Abstract: I exploit the large variation in resident tuitions and subsidies to public universities across states to assess the efficiency of subsidizing higher education for state residents. The focus is on substitution between public in-state 4-year universities (low tuition for residents) and private or public out-of-state 4-year universities (high tuition). Utilizing NPSAS 1995-1996 data on individual students, and data on universities, I estimate demand for public in-state universities, accounting for differences in university quality and individual characteristics. In the process, this paper presents a model of how states decide on subsidies and resident tuitions and offers some instruments to rebut the possibility that state policies are caused by the differences in the unobservable. Behavior of individuals has been modeled as a discrete choice model with probability for different choice sets being estimated together with parameters of utility. My results show that a $1000 \textsuperscript{1} increase in resident tuition induces a 17% drop in the number of students in public in-state institutions in an average state (here 100% corresponds to all the state students in any public or private 4-year school). A major consequence of subsidies to public universities is that people go to schools they would be unlikely to attend otherwise; substantial portion of the total subsidy dissipates as a deadweight loss.

1. Introduction

Two types of institutions coexist in the U.S. higher education market – public and private universities. Public universities normally receive a direct subsidy (appropriation)
from the state they are located in and set a low tuition for in-state students\(^3\). Private universities are not directly subsidized and treat residents and nonresidents the same.

The subsidies given by different states to their public institutions vary a great deal. Consequently, in-state tuition and the share of students enrolled in public institutions change a lot, too. It is difficult to measure the amount of education received in different institutions directly; however, people’s choices can tell us what value of education is produced by one university versus another. This paper exploits the variation in quality and costs of public schools mostly across the states to identify the utility differential between going to an in-state public school (and thus taking advantage of the subsidy) and going elsewhere, i.e., to a private university or an out-of-state public university (and thus foregoing the subsidy).

The primary goal of the subsidies to public institutions and various kinds of financial aid is to induce college going in people who would be unlikely to attend otherwise. The economic explanation involves either financial constraints affecting certain groups of population or positive externalities derived from the education by the rest of the society. My data are merely not suited to estimate the importance of these effects. Ultimately, the estimates of inefficiency I obtain should be adjusted for the value of the effects.

There is mixed evidence in the literature on how successful tuition subsidies are in increasing college enrollment. The estimates vary considerably depending upon the type of colleges. My paper focuses on private and public 4-year schools only. This is the type of schooling for which tuition subsidies seem to be the least effective.

One issue is usually overlooked. States distort the price of education in public in-state universities by subsidizing tuition for the state residents. This is a blanket subsidy given to everybody who enrolls in one of the public in-state universities. It is not specifically targeted at financially constrained individuals. Most of the students in public 4-year universities are still likely to attend college without the subsidy; just it might be a

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\(^3\) Here the public universities are any public 4-year institutions except the federally financed ones. Overwhelming majority of them is run by the states with the exception of CUNY which is run jointly by New York City and the state. All of them receive substantial subsidies from the state governments. Financial support from the local governments is usually a small figure (including CUNY). The state subsidy accounts for more than half of the total education expenditures in an average public university. Federally financed universities, West Point, Naval, Border Guard, and Air Force Academies, are not considered in this paper. These are military education institutions and, thus, are hardly a substitute for the usual college.
different college as the subsidy is given to only about a third of all 4-year universities in the U.S. The ones who would not enroll in any 4-year college might simply find the schooling not worthwhile without a subsidy; that may have nothing to do with them being financially constrained.

From this point of view, state subsidies to public education are not just a transfer. There is a deadweight loss associated with them. As the amount of subsidy increases, people start attending universities that they would not go to without a subsidy. In fact, states subsidize them to take a non-optimal decision, and consequently part of the surplus is dissipated. I use the demand I recover from the data to estimate the magnitude of the losses.

Public universities serve vastly different shares of the student population in various states. This share varies from about 29 percent in Massachusetts to over 80 percent in Louisiana and Utah (see Table A1 in the appendix for more on this). Other characteristics of the population, such as income and test scores, may partially explain the differences in this case. Still, the differences remain very large even if we look at neighboring and otherwise similar states. For instance, let us take South Carolina and North Carolina, which are similar with respect to income and test scores. The share of residents of South Carolina who attend public 4-year institutions in South Carolina is about 55 percent of all the residents of the state enrolled in any 4-year institution. It is 68 percent for North Carolina. In this case, a larger portion of the difference stems from the disparity in the level of public support for higher education between the states. I use micro data for the estimation, and my approach will separate the responses due to the differences in the composition of the state population and the range and characteristics of public schools in different states.

I construct a discrete choice model to describe the demand (utility differential) for public 4-year schools versus the outside option, conditional upon the characteristics of the individual. The outside option consists of private and public out-of-state 4-year universities. Every student eventually chooses the school to attend from the group of institutions the student was admitted to. This group is unknown to the researcher. So, the framework was specifically built to model both the choice of the students and the choice sets they are choosing from.
In-state tuition, subsidy, and educational expenditures may be endogenous. The estimates obtained from the raw data are subject to the measurement error bias. Instrumental variables can overcome these problems. I develop a small model that illustrates the way states handle their public universities and also suggests some instruments. The discrete choice model was reestimated with those instruments using a control function approach.

The estimates show a large substitution between the subsidized public in-state schools and unsubsidized higher education institutions. An increase in the in-state tuition of $1000 decreases the probability of attending a public in-state institution by approximately 17 percent. Here 100 percent corresponds to the total chances of attending any private or public 4-year university.

The estimated demand is used to evaluate the effectiveness of state subsidies to public institutions versus the unsubsidized alternative. Two things are considered: deadweight losses and how efficiently resources are used.

I find that a substantial part of the subsidy is wasted because of the deadweight loss. The empirical evidence shows that the deadweight losses make up about half of the “excess” subsidies, i.e., the subsidies that actually cause the disparity between resident tuition in public in-state universities and the tuition in private and public out-of-state universities. The other half constitutes a transfer.

I also find some evidence of overall inefficiency of funds spent in the public sector of higher education. This result should be taken very carefully because it is based on out-of-sample extrapolation of demand.

Most of the work done on education focuses on college participation decisions and the return to education. The specifics of the market, such as which school students go to, are still largely untreated. My paper focuses on the substitution of private universities for public ones and what we can learn from this. To my knowledge this has not been a subject of serious research before, with the exception of Peltzman (1973).

This paper is organized as follows. Section 2 introduces a simple model to illustrate the way states run their public universities. It also suggests the instruments for the subsequent estimation. Section 3 describes the data. Section 4 discusses the estimation approach and presents the results. It does this in two steps. First, I develop and estimate a
discrete choice model to describe the choice between the subsidized public in-state universities and the unsubsidized outside option, which aggregates the private and public out-of-state universities. Second, I reestimate the model using a control function approach. Section 5 discusses the empirical results. Section 6 concludes.

2. Model

Most of this paper will be devoted to how to model and estimate demand for public universities. That part looks at the situation primarily from the point of view of an individual.

This section is mainly about the supply of public higher education and, thus, looks at the situation for the most part from the point of view of the state. However, it offers a general approach to how to think about the problem and offers the same context for both decisions of the state and the individual. This way of thinking eventually helps me to find instruments for the estimation.

Almost every state in the United States has more than one public university.

I think of a state as an entity that runs its own public higher education system. This is clearly a simplification, but it seems to fit well with reality. State governments decide on financing, tuition, and admission cutoffs (i.e., type of students a specific university is designed for) for their public universities. The money to support any public institution within a state comes from one source—the state budget. The decision regarding which university receives what rests on one body, which is the state government. The decision on tuition, even if made by an individual university, is normally dictated by the difference between the amount of spending necessary and the amount of state appropriation received. The decisions for every particular university are coordinated with the decisions for all other public universities in the state.

Overall, the decisions of the state are constrained by the availability of funds. I set up the problem of a state as the maximization of the number of participants accounting for the alternative use of funds.

Suppose there are \( n \) ability levels that the state offers education for. Each of those ability levels corresponds to an individual public university. \( p_i \) denotes the probability that a student of ability \( a_i \) chooses to go to a public university \( i \). Correspondingly \( (1 - p_i) \)
gives the share of students going to private or public out-of-state universities. \( g_i \) stands for the total mass of students with ability \( a_i \). Let us denote the tuition charged to a student as \( t_i \) and the subsidy per student given to the institution \( i \) as \( s_i \). Thus, the total expenditures per student in the institution \( i \) are a sum of tuition \( t_i \) and the subsidy \( s_i \).

