Market Power and Price Discrimination in the U.S. Market for Higher Education*

Dennis Epple

Carnegie Mellon University and NBER

Richard Romano

University of Florida

Sinan Sarpça

Koç University

Holger Sieg

University of Pennsylvania and NBER

Melanie Zaber

Carnegie Mellon University

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Abstract

The main purpose of this paper is to develop a new equilibrium model of private and public school competition that captures the key institutional features of the U.S. market of higher education and can generate realistic pricing patterns for private universities. We show that the parameters of the model are identified and can be estimated using a semi-parametric estimator given data from the NPSAS. We find that a $10,000 increase in family income increases tuition at private schools by on average $120 to $140. A one standard deviation increase in ability decreases tuition by approximately $830 to $1,750 depending on the selectivity of the college. Discounts for minority students are approximately $5,750 at the most selective private colleges. Average mark-ups are modest and range between 7 and 20 percent.

KEYWORDS: Higher education, private and public colleges, competition, federal financial aid policies, peer effects, price discrimination, market power.

1 Introduction

The net tuition paid by any two students sitting in the same college classroom is often quite different. Product differentiation and market segmentation together with idiosyncratic preference shocks can generate market power for private colleges. In addition, private colleges and universities engage in third-degree price discrimination, conditioning institutional financial aid on student ability, household income, and other characteristics such as minority status. Colleges compete to attract higher ability students and students who increase diversity, while also wanting high income students who might cross subsidize desirable lower income students. The exercise of market power can then be expected to vary across student types. The main purpose of this paper is to develop and estimate a new equilibrium model of private and public school competition that captures these key institutional features of the market and can generate realistic pricing patterns for private universities.

To explain the observed pricing patterns, we need a model of demand for higher education that captures the main restrictions that are placed on the available choice set of each student. In our model students differ by income, ability, minority status, state of residence, and unobserved idiosyncratic preferences for colleges. Given the large amount of heterogeneity among students and the observed differentiation among colleges, a key challenge is to characterize the admission and tuition policies of each college and hence the set of feasible choices for each student. The model needs to account for the fact not all students are admitted to selective colleges.

We model the coexistence of a variety of quality-differentiated public and private colleges that compete for students by adopting admission and tuition policies. While public colleges typically do not engage in price discrimination, they offer a relatively affordable alternative to private colleges and thus impact the price and income elasticities of demand for private education. We assume that public universities maximize the aggregate achievement of in-state students. Public universities also face regulated price caps, but obtain direct subsidies from their state legislatures. Moreover, their regulated tuitions generally differ between in- and out-of-state students. With such a characterization of state colleges, our model shows

that state colleges optimally use minimum ability admission thresholds that differ between in- and out-of-state students and between minority and non-minority students. Given these admission thresholds, we can determine the set of public schools that are feasible for each student type.

Modeling the behavior of private schools is more challenging. We assume that private schools maximize quality, which depends on the measured abilities of their students, the educational resources they provide to their students, and a racial diversity measure.[1] We also assume that tuitions are constrained by an exogenously determined price cap. Assuming a model of monopolistic competition, we derive the optimal admission and pricing policy for each private school.

The equilibrium of the model has a number of attractive properties. First, because private schools impose a price cap, a minimum ability threshold that characterizes admission policies of private colleges arises. Not surprisingly, higher quality schools will have higher ability cut-offs in equilibrium. A certain fraction of students do not obtain financial aid and pay the maximum tuition. These are students that are below the mean ability of the school and thus do not qualify for merit aid. Moreover, these students must have income sufficiently high so that the price cap is binding.

For all other students, net tuition can be expressed as "effective marginal cost" plus a mark-up. While this is not surprising, there are however important differences that distinguish our model from a standard oligopolistic pricing model. First, effective marginal cost depends on the ability and minority status of a student. Pricing by ability or merit-based aid arises because high ability students increase college quality through reputation and peer effects. Discounts for minority students arise because they enhance diversity. Second, the mark-up term does not depend on the overall market share of the college, but on the market share conditional on observed student characteristics. We show that these terms can differ by large margins among students, especially for highly selective colleges. Hence local or con-

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[1]The resulting pricing equation is identical in form to a model in which private colleges maximize profits. As such our empirical approach is robust to alternative specifications of the colleges' objective functions. Other features of the equilibrium differ as quality maximizers spend all resources on education while profit maximizers seek to return profits to owners.

ditional market shares drive mark-ups in the model, and not overall market shares. Third, the mark-up can be decomposed into two additive terms. The first term takes the standard form derived in standard discrete choice demand models. This term reflects idiosyncratic preferences for the school and product differentiation. The second term is monotonically increasing in student or household income capturing pricing by income and arises due to price discrimination. As a consequence, our model is sufficiently rich to generate the qualitative features of tuition policies observed in the U.S. market for higher education.

We then derive and implement a semi-parametric sequential estimator. In the first step, we can identify and estimate a subset of the parameters using a method of moments estimator that is based on the difference between the observed and predicted price functions at private colleges. To implement this estimator we need a non-parametric plug-in estimator of the conditional market share for each student at the school that is attended in equilibrium. The remaining parameters of the model can be estimated using a modified version of Berry's (1994) estimator.

Two additional challenges to estimation are present that are typically not encountered in standard demand analysis. First, the potential choice set is unobserved by the econometrician. Our model implies, however, that both private and public schools use minimum-ability threshold rules to determine admission functions. These thresholds arise because both private and public colleges face binding price caps. We observe attendance in equilibrium and as a consequence can estimate minimum admission thresholds using order statistics. This allows us to characterize the relevant choice set for each student in the sample.

Second, private colleges engage in third-degree price discrimination. Hence institutional aid and net tuition policies of all private colleges are functions of income and ability as long as the price cap is not binding. A key challenge encountered in estimation is that the institutional aid is only observed at the college that is attended in equilibrium. The econometrician does not observe the financial aid packages and, hence the net tuition, that were offered by the colleges that also admitted the student, but were ultimately rejected by the student. As a consequence, we cannot directly evaluate the conditional choice probabilities

for each student. However, we can consistently estimate the institutional aid functions of each college type using nonparametric techniques such as kernel or sieve estimators. Given these consistent estimators we then can compute the conditional choice probabilities of each student.

Our estimation approach does not require us to solve for the equilibrium of the model.[2] This has the virtue of simplicity and can be applied for a model with a large number of colleges. It is also computationally feasible since we do not need to use a nested fixed point algorithm.

We estimate the model using data from the National Postsecondary Student Aid Study. Our sample size consists of approximately 9,500 students that attended a two-year public community college, a four-year public college, or a four-year private college in the U.S. in 2012. While our sample size is large, it is not large enough to estimate a model at the individual college level.[3] We, therefore, use clustering algorithms to aggregate four-year private colleges into ten types, public four-year colleges into four types, and public two-year colleges into one type. Our empirical model thus has 15 different college types. To our knowledge, this is the most disaggregate demand model for higher education that has ever been estimated.

We find that the majority of private colleges engage in pricing by income, ability, and minority status. A $10,000 increase in family income increases tuition at private schools by on average $120 to $140. A one standard deviation increase in ability decreases tuition by approximately $830 to $1,750 depending on the selectivity of the college. There are large and substantial discounts for minority students that range between approximately $100 (at historically black colleges) and $5,750. Average mark-ups are modest and range between 7 and 20 percent. There is, however, much more heterogeneity and some much larger mark-ups

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[2]The idea of conditioning on observed choice probabilities is similar to Heckman (1979), Hotz and Miller (1993), Berry (1994), and Aguirregabiria and Mira (2002). Our quasi maximum likelihood estimator is most similar to the one proposed by Bajari, Hong, and Nekipelov (2010) to estimate games with incomplete information.

[3]The NPSAS is the most comprehensive data set available for the U.S., but only samples a subset of all colleges in the U.S. As a consequence some sort of aggregation is unavoidable if one estimates any demand model for higher education using this data set.

within colleges than among colleges.

Our paper is related to at least three different areas of research that have focused on markets for higher education. First, there are many empirical papers that have documented that pricing by income, ability and minority status is prevalent in the financial aid data.[4] Previous structural papers have either ignored this or explained pricing by income by appealing to a motive of serving the poor or providing important socio-economic diversity on campus.[5]

Second, our work is related to research that has modeled admission and attendance decisions in the market for higher education. The informational environment in our model implies students face no uncertainty in admissions, so we can abstract from an application-admission game with incomplete information. Avery and Levin (2010), Chade, Lewis, and Smith (2014) and Fu (2014) provide a detailed analysis of these issues. Our model also abstracts from choices made by students once they enter college. The most important decision is the choice of a major. Arcidiacono (2005) and Bordon and Fu (2015) develop and estimate a dynamic models of choice of academic major under uncertainty.[6] Last, in Epple, Romano, Sarpca, and Sieg (2016), we employ a simplified version of the theoretical model to examine computationally effects of policy changes on attendance patterns and student costs. We abstract from minority status, have fewer colleges, and impose an equilibrium selection criteria. These simplifications allow us to solve for equilibrium in the model and perform policy analysis. Most importantly, we do not estimate the parameters of the model or conduct any empirical analysis of price discrimination and market power in that paper.

