Is A Dream Deferred a Dream Denied? College Enrollment and Time-Varying Opportunity Costs[#]

Preliminary – suggestions welcome

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Abstract

A public college in Mexico City randomly assigns applicants into a group that can immediately enroll and a group that can only do so after one year. I show that the standard model of educational decisions predicts no (or minimal) effect of deferral on educational attainment. I surveyed the applicants to this college for the 2007/2008 academic year. Using data from that survey, I find that, one and a half years after the first group enrolled, individuals in that group were 19 percentage points more likely to be enrolled than those that had to wait. This implies that offering more slots in a public college increases educational attainment. I find that one additional slot increases the attainment of about 0.3 individuals of the applicant pool and that offering them to individuals of poorer backgrounds has an even larger effect. To account for these results, I extend the standard model by allowing wages to vary due to random shocks. I derive testable implications of the model and show that they are verified empirically. I estimate the parameters of the model and show that the model can explain the observed patterns under reasonable assumptions. The conclusion is twofold. First, public supply of college slots can impact the attainment of the target population. Second, within-individual variation in opportunity costs is an important element in determining educational attainment. This latter point can have implications for how systems of higher education systems should be designed.

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1 Introduction

Why do some people choose not to go to college? Many social scientists believe that the benefits of extending the levels of educational attainment outweigh the costs (Oreopoulos and Salvanes 2011). Understanding educational decision-making is necessary to predict the effects of subsidizing colleges on educational attainment and forecast the effects on attainment of phenomena such as recessions and changes in skill premia.

The costs of education include the financial direct costs of schooling (tuition, books, etc.) and opportunity costs. Researchers interested in policy have studied the effects of subsidizing post-secondary education on enrollment and attainment. These include studies on the effect of a reduction on tuition (for example: Dynarski, 2003 Kane, 1999 and Kane, 2007) and the effect of opening new institutions (Cellini, 2010). On the other hand, some economists have investigated the role of opportunity costs, mainly to learn about the cyclicality of enrollments. Goldin (1999), Bozick (2009), Clark(2009), Dellas and Sakellaris (2003) and Mattila (1982) study the cuyclicality of ernorllments in developed countries and Binder (1995), Ferreira and Schady (2008), and McKenzie (2005) study the cyclicality of enrollments in developing countries. In addition, Duryea and Arends-Kuenning (2003) and Atkin (2010) show that the higher-wage opportunities for young adults reduce school enrollment.

I investigate the importance of variation in opportunity costs for the timing of the decision to go to college. Earnings are often larger than tuition, pointing to the importance of opportunity costs. At the same time, there is literature demonstrating the existence of much variation in earnings across individuals with similar skills and even for the same individuals across time (Jacobson et al 1993). These two points together led us to hypothesize that variation in opportunity costs is an important determinant of the decision to go to college.

I study the applicants to a college in Mexico City (which I call ”Uni” throughout the paper) where admission decisions are made by lottery. Successful applicants can enter immediately, while the unlucky ones must wait one year before enrolling (from here on, I refer to this as “deferral”). I study the effect of deferral on enrollment and show its implications for the study of the role of time-varying opportunity costs

In the economic model of educational decision-making (that I present later in the study), the expected life-time benefit of additional education for a young individual does not change by much from one year to the next because he still has many years to reap the reward of his investment. Thus, if wages -and therefore opportunity costs- are fixed from year to year, delaying school by one year changes very little the net-benefit for a young individual. In this case the model predicts that almost the entirety of applicants should be willing to start college the following year. Therefore, the model would predict that very few people will be affected by deferral. On the other hand, when earnings have a component that varies randomly, deferral can have a significant impact on attainment.

I find, empirically, a substantial effect of deferral. I surveyed the applicants in the fall of 2008, at a time by which every applicant (admitted and deferred) had the chance to enroll. I find that admitted individuals were still more likely to attend college than those whose admission was deferred. Immediate admission increased the probability that the applicant attended college by almost 20 percentage points (a 30 percent increase). This result is compatible with a model of education decision-making where opportunity costs (for the same individual) vary substantially from year to year. The hypothesis is that deferred applicants worked after being deferred and, during that time, received new wage offers. Thus, by the time they had the chance to enroll at the Uni, their opportunity costs had changed, which explains the substantial effect of deferral.

This model implies that, among deferred applicants, those who earned higher wages in the interim year should have been less likely to go back to study. I first show that this implication is verified empirically. I also discuss other facts unveiled by the survey and show that the proposed model is consistent with them. By matching a collection of empirical moments, I estimate the parameters of the model and show that it can account for the observed patterns. I also argue that the estimated parameters are reasonable in that they are not far from others in the literature. I use the model to estimate the probability that a deferred applicant who did not attend college in 2008/2009 would return and apply to college again at some other point.

The findings of the impact of deferral shed light on the impact of the public supply of college slots on attainment. If the college were larger, it would be able to offer immediate admission to more applicants. The additionally admitted individuals would be almost 20 percentage points (30%) more likely to be enrolled in college two years later and about 16 percentage points more likely to ever attend college.

This article is organized as follows: Section 2 presents the setting and admission process at the Uni and introduces the data; Section 3 analyzes the quasi-experimental results of the effect of deferral. It establishes that being admitted for immediate entry had a causal effect on attainment. In that section, I also show that deferral had a larger effect for individuals from a poorer background. In section 4, I develop the educational decision-making model with time-varying opportunity cost and show that it can account for the facts revealed in the previous section when we allow individual wages to vary. We present implications of the model for the effect of deferral on ever-attending college (overall and for different subgroups of applicants). Section 5 presents the conclusions.

2 The Setting

About a third of the population of the relevant age group in Mexico City obtains some college education[1]. Public sector institutions are not able to absorb all the demand for higher education [2] and the private sector has boomed and now accounts for half of the college-student population[3]. The private sector includes a large netork of institutions that are small and spread out across the city and more affordable than the traditional elite private schools. Many of these colleges charged, in 2006, around USD$1,000 per year in tuition, offered admission two or three times a year and had minimal entry requirements (sometimes just

[1]see Table 1

[2]For example, UNAM, the largest university, uses an entrance exam to screen its applicants, and this exam is passed by only 10% out of the approximately 100,000 test takers (Salcedo; 2009)

[3]ANUIES, 2008

a high school degree, or additionally a GPA above some threshold that is usually set very low.[4]: 7 out of 10) [5].

