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The Intended and Unintended Consequences of Regulating for-Profit Colleges: A Model of College Choice and Retention

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Abstract
This dissertation investigates individuals' college choice and dropout behavior in the market for vocational training, specifically in response to a recently proposed financial aid regulation. Vocational training is an important component of the postsecondary education arena and has been promoted by political leaders as an option for high school graduates who do not wish to attend traditional 4 year colleges. The major players in this market are for-profit colleges and community colleges, both of which offer open admission and mainly confer certificates and associate degrees. This paper evaluates the implications of a regulation proposed by the Obama administration to restrict federal student financial aid to for-profit colleges. Specifically, I examine the effect of this policy change on students' college enrollment and college retention. To that end, I develop and estimate a two-period discrete choice model of differentiated products, where the products are vocational colleges. In the first period, forward-looking and risk-neutral individuals choose a vocational college to attend or the outside option of no college. In the second period, those who are enrolled in a college decide whether or not to drop out of school upon learning more about their postgraduation outcomes. I estimate this model using Generalized Methods of Moments with school-level data collected from the Department of Education. Model estimates reveal heterogeneous preference across demographic groups and several differentiating factors between for-profit colleges and community colleges. I find that for-profit college enrollment is highly responsive to federal student financial aid availability and that most of those who attend for-profit colleges would rather forgo college altogether than substitute to community colleges. Counterfactual simulations reveal that the proposed regulation would be successful at steering students away from for-profit colleges, as intended by policy makers, but an unintended consequence of the regulation is that 77% of those who would have otherwise gone to for-profit colleges would rather choose the no college option than the community college option. This would amount to a net decline of 15% in college enrollment in the market for vocational training. Furthermore, I find that for those who would substitute from for-profit colleges to community colleges in response to the proposed regulation, their dropout probabilities on average would increase by 24 percent points due to mismatch.

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To my family and friends

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ABSTRACT

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This dissertation investigates individuals' college choice and dropout behavior in the market for vocational training, specifically in response to a recently proposed financial aid regulation. Vocational training is an important component of the postsecondary education arena and has been promoted by political leaders as an option for high school graduates who do not wish to attend traditional 4 year colleges. The major players in this market are for-profit colleges and community colleges, both of which offer open admission and mainly confer certificates and associate degrees. This paper evaluates the implications of a regulation proposed by the Obama administration to restrict federal student financial aid to for-profit colleges. Specifically, I examine the effect of this policy change on students' college enrollment and college retention. To that end, I develop and estimate a two-period discrete choice model of differentiated products, where the products are vocational colleges. In the first period, forward-looking and risk-neutral individuals choose a vocational college to attend or the outside option of no college. In the second period, those who are enrolled in a college decide whether or not to drop out of school upon learning more about their postgraduation outcomes. I estimate this model using Generalized Methods of Moments with school-level data collected from the Department of Education. Model estimates reveal heterogeneous preference across demographic groups and several differentiating factors between for-profit colleges and community colleges. I find that for-profit college enrollment is highly responsive to federal student financial aid availability and that most of those who attend for-profit colleges would rather forgo college altogether than substitute to community colleges. Counterfactual simulations reveal that the proposed regulation would be successful at steering students away from for-profit colleges, as intended by policy makers, but an unintended consequence of the regulation is that 77% of those who would have otherwise gone to for-profit colleges would rather choose the no college option than the community college option. This would amount to a net decline of 15% in college enrollment in the market for vocational training. Furthermore, I find that for those who would substitute from for-profit colleges to community colleges in response to the proposed regulation, their dropout probabilities on average would increase by 24 percent points due to mismatch.

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1 Introduction

For-profit colleges are postsecondary institutions that primarily provide vocational training through certificate and associate degree programs[1]. Their main competitors are community colleges, and like community colleges, for-profit colleges have no admission standards. I refer to the market in which for-profit and community colleges operate as the market for postsecondary vocational training[2]. Vocational training occupies an important space in the higher education arena for those who seek a more specialized and career-oriented education. Compared to traditional 4 year colleges, vocational schools tend to attract a student population that is of lower socioeconomic status and lower ability. In recent years, political leaders have advocated vocational training as an option for those who do not wish to pursue a traditional 4 year Bachelor's degree[3][4].

Although for-profit colleges have existed since colonial times as trade schools and apprenticeships, they have become a major player in the higher education arena only within the past decade. From 2000 to 2010, undergraduate enrollment at for-profit colleges grew by 400%, compared to 30% growth at public colleges and 20% growth at private non-profit colleges over the same period (National Center for Education Statistics, 2015c). Currently, for-profit colleges account for 12% of the total undergraduate enrollment in the US. However, these institutions have also attracted much scrutiny from policy makers due to their high tuition, significant reliance on federal student financial aid, and considerable federal

[1]Well-known examples of for-profit colleges include University of Phoenix, DeVry University, ITT Tech, Strayer University, etc.

