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 enrollment, dropout decisions, and adult earnings. Specifically, we investigate the State Guaranteed Loan (SGL), the largest source of public funding for higher education in Chile. Using longitudinal data from administrative records, we estimate a sequential schooling decision model and compute several treatment effects of interest. We show that the program increases enrollment and reduces dropout rates. However, SGL beneficiaries earn significantly less than non-beneficiaries. We analyze the role of selection and economic incentives of higher education institution to retain students as plausible explanations of this finding.

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1 Introduction

This paper investigates the short and long-term impact of loans for higher education on enrollment, dropout decisions, and adult earnings in the context of a developing economy. In theory, access to loans should alleviate the short term financial constraints preventing students from enrolling in post-secondary education. Furthermore, awareness of the future economic obligations should motivate

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marginal students to increase effort, which itself should lead to a lower probability of dropping out and a better performance in the labor market. However, this hinges on the assumption that the loan agreement does not affect the quality of education offered by higher education institutions (HEI). In practice, however, this may not be the case. Poorly designed contracts might increase enrollment and decrease dropout rates at the expense of education quality.

This article contributes to the literature analyzing the impact of access to student loans on enrollment and the decision to drop out of a Higher Education Institution (HEI). We analyze the case of Chile, a country which has experienced a massive increment in college enrollment during the last decade. This process has been, at least in part, the result of public policies aimed at alleviating short term credit constraints through a student loan programs. Our analysis is particularly relevant in the context of the recent expansion of student loan programs in developing and developed economies. We empirically document how an imperfect design of these contracts can lead to unexpected consequences.[1]

Specifically, we use a rich panel of administrative records from the Chilean higher education system to estimate a structural model of sequential schooling decisions with unobserved heterogeneity and labor market outcomes. The empirical model takes into account the complexities of the Chilean college admission system, including the loan application process. We follow Heckman, Stixrud, and Urzúa (2006), and interpret unobserved heterogeneity as a combination of cognitive and non-cognitive skills.

Using this framework, we estimate the impact of the State Guaranteed Loan program (SGL) on enrollment and the decision to drop out of tertiary education.[2] This loan program is similar to the Federal Guaranteed Loan (Stafford Loan) in the US: both provide subsidized interest rates and guarantee repayment to the lender if a student defaults. However, the SGL program does not consider waivers and makes the HEI responsible for the balance of the loan if the student drops

[1] See Cameron and Heckman, 1998, 2001; Carneiro and Heckman, 2002; Kane, 1996; Keane and Wolpin, 2001; Stinebrickner and Stinebrickner (2008) for an analysis of the importance of credit constraints in the context of the United States. Stinebrickner and Stinebrickner (2008) directly asks students if they would borrow more at a fair interest rate. Their results indicate that while credit constraints likely play an important role in the drop-out decisions, the majority of attrition of students from low income families should be primarily attributed to reasons other than credit constraints. On the other hand, Restuccia and Urrutia (2004) develop an overlapping generations model and use it to show that increasing college subsidies increases both the aggregate college enrollment rate (especially for poorest families) and the aggregate college dropout rate. For Chile, González and Uribe (2002), Microdatos (2008) and Meller (2010) analyze the determinants of the dropout decision. The empirical findings document that preferences, familiar problems, and economic reasons are the most important determinants of dropping out of college.

[2] The name of the program is *Crédito con Aval del Estado*, usually referred as CAE.

out. We discuss the potential consequences of this feature on education quality. Table 1 shows the importance of the SGL program in Chile. Between 2006 and 2010, the allocation of SGL loans quadrupled, rising from 10% of total student aid (loans and scholarships) in 2006 to 43% of aid in 2010. The administrative SGL records provide information on all loan applicants, allowing the precise identification of which individuals apply and obtain the loans.

In addition to modeling the sequential decisions of enrollment and dropping out from higher education, we analyze the impact of the SGL on labor market outcomes. We show that the potential impact of SGL on earnings is strongly dependent on the details of its design. In particular, SGL creates incentives for HEIs to reduce dropout rates since they are obliged to repay the lender if a student drops out. In order to prevent students from dropping out, some HEIs may lower their standards and shift resources to activities that are less successful at producing human capital but more attractive to students on the margin between continuing their education and dropping out. This can have labor market consequences because of the reduction in accumulated human capital resulting from the shift in the HEI objectives. By merging the administrative SGL records with individual-level information on earnings from Chile's unemployment insurance (UI) system, we are able to present an empirical analysis of this hypothesis.

Our empirical strategy allows for the existence of unobserved factors that influence the decision to dropout. Not allowing for this heterogeneity can bias estimates of the impact of the SGL on dropping out (Dynarski, 2002; Stinebrickner and Stinebrickner, 2008, 2012) if there is important sorting on student ability. One explanation for this sorting pattern is what Carneiro and Heckman (2002) calls "long-run constraints". These constraints are related to long-run characteristics such as ability unlike short-run constraints which are assumed to be largely financial. This paper evaluates the importance of both types of constraints on the probability of dropping out.

Additionally, our model allows for students to select into two different types of HEIs: universities offering five-year college degrees, and a category combining Technical Institutes (two-year college degrees) and Professional Institutes (four-year college degrees). 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. After controlling for ability, we find that the SGL increases the overall probability of post-secondary enrollment by 24% and reduces the dropout rate after the first year by 6.8% for universities and and 64.3% for TI-PI. These effects are lower than those obtained with reduced form approaches.[3] Our results suggest that both short and long run constraints are binding.

Despite reducing dropout rates, we also find that the SGL negatively affects labor market outcomes. Specifically, we find that SGL beneficiaries have lower wages (up to 6.4% less than non beneficiaries) even after adjusting for individual characteristics, measures of the quality of the higher education institution, ability and selection bias. This could be the result of perverse incentives for HEIs generated by the SGL.

The paper is organized as follows. Section 2 describes the SGL program and the Chilean education system in detail. In Section 3, we present our model of sequential decisions with unobserved heterogeneity. Section 4 describes the database and presents descriptive statistics. In Section 5, we present results and an analysis of sorting on ability. In Section 6, we compute some relevant treatments effects, and in Section 7 we conclude.

2 The Chilean Institutions

The education reforms implemented in the 1980s created incentives for private agents to participate in the Chilean education system. This permitted the incorporation of a large number of private HEIs including universities, Professional Institutes (PI) and Technical Institutes (TI).[4] As shown in Figure 1, enrollment in higher education institutions quadrupled between 1984 and 2010, driven largely by the increase in the number of universities (from 10 to 60 in the 1981-2009 period) shown in Figure 2.

A second enrollment boom took place during the early 1990s, when the effects of the educational reform seems to be larger as pointed out by Meller (2010).

Though the expansion of the higher education sector increased aggregate post-secondary enrollment, it did not increase enrollment evenly (Espinoza et al. 2006). To address this, in 2006 the Chilean government began providing increased financial support for vulnerable students in the form of grants and loans. Figure 3 shows the total amount of financial aid awarded to undergraduate

[3]Solis (2012) analyzes the effect of two loan programs (SGL and a different program for students from a small set of public universities) and finds significant positive effects on enrollment and negative effects on dropout rates. He exploits a discontinuity in the assignment rule to estimate a local average treatment effect for students within a narrow band 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.

[4]The TI are institutions that are allowed to grant technical degrees and PI are permitted to grant technical and professional degrees that not require a bachelor's degree.

students between 1989 and 2009.

Also in 2006, the Ministry of Education of Chile (MINEDUC) started implementing a new system of loans, the State Guaranteed Loan (SGL), where the Chilean government is the guarantor. The creation of the SGL filled a considerable void in the student loan market as private financial institutions had been reluctant to offer loans to vulnerable students.

Since its inception, the SGL has increased in importance. Figure 4 shows the increase in student aid coverage since 2006. This increase coincides with implementation of the SGL. Annual allocation statistics for SGL are presented in Table 1. This table also illustrates a substantial growth in the ratio of SGL financial aid disbursements to all other student aid awarded since 2006.

In addition to increased coverage, a second reason for creating the SGL was to reduce the high dropout rates in higher education. Strikingly, nearly 50% of students enrolled in university in Chile do not complete their studies. This figure is similar to those reported for the US (Restuccia and Urrutia, 2004; Chatterjee and Ionescu, 2012). For TIs and CIs the proportion is even larger. In this context, SGL loan program was designed to alleviate the short term credit faced by a large fraction of the students. The loans should prevent them from working, reducing the probability of dropping out from HEIs. A number of previous papers present evidence supporting this idea (González and Uribe, 2002; Meller, 2010; Goldrick-Rab, Harris, and Trostel, 2009). Table 2 presents aggregate first-year dropout rates for different types of HEI. We observe that even after one year, 9.5% of students attending universities decide not to continue their education. For TIs and CIs, the first-year dropout rate reaches 17.7%. The table also displays the aggregate dropout rates for those applying to the SGL as well as for its recipients. In both cases we observe significant reductions for universities and TI/PI compare with the unconditional figures. This fact motives our analysis.

To receive a loan through the SGL, applicants must meet certain requirements. They must be Chilean, score above 475 points on the University Selection Test (PSU), maintain satisfactory academic performance, not have graduated from any HEI, not have dropped out more than once from a higher education institution, have a socio-economic environment that justifies the allocation of SGL, and be currently enrolled at a HEI (certificate of registry or letter of acceptance).[5] [6] The Chilean government sells packages of student loans (which are bundled to be as homogeneous as possible in terms of risk and number of loans) by using auctions where financial institutions bid on two key variables. The percentage of loans they would like to resell to the state and the percentage of surcharge on the face value of the loan package. The product between these two figures gives the total overcost and bids with lower overcost win the loans packages. In the 2006 auction, the percentage of loans that financial institutions were allowed to resell was 25%, and the surcharge on the face value of the loan package was 43%, giving a total over cost of 10.8%.[7]

Once they are approved for a loan through the SGL, beneficiaries must continue to meet a list requirements which vary by level of study. If the beneficiary drops out from a HEI, it triggers a "guarantee for academic dropout"[8]. In effect, the HEI guarantees payment of a significant portion of the loan amount (at most 90% of the principal plus interest) to the lending institution. When an SGL recipient student drops out, the HEI must pay the guarantee amount. If the HEI guarantee is less than 90% of the capital (plus interest), the government covers the additional amount (up to 90%). In Table 3 we present the percentage of the academic dropout guarantee that HEI and the government cover.

The HEIs, even when a student is on the verge of graduating, always covers a significant percentage of the loan awarded to the student in the event of a drop out.[9] The HEI is required to make loan payments to the financial institution until the guarantee has been met.

For HEIs, making students who drop out financially responsible for loan repayment can be very complicated and expensive. Thus, the SGL creates incentives for HEIs to reduce dropout rates. To the extent that the reduction in dropout rates is achieved by imposing lower academic standards,

[5] 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. Mathematics and language are required and students must take one of the last two.

[6] In case a student is applying for a TI or PI 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.

[7] The real interest rate of this loan is regulated and it was about 5.8% until 2012 when, after student pressures, the government decided to subsidize the interest rate for all the student loans (retroactively) ending in a real 2%. The amount of each loan is also regulated according to a tuition reference rate (*arancel de referencia*). However, HEIs are allowed to charge above this reference tuition. To the best of our knowledge, there is no studies analyzing the impact of the SGL on tuitions but the tuition cap may prevent HEIs to raise tuitions and capture the aid as reported by Cellini and Goldin (2012) in the U.S.

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

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

the SGL could negatively impact the quality of education.[10] We present evidence that suggests that this may be the case.

When SGL beneficiaries graduate a different collection mechanism operates: the "state guarantee". If the graduate cannot make the SGL loan payments (after allowing for a grace period of 18 months after graduation), financial institutions may start legal proceedings against the beneficiary. Alternatively, institutions have the right to require to Chile to pay the guarantee (90% of the amount due including capitalized interest).

3 A Simple Structural Model for Dropout Decisions with Unobserved Heterogeneity

An individual's schooling attainment is the outcome of a sequence of decisions where choice sets are determined by the education system. When modeling schooling attainment, it is important to acknowledge that the individual's decisions are conditional on a set of feasible alternatives. Furthermore, observed choices will also depend on the decision maker's skills and preferences. As a result, simply comparing observed results (sequences of decision) across individuals can be misleading.

Below we present a model that allows for "dropping out" to be the final result of a sequence of decisions. At each node in the model, observed choices are influenced by observable and unobservable characteristics. Even after controlling for potential endogeneity in decision-making, selectivity, and observable characteristics, we may see observationally equivalent individuals responding differently to the same stimulus. This can be explained by the presence of unobserved heterogeneity in endowments as in Hansen, Heckman, and Mullen (2004), Heckman, Stixrud, and Urzúa (2006), Urzúa (2008), and Rau, Sánchez, and Urzúa (2011). These unobserved endowments are a combination of cognitive and noncognitive skills, and they can vary considerably among individuals.