The Uni is a relatively new public 4-year college in Mexico City, founded in 2001 by the city's government to try to meet the increasing demand for higher education. No tuition is charged to students. The only requirements to enter are having a high school diploma and a domicile in Mexico City. Students fill an online application, where a required field is a phone number with a Mexico City area code. Applicants have to choose two combinations of major, campus and time of day when they want to study (morning or afternoon). Throughout the paper, I call these combinations the "options."

From the available slots for new entrants, the Uni assigns slots first to individuals in a wait-list (applicants from previous years who did not secure a slot). It then offers spots for graduates of a system of high schools with which it has an agreement of direct entry. The remaining slots are offered to new applicants through a lottery[6]. I study the population of new applicants for the 2007/2008 academic year.

In the 2007/2008 admission process, there were 5,437 new applicants to the Uni. About 40% of them were admitted and the rest were placed on the waiting list. Those in the wait-list had priority for the 2008/2009 school year. Every applicant ended up having the chance to enter in 2008/2009. I use the term "deferred" to describe those who were unsuccessful in the lottery.

Every applicant was assigned a random number, and applicants were sorted by their numbers within separate lists for each option. The key feature of this process for my purposes is that admission (deferral) was random conditional on the applicant's stated preferences: two students with identical preferences had the same probability of admission (deferral).[7]

[4]96.5% of the surveyed applicants to the Uni had a GPA equal or larger than 7.

[5]ANUIES (2008)

[6]The Uni uses this system because its administration believes that everyone has the right to education and that past achievement partly reflects the opportunities students have had in the past; basing admissions on a test would worsen such inequalities.

[7]If an applicant believes that some option is less demanded, it might be in an applicant's best interest to apply to it even if it is not the most desirable for him. However, given the stated preferences (and within options) admission was random.

2.1 The Survey

I obtained the names and phone numbers of the full 5,437 applicants to the 2007 lottery for admission at the Uni. At least one telephone number was obtained for each of the applicants (in many cases two numbers). Except for 196 records which were chosen at random for a pilot, I attempted to contact all of them. The interviews took place between September and December of 2008.

All 5,241 remaining records were called six times or until a response was obtained (either answering the survey or declining to participate). It was determined that for about 1,000 applicants none of the phone numbers were working (I can not know if the numbers were false or they had been permanently disconnected between the time of the application and the time of the survey). I obtained 2,344 answered interviews which yield a response rate of 45% (or 55% if estimated out of the valid phone numbers only)[8]. Most of the failures happened because the applicant couldn't be contacted, usually because he was not home during our attempts. Less than 10% directly rejected participating in the survey.

The survey included a module to obtain background information on the applicants. Besides parental education, the survey included a series of questions on the socioeconomic status of the family when the applicant was sixteen years old. Panel A of Table 1 shows the mean characteristics of the population that responded the survey. Many of the applicants were well above the typical age for a recent high school graduate, with about 50% of the applicants older than 21. Note that this is contrary to one of the predictions of the model previously presented. Panel B presents comparable socioeconomic characteristics of the average population in Mexico City using the ENIGH[9] of 2004, a household survey which included a representative sample of Mexico City's population. Panel C presents the same statistics but of only those who either attend college or have some college education. Applicants to the Uni were brought up in families that lived in more crowded houses, had fewer cars and had lower educational attainment than the average individual with some college education. Their characteristics were more in line with those of the average inhabitant of Mexico City of the relevant age group.

[8]None of this information is checked before the draw, therefore many of the applications were probably false (i.e. they contain false information). This can explain the large proportion of invalid or erroneous phone numbers.

[9]INEGI (2004): "Encuesta Nacional de Ingresos y Gastos de los Hogares"

Two sections of the survey questionnaire inquired about the activities of the applicants. The first one asked about the activities pursued in the year immediately after the lottery. In particular, the attendance variable that I use throughout comes from the answer to the question ”Between September 2007 and June 2008, were you studying?”. Additionally it asked about the name of the institution attended, the course load and hours studied. A series of questions about work for pay followed. A battery of questions about current activities followed (which are relevant for the second year after the lottery application). These include questions on current college attendance and also a series of questions about work.

Table 2 shows the percentages of the population who were studying in each academic year[10]. The main thing to note is that individuals admitted in the first year were going to college in larger proportions than deferred ones (80% versus 40%). Even in 2008/2009, the percentage of deferred applicants who were studying was substantially lower (80% versus 64%). The following section will expand on this to show that this in fact follows causally from admission.

Many deferred applicants started college right away in different institutions. Out of 1380 unsuccessful applicants, almost 40% were studying during the 2007/2008 school year, either in private or in a different public institution. Less than a third of the remaining 855 returned to study at the Uni one year later, even though they had the option. In contrast, among the close to one thousand accepted applicants, about 80% of them were studying in each academic year. Most of them did so at the Uni: out of the admitted applicants who did study, 81% did so at the Uni, 12% at a different public school and the remaining at some private college or school.

3 Quasi-Experimental Estimates of the Effect of Immediate Admission (versus Deferral)

I start by showing that that the randomization was effective. The characteristics that could not have been changed by the randomization are in fact similar across the two groups. Table 3 shows the results of estimating separate equations where the dependent variable is presumed to be predetermined on admission

[10]Care should be taken when comparing the attendance rates across the two years. Due to the fact that the previous year’s activities are obtained in retrospect, the two variables might not be fully comparable.

status (always controlling with the ”option” dummies). None of these regressions show a statistically significant coefficient for admission. The hypothesis that all coefficients are equal to zero cannot be rejected (the p-value equals 0.66).

I estimate the impact of deferral on the probability of going to school, holding the option fixed. I do this by estimating a probit regression of ”being in school” against a dummy variable for deferral and dummy variables for each option. This gives an unbiased estimate of the impact on schooling of being offered a place in the Uni as admission to the university for the school year is random given the option chosen. I run regressions where attendance corresponds to each of the 2007/2008 and 2008/2009 academic years.

The results for attendance in 2007/2008 are shown in columns 1 to 4 of Table 4. Deferral reduced the probability that an applicant studied in the first year after the lottery by about 27 percentage points. This is perhaps not entirely surprising, as only admitted individuals had the option of attending the Uni and alternative schools were costly.

The second column includes, in addition to the option dummies, age and gender controls. The third column additionally includes other presumably exogenous background characteristics. Because admission status is random conditional on the options, inclusion of these characteristics should not matter. In fact, the coefficient for admission does not change much across the first three columns. The fourth column shows the coefficient when options are not included in the regression. Remember that when they are not included, the orthogonality of the lottery outcome cannot be assured. Excluding the options would slightly bias upwards the estimate of the impact of deferral.