[2]Examples of vocational programs include massage therapy, stenography, dental hygiene, etc.

[3]https://www.whitehouse.gov/issues/education/higher-education/building-american-skills-through-community-colleges

[4]https://marcorubio.com/issues-2/marco-rubio-position-higher-education-policy-college/

student loan default rates (United States Senate Health, Education, Labor and Pensions Committee, 2012)[5]. In response to these criticism and to combat high federal student loan default rates among for-profit college students, the Obama administration has recently proposed to regulate for-profit colleges by restricting their students' access to federal student financial aid (Pell grants and federal student loans). The intention of this regulation is to steer students away from for-profit colleges that are likely to leave them heavily in debt and unable to repay their student loans, and toward cheaper community colleges that offer the same programs.

The proposed regulation is a related to a broader public debate over the role that for-profit college play in the higher education arena. Opponents of for-profit higher education accuse these institutions of gaming federal student financial aid to support their exorbitant tuition, a significant amount of which is kept as profit rather than spent on students[6]. Critics have called for-profit colleges scams that charge a much higher tuition for the same programs that can be found at community colleges. On the other hand, proponents of for-profit higher education argue that these colleges target a niche student population that would not otherwise attend community colleges; therefore, without for-profit colleges, a significant portion of the student population would be left without a viable college option.

In this paper, I address some of the claims made in the public debate over for-profit higher education and evaluate the effects of the proposed regulation on students' college choice and dropout behavior in the market for postsecondary vocational training. To this end, I use a revealed preference approach to uncover demand parameters from students'

[5]Although for-profit colleges only serve 12% of the undergraduate population, they are responsible for 45% of all federal student loan defaults.

[6]According to a 2 year investigation into 30 large for-profit colleges conducted by the Senate Health, Education, Labor and Pensions Committee published in 2012, on average these schools keep 19.4% of revenue as profit while only spending 17.2% on instructions.

enrollment and dropout behavior. More specifically, I develop a novel two-period discrete choice model of differentiated products that is a modified version of Berry, Levinsohn and Pakes (1995) and Petrin (2002), and I estimate this model using a school-level dataset that I have assembled on vocational colleges. In the first period, risk neutral and forward-looking individuals choose among vocational colleges in their choice sets based on school characteristics, tuition, and financial aid availability. They also have the outside option of not attending college. At this stage, individuals know their lifetime payoffs for not attending college but are uncertain about the payoffs associated with graduating from each college in their choice sets. In the second period, those who are enrolled in a college learn more about their schools and their individual payoffs from graduating from their respective colleges. With this information in hand, students then decide whether to stay in school and graduate or to drop out. Upon making this decision, students receive their corresponding lifetime payoffs net any student loan repayments. My model accounts for heterogeneous preferences among different demographic groups and is able to capture in detail the financial aid process, which is a key element in the market for postsecondary vocational training.

Estimation results show that for-profit college enrollment is very responsive to federal student financial aid availability, and that these schools are indeed serving a niche student population that does not find community colleges to be a reasonable alternative. Using model estimates, I conduct the following counterfactual experiments: 1) restrict for-profit college students' access to federal student financial aid in terms of Pell grants and federal student loans, and 2) close down all for-profit colleges. Counterfactual simulations indicate that denying for-profit college students access to federal student financial aid would result in a 74% drop in for-profit college enrollment. Of those who leave for-profit colleges, 77%

would rather abandon college plans altogether than substitute to cheaper community colleges. Overall, my results indicate that the proposed regulation would induce a 15% decrease in college enrollment in the market for postsecondary vocational training. In addition, for those who would switch to a community college in response to the regulation, I find that their dropout rates on average would increase by 24 percentage points due to mismatch. Counterfactual simulations also reveal that for-profit colleges target a niche student population that is more likely to be female, black, older and lower-income than those who would attend community colleges.

Estimated preference parameters illustrate significant heterogeneity among prospective students from different demographic groups. The existence of such heterogeneity explains for-profit colleges' ability to target a niche student population. Furthermore, I find that, from prospective students' point of view, for-profit colleges and community college are differentiated beyond tuition and program offerings. In particular, preference estimates reveal that for-profit colleges are more effective with their instructional expenditure in terms of attracting new enrollment and that they have comparative advantages in certain programs relative to community colleges. I also find that prospective students derive more utility from community colleges when they are in school but they see for-profit colleges as better in offering higher post-graduation payoffs and higher graduation rates, conditional on observables. Higher graduation rates is particularly important in the market of vocational training as most vocational jobs require the relevant certifications or degrees.

This paper builds upon the nascent but growing literature on for-profit colleges. Most of the existing studies have focused on examining post-graduation labor market outcomes of for-profit college students using individual-level data (Cellini and Chaudhary 2012; Deming et al. 2012; Lang and Weinstein 2013; Liu and Belfield 2014), or on evaluating the effect of government aid on for-profit colleges' tuition (Cellini 2009, 2010; Cellini and Goldin 2014). My paper aims to understand students' college choice and dropout decisions in the market for postsecondary vocational training.