The timing of decisions in our model is as follows: before taking the University Selection Test (PSU), if they decide to study, students can apply for the SGL and then, after learning the test results, they can enroll in Technical Institutes (TI), Professional Institutes (PI) or in universities.[11]

[10] For instance, lowering course failure rates or relaxing dismissal policies are mechanisms that HEI can use to prevent dropouts. These measures have a direct effect on the quality of education.

[11] For purposes of this paper we consider two groups of institutions: universities and non universities, the TI-PI.

3.1 The Model

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

Consider a choice node j (for instance, whether to apply to the SGL). Let $V_{id(j)}$ represent the indirect utility that individual i obtains when choosing alternative d (with $d \in \{0,1\}$) from the alternative set at 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 the individual's schooling decision and $\mu_{id(j)}$ is an error term.[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 with observed choices represented by $\mathbf{D}_l$, with $l = 1, 2, \ldots, L$.[14] In Figure 5 we show the tree of sequential decisions. In our model $L = 6$.

Finally, after observing the sequences of optimal schooling decisions we observe two outcomes: higher education completion (i.e. dropout or non-dropout) and wages (for both dropouts and

[12]In particular, we consider six nodes: the first one is the decision to enroll or not in a higher education institution, the second one is to apply to SGL, the third and fourth consider the decision of enrolling into a university or TI/PI conditional on having applied or not to the SGL. The fifth and sixth nodes consider the allocation of the SGL conditional in that individuals enroll in a university or TI/PI and apply to the SGL.

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

[14]For instance, $\mathbf{D}_1$ is the sequence for students that decided to enroll in a higher education institution, applied to the SGL, enrolled in a university, and obtained the SGL.

non-dropouts). The equation we use to model 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. 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 with the choice Λ at node $\mathbf{D}_l$ for individual i, $\mathbf{M}_{i\Lambda}^{\mathbf{D}_l}$ is a vector containing observed characteristics which also determine wages for individual i under choice , and $\nu_{i\Lambda}^{\mathbf{D}_l}$ is an error term. The observed outcome vector is given by the dropout decision and the observed wage, denoted by:

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

It is important to mention that the model allows for all of the error terms $(\nu_{\Lambda}^{\mathbf{D}_l})$ to be correlated. Thus, schooling decisions are correlated with outcomes through unobservable factors. The model allows for unobserved heterogeneity, which we refer to as an individual's *factor* and denote with f. The factor represents the individual's unobserved ability and plays an important role in the decisions made at each node. With this model we are able to estimate counterfactual outcomes and treatment effects for different policies, as it will be shown in Section 6. Imposing some structure on the factor allows us to identify the effect of ability on the sequential choices. We impose the following structure:

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

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

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 Urzúa (2006), we posit a linear measurement system and use it 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 purely a combination of different abilities (cognitive and non-cognitive). The ability measurements we use are the University Selection Test (PSU) and high school GPA. To simplify discussion, we refer to both measurements as "test scores".[15] The test score equations are

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

Where T_{ik} is test score k of individual i, $\mathbf{X}_{ik}$ is a vector containing observed characteristics (e.g. socioeconomic characteristics, parents' education, type of school attended) and λ_{ik} is an error term for test score k for individual i.[16] As before, we impose a factor structure for the 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 the 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 follows:

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

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

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

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

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

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

on the factor we have:

$$\Pr\left(D_{id(j)}=1|\mathbf{Z}_{id(j)},f_i,D_{id(j-1)}\right)=\Pr\left(V_{id(j)}\geq 0|\mathbf{Z}_{id(j)},f_i,D_{id(j-1)}\right) \tag{10}$$

$$=\Phi\left(\mathbf{Z}_{id(j)}\delta_{d(j)}+\eta_{d(j)}f_i\right) \tag{11}$$

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 observing a particular schooling sequence $\mathbf{D}_l$ for individual i, given the observed characteristics and the factor f, in the following way:

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

H_i represents 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 a method similar to those used by Hansen, Heckman, and Mullen (2004) and Kotlarski (1967)to identify the distribution of the factor and the parameters of the model.

3.2 Implementing the Model

To estimate the model, we use observed schooling decisions, individual characteristics, the outcome vector, and test scores ($\mathbf{D}_l$, $\mathbf{Z}$, $\mathbf{Y}$, $\mathbf{M}$, $\mathbf{T}$ and $\mathbf{X}$, respectively). We assume the decision timing is as described above. We observe wages after the schooling sequence is completed.

The model allows for the existence of endogeneity in decisions since the choices made at each node depend on unobserved characteristics which are likely to be correlated with some characteristics. The assumption of independence between the error terms and the factor, after conditioning on unobserved ability, is crucial since it allows us to write the likelihood function as follows:

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

Where we integrate with respect to the density of the unobserved factor. We assume the factor is drawn from a *mixture* of normal distributions which is flexible enough to allow 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 imply 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).

One final comment with regard to the factor is that because there is no intrinsic scale for ability, it is necessary to normalize the mean of the factor to 0 and to normalize the loading parameter on the factor in the math test score equation to 1. We also normalize all of the test scores so they have zero mean and standard deviation one.

4 Data

The data used in this paper is constructed from several different administrative records.[17] To identify dropouts we use administrative enrollment data from the Chilean Higher Education System that cover the 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 2012 (January-August). If we include individuals enrolled for the first time in 2007 it is likely that a large fraction of them would not be in the labor market by 2012. Second, in 2006 the SGL was mistakenly assigned to individuals from all quintiles of the income distribution. This did not happened in 2007.[18] Because individuals from all quintiles were allowed to receive SGL loans in 2006, we will be able to estimate different parameters for individuals from each income quintile.

The enrollment data was merged with administrative records from the University Selection Test (PSU) from 2005. From these records we observe test scores, socioeconomic characteristics, and family background characteristics. Additionally, administrative data from the SGL permit

[17] The data were provided by the Budget Office of the Chilean Ministry of Finance.

[18] The misallocation of the loans was due to a computational mistake that assigned the SGL 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 Ingresa (2010).

the identification of SGL applicants and recipients in 2006. The merged database contains 47,115 observations, 33,814 of which enrolled at a HEI. [19] In Figure 5 we display the number of observations at each decision node.

The variables included as controls are a male dummy , age (in 2006), geographic location dummies, family size, and family income (converted into income categories with 0 to $278.000 Chilean pesos as the base category) . We also include dummies for parents' years of schooling (with less than 8 years of schooling as the base category), dummies for the type of high school (public, private-voucher, or private), a dummy for whether the individual received a scholarship during the first year, dummies for post-secondary area of study (with Administration and Commerce as the base category), a measure of the designed length of the post-secondary program in semesters, years of certification of the higher education institutions in 2006 (a measure of HEI quality), and test scores (mathematics and language and high school GPA.

In Tables 4 and 5 we show some descriptive statistics by decision node and observed choice at each decision node. The sample appears well balanced at each decision nodes. However, there are some important observable differences at node D_5 (enrolled in a university) with respect to GPA and test scores. Students enrolled in university score significantly higher than students enrolled at a TI-PI or those not enrolled at any HEI.

5 Results

Table 6 presents the parameter estimates at each of the six decision nodes and we describe some results below.

Overall, men are more likely to study and have a lower probability of applying to SGL, receiving a loan through SGL, and enrolling in a university. Older individuals have a lower probability of attending an HEI. When they do decide to attend an HEI, older individuals are more likely to enroll at a university. Also, conditional on applying for a loan through the SGL, age is positively associated with being selected as an SGL beneficiary.

Socioeconomic characteristics are important in the student's decision patterns. Individuals from high-income families are more likely to attend an HEI, more likely to attend a university conditional

[19] These 47,115 observations include only individuals with no missing values. We did not use imputation methods to increase the number of observations.

on attending an HEI, and less likely to apply to the SGL program. Owing to the previously described loan misallocation in 2006, the probability of obtaining an SGL loan is increasing in household income for students enrolled at universities(Ingresa, 2010).

Last, we can see the importance of ability (as measured by the factor) in the schooling and loan take-up decisions. Individuals with higher ability are more likely to attend any HEI, more likely to attend a university conditional on attending an HEI, and more likely to apply to the SGL program. Also, high ability applicants have a higher probability of receiving the SGL. This is interesting since credit is not supposed to be assigned based on academic merit or ability.[20]

Table 7 presents parameter estimates from the decision nodes corresponding to the drop out decision.[21] At some nodes, men have a higher probability of dropping out. In four nodes ($\mathbf{D}_2, \mathbf{D}_4, \mathbf{D}_5, \mathbf{D}_6$) older students have a higher probability of dropping out. Geographic region dummies appear to not explaining the dropout decision, except for students who enrolled in a higher education institution and did not obtain an SGL loan and for students who did not apply to the SGL but enrolled in a TI/PI. In the former case, being from the north or the south is associated with a lower likelihood of dropping out. In the latter case being from the north or the south is associated with a higher likelihood of dropping out.

Students from larger households have a higher probability of dropping out and higher family income is associated with a lower probability of dropping out. Attending a public or private-voucher school increases the probability of dropping out from a HEI. The association is particularly strong for students enrolled in universities and those who did not apply to SGL. Having received a scholarship significantly decreases the probability of dropping out after the first year in most of the terminal nodes.

Program length increases the probability of dropping out for students enrolled at a university who did not receive the SGL. On the other hand, program quality, as measured by the length (in years) of certification, reduces this probability for students enrolled in a TI/PI that did not obtain the SGL. We also see that ability (as 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.

[20] 475 in PSU test score or a GPA of 5.3 for the case of TI and PI.

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

Table 8 presents results from the wage equations.[22] In most cases men have higher wages than women and wages increase with age as expected. The program length is negatively related with wages, which is likely related to the fact that those enrolled in longer programs have spent less time in the labor market. Finally, we see that ability is strongly and positively related to wages for non-dropouts, for dropouts from a TI/PI that did not receive the SGL and for individuals who did not attend any HEI.

Next we analyze the results from the test score equations. In Table 9 we see that men perform better than women on the mathematics examinations and worse on the language examinations. Age is positively correlated with the language score but negatively correlated with high school GPA and the mathematics score.

Household size is negatively correlated with PSU scores and GPA while family income is positively correlated with both. Having attended a public or private-voucher school is negatively associated with all three scores.Parent's education is positively associated with PSU scores but negatively correlated with high school GPA. Lastly, ability is strongly positively correlated with the three test scores. This suggests that the factor is strongly related with true ability.

5.1 Goodness of fit

We compute goodness of fit statistics for the model. Specifically, we compute χ^2 tests to contrast the estimated and the actual proportions of individuals making each choice at each decision node.[23] We first implement a simple hypothesis test through decision nodes. Table 10 displays the results.

In particular, the table displays the p-values from the test of equality between the model predictions and the actual data. In most cases we are unable to rejected the null hypothesis of equality at the 1% level. This suggests that our structural model performs well at predicting the data averages.

5.2 The Role of Ability in the Sequential Decisions

In this subsection we analyze in detail the role that ability plays in determining individual choices in our structural model. In particular, we study if there is *sorting* on ability. To do so, we use the

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

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

estimated structural parameters of our model to simulate the distribution of the ability *factor*.[24]

Figure 6 shows the unconditional distribution of the factor and the estimated parameters from the mixture of normals that generate it. Clearly, the distribution is non-standard which suggests we were right to relax normality assumptions.[25]

Next, we show the distribution of ability for those who decided to continue studying at an HEI relative to those who did not. Unsurprisingly, students attending HEIs are higher ability than those who do not attend a post-secondary institution. In fact, the ability distribution for HEI attendees first order stochastically dominates the distribution for non-attendees. A similar relationship is observed between SGL applicants and non-applicants.

The distribution of ability by type of HEI is presented in Figure 9. There is a positive sorting into universities (relative to TI/PI) . This is consistent with the evidence presented in Table 6.

Figure 10 presents the distribution of the ability factor by whether the student was awarded a loan through the SGL program or not conditional on having applied. For students enrolled in a university or a TI/PI, more able students have a higher probability of being awarded a loan through SGL. This sorting is strongest for those enrolled in a TI/PI. This is also consistent with the estimates shown in Table 6. Finally, in Figure 11 we observe sorting in the decision to drop out of a HEI. Less able students have a higher probability of dropping out, even after controlling for observable characteristics. This result is consistent across decision nodes . Again these results coincide with Table 7, where the ability factor is consistently negatively predictive of the decision to drop out.[26]

6 Treatment Effects

In this section we estimate the causal effect of the SGL program on the probability of enrolling in a HEI, the probability of dropping out after the first year, and on observed wages five years after enrolling in a HEI for students who did not drop out during their first year. To do so, we employ less structural approaches (OLS and Regression Discontinuity Design) as well as our structural approach. Given that receiving an SGL loan is perfectly predictive of ever enrolling at an HEI, we

[24] The simulation considers one million observations.

