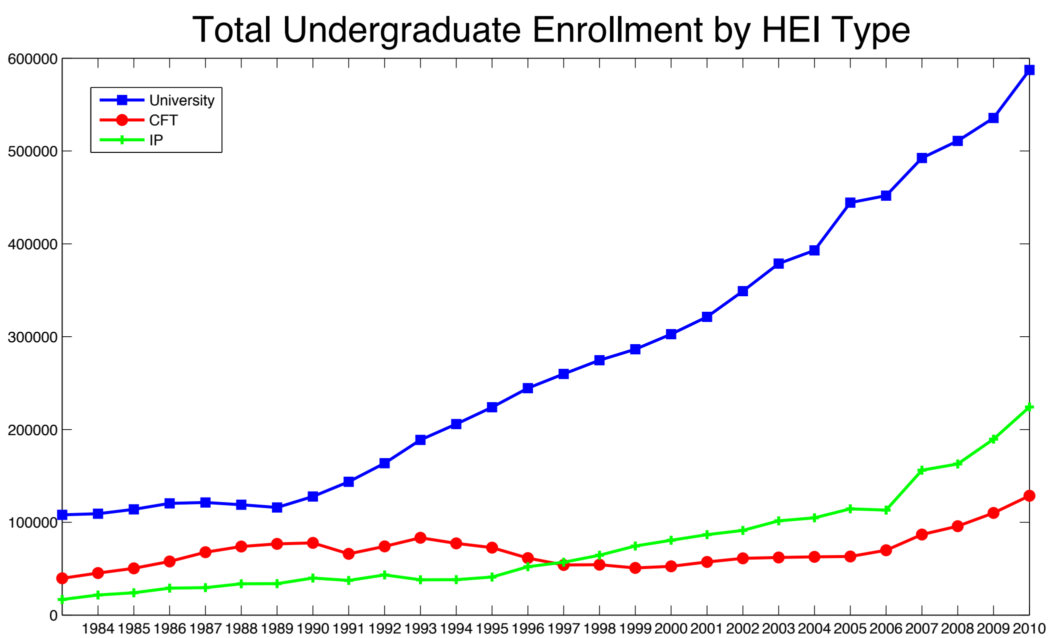


Figure 2: Total Undergraduate Enrollment by HEI Type. Source: SIES/MINEDUC.

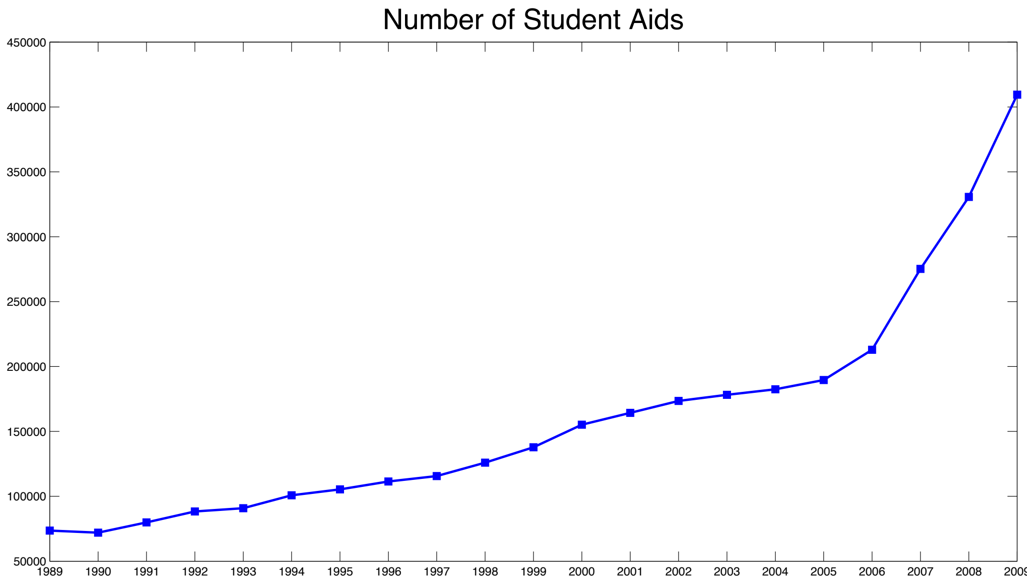


Figure 3: Number of Student Aids. Source: SIES/MINEDUC.