Finally, our paper is related to recent research on the importance of peer effects in education. Regarding peer effects in schools, there is a large literature by social scientists. Methodological issues are discussed in Manski (1993), Moffitt (2001), and Brock and Durlauf (2001). Recent research on peer effects in higher education includes studies of college dormi-

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[4]For a discussion of that literature see, among others, Hoxby (1997, 1999), Epple, Romano, and Sieg (2003), and McPherson and Schapiro (2006).

[5]The former approach is taken in most theoretical papers on higher education. The latter approach is taken in Epple, Romano, and Sieg (2006).

[6]Wiswall and Zafar (2015) exploit an informational experiment to study major choice.

tory roommates (Sacerdote (2001), Zimmerman (2003), Boisjoly, Duncan, Kremer, Levy, and Eccles (2006), Stinebrickner and Stinebrickner (2006) and Kremer and Levy (2008)), dormitory residential groupings (Foster, 2006), randomly formed groups in military academies (Lyle (2007, 2009) and Carrell, Fullerton, and West (2009)), classroom peer effects (Arcidiacono, Foster, Goodpaster, and Kinsler, 2012), effects of high school peers (Betts and Morell, 1999), and peer effects among medical students (Arcidiacono and Nickolson, 2005).[7] We do not provide any direct evidence on the importance of peer effects, but provide strong indirect evidence based on our analysis of pricing by ability, income, and minority status.

The rest of the paper is organized as follows. Section 2 introduces the model that characterizes student sorting and price and admission policies in equilibrium. Section 3 introduces a parametrization and discusses our estimator. Section 4 introduces our data set and provides descriptive statistics. Section 5 reports our parameter estimates and summarizes our main empirical findings. Section 6 concludes the analysis.

2　A Model of Price Discrimination

We consider a model with S regions or states and normalize the student population in the economy to 1. Let π_s denote the student population proportions or size of each state and note that $\sum_{s=1}^{S} \pi_s = 1$. Students in each state differ continuously by after-tax income y and ability b. Students also differ by minority status which is a discrete indicator variable $m \in \{0, 1\}$. Let $f_s(b, y|m)$ denote the density of (b, y) in state s conditional on m. The fraction of of type m households in state s is denoted by π_{sm} and note that $\sum_m \pi_{sm} = \pi_s$.

For expositional simplicity, we assume each state operates one public university. In our application discussed below, we extend the model and allow for product differentiation among public colleges within a state.[8] In addition to the S public universities, there are P private universities that operate nationwide and also compete for students. There is an outside option which we model as attending a two-year public college. The total number of alternatives

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[7]See Epple and Romano (2010) and (Sacerdote, 2011) for a more complete literature survey.
[8]Our empirical model allows for up to four types in each state.

is then $J = S + P + 1$.[9]

A student with ability b that attends a university of quality q_j has an achievement denoted by $a(q_j, b)$. Let $p_{sj}(m, b, y)$ denote the tuition that a student from state s with ability b, income y, and minority status m pays for attending college j. Let $A_{sj}(y)$ denote federal aid and L the cost of living of attending a college. As detailed below, federal aid depends on income and the cost of attending a college, which varies with a student's state of residence if attending a state college. Let ε_j denote an idiosyncratic preference shock for college j, which is private information of the student.

Assumption 1 *The utility of student (s, m, b, y) for college j is additively separable in the idiosyncratic component and given by:*

$$U_j(s, m, b, y, \varepsilon_j) = U(y - p_{sj}(m, b, y) - L + A_{sj}(y), a(q_j, b)) + \varepsilon_j. \tag{1}$$

$U(\cdot)$ is an increasing, twice differentiable, and quasi-concave function of the numeraire and educational achievement, $a(\cdot)$. Educational achievement is an increasing, twice differentiable, and strictly quasi-concave function of college quality and own ability.

Utility depends on location and minority status only because tuition depends on location and minority status. The dependence on location can arise for two reasons. First, state colleges are likely to give preferential treatment to locals. Second, private colleges may use different mark-ups to students coming from different states because these students may face different state college options. The dependence on minority status follows from the fact that colleges value diversity as discussed below.

Let $S_a(s, m, b)$ denote the subset of state colleges to which student (s, m, b, y) is admitted, $P_a(s, m, b)$ the same for private colleges, and $J_a(s, m, b) \subset S_a(s, m, b) \cup P_a(s, m, b) \cup O$ the options that provide positive utility available to the student. Taking as given tuitions,

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[9]We abuse notation for convenience by using S to denote both the number of state colleges and the set of them $\{1, 2, \ldots, S\}$, and likewise for P and J (which usage will be obvious by context). Also for expositional convenience, we sometimes refer to university j from the set of all alternatives J, though this includes non-universities like the two-year public college.

qualities, and non-institutional aid, student (s, m, b, y) chooses among $j \in J_a(s, m, b)$ to maximize utility (1). Let the optimal decision rule be denoted by $\delta(s, m, b, y, \varepsilon)$.

Assumption 2 *The vector ε satisfies standard regularity assumptions in McFadden (1974).*

Integrating out the idiosyncratic taste components yields conditional choice probabilities for each type:

$$r_{sj}(m, b, y; P(m, s, b, y), Q) = \int 1\{\delta_j(s, m, b, y, \varepsilon) = 1\} \, g(\varepsilon) \, d\varepsilon, \qquad (2)$$

where $1\{\cdot\}$ is an indicator function, $\delta_j(\cdot) = 1$ means college j is chosen, $P(s, m, b, y)$ denotes the vector of tuitions that apply to student type (s, m, b, y), and Q denotes the vector of college qualities.

Private colleges attract students from all states of the country. Their objective is to maximize quality. College j has a cost function

$$C_j(k_j, I_j) = F_j + V_j(k_j) + k_j I_j, \qquad (3)$$

where k_j denotes the size of college j's student body and I_j expenditures per student on educational resources in college j. The costs $F_j + V_j(k_j)$ are independent of educational quality, which we refer to as "custodial costs." Moreover, each college obtains an exogenous amount of non-tuition income denoted by E_j. Finally, private colleges also have exogenous price caps, denoted by $\bar{p}_j$.

Letting θ_j denote mean ability in college j's student body and Γ_j the fraction of minority students, college quality is given by

$$q_j = q_j(\theta_j, I_j, \Gamma_j) \qquad (4)$$

which is a twice differentiable, increasing, and strictly quasi-concave function of $(\theta_j, I_j, \Gamma_j)$. Quality increases with average student ability due to a combination of peer learning effects,

non-learning externalities from developing relationships with high ability peers, and reputation effects.[10] Quality increases with diversity as having diverse student peers enhances post-college success in a diverse workplace.[11]

Colleges maximize quality behaving as competitive monopolists. Private college j takes as given other colleges' tuitions and qualities when maximizing quality. We can write the quality optimization problem of private college j as follows:

$$\max_{\theta_j, I_j, \Gamma_j, k_j, p_{sj}(b,y)} q(\theta_j, I_j, \Gamma_j) \tag{5}$$

subject to a revenue constraint

$$R_j = \int \int \sum_{s=1}^{S} \sum_{m} \pi_{sm} \, p_{sj}(m,b,y) \, r_{sj}(m,b,y; P(m,s,b,y), Q) \, f_s(b,y|m) \, db \, dy \, + \, E_j \tag{6}$$

a budget constraint

$$R_j = F_j + V_j(k_j) + k_j I_j \tag{7}$$

identity constraints,

$$\theta_j = \frac{1}{k_j} \int\int b \left(\sum_{s=1}^{S} \sum_{m} \pi_{sm} r_{sj}(m,b,y; P(m,s,b,y), Q) f_s(b,y|m) \right) db \, dy \tag{8}$$

$$k_j = \int\int \left(\sum_{s=1}^{S} \sum_{m} \pi_{sm} r_{sj}(m,b,y; P(m,s,b,y), Q) f_s(b,y|m) \right) db \, dy, \tag{9}$$

$$\Gamma_j = \int\int \left(\sum_{s=1}^{S} \pi_{s1} r_{sj}(1,b,y; P(1,s,b,y), Q) f_s(b,y|1) \right) db \, dy \Big/ k_j, \tag{10}$$

and the price cap constraint

$$p_{sj}(m,b,y) \le \bar{p}_j. \tag{11}$$

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[10]In as much as there are non-learning and reputation effects of having higher ability peers embodied in θ, what we have labeled "achievement" must be more broadly interpreted as any utility enhancing college effect. See, for example, MacLeod and Urquiola (2015).