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

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

restrict our analysis to impact of SGL on the likelihood of dropping out during the first year and wages five years after initial enrollment.[27]

6.1 Effects of SGL on Enrollment Decision

6.1.1 Structural Approach

We start by estimating the effect of the SGL program on the enrollment decision. We control for both observable characteristics and unobserved heterogeneity. Given that enrollment is not a final node, we estimate the probability of enrollment in any HEI conditional on applying and obtaining the SGL and compare with the probability of enrollment conditional on not having the SGL.

$$\Omega_{D_1}^{\text{SGL}} = \int \Pr(D_1 = 1|\text{SGL} = 1, D_2 = 1, \zeta) dF_{f|\text{SGL}=1,D_2=1}(\zeta) - \int \Pr(D_1 = 1|\text{SGL} = 0, \zeta) dF_{f|\text{SGL}=0}(\zeta) \tag{13}$$

In Table 11 we present the estimated treatment effects of SGL on enrollment for different household income categories. Receiving an SGL loan increases the probability of ever enrolling by 15.6 percentage points on average. The point estimate is higher for low income students. Our results are in line with those found by Solis (2012) who estimate an effect of 18 percentage points for students just above and just below the PSU eligibility cutoff (475 points) using a Regression Discontinuity (RD) approach. However, the impact we estimate is considerably lower since our 15.6 percentage points corresponds to 24.1% of total enrollment and Solis' (2012) 18 percentage points corresponds to 100% for those around the cutoff. As Solis remarks, "...access to the loan programs increases the college enrollment probability by 18 percentage points - equivalent to a nearly 100% increase in the enrollment rate of the group with test scores just below the eligibility threshold." Hence, our results are much smaller than those found by Solis. Certainly the interpretation of RD estimates must be taken with caution as with any local average treatment effect.

Because people who decide to not enroll at an HEI are grouped together, we cannot compare within this group along different paths of the decision tree. For the dropout decision and wages we will have more counterfactual alternatives as explained below.

[27] We do not observe individuals that were offered the SGL and decided to not enroll at a HEI, then individuals with SGL are enrolled with probability one in our sample

6.2 Effects of SGL on Dropout Decision

6.2.1 A conventional approach

We estimate the effect of being an SGL beneficiary on the probability of dropping out from an HEI in the first year using a fuzzy RD approach implemented as Two Stage Least Squares (2SLS) as follows:

$$D_i = \lambda_0 + \lambda_1 \cdot \mathrm{SGL}_i + \lambda_2 \cdot f(T_i - 475) + \mu_i, \tag{14}$$

$$\mathrm{SGL}_i = \zeta_0 + \zeta_1 \cdot \mathbb{1}(T_i \geq 475) + \zeta_2 \cdot f(T_i - 475) + \upsilon_i, \tag{15}$$

where D_i is a binary variable that is equal to 1 if individual i decides to dropout from a HEI and 0 if not. SGL_i is a binary variable that takes the value of 1 if the individual is eligible for the SGL (i.e. has at least 475 points on average on the mathematics and language PSU scores) and 0 if not. $f(T_i - 475)$ is a function that flexibly controls for the distance from the threshold.

One thing to consider is that proper identification of the treatment effect with an RD approach may not be possible for students enrolled in TI/PIs. This is because the eligibility conditions for these students is a minimum score of 475 on the PSU (average between the mathematics and language tests) or a GPA of 5.3 in high school. Hence, the eligibility condition we consider (at least 475 points in the PSU) may be a weak instrument. As such, we cannot accurately estimate the desired treatment parameter for students enrolled in TI/PIs.

The results the RD estimation suggest that receiving an SGL loan reduces the likelihood of dropping out from a university by 9.3 percentage points. This is significant at the 10% level. This implies that receipt of an SGL loan decreases the probability of dropping out by 112%. This is again similar to the estimates obtained by Solis (2012).

6.3 Structural Approach

We estimate the causal impact of the SGL on the probability of dropping out of an HEI by type of institution. It is important to realize that naive estimates are likely to suffer from endogeneity and selection issues (Dynarski, 2002; Acuña, Makovec, and Mizala, 2010). However, we are able to control for these issues by modeling the decision process at each node in our structural model.

This allows us to estimate counterfactual scenarios and to compute treatment effects of interest after having purged the effects of endogeneity.

In Table 2 we compared the first-year dropout rates in our sample, finding large differences depending on whether or not the students participated in the SGL program. However, these simple comparisons do not account for observable characteristics and unobserved ability affecting individuals' decisions such as enrollment in HEI and applying for the SGL program. We deal with the role of individual's characteristics and self-selection in what follows.

We first define the unconditional impact of SGL on dropping out of a HEI after the first year,[28] as follows:

$$\Upsilon^{\text{SGL}}_{D_3=1} = \int E(\Lambda^{\mathbf{D}_1} - \Lambda^{\mathbf{D}_2} | D_3 = 1, f = \zeta) dF_{f|D_3=1}(\zeta) \tag{16}$$

$$\Upsilon^{\text{SGL}}_{D_3=0} = \int E(\Lambda^{\mathbf{D}_3} - \Lambda^{\mathbf{D}_4} | D_3 = 0, f = \zeta) dF_{f|D_3=0}(\zeta), \tag{17}$$

where $\Upsilon^{\text{SGL}}_{D_3=1}$ is the treatment effect for university students and $\Upsilon^{\text{SGL}}_{D_3=0}$ is the treatment effect for TI/PI students.[29]

In Table 12 we present the treatment effect estimates. The impacts of the SGL program on the probability of dropping out of an HEI are statistically significant (we reject the null hypotheses that $\Upsilon^{\text{SGL}}_{D_3=1} = 0$ and $\Upsilon^{\text{SGL}}_{D_3=0} = 0$ at the 1% level) and heterogeneous. For students enrolled at a university the SGL reduces the probability of dropping out by 0.5 percentage points. This corresponds to a reduction of 6.8% in the dropout rate. For students enrolled in a TI/PI, we estimate a 9.2 percentage point reduction in the dropout rate. This corresponds to a decrease of 64.3%.[30] Our results differ considerably from those of Solis (2012). He finds that SGL receipt leads to a decrease of 6 percentage points for students enrolled in universities. In his data, this corresponds to a decrease of 82.1% in the dropout rate. This is vastly different from the 6.8% reduction that we find. Our RD estimates also differ significantly from our structural model. Of course, our structural estimates are average treatment effects while the RD estimates represent local average treatment

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

[29] These parameters are not conditioned on having obtained the SGL or not. Hence, they estimate the effect of the SGL on the probability of dropping out in the first year for an average student, enrolled in a higher education institution, who applied to the SGL.

[30] For these calculations we consider the dropout rates simulated in our structural model. The simulated dropout rate for students enrolled in a university is 7.3% and 14.3% for those enrolled in a TI/PI.

effects.

We next turn to conditioning on variables other than the type of HEI. In order to see if the impact of SGL on the probability of dropping out after the first year varies by income level or quintile of the unobserved factor distribution, we estimate the following treatment parameters:

$$\tilde{\Upsilon}^{\text{SGL}}_{D_3=1} = \int E(\Lambda^{\mathbf{D}_1} - \Lambda^{\mathbf{D}_2} | D_3 = 1, X = x, f = \zeta) dF_{f|D_3=1,X=x}(\zeta) \tag{18}$$

$$\tilde{\Upsilon}^{\text{SGL}}_{D_3=0} = \int E(\Lambda^{\mathbf{D}_3} - \Lambda^{\mathbf{D}_4} | D_3 = 0, X = x, f = \zeta) dF_{f|D_3=0,X=x}(\zeta), \tag{19}$$

where the vector X includes family income categories, quintiles of the ability factor, and quintiles of the PSU score.[31] The ability factor quintiles represent a mix of cognitive and noncognitive ability and the PSU quintiles are a proxy for cognitive ability. We consider only three income categories because of the reduced number of observations in the right tail of the income distribution in our sample.[32]

In Table 13 we present the estimated effect of SGL on dropout rates for students enrolled in a university who applied to the SGL by income category and ability factor quintile. Similarly, in Table 14 we present the same effects but use PSU quintiles instead of ability factor quintiles. It is important to note that students enrolled in universities from high-income families benefit more in reduction in dropout rates. When just ability factor quintiles are considered, we see that individuals with less ability benefit more. However, when we condition on both the household income category and the factor quintile (or the PSU score quintile) there is no clear pattern. In general, less able students from the highest and lowest income categories benefit more than those from the middle income category.

Similarly, Tables 15 and 16 show the effect of SGL on dropout rates for those enrolled in a TI/PI by income category and factor (PSU score) quintile. There are three interesting results in these tables. First, student from low-income families benefit the most. Second, students with less ability benefit significantly more than those in the upper 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 reduced dropout rates.

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

[32] 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).

In Figure 12 we summarize the previous results. We plot the percentage point impact of the SGL program on dropout rates by income category and factor (PSU scores) quintiles for each type of HEI.

The results suggest that short run constraints, related to income, are binding in Chile. Additionally, there is evidence that long-term constraints, related to human capital, are also important. The reductions are larger for students with low ability levels who come from low-income families and attend TI/PIs. The reductions are also large for students with low ability levels who come from high-income families and attend a university.

6.4 SGL access and Wages

6.4.1 A conventional approach

We consider an RD approach to estimate the effect of the SGL program on wages. As previously discussed, the eligibility may be a weak instrument for those enrolled in TI/PIs. Thus, we do not analyze the effect of SGL on wages for students who attend a TI/PI and focus only in students who attend universities. The specification we estimate is as follows:

$$\ln W_i = \tau_0 + \tau_1 \cdot \mathrm{SGL}_i + \tau_2 \cdot f(T_i - 475) + \vartheta_i, \tag{20}$$

$$\mathrm{SGL}_i = \rho_0 + \rho_1 \cdot \mathbb{1}(T_i \geq 475) + \rho_2 \cdot f(T_i - 475) + \sigma_i, \tag{21}$$

where $\ln W_i$ is the log wage of individual i, SGL_i is a binary variable that is equal to 1 if the individual obtained the SGL and 0 otherwise, and $f(T_i - 475)$ is a function that accounts for the distance from the threshold. We approximate $f(\cdot)$ with a local linear estimator and the bandwidth suggested in Imbens and Kalyanaraman (2012). The results of the RD estimation suggest that SGL eligibility decreases wages by 11% on average (for the LATE population). However, this estimate is statistically insignificant at conventional levels. When we restrict to non-dropouts the point estimate suggests a decrease of 5.4%. Again, this result is insignificant.

6.4.2 Structural Approach

We now estimate the impact of SGL on wages using our structural model. As discussed earlier, the design of the SGL program could incentivize higher education institutions to reduce dropout rates at the expense of overall education quality.[33] Although the Chilean higher education system does not have a method to measure the quality of its graduates, we can use information on the labor market performance of individuals as a proxy of quality. To investigate this question we estimate wage equations and interpret the results to differences in quality among SGL recipients and non-recipients.

To estimate the impact of SGL on wages, we first recognize that SGL receipt could have an effect on two different decisions. First, the prospective student decides whether or not to apply to the SGL. This not only determines the type of financing that she will eventually have access to, but also the type of institution where she decides to study. This second instance is defined by obtaining the loan (conditional on the application). Hence, we can define two pairs of treatment effects, depending on the HEI where the individual is enrolled:

$$\Delta^{\text{SGL}}_{\mathbf{D}_1,\mathbf{D}_2} = \int E(W^{\mathbf{D}_1}_{\Lambda=0} - W^{\mathbf{D}_2}_{\Lambda=0} | D_5 = 1, \Lambda^{\mathbf{D}_1} = 0, \zeta) dF_{f|D_5=1,\Lambda^{\mathbf{D}_1}=0}(\zeta), \tag{22}$$

$$\Delta^{\text{SGL}}_{\mathbf{D}_3,\mathbf{D}_4} = \int E(W^{\mathbf{D}_3}_{\Lambda=0} - W^{\mathbf{D}_4}_{\Lambda=0} | D_6 = 1, \Lambda^{\mathbf{D}_3} = 0, \zeta) dF_{f|D_6=1,\Lambda^{\mathbf{D}_3}=0}(\zeta), \tag{23}$$

and

$$\Delta^{\text{SGL}}_{\mathbf{D}_1,\mathbf{D}_5} = \int E(W^{\mathbf{D}_1}_{\Lambda=0} - W^{\mathbf{D}_5}_{\Lambda=0} | D_5 = 1, \Lambda^{\mathbf{D}_1} = 0, \zeta) dF_{f|D_5=1,\Lambda^{\mathbf{D}_1}=0}(\zeta), \tag{24}$$

$$\Delta^{\text{SGL}}_{\mathbf{D}_3,\mathbf{D}_6} = \int E(W^{\mathbf{D}_3}_{\Lambda=0} - W^{\mathbf{D}_6}_{\Lambda=0} | D_6 = 1, \Lambda^{\mathbf{D}_3} = 0, \zeta) dF_{f|D_6=1,\Lambda^{\mathbf{D}_3}=0}(\zeta). \tag{25}$$

It is important to note that the effects above are conditional on the student applying to the SGL program, enrolling in a particular type of HEI, being awarded an SGL loan, and not dropping out in the first year.

Hence, the first pair of parameters identify the effect of SGL on wages for students that applied for an SGL loan and did not dropout during their first year.[34] The second pair of parameters identify the impact of receiving the SGL versus not having applied for an SGL loan.[35]

[33] Table 3 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).