The state maximizes:

\[
\max_{s_i, t_i} \left( \sum_{i=1}^{n} g_i p_i + B(m - \sum_{i=1}^{n} g_i p_i s_i) \right) \tag{2.1}
\]

The first term in the brackets is the number of people who choose to attend public in-state schools. The second term in the brackets represents the utility the state derives from the alternative use of funds with \( m \) standing for the total amount of money available in the state budget. Naturally, the subsidies to the public schools decrease the funds that go to the alternative projects.

Normally we think of \( p_i \) as some increasing function of \((U_i - U_0)\), where \( U_i \) denotes the utility an individual derives from going to institution \( i \), and \( U_0 \) stands for the utility obtained outside of a public in-state university, i.e. from going to a private or public out-of-state 4-year university. The true value of each option to some particular individual consists of the correspondent \( U \) common to everybody plus some unobservable shock to the preferences (“error”). The distribution of this shock across the individuals determines the shape of \( p_i \) as a function of \((U_i - U_0)\).

Clearly, the utility \( U_i \) should depend upon the characteristics of the school \( i \) such as tuition \( t_i \), the expenditures per student \((s_i + t_i)\), and ability of the students in the school \( a_i \). The probability \( p_i \) depends upon those same parameters indirectly, through \( U_i \).

First order conditions for maximization problem (2.1) are:

\[
\frac{\partial p_i}{\partial s_i} = \frac{\partial B}{\partial m} \left( \frac{\partial p_i}{\partial s_i} s_i + p_i \right) \quad \text{for } i=1,\ldots,n \tag{2.2}
\]

\[
\frac{\partial p_i}{\partial t_i} = 0
\]
measures the response in the state objective from one extra unit of funds. In other words, it is a shadow price of funds, which is the Lagrange multiplier for the same problem written in a slightly different way. From here on, I refer to $\frac{\partial B}{\partial m}$ as $\lambda$.

(2.2) implies:

$$\frac{1}{\lambda} = s_i + \frac{p_i}{\partial p_i} \partial s_i$$

(2.4)

$$\frac{\partial U_i}{\partial t_i} = 0$$

(2.5)

Equation (2.4) is analogous to the condition for the optimal price-cost margin for a monopoly and can be rewritten as: $\frac{1 - \lambda s_i}{\lambda s_i} = \frac{1}{\varepsilon}$, where $\lambda s_i$ is the marginal cost of one person to the state and $\varepsilon$ is the elasticity of demand for institution $i$. Here 1 (i.e., one person) stands for the gain obtained from spending $\lambda s_i$; thus, it is like a price in the optimal monopoly condition.

Equation (2.5) means that the state maximizes the utility of an individual conditional upon the optimal subsidy $s_i^*$ while setting tuition optimally. In other words, the optimal subsidy $s_i^*$ and tuition $t_i^*$ satisfy the following:

$$t_i^* = \arg \max_{t_i} U_i \bigg|_{s_i = s_i^*}$$

(2.6)

Suppose the university cares only about the utility of its students and takes the state subsidy as given. Then it is clear that the state does not necessarily need to decide on tuition by itself and can “outsource” this decision to the university. This does not produce any difference in the optimal action. The university sets the tuition to solve the maximization problem (2.6) and that means that the first order condition (2.5)$^4$ is going to be exactly satisfied.

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$^4$ Equation (2.5) also has some implications for the estimation, which I will discuss later.
Let us denote \( \frac{P_i}{\partial p_i} = f(U_i - U_0) \). Then (4) becomes:

\[
\frac{1}{\lambda} = s_i + f(U_i - U_0) \frac{1}{\partial U_i} \frac{\partial}{\partial s_i}
\]

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\[
\frac{1}{\lambda} = s_i + f(U_i - U_0) \frac{1}{\partial U_i} \frac{\partial}{\partial s_i}
\] (2.7)

I assume that:

\[
\frac{\partial f(U_i - U_0)}{\partial U_i} > 0
\] (2.8)

The shape of \( f(.) \) depends upon the shape of the probability \( P_i \) as a function of \( U_i - U_0 \). As I have mentioned above, the behavior of \( P_i \) is determined by the distribution of unobservable shock to the individual preferences. There are plenty of distributions that will satisfy condition (2.8). Logistic, normal, and uniform are among the most notable examples.

Suppose that the utility of an individual consumer can be written as a difference of the benefit \( Q(a_i, s_i + t_i) \) (i.e., quality of education) the individual receives from attending the school \( i \) and the costs \( C(t_i, I) \) the individual incurs. Here \( I \) denotes the income of the population in the state. Hence I assume:

\[
U_i = Q(a_i, s_i + t_i) - C(t_i, I)
\] (2.9)

where the quality \( Q(a_i, s_i + t_i) \) is increasing in the ability \( a_i \), increasing and concave in the expenses per student \( (s_i + t_i) \), and has positive cross partial; the costs \( C(t_i, I) \) are increasing and convex in tuition \( t_i \), decreasing in income \( I \), and have negative cross partial. Reiterating, (2.9) satisfies the following properties for its components:

\[
\frac{\partial Q(a_i, s_i + t_i)}{\partial s_i} > 0; \quad \frac{\partial^2 Q(a_i, s_i + t_i)}{\partial s_i^2} < 0; \quad \frac{\partial C(t_i, I)}{\partial t_i} > 0; \quad \frac{\partial^2 C(t_i, I)}{\partial t_i^2} > 0;
\]

\[
\frac{\partial Q(a_i, s_i + t_i)}{\partial a_i} > 0; \quad \frac{\partial^2 Q(a_i, s_i + t_i)}{\partial a_i \partial s_i} > 0; \quad \frac{\partial C(t_i, I)}{\partial I} < 0; \quad \frac{\partial^2 C(t_i, I)}{\partial I \partial t_i} < 0
\] (2.10)

Using (2.9), (2.5) yields:
\[
\frac{\partial Q(t_i,s_i+t_i)}{\partial (s_i+t_i)} = \frac{\partial C(t_i,I)}{\partial t_i} \quad (2.11)
\]

Differentiating first order conditions (2.7) and (2.11) and applying conditions (2.10), I can describe the response of optimal tuition and expenditures per person (subsidy per person) to exogenous shocks. I do this in words below. The relevant algebraic computations can be found in the Appendix A.

First order conditions (2.7) and (2.11) can be represented as two lines in two-dimensional space with tuition \( t_i \) on the horizontal axis and expenditures per student \((s_i + t_i)\) on the vertical axis. Condition (2.7) produces a line that slopes upward. Condition (2.11) yields a line sloping downward. The shocks to the income of population \( I \) and the shadow price of government funds \( \lambda \) can be understood through the shifts they induce in these lines.

An increase in \( \lambda \) (the state funds become scarcer) does not affect the position of line (2.11) (light line on the picture), but it shifts the dark line (2.7) down, thus increasing the optimal tuition charged while the total spending per student \((s_i + t_i)\) is falling. This decreases the optimal subsidy \( s_i \).
An increase in income $I$ implies a smaller value for $\frac{\partial C(t_i, I)}{\partial t_i}$. This shifts the light line up. The dark line (2.7) is likely to shift upward as well, although, probably, with a relatively smaller magnitude. Then increase in $I$ leads to larger optimal expenditures per student. The change in tuition is less obvious; tuition increases if the shift in line (2.11) dominates the shift in line (2.7).

As the average ability of the student body in school increases, both lines move up, so, expenditures per a student $(s_i + t_i)$ definitely increase. Change in the optimal tuition $t_i$ is generally ambiguous and will be positive if the shift in (2.11) dominates the shift in (2.7).

In describing the setup, I have assumed that every individual of certain ability chooses only between the public in-state institution of the same ability and the outside unsubsidized option. There was no alternative of attending a public in-state school with average ability below the ability of the individual. This assumption simplifies the exposition but is in fact unnecessary and may be relaxed. Every individual in this environment will find it optimal to go to the public school with the highest possible ability because the utility provided by different public schools within the same state grows with the average ability of the students. This has been proved in the Appendix A. Therefore, incorporating the option of attending a public in-state school of lower ability is immaterial and does not affect people's choices.

This model essentially stresses the point that the state has a consistent policy for all in-state public institutions and that there are some simple links between optimal tuition $t_i$, expenditures per student $(s_i + t_i)$, and shifters such as the income of population $I$ and scarcity of state funds as reflected by the value of $\lambda$. The model allows for horizontal product differentiation only, i.e., the differentiation between the subsidized in-state option and the unsubsidized option provided by private and public out-of-state universities. The differentiation between public schools was on a vertical dimension only; thus every student chooses the highest-quality public in-state university from the choices available to that student. Clearly, a small amount of horizontal differentiation within public schools would not change anything but merely make the model less transparent.