[11]Our assumption that quality increases with the proportion of minorities assumes they are underrepresented. In fact we estimate the opposite in historically black colleges.

We can solve the private college's problem.[12] Assuming that the price cap is not binding, for any student (s, m, b, y) with $r_{sj} > 0$, tuition satisfies:

$$p_{sj}(m, b, y) + \frac{r_{sj}(m, b, y; \cdot)}{\partial r_{sj}(m, b, y; \cdot)/\partial p_{sj}(m, b, y)} = EMC_j(m, b) \tag{12}$$

where

$$EMC_j(m, b) \equiv V_j' + I_j + \frac{q_\theta}{q_I}(\theta_j - b) + \frac{q_\Gamma}{q_I}(\Gamma_j - m) \tag{13}$$

The left-hand side of (12) is the usual expression for marginal revenue. The right-hand side of expression (12) is the "effective marginal cost" of student (s, m, b, y)'s attendance, which sums the marginal resource cost given by the first two terms and the marginal peer costs given by the last two terms. The ability-based marginal peer cost (third term) multiplies the negative of the student's effect on the peer measure (equal to $(\theta - b)/k$) by the resource cost of maintaining quality (equal to $\frac{\partial q/\partial \theta}{\partial q/\partial I}k$). The diversity marginal peer cost has analogous decomposition. Note that EMC varies with students in college j only with the student's ability and minority status. The ability-based marginal peer cost is negative for students of ability exceeding the college's mean, and the diversity-based marginal peer cost is negative for minorities.

Students are admitted to the college if and only if

$$\min\{\bar{p}_j, p_{sj}(m, b, y)\} \geq EMC_j(m, b) \tag{14}$$

Equation (14) yields minimum ability thresholds that vary with minority status for each private college implicitly defined by:

$$\bar{p}_j = EMC_j(m, b_{jm}^{min}) \tag{15}$$

Since effective marginal cost decreases with ability and is lower for a minority student of

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[12]An appendix is available upon request from the authors that derives the optimality conditions for the private and the public school's optimization problem.

given ability, the admission threshold for minorities is lower.

It is interesting to compare this result to that for a profit-maximizing private college. It is not hard to show that a profit-maximizing college would have a tuition function that is of the exact *form* of (12). The main objective of the paper is to determine the empirical content of the pricing equation in (12). Our estimation approach, discussed in detail in the next section, is therefore consistent with quality or profit maximization assumptions.

Distinguishing quality and profit maximization empirically would require distinguishing relatively subtle differences between equilibria under the two alternatives.[13] Given educational inputs, the quality maximizing college sets tuition to maximize profits, while taking account of the peer value effects, so as to have the maximum funds to increase quality. However, the quality maximizing college has stronger incentive to spend on educational inputs, implying inputs will be higher in (12). Moreover, for $q_{II} < 0$, the latter implies the weight on the ability-based peer effect $(\theta - b)$ in (12) will differ, implying the quality maximizer has stronger incentives to attract higher ability students. Likewise, the quality maximizer has stronger incentives to attract minorities.

To test the implications of equation (12), we need to close the demand model and derive the conditional market shares for each private college. For that we need to derive the admission policies of state schools. From an empirical perspective, we will only require that public colleges adopt minimum ability admission thresholds that depend on the state of residence and the minority status of the student. Next we present a model of state colleges that generates admission policies that have these properties.

From the perspective of a state college, a student with characteristics (m, b, y) is either an in-state student or an out-of-state student. We assume that tuition charged to in-state students is fixed exogenously at T_s and to out-of-state students at T_{so}. The state also provides its college an exogenous per student subsidy of z_s, financed by a balanced budget state income tax denoted t_s.

We also assume a state college maximizes the aggregate achievement of its in-state stu-

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[13]See Epple and Romano (1998, 2008) for an analysis of profit maximization by (secondary) schools in a related model.

dents. Letting $\gamma_s(m, b, y) \in [0, 1]$ denote the fraction of in-state students of type (m, b, y) state college s admits and $r_{ss}(m, b, y)$ the fraction of those admitted that attend, the state college maximizes:

$$\iint \sum_m \pi_{sm}\, a(q(\theta_s, I_s, \Gamma_s), m, b)\, \gamma_s(m, b, y)\, r_{ss}(m, b, y; P, Q)\, f_s(b, y|m)\, db\, dy. \tag{16}$$

To write a state college's optimization problem while taking account of the constraints, let $\gamma_{so}(m, b, y) \in [0, 1]$ denote the proportion of out-of-state students of type (m, b, y) the college admits and $r_{ts}(m, b, y; P, Q)$ the fraction of those admitted from state $t \neq s$ that attend.[14] State college s solves:

$$\max_{\theta_s, I_s, k_s, \gamma_s(b,y), \gamma_{so}(b,y)} \iint \sum_m \pi_{sm}\, a(q(\theta_s, I_s, \Gamma_s), m, b)\, \gamma_s(m, b, y)\, r_{ss}(m, b, y; P, Q)\, f_s(b, y|m)\, db\, dy$$

subject to the identity constraints:

$$\begin{aligned}
\theta_s &= \frac{1}{k_s} \iint \sum_m b\, \pi_{sm}\, \gamma_s(m, b, y) r_{ss}(m, b, y; P, Q) f_s(b, y|m) db\, dy \\
&+ \frac{1}{k_s} \iint \sum_m b\, \gamma_{so}(m, b, y) \left(\sum_{t \neq s} \pi_{tm} r_{ts}(m, b, y; P, Q) f_t(b, y|m) \right) db\, dy \tag{17}
\end{aligned}$$

and

$$\begin{aligned}
k_s &= \iint \sum_m \pi_{sm} \gamma_s(m, b, y) r_{ss}(m, b, y; P, Q) f_s(b, y|m)\, db\, dy \\
&+ \iint \sum_m \gamma_{so}(m, b, y) \left(\sum_{t \neq s} \pi_{tm} r_{ts}(m, b, y; P, Q) f_t(b, y|m) \right) db\, dy \tag{18}
\end{aligned}$$

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[14]The value to college s of attracting an out-of-state student of type (m, b, y) does not vary with the state, implying it is optimal to admit out-of-state students of type (m, b, y) with the same frequency, i.e. γ need not vary by the outside state. The yield will vary in general, however.

and

$$\Gamma_s \;=\; \frac{1}{k_s} \iint \pi_{s1}\gamma_s(1,b,y)r_{ss}(1,b,y;P,Q)f_s(b,y|1)\; db\; dy$$

$$+\; \frac{1}{k_s} \iint \sum_m \gamma_{so}(1,b,y) \left(\sum_{t\neq s} \pi_{t1}r_{ts}(1,b,y;P,Q)f_t(b,y|1) \right)\; dbdy \qquad (19)$$

the budget constraint:

$$F_s \;+\; V_s(k_s) \;+\; k_sI_s \;-\; z_sk_s = R_s \qquad (20)$$

the revenue constraint:

$$R_s \;=\; \iint \sum_m p_{ss}(m,b,y)\pi_s\gamma_s(m,b,y)r_{ss}(mb,y;P,Q)f_s(b,y|m)dbdy \qquad (21)$$

$$+\; \iint \sum_m \gamma_{so}(m,b,y) \left(\sum_{t\neq s} \pi_{tm}p_{ts}(m,b,y)r_{ts}(m,b,y;P,Q)f_t(b,y|m) \right) dbdy$$

the tuition regulation constraint:

$$p_{ts}(m,b,y) \;=\; \begin{cases} T_s \text{ for all students } (t,m,b,y) \text{ with } t = s \\ T_{so} \text{ for all students } (t,m,b,y) \text{ with } t \neq s \end{cases} \qquad (22)$$

and the feasibility constraints:

$$\gamma_s(m,b,y), \gamma_{so}(m,b,y) \;\in\; [0,1] \text{ for all students } (s,m,b,y) \qquad (23)$$