[34] 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 TI/PI, 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.

[35] According to Figure 5 this is equivalent to compare wages of those in node $\mathbf{D}_1$ who did not drop out with those

In Table 17 we present the results of the estimation. For students enrolled in a university, the impact of getting the SGL on wages is -2.8%. This is statistically significant at the 1% level.[36] For students enrolled in a TI/PI, the impact of SGL on wages is 0.5% and not statistically significant. These results are quite different from naive comparisons of means. For university students the naive wage gap is -3.2%. For TI/PI students the wage gap is 8.6%. When comparing the estimates from the structural model with those from the RD approach, we also observe important differences. This suggests that selectivity bias and/or endogeneity issues are important.

The estimated treatment effects $\Delta^{\text{SGL}}_{\mathbf{D}_1,\mathbf{D}_5}$ and $\Delta^{\text{SGL}}_{\mathbf{D}_3,\mathbf{D}_6}$, indicate even larger reductions in wages. Compared with those who did not apply to the SGL program, individuals enrolled in universities who received an SGL loan earn 6.4% lower wages. The corresponding figure for TI/PI is 1.1%. These results are statistically significant at 1% level and the 10% level, respectively.[37]

In Tables 18 to 21 we present estimates that also condition on the household income categories and the ability factor quintiles. The negative effect of the SGL program on wages appears to be strongest for students with lower levels of ability and from low income households.

Finally, Tables 22 and 23 show the effects of the SGL on wages after also conditioning on our measure of institution quality (years of certification) and the ability factor quintiles. We see that the SGL decreases wages most for low-skilled students who are enrolled in HEIs that are of lower quality. In contrast, high-skilled students enrolled in institutions with a large number of years of certification obtain greater wages as a result of the SGL.

The results suggest that after controlling for self-selection and endogeneity, students who receive SGL loans in their first year (especially those enrolled in universities) have lower wages six years later in comparison with students who do not receive an SGL loan.

6.4.3 Understanding the Wage Gap

According to the previously discussed results, the SGL program reduces the probability of dropping out after the first year. Thus, a simple comparison of the wages of those who did not dropout and received an SGL loan with the wages of those who did not obtain an SGL loan could be biased by

from people at node $\mathbf{D}_5$ and did not drop out either. For those enrolled in a TI/PI 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.

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

[37] Similarly, uncorrected measures shows a wage gap of -9.7% for those enrolled in universities and 8.2% for those in TI/PI. This suggests that endogeneity and selectivity bias is present, especially for those in TI/PI.

differences in potential labor market experience. Specifically, those who drop out of school earlier have more potential years of work experience. To the extent that labor market experience positively impacts wages, naive estimates will tend to understate (i.e. make more negative) the true effect of the SGL program.

In Tables 24 and 25 we show the cumulative average number of pension contributions between 2007 and 2010 for individuals enrolled in universities and TI/PI. For university enrollees we fail to reject the null hypothesis of equality of pension contributions between SGL and non-SGL recipients for most years. On the other hand, for TI/PI enrollees, the number of pension contributions is significantly larger for those who did not obtain the SGL. The difference, on average, is 3.7 contributions. It seems unlikely that this would account for the entire wage gap. For instance, according to Sapelli (2009) the average annual return to experience is 2.4%. Thus, the increase in the number of pension contributions could explain a 0.07% wage gap but we observe a wage gap of at least -4.8% (depending on the treatment effect considered) between SGL recipients and non-recipients.

One plausible hypothesis for the observed wage gap, is that the incentive for HEIs to retain SGL students may decrease the retention requirements for students with the loan. As explained before, HEIs are responsible for the loan (up to 90% of principal plus interests) during the period in which beneficiaries are enrolled. Thus, higher education institutions have an incentive to ensure graduation. This may affect the average quality of SGL graduates, which could then be reflected in initial wages.

Indeed, according to MINEDUC (2012), the first year retention rate increased 3.0 pp (4.4%) between 2007 and 2010. This increase was more pronounced among Professional Institutes (PI) (6.3pp or 11%).[38] Additionally, during this period, first year retention rates showed significant improvements among individuals with low PSU scores (below 500 points) coming from low income families.

Evidence of perverse incentives to reduce dropout rates have also been reported at the high school level in the US. In Texas, schools are evaluated based on standardized test scores, attendance, and dropout rates, and cash bonuses are granted to the staff of successful schools. A major scandal occurred at Sharpstown High School in 2003 where dropouts were misclassified as transfers in

[38] It is worth noting that SGL beneficiaries accounts for 31% of the total enrollment in this institutions.

order to boost the district's graduation rate (Domina, Ghosh-Dastidar, and Tienda, 2010). We do not claim to have evidence of this behavior in Chile. However, there is some evidence of irregular certification of some private universities by the National Certification Commission (CNA), the government agency that certifies universities in Chile. A former president of the CNA is under investigation for allegedly accepting bribes in exchange for certifying a number of private universities[39]. Hence, we believe that it may be beneficial to revise the design of this loan program in order to reduce the incentive for universities to dilute education quality at the expense of dropout rates.

Another potential explanation for the negative effect of receiving an SGL loan is what Lochner and Monge-Naranjo (2011) calls *over-invest*ing. According to the authors, under certain circumstances poor low ability students may invest so much in education that marginal return is below the marginal cost. However, we believe this explanation is less plausible in our setting. This is because we find a negative effect of having the SGL on wages.

7 Conclusions

The relationship between access to credit and dropping out from higher education is an important topic in economics. Previous papers have attempted to estimate this effect using reduced form techniques. However, the evidence is mixed and there is little clarity as to the importance of credit constraints on student dropouts Kane (2007).

In this paper we analyze the effect of loans for higher education on enrollment, dropouts, and adult earnings using a unique database that includes information on the 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 State Guaranteed Loan (SGL) program, the most important funding program in Chile, on the probability of dropping out from a HEI. We also estimate the effect of the SGL program on wages for non-dropouts.

Our findings document large heterogeneity in the estimated effect of the SGL program on the likelihood of dropping out of an HEI. In particular, we find that the SGL increases enrollment

[39] Once certified, universities are eligible to public funding for student loans (such as SGL) and scholarships.

by 24% and reduces the dropout rate during the first year by 6.8% for universities and 64.3% for TI-PI.

We also compute the heterogeneous impact of the SGL for different levels of family income and ability. This allows us to investigate if there are short- (related to income) and long-term (related to ability) constraints, as defined by Carneiro and Heckman (2002). We find a significantly higher impact on dropout rates for students with low levels of ability from poorer families.

Although the SGL has positive effects on dropout rates, it also has negative effects. In particular, we find that students with SGL loans have lower wages even after adjusting for ability and HEI quality measures. This may reflect serious issues in the design of the SGL program that encourage HEIs to retain marginal students at the cost of the overall education quality.

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Tables

Table 1: SGL Assignment and share over student aids

Year	2006	2007	2008	2009	2010
SGL	21,251	35,035	42,696	69,901	91,202
Share	10.0%	19.8%	27.5%	36.2%	42.9%

Source: Authors' elaboration based on SIES/MINEDUC.

Table 2: First year Dropout Rates by HEI Type

	University	TI/PI
Overall	9.5%	17.7%
Conditional on applying to SGL	8.2%	13.1%
Conditional on receiving SGL	6.1%	5.9%

Source: Authors' calculations based on administrative records. PI stands for *Professional Institutes* and TI for *Technical Institutes*.

Table 3: The Structure of the State 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 4: Summary Statistics by Choices D_1, D_2, D_3, D_4, D_5 and D_6.

Variable	D_1	D_2	D_3	D_4	D_5	D_6
Gender	0.501	0.506	0.486	0.521	0.471	0.538
	(0.500)	(0.500)	(0.500)	(0.500)	(0.499)	(0.499)
Age	18.731	18.664	18.732	18.613	18.754	18.655
	(2.123)	(1.767)	(1.786)	(1.752)	(1.817)	(1.668)
North	0.129	0.134	0.108	0.153	0.111	0.094
	(0.335)	(0.340)	(0.310)	(0.360)	(0.315)	(0.292)
South	0.213	0.21	0.243	0.186	0.251	0.212
	(0.409)	(0.408)	(0.429)	(0.389)	(0.434)	(0.408)
Size of Familiar Group	4.906	4.866	4.797	4.917	4.792	4.814
	(1.578)	(1.510)	(1.452)	(1.551)	(1.433)	(1.516)
Household Income 278-834 (Thousands of Pesos)	0.309	0.358	0.338	0.374	0.353	0.285
	(0.462)	(0.480)	(0.473)	(0.484)	(0.478)	(0.452)
Household Income 834-1.400 (Thousands of Pesos)	0.054	0.068	0.031	0.095	0.035	0.016
	(0.227)	(0.251)	(0.174)	(0.293)	(0.185)	(0.127)
Household Income 1.400-1.950 (Thousands of Pesos)	0.019	0.024	0.006	0.038	0.007	0.002
	(0.138)	(0.154)	(0.074)	(0.192)	(0.081)	(0.040)
Household Income 1.950 and More (Thousands of Pesos)	0.029	0.038	0.003	0.064	0.003	0.001
	(0.169)	(0.190)	(0.051)	(0.244)	(0.055)	(0.035)
Father's Education: 8-12 Years	0.244	0.211	0.237	0.191	0.225	0.279
	(0.429)	(0.408)	(0.425)	(0.393)	(0.418)	(0.449)
Father's Education: 12 Years	0.352	0.363	0.383	0.349	0.381	0.387
	(0.478)	(0.481)	(0.486)	(0.477)	(0.486)	(0.487)
Father's Education: More than 12 Years	0.287	0.344	0.287	0.385	0.307	0.218
	(0.452)	(0.475)	(0.453)	(0.487)	(0.461)	(0.413)
Mother's Education: 8-12 Years	0.274	0.238	0.254	0.226	0.246	0.284
	(0.446)	(0.426)	(0.435)	(0.418)	(0.431)	(0.451)
Mother's Education: 12 Years	0.372	0.391	0.417	0.372	0.415	0.424
	(0.483)	(0.488)	(0.493)	(0.483)	(0.493)	(0.494)
Mother's Education: More than 12 Years	0.24	0.292	0.241	0.33	0.258	0.179
	(0.427)	(0.455)	(0.427)	(0.470)	(0.438)	(0.383)
Public School	0.451	0.401	0.457	0.36	0.445	0.5
	(0.498)	(0.490)	(0.498)	(0.480)	(0.497)	(0.500)
Private-Voucher School	0.45	0.474	0.491	0.461	0.496	0.474
	(0.497)	(0.499)	(0.500)	(0.498)	(0.500)	(0.499)

Note: Standard errors in parentheses.

Table 5: Summary Statistics by Choices D_1, D_2, D_3, D_4, D_5 and D_6 (Continuation).

Variable	D_1	D_2	D_3	D_4	D_5	D_6
Scholarship	0.06	0.083	0.122	0.054	0.112	0.155
	(0.237)	(0.276)	(0.327)	(0.227)	(0.315)	(0.362)
Agriculture and Livestock	0.025	0.035	0.037	0.034	0.041	0.025
	(0.157)	(0.184)	(0.189)	(0.180)	(0.198)	(0.155)
Arts and Architecture	0.046	0.064	0.057	0.07	0.042	0.108
	(0.210)	(0.245)	(0.231)	(0.255)	(0.201)	(0.310)
Basic Sciences	0.016	0.023	0.028	0.019	0.035	0.001
	(0.126)	(0.149)	(0.164)	(0.136)	(0.184)	(0.031)
Social Sciences	0.096	0.134	0.127	0.139	0.143	0.072
	(0.294)	(0.340)	(0.333)	(0.345)	(0.350)	(0.259)
Law	0.048	0.067	0.059	0.073	0.05	0.093
	(0.214)	(0.250)	(0.236)	(0.260)	(0.218)	(0.291)
Education	0.133	0.185	0.211	0.165	0.256	0.052
	(0.339)	(0.388)	(0.408)	(0.372)	(0.436)	(0.221)
Humanities	0.013	0.018	0.018	0.018	0.023	0.004
	(0.113)	(0.133)	(0.135)	(0.131)	(0.148)	(0.064)
Health	0.083	0.116	0.126	0.109	0.125	0.129
	(0.277)	(0.321)	(0.331)	(0.312)	(0.330)	(0.335)
Technology	0.183	0.255	0.246	0.263	0.221	0.332
	(0.387)	(0.436)	(0.431)	(0.440)	(0.415)	(0.471)
Number of Semesters	6.06	8.443	8.707	8.247	9.367	6.376
	(4.234)	(2.203)	(2.086)	(2.267)	(1.679)	(1.669)
HEI Years of Certification	1.774	2.472	2.572	2.397	2.33	3.427
	(2.284)	(2.355)	(2.286)	(2.402)	(2.155)	(2.520)
GPA	-0.147	-0.029	0.135	-0.152	0.267	-0.329
	(0.965)	(0.971)	(0.934)	(0.981)	(0.917)	(0.840)
Mathematics	-0.177	0.043	0.162	-0.046	0.333	-0.442
	(0.945)	(0.916)	(0.809)	(0.978)	(0.748)	(0.725)
Language	-0.188	0.034	0.192	-0.084	0.365	-0.417
	(0.955)	(0.907)	(0.797)	(0.964)	(0.732)	(0.715)
Number of Observations	47,115	33,814	14,424	19,390	11,242	3,182

Note: Standard errors in parentheses.