The model also suggests a way to look for instruments for tuitions and educational expenditures in order to estimate the demand for a public university consistently.
Essentially any exogenous variable correlated with either income $I$ or $\lambda$, or both, but uncorrelated with the error term in an individual’s utility $U_i$ could serve as an instrument.

3. Data

The data for this paper come from several sources.

The micro data on students are obtained from the restricted use files for the National Postsecondary Student Aid Survey, 1995-1996. It is a comprehensive survey of students that contains data on test scores of the students; their “effective family contributions” (that is, a composite of current income and savings); amounts, types and sources of financial aid they receive; attendance status; state of legal residence; institutions the students go to; etc. I have used the data on all the students except African Americans. They are somewhat more likely to receive financial aid compared with the rest of the population, and their response to differences in tuition seems somewhat muted.

Weights on individual students are really important because this is a two-tier survey in which both universities and students were sampled with different frequencies. First, a sample of universities was taken at random; then a sample of students was chosen from each sampled university. The survey provides weights for each student. Because not everybody who was considered a respondent by the survey had data on effective family contribution and SAT score, I needed to readjust the weights accordingly.

The data on individual students have been merged with the data on institutions received from U.S. News and World Report for 1995 and financial data on institutions obtained from the Integrated Postsecondary Education System (IPEDS). U.S. News and World Report data provide average, first, and third quartiles of test scores for incoming freshmen. IPEDS contains information on the financial characteristics of the institutions, such as the sources of revenue, expenses, and some characteristics of the student body. These data have been supplemented with some information on state population, incomes, taxes, and expenditures obtained from the U.S. Census and Survey of Current Business. I have also used the data on average proficiency in mathematics for eighth graders by state in 1992 as provided in the Digest of Education Statistics.
4. Empirical Approach, Identification, and Estimation Results

In this section I develop a discrete choice model that describes the behavior of an individual. I estimate the model on raw data, and using a control function approach.

4.1. Estimating Demand for Public Universities

Every applicant in the United States is normally a resident of some state and, therefore, has a choice between going to an in-state public institution and enrolling in a private or out-of-state public institution.

Let us take a person who is exactly indifferent between the in-state public school option and some private university. Frequently, the situation is such that the private university provides a better-quality option but also charges a higher tuition. For this person, the price (tuition) differential between two schools is worth precisely the quality differential between the public and private institutions. If the state increases the amount of subsidy provided to a public institution, then either the quality of the university increases or the tuition decreases. This will make the person, previously indifferent, prefer the public in-state option over going to the private university. Thus, state subsidies shift the value of the in-state public university option, which shifts the choice of people from the unsubsidized private and public out-of-state universities to subsidized public in-state universities.

In principle, the variation across states might allow us to recover the quality differentials between all schools, public and private. Unfortunately, this is not realistic.

There are about 1,200 institutions represented in the data. A person can go to most of them provided that the person’s test score is high enough; thus, some people can have over 1,000 alternatives to choose from. That makes the estimation a difficult problem in practice.

These problems can be avoided by compressing all the private institutions and public out-of-state institutions into one outside option that depends upon the individual characteristics of the person. Then each person decides between choosing one of the students.

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5 This approach has some minor drawbacks. First, I neglect the local differences in the choice sets because of different locations of private universities with respect to a specific person. Second, I disregard the differences created by the following consideration – people in West Virginia have The University of Virginia as a part of their out-of-state option, but people in Virginia have The University of West Virginia as a part of their out-of-state option. These things are considered a part of noise.
public universities in her state and taking advantage of the outside option. The number of alternatives shrinks to twenty four at most and is equal to the number of in-state public universities plus one for the outside option.

Let us construct a discrete choice model that will describe how people choose between public in-state universities and the outside option.

The utility derived from university $i$, with the average SAT for the university’s student body $AvSAT_i$, education expenses per student $EEpP_i$, and in-state tuition $ITui_i$ is given by:

$$U_i = k_0 + k_1 AvSAT_i + k_2 EEpP_i - k_3 ITui_i + \varepsilon_i$$

(4.1)

The first three terms in (4.1) give university quality. The fourth term describes the costs incurred by the individual attending school $i$. The last term, $\varepsilon_i$, is just an error.

Notwithstanding the state of residency for the individual, all private and public out-of-state institutions treat everyone in the same fashion conditional upon their test score and income. I specify the outside option $U_o$ to be a function of a person’s SAT score ($IndSAT_i$) and income measured by “effective family contribution” ($EFC_i$ is an aggregate of current household income and savings):

$$U_o = \gamma_0 + \gamma_1 IndSAT_i + \gamma_2 EFC_i + \varepsilon_0$$

(4.2)

Both people’s preferences and what options are open to them determine the decision regarding which college to attend. Usually a choice set for an individual is known or rather assumed to be known in most of the applications of discrete choice models; however, this does not seem appropriate in my situation. Instead I recover both the preferences and the probabilities of admission from the data rather than make assumptions about the choice sets.

The choice set for a student includes all the universities that the student has been admitted to. Whether someone gains admission to a given school depends upon that person’s test scores, high school GPA, recommendations, admission standards of the school, etc. These characteristics vary across schools and individuals, and the probability of admission to different schools varies accordingly. Clearly, many different choice sets may occur for the same individual, and each of them can be assigned some probability
depending on what the underlying probabilities of admission/rejection are for different schools.

Assuming an extreme value distribution for the error terms $\varepsilon_o$ and $\varepsilon_i$, the probability of choosing university $i$ for some particular individual is:

$$\Pr(i) = \sum_{H \in S} \left( \Pr(H) \Pr\left( \text{choose } i \mid \text{choice set } H \right) \right) = \sum_{H \in S} \Pr(H) \frac{e^{U_i-U_o}}{1 + \sum_{j \in H} e^{U_j-U_o}}$$

(4.3)

where $\Pr(H)$ denotes the probability of admission to all the universities in set $H$ but rejection by every university that does not belong to $H$:

$$\Pr(H) = \prod_{i \in H} \Pr(\text{admitted to } i) \prod_{k \in A \setminus H} \Pr(\text{rejected by } k) =$$

$$= \prod_{i \in H} \Pr(\text{admitted to } i) \prod_{k \in A \setminus H} (1 - \Pr(\text{admitted to } k))$$

(4.4)

Here $S$ is the set of all possible choice sets (combinations of universities) that include option $i$; $H$ is a member of $S$; and $A$ is the set of all public universities in the state plus the outside option.

Most of the information that affects the chance of admission to a university is not observable. Basically, I see only the test scores for both the individuals and universities. I model the probability of admission as a logit that depends on a linear function of both average SAT for the school and SAT for the individual:

$$\Pr(\text{admitted } i) = \frac{1}{1 + e^{h_i + h_i \text{SAT}_H - h_i \text{IndSAT}_i}}$$

(4.5)

The probability of admission was set to one for the outside option. The total number of schools in United States is well over 1,000. Each state has at most 23 public schools in my data and the rest will constitute the outside option. The chance of being admitted to at least some private or public out-of-state university is large; thus, it is reasonable to consider the outside option as open to everyone.

Then the log likelihood is:

$$LL = \sum_i \ln(\Pr(i)) = \sum_i \ln \left( \sum_{H \in S} \Pr(H) \frac{e^{U_i-U_o}}{1 + \sum_{j \in H} e^{U_j-U_o}} \right)$$

(4.6)
I wrote a Matlab program that optimizes the log likelihood (4.6) after (4.1)-(4.2) and (4.4)-(4.5) have been substituted inside.

The number of elements in the interior sum increases exponentially with the number of schools \( n \) and is equal to \( 2^n \). Three states -- California, Texas, and New York -- have more than 20 schools in my data; thus, there are a couple of million components in the interior sum in (4.6) for every resident of these states. It becomes computationally difficult, if possible at all, to calculate this sum for large \( n \) (larger than 16 in my experience). I can either disregard the largest states and use the rest of the data or simulate the log likelihood (4.6) without computing it precisely. Obviously, simulation is the preferred line of attack.

The log likelihood for an individual (4.3) looks like an expected value of a logit function. The expectation is computed over all possible choice sets. A straightforward approach to simulation is to take draws out of a probability distribution over all possible choice sets, compute the logits corresponding to the sampled choice sets, and average them. Taken literally, this requires computation of the probabilities for all possible choice sets first. That would be about half of the task of precisely computing (4.6) – the task that I have found to be computationally infeasible.