Solving the optimization problem, we find that a state college s admits all in-state students with $b \geq b_{sm}^{\min}$, the latter satisfying

$$a(q(\theta_s, I_s, \Gamma_s), b_{sm}^{\min})/\lambda \;+\; T_s \;+\; z_s \;-\; EMC_s(m, b_{sm}^{\min}) \;=\; 0; \qquad (24)$$

where λ is the positive multiplier on the budget constraint. All out-of-state students with

$b \geq b_{om}^{\min}$ are admitted, where

$$T_{so} + z_s - EMC_{sm}(m, b_{om}^{\min}) = 0 \qquad (25)$$

Out-of-state students are admitted if and only if the revenue they generate covers their $EMC(m, b)$. Their value to the state school comes from their tuition and, perhaps, positive peer effects on in-state students. In-state students have an additional marginal value of attendance, specifically their direct contribution to the college's objective of in-state achievement maximization. The term a/λ in (25) equals the monetized value of the increase in aggregate state achievement from the in-state student's attendance. The admission thresholds for in-state and out-of-state minority students will be lower relative to their respective non-minority in-state and out-of-state counterparts. Given minority status, comparing admission thresholds of in-state and out-of-state students, (25) and (26) imply:

$$b_{sm}^{\min} < (=) (>) b_{o,m}^{\min} \ as \ a(q(\theta_s, I_s, \Gamma_s), b_{sm}^{\min})/\lambda + T_s > (=) (<) T_{so}. \qquad (26)$$

While $T_s < T_{so}$ empirically, it may also be that $a(q(\theta_s, I_s, \Gamma_s), b_{sm}^{\min})/\lambda + T_s > T_{so}$, implying lower admission standards for in-state students. This is what we find empirically.

In summary, we have derived the optimal pricing equation for each private college and shown how to derive the effective choice sets for each student. As a consequence, we are now in a position to turn to empirical analysis and determine whether the pricing and sorting predictions of this model are consistent with the observed data.

3 Estimation

3.1 A Parametrization

To estimate the model we need to invoke some additional parametric assumptions.

Assumption 3

a) The quality function is given by

$$q_j = \theta_j^\gamma \, I_j^\omega \, \Gamma_j^\kappa \, e^{u_j}, \quad \gamma, \omega, \kappa > 0 \tag{27}$$

where u_j is an unobserved exogenous characteristic.

b) The utility function is given by:

$$U_j(y - p_{sj} - L + A_{sj}, a(q_j, b)) = \alpha \ln(y - p_{sj} - L + A_{sj}) + \alpha \ln(q_j b^\beta) + \epsilon_j, \quad \beta, \alpha > 0 \tag{28}$$

where α parameterizes the weight on the systematic component of utility.

c) The disturbances ε_j are independent and identically distributed with Type I Extreme Value Distribution.

The assumptions above then imply that the conditional choice probability for type (s, m, b, y) is given by, for $j \in J_a(m, s, b)$:

$$r_{sj}(m, b, y) = \frac{[(y - p_{sj}(m, b, y) - L + A_{sj}(y)) \, q_j]^\alpha}{\sum_{k \in J_a(m,s,b)}[(y - p_{sk}(m, b, y) - L + A_{sk}(y)) \, q_k]^\alpha}. \tag{29}$$

The pricing equation for private colleges satisfies:

$$p_{sj}(m, b, y) = \frac{(1 - r_{sj})\alpha}{1 + (1 - r_{sj})\alpha} EMC_j(m, b) + \frac{1}{1 + (1 - r_{js})\alpha} (y - L + A_{sj}(y)) \tag{30}$$

Effective marginal costs at private colleges are given by:

$$EMC_j(m, b) = V_j' + I_j + \frac{\gamma I_j}{\omega \theta_j} (\theta_j - b) + \frac{\kappa I_j}{\omega \Gamma_j}(\Gamma_j^m - m) \tag{31}$$

The pricing function for all students not at the cap can be written as:

$$\begin{aligned}
p_{sj}(m, b, y) &= \frac{(1 - r_{sj})\alpha}{1 + (1 - r_{sj})\alpha} \left(V_j' + I_j + \frac{\gamma I_j}{\omega \theta_j} (\theta_j - b) + \frac{\kappa I_j}{\omega \Gamma_j}(\Gamma_j - m) \right) \\
&+ \frac{1}{1 + (1 - r_{js})\alpha} \left(y - L + A_{sj}(y) \right)
\end{aligned} \tag{32}$$

In addition we simplify notation by writing the marginal resource costs as

$$V_j \;=\; V'(k_j) \;+\; I_j \qquad\qquad (33)$$

We treat the $V_1, ... V_J$ as additional parameters to be estimated.

The model implies an appealing decomposition of tuition. From (30), observe that tuition to student (s, m, b, y) is a convex combination of the student's effective marginal cost and cost adjusted income. The weight on income increases with the student type's market share at the college indicating increased market power over the student. The weight on income decreases with α, the weight on the systematic component of utility. This indicates that market power declines as idiosyncratic preferences become less important.

3.2   The Information Set

The information set of the econometrician can be characterized as follows.

Assumption 4

- *We observe a sample $i = 1, ..., N$. Let s_i denote the state of student i, m_i the minority status, b_i ability, y_i income and $p_{s,j,i}$, the tuition at college j. Note that we only observe the tuition at the college attended in equilibrium. Let d_{ji} denote an indicator which is equal to one if student i attends college j and zero otherwise.*

- *L is known.*

- *θ_j, I_j, k_j are known for all j.*

- *In- and out-of-state tuitions at state colleges $(\bar{p}_{js})$ and price caps at private colleges $(\bar{p}_j)$ are known.*

- *$A_{s_ij}(y_i)$ are observed for all i and j.*

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- *Prices for all students at private colleges that are not paying the cap are measured with classical error:*

$$\tilde{p}_{sji} \;=\; p_{s_i,j}(m_i, b_i, y_i) + v_{i,j} \tag{34}$$

where $v_{i,j}$ is iid across i and j.

3.3 A Semi-parametric Estimator

Consider the subsample of students that attend private colleges and are not at the price cap. Using this subsample we can identify and estimate most of the parameters of the model using the predictions of the model about price discrimination. In particular, we can implement the following sequential estimator.

We non-parametrically estimate the conditional market shares $r_{sj}(m, b, y)$ for all students for the private college that is attended in the data. We use a simple flexible Logit estimator using a quadratic approximation in b and y, where the coefficients depend on m and s. We then use the estimated Logit model to predict the conditional choice probability denoted by $\hat{r}_{sj}(m, b, y)$. Alternatively we could use nonparametric techniques such as kernel or sieve estimators.

Substituting the estimator of the conditional market share into the pricing equation, we obtain:

$$
\begin{aligned}
p_{sj}(m, b, y) \;=\; & \frac{(1 - \hat{r}_{sj})\alpha}{1 + (1 - \hat{r}_{sj})\alpha} \left(V_j + I_j + \frac{\gamma I_j}{\omega \theta_j}\,(\theta_j - b) + \frac{\kappa I_j}{\omega \Gamma_j}(\Gamma_j - m) \right) \\
& + \frac{1}{1 + (1 - \hat{r}_{js})\alpha} \left(y - L + A_{sj}(y) \right) \;+\; v_{sji}
\end{aligned} \tag{35}
$$

where v_{sji} is the measurement error term. We can, therefore, identify and estimate α, the ratios γ/ω and κ/ω, as well as the marginal costs $V_1, ..., V_J$ using a semi-parametric NLLS estimator based on equation (35). We use a bootstrap algorithm to estimate the standard errors to account for the sequential nature of the estimation procedure.

Most of the empirical results reported on this paper are based on this estimator. One nice property of this estimator is that it is consistent for large N, but small J. This scenario is relevant for most practical applications.

For certain applications knowledge of the level of ω, γ, and κ is useful. We, therefore, finish this section by discussing how to identify and estimate the levels of these parameters using a modified version of the estimator suggested by Berry (1994). Consider the full sample of all students including those students that attend private colleges and that are at the cap as well as students attending public colleges and universities.

We can construct the minimum ability threshold for each college, by computing the minimum ability of the students. Let our estimator be denoted by b_{jm}^{min}. We can then identify the choice set for all students as follows:

$$J_a(m, s, b) = \{s | b \geq b_{sm}^{min}\} \ \cup \ \{o \in S \setminus \{s\} | b \geq b_{om}^{min}\} \ \cup \ \{j \in P | b \geq b_{jm}^{min}\} \ \cup \ \{0\} \qquad (36)$$

The first and second sets are, respectively, the in-state public colleges and the out-of state public colleges admitting the student. The third set denotes the set of all private colleges to which the student is admitted, and the last set is the outside option.