Table 6: Estimation Results for Choices D_1, D_2, D_3, D_4, D_5 and D_6.

	D_1	D_2	D_3	D_4	D_5	D_6
Constant	1.587	-0.437	0.104	-0.007	-0.699	0.405
	(0.077)	(0.088)	(0.186)	(0.138)	(0.160)	(0.334)
Gender	0.033	-0.091	-0.246	-0.266	-0.073	-0.232
	(0.015)	(0.015)	(0.031)	(0.024)	(0.027)	(0.048)
Age	-0.031	0.007	0.045	0.046	0.027	-0.016
	(0.003)	(0.004)	(0.009)	(0.007)	(0.007)	(0.014)
North	0.192	-0.264	0.318	0.337	-0.626	-0.095
	(0.023)	(0.023)	(0.053)	(0.035)	(0.052)	(0.086)
South	0.130	0.109	0.421	0.299	-0.518	0.112
	(0.018)	(0.019)	(0.037)	(0.032)	(0.034)	(0.060)
Size of Familiar Group	-0.053	-0.003	-0.022	0.001	-0.038	-0.044
	(0.005)	(0.005)	(0.010)	(0.008)	(0.010)	(0.016)
Household Income 278-834 (Thousands of Pesos)	0.643	-0.212	0.403	0.402	0.378	0.173
	(0.018)	(0.017)	(0.035)	(0.027)	(0.030)	(0.055)
Household Income 834-1.400 (Thousands of Pesos)	0.801	-0.762	0.738	0.719	0.714	0.243
	(0.042)	(0.034)	(0.108)	(0.049)	(0.070)	(0.194)
Household Income 1.400-1.950 (Thousands of Pesos)	0.808	-1.176	1.223	1.042	0.736	0.281
	(0.069)	(0.067)	(0.292)	(0.090)	(0.146)	(0.627)
Household Income 1.950 and More (Thousands of Pesos)	0.913	-1.759	0.768	1.073	0.671	-0.380
	(0.066)	(0.079)	(0.350)	(0.080)	(0.222)	(0.712)
Public School	-0.528	0.303	-0.675	-0.723	-0.467	-0.086
	(0.038)	(0.033)	(0.084)	(0.047)	(0.058)	(0.160)
Private-Voucher School	-0.273	0.301	-0.466	-0.513	-0.353	-0.058
	(0.037)	(0.031)	(0.082)	(0.043)	(0.056)	(0.158)
Factor	0.846	0.561	1.503	1.258	0.077	0.724
	(0.013)	(0.012)	(0.035)	(0.025)	(0.029)	(0.061)

Note: Standard errors in parentheses.

Table 7: Estimation Results for Choices $\Lambda^{\mathbf{D}_1}$, $\Lambda^{\mathbf{D}_2}$, $\Lambda^{\mathbf{D}_3}$, $\Lambda^{\mathbf{D}_4}$, $\Lambda^{\mathbf{D}_5}$ and $\Lambda^{\mathbf{D}_6}$.

	$\Lambda^{\mathbf{D}_1}$	$\Lambda^{\mathbf{D}_2}$	$\Lambda^{\mathbf{D}_3}$	$\Lambda^{\mathbf{D}_4}$	$\Lambda^{\mathbf{D}_5}$	$\Lambda^{\mathbf{D}_6}$
Constant	-2.567	-3.139	-1.872	-3.716	-2.579	-2.146
	(0.440)	(0.275)	(0.819)	(0.543)	(0.205)	(0.251)
Gender	0.342	0.090	0.406	0.152	0.136	0.103
	(0.081)	(0.045)	(0.126)	(0.083)	(0.034)	(0.045)
Age	0.037	0.058	-0.029	0.083	0.044	0.039
	(0.019)	(0.010)	(0.043)	(0.020)	(0.008)	(0.010)
North	0.201	0.043	-0.053	0.233	-0.005	0.228
	(0.170)	(0.063)	(0.230)	(0.108)	(0.045)	(0.057)
South	-0.141	-0.153	-0.098	-0.150	-0.069	-0.071
	(0.128)	(0.051)	(0.158)	(0.091)	(0.041)	(0.054)
Size of Familiar Group	-0.003	0.039	0.100	0.028	0.043	0.063
	(0.028)	(0.014)	(0.040)	(0.021)	(0.01)	(0.012)
Household Income 278-834 (Thousands of Pesos)	0.089	-0.145	0.015	-0.287	-0.293	-0.377
	(0.085)	(0.046)	(0.137)	(0.088)	(0.036)	(0.042)
Household Income 834-1.400 (Thousands of Pesos)	-0.178	-0.138	0.161	-0.425	-0.436	-0.725
	(0.203)	(0.140)	(0.136)	(0.339)	(0.063)	(0.119)
Household Income 1.400-1.950 (Thousands of Pesos)	0.118	0.345	-	0.736	-0.421	-0.718
	(0.344)	(0.277)	-	(0.794)	(0.094)	(0.241)
Household Income 1.950 and More (Thousands of Pesos)	-	0.253	-	0.494	-0.677	-0.479
	-	(0.406)	-	(0.827)	(0.095)	(0.174)
Public School	0.497	0.542	-	0.982	0.439	0.475
	(0.177)	(0.124)	-	(0.320)	(0.061)	(0.106)
Private-Voucher School	0.412	0.376	-	0.770	0.285	0.364
	(0.161)	(0.122)	-	(0.318)	(0.057)	(0.103)
Scholarship	-	-0.694	-	-0.257	-0.616	-0.296
	-	(0.105)	-	(0.122)	(0.113)	(0.087)
Agriculture and Livestock	-	0.028	-	0.096	0.201	-0.038
	-	(0.127)	-	(0.254)	(0.106)	(0.119)
Arts and Architecture	-	0.125	-	0.207	0.194	-0.095
	-	(0.117)	-	(0.135)	(0.099)	(0.082)
Basic Sciences	-	0.336	-	-	0.170	-
	-	(0.128)	-	-	(0.131)	-
Social Sciences	-	-0.176	-	0.205	-0.028	-0.015
	-	(0.098)	-	(0.152)	(0.081)	(0.092)
Law	-	0.067	-	0.084	0.285	-0.017
	-	(0.117)	-	(0.146)	(0.088)	(0.071)
Education	-	-0.377	-	0.005	-0.060	-0.159
	-	(0.089)	-	(0.155)	(0.076)	(0.084)
Humanities	-	0.205	-	-	0.436	-
	-	(0.150)	-	-	(0.111)	-
Health	-	-0.107	-	0.100	0.200	-0.279
	-	(0.106)	-	(0.129)	(0.084)	(0.073)
Technology	-	0.008	-	0.126	0.181	0.034
	-	(0.092)	-	(0.111)	(0.077)	(0.057)
Number of Semesters	-	0.058	-	0.020	0.016	0.001
	-	(0.013)	-	(0.022)	(0.010)	(0.012)
HEI Years of Certification	-0.008	-0.006	-	-0.073	-0.013	-0.101
	(0.027)	(0.011)	-	(0.015)	(0.009)	(0.008)
Factor	-0.576	-0.710	-0.565	-0.552	-0.542	-0.568
	(0.124)	(0.050)	(0.182)	(0.091)	(0.035)	(0.048)

Note: Standard errors in parentheses.

Table 8: Estimation Results for Wage Equations.

	$W^{\mathbf{D}_1}$		$W^{\mathbf{D}_2}$		$W^{\mathbf{D}_3}$		$W^{\mathbf{D}_4}$		$W^{\mathbf{D}_5}$		$W^{\mathbf{D}_6}$		Don't Study
	$\Lambda^{\mathbf{D}_1}=1$	$\Lambda^{\mathbf{D}_1}=0$	$\Lambda^{\mathbf{D}_2}=1$	$\Lambda^{\mathbf{D}_2}=0$	$\Lambda^{\mathbf{D}_3}=1$	$\Lambda^{\mathbf{D}_3}=0$	$\Lambda^{\mathbf{D}_4}=1$	$\Lambda^{\mathbf{D}_4}=0$	$\Lambda^{\mathbf{D}_5}=1$	$\Lambda^{\mathbf{D}_5}=0$	$\Lambda^{\mathbf{D}_6}=1$	$\Lambda^{\mathbf{D}_6}=0$	
Constant	12.118	12.882	11.65	13.236	14.432	12.360	12.405	12.673	11.854	13.021	12.161	12.594	12.273
	(0.552)	(0.233)	(0.248)	(0.117)	(1.388)	(0.270)	(0.377)	(0.202)	(0.191)	(0.099)	(0.178)	(0.122)	(0.043)
Gender	0.052	-0.008	0.109	-0.044	0.471	0.079	0.253	0.055	0.175	0.001	0.200	0.024	0.222
	(0.129)	(0.039)	(0.053)	(0.020)	(0.200)	(0.049)	(0.080)	(0.040)	(0.042)	(0.016)	(0.037)	(0.023)	(0.012)
Age	0.019	0.014	0.043	0.009	-0.121	0.014	0.006	-0.001	0.032	0.008	0.023	0.009	0.013
	(0.029)	(0.010)	(0.013)	(0.005)	(0.076)	(0.013)	(0.020)	(0.010)	(0.010)	(0.005)	(0.009)	(0.006)	(0.002)
Agriculture and Livestock	-	-0.697	-	-0.444	-	-0.368	-	-0.223	-	-0.400	-	-0.134	-
	-	(0.111)	-	(0.060)	-	(0.128)	-	(0.135)	-	(0.054)	-	(0.063)	-
Arts and Architecture	-	-0.467	-	-0.523	-	-0.268	-	-0.348	-	-0.357	-	-0.179	-
	-	(0.114)	-	(0.059)	-	(0.076)	-	(0.068)	-	(0.046)	-	(0.038)	-
Basic Sciences	-	-0.775	-	-0.558	-	-	-	-	-	-0.411	-	-	-
	-	(0.126)	-	(0.067)	-	-	-	-	-	(0.055)	-	-	-
Social Sciences	-	-0.140	-	-0.157	-	-0.107	-	-0.050	-	0.096	-	-0.087	-
	-	(0.085)	-	(0.045)	-	(0.093)	-	(0.078)	-	(0.037)	-	(0.048)	-
Law	-	-0.735	-	-0.463	-	-0.338	-	-0.216	-	-0.332	-	-0.262	-
	-	(0.106)	-	(0.057)	-	(0.082)	-	(0.069)	-	(0.046)	-	(0.041)	-
Education	-	-0.176	-	-0.145	-	-0.27	-	-0.078	-	-0.188	-	-0.156	-
	-	(0.084)	-	(0.040)	-	(0.129)	-	(0.081)	-	(0.036)	-	(0.049)	-
Humanities	-	-0.728	-	-0.410	-	-0.295	-	-	-	-0.337	-	-	-
	-	(0.131)	-	(0.075)	-	(0.675)	-	-	-	(0.062)	-	-	-
Health	-	-0.393	-	-0.151	-	-0.08	-	-0.185	-	-0.259	-	-0.196	-
	-	(0.086)	-	(0.046)	-	(0.082)	-	(0.062)	-	(0.041)	-	(0.037)	-
Technology	-	-0.101	-	-0.102	-	0.143	-	0.115	-	-0.075	-	0.160	-
	-	(0.093)	-	(0.042)	-	(0.064)	-	(0.051)	-	(0.037)	-	(0.029)	-
Number of Semesters	-	-0.038	-	-0.064	-	0.023	-	0.017	-	-0.029	-	0.002	-
	-	(0.012)	-	(0.006)	-	(0.016)	-	(0.011)	-	(0.005)	-	(0.006)	-
HEI Years of Certification	-	0.007	-	-0.012	-	0.017	-	0.010	-	0.000	-	0.013	-
	-	(0.011)	-	(0.004)	-	(0.013)	-	(0.008)	-	(0.004)	-	(0.004)	-
Factor	0.151	0.358	0.062	0.247	-0.205	0.225	0.196	0.166	0.059	0.182	0.175	0.166	0.071
	(0.187)	(0.050)	(0.059)	(0.020)	(0.262)	(0.057)	(0.090)	(0.042)	(0.042)	(0.015)	(0.047)	(0.022)	(0.013)

Note: Standard errors in parentheses.

Table 9: Estimation Results for Test Score Equations.