Fortunately, there is an alternative approach to sampling choice sets. I can “sample” universities instead. The “sampled” universities are used to construct a draw out of the distribution of choice sets. Each choice set consists of the universities to which the person was admitted. The chance of admission to a specific university (that is, expression (4.5)) is easy to compute. I take draws from Bernoulli distributions characterized by corresponding \( \Pr(\text{admitted to university}) \); thus, the probability of drawing “1” is the same as the probability of being admitted to the university. If “0” is drawn, then the person is rejected by the university. Taking one draw for each university in the state allows me to construct one draw from the distribution of choice sets. The sampled choice set consists of the universities for which 1’s were drawn. Clearly, the probability of constructing any particular choice set is exactly the same as the probability of this same choice set being drawn out of the distribution described by probabilities \( \Pr(H) \) for each possible choice set \( H \). But now I do not need to compute any \( \Pr(H) \).
The log likelihood has been simulated in the following fashion. Two steps are repeated for each observation (person). First, a number of draws are taken from the distribution of all possible choice sets in the way I have just described above. Scrambled Halton sequences were used instead of the true random draws because they perform better for simulated integration. Second, for each of the drawn choice sets, I compute the probability of choosing the university the person is in fact attending (i.e., the logits in (4.6)). The value of the simulated log likelihood for the person is the logarithm of the average of these probabilities.

Simulated this way, the log likelihood is not a continuous function of parameters, but it does get closer to continuous as more draws are taken. The discontinuity is caused by the discreteness of the set of all possible choice situations and by the fact that draws of the choice sets differ every iteration. This is not important when the log likelihood is steep, i.e., the values of the parameters are far away from the optimum. But discontinuity may create difficulties for convergence in the regions where log likelihood is relatively flat. The severity of this problem is actually an empirical question and depends upon each particular application (model and data set).

Discontinuity does not pose any serious problem for the convergence in my case if I sample enough choice sets and do not use instrumental variables (IVs). Table 1 presents the results obtained with precise computation of the log likelihood on a subset of the true data versus the results for a simulated log likelihood (columns (1) and (2)). The estimates of the coefficients are indeed close, but the estimates of the Hessian and standard errors differ substantially for some of the coefficients. This is natural because eventually the iteration process stops when there are some wrinkles on the log likelihood (discontinuity) and the gradient of log likelihood is not simulated well. The Hessian is obtained by taking differences of the gradient and cannot be simulated better than the gradient itself. In response to this problem, I have used an “outer product of the gradient” approach that relies on the variance in the individual components of the gradient of the log likelihood to compute standard errors. As Table 1 shows, this approach performs much better for this version of the simulated log likelihood.

There were some problems with the convergence when I used IVs or, more precisely, control functions (see next section for the description). The shape of the log likelihood
changes when control functions have been introduced into the specification. In those cases, I have resorted to the Nelder-Mead optimization routine that does not use a gradient and can handle some discontinuities. I have also tried restarting the procedure with a different set of random draws to eliminate the possibility that the iterative process stops too soon.

An ordinary logit assumes that every error is independent and has extreme value distribution. This is highly unrealistic and may bias coefficients. The usual way to relax the independence of errors is to allow for some heterogeneity in the population of consumers. This is done by making the coefficients in the utility random variables; thus, the original logit is mixed with the distributions of the coefficients in utility.

The public instate alternatives are evaluated against the outside option for each person. At the very least, it is reasonable to expect that there are some shocks to the outside option not captured by the error term with an extreme value distribution, i.e. there is some heterogeneity in the outside option.

Random draws of choice sets have already been used to compute the simulated log likelihood. To introduce heterogeneity, I take a random draw out of the distribution of random coefficients in utility for each draw of the choice sets. I have allowed only the coefficients on the outside option (that is, individual SAT and EFC) and constant term to be random variables. Normal distributions were assumed for the random coefficients.

The model I have just described was estimated on the raw data for the simulated log likelihood both with and without random coefficients in utility. The results of the estimation are given in Table 2. I postpone the discussion of results to the next section.

I have created and used several variables for educational expenses per person. Only the results for two of them are reported in Table 2. The first one is a sum of “Instruction Expenditures”, “Academic Support”, “Student Services”, “Institutional Support”, and “Operation & Maintenance of Plant” divided by the total number of enrolled students, including both graduate and undergraduate students. The second one is “Instruction Expenditures” divided by the number of students. Neither measure includes research expenditures because these expenses are mostly likely to benefit graduate students. The

---

6 All of the components in the sum are variables in the IPEDS data for universities.
### Table 1

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>Stnd Error</td>
</tr>
<tr>
<td>Utility Parameters</td>
<td></td>
<td></td>
</tr>
<tr>
<td>cnst</td>
<td>-6.387392</td>
<td>0.313101</td>
</tr>
<tr>
<td>(Stnd Dev)</td>
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<td></td>
</tr>
<tr>
<td>IndSAT</td>
<td>-0.003798</td>
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</tr>
<tr>
<td>(Stnd Dev)</td>
<td></td>
<td></td>
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<tr>
<td>EFC</td>
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<tr>
<td>(Stnd Dev)</td>
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<tr>
<td>AvSAT</td>
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<td>0.000425</td>
</tr>
<tr>
<td>EEpP</td>
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<td>1.38E-05</td>
</tr>
<tr>
<td>ITui</td>
<td>-0.000581</td>
<td>2.91E-05</td>
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<tr>
<td>Admission Parameters</td>
<td></td>
<td></td>
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<tr>
<td>cnst</td>
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<td>0.76569</td>
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<tr>
<td>IndSAT</td>
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<td>0.000482</td>
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<tr>
<td>AvSAT</td>
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<td>0.000897</td>
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<tr>
<td>Log Likelihood</td>
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<td></td>
</tr>
<tr>
<td>Total # of Alternatives</td>
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<td></td>
</tr>
<tr>
<td>Total # of Observations</td>
<td>7110</td>
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</tr>
<tr>
<td># of Draws</td>
<td>300</td>
<td></td>
</tr>
</tbody>
</table>

(1): No Sampling -- the precise log likelihood (4.6) was optimized
(2): Sampling of choice sets, but no random coefficients in utility
(3): Sampling of choice sets, random coefficients on variables that describe outside option

A subset of real data was used for the estimation. It does not include the largest states (CA, NY, TX, PA) and the states which did not participate in the test of mathematics proficiency for 8th-graders

Education expenditures per person EEpP were computed as a ratio of "Instruction Expenditures" divided by the total number of students (both Graduate and Undergraduate)
undergraduates gain from them only indirectly, for instance, through a higher quality of faculty employed for both research and teaching, or through higher quality of graduate teaching assistants. At any rate, including research expenditures produces very similar results.

Clearly, all of these variables are rather noisy estimates of the true expenditure and are likely worse for schools with large graduate programs. Some bias because of the measurement error is likely taking place. Actually, even tuition is not measured perfectly because it does not account for grants and does not necessarily include all of the extra fees for everybody.

There are several other problems with the estimation of the model on the raw data.

First, educational expenditures per person cannot be directly observed. Ideally, these should be data on marginal expenses for teaching undergraduates. IPEDS contains the data on university expenditures by categories, but those are aggregates for all the students, graduate and undergraduate, and include the support for some other university activities as well, not solely the teaching of undergraduates. Naturally, one can only wish for some distinction between the variable and fixed costs.

There is another empirical problem worth discussing. Let us recall the first order condition (2.5):

\[
\frac{dU_i}{dt_i} = 0 \Rightarrow \frac{\partial U_i(s_i + t_i, t_i)}{\partial(s_i + t_i)} - \frac{\partial U_i(s_i + t_i, t_i)}{\partial t_i} = 0 \tag{4.7}
\]

Suppose both educational expenditures, \(s_i + t_i\), and tuition \(t_i\), increase by some small amount. Then equation (4.7) implies that there will be no response in utility. In other words, small deviations in tuition, if accompanied by the same deviations in educational expenditures, will produce no noticeable change in people’s actions.

When setting tuition, the state (or university) is unlikely to solve the corresponding optimization problem precisely. Tuition will be set with some error. However, there will be no obvious difference if the tuition is close enough to the optimal and the expenditures vary correspondingly, so, the amount of subsidy is kept the same. I do not see the true expenditures – they are measured poorly and come together with quite a lot of noise. Thus, some of the variance in tuition is imperfectly offset by noisy educational expenses.
and this will bias\textsuperscript{7} the coefficient on tuition also. To summarize, estimation of the model on raw data is likely to produce biased coefficients even if the state and university decisions are not affected by the unobservable in demand and are in fact exogenous. This resembles the bias that arises from measurement error; however, in my case the “measurement” errors are positively correlated for two noisy variables. Only the variation in $s_i + t_i$ and $t_i$ that differs from this pattern can be useful to estimate the true coefficients on the model. (This problem and the endogeneity problem below are also discussed in Appendix B).