Columns 4 to 8 show the effect of immediate-admission on attendance in 2008/2009. As above, the first three columns show the estimates when including the option dummies; Columns 2 and 3 include some additional controls. These results show that admitted individuals were still significantly more likely to attend college in the academic year 2008/2009, even though by then everybody had the chance to enroll at the Uni. Thus, deferral had a persistent effect in the rate of college-going.

A coefficient of 19 percentage points implies that almost 25% of those willing to start college will be affected by deferral[11]. Thus, we conclude that a significant fraction was affected by deferral, i.e. a substantial fraction (25%) of those who are offerred deferred admission and would have otherwise started college will not do so.

3.1 Possible confounding factors

An important advantage of this study is that I can compare admitted and deferred applicants that are known to be ex-ante identical in expectation. As in most experiments, exploiting the randomization does not come without problems. Although assignment to ”treatment” (being admitted for immediate entry) was random, survey non-response could introduce bias. Whether my estimates apply for the whole population of applicants is unknown. However, as I argue in this section, it is unlikely that the main qualitative results are greatly affected by non-random selection into responding the survey.

One reason to worry is that being admitted could make the individuals more likely to respond the survey. If individuals in the margin between answering the survey or not are different in some unobserved ways, the fact that these individuals are observed if they are admitted can bias the estimate of the admission status coefficient. To understand this problem I consider the following scenario: Suppose there are two types of individuals. Those of the first type are willing to answer the survey but those of the second type are not unless they are admitted. Among survey respondents, the admitted group will contain individuals of both types, while the deferred group will contain only people from the first type. As long as the first and second type are different in other characteristics besides being more inclined to answer surveys, any comparison between the admitted and deferred groups will combine the causal effect of being admitted with the differences between the two types of individuals.

The admission variable that I use comes from an item in the questionnaire, and therefore cannot be used to determine whether admitted applicants were more likely participate in the survey. I have an alternative measure of admission status from the administrative records. The results in this subsection use this alternative variable.

[11]the 25% comes from dividing 19% by 80%, which is the proportion of those admitted who actually enrolled in college in the first place

The survey response rate is slightly larger among the admitted group, suggesting that being admitted made people more willing to answer the survey. A regression of responding to the survey on admission status (controlling for the option chosen) yields a small but positive and significant coefficient for being admitted (results available upon request). However, the difference is relatively small (5 percentage points), while the corresponding difference between having studied or not in 2007-2008 is 17.8 percentage points (Table 4). Even if all of the additional respondents (those who responded the survey because they were admitted but who wouldn't have answered it otherwise) were studying and were among those studying irrespective of the randomization outcome, our results would qualitatively be unchanged.

Quantitatively the bias must be small since, under the (implausible) assumption that all of the "additional respondents" were studying and would be studying regardless, my estimates of the impact of admission on the probability of studying would change by about 3 percentage points. To formalize this, I use the framework of Lee (2009). He constructs efficient bounds for the treatment effect under two conditions: independence of treatment status with respect to the relevant characteristics and monotonicity (i.e. that the effect of treatment on the likelihood of responding goes in one direction). In this case, the first assumption is guaranteed at the option level by the randomization. The second assumption is likely to hold but is uncheckable. I find that a lower bound for the effect of being admitted is three percentage points lower than the point estimated. That is, being admitted increased enrollment in 2008/2009 by at least 16 percentage points. The details of the method and results are presented in an appendix available from the author upon request.

3.2 Deferral Effects by Sub-groups

There is significant variance in terms of the background characteristics of the applicants. An interesting question is whether deferral has a stronger impact among the poorest, female, and/or older applicants. I constructed a wealth index by summing the standardized versions of the following variables: paternal and maternal education, car ownership, rooms per person in family's house,[12] and whether the individual

[12] Rooms per person and car ownership refer to the family when the applicant was 16 years of age.

attended a private high school. I run regressions like the ones shown so far, but now include the level of the wealth index for individual i (w_i) and, more importantly, its interaction with admission status.

$$\Pr(s_i^t = 1) = \Phi(\alpha + \beta T_i + \psi w_i + \gamma(w_i * T_i) + d_{ij}) \tag{1}$$

The coefficient for the interaction of wealth with admission status γ is interpreted as the change in the effect of being admitted caused by being wealthier. Table 5 reports the marginal effects of the variables in Equation 1. For an individual with a wealth index of one standard deviation below the mean, the impact of being admitted is twice as large as for one with a standard deviation above the mean. This result implies that deferral has a larger effect for the poorest applicants.

The impact of deferral does not vary with age, but is found to be larger for women. Deferral reduces the probability of a female applicant's studying by 44% more than it does for men. This suggests that offering more spaces in the public education system will increase the educational attainment of women significantly more than it does for men.

4 A model of educational decisions with time-varying opportunity costs

At a moment when job opportunities are weak, an individual is more likely to want to go to school, as the total cost of schooling is lower. However, if for some external reason the individual does not go to school at that time, his job opportunities might improve, and it might no longer be worthwhile for him to go to school.

At $t - \varepsilon$, just before the start of year t, individuals were working and earning a wage $w_{i,t-\varepsilon}$ which varies across individuals exclusively due to chance. The opportunity cost of that year of schooling is given by the expected wage they would obtain if they did not go to school (denoted here by $E(w_{i,t})$), which is an increasing function of $w_{i,t-\varepsilon}$. Therefore, there is a critical wage w^* such that individuals will want to go to college if and only if their wages are lower than w_t^*. Those whose $w_{i,t} < w^*$ stay working and decide again in the following year whether they want to go back to school. By that time $(t+1-\varepsilon)$, they face exactly the same decision except that their wages are now $w_{i,t+1-\varepsilon}$. Wages change from year to year because of new and higher random wage offers but also through random separation from previous jobs. Those whose wage has increased by enough (so that $w_{i,t+1-\varepsilon} > w^*$) will no longer want to go to college. Furthermore, because the sample of applicants is composed of individuals who had relatively low earnings, wages will increase on average. Exactly how large this expected wage increase is depends on how strongly applicants are selected. A low critical wage means applicants are strongly selected (strong potential for mean reversions) and yields a greater likelihood that $w_{i,t+1-\varepsilon}$ will surpass w^*.