	GPA	Mathematics	Language
Constant	1.217	0.005	-0.455
	(0.048)	(0.044)	(0.045)
Gender	-0.346	0.185	-0.100
	(0.009)	(0.008)	(0.008)
Age	-0.043	-0.004	0.023
	(0.002)	(0.002)	(0.002)
North	0.025	-0.119	-0.212
	(0.013)	(0.012)	(0.012)
South	0.053	0.065	0.026
	(0.011)	(0.010)	(0.010)
Size of Familiar Group	-0.008	-0.013	-0.020
	(0.003)	(0.002)	(0.002)
Household Income 278-834 (Thousands of Pesos)	0.034	0.186	0.169
	(0.011)	(0.009)	(0.010)
Household Income 834-1.400 (Thousands of Pesos)	0.135	0.335	0.286
	(0.021)	(0.019)	(0.019)
Household Income 1.400-1.950 (Thousands of Pesos)	0.280	0.531	0.418
	(0.035)	(0.031)	(0.031)
Household Income 1.950 and More (Thousands of Pesos)	0.393	0.662	0.534
	(0.031)	(0.028)	(0.029)
Public School	-0.180	-0.473	-0.423
	(0.019)	(0.018)	(0.018)
Private-Voucher School	-0.189	-0.397	-0.294
	(0.018)	(0.016)	(0.016)
Father's Education: 8-12 Years	-0.091	0.029	0.037
	(0.015)	(0.013)	(0.013)
Father's Education: 12 Years	-0.173	0.036	0.084
	(0.015)	(0.013)	(0.013)
Father's Education: More than 12 Years	-0.135	0.190	0.225
	(0.017)	(0.015)	(0.015)
Mother's Education: 8-12 Years	-0.117	0.026	0.054
	(0.015)	(0.013)	(0.013)
Mother's Education: 12 Years	-0.141	0.085	0.134
	(0.016)	(0.013)	(0.014)
Mother's Education: More than 12 Years	-0.082	0.196	0.269
	(0.018)	(0.015)	(0.016)
Factor	0.818	1.000	0.986
	(0.006)	(0.000)	(0.006)

Note: Standard errors in parentheses.

Table 10: Goodness of Fit - Model Choices.

	Actual	Model	P-Value
D_1	0.718	0.719	0.841
D_2	0.427	0.427	0.969
D_3	0.779	0.772	0.120
D_4	0.663	0.672	0.096
D_5	0.234	0.234	0.986
D_6	0.367	0.357	0.065

Table 11: Estimated Impact of the SGL $\left(\Omega_{D_1}^{\text{SGL}}\right)$ on Enrollment.

	Income Category			
	1	2	3	Unconditional
Percentage Points	0.174***	0.080***	0.113***	0.156***
Percentage (%)	30.7%	14.4%	9.3%	24.1%

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 12: Estimated Impact of the SGL on Dropout Rates.

$\Upsilon_{D_4=1}^{\text{SGL}}$	−0.005***
$\Upsilon_{D_5=1}^{\text{SGL}}$	−0.092***

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

Table 13: Estimated Impact of the SGL on Dropout Rates Conditional on Income and Factor (University).

		Income Category			
		1	2	3	Unconditional
Factor Quintile	1	−0.034***	−0.013***	−0.076***	−0.028***
	2	−0.012***	0.010***	−0.043***	−0.006***
	3	−0.005**	0.010***	−0.035***	−0.001
	4	−0.003*	0.011**	−0.010*	0.002
	5	0.005***	0.012	−0.011***	0.006***
	Unconditional	−0.009***	0.005**	−0.036***	−0.005***

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 14: Estimated Impact of the SGL on Dropout Rates Conditional on Income and PSU (University).

		Income Category			
		1	2	3	Unconditional
PSU Quintile	1	−0.028***	−0.008*	−0.071***	−0.022***
	2	−0.007***	0.005	−0.062***	−0.004***
	3	−0.003*	0.008***	−0.049***	−0.001
	4	−0.004***	0.009***	−0.034***	−0.001
	5	−0.000	0.009***	−0.021***	0.002*
	Unconditional	−0.009***	0.005**	−0.036***	−0.005***

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 SGL on Dropout Rates Conditional on Income and Factor (TI/PI).

		Income Category			
		1	2	3	Unconditional
	1	-0.156^{***}	-0.061^{***}	-0.058^{**}	-0.118^{***}
Factor	2	-0.138^{***}	-0.059^{***}	-0.009	-0.111^{***}
Quintile	3	-0.114^{***}	-0.039^{***}	-0.026	-0.092^{***}
	4	-0.089^{***}	-0.043^{***}	-0.053^{**}	-0.078^{***}
	5	-0.067^{***}	-0.024^{***}	-0.069^{***}	-0.059^{***}
	Unconditional	-0.110^{***}	-0.047^{***}	-0.043^{***}	-0.092^{***}

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 SGL on Dropout Rates Conditional on Income and PSU (TI/PI).

		Income Category			
		1	2	3	Unconditional
	1	-0.147^{***}	-0.061^{***}	-0.022	-0.125^{***}
PSU	2	-0.131^{***}	-0.063^{***}	-0.020	-0.111^{***}
Quintile	3	-0.113^{***}	-0.047^{***}	-0.034	-0.093^{***}
	4	-0.085^{***}	-0.039^{***}	-0.058^{**}	-0.071^{***}
	5	-0.071^{***}	-0.032^{***}	-0.066^{***}	-0.056^{***}
	Unconditional	-0.110^{***}	-0.047^{***}	-0.043^{***}	-0.092^{***}

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

Parameter	Estimate
$\Delta^{\mathrm{SGL}}_{\mathbf{D}_1,\mathbf{D}_2}$	-0.028^{***}
$\Delta^{\mathrm{SGL}}_{\mathbf{D}_3,\mathbf{D}_4}$	0.005
$\Delta^{\mathrm{SGL}}_{\mathbf{D}_1,\mathbf{D}_5}$	-0.064^{***}
$\Delta^{\mathrm{SGL}}_{\mathbf{D}_3,\mathbf{D}_6}$	-0.011^{*}

Note: ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively.

Table 18: Estimated Impact of Having Attended a HEI with SGL on Wages $\left(\tilde{\Delta}^{\mathrm{SGL}}_{\mathbf{D}_1,\mathbf{D}_2}\right)$ Conditional on Income and Factor (University).

		Income Category			
		1	2	3	Unconditional
	1	-0.150^{***}	-0.116^{***}	-0.132^{***}	-0.130^{***}
Factor	2	-0.115^{***}	0.038^{**}	-0.034	-0.071^{***}
Quintile	3	-0.072^{***}	-0.005	0.075^{*}	-0.028^{***}
	4	0.002	0.034^{*}	0.082^{**}	0.023^{*}
	5	0.010	0.060^{***}	0.133^{**}	0.043^{***}
	Unconditional	-0.056^{***}	-0.014^{*}	0.027	-0.028^{***}

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: Estimated Impact of Having Attended a HEI with SGL on Wages $\left(\tilde{\Delta}^{\mathrm{SGL}}_{\mathbf{D}_3,\mathbf{D}_4}\right)$ Conditional on Income and Factor (TI/PI).

		Income Category			
		1	2	3	Unconditional
	1	-0.087^{***}	-0.048	-0.114	-0.072^{***}
Factor	2	-0.061^{***}	-0.004	0.014	-0.040^{***}
Quintile	3	-0.017	0.069^{***}	0.068	0.012
	4	0.015	0.036	0.199^{*}	0.024^{*}
	5	0.015	0.089^{***}	0.111	0.032^{***}
	Unconditional	-0.009	0.036^{***}	0.064	0.005

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 20: Estimated Impact of Having Attended a HEI with SGL on Wages $\left(\tilde{\Delta}^{\mathrm{SGL}}_{\mathbf{D}_1,\mathbf{D}_5}\right)$ Conditional on Income and Factor (University).

		Income Category			
		1	2	3	Unconditional
	1	-0.179^{***}	-0.236^{***}	-0.270^{***}	-0.219^{***}
Factor	2	-0.112^{***}	-0.137^{***}	-0.141^{***}	-0.126^{***}
Quintile	3	-0.047^{***}	-0.063^{***}	-0.082^{***}	-0.060^{***}
	4	0.011	-0.024	-0.082^{**}	-0.013
	5	0.096^{***}	0.036^{**}	0.035	0.065^{***}
	Unconditional	-0.031^{***}	-0.086^{***}	-0.110^{***}	-0.064^{***}

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 21: Estimated Impact of Having Attended a HEI with SGL on Wages $\left(\tilde{\Delta}^{\text{SGL}}_{\mathbf{D}_3,\mathbf{D}_6}\right)$ Conditional on Income and Factor (TI/PI).

		Income Category			
		1	2	3	Unconditional
	1	-0.096^{***}	-0.031	-0.182	-0.072^{***}
Factor	2	-0.075^{***}	-0.007	0.110	-0.052^{***}
Quintile	3	-0.010	0.052^{**}	0.197	0.013
	4	-0.019	-0.005	0.128	-0.013
	5	-0.001	0.055^{***}	0.293^{***}	0.014
	Unconditional	-0.025^{***}	0.017	0.075	-0.011^{*}

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 22: Estimated Impact of the CAE on Wages Conditional on Years of Certification and Factor (University).

		Years of Certification							
		0	2	3	4	5	6	7	Unconditional
Factor Quintile	1	−0.201***	−0.158***	-0.041	0.016	−0.097*	0.002	-0.088	−0.130***
	2	−0.157***	-0.025	0.004	0.032	0.059	0.127***	-0.081	−0.071***
	3	−0.087***	-0.07	0.018	-0.009	0.081*	0.162***	0.135*	−0.028***
	4	−0.042***	0.017	0.069*	0.164***	0.123***	0.146***	0.157*	0.023*
	5	−0.027*	0.060	0.113***	0.140***	0.141***	0.166***	0.270**	0.043***
	Unconditional	−0.167***	−0.188***	0.015	0.063*	−0.071*	0.016	0.090	−0.028***

Note: ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively.

Table 23: Estimated Impact of the CAE on Wages Conditional on Years of Certification and Factor (TI/PI).

		Years of Certification							
		0	2	3	4	5	6	7	Unconditional
	1	-0.092^{***}	-0.100	-0.052	-0.167^{**}	0.097	0.025	-0.050	-0.072^{***}
Factor	2	-0.073^{***}	-0.016	-0.045	-0.032	0.033	0.082	0.035	-0.040^{***}
Quintile	3	-0.011	-0.068	0.049	-0.005	0.117	0.158^{***}	-0.069	0.012
	4	0.01	0.061	-0.04	-0.003	0.098^{*}	0.099^{**}	0.151	0.024^{*}
	5	0.003	-0.028	0.035	0.128^{***}	-0.013^{*}	0.196^{***}	0.288^{***}	0.032^{***}
	Unconditional	-0.018^{**}	-0.020	-0.002	0.012	0.058^{**}	0.128^{***}	0.109^{*}	0.005

Note: ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively.

Table 24: Number of Average Pension Contributions for University Enrolled Students.

Year	SGL	No SGL	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 25: Number of Average Pension Contributions for TI/PI Enrolled Students.

Year	SGL	No SGL	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

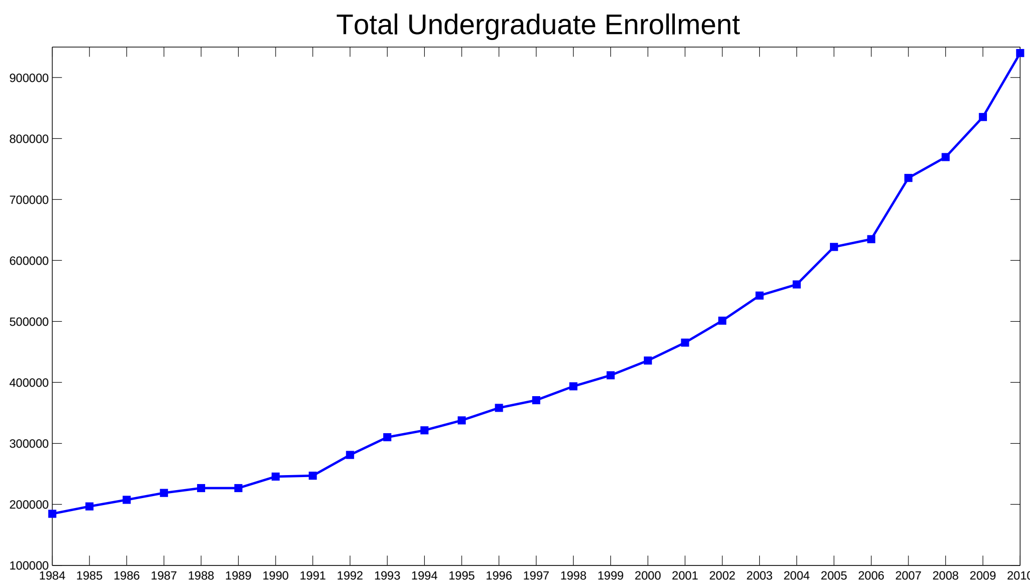


Figure 1: Total Undergraduate Enrollment. Source: SIES/MINEDUC.