To the best of my knowledge, this paper is the first to address policy questions regarding for-profit higher education. A unique advantage of my modeling framework is its ability to accommodate large for-profit colleges' multi-state or national operations, including online programs. This allows me to study the for-profit college industry in its entirety rather than only focusing on local schools within specific states as done in previous works. Being able to model the operations of large for-profit colleges is particularly important as these schools constitute the bulk of for-profit college enrollment. Another attractive feature of my model is that it accounts for the non-pecuniary benefits of college. Most of the existing literature on the labor market returns to for-profit higher education find no wage difference from those of community colleges despite the sizable difference in tuition. This result alludes to the presence of non-pecuniary benefits.

My paper is also related to a much broader literature on the relationship between credit constraint and college enrollment (e.g., Keane and Wolpin 2001; Cameron and Taber 2004; Epple et al. 2004). Contrary to my results, most of the papers in this literature find the effect of credit constraint on college enrollment to be small. This difference in results is due to the fact that most papers in this literature study selective 4 year institutions whose students come from a higher socioeconomic stratum or cheap community colleges. In contrast, for-profit colleges students are of much lower socioeconomic status and the only means for them to finance their expensive for-profit education is through federal student financial aid.

Counterfactual experiments reveal that credit constraint can result in a significant decline in college enrollment in the market for postsecondary vocational training.

The remainder of this paper is organized as follows. Section 2 describes the available data and presents some stylized facts that motivate the model specification. Section 3 presents the model. Section 4 discusses model predictions and the estimation method. Section 5 presents the empirical specification. Section 6 reports the estimation results and model fit. Section 7 presents counterfactual analyses. Finally, section 8 concludes.

2 Data

The main source of data used in this paper is the Integrated Postsecondary Education Data System (IPEDS). IPEDS conducts a series of surveys each year for all the Title IV (federal student financial aid) eligible postsecondary institutions in the US[7]. I extract from these surveys data on school name/type, program offerings, new student enrollment, graduation count, number of students that continued onto the next school year, student demographics in terms of age, gender and race, and financial aid in terms of Pell/non-Pell grants and federal student loans for all schools within my sample.[8] All data from IPEDS are at the school level. I match IPEDS data to campus location data from the Postsecondary

[7] I draw data from the following surveys conducted by IPEDS: Institutional Characteristics, 12-Month Enrollment, Fall Enrollment, Completion, Finance, and Student Financial Aid.

[8] New student enrollment and student demographics are constructed by extrapolating the percentage of new students and the demographic distribution from the Fall enrollment survey to the 12 months enrollment survey. Surveys are matched first by UNITID and non-matches are then matched by their main OPEIDs. IPEDS defines an observation by its UNITID but a school can have multiple UNITID's if it has multiple campuses. A school with multiple campuses can either report data for each of its campuses separately or report aggregate data for groups of campuses in a parent/child relationship, in which multiple UNITID's are matched to the same aggregate data. Parent/child relationships differ across surveys. In my sample, a school with multiple UNITID's are disaggregated into the finest set of groups such that the UNITID's in each group do not share parent/child aggregate reporting relationships with the UNITID's of any other group, and that each group has non-overlapping service areas with other groups. In the case where a school can be disaggregated into multiple groups as previously described, each group is considered a separate school in my sample.

Education Participants System (PEPS) in order to pinpoint the physical presence of schools with multiple campus locations.[9]

I further supplement school data with demographics data from the American Community Survey (ACS) and the Census. I use the ACS to estimate an empirical distribution of family income adjusted by family size ($famincpp$ = family income per person) as a function of the demographics I observe in IPEDS. I simulate draws of $famincpp$ from this distribution conditional on observed demographics in order to integrate out $famincpp$ during estimation as it is unobserved in the school dataset. Different schools face different income distributions because they attract different student demographics. The Census is mainly used to construct market size and demographic distributions at the Core-Based Statistical Area (CBSA) level. I combine data from the aforementioned surveys to construct a cross-sectional data set for the 2009-2010 school year, which marked the height of the for-profit college industry[10].

3 Sample Description

The set of schools included in my sample are all Title IV-eligible institutions with no admission standards that are operating in the 2009-2010 school year [11]. This group consists of 2,228 schools, of which 972 are for-profit, 1,140 are public, and 116 are private non-profit.

[9] This match is done by main OPEID.

[10] I opted for a cross-sectional approach rather than a panel data approach because for-profit colleges are created, closed, and bought/sold to other for-profit colleges on a fairly frequent basis. On top of that, IPEDS does not keep track of schools that change ownership or had to reapply for Title IV funding for some reason; in these cases, the school would have a new identifier and there is no direct way for it to be connected to its entry in previous rounds of surveys.