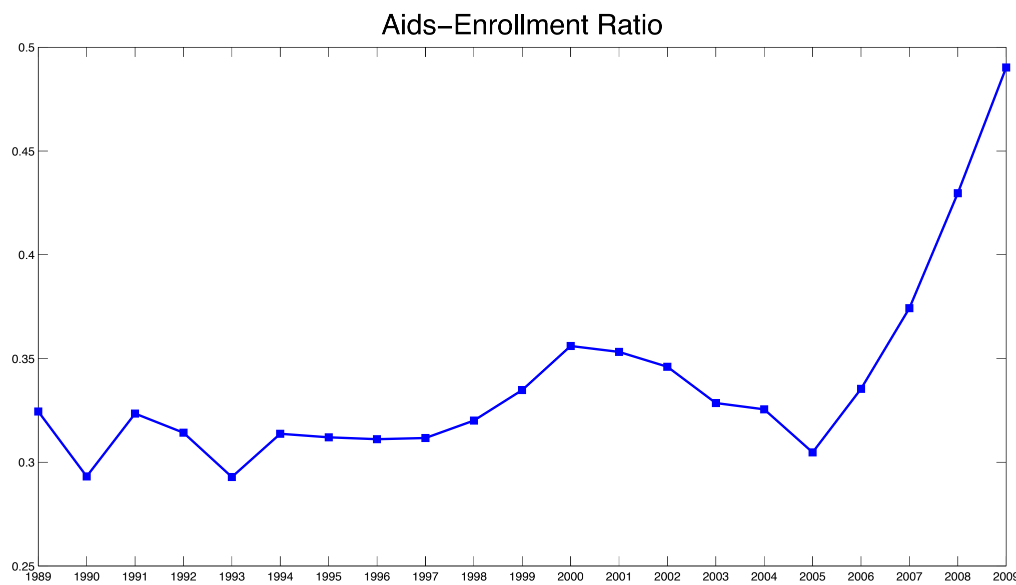


Figure 4: Aids-Enrollment Ratio. Source: Authors' Elaboration based on SIES/MINEDUC.