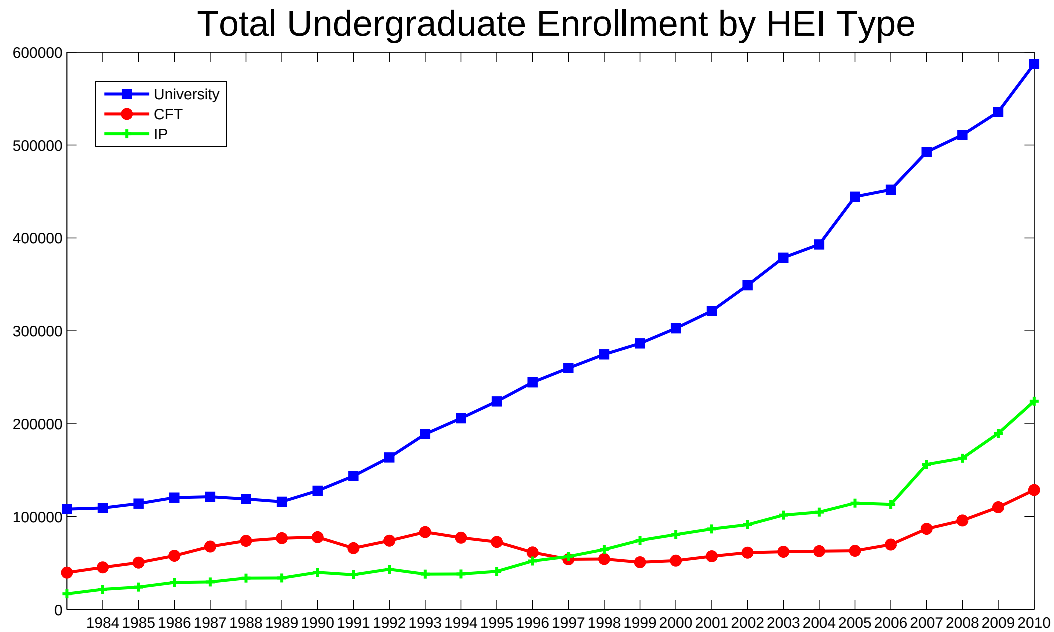


Figure 2: Total Undergraduate Enrollment by HEI Type. Source: SIES/MINEDUC.

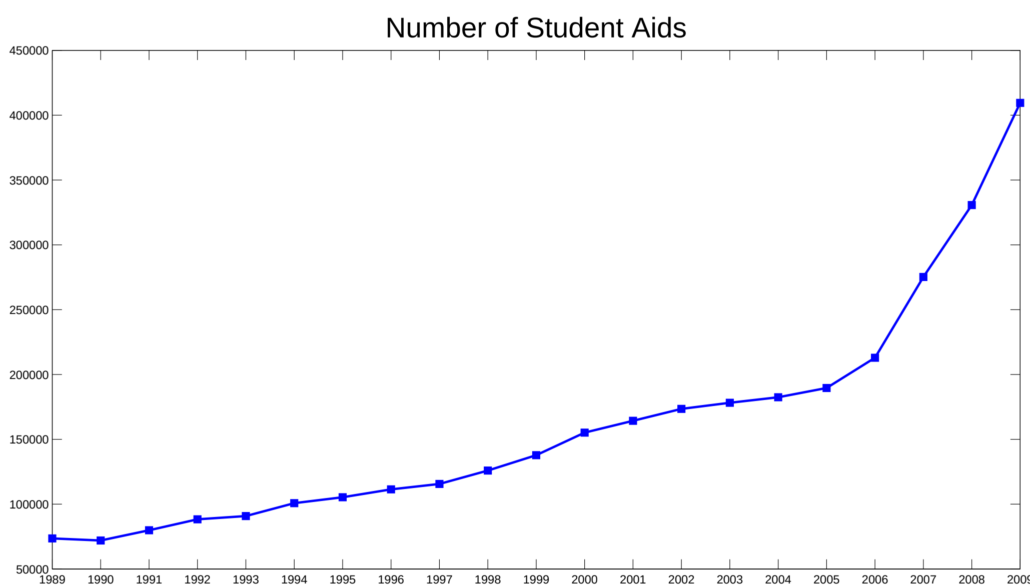


Figure 3: Number of Student Aids. Source: SIES/MINEDUC.

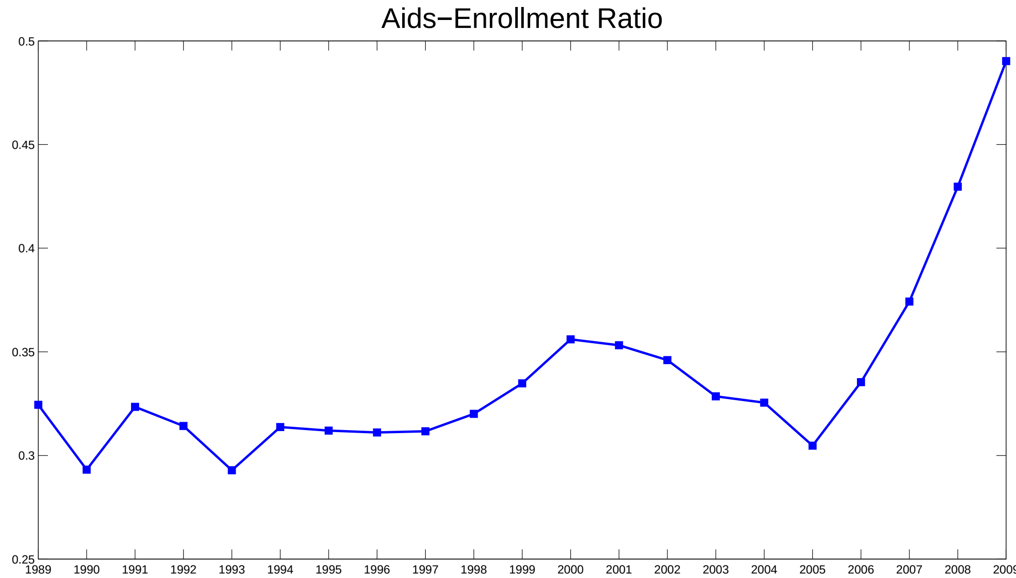


Figure 4: Aids-Enrollment Ratio. Source: Authors' Elaboration based on SIES/MINEDUC.

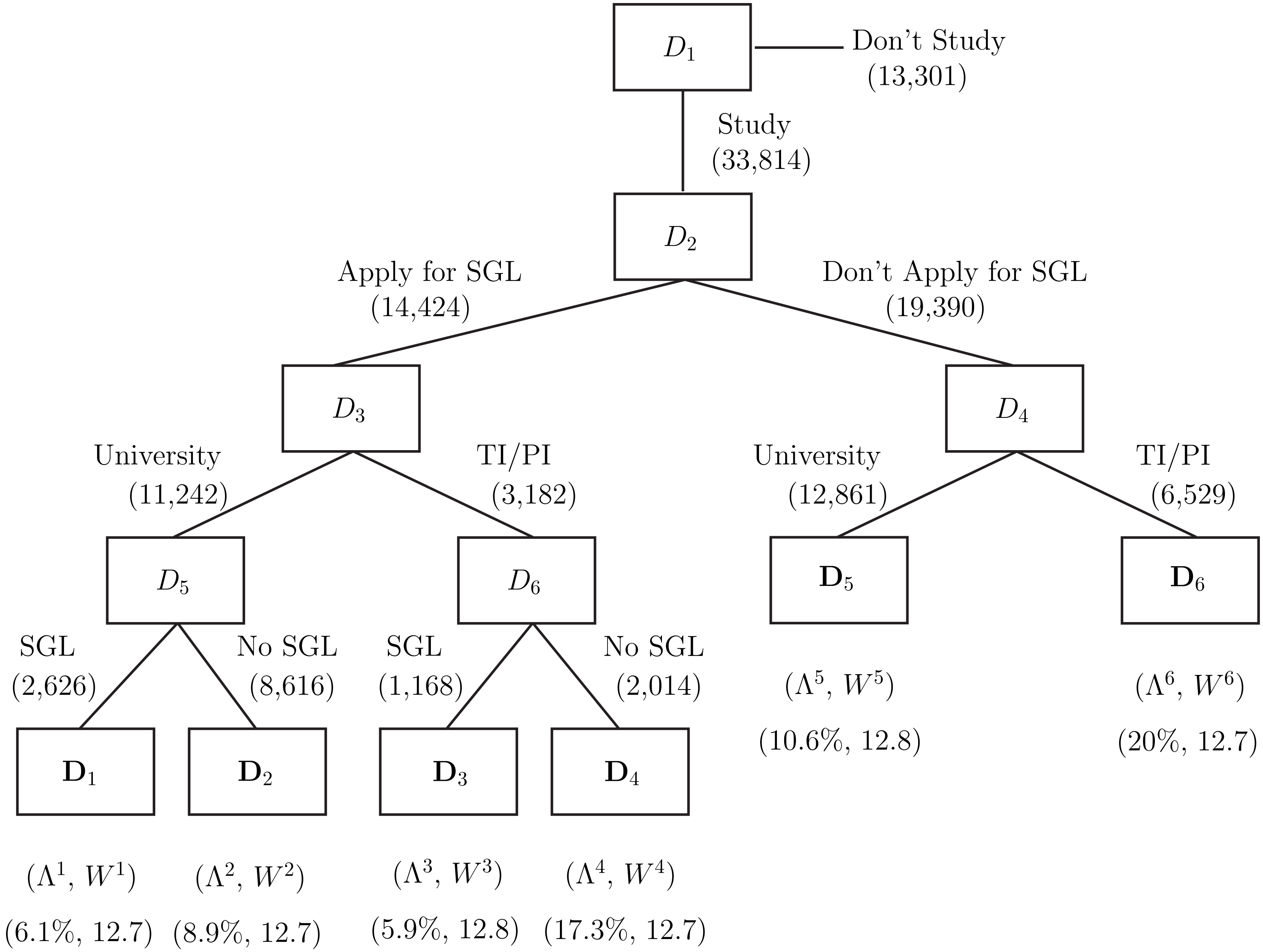


Figure 5: Decision Scheme. Number of Observations by Node, Average Dropout Rates and Average Natural Logarithm of Wages in parentheses.

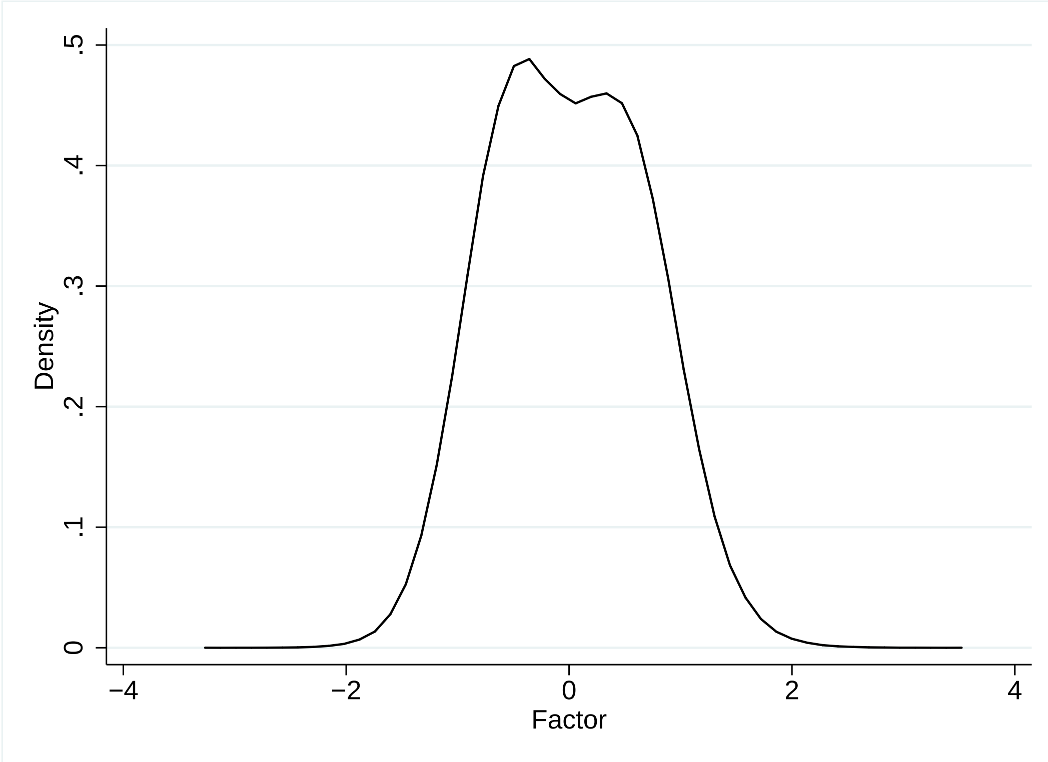


Figure 6: Unconditional Distribution of the Factor.