[11] For-profit and community colleges do not have admission standards. These schools are inherently different from selective traditional 4 year institutions not only in entrance requirements but also in the type of education they offer. I assume that students interested in for-profit colleges would not be interested in selective traditional 4 year institutions and vice versa. This assumption is validated by the fact that most selective traditional 4 year institutions do not accept credit transfers from for-profit colleges. On the other hand, some selective traditional 4 year institutions do accept credit transfers from community colleges. But since I am mainly concerned about the substitution patterns of for-profit college students, I can safely preclude selective traditional 4 year institutions from my choice set of schools.

For the rest of this paper, I will refer to the public and private non-profit colleges in my sample as peer colleges because they are the relevant peer group to for-profit colleges. The set of individuals I include in my market size definition are those ages 18-44 who have at least a high school diploma but less than a Bachelor's degree.

For-profit colleges are systematically different from peer colleges in several dimensions, as shown in tables 1 and 2. In terms of enrollment, for-profit colleges on average are smaller than peer colleges. The average enrollment at for-profit colleges is 1,666 compared to 3,439 at peer colleges[12] [13]. For-profit college students on average are more likely to be female, black, and older than peer college students, which motivates the possibility that for-profit colleges may be serving a niche student population. In terms of program offerings, for-profit colleges on average are more specialized and offer fewer programs than peer colleges, which tend to offer a full spectrum of programs, and every program offered by for-profit colleges can be found at peer colleges. The average number of programs is 5 (median 4) at for-profit colleges, whereas the average number of programs is 38 (median 34) at peer colleges.

Another point of differentiation between the two types of colleges is in graduation rates; for-profit colleges on average offer higher graduation rates than peer colleges. The only official graduation rate/dropout rate available is for first-time, full-time students, but this population is not representative of the students in the market for postsecondary vocational training; in fact, some colleges in my sample do not have any first-time, full-time students. Therefore, I opt to construct my own measure of graduation rate. Figure 1 illustrates the flow of students in and out of a school in years t and $t+1$, where S_t^{Total} is the total enrollment

[12] Although there are a handful of for-profit colleges with nationwide presence that have much higher enrollment than the typical peer college.

[13] I define enrollment as those who are degree/certificate-seeking. Students who casually take classes without an objective of pursuing a degree or a certificate are not counted as part of enrollment or market share. Part-time degree-seeking students are counted as one half of a full-time student.

of this school in year t, S_t^{New} is the number of new students entering in year t, C_t is the number of students who were enrolled in year t and continued on to the next school year, G_t is the number of students who graduated with a degree or certificate in year t, and D_t is the number of students who dropped out in year t; all except D_t is observed. To construct the graduation rate, I assume steady state in the proportion of graduates and dropouts each year. More specifically, I define the graduation rate as the percentage of graduates (G) out of those who did not continue onto the next school year ($S^{Total} - C$); i.e.

$$\begin{aligned} graduation\,rate &= \frac{G}{S^{Total} - C} \\ dropout\,rate &= 1 - \frac{G}{S^{Total} - C}. \end{aligned} \tag{1}$$

In my sample the average graduation rate is much higher at for-profit colleges (51%) than at peer colleges (30%). This pattern is consistent with the official graduation rates of the first-time, full-time population.

The values of my constructed graduation rate/dropout rate are in line with a similarly defined dropout rate that is documented in the Senate HELP Committee report on a two year (2008-2010) investigation into 30 large for-profit colleges (United States Senate Health, Education, Labor and Pensions Committee, 2012). The average graduation rate in my sample is 40%, which is also very similar to the 34% average graduation rate among first-time, full-time Bachelor's degree-seeking students at 4 year institutions with no admission standards for the 2007 cohort as reported by the National Center for Education Statistics (2015b).[14] In order to parse out differences in graduation rates due to program offerings and student composition, I estimate a linear probability model of graduation rates the results

[14] Graduation is defined by the National Center for Education Statistics as the percentage who graduated within 6 years.

of which are presented in table 5. After controlling for all observables, for-profit colleges still have significantly higher graduation rates, on average by 7 percentage points, than peer colleges. This finding is consistent with for-profit colleges' profit-maximization objective as these institutions have a monetary incentive to keep students in school for as long as possible (till graduation) in order to extract the maximum amount of tuition from them.

A key element in the market for postsecondary vocation training is the financial aid process. I observe federal student financial aid in terms of Pell grants and student loans, as well as non-Pell grants which include institutional grants and state/local grants[15]. In the 2009-2010 school year, 76% of for-profit college students took out federal student loans and 61% received Pell grants; this is significantly higher than the federal student financial aid uptake rate for peer college students, which are 23% and 39% respectively. Not only do more for-profit college students receive federal student financial aid, they receive a higher amount conditional on receiving it. However, for-profit colleges students on average receive less non-Pell grants; this is most likely because for-profit colleges rarely give out institutional grants and sometimes they are not eligible for state/local grants.