University tuition cannot be affected by a single individual. In our case, the prices are not even set by the market but by state governments. Still, endogeneity may potentially be a problem if there are some common elements in the unobservable that are correlated with state policies (values of tuition and education expenditures per person).

To obtain consistent estimates, people should be the same across regions, conditional on their income (“effective family contribution”) and test scores, i.e., there are no substantial regional differences in the distribution of the unobservable in the individual demand correlated with tuition or educational expenses. Violating this requirement\textsuperscript{8} is dangerous in the case where errors in demand become responsible for the variation in state subsidies and tuitions. That would simply mean that the regressor is correlated with an error.

The individual demand was specified conditional upon the individual’s income and test score. This allows the distributions of income and test scores to vary freely across states. Specifically, there is no need for the average income or test score to be the same across the states to estimate the demand consistently and, more importantly, state policies (educational expenditures per person and tuition) may depend upon the characteristics of income and test score distributions but remain uncorrelated with the error.

\textsuperscript{7} Actually even without the mistakes, but with correlated regressors and measurement error, all of the coefficients on the variables correlated with the poorly measured one will be biased. The mistakes I am talking about make the problem even more severe.

\textsuperscript{8} If this does not hold then peoples’ choices among private universities should differ across states. In principle, this allows testing for compliance of the data with the requirement but such tests are likely impossible with the amount of the data I have.
**Table 2**

<table>
<thead>
<tr>
<th>Utility Parameters</th>
<th>Coefficient</th>
<th>OPG Stnd Error</th>
<th>Coefficient</th>
<th>OPG Stnd Error</th>
<th>Coefficient</th>
<th>OPG Stnd Error</th>
<th>Coefficient</th>
<th>OPG Stnd Error</th>
<th>Coefficient</th>
<th>OPG Stnd Error</th>
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</thead>
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<td>0.2477809</td>
<td>-4.1224127</td>
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<td>IndSAT</td>
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<td>AvSAT</td>
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<td>23516.5</td>
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<td>142248</td>
<td>142248</td>
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<tr>
<td>Total # of Observations</td>
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<td>10141</td>
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</tr>
</tbody>
</table>

(1): Sampling of choice sets, but no random coefficients in utility
(2): Sampling of choice sets, random coefficients on variables that describe outside option
(3): Sampling of choice sets, but no random coefficients in utility
(4): Sampling of choice sets, random coefficients on variables that describe outside option

All states that participated in the test of mathematics proficiency for 8th graders were used for the estimation

**Education Expenditures per Person (Version 1)** are "Instruction Expenditures" divided by the total number of students (both graduate and undergraduate)

**Education Expenditures per Person (Version 2)** are sum of "Instruction Expenditures", "Academic Support", "Student Services", "Institutional Support", and "Operation & Maintenance of Plant " divided by the total number of students (both Graduate and Undergraduate)
An error in the quality production function is a part of the error in the specification of utility. It is a source of potential trouble if states set tuitions and subsidies in response to these errors in the productivity of their public universities. This situation is actually indistinguishable from the error in demand and endogeneity discussed above.

All of these problems can be alleviated by using instrumental variables. I utilize IVs in the next subsection.

4.2. A Control Function Approach to Estimating Demand

In the case of logit, econometric theory questions the standard two stage IV approach that uses fitted values of endogenous variables instead of the original ones during the second stage. But a control function\(^9\) approach can be employed without substantial theoretical objections.\(^10\)

During the second stage, the model is estimated with the utility being a function of the original endogenous variables and the residuals from the first stage regressions. These residuals play the role of a control function and pick up the variation in the endogenous variables that cannot be explained by the instruments and, so, may be endogenous. Then the coefficients upon the original variables should be unbiased. The assumption about the distribution of the error term is changed correspondingly. Now an extreme value distribution is assumed for the remaining error in utility that is not accounted for by neither the original regressors nor the residuals from the first stage. I discuss the control function approach in a greater detail in Appendix B.

My instruments are state-level variables such as the median household income in state \(s\) (variable \(mdinc\_s\)) and the percentage of the eighth grade pupils in the state who scored 300 or more on the mathematics proficiency test in 1992 (variable \(math300\_s\)). The individual demand is conditioned upon effective family contribution (which is a measure of income) and the student’s SAT, so, the error in the specification of utility is orthogonal

---

\(^9\) Another possibility is to attempt some modification of BLP approach (Berry, Levinsohn, and Pakes (1995)). It requires a similar set of assumptions comparing with the control function approach, and it looks computationally even more difficult. For instance, it is not really clear how well would BLP contraction procedure work, when the choice sets are not known for sure, but are estimated from the data, like it is in my case. Also, I would not be able to use all the available information on the universities, but only the information on those universities that have at least some students in the sample.

\(^10\) See Petrin & Train (2003, 2005a, 2005b) and Appendix B for more on this. In my experiments, both a standard two stage IV approach and a control function approach were producing similar results.
to these variables. Then the state aggregates of income and test scores are uncorrelated
with the error in the individual demand. Thus, both variables, \( mdinc_s \) and \( math300_s \),
should be exogenous from the shocks in the individual demand for public schools. Still,
these aggregates affect the state decisions on resident tuition and subsidies (educational
expenditures) and, therefore, are valid instruments.

Let us recall the model of state behavior from Section 2. It basically distinguishes two
factors that influence state decisions. These were the income of the population and the
shadow price of funds \( \lambda \), which measures the usefulness of the funds in their alternative
applications. My instruments will operate through both of the theoretical concepts. The
connection between the income in theory and the median income of the household is
clear. I should note though that the increase in median income also implies an increase in
the tax base and, so, partially operates through \( \lambda \) as well. The percentage of pupils with
high math scores works mainly through \( \lambda \). The money becomes scarcer when state
schools need to serve a higher share of the population.

I run the following regressions over all the public institutions in my sample:

\[
EEpP_i = \alpha_0 + \alpha_1 ASAT_i + \alpha_2 mdinc_i + \alpha_3 math300_i + \alpha_4 mdincASAT_i + \alpha_5 mathASAT_i + d_i \tag{4.8}
\]

\[
ITui_i = \alpha_0 + \alpha_1 ASAT_i + \alpha_2 mdinc_i + \alpha_3 math300_i + \alpha_4 mdincASAT_i + \alpha_5 mathASAT_i + u_i \tag{4.9}
\]

Here \( EEpP_i \) denotes educational expenditures per person in university \( i \); \( ASAT_i \) is the
average SAT score for the undergraduate entering class; \( ITui_i \) stands for in-state tuition
for university \( i \); \( mdincASAT_i \) denotes the interaction term between \( mdinc_i \) and \( ASAT_i \);
and \( mathASAT_i \) is the interaction term between \( math300_s \) and \( ASAT_i \). I have used
centered variables to form the interaction terms. \( d_i \) and \( u_i \) are just error terms.

Table 3 presents the results of the regressions (4.8)-(4.9). These are my first stage
regressions.

The signs of the coefficients correspond to what the theory predicts. Median income
in the state \( mdinc_s \) has a positive sign in all regressions. It is the sign in the theory for the
income of the state population. The mathematics proficiency of high school pupils has a
positive sign in the regression for in-state tuition and a negative sign in educational expenses regressions. That is how an increase in scarcity of funds $\lambda$ works in the model. The theory does not say much about the signs of the interaction terms.

Clearly, the instruments work better for resident tuition. Twice as much of the variance is explained in that regression as in the regressions for the educational expenditures.