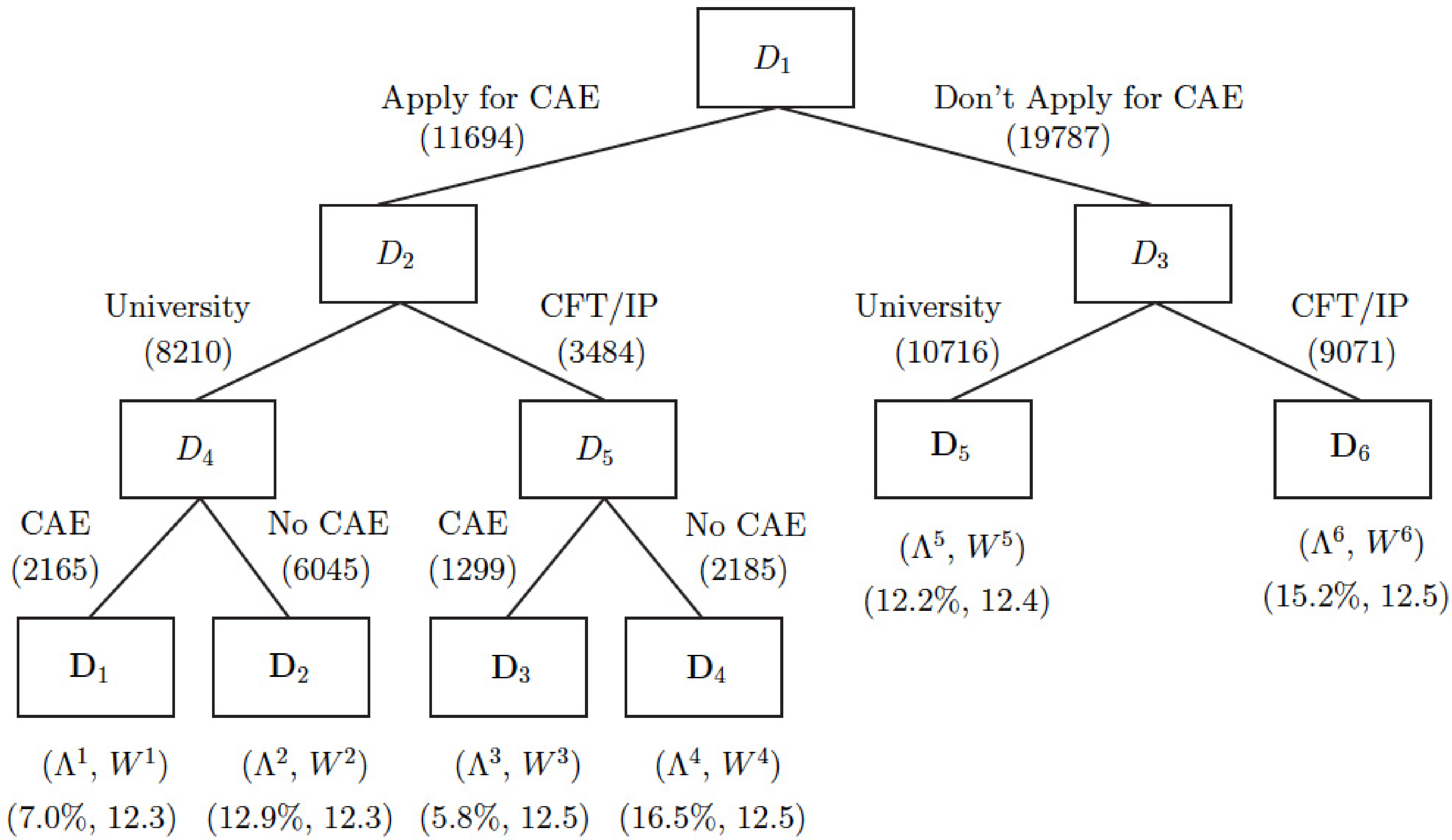


Figure 5: Decision Scheme. Number of Observations by Node, Average Dropout Rates and Average Natural Logarithm of Wages in parentheses.