Part of the difference in federal student financial aid uptake between for-profit college students and peer college students is due to the higher tuition charged by for-profit colleges. On average, for-profit college students pay $8,684 in tuition, compared to $2,769 for peer college students. However, the average out-of-pocket expenditure of for-profit college students (-$1,201) is lower than that of peer college students (-$871)[16]. I further investigate the difference in financial aid uptake between for-profit college students and peer college students

[15] Another source of financial aid is private loans, which is not observed in my data but they only account for 7.2% of the student loan market.

[16] Students can borrow more than tuition in order to cover to living expenses. In particular, students are free to borrow unsubsidized federal student loans up to the maximum limit.

by controlling for tuition and student composition in a series of reduced form regressions presented in tables 3 and 4. Regression estimates suggest that even after controlling for tuition and student composition, for-profit college students on average are more likely to receive federal student financial aid (Pell grants and loans) and receive a higher amount conditional on receiving it. These results are consistent with the fact that for-profit colleges advertise the amount of financial aid their students receive and that they commonly provide hands-on assistance to students on federal student financial aid applications (New York Times, 2014). Bettinger, Oreopoulos, and Sanbonmatsu (2012) find that helping low-income individuals with the Free Application for Federal Student Aid (FAFSA) and providing them with information on financial aid in relation to tuition costs are very effective in increasing federal student financial aid uptake, as well as encouraging college enrollment and persistence. Regression estimates also show that even after controlling for tuition and student composition, for-profit college students receive lower non-Pell grants than peer college students.

Despite charging much higher tuition, for-profit colleges on average spend as much on students as peer colleges, but they tend to spend less on instructions and more on non-instructional items. One of the standing criticisms of for-profit colleges is that they spend too little on student instructions, which is usually considered a proxy for education quality.

4 Model

I develop a two-period discrete choice model of differentiated products to capture students' college choice and subsequent dropout decisions in the market for postsecondary vocational training. In the first period, individuals choose a college within their choice sets to attend; they also have the outside option of not attending college; in the second period, those who are enrolled in a school decide whether to continue and graduate or to drop out of college. Upon making the dropout decision, students receive the corresponding discounted lifetime payoffs; they are also liable to start repayment on their student loans upon leaving school.

4.1 School Choice

In the first period, individual i chooses among the schools in his/her choice set or the outside option of no school. At this stage, individual i knows his/her lifetime payoff from not attending school, Y_i^0, but is uncertain about the payoff associated with graduating from school j, Y_{ij}^1. I assume that the lifetime payoff for enrolling in a college but then dropping out is also Y_i^0[17]. Here, lifetime payoff encompasses both earnings and non-pecuniary benefits. I parameterize the distribution of Y_i^0 and Y_{ij}^1 to be jointly normal

$$\begin{pmatrix} Y_{ij}^1 \\ Y_i^0 \end{pmatrix} \sim N\left(\begin{pmatrix} \mu_{ij}^1 \\ \mu_i^0 \end{pmatrix}, \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_0 \\ \rho\sigma_1\sigma_0 & \sigma_0^2 \end{pmatrix} \right). \tag{2}$$

which implies

$$\begin{aligned} Y_{ij}^1 | Y_i^0 &\sim N(\mu_{ij}^1 + \rho\frac{\sigma_1}{\sigma_0}(Y_i^0 - \mu_{ij}^1), (1-\rho^2)\sigma_1^2) \\ Y_{ij}^1 - Y_i^0 | Y_i^0 &\sim N(\mu_{ij}^1 + \rho\frac{\sigma_1}{\sigma_0}(Y_i^0 - \mu_{ij}^1) - Y_i^0, \sigma_Y^2) \end{aligned} \tag{3}$$

where $\sigma_Y^2 \equiv (1-\rho^2)\sigma_1^2$. I further parameterize the expected return to graduating from college as

[17] This is a reasonable assumption because most of the jobs that students pursue after receiving vocational training require the relevant certification or degree; for example, in order for an individual to become a physical therapist he must be certified. Therefore, the return to attending a vocational college but not graduating is minimal.

$$
\begin{aligned}
E(Y_{ij}^1 - Y_i^0 | Y_i^0) &= \mu_{ij}^1 + \rho\frac{\sigma_1}{\sigma_0}(Y_i^0 - \mu_{ij}^1) - Y_i^0 \\
&= \mu_{ij}^1 - \rho\frac{\sigma_1}{\sigma_0}\mu_{ij}^1 + (\rho\frac{\sigma_1}{\sigma_0} - 1)Y_i^0 \\
&= X_j^1\beta_i^1 + \nu_j + \beta_i^0 \\
&= X_j\beta_i + \nu_j
\end{aligned} \tag{4}
$$

where $X_j \equiv [1, X_j^1]$ and X_j^1 is the set of school j's characteristics that are observable to the econometrician, coefficient vector $\beta_i = [\beta_i^0, \beta_i^1]$ include $\beta_i^0 \equiv (\rho\frac{\sigma_1}{\sigma_0} - 1)Y_i^0$ and β_i^1 which describes individual i's preference for X_j^1, and ν_j is a school-specific quality index that affects students' post-graduation payoffs but is unobserved by the econometrician; more specifically, I adopt the parameterization $\mu_{ij}^1 - \rho\frac{\sigma_1}{\sigma_0}\mu_{ij}^1 \equiv X_j^1\beta_i^1 + \nu_j$[18] [19].