We then non-parametrically estimate the prices for each student at each college to which the student was admitted based on the observed tuition levels, using a local smoothing quadratic polynomial that uses a bin width of half of all points for each local estimation. Let us denote these estimates by $\hat{p}_{sji}^{np}$.[15]

Substituting the nonparametric estimates of the tuitions into the conditional choice probabilities, we obtain

$$\hat{r}_{ji} \ = \ \frac{[(y_i - \hat{p}_{sji}^{np} - L + A_{s_i,j}(y_i))q_j]^\alpha}{\sum_{k \in J_a(m_i, s_i, b_i)}[(y_- \hat{p}_{ski}^{np} - L + A_{sk}(y_i))q_k]^\alpha} \qquad (37)$$

Following Berry (1994), the quality levels for each school are determined by the fixed

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[15]Details about the implementation of this estimator are given in Appendix B.

point of the following mapping:

$$\tilde{q}_j = q_j + ln(s_j^N) - ln(s_j(q)) \quad j = 1, ..., J - 1 \tag{38}$$

where: q_j is initial guess of the quality, s_j^N is the average empirical market share of college j observed in the data, and $s_j(q)$ is the predicted average market share using the initial guess about the vector of qualities:

$$s_j(q) = \frac{1}{N} \sum_{i=1}^{n} \hat{r}_{ji} \tag{39}$$

We can identify q_j's for each college, subject to a normalization such as $q_1 = 1$. The normalization of quality is necessary since market shares add up to one.

Using the fact that $q_j = \theta_j^\gamma I_j^\omega \Gamma_j^\kappa e^{u_j}$ we obtain the the following regression model:

$$\ln(q_j/q_1) = \omega \left(\frac{\gamma}{\omega} \ln(\theta_j) + \frac{\kappa}{\omega} \ln(\Gamma_j) + \ln(I_j) - \frac{\gamma}{\omega} \ln(\theta_1) - \frac{\kappa}{\omega} \ln(\Gamma_1) - \ln(I_1) \right) + u_j - u_1 \tag{40}$$

Define

$$w_j = \frac{\gamma}{\omega} \ln(\theta_j) + \frac{\kappa}{\omega} \ln(\Gamma_j) + \ln(I_j) - \frac{\gamma}{\omega} \ln(\theta_1) - \frac{\kappa}{\omega} \ln(\Gamma_1) - \ln(I_1) \tag{41}$$

and note that w_j is known at this point. Rewriting equation (40) as

$$\ln(q_j/q_1) = \omega \, w_j \, + \, u_j - u_1 \tag{42}$$

and hence ω can be estimated using least squares. Note that OLS is consistent despite the fact that w_j and $u_j - u_1$ may not be independent because the regression above does not have an intercept. Note that the last step of the estimator requires a large number of colleges or preferably multiple markets.

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4 Data

Our data source is the 2011-12 National Postsecondary Student Aid Study (NPSAS) from the National Center for Education Statistics (NCES).[16] Our model focuses on initial attendance/matriculation outcomes. We construct our sample using first-year students, who are oversampled in this wave of the NPSAS and constitute more than half of all observations.[17] We drop some students whose behavior or characteristics require separate modeling. These include multiple attenders–students who switch institutions in their first academic year.[18] These also include a larger number of students with atypical attendance patterns–those who attend part-time or part-year, as is often the case at two-year colleges. We also drop veterans and athletes because their financial aid opportunities are different from those faced by the average student, and their priorities in selecting an institution may also differ. We drop foreign students (or students with no state residence) for two reasons: (i) Their choice sets possibly include the universities in their home country, as well as universities in other non-home countries (based on their decision to study abroad); (ii) Their eligibility for financial aid and their pricing by colleges may differ.

Ability is a key variable in our analysis and we drop observations with missing components of the ability measures (ACT or SAT score and high school GPA).[19] We drop all students attending schools at which we cannot match institutional expenditures. Finally there are a few sample schools that offer both 4-year and 2-year degrees, and we drop their 2-year enrollees (the minority) and treat them as 4-year institutions. The resulting sample consists

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[16]The NPSAS data are accompanied by inverse probability weights that account for the composite probability of sampling, both at the college and individual level. We use these weights throughout the empirical analysis.

[17]College completion and continuation decisions are likely to differ from the initial matriculation decision. Also, family resources and aid packages in later years of attendance need not be identical to those in the student's first year. For these reasons we use first-year students in our analysis.

[18]These constitute about 4 percent of the sample, dropped because we cannot know if the switch was planned from the point of matriculation, and so the decision space would become much more complex.

[19]As approximately 40% of first-year public 2-year students do not take SATs or ACTs, it is possible that the remaining sample is of higher ability than the general student body. Thus, our measure of average peer quality may be biased upward for this college, and we will underestimate the quality-differentiation among colleges. However, there is no other viable measure of student ability, and so this is an unavoidable challenge to estimation.

of approximately 9,490 students. Table 1 presents the numbers of these groups of students along with their distribution over different types of colleges.

Table 1: Sample Selection

	2-year public	4-year public	4-year private	Total
Full NPSAS 2012	31,000	17,300	9,010	57,300
First-year only	17,860	4,530	4,210	26,590
No atypical attendance	5,380	3,370	3,470	12,220
No athletes	5,330	3,310	3,280	11,910
No veterans	5,190	3,230	3,230	11,660
No missing ability	4,180	3,160	3,170	10,510
No missing state	4,150	3,130	3,090	10,370
No missing school expenditures	3,510	2,910	3,070	9,490

Note: Unweighted counts rounded to nearest 10 as per NCES policy.

Table 2 presents selected statistics from our sample. Our measure of ability is predicted college GPA–we model college GPA as a function of high school GPA, ACT or SAT score, gender, and college fixed effects in a sample of non-minority four-year college students. We then predict GPA at a generic college, using only the recovered parameters for high school GPA, ACT/SAT score, and gender.[20] This ability measure is then transformed to have unit standard deviation and positive mean. The choice of mean ensures that the average ability at each college is weakly greater than zero.[21]

Our measure of income is adjusted gross income in 2010. Where possible, NPSAS computes this value based on the federal financial aid application, and uses total income (of family or student as implied by dependency status) reported in the student interview where no application or tax return are available. The 2010 value is used as federal financial aid eligibility for 2011-2012 school year would be based on 2010 income. Race, ethnicity, and gender are drawn from the student interview where possible, and from student records when no interview is possible.

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[20]We do not account for minority status in this regression although it could be easily done. A priori one can make arguments in favor and against either approach.

[21]Appendix A provides additional details. It also explains the construction of the ability thresholds used for each cluster/

In-state status is determined by comparing the student's reported state of residence with the imputed availability of public college types. We calculate total institutional aid by taking the sum of grants, one-half of work study, and one-quarter of loans. Thus, net tuition is the posted tuition less the sum of institutional aid (federal aid is considered separately).

Table 2: Selected Characteristics for NPSAS 2012 Sample

	Public 2-yr	Public 4-yr	Private 4-yr	All
Number of students	3,510	2,910	3,070	9,490
Number of students *(weighted)**	521,638	583,844	342,519	1,448,001
Number of Colleges	300	250	350	900
Number of Colleges *(weighted)***	1549	713	1286	3548
Average ACT Score	19.72	21.88	23.79	21.55
Average Ability	0.00	0.45	0.81	0.37
Average In-state Tuition***	3.00	5.73	26.37	12.02
Average Out-of-state Tuition	6.48	15.48	26.37	15.50
Average Income	48.4	76.9	94.8	70.9
Female	0.53	0.54	0.57	0.55
Black	0.18	0.17	0.14	0.17
Hispanic	0.19	0.13	0.11	0.15

*Students are weighted to be nationally representative, using inverse probability weights provided by the NCES. All other student-level statistics (e.g. ACT score, gender) are also weighted.
**Colleges are weighted to be nationally representative, using inverse probability weights provided by the NCES. Tuition values are also weighted.
***Tuition and income reported in $1,000s.

Note: Unweighted counts rounded to nearest 10 as per NCES policy.

Federal aid is limited to Pell grants, which are calculated by the formula

$$A = \min \left\{ \max \left\{ 0, COA - EFC(y) \right\}, 5500 \right\}, \tag{43}$$

where COA is the federally determined cost–of–attendance and $EFC(y)$ the federally determined expected family contribution, which increases with household income. Pell grants are awarded up to $COA - EFC$ if positive, but with a maximum of $5500. However, in practice, we use the amended formula:

$$A = \min \left\{ \max \left\{ 0, \bar{p}_j + L - EFC(y) \right\}, 5500 \right\}, \tag{44}$$

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as cost of attendance (tuition plus estimated non-tuition costs) varies by student-college combination and is only occasionally observed at the attended college, and never observed for potential alternatives. EFC is directly reported in the NPSAS, and thus can be used both for the attended college as well as the potential alternatives.