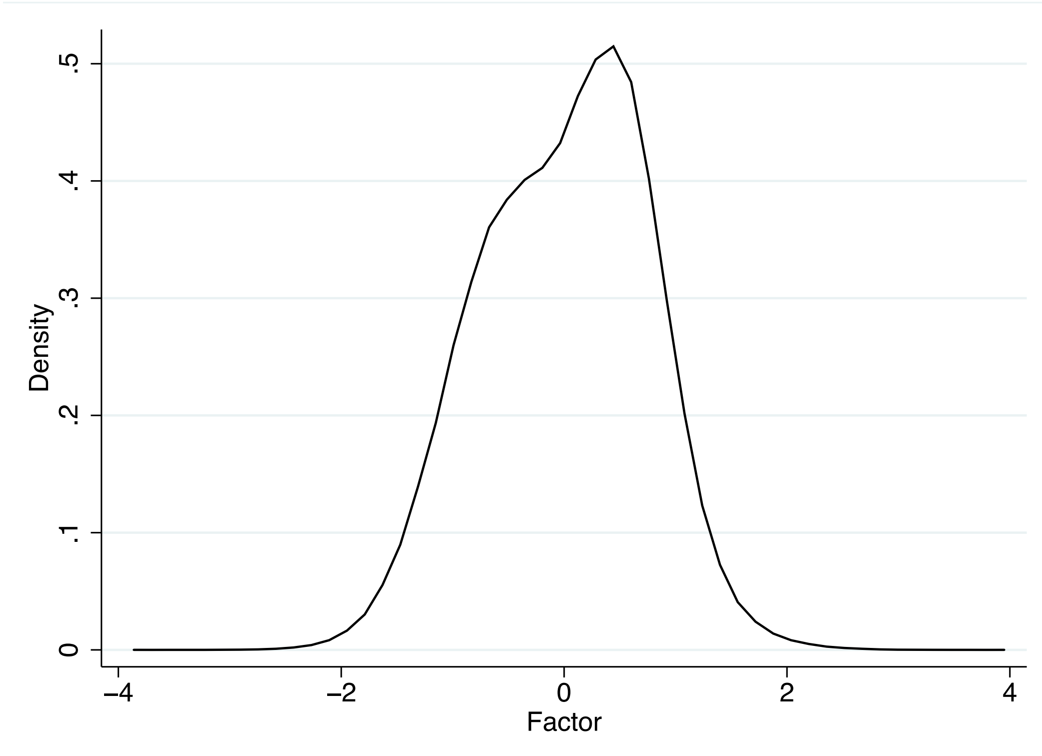


Figure 6: Unconditional Distribution of the Factor.

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:

$$\tau = (-0.598 \quad 0.515 \quad 0.194)$$
$$\sigma^2 = (3.638 \quad 6.533 \quad 1.657)$$
$$\rho = (0.371 \quad 0.350 \quad 0.279)$$