At the enrollment stage, I assume individuals observe X_j but do not observe ν_j, which they learn after enrollment; instead, prospective students only observe $\bar{\nu}_\tau$ for schools of type τ. I assume rational expectation in the sense that $\bar{\nu}_\tau = \frac{1}{|\tau|}\sum_{j\in\tau}\nu_j$. Therefore, individual i perceives the lifetime return to graduating from school $j \in \tau$ as a draw from the following distribution

[18] σ_Y and ν_j are identified by school-level dropout rates. I opt to parameterize the dropout rate heterogeneity as heterogeneity in mean rather than variance because the variance captures individuals' uncertainty and is more aptly identified by individual-level or demographic-level dropout rates, which are not available. Also, from a computational standpoint, allowing the variance σ_Y to vary by school is exponentially more difficult to estimate.

[19] I opt to parameterize the return to schooling as a function of observed school characteristics because I do not observe post-graduation earnings. This parameterization is also justified by the fact that students do not know of their post-graduation earnings at the school choice stage because college is an experience good; instead they infer such information from the characteristics of the schools that they do observe. In October 2015, President Obama released College Scorecard, which is a website that contains various data elements on Title-IV eligible postsecondary institutions, including the average post-graduation earning of students who received any federal student financial aid. This resource became available too late to be included in the current draft of this paper, but I fully intend to utilize the additional information from College Scorecard in the next version of this paper.

$$Y_{ij}^1 - Y_i^0 | Y_i^0 \sim N(X_j\beta_i + \bar{\nu}_\tau, \sigma_Y^2) \tag{5}$$

Note that the realized lifetime return to graduating from college could be negative; as such, individual i accounts for the possibility of dropping out in the second period when making his/her school choice decision[20]. Let $\overline{p}_{ij}$ be individual i's annual out-of-pocket cost (tuition net financial aid) at college j, let L_{ij}^n be his/her net present value of loan repayments for n years worth of federal student loans, and let r be the discount rate, then student i will drop out of a two year program at college j after one year if the realized Y_{ij}^1 is such that the benefit to graduating is not worth the additional cost; i.e.

$$-\alpha_i\overline{p}_{ij} - \alpha_i L_{ij}^2 + \frac{1}{1+r}Y_{ij}^1 < -\alpha_i L_{ij}^1 + \frac{1}{1+r}Y_i^0, \tag{6}$$

where α_i is the price sensitivity coefficient. I abstract from modeling students' wage in school as I do not have data on how much students in this market work and their earnings. Therefore, I assume that students make the same wage in school w^s as they would while not attending school w^0; i.e., $w^s = w^0$. Since only the wage differential $w^s - w^0$ matters in making enrollment and dropout decisions, without loss of generality, I omit the per-period wage from my model specification for the duration of the program under consideration (in this case the duration of the program under consideration is 2 years).

At the enrollment stage, individual i's perceives that he/she will drop out from a 2 year program in school j after the first year with probability

[20] I assume the dropout decision is made after one year.

$$
\begin{aligned}
d_{ij}^{p} &= pr(-\alpha_i\bar{p}_{ij} - \alpha_i L_{ij}^2 + \frac{1}{1+r}Y_{ij}^1 < -\alpha_i L_{ij}^1 + \frac{1}{1+r}Y_i^0 | Y_i^0, X_j, \bar{\nu}_\tau) \\
&= \Phi(\frac{(1+r)\alpha_i(\bar{p}_{ij} + L_{ij}^2 - L_{ij}^1) - (X_j\beta_i + \bar{\nu}_\tau)}{\sigma_Y})
\end{aligned}
\tag{7}
$$

The distinction between the perceived dropout probability and the actual dropout probability is that the former is constructed using information known at the enrollment stage whereas the actual dropout decision is made based on the post-enrollment information set. In particular, the perceived dropout probability is constructed using $\bar{\nu}_\tau$, while the actual dropout probability is constructed using ν_j, which is only observed post-enrollment and supplants the ex-ante noisy measure $\bar{\nu}_\tau$.