4.1 The Model

After finishing high school, individuals receive a wage offer. While working, every month individuals receive a new wage offer m_l with a probability p. All wage offers are drawn from identical distributions. In particular, I assume that the logarithm of wage offers is distributed normally with mean μ and standard deviation σ.

Individuals decide whether to work or go to college (no part-time is allowed). I assume that college lasts for s years, during which time the student earns nothing. After college, individuals receive a ”fresh” offer, and their wage process starts again identically as for high school graduates, except that wage offers are multiplied by the constant $(1+\delta)^s$, where δ is the yearly return to college and s is the number of years that college lasts. After college, there is no further education. Individuals live for T years, and maximize their discounted life-time earnings. Future utility is discounted at the rate of β.

- The following list summarizes the assumptions described so far:
- At age 18, individuals graduate from high school, receive their first wage offer, and decide whether or not to apply for college.
- Individuals decide to apply to college ε days before the start of each year
- College lasts for s years.

- Individuals live T years. [13]

- Every day, there is a probability p that an individual will receive a wage offer. An individual who is not studying does not receive a wage offer.

- $\log m_l \sim N(\mu, \sigma)$

- Individuals lose their current job with probability $\lambda \in [0,1)$. If the individual loses his job, the wage for the next period equals the new wage offer. If the individual keeps his job, the wage for the next period equals the largest of their previous wage and the new wage offer. That is, the wage at period l equals m_l with probability λ and $\max\{w_{l-1}, m_l\}$ with probability $1-\lambda$.

- After college, the wage equals $(1+\delta)^s$ multiplied by a fresh draw of the wage offer distribution..From then on, wages follow the same path as the non-college except that offers are always multiplied by $(1+\delta)^s$

- Individuals maximize the expected discounted flow of income

  In the special case where $\lambda = 0$,it follows from the above assumptions that, every year t.individuals go to school if and only if: $\sum_{l=t+s}^{T} \beta^{l-t}(1+\delta)^s E_t(w_l) - c \geq \sum_{l=t}^{T} \beta^{l-t} E_t(w_l|w_t)$.The left-hand side of this expression represents the earnings after s years of college minus the direct costs of schooling, while the right-hand side represents the earnings if the individual does not enroll in college at any moment. Note that the LHS does not change and that the RHS is weakly increasing in time. Therefore, an individual who does not enroll in college at t, will not do so at any time $m > t$. Because the left-hand side is independent of w_t, and the RHS is monotonically strictly increasing in w_t, there exists a critical $w^*(l)$ such that individuals go to school if and only if w_t is lower than $w^*(l)$, where l represents the age of the individual. The critical wage depends on the age because the remaining number of periods after the decision (in which he can reap the benefits of education) depends on the age of the decision-maker.

[13] A model with infinite lifetime can also be constructed with the same predictions which underlines that, if an individual does not come back to school, it is not necessarily because he has less time to reap the benefits of education. This shows that the effect of deferral can be fully explained by variability in opportunity costs.

However, if $\lambda = 0$, the model would not be able to explain why there are so many college applicants above 18 or 19, the typical age of high school graduation. Since we allow for the possibility that individuals can lose their jobs (i.e. $\lambda > 0$), the model can explain this. However,it becomes slightly more complicated to solve. Since $\lambda > 0$, an individual who does not want to study at time t knows that he might want to do so later. Therefore, the value of not going to school includes the option value of going to college. Thus, the problem cannot be described by a single inequality as above. It will still be the case, however, that an individual will study at time t if and only if w_t is smaller than some critical wage $w^*(l)$. Now, $w^*(l)$ comes from solving the following dynamic problem: define S as the discounted expected income flow after college ($S = \sum_{l=s}^{\infty} \beta^l (1+\delta)\mu$), and define a value function as: $V_t = \max\{w_t + \beta V_{t+1}, S\}$. The critical wage $w^*(l)$ is then the associated policy function.

4.2 Testable Implications

The model presented above predicts that some of the deferred applicants will not accept the later admission date. In addition, the model above implies that, *among applicants, the wage in year t predicts college enrollment in year t+1 (those earning higher wages at t will have higher expected wages for t+1 and therefore face a higher opportunity cost to collegein that year).*

I use information collected in the survey of college applicants to test this implication. As described in previous sections, the interviews were applied between September of 2008 and January of 2009. The survey included a question about earnings in a typical week of the period September 2007-June 2008 (year t in our model), and a question about current earnings (first few months of year t+1 in our model). Since the first question asked for typical earnings in the previous year, it can be best translated into our theoretical framework as the mode of earnings in year t. Panel A of Table 6 shows the mean hourly wages and monthly earnings of the 2007 deferred applicants to the Uni. The modal wage for the Sep2007-Jun2008 period was significantly higher among the applicants who did not return to school than among those who did.

This result also holds in a regression framework with multiple controls. Table 7 reports these estimates. The dependent variable is an indicator of whether the individual was going to school in the 2008 academic year; the regressor of interest are, in separate columns: monthly earnings, hourly wage and hours worked, in 2007/2008 and in 2008/2009. The sample comprises all deferred applicants who did not study in the 2007 academic year. Although the set of variables available for our use might not be comprehensive enough to fully control for differences in ability, the lack of inclusion of these variables is more likely to bias against my findings. The story would go as follows: more able people are more likely to go to college and have higher wages for any level of education; therefore, we would observe a positive relationship between wages at time t and schooling at time t+1.[14] Conditioning the sample to observations where respondents stated that their main activity was working does not change results in any significant manner (results available from the author upon request).

This model also can account for two other relationships that are verified in the data:

1. *A significant fraction of applicants who were admitted decided not to enroll because they received high wage offers between applying and enrolling.* This is consistent with the model since, although short, there is a period between the moment of application and the start of the school year (i.e., the ε is at least two and a half months as individuals apply before June to start early September). If someone's work opportunities improved in that period, the individual might have changed his college-going decision.

   Thus, the model also predicts that those admitted who did not to enroll in 2007/2008 will have earned higher wages than those that were deferred. According to the model, the reason why admitted applicants would not go to school is that they received a high wage offer between the time of admission and the time to start college. Instead, the group of deferred applicants includes both individuals who received a wage offer during that time and individuals who did not. This predic-

[14]An alternative explanation of why there is a negative correlation between wages in year t and the probability of enrollment in year t+1 is the following: some applicants decided (for whatever reason) that they did not want to study anymore and therefore exerted a lot of effort in finding a good job that paid well, while those who knew that they were going to come back to school settled for a lower-paying job, as they knew that they were not going to stay there for long. I cannot fully rule out this explanation of this fact.

tion is also verified empirically. Panel B of Table 6 shows that admitted applicants who worked in 2007/2008 made on average MX$27.2 per hour, compared to only MX$24.3 for deferred applicants.