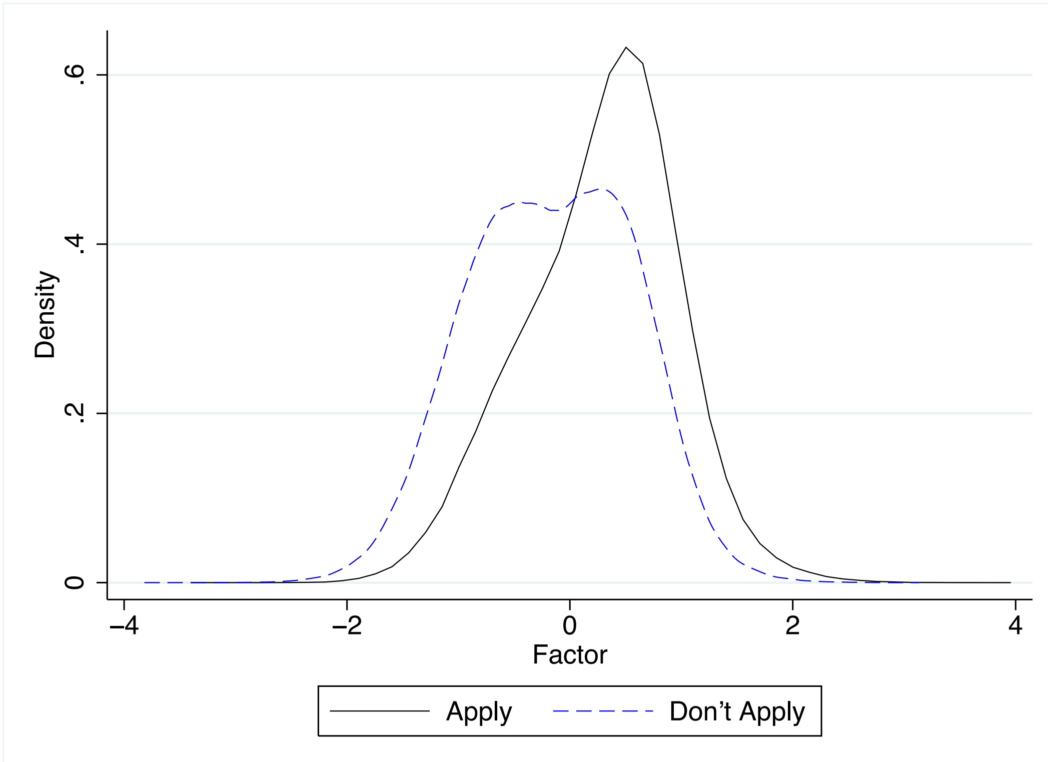
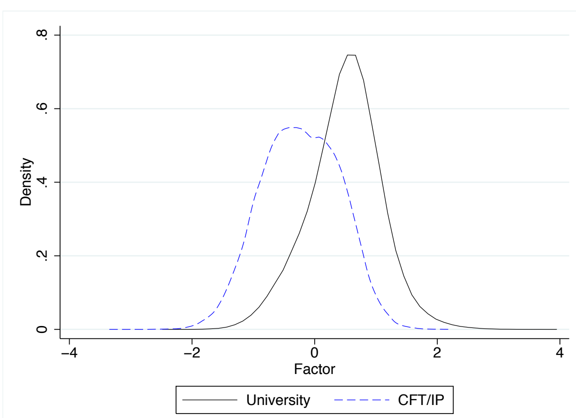
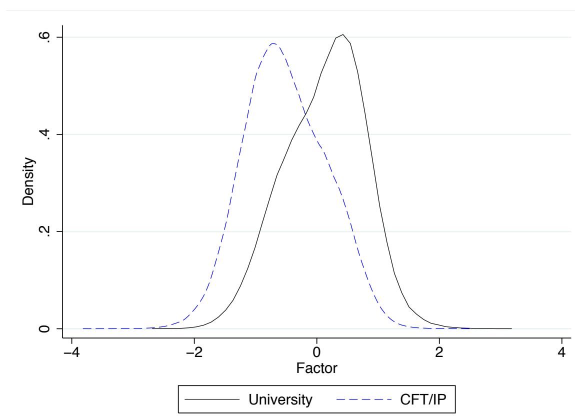


Figure 7: Distribution of Factor by CAE Application.