Table 3

<table>
<thead>
<tr>
<th>Education Expenditures per Person (Version 1)</th>
<th>Education Expenditures per Person (Version 2)</th>
<th>In-state Tuition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficient</td>
<td>Robust Standard Errors</td>
<td>Coefficient</td>
</tr>
<tr>
<td>ASAT</td>
<td>5.057</td>
<td>0.876</td>
</tr>
<tr>
<td>mdinc</td>
<td>0.056</td>
<td>0.022</td>
</tr>
<tr>
<td>mdincASAT</td>
<td>0.00020</td>
<td>0.00017</td>
</tr>
<tr>
<td>mathASAT</td>
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<td>0.210</td>
</tr>
<tr>
<td>_cons</td>
<td>-1990.999</td>
<td>1198.222</td>
</tr>
</tbody>
</table>

R2                | 0.1925                      | 0.1997            | 0.3875                |
F(5,40)           | 7.96                        | 5.81              | 28.82                 |
# of obs          | 361                         | 361               | 361                   |

*Education Expenditures per Person (Version 1) are "Instruction Expenditures" divided by the total number of students (both graduate and undergraduate)*

*Education Expenditures per Person (Version 2) are the sum of "Instruction Expenditures", "Academic Support", "Student Services", "Institutional Support", and "Operation & Maintenance of Plant" divided by the total number of students (both graduate and undergraduate)*

*The standard errors are robust and clustered by states. Only 41 states participated in the test of mathematics proficiency for 8th-grade students.*
Variation in the data can roughly be classified into two types – variation within the states and across the states. In-state tuition varies mostly across states. Variation in educational expenditures per student mainly arises from the differences between schools within the states. I rely upon the instruments that pick up mainly across-states variation. That way I lose a lot of variation in educational expenses but, so far, I have no reliable instruments to remedy this deficiency. Overall, this is still acceptable because my main focus of interest is to recover the demand sensitivity to tuition (price).

The discrete choice model was reestimated with the residuals from regressions (4.8)-(4.9) used as extra explanatory variables in addition to the original ones. Table 4 contains the results of the estimation. I discuss the results in the next section.

5. Discussion

The results presented in Tables 2 and 4 have the signs everyone would expect.

The coefficients on student’s test score (\(IndSAT\)) and effective family contribution (\(EFC\)) show how the outside option varies with the characteristics of the individual. Private universities become more attractive as the SAT score and income of the individual increase. The coefficient on income (\(EFC\)) was negative and statistically significant in all models. Thus, income may not matter that much in the decision to receive some college degree (at least, economists are struggling to show that), but it is important when people choose between public in-state and private colleges.

Coefficients on the rest of the variables in the specification indicate how utility depends upon the characteristics of public universities as measured relative to the outside option. As expected, a decrease in in-state tuition improves utility, while a decrease in the quality of the public university, as expressed by a decrease in the average ability of the student body or in educational expenditures, makes people worse off.

All results show a similar pattern, but the magnitude of the coefficients differ noticeably in two directions. First, including control functions shifts the coefficients that characterize the value of public institutions. It increases both the absolute value of coefficients on educational expenditures per student and on resident tuition. Second, the results for the models with random coefficients differ from the discrete choice models
### Table 4

<table>
<thead>
<tr>
<th>Utility Parameters</th>
<th>Coefficient</th>
<th>OPG Std Error</th>
<th>Coefficient</th>
<th>OPG Std Error</th>
<th>Coefficient</th>
<th>OPG Std Error</th>
<th>Coefficient</th>
<th>OPG Std Error</th>
</tr>
</thead>
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<td>-2.981661</td>
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<td>-0.004144</td>
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<td>-0.0000237</td>
<td>0.0000475</td>
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<th>OPG Std Error</th>
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(1): Sampling of choice sets, but no random coefficients in utility
(2): Sampling of choice sets, random coefficients on variables that describe the outside option
(3): Sampling of choice sets, but no random coefficients in utility
(4): Sampling of choice sets, random coefficients on variables that describe the outside option

Data for all states that participated in the test of mathematics proficiency for 8th graders were used for the estimation

**Education Expenditures per Person (Version 1)** are "Instruction Expenditures" divided by the total number of students (both Graduate and Undergraduate)

**Education Expenditures per Person (Version 2)** are the sum of "Instruction Expenditures", "Academic Support", "Student Services", "Institutional Support", and "Operation & Maintenance of Plant" divided by the total number of students (both Graduate and Undergraduate)
without random coefficients in utility. That difference may be misleading. For example, the increase in the value of the coefficient on tuition does not necessarily mean a stronger response in the dependent variable. As we’ll see below, the higher coefficient on tuition will be offset by the variance in the value of the outside option.

Admission parameters were very similar across all models. The coefficient on individual SAT score is negative; thus, an increase in this variable decreases the denominator in (4.5) and increases the probability of admission. The coefficient on average SAT score in the institution is positive; thus, as average SAT increases the probability of admission for a given individual falls. The value of the coefficient on individual SAT is about half of the coefficient on average SAT. Therefore, the same increase in both individual and average SAT scores will lead to a smaller probability of admission. Simply put, as average SAT of the school rises, the institution is more difficult to get into and is more likely to reject applicants with lower ability relative to the average ability of the student body.

After recovering demand, one can try to ask some simple questions such as how substantial the deadweight losses are. In addition, knowing demand might provide some evidence of how efficient the public institutions are. The logic is simple. If no one values some good at more than the price plus subsidy, then it is clear that the production of the good is not a good idea unless there are also some externalities present. But first I need to find out what the tuition would be without the subsidy, that is, how much it costs to produce education in public universities compared with private universities.

The differences in the expenses per student between public and private universities are not as high as often thought. In reality, there are no substantial differences in expenditures per student between public and private schools that serve a lower SAT score range. As the average SAT of the students in the university rises, the private universities outspend the public ones but not by a huge margin. On average, a student in a private university contributes (average tuition - institutional grants)/educational expenditures, i.e. (14344.98 - 3401.131)/13522.49=80.9% of total educational expenditures. Similarly, the average resident student in a public university contributes (3014.02-243.04)/

\[\text{For public out-of-state universities, tuition revenues are approximately 85% of educational expenditures.}\]
9261.342$^1_2=29.9\%$ of expenses.$^3$ This implies that the resident students in public universities underpay about 50 percent of the expenses, or more than $4,600, compared with the proportion paid by unsubsidized students.

For comparison, the average state appropriation is approximately $7100 per a resident student in my data, if I assume zero appropriation for nonresident students in public universities. It is approximately $5800 per a student if I do not account for the residency. I do not distinguish between undergraduate and graduate students while computing the numbers. Thus, these numbers are rough estimates of the true average state appropriation per a resident undergraduate student in public universities.

Both types of the institutions receive other funds except the tuition revenues. These funds come either from government or private donations, but not from the students; thus one can claim that all universities are subsidized. However, it is clear that public schools are subsidized in excess of private universities with a specific purpose to decrease the tuition paid by the residents of the state. This excess subsidy (i.e., the amount of $4,600 above) causes the difference in tuition between two types of institutions and has a distorting effect on people’s decisions.

The numbers above do not account for all sources of financial aid, but that seems unnecessary. There is no substantial difference in federal grants students receive in public versus private universities. Data show that, in fact, higher grants are given by the states to students in public universities compared with private universities, but the difference is quite small. Of course, loans are higher in private universities; however, the loans are to be repaid sooner or later. The most substantial difference is in the amounts of institutional grants between the two kinds of universities, and it has been accounted for.

It is not straightforward to interpret the values of the coefficients in discrete choice models. The models describe the behavior of individuals. The same change in tuition will bring different changes in the probability of choosing the outside option, depending upon the characteristics of the individuals (SAT and EFC) and the characteristics of the in-state

$^1_2$ Large part of the difference between the average educational expenditures in private versus public universities can be attributed to the fact that private universities are relatively more concentrated at the upper range of the SAT scores and educational expenditures increase in the average SAT of the student body for any type of institution.

$^3$ Here educational expenditures are defined as a ratio of the sum of "Instruction Expenditures", "Academic Support", "Student Services", "Institutional Support", and "Operation & Maintenance of Plant" over the total number of students (both graduate and undergraduate).
options. I aggregate individual demands to facilitate the interpretation. The individual
class characteristics, quality of schools, number of options, and values of control functions are
kept the same as in the original data. Only tuition takes on different values. The
probabilities of using the outside option are aggregated over the individuals for each of
those tuition values. In this way, I look into the average of the individual behavior in
some “average” state\textsuperscript{14}.