2. *The population of applicants is not comprised only of 18-year-old, fresh out of high-school applicants.* There is a significant number of individuals in their late twenties.Fifty percent were 21 or older and 25% were 24 or older (see Table 1). This is not only true for the population I am studying here; in 2005, 38%[15] of US college students were above 25. In Mexico, this proportion equals 15%[16]. This is contrary to the prediction that all students would attain educational attainment early on in their careers, a prediction that is derived from models where opportunity costs are constant (i.e. Becker, 1965).

4.3 Estimation

I estimate the parameters that make the model quantitatively compatible with the testable implications presented above. I show that with an arguably reasonable set of parameters, the model produces patterns that are close to the ones observed. Estimating the model then allows to make predictions on the future education paths of the deferred applicants.

The estimation proceeded as follows: choose a vector of parameters, then simulate the model N*Z times, where N equals the number of observations in the data and Z is the number of replications (I use 100). Then, I compute a series of moments and compare them to those in the data. I compute the proportion of deferred applicants who ”come back” in my simulated data set and compare it with the actual proportion who came back. I attempt to match the moments that are derived from the testable implications above:the proportion of deferred applicants who ”come back” to college; the mean wage in year 2007/2008 for those who ”do not return” and for those who do; the mean wage in 2008/2009 for those who continued working; and the fraction of admitted applicants who did not start college in 2007, and the proportion of applicants who are 21 years-old or more.

[15] U.S. Census Bureau(2006)
[16] ENIGH

To find the set of parameters with which the model best fits the data, I do a search within the parameter space to find the point where the distance between the actual and simulated moments is minimal. However, certain combinations of parameters produce the exact same simulated data and are therefore not identified. In particular, different combinations of the discount factor β and the return to school δ produce the exact same moments. The reason for this is that I do not have information about earnings after college. Therefore, the only way that the returns to schooling enter into the model is indirectly through the value that individuals give to college: a higher δ indicates a higher value of schooling. However, this is also the way in which β enters the model; a high discount factor implies a high valuation of schooling. A case in which individuals have a lower β but a high δ is indistinguishable from a case in which they have a high β but a low δ. Another way to describing is that there are multiple combinations of β and δ that translate into the same critical wage function $w^*(l)$. Therefore, I can only estimate combinations of β, δ. For a given combination of β and δ, $w^*(l)$ is a given function of age - which I estimate numerically in each iteration.

I estimate the distribution of the wage offers which, assuming log normality, is fully defined by the mean μ and standard deviation σ; and variables such as the probability of losing a job λ and the probability of receiving a wage offer p.[17] I also assume that I observe wages with error, $w_{i,t}^{obs} = w_{i,t} + \varepsilon_{i,t}^{obs}$, and $\varepsilon_{i,t}^{obs} \sim N(0, \sigma_{obs})$.

Fixing δ, the aim is to find the values of $\mu, \sigma, \beta, \lambda, p, \sigma_{obs}$ that minimize the distance between the six observed and simulated moments. I use eight moments: the average logarithm of wages in 2007-2008 of those who do not return (w_{nr}) and of those who do (w_r); the average of the log of the wages in 2008/2009 (only for those working at that point); the proportion of individuals who return to college in 2008/2009; the standard deviation of the log of the wages for those who return to school and for those

[17]This constitutes the Method of Simulated Moments which was pioneered by McFadden (1989), Pakes and Pollard(1989), Lee and Ingram (1991) and Duffie and Singleton(1993). The MSM estimator is defined as the vector of parameters θ that minimizes the distance between the simulated and the observed moments.The weighting matrix consists of a diagonal whose elements are the variances of the data moments.

who do not return; the proportion of admitted applicants who did not start college and the median age of the applicants. .I use a simplex algorithm to obtain the estimates[18]. Table 8 presents the results.

The overall level of wages (three moments wages of those that return to school and don't in 2007-2008 and those that don't return to school in 2008-2009) is shifted with μ; the higher the standard deviation the higher the average difference in wages among those that return and those that don't given any critical wage which is affected (and therefore determines the proportion who return to school) by the discount rate β: the lowest it is the more important a low current wage is in the decision to return to school. The age profile of the applicants helps identify the probability of job joss λ although it is also affected by the probability of receiving a job offer in any given period p.

The share of those admitted who do not go to school is determined by how many receive a good wage offer in the three months between the application period and the start of school which is mostly affected by p. The wage growth between 2007/2008 and 2008/2009 increases significantly with p.

Panel B of Table 8 shows the observed and simulated moments (with the optimal parameters reported in Panel A). As can be appreciated, the model can produce moments that are close to the observed moments. However, a formal test rejects this model. This is not entirely surprising given the simplicity of the model. However, this is no reason to dismiss it. On the contrary, the model presented herein seems to provide a reasonable approximation of the observed data. To evaluate how close the simulated moments are to the actual data moments, previous literature [19] compared the differences between observed and simulated moments with the standard error or the standard deviation of the data moments. In all but one case, the difference between the moments is smaller than 1.96 standard errors. The one exception is the proportion of admitted individuals who did not study in year 2007/2008. The model can predict that 12% of admitted will not start, but cannot predict a number closer to the observed 20%. The reason is that, to predict such a high number, it would require a higher p (so that a large proportion gets an offer in the three months between the application and the start of classes), but a higher p also drives overall wages higher (and particularly the difference between the wages in 2007 and 2008, which is why a higher p cannot be

[18]Nelder-Mead Simplex Direct Search algorithm in Matlab
[19]Franke (2009)

fully compensated with a lower μ). Particularly of interest is that the simulated proportion of deferred applicants is 37%, very close to the observed 38%; the model has no difficulty in predicting that a large fraction of deferred applicants will not enroll in college one year later. This is in stark contrast with what the model would predict with constant opporunity costs[20].