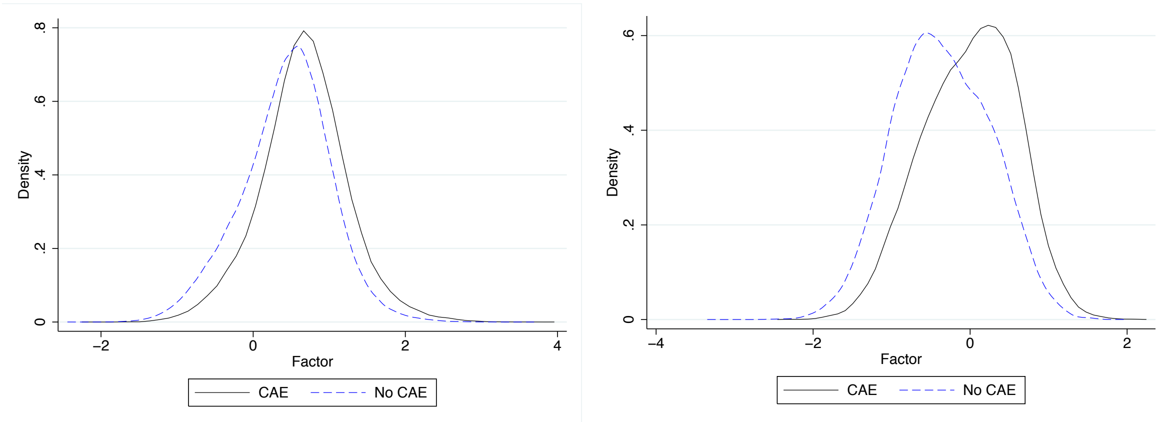


(a) Apply for CAE



(b) Don't Apply for CAE

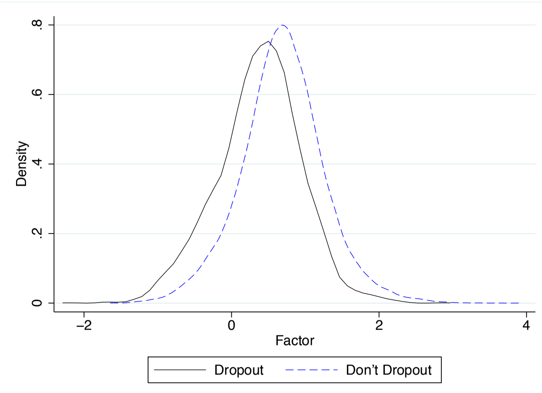
Figure 8: Distribution of Factor by HEI Type.



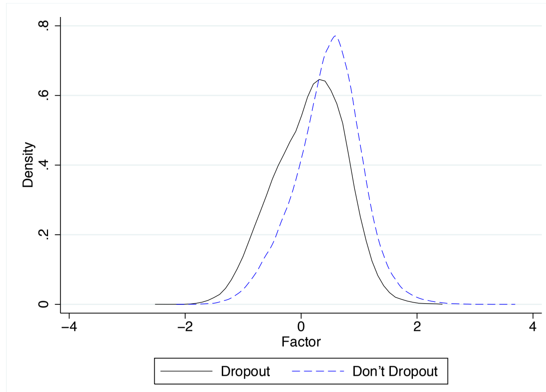
(a) University

(b) CFT/IP

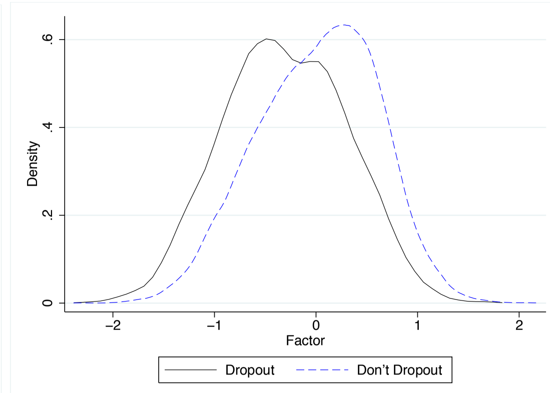
Figure 9: Distribution of Factor by CAE Assignment.