I compute the aggregate demands for several estimated models and plot them on the
graph below. Specifically these were the estimates in columns (4) and (6) in Table 2, and
in columns (8) and (9) in Table 4. As one can see, different models produce similar
results. The main difference is between the raw data estimates and the control function
estimates. The raw data estimates imply less elastic demand. A control function approach
produces more elastic demand. Allowing for the random coefficients in the outside option
decreases elasticity slightly.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{aggregate_demand.png}
\caption{Aggregate Demand for the Average State}
\end{figure}

\textsuperscript{14} Here “average” means that the states are weighted by the number of students to produce the average.
The discrete choice model (8) in Table 4 implies a fairly large effect of in-state tuition -- a $1,000 change in tuition corresponds to about a 20 percent drop in the number of students in public institutions in an average state, holding all other things constant. This implies that an attempt to decrease the state subsidy (appropriation) to the level of 20 percent of the total expenditures per student (that would be the same as raising in-state tuition by $4,000 at least) would basically eliminate the public universities from the market, decreasing the resident enrollment to about 4 percent of all students. This result suggests that public universities are considerably less efficient in producing education -- they seem to produce less education from similar amounts of resources compared with the private universities. The discrete choice model with random coefficients (column 9 in Table 4) implies a smaller effect of resident tuition, corresponding to about a 17 percent change in the share of students in public in-state institutions per $1,000 change in tuition. An increase in in-state tuition of $4,000 leaves only 6 percent of the total student population still enrolled in in-state public schools, down from the current 60 percent. Presently, about 20 percent of people who use outside option go to another public institution in a different state. Keeping the proportion the same, the total share of people enrolled currently in public schools would approach 19 percent after the increase in tuition. But the proportion of public schools is higher than that. Of all the institutions in the US news and World Report data 35.5 percent are public. This indicates that public institutions may be inefficient compared with the private institutions, though the evidence is not overwhelming. In fact, these are out of sample predictions. Basically, I take the response in probability of attending an in-state public university where the data are (that is, in the middle of the graph) and try to extrapolate it to the area where there are few data.

I have used the estimated aggregate demands to compute deadweight losses associated with a subsidy at $4,000. Table 5 below presents the numbers which are substantial.

---

15 Average state has about 56% of students attending public in-state institutions. The rest go either to private (78%) or public out-of-state universities (22%).
Table 5

<table>
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<th>Demand Estimate</th>
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<td>Raw Data, (4)</td>
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<td>Control Function, (8)</td>
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<td>Control Function, (9)</td>
<td>51.9%</td>
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This paper has one notable shortcoming. I had considered a limited menu of choices – either an individual enrolls at some in-state public school or takes advantage of the outside option, consisting of private and public out-of-state universities. The possibility of not enrolling at all or enrolling in a different type of institution is not on the list. This was dictated by the limitations of the data I have. The Department of Education does not do a good job of surveying people who are not students. I do have some information on people attending two-year colleges but that information is not adequate. For instance, individual test scores are usually not reported for students at two year colleges. *U.S. News and World Report* does not collect the average test scores for such colleges. Thus, I am not able to properly recover the choice sets of individuals in two-year colleges. Basically, I am limited to considering what I have considered so far.

Fortunately, this omission should not be critical.

First, it does not matter much for the estimate of the deadweight loss. The deadweight losses come from the fact that the subsidy makes people switch to the subsidized option from the options that would be better if not for a subsidy. In principle, which option they come from is not important. This being said, the situation here is more complicated because students may switch from another subsidized option, such as public two-year colleges. However, the subsidy in four-year institutions is substantially larger than the subsidy in two-year colleges and deadweight loss is unlikely to decrease much after the proper accounting for all subsidies.

Second, there are several studies that looked at how the probability of enrolling in a 4-year college responds to tuition. These studies did not find any large influence.\(^{16}\)

Cameron & Heckman (1999) report “virtually no response” in the total probability to enroll in 4-year school of any type to the increases in resident tuition in public 4-year institutions after they have controlled for test score and family background. They used the

\(^{16}\) Unlike 4-year schools, enrollment in two-year colleges or similar postsecondary schools exhibits a rather large response to tuition levels.
National Longitudinal Survey of Youth micro data. The variation in tuition was across states and counties for public schools. It is basically the same source of variation as in my paper.

Kane (1995) looks at the response of enrollment to the changes in resident tuition across time. He reports a negative 1.2% response in public 4-year college enrollment to a $1,000 tuition hike expressed in 1991 dollars. The enrollment rates were computed as a ratio of total public college enrollment in the state divided by the number of 15 to 24 year-olds; thus, the total enrollment for public and private 4-year colleges was 22.3 percent. That is a fairly small change compared with the numbers that I obtain. It is interesting, though, that Kane also reports a partially offsetting response of 0.5 percent in private in-state college enrollment to a tuition increase of $1,000 in public 4-year schools. This number may grossly underestimate the true effect because, on average, there are about the same number of people going to private out-of-state as to private in-state colleges. Also some people go to public out-of-state universities. If I account for the people enrolling in out-of-state universities, both private and public, the gap between the offsetting increase in private and public out-of-state enrollment and the decrease in public in-state enrollment is likely to disappear completely.

Another technical shortcoming of my paper involves the standard errors reported for the estimates when I use a control function approach. These standard errors are computed treating control functions as usual regressors, which is not the case. The standard errors are likely to be biased downward. Bootstrapping looks like a possible way to correct the estimates. To do it though, I would first need a faster estimation and more reliable convergence while maximizing the simulated log likelihood. This would be the priority in proceeding farther.

Conclusion
This paper finds that a major effect of subsidies to public universities is that people switch from unsubsidized private and public out-of-state to subsidized public in-state universities. This causes a substantial deadweight loss of about half of “excess” subsidy, that is the subsidy that actually causes the difference in tuition between public in-state and private or public out-of-state 4-year universities.
The deadweight loss is a consequence of the suboptimal decisions induced by the subsidy. Basically, people are paid to go to public schools instead of private ones. It has nothing to do with the average level of prices because the magnitude of the subsidized differences in prices and the elasticity of substitution determine the amount of the deadweight losses. The subsidy would induce little loss if the demand for the subsidized education was relatively inelastic. But this is not the case in reality. The evidence in the literature seems to point to a small substitution on the margin between a 4-year college and other choices. In fact, subsidizing all 4-year institutions, both private and public, by the same amount or not subsidizing any, seems a better choice than providing “excess” subsidies to only a handful of schools. The absence of the subsidized differences in prices between public and private schools would eliminate the deadweight loss caused by people switching from private to public universities because of the subsidy. The substitution on the margin between 4-year schools and all the other options seems to be small; thus, the losses on this margin should be small as well. At the same time, it is the substitution on this margin, not on the margin between public in-state and private or public out-of-state schools, which generates the positive effects like increase in schooling and relaxing financial constraints (I did not account for these effects in my analysis).

I can hardly claim that there is enough evidence in this paper to establish the necessity of such a drastic change. There may be still reasons enough to justify the current organization of higher education in the United States. However, we should be aware of the results of the current way in which the subsidies are administered.

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Appendix A

Slopes of the lines.

Differentiating the first order condition (2.11) and using (2.10), I obtain:

\[
\frac{d(s_i + t_i)}{dt_i} = \frac{\partial^2 C(t, I)}{\partial t_i^2} - \frac{\partial^2 Q(a_i, s_i + t_i)}{\partial (s_i + t_i)^2} < 0
\]  

(A.1)

Hence the line that represents (2.11) slopes downward.

Rewriting (2.7) as:

\[
\frac{1}{\lambda} = (s_i + t_i) + \frac{f(U_i - U_0)}{\partial Q_i} - t_i
\]

\[
\frac{\partial}{\partial (s_i + t_i)}
\]

and differentiating, I obtain:
Hence the line representing (2.7) slopes upward.

Actually the derivative (A.2) is not just positive but also more than 1 at the point of intersection of the lines representing (2.7) and (2.11). That easily follows from substitution (2.11) in the nominator of (A.2).

**Change in $\lambda$.**

The value of $\lambda$ affects (2.7) but it does not affect (2.11). Differentiating (2.7) with respect to $\lambda$ and $(s_i + t_i)$, I obtain:

$$
\frac{d(s_i + t_i)}{d\lambda} = \frac{-1}{\lambda^2} \left( 1 + \frac{\partial f(U_i - U_0)}{\partial(U_i - U_0)} \frac{\partial C_i}{\partial t_i} \frac{1}{\partial(s_i + t_i)} \right) > 0 \quad (A.3)
$$

Thus, an increase in $\lambda$ moves the line representing (2.7) downward, which increases tuition and decreases total spending per a student.