Thus, I conclude that the model can explain the moments of the data and therefore the testable implications, and get close to them quantitatively, with the exception of the proportion of admitted who do not return where the model falls slightly short.[21] The next question is whether the parameters that make the model match the empirical moments are "reasonable". I first look at the combinations of β and δ that are consistent with the estimated parameters. As I mentioned earlier, β and δ are not separately identifiable. However, fixing δ at a yearly 10% (which is often found in studies of the returns to education), I obtained a β of close to 0.9, which would denote a relatively high level of impatience -which many argue is true for college age individuals-[22]. Fixing δ at 5% (below most literature estimates but not unreasonable either) yields a β of 0.943. Other parameters are less readily comparable to previous literature estimates. The monthly probability of losing a job λ, is estimated to equal 0.007 monthly, while the probability of receiving a wage offer p in any given month is estimated to equal 0.08. I compare what the level of job transitions that the model predicts with these parameters for average young workers. The model predicts that 12.2% of 25/26-year olds will obtain a better job offer and change jobs to a higher paying one[23] . It also predicts that 7.1% will be forced to lose their job and become unemployed or move to a lower paying job. Thus, 19.3% change jobs in a given year, 36.8% of whom do so because of job loss. As a point of comparison, results from a new national survey, Encuesta de Trayectorias Laborales (ETL),[24] show that

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[20]I estimated the same model without new wage offers, i.e. where the only reason an individual would not come back is that he has become one year older. This model would predict that the prediction of deferred applicants that comes back is lower than one percent.

[21]According to this model, the decision of 8% of admitted applicants cannot be rationalized in terms of wage offers and time-varying opportunity costs. Given the ease of applying, it would not be surprising that some of the applications were not serious to start with.

[22]For example, Oreopoulos & Salvanes (2011)

[23]This number is for every worker, not on the subsample with low initial wages who are the college applicants.

[24]CONSAR and INEGI (2012), Encuesta Nacional de Trayectorias Laborales, http://www.consar.gob.mx/sala_prensa/pdf/presentaciones/2012/encuesta_trayectorias_laborales.pdf

21.3% stay for less than one year in their job and that 33% of job changes are due to job loss. These numbers are surprisingly close (though they refer to the average working population and not specifically to the young).

4.3.1 Using the model to calculate the opportunity costs of attending college for applicants before and after deferral

We can use the estimated model to estimate the total difference in opportunity cost of going to college in the year in which they applied and one year later. I calculate this for the average applicant. The model predicts that, for an average 20 year old applicant, the difference in opportunity costs of going to college from the time of application to one year later equaled MX$9,394. To have a basis of comparison, I obtained the yearly tuition costs at the ”alternative” private colleges which were were as low as MX$12,500.[25]. Thus, the variation in wage opportunities from one year to the next imply that the oppportunity costs increased by the equivalent of almos one year of tuition at a private school From this perspective then, it is not surprising that deferral had such impact.

4.3.2 Using the model to estimate the long-run impact of deferral on college attainment

The above results have implications for the effect of the supply of public education on attainment. Imagine that the Uni increases in size just enough to offer one more slot. What would be the effect of this on the educational attainment of the population? The Uni would offer immediate entry to one more applicant. From the reduced-form results of Section 3 we know he will be about 30 percentage points more likely to be studying in the year for which he applied and 20 percentage points more likely to be studying one year afterwards (an increase of about 30 percent). However, we cannot infer directly from those results for yeat $t+1$ that those who were not studying at year $t+1$ will never come back and apply again for college. One of the ingredients needed to make that calculation is the probability for a deferred applicant

[25] I collected the names of the institutions where applicants to the Uni were actually studying, and I am using this information to obtain the actual tuition that is relevant for them.

who did not return in $t+1$ will not come back and apply in $t+2$ or any subsequent year. Having estimated the model above, we can use the model to predict such probability by taking into consideration the age they will be and the likelihood that their wage will fall below the reservation wage at that point. Figure 1 shows the probability that an average rejected applicant returns after being deferred. It is likely that the indivdiual decides to study at time $t+1$, as we have seen. After that, however, for an individual to return at $t+2$, they would need to receive a shock that reduces their likelihood of studying. The relatively low job loss probability (0.007 in any given month) reduces dramatically (by about a 90%) the probability of returning to school in $t+2$. From then on, the probability falls steadily reflecting the fact that the older the individual, the lower the total benefit in earnings of going to college.

To translate that into an "impact of deferral" we have to consider, in addition, the probability of going to college given being admitted (since, as we have showed, under 20% of applicants decide not to go even if originally admitted), and the probability of going to some other college in time t if deferred. Considering that about 40% of the deferred applicants enrolled in other colleges at time t, and also simulating the enrollment patterns of the 20% of admitted applicants that did go to college, we calculate the overall effect of deferral to equal 15.2 percentage points, about 4 percentage points below the reduced-form, quasi-experimental effect of deferral on $t+1$ presented in section 3. Assuming no general equilibrium effects, this implies that if the Uni were larger and offered more spots, more people would have gone to college at some point in their lives[26]. This therefore presents case-study evidence of the effect of increased public higher education on total educational attainment. The next subsection investigates whether the Uni could increase its impact on attainment if it focused more strongly on specific groups.

[26]There could be two types of general equilibrium effects of supplying more education: the returns to schooling could change, and the cost of private universities could also be affected. The direction of the effect of increasing the number of students on the returns to schooling is indeterminate. In a standard model with a fixed demand for a given skill level, more college students would drive the return downwards. If, however, there are complementarities, as proposed in some macroeconomic models , there could be a positive effect on the return to skill. Assuming constant returns to scale in the production of higher education, one individual staying longer in school does not drive tuition fees up. However, I have no evidence regarding this topic.

4.3.3 Using the model to estimate the long-run impact of deferral on college attainment for applicants of different characteristics

The model can be made more flexible to allow for different effects for different groups. I do this by allowing the mean of the wage offers to depend on the characteristics (age, gender and socio-economic background) of the individuals $m_{i,t} \sim \log N(\mu + X_i b, \sigma)$. I also allow β and p the discount rate, to vary across characteristics. Since the probability of job-loss λ is identified out of the age profile of the applicants, I cannot allow it to vary with age. The moments used in the estimation are now broken down into groups of gender, age and wealth. I divide by age above the median and below the median; and by wealth-background above the mean and below the mean. The set of moments to be estimated includes the same as in the previous models, but (exept for median age of applicants) is now used for each of eight groups, i.e., the cross-product of sex, age (above and below median) and wealth[27](above and below the mean). The number of moments to be estimated is now 57 while I only added two parameters for each of those groups. Therefore, I am in this case attempting to match 48 moments with only 12 parameters.[28].