When making their school choice decision, prospective students also know the grants g_{ij} and loans l_{ij} they would receive for attending each school in their choice sets. Grants can take the form of Pell grants g_{ij}^p or non-Pell grants g_{ij}^{np}, and loans are federal student loans.[21] The annual g_{ij} and l_{ij} individual i receives from attending school j are

$$
\begin{aligned}
g_{ij} &= pr(g_{ij}^p > 0)E(g_{ij}^p | g_{ij}^p > 0) + E(g_{ij}^{np}) \\
l_{ij} &= pr(l_{ij} > 0)E(l_{ij} | l_{ij} > 0)
\end{aligned}
\tag{8}
$$

where I parameterize each component of the grant and loan functions by school type (for-profit or peer), tuition p_j, and family income adjusted by family size (family income per-person $famincpp_i$)

[21] From IPEDS, I observe at the school level the proportion of students with Pell grants, average annual Pell grant for recipients, average annual non-Pell grants, the proportion of students with Federal student loans, and average annual federal student loan for recipients. Private student loans are unobserved but they only constitutes 7.2% of the student loan market.

$$
\begin{aligned}
pr(g_{ij}^p > 0) &= \frac{exp(W_{ij}\gamma_1)}{1 + exp(W_{ij}\gamma_1)} \\
E(g_{ij}^p | g_{ij}^p > 0) &= min\{exp(W_{ij}\gamma_2), \$5,350\} \\
E(g_{ij}^{np}) &= exp(W_{ij}\gamma_3) \\
pr(l_{ij} > 0) &= \frac{exp(W_{ij}\lambda_1)}{1 + exp(W_{ij}\lambda_1)} \\
E(l_{ij} | l_{ij} > 0) &= min\{exp(W_{ij}\lambda_2), \$12,500\}
\end{aligned}
\tag{9}
$$

where $W_{izj} = [1 \quad 1(j \text{ is for-profit}) \quad log(p_j) \quad log(famincpp_i)]$, $\$5,350$ is the maximum annual Pell grant, and $\$12,500$ is the maximum annual unsubsidized federal student loans for independent students in the 2009-2010 school year. Individual i's annual out-of-pocket cost for attending school j is $\bar{p}_{ij} = p_j - g_{ij} - l_{ij}$, and his/her net present value of loan repayments L_{ij}^n is a function of l_{ij} and the number of years of loans taken n, which is the program length.

I assume individuals are risk neutral and forward looking with respect to the dropout probability. The utility individual i derives from attending a two-year program is

$$
\begin{aligned}
u_{ij} = & -\alpha_i \bar{p}_{ij} + \delta_j + \epsilon_{ij} \\
& + \frac{1}{1+r}\{(1 - d_{ij}^p)[-\alpha_i \bar{p}_{ij} - \alpha_i L_{ij}^2 + \frac{1}{1+r} E(Y_{ij}^1 | Y_i^0, X_j, \bar{\nu}_\tau, graduate)] \\
& \qquad + d_{ij}^p(-\alpha_i L_{ij}^1 + \frac{1}{1+r} Y_i^0)\}
\end{aligned}
\tag{10}
$$

where δ_j is the flow utility students derive from enrolling in school j, which captures factors such as the ease of applying and students' in-school experience, and *graduate* refers to the condition that the inequality in (6) holds. Everyone who attends school must pay the annual out-of-pocket cost $\bar{p}_{ij}$ for the first year, but only those who wish to stay in school and graduate would pay tuition for the remainder of the program. Also, those who decide to drop out after one year are only liable to repay one year of student loans, whereas those who decide to stay in school and graduate from a two year program must begin repayment on two years of student loans upon graduation. Finally, the expected lifetime payoffs of those who graduate is different from those of college dropouts.

On the other hand, the utility individual i derives from not attending college is

$$u_{i0} = \frac{1}{(1+r)^2} Y_i^0 + \epsilon_{i0} \tag{11}$$

where ϵ_{ij} and ϵ_{i0} are distributed standard Type I extreme value.[22] Therefore, the utility gain individual i derives from attending college over the no college option is

$$\begin{aligned} u_{ij} - u_{i0} = & -\alpha_i \bar{p}_{ij} + \delta_j + \epsilon_{ij} \\ & + \frac{1}{1+r}\{(1-d_{ij}^p)[-\alpha_i \bar{p}_{ij} - \alpha_i L_{ij}^2 + \frac{1}{1+r} E(Y_{ij}^1 - Y_i^0 | Y_i^0, X_j, \bar{\nu}_\tau, graduate)] \\ & + d_{ij}^p(-\alpha_i L_{ij}^1)\} \end{aligned} \tag{12}$$

where

$$E(Y_{ij}^1 - Y_i^0 | Y_i^0, X_j, \bar{\nu}_\tau, graduate) = X_j\beta_i + \bar{\nu}_\tau + \sigma_Y \frac{\phi(\frac{(1+r)\alpha_i(\bar{p}_{ij} + L_{ij}^2 - L_{ij}^1) - (X_j\beta_i + \bar{\nu}_\tau)}{\sigma_Y})}{1 - \Phi(\frac{(1+r)\alpha_i(\bar{p}_{ij} + L_{ij}^2 - L_{ij}^1) - (X_j\beta_i + \bar{\nu}_\tau)}{\sigma_Y})} \tag{13}$$

[22] Recall that per-period wage is assumed to be same whether or not individuals are enrolled in a school for the duration of the program under consideration; in this case, the program under consideration has a length of two years and therefore Y_i^0 is discounted by $\frac{1}{(1+r)^2}$. Since only the difference between the per-period wages matters, I omit them from my utility specification without loss of generality.