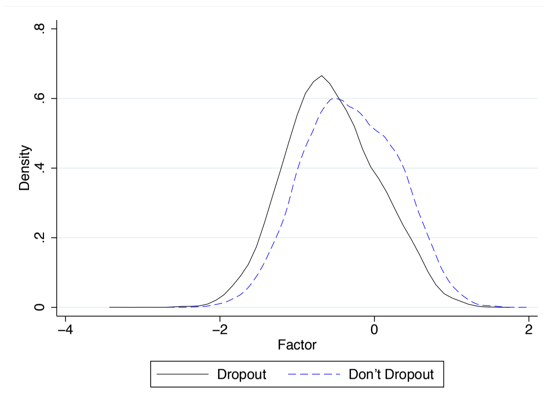
(a) Apply, University and CAE



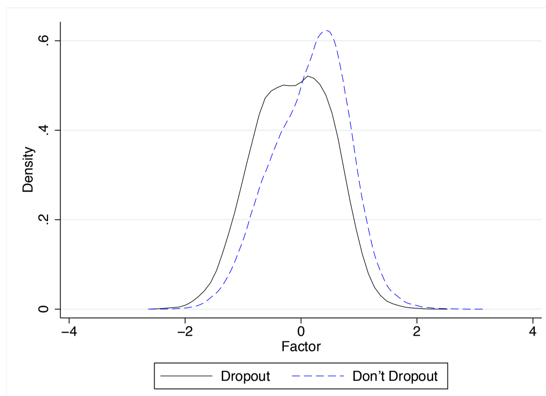
(b) Apply, University and No CAE



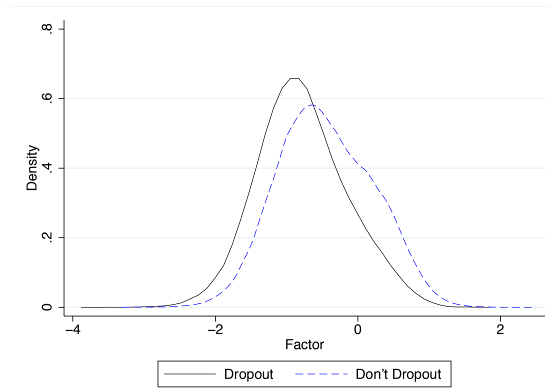
(c) Apply, CFT/IP and CAE



(d) Apply, CFT/IP and No CAE



(e) Don't Apply and University



(f) Don't Apply and CFT/IP

Figure 10: Distribution of Factor by Dropout Decision.

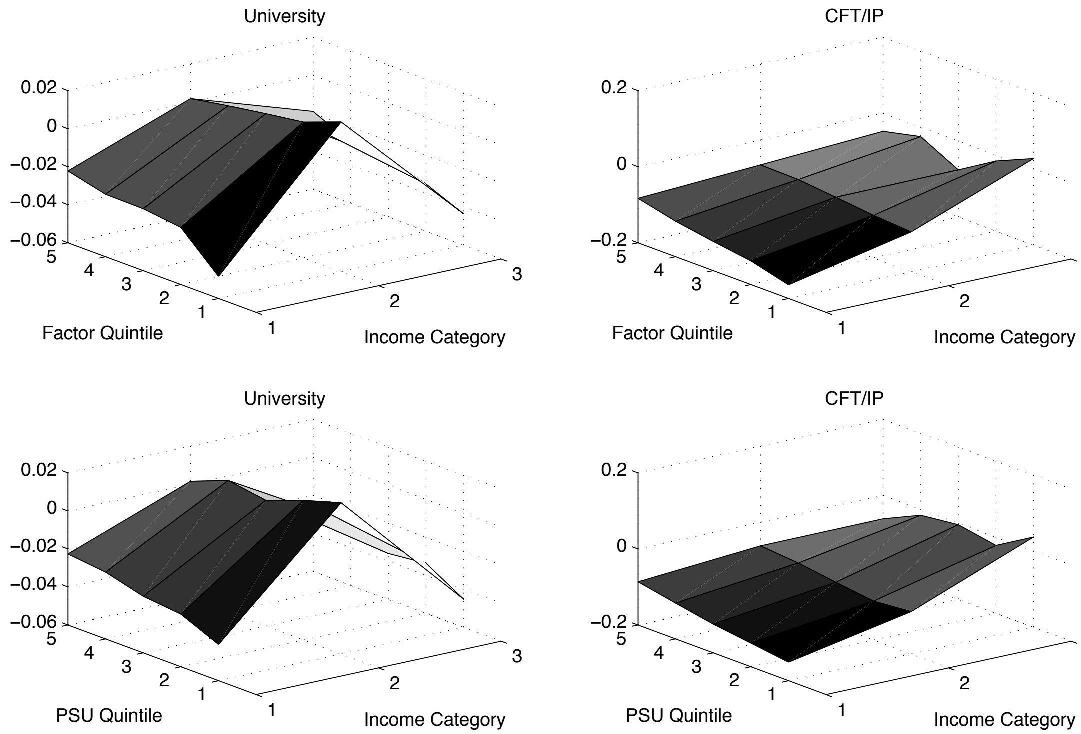


Figure 11: Impact of the CAE on Dropout Rates Conditional on Income and Skill Measures.