Then we calculate the Pell aid at each college using the above formula, also adjusting to account for the Pell minimum award (in 2012, 555 dollars). Any student offered at least half of the minimum, but less than the minimum, is given the minimum, and any student eligible for less than half of the minimum was awarded no aid. Additionally, we have many "never-takers" in our sample, and so if we observe a student to be a never-taker at the attended college when eligible for some aid, we assume he is a never-taker at all colleges.

Our sample includes observations from approximately 900 colleges. The number of students observed per college averages about 11. Having more observations per college is desirable for precision when testing within-college predictions of the model. At the same time, our model implies that colleges with similar characteristics would make similar admission and pricing decisions. Working with smaller choice sets (fewer colleges) also has computational advantages. For these reasons, we group together colleges that are similar in their key characteristics for our purposes. In particular, we group public and private colleges separately based on the joint variance of sticker price tuition, average ACT score, and instructional expenditures per student, using k-means clustering. We choose the number of clusters based on the elbow method, increasing the number of clusters until the marginal cluster does not significantly decrease the within-group variance, which suggests approximately four clusters of public four-year colleges, and approximately twelve clusters of private four-year colleges.

The "rule of thumb" relates the suggested k to the number of schools to cluster, $k = \sqrt{\frac{n}{2}}$, implies approximately 13 private clusters (n_{priv}=350). We initially create twelve private clusters, but then combine two sets of resulting cluster pairs to ensure an adequate sample size of students at each cluster. Table 3 presents the key characteristics of private and public clusters, ordered within the two college groups by mean ACT. The term "college" will refer to a cluster in the rest of the paper.

Table 3: Characteristics of Clusters

cluster	in-state admit	out-state admit	min ability	mean ability	mean ACT	mean sticker	mean tuition	instruct. expend.	percent black	percent Hispanic	count colleges	count students	weighted students
						Private 4-Year Colleges							
1	-0.40	-0.40	-1.72	1.66	28.59	39.31	25.28	37.96	0.07	0.11	20	450	36,758
2	0.35	0.35	-0.80	1.48	27.77	41.63	29.75	17.30	0.06	0.10	20	290	38,264
3	-1.42	-1.42	-1.42	0.93	24.81	30.74	19.30	12.86	0.03	0.09	10	130	16,269
4	-1.26	-1.26	-1.26	0.82	24.47	36.66	22.25	11.52	0.08	0.11	40	420	45,429
5	-1.88	-1.88	-1.88	0.76	23.07	23.76	15.41	9.07	0.16	0.11	40	330	30,431
6	-1.42	-1.42	-1.42	0.61	22.61	31.11	17.26	8.34	0.16	0.16	50	390	51,837
7	-1.86	-1.86	-1.86	0.49	21.80	26.73	14.47	6.66	0.14	0.09	60	490	49,517
8	-1.87	-1.87	-1.87	0.43	21.33	18.22	12.07	6.29	0.18	0.10	30	170	27,424
9	-1.61	-1.61	-1.61	0.39	21.09	21.78	11.57	5.42	0.19	0.12	40	240	26,491
10	-1.45	-1.45	-1.45	0.22	20.93	12.19	8.18	5.47	0.36	0.06	30	170	20,099
						Public 4-Year Colleges							
11	-0.53	-0.53	-0.53	0.69	23.05	15.52	13.18	10.43	0.05	0.19	10	140	31,538
12	-1.73	-1.17	-1.73	0.58	22.50	11.17	9.33	9.36	0.13	0.08	60	840	165,888
13	-1.76	-1.42	-1.76	0.43	22.04	7.33	6.06	7.50	0.15	0.15	110	1,180	242,419
14	-2.38	-1.49	-2.38	0.27	20.64	4.31	3.50	6.05	0.28	0.15	80	750	143,998
						Public 2-Year Colleges							
15	n/a	n/a	-2.45	0.00	19.72	3.18	2.98	4.48	0.18	0.19	300	3,510	521,638

Instructional expenditures weighted by institutional weight. All other means weighted by individual weight

Unweighted counts rounded to the nearest 10 as per NCES policy.

Tuition and expenditures reported in $1,000.

Table 4 reports "local" market shares for non-minority students at the two most selective private colleges, with these market shares conditional on deciles for income and ability.[22] Because colleges value student ability and price discriminate according to income and ability, the equilibrium exercise of market power will vary with student characteristics. We provide evidence on this below–the conditional market shares for high ability and high income students in these clusters are much larger than the overall unconditional market share, which is equal to 0.08. As a consequence the college has significantly larger local market power than is suggested by its overall market share.

Table 4: Student Sorting at High Quality Colleges (Clusters 1 and 2)

	income percentile									
ability	10	20	30	40	50	60	70	80	90	100
10	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.02	0.00
20	0.01	0.02	0.00	0.00	0.00	0.03	0.01	0.02	0.03	0.06
30	0.01	0.00	0.00	0.00	0.02	0.05	0.00	0.04	0.03	0.05
40	0.03	0.02	0.01	0.01	0.04	0.01	0.01	0.00	0.04	0.02
50	0.02	0.01	0.00	0.02	0.02	0.06	0.03	0.04	0.09	0.11
60	0.00	0.02	0.01	0.00	0.02	0.04	0.08	0.05	0.04	0.05
70	0.00	0.01	0.01	0.02	0.06	0.05	0.03	0.10	0.08	0.08
80	0.04	0.08	0.05	0.07	0.07	0.11	0.04	0.05	0.07	0.24
90	0.08	0.07	0.04	0.07	0.13	0.20	0.10	0.07	0.20	0.23
100	0.22	0.28	0.37	0.18	0.29	0.28	0.38	0.31	0.41	0.53

Note: Table gives proportion of each income-ability percentile combination attending colleges in Cluster 1 or 2. Proportions are unweighted.

Table 5 summarizes the reduced form evidence regarding pricing by income and ability in private colleges. Tuition is regressed on student characteristics for each cluster. Note that clusters 1 and 2 are the most selective private colleges. For those we find significant pricing by income on the magnitude between 0.024 and 0.044, i.e. a \$10,000 increase in family income increase tuition by \$240 to \$440, on average. In contrast, the four colleges with the lowest average peer quality, 7, 8, 9, and 10, show no indication of significant pricing by income.

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[22]We use deciles, though localness can be defined using a finer or broader delineation.

Table 5: Pricing By Income, Ability, and Minority Status

	(1)	(2)	(3)	(4)	(5)
Constant	1.201***	1.457***	1.803***	1.887***	1.519***
	(0.262)	(0.232)	(0.108)	(0.076)	(0.066)
Income	0.044***	0.024***	0.003	0.018***	-0.002
	(0.012)	(0.005)	(0.005)	(0.004)	(0.005)
Ability	-0.152	0.021	-0.239***	-0.204***	-0.086**
	(0.129)	(0.132)	(0.064)	(0.05)	(0.04)
Minority	-0.241	-0.476	0.143	-0.440***	-0.213**
	(0.364)	(0.375)	(0.346)	(0.159)	(0.106)
N	140	140	100	350	290
R^2	0.099	0.147	0.143	0.104	0.025

	(6)	(7)	(8)	(9)	(10)
Constant	1.520***	1.319***	1.100***	1.123***	0.464***
	(0.063)	(0.044)	(0.055)	(0.065)	(0.128)
Income	0.016***	0.001	-0.002	0.004	0.016
	(0.004)	(0.003)	(0.006)	(0.008)	(0.013)
Ability	-0.098**	-0.024	-0.119***	-0.190***	-0.048
	(0.041)	(0.032)	(0.04)	(0.037)	(0.07)
Minority	-0.231**	-0.075	-0.036	-0.005	0.235
	(0.1)	(0.083)	(0.104)	(0.092)	(0.188)
N	350	450	130	210	100
R^2	0.083	0.003	0.068	0.117	0.033

Note *p<0.1; **p<0.05; ***p<0.01
Unweighted counts rounded to the nearest 10 as per NCES policy.
Sample is private school students receiving some institutional aid.

Moreover, colleges engage in significant pricing by ability. Six of the ten estimated coefficients are negative and statistically significant. Interestingly, the colleges with significant pricing by ability come from the middle of the average peer quality distribution–neither the highest nor the lowest quality colleges have significant pricing by ability. A one standard deviation increase in ability decreases tuition by up to $2,390.