Then I can make predictions for the impact of deferral for particular subgroups. This allows responding to the question of whether the Uni could have more impact if they offered more college slots to applicants of different characteristics. The reduced form results presented in Table 5 showed that deferral effect on college attendence in the two years following the lottery is stronger for women than for men. We can use the model to simulate the gendered effect of deferral on the probability that the applicant ever attains some college education. Overall, this exercise shows that the reduced form results by subgroups of the impact of deferral on enrollment at time t and $t+1$ presented in section 3 extend to lifetime attainment. The effect of deferral is larger for women and individuals of poorer family backgrounds and is about the same for applicants one standardad deviation above and below the median age.

The model predicts that the effect of deferring college for a female applicant (with otherwise average

[27] the wealth index described in Section 3

[28] A table with the results is available online (see table 9 in **www.rand.org/about/people/p/perez-arce_francisco.html)#)publications).**
or by request.

characteristics) will be to reduce the probability that they ever attend college by 20.1 percentage points*, while for men it reduces it only by 13.7 percentage points*.

The estimated model shows that the critical wage does not change substantially over a few years (i.e comparing that of an 18 year old with that of a 21 year old). The wage patterns predicted by the model result on the prediction that the lifetime education attainment of a 21 year old is affected slightly less by deferral than that of an 18 year old (although a 24 year old is affected more strongly). In particular, deferring the entrance for a 24-year old will reduce the probability that he ever attains college by 18 percentage points (from x to y) while doing the same for an 18 year old would reduce it by 16 percentage points.

Similarly, one can ask whether the impact of deferral is higher or lower for applicants with poorer or richer family backgrounds. Although it probably would not be feasible to use wealth as a condition for admission, it could influence the probability of admission for different backgrounds by, for example, increasing its marginal slot in the campus located in the poorest geographical area. The simulation confirms the reduced-form result that the impact would be substantially larger for an individual from a poorer background if an additional slot is offered to an individual whose family wealth index is one standard deviation below the mean than if it is offered to one whose index is one standard deviation highest (53% larger for an individual one standard deviation below the mean wealht index).

5 Conclusions

Understanding how individuals decide whether to acquire more schooling is of great importance for the economics of education. I analyzed the case of the applicants to a new public college in Mexico City. These applicants were randomized into two groups. The first group could start right away, while the second had to wait one year. The standard model of educational decision making with fixed opportunity costs would predict that the attainment of these two groups will be similar. However, I find that being offered immediate admission increases the probability of being enrolled in any institution.

I propose an explanation based on time-varying opportunity costs in a model of educational decisions. According to this model, deferred applicants went back to work. During the following year, they received new wage offers, changing the opportunity costs of schooling. For many of them, by the time they had the chance to enroll, it was no longer worthwhile to attend college. I showed that this model can explain the observed patterns.

This result has direct policy implications. It shows that offering more slots in increases the educational attainment of the targeted population. Each additional admission increases the probability of ever attending college by about 25%. I also show that the impact is larger for slots offered to individuals of poorer backgrounds and women. Compared to an individual who is close to the mean, the impact of offering admission to an applicant who is one standard deviation below the mean wealth level is about 50% larger.

A better understanding of the decision-making of individuals can help guide policy making. For example, increasing the supply of public higher education can improve attainment by providing, at the right moment, the opportunity to study to individuals who are willing to take advantage of it. The estimated model predicts that offering a slot in this college will permanently affect the applicant's educational attainment; and this effect is larger for female applicants. It also predicts that the effect on attainment of offering a slot does not vary with the age of the applicant.

Cross-time variability in an individual's opportunity costs of schooling can explain other phenomena: such as why a significant fraction of the population is willing to start college only at specific moments in their lives and, in turn, explain why a significant fraction of the population starts higher education at a later age.

I have shown that an individual's decision to go to college can change in a very short span of time. These individuals will be much more likely to attain a college education if there are sufficiently flexible institutions where they can start college at the moment when they need to start and that do not have strong entry requirements. Community colleges in the U.S. have these characteristics. Most of the increase in college attainment during the last three decades [29]has occurred within these institutions. The private

[29]Card and Lemieux

sector in Mexico has also realized the importance of this flexibility; most institutions allow individuals to enter at any three points in time[30] and have minimal requirements. If it intends to increase the levels of college attainment, perhaps the public sector should follow suit.

[30] ANUIES()

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Table 1. Summary Statistics per Age Group

Age	Rooms per person[(a)]	Cars per person[(b)]	Years of Parental Education	Years of Maternal Education	Private High School [(c)]	% College*
(1)	(2)	(3)	(4)	(5)	(6)	(8)
			Panel A: UNI Applicants			
16-19	0.91	0.08	9.64	9.21	0.10	
20-24	0.90	0.09	9.47	8.97	0.11	
25-29	0.91	0.08	9.54	8.56	0.15	
30-34	0.83	0.09	9.38	7.79	0.13	
Percentile	Age					
25	19.00					
50	21.00					
75	24.00					
			Panel B: All population in Mexico City[(t)]			
16-19	0.97	0.11	9.44	8.58		0.14
20-24	0.96	0.14	9.60	7.78		0.34
25-29	1.00	0.15	8.90	6.74		0.29
30-34	0.99	0.14	7.11	5.63		0.25
			Panel C: Population in Mexico City with some college[(t)]*			
16-19	1.25	0.17	11.80	10.39		
20-24	1.21	0.26	12.44	10.66		
25-29	1.14	0.22	11.86	8.53		
30-34	1.16	0.19	8.05	4.54		

(a) Number of rooms divided by number of inhabitants of houehold when the respondent was 16 years old

(b) Numbers of cars owned by family, divided by number of family members when the respondent was 16 years old

(c) Proportion of individuals whose high school was private

* Either attends college or has at least one year of college education

(t) Source: ENIGH 2005 Either assists college or has at least one year of college education

Table 2. Percentage of Applicants Attending* College

	Accepted	Rejected
2007/2008 academic year	80%	42%
2008/2009 academic year	80%	64%

Note : includes individual who either answered yes to the question: "Do you study?" or answered study to "What is your Main Activity?". Includes individuals who said they were "enrolled at the Uni"

Table 3. Testing Randomization

	Dependent variable						
	Female	Rooms per person	Car	Years of Parental Education	Years of Maternal Education	Private High School	High School system 1
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Deferred	0.025	0.013	-0.019	0.311	0.178	-0.014	0.002
	(0.022)	(0.022)	(0.022)	(0.216)	(0.192)	(0.015)	(0.022)
Obs.	2234	2220	2234	2234	2234	2223	2234
R-squared	0.124	0.021	0.032	0.038	0.043	0.038	0.031

	Dependent variable					
	High School system 2	High School system 3	High School system 4	High School system 6	High School system 7	High School system 8
	(8)	(9)	(10)	(11)	(12)	(13)
Deferred	0.006	0.008	0.013	0.005	-0.003	0.006
	(0.017)	(0.013)	(0.012)	(0.007)	(0.011)	(0.008)
Obs.	2234	2234	2234	2234	2234	2234
R-squared	0.031	0.037	0.044	0.019	0.057	0.022

Note: All include "option" dummies. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0. All are linear regressions.