**Change in $I$.**

Change in income $I$ affects both (2.7) and (2.11). For (2.11) I obtain:

$$
\frac{d(s_i + t_i)}{dI} = \frac{\partial^2 Q(t_i, I)}{\partial t_i^2} > 0 \quad (A.4)
$$

Therefore, an increase in the income of the population shifts the line that represents (2.11) upward.
Differentiating (2.7), I obtain:

\[
\frac{d(s_i + t_i)}{dI} = -\left[ \frac{\partial f(U_i - U_0)}{\partial (U_i - U_0)} \frac{\partial (U_i - U_0)}{\partial Q_i} \frac{\partial^2 Q_i}{\partial (s_i + t_i)^2} \right] > 0 \quad \text{(A.5)}
\]

The effect on line (2.7) depends upon the sign of derivative \( \frac{\partial (U_i - U_0)}{\partial I} \). It is reasonable to expect this derivative to be negative. The tuition associated with the outside option (i.e., tuition paid at a private or public out-of-state university) is usually substantially higher than the resident tuition \( t_i \). Let us note that

\[
\frac{\partial (U_i - U_0)}{\partial I} = \frac{\partial (C(t_i, I) - C(t_0, I))}{\partial I} \quad \text{.}
\]

Since \( C(t_i, I) \) has negative cross partial, the derivative \( \frac{\partial (U_i - U_0)}{\partial I} \) is expected to be negative. I need to note though, that \( t_0 \) will also react to the change in income, thus, likely decreasing the absolute value of the derivative \( \frac{\partial (U_i - U_0)}{\partial I} \).

An increase in \( I \) is likely to push both lines up and, thus, leads to a higher expenditure per student. In principle, the effect on tuition could go either way; for instance, an increase in tuition will happen if the shift in line (2.11) dominates the shift in (2.7)\(^{17}\).

**Change in** \( a_i \).

For (2.7):

---

\(^{17}\) Careful consideration of all the components in (A.5) reveals that the shift in line (2.11) is likely to be larger than the shift in line (2.7) even without accounting for the effect in \( t_0 \).
For (2.11):

\[
\frac{d(s_i + t_i)}{da_i} = -\frac{\partial^2 Q_i}{\partial a_i \partial (s_i + t_i)} > 0
\]  
(A.7)

Hence both lines (2.7) and (2.11) move up with increase in the average ability of students in the school, thus, the expenditure per student rises. The effect on tuition depends upon the relative shift in each of the lines; tuition grows if shift in (2.11) dominates the shift in (2.7).

**Change in utility between universities with different average ability within the same state**

The first order condition (2.5) implies that the utility derived from university \(i\) is the value function for the following optimization problem:

\[
U^* = \max_{U_i} U_i \bigg|_{a_i = \text{const}}
\]  
(A.8)

Both the average ability of students \(a_i\) and the subsidy \(s_i\) are parameters for this maximization problem. Applying envelope theorem:

\[
\frac{dU^*}{da_i} = \frac{\partial U^*}{\partial a_i} + \frac{\partial U^*}{\partial s_i} \frac{\partial s_i}{\partial a_i}
\]  
(A.9)

The derivatives \(\frac{\partial U^*}{\partial a_i}\) and \(\frac{\partial U^*}{\partial s_i}\) are clearly positive. The derivative \(\frac{\partial s_i}{\partial a_i}\) is the same as the derivative \(\frac{d(s_i + t_i)}{da_i}\) of (A.6) which is positive. Thus, the right-hand side of the
expression (A.9) is positive as well. This means that the utility derived out of a public university is increasing in the average ability of the student body of the university.

**Appendix B**

In Section 4.1, I have discussed two main things that may go wrong with estimating the model on raw data.

First problem is endogeneity, i.e., shocks to utility may induce a response in educational expenditures (subsidy) and resident tuition charged by the public in-state schools. Then the tuition and expenditures become correlated with the error in utility.

The simplest way to think about the endogeneity is to consider some additive shock \( \xi_i \) to the utility \( U_i \), derived from university \( i \), and trace how it is reflected in the tuition and educational expenditures per person (or subsidy) in the model. If the shock is additive, it does not change neither the shape of the education quality function \( Q(a_i, s_i + t_i) \) nor the shape of the cost function \( C(t_i, I) \) in expression (2.9). Therefore, the first order condition (2.11) is unaffected by the additive shock to \( U_i \) and the line representing this first order condition on Figure 1 does not change the position. The positive shock increases the value of \( f(U_i - U_o) \) in the first order condition (2.7), because \( f() \) is an increasing function by assumption (2.8). Thus, the line representing (2.7) on Figure 1 will move down, resulting in a smaller education expenditures per person (smaller subsidy) and higher tuition. Basically I have just shown that: *Educational expenditures per person is a decreasing function of the shock \( \xi_i \) and resident tuition is an increasing function of the shock \( \xi_i \).*

Second problem\(^{18}\) is that small joint increases (or decreases) in both tuition and educational expenditures for some university (so the amount of subsidy stays the same) have a negligible effect on people’s actions, as they produce no noticeable change in the utility people derive from that university. This means that such mistakes in setting optimal tuition and educational expenses are essentially costless to all the parties and,

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\(^{18}\) See also expression (4.7) and discussion that follows that expression.
thus, are likely to happen. These mistakes induce an extra positive correlation between educational expenses and resident tuition in addition to the positive correlation created by the objective factors (like the instruments I have used), affecting both the optimal educational expenditure per student and resident tuition. On top of this, the educational expenses are very imperfectly measured and come together with a lot of noise, that biases the coefficient on expenditures. Since the resident tuition and expenditures are correlated, the bias is transmitted to the coefficient on tuition as well, even if tuition is measured without any error. The extra correlation induced by the joint mistakes in setting tuition and educational expenditures merely increases the bias.

Summarizing, I estimate the following expression on raw data:

$$U_i = k_0 + k_1 \text{AvSAT}_i + k_2 \left( E(z_i) + \frac{E(\xi_i)}{EEpP_i} + v_i + w_i \right) - k_3 \left( T(z_i) + \frac{T(\xi_i)}{ITui_i} + v_i \right) + \xi_i + e_i$$

where $\xi_i$ is the additive shock to utility; this shock $\xi_i$ causes the response $\tilde{E}(\xi_i)$ in educational expenditures $EEpP_i$ and $\tilde{T}(\xi_i)$ in resident tuition $ITui_i$; $z_i$ stands for the instruments that determine the value of the component $E(z_i)$ in the educational expenditures $EEpP_i$ and $T(z_i)$ in resident tuition $ITui_i$; $v_i$ is the common deviation in both tuition and educational expenditures from their optimal values, i.e. the mistake that cancels out in utility and does not cause any response in people’s choices; $w_i$ is a measurement error in educational expenditures per person$^{19}$; $e_i$ is just an error term.

The residuals from the first stage regressions (4.8) and (4.9) are the estimates of $d_i = \tilde{E}(\xi_i) + v_i + w_i$ and $u_i = \tilde{T}(\xi_i) + v_i$. Including them into the specification of utility $U_i$ absorbs the variation in $EEpP_i$ and $ITui_i$ that is not exogenous. They will also absorb the shock $\xi_i$ itself. Then imposing the extreme value distribution upon the remaining error $e_i$ and estimating the model with this new specification of utility $U_i$ produces

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$^{19}$ I can also add a measurement error into the resident tuition $ITui_i$. The logic would stay completely the same.
unbiased coefficients on educational expenditures $EEp_{it}$ and resident tuition $ITui_{it}$. This is the general logic of the control function approach\textsuperscript{20}.

Let us note that the there are two factors behind the values of $d_i$ and $u_i$. These are the shock to utility $\xi_i$ and “common mistake” $\nu_i$. The measurement error $w_i$ is just a noise. As it has been shown above, $\bar{E}(\xi_i)$ increases in $\xi_i$ while $\bar{T}(\xi_i)$ decreases in $\xi_i$. Therefore, the values of $d_i$ and $u_i$ can be inverted to obtain the values of $\xi_i$ and $\nu_i$\textsuperscript{21}. Such invertability is one of the key requirements for the validity of control function approach. Petrin (2005b) discusses it in a much greater detail.

\textsuperscript{20} Let us think about applying the usual two stage IV scheme, that is just using the fitted values of expenditure and tuition from the first stage regression instead of the original $EEp_{it}$ and $ITui_{it}$ variables. The control functions are then omitted from the specification and become the part of the error. Logit implies extreme value distribution and independent draws for the error term at every instance. This is in clear contradiction with the error term containing the control functions. Both the distributional assumption and independence would be invalid and, so, the choice probabilities would be misspecified if they have been set up as logits.

\textsuperscript{21} One may think about a system of two linear equations in two unknowns to clarify the intuition. The fact, that $\bar{E}(\xi_i)$ increases in $\xi_i$ while $\bar{T}(\xi_i)$ decreases in $\xi_i$, warranties that the system has a unique solution.
I have used IPEDS data on university enrollment in 1996-97 academic year to compute first and second columns in the table.