The majority of colleges have minority coefficients with a negative sign; notably, cluster 10, which contains several historically black colleges, has a nearly significant *positive* sign. Where significant, pricing by minority varies in magnitude from a $2,130 discount to a $4,400 discount for minority students.

5   Empirical Findings

Table 6 summarizes the parameter estimates for the first stage of the sequential estimator. Note that these estimates are based on the subsample of students at private universities that received a positive amount of institutional financial aid. The relevant sample size is 2,270.

Using the weights suggested by NPSAS, we obtain an estimate of α which is equal to 70.27 with an estimated standard error of 6.68 (see column 2). As a consequence we find that our estimate is highly significant at standard levels of significance. Note that α is primarily identified from the observed pricing by income. The average predicted marginal effect of income on price is 0.015. The other structural parameter that is identified is the ratio of $\frac{\gamma}{\omega}$. Our point estimate equals 0.073 with an estimated standard error of 0.012. Recall that this ratio is primarily identified off the observed merit based aid. The average predicted marginal effect of ability on price is -0.116. We conclude that both key parameters are estimated with high precision. Furthermore, they are consistent with reduced form evidence of these effects.

We can also estimate the marginal resource costs of admitting an additional student to the college. Not surprisingly we find that there is much heterogeneity in marginal costs. Our estimates range between approximately $5,414 and $16,527. Note that these estimates combine marginal expenditures on educational inputs and marginal custodial costs.

Table 6: Parameter Estimates I

	(1)	(2)	(3)	(4)	(5)
Clusters		all	all	1 & 2	1 & 2
Weights	No	Yes	Yes	Yes	Yes
α	86.56***	70.26***	72.72***	76.88***	78.54***
	(8.58)	(6.68)	(7.13)	(17.01)	(17.75)
$\frac{\gamma}{\omega}$	0.074***	0.0734***	0.079***	0.046	0.056
	(0.012)	(0.012)	(0.012)	(0.049)	(0.049)
$\frac{\kappa}{\omega}$			0.012***		0.008
			(0.003)		(0.006)
V_1	1.22***	1.21***	1.23***	1.17***	1.19***
	(0.07)	(0.07)	(0.07)	(0.11)	(0.11)
V_2	1.69***	1.65***	1.66***	1.56***	1.56***
	(0.07)	(0.07)	(0.07)	(0.11)	(0.11)
V_3	1.43***	1.40***	1.41***		
	(0.08)	(0.08)	(0.08)		
V_4	1.82***	1.81***	1.82***		
	(0.05)	(0.05)	(0.05)		
V_5	1.15***	1.14***	1.14***		
	(0.05)	(0.05)	(0.05)		
V_6	1.48***	1.46***	1.46***		
	(0.04)	(0.04)	(0.04)		
V_7	1.15***	1.13***	1.14***		
	(0.04)	(0.04)	(0.04)		
V_8	0.93***	0.92***	0.92***		
	(0.07)	(0.07)	(0.07)		
V_9	1.09***	1.08***	1.08***		
	(0.05)	(0.05)	(0.05)		
V_{10}	0.56***	0.54***	0.54***		
	(0.08)	(0.08)	(0.08)		
Implied Pricing by Ability and Income					
$\frac{\partial p}{\partial b}$	-0.095	-0.105	-0.112	-0.066	-0.096
$\frac{\partial p}{\partial y}$	0.013	0.015	0.014	0.014	0.015
Reduced Form (OLS) Estimates of Pricing by Ability and Income					
$\frac{\partial p}{\partial b}$	-0.113***	-0.112***	-0.121***	-0.063***	-0.052***
$\frac{\partial p}{\partial y}$	0.017***	0.016***	0.016***	0.027	0.028

Note *p<0.1; **p<0.05; ***p<0.01

Columns 3 and 5 allow the consideration of minority status in pricing.

OLS estimates account for a cluster fixed effects

Comparing the weighted estimates in Column 1 with the unweighted estimates in Column 2, we find only small differences in the estimated parameter values. The main difference is that the unweighted estimator yields a somewhat greater point estimate of α.

In Column 3 we add minority to our model. We can estimate the ratio of $\frac{\kappa}{\omega}$. Our point estimate is 0.012 with a standard error of 0.003. Recall that this ratio is primarily identified off the observed aid to minority students holding income and ability fixed. The average predicted marginal effect of minority in our model is a \$900 discount. We conclude that our model provides strong evidence that private schools care about racial diversity.

Our parameter estimates are reasonably robust across subsamples. To show this we also estimated our model for the subsample that consistent of students that attended colleges that seem to engage in the largest amount of pricing by income which are clusters 1 and 2. The results are reported in columns 4 and 5 of Table 6. We obtain an estimate of α that is equal to 76.89. Moreover our estimate of $\frac{\gamma}{\omega}$ is marginally smaller at 0.046, though the two are not significantly different. The inclusion of minority status also has little impact on the first two parameter estimates, and the minority marginal cost parameter is statistically significant for the main sample.

Table 7: Predicted Mark-ups and Pricing by Income, Ability, and Minority Status

	(1)	(2)	(3)	(4)	(5)
markup	13.16	13.22	5.30	4.11	4.05
ability	-1.80	-0.92	-1.11	-1.12	-0.94
income	0.35	0.31	0.21	0.25	0.26
minority status	-5.75	-3.08	-4.23	-1.60	-0.58
	(6)	(7)	(8)	(9)	(10)
markup	2.66	3.09	2.86	0.75	2.77
ability	-1.06	-1.06	-1.14	-1.09	-1.96
income	0.47	0.37	0.42	0.51	0.28
minority status	-0.51	-0.50	-0.33	-0.27	-0.11

Note: Markups include pricing by minority status.
Figures (in \$1,000) calculated using full sample, not
just those observed to receive aid.

To gain some additional insights into the predicted magnitude of pricing by income and

ability as well as the extent of market power, it useful to decompose the prices paid by students into the different components. Using (33), for students not at the price cap, the marginal effect of ability on price is approximately given by:

$$\frac{\partial p_{sj}(m,b,y)}{\partial b} \approx -\frac{(1-r_{sj})\alpha}{1+(1-r_{sj})\alpha}\frac{\gamma I_j}{\omega\theta_j} \tag{45}$$

The marginal effect of income on price is approximately:

$$\frac{\partial p_{sj}(m,b,y)}{\partial y} \approx \frac{1}{1+(1-r_{js})\alpha} \tag{46}$$

Finally, the mark-up is the difference between price and effective marginal cost:

$$\text{mark-up}_j(s,m,b,y) = p_{sj}(m,b,y) - EMC_j(m,b). \tag{47}$$

To measure the market power of private colleges, we compute the average tuition mark-ups over marginal cost along the quality hierarchy.

Table 7 shows the value of the average mark-up and pricing by ability and income terms for each cluster. While mark-ups at lower quality colleges are relatively modest, markups rise rapidly along the quality hierarchy, ranging above \$13,000 for elite colleges. Our estimates imply little difference in average pricing by income. The average effects range between 0.021 and 0.051 among the 10 clusters. However, our estimates imply much more variation in pricing by ability and mark-ups. Average pricing by ability ranges between -0.092 to -0.196. The largest discounts for minority status occur at the four highest ability schools, with discounts ranging from \$1,600 to \$5,750. Overall average markups range between 3.5% and 35.5%. We thus conclude that the most selective colleges have significant market power.

There is also much price discrimination within colleges. To illustrate the magnitude of these effects, we focus on Clusters 1 and 2, which include the most selective colleges. Table 8 reports predicted mark-ups over effective marginal cost by income and ability for white students at these colleges.

Table 8: Predicted Markups at Quintile Medians

Cluster 1					
ability\income	0%-20%	20%-40%	40%-60%	60%-80%	80%-100%
0%-20%	-	0.25	0.66	1.17	9.40
20%-40%	-	0.27	0.68	1.19	9.47
40%-60%	-	0.28	0.70	1.21	10.12
60%-80%	-	0.29	0.71	1.28	11.59
80%-100%	0.00	0.32	0.74	1.24	19.47
Cluster 2					
ability\income	0%-20%	20%-40%	40%-60%	60%-80%	80%-100%
0%-20%	-	0.27	0.69	1.19	26.20
20%-40%	-	0.27	0.70	1.20	26.64
40%-60%	-	0.28	0.70	1.20	21.14
60%-80%	-	0.28	0.71	1.22	16.64
80%-100%	0.00	0.30	0.72	1.22	9.63

Separate quintiles generated for each school, omitting legacy students.
Figures in $1,000. Predicted prices are capped.