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:

$$\tau = (-0.547 \quad 0.510 \quad 0.136)$$
$$\sigma^2 = (5.612 \quad 5.191 \quad 2.280)$$
$$\rho = (0.412 \quad 0.391 \quad 0.197)$$

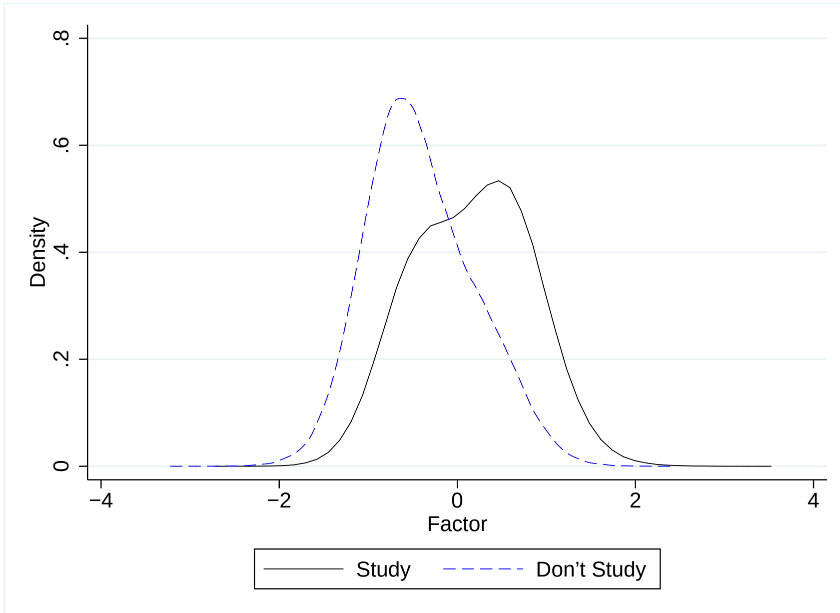


Figure 7: Distribution of Factor by Study Decision.

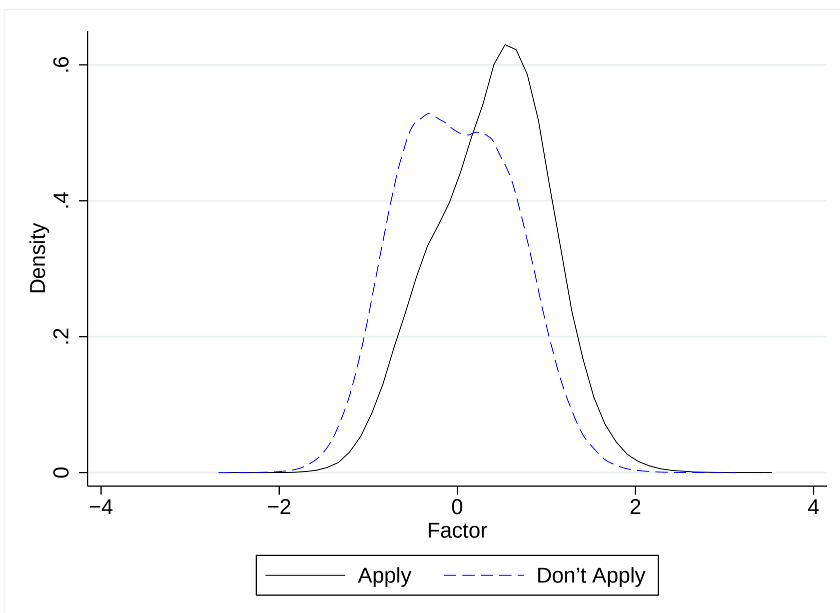
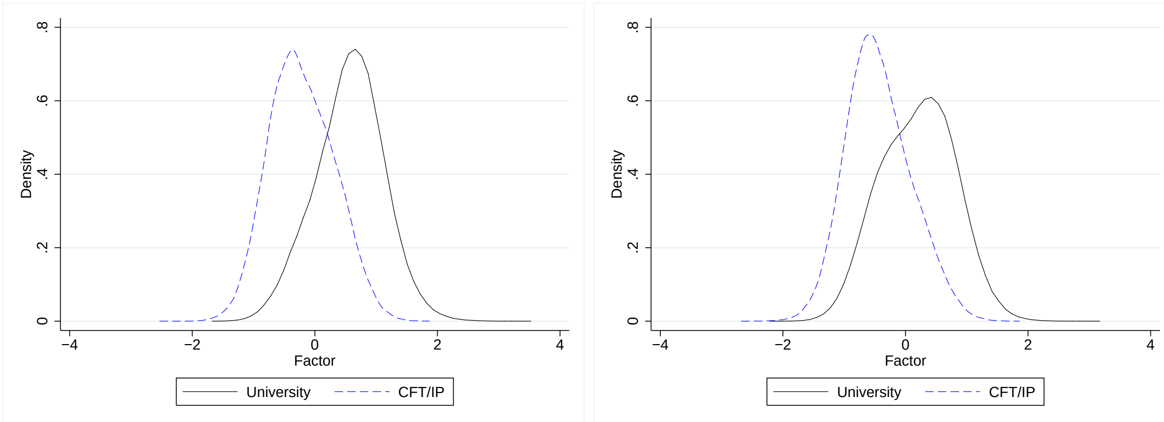


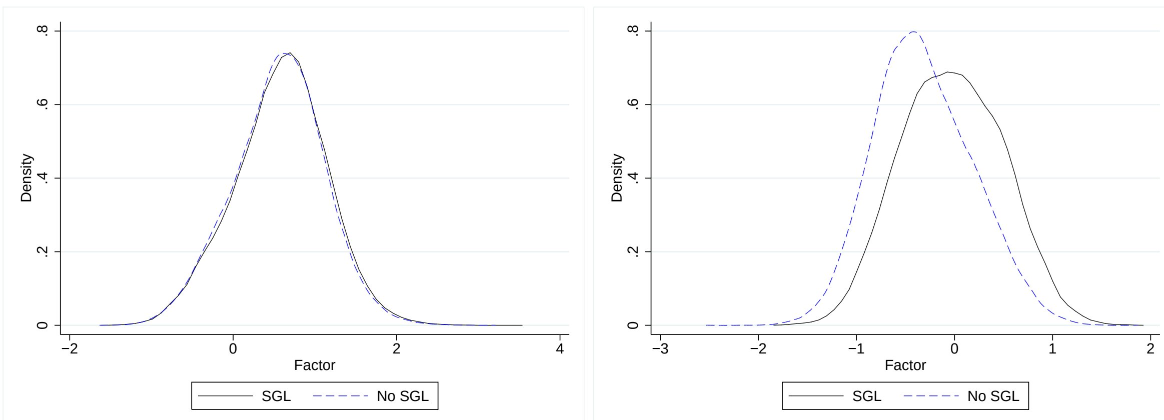
Figure 8: Distribution of Factor by SGL Application.



(a) Apply for SGL

(b) Don't Apply for SGL

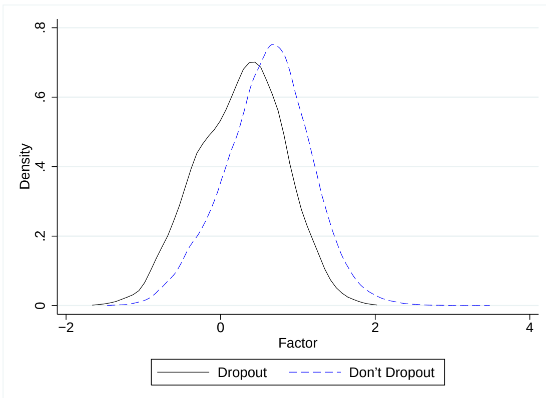
Figure 9: Distribution of Factor by HEI Type.



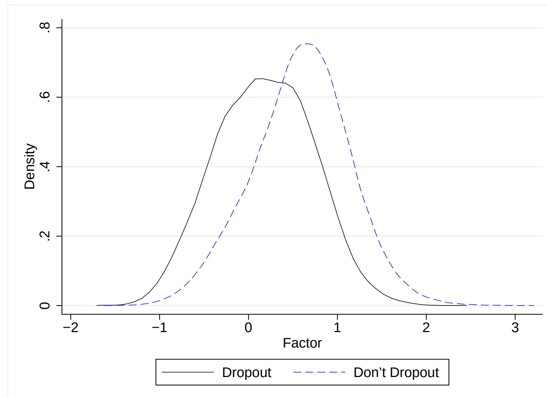
(a) University

(b) TI/PI

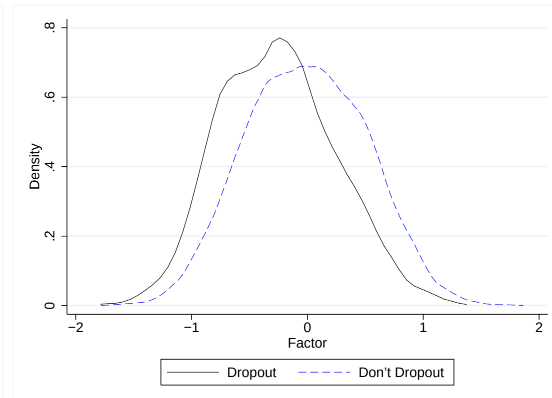
Figure 10: Distribution of Factor by SGL Assignment.



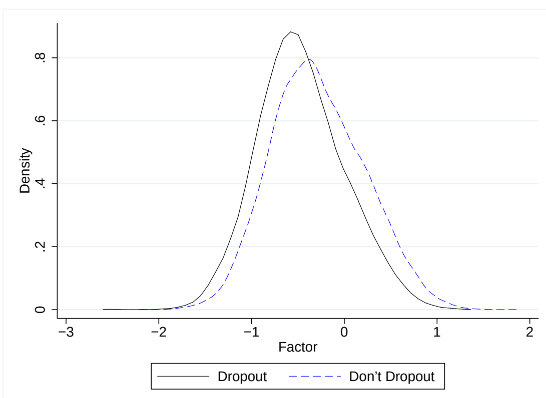
(a) Apply, University and SGL



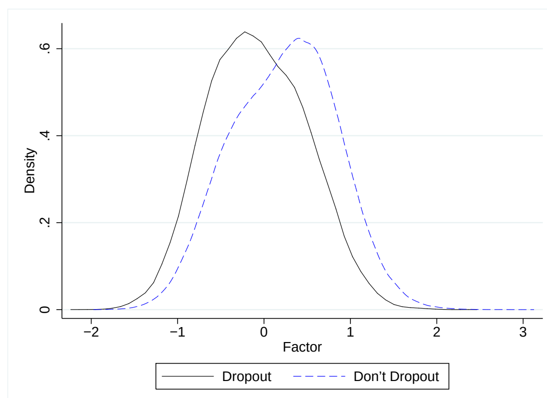
(b) Apply, University and No SGL



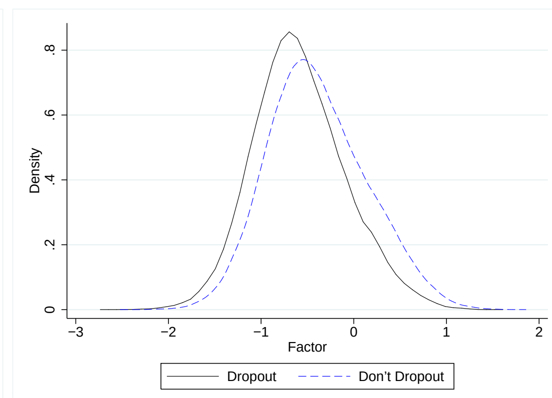
(c) Apply, TI/PI and SGL



(d) Apply, TI/PI and No SGL



(e) Don't Apply and University



(f) Don't Apply and TI/PI

Figure 11: Distribution of Factor by Dropout Decision.

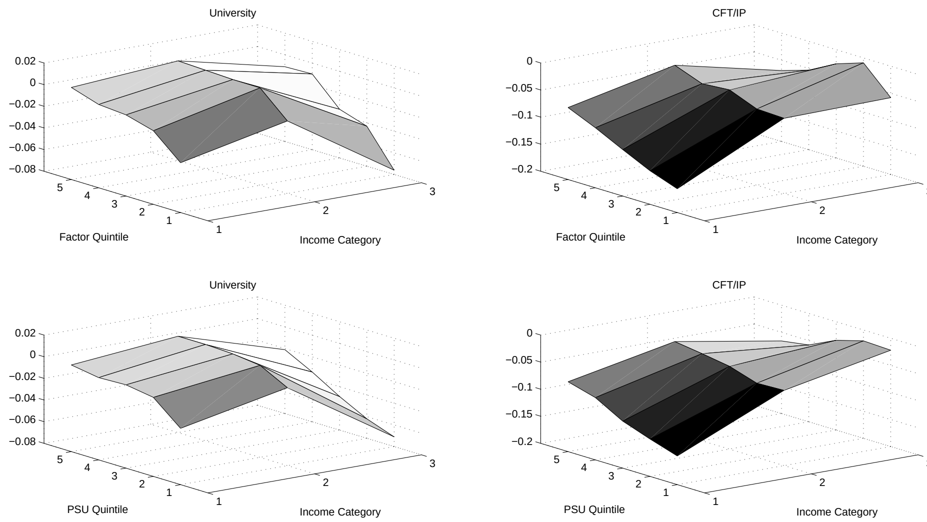


Figure 12: Impact of the SGL on Dropout Rates Conditional on Income and Skill Measures.