Table 4. The Impact of the Deferral on Enrollment

	Dependent variable:							
	Studied in the 2007/2008 academic year				Studied in the 2008/2009 academic year			
Marginal Effects	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Deferred	-0.265***	-0.270***	-0.275***	-0.296***	-0.178***	-0.186***	-0.190***	-0.172***
	(0.023)	(0.023)	(0.023)	(0.021)	(0.021)	(0.021)	(0.021)	(0.019)
Female		0.022	0.040*			-0.022	-0.011	
		(0.024)	(0.024)			(0.022)	(0.022)	
Age		-0.007***	-0.006***			-0.013***	-0.012***	
		(0.002)	(0.002)			(0.002)	(0.002)	
Household Characteristics	No	No	Yes	No	No	No	Yes	No
High School System	No	No	Yes	No	Yes	Yes	Yes	No
Option Dummies	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Pseudo R-squared	0.088	0.092	0.104	0.061	0.055	0.074	0.085	0.027
Observations	2234	2234	2232	2235	2216	2216	2214	2235

Probit models also include Dummy Variables for each option (where an option is a major*campus*time-of-day). Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0. Background controls: age, sex, rooms per person, homes per dwelling, family owned car, years of paternal education, years of maternal education, private high school. High school system 1-8 are dummies for the system to which the student's high school belonged.

(t) Outcome when the respondent was 16 years old

Table 5. Differential Impact of Deferral by Group

	Dependent variable:							
	Currently Studies							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Deferred	-0.178***	-0.135***	-0.225***	-0.200**	-0.189***	-0.155***	-0.233***	-0.211***
	(0.021)	(0.029)	(0.073)	(0.081)	(0.021)	(0.029)	(0.073)	(0.081)
Deferred*Wealth	0.094***			0.097***	0.096***			0.097***
	(0.036)			(0.036)	(0.036)			(0.036)
Deferral*Female		-0.088**		-0.068*		-0.072*		-0.063
		(0.039)		(0.041)		(0.040)		(0.041)
Deferral*Age			0.002	0.002			0.002	0.002
			(0.003)	(0.003)			(0.003)	(0.003)
Wealth Index	0.076***			0.059***	0.138	0.098	0.105	0.136
	(0.021)			(0.022)	(0.121)	(0.120)	(0.120)	(0.121)
Female		-0.034		-0.041	-0.014	-0.038	-0.014	-0.035
		(0.026)		(0.026)	(0.022)	(0.026)	(0.022)	(0.026)
Age			-0.012***	-0.012***	-0.011***	-0.011***	-0.010***	-0.010***
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Background controls	No	No	No	No	Yes	Yes	Yes	Yes
Pseudo R-Squared	0.060	0.057	0.074	0.079	0.088	0.087	0.086	0.089
No. of observations	2216	2216	2216	2216	2216	2216	2216	2216

Note: Probit Model also includes Dummy Variables for each high school system and option (where an option is a major*campus*time-of-day). Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0

Table 6. Wages and Earnings of Applicants

Panel A: Earnings of Rejected Applicants

		Studied in the 2008/2009 academic year	Did not studied in the 2008\2009 academic year	All
2007/2008 academic year	hourly wage	21.6	26	24.3
	monthly earnings	3,228	4,196	3,817
2008/2009 academic year	hourly wage	X	27.7	X
	monthly earnings	X	4,609	X

Panel B: Earnings of Rejected and Admitted Applicants

		Rejected Applicants	Admitted Applicants
2007/2008 academic year	Hourly wage	24.3	27.24
	Monthly earnings	3,817	4,317

Note : Sample in Panel A includes only rejected applicants who were not studying in the 2007/2008 academic year. Panel B includes only rejected and admitted applicants who did not study in the 2007/2008

Table 7. The Impact of Wages on Probability of Future Enrollment

	All Rejected who did not study in 2007/2008 academic year								
	Dependent variable:Studied in 2008/2009								
Explanatory Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
monthly earnings in 2007/2008 academic year	-0.141*** (0.029)			-0.111*** (0.033)			-0.128*** (0.035)		
hourly wage in 2007/2008 academic year		-0.075*** (0.024)			-0.045* (0.026)			-0.064** (0.028)	
hours worked in 2007/2008 academic year			-0.002 (0.001)			-0.002* (0.001)			-0.002* (0.001)
No of Observations	686	649	685	674	638	673	651	611	650
Background Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Option Dummies	No	No	No	No	No	No	Yes	Yes	Yes

Note: Probit models, standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1 Background controls: age, sex, rooms per person, homes per dwelling, family owned car, years of paternal education, years of maternal education, private high. Option Dummies: Dummy variables for the option chosen (major, campus and time of day

Table 8. Model Estimates

Panel A. Parameter Estimates

Free Parameters	Estimate	S.E.
Mean of Wage Offers	3.15	0.057
Dispersion of Wage Offers	0.17	0.03
Probability of Getting a Wage Offer*	0.081	0.001
Probability of Losing Job*	0.007	0.001
Discount Rate**	0.897	0.011

Panel B: Observed and Simulated Moments

Moments	Observed Moment	S.E. (obsvd moment)	Simulated Moment
Mean Wage in 2007 (Worked in 2008)	3.06	0.03	3.02
Mean Wage in 2007 (Studied in 2008)	2.91	0.06	2.88
Std Dev Wage (Worked in 2008)	0.37	0.04	0.30
Std Dev Wage (Studied in 2008)	0.31	0.06	0.29
Mean Wage in 2008 (Did not study in 2008)	3.14	0.06	3.24
% studying in 2008	0.38	0.02	0.37
% of admitted who do not study in 2007	0.2	0.01	0.12
Median Age	21	0	21.00

Note : *monthly, **fixing yearly return to school at .10, fixing it at at 0.5, the discount rate equaled 0.943