Mark-ups range from $0 to $19,470 at Cluster 1 and from $0 to $26,640 at Cluster 2. Using (30), it is straightforward to show that mark-ups are increasing in market share and income and decreasing in EMC. The latter implies that decreases in EMC are only partially passed along in the form of lower tuition for the student. The relatively small mark-ups in both clusters for income types below the 80th percentile are a result of small market shares and limited incomes. Mark-ups for the highest income types are much higher and vary substantially with ability and between the two clusters. As seen in Table 3, instructional expenditure per student is much higher in Cluster 1 than 2 (i.e., $37,960 and $17,300 respectively), the implied higher EMC in Cluster 1 explaining the generally lower mark-ups among high income students there.[23] Effective marginal cost also declines much more steeply with ability in Cluster 1, again due to higher instructional expenditure (see equation (31)). Keeping in mind the property that mark-ups decrease with EMC, this explains the opposite gradients in mark-ups as ability increases in the two clusters among the highest income

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[23]A lower mark-up does not imply a lower net tuition, though average tuition is in fact lower in Cluster 1 than in Cluster 2 (see Table 3). Colleges in Cluster 1 likely have greater endowments, part of which is used to provide more financial aid.

types.

Table 9: Parameter Estimates II

	(1)	(2)	(3)
ω	0.0369***	0.0293***	0.0154
	(0.008)	(0.008)	(0.0124)
Implied by ω Estimate			
γ	0.0027	0.0021	0.0012
κ			0.0002
R^2	0.6328	0.5026	0.1054
Weights?	No	Yes	Yes

Note: Column 3 accounts for minority status.

We then implement the last two stages of our estimator to obtain the point estimates for γ, κ, and ω. We find that our estimates for ω range between 0.015 and 0.037.

Table 10: Average Tuition by Income and Ability, Private College Students

	Predicted							Actual				
	b_1	b_2	b_3	b_4	b_5			b_1	b_2	b_3	b_4	b_5
y_1	13.62	12.93	13.10	12.83	12.59		y_1	15.48	15.66	16.71	16.25	17.35
y_2	14.47	13.91	14.05	13.50	12.66		y_2	15.91	16.82	17.38	17.14	17.87
y_3	15.70	15.68	14.60	14.60	15.24		y_3	18.10	17.60	17.24	15.29	23.63
y_4	15.88	16.41	15.42	16.56	18.17		y_4	17.34	20.12	20.43	20.24	21.74
y_5	18.84	19.86	20.27	20.43	22.29		y_5	22.67	22.36	25.39	25.37	29.18

Figures in $1,000.

Finally we performed goodness of fit analyses. Given the focus of the paper, we provide evidence on the fit of the pricing equation for students in private colleges. We focus on tuition in private colleges because we take in-state and out-of-state tuitions of public colleges as given by state government policy. Of course, these public college tuitions affect private tuitions. Table 10 compares predicted and actual prices by income and ability for all students at private colleges. This table was created as follows. Using the actual data, we divided students by income to create five quintiles of equal size, with boundaries $0, y_1, ...y_5$. Similarly, we created five quintiles of ability of equal size with boundaries $0, b_1, ...b_5$. Using the resulting income and ability boundaries, we created the cross-tabulations in Table 10 with mean tuition of the

relevant students in each cell. We see that the pattern of predicted tuitions follows broadly the same pattern as that for actual tuitions. Table 11 is similarly constructed using data for the subset of private school students who received aid. The patterns of predicted and actual tuitions in Table 11 match up well. Thus, the tables demonstrate that our model is indeed capturing key features of pricing by income and ability.

Table 11: Average Tuition by Income and Ability, Private College Aid Receivers

	Predicted						Actual				
	b_1	b_2	b_3	b_4	b_5		b_1	b_2	b_3	b_4	b_5
y_1	13.65	12.78	13.04	13.04	12.63	y_1	12.41	13.84	13.88	12.42	9.71
y_2	14.28	13.63	13.94	13.09	12.53	y_2	13.23	13.49	13.89	12.60	8.90
y_3	15.43	15.04	14.27	14.84	13.70	y_3	14.87	13.48	14.50	12.73	10.95
y_4	15.51	15.51	15.21	15.66	15.88	y_4	13.57	15.31	16.31	14.57	12.22
y_5	18.84	19.12	19.11	18.54	20.12	y_5	19.97	19.05	21.77	19.15	20.86

Figures in $1,000.

6 Conclusions

We have developed a new equilibrium model of private and public school competition that captures the key institutional features of the U.S. market of higher education. We have shown that the model can generate realistic demand and pricing patterns for private universities. We have developed and implemented a new semi-parametric estimator for the parameters of this model using data from the NPSAS. We obtain reasonable estimates for all of the key parameters. Moreover, the model fits the data well.

Our empirical findings suggest that the majority of private colleges in the U.S. engage in pricing by income, ability, and minority status. A $10,000 increase in family income increases tuition at private schools by an average of $210 to $510. A one standard deviation increase in ability decreases tuition by approximately $940 to $1,960 depending on the selectivity of the college. There are large and substantial discounts for minority students which range between approximately $110 (at historically black colleges) and $5,750 dollars. Average mark-ups are modest, ranging between 3.5 and 33.5 percent, but are very large for high income students.

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There is much more heterogeneity in mark-ups within colleges than among colleges. Our analysis suggests that highly selective colleges have significant market power, especially for high income, high ability, non-minority students.

We view the results of this paper as promising for future research. One might modify the objectives of state and private colleges or consider the presence of more providers of higher education with other objectives. We have implicitly assumed in our empirical analysis that colleges within a cluster are colluding, i.e. setting the same price, admission and expenditure policies. In practice, there are small differences among the colleges within a cluster and colleges may engage in some limited competition for students.

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A Construction of the Ability Measure and Ability Thresholds

We measure ability by predicting students' first-semester GPA as a function of their high school GPA, ACT score (or SAT score converted to ACT score), gender, major, and college choice.

The predicted GPA for student i at school j in discipline d is given by:

$$GPA_{ijd} = \beta_0 + \beta_1 HSGPA_i + \beta_2 ACT_i + \beta_3 HSGPA_i * ACT_i + \beta_4 female_i + \beta_j + \beta_d + \epsilon_{ijd} \quad (48)$$

where β_j represents a college fixed effect and β_d represents a major fixed effect (12 majors, humanities omitted). Using a sample of approximately 5,000 white students at 4-year public or private universities, we obtain the following prediction (for a generic discipline at a generic school as these fixed effects and the intercept are dropped):

$$\widehat{GPA_i} = -3.184 HSGPA_i + -2.559 ACT_i + 0.918 HSGPA_i * ACT_i + 21.961 female_i \quad (49)$$

The R^2 for the estimated model (including fixed effects) is 0.9342. After clustering, we then standardize the ability measure to have standard deviation 1 and mean 0.415, such that all schools have $\theta_j \geq 0$.

There are no explicit ability admission thresholds in the data. We estimate these thresholds using all students except a small number of "legacy students" at some of the most selective universities.[24] We construct these by taking the first percentile predicted GPA at any public college with at least ten non-minority students (as our model implies different admission thresholds for minority students), and applying the minimum within cluster as the cluster admission threshold. Any students below this threshold presumably have characteris-

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[24]Legacy students are believed to contribute additional value to the school (perhaps through alumni donations), and thus are subject to different admission criteria. Due to this unobserved characteristic, they have a lower net marginal cost for the school and may be admitted despite lower ability. Legacy students are identified off the empirical CDF of ability within a school–they precede the lowest flat region in the CDF. In support of our hypothesis, such students tend to be non-minority students with high family income.

tics desirable to a college, and so these students are "bumped up" to the threshold predicted GPA. This new measure is used in admission and tuition estimation for all colleges.

We considered other approaches to construct these admission thresholds, and found that the main results reported in this paper are not sensitive to the specifics discussed above.

B   Nonparametric Estimation of Tuition Functions

For private colleges, we use a local polynomial smoothing estimator to estimate the tuition function. The polynomial constructs a non-parametric estimate of tuition based on ability and income, and interpolates only where the observed data span. That is, if we observe an individual with a similar ability and income attending the college with a given tuition, the LOESS estimator calculates a polynomial relationship among tuition, ability, and income within the relevant bandwidth and predicts tuition locally. However, the resulting admission set–where a tuition can be predicted–is really a combination of admission and matriculation. Thus, many lower quality colleges would appear to reject high-quality applicants, because no such applicants are observed at the college. Hence we assume that if a college accepts an individual with ability b^{min}, it accepts all individuals where $b_i \geq b^{min}$. Then, we extrapolate the local polynomial to such individuals to ensure all admitted individuals have a valid first-stage tuition offer.