Given the extreme value assumption, the probability individual i attends a two year program in school j is

$$s_{ij} = \frac{exp(V_{ij})}{1 + \Sigma_{k \in l} exp(V_{ik})} \tag{14}$$

where

$$\begin{aligned} V_{ij} &\equiv -\alpha_i \bar{p}_{ij} + \delta_j \\ &+ \frac{1}{1+r}\{(1 - d^p_{ij})[-\alpha_i \bar{p}_{ij} - \alpha_i L^2_{ij} + \frac{1}{1+r} E(Y^1_{ij} - Y^0_i | Y^0_i, X_j, \bar{\nu}_\tau, graduate)] \\ &+ d^p_{ij}(-\alpha_i L^1_{ij})\} \end{aligned} \tag{15}$$

4.2 Dropout Decision

If individual i decided to enroll in school j in the first period, then at the end of the first year in college he/she will decide whether to drop out or to stay for the duration of the program and graduate. Post-enrollment, individual i learns of the lifetime return $Y^1_{ij} - Y^0_i$ to graduating from college j, which is a draw from the following distribution

$$Y^1_{ij} - Y^0_i | Y^0_i \sim N(X_j \beta_i + \nu_j, \sigma^2_Y). \tag{16}$$

Note that ν_j is used instead of $\bar{\nu}_\tau$ because ν_j is the true post-graduation quality index of school j whereas $\bar{\nu}_\tau$ is merely individual i's perceived quality index under ex-ante uncertainty in the school choice stage. Therefore, individual i's actual dropout probability is

$$\begin{aligned} d_{ij} &= pr(-\alpha_i \bar{p}_{ij} - \alpha_i L^2_{ij} + \frac{1}{1+r} Y^1_{ij} < -\alpha_i L^1_{ij} + \frac{1}{1+r} Y^0_i | Y^0_i, X_j, \nu_j) \\ &= \Phi(\frac{(1+r)\alpha_i(\bar{p}_{ij} + L^2_{ij} - L^1_{ij}) - (X_j \beta_i + \nu_j)}{\sigma_Y}) \end{aligned} \tag{17}$$

The randomness surrounding the realization of $Y_{ij}^1 - Y_i^0$ captures both the uncertainty surrounding the return to schooling at the school choice stage and the idiosyncrasies of outside opportunities. For example, a low realization of $Y_{ij}^1 - Y_i^0$ can be due to the student discovering that his/her education is not as lucrative as he/she originally expected, or it can be due to the student receiving a very attractive outside opportunity.

4.3 Market Definition

Students in the market for postsecondary vocational training only attend schools locally; I take this fact into account by delineating an individual's choice set as the set of schools that are available in his/her Core-Based Statistical Area (CBSA)[23]. A school's service area is the set of CBSAs in which it is available. With online offerings, defining a school's service area is less than obvious. I adopt the convention that a school's service area is the set of CBSAs in which it has at least one campus[24]. This definition is straightforward in the case of community colleges as these schools are designed to serve local students, but I contend that this is also a reasonable definition for for-profit colleges because even though theoretically anyone in the United States can attend a school with online offerings, a large majority of schools are much smaller in size than would be expected if they drew enrollment from all over the country. Also, since some functions may have to be done on campus and students may opt for a mixture of online and on-campus classes, it makes sense for smaller schools to only advertise and be known in the surrounding communities. There are a few schools that are exceptions to this rule and these are schools that are known to have extensive, nation-wide online offerings, such as the University of Phoenix and DeVry University. The

[23]A CBSA is either a metropolitan statistical area or a micropolitan statistical area.

[24]For those campuses that are not located in any CBSAs, I assign them to the closest CBSA. The vast majority of campuses are located in CBSAs

enrollment counts at these schools are significantly greater than those of local colleges with online offerings, and these schools also have campuses across the country. University of Phoenix, for example, has around 200,000 undergraduate students and over 100 campuses nationwide. For these exceptions, I designate their service areas to be all the CBSAs in my sample, regardless of their campus locations; there are 26 schools in my sample that fall under this exception.

I include a CBSA in my sample if it contains at least one campus from the schools in my sample. There is a total of 852 CBSAs in my sample; all have both for-profit and peer options. The average number of schools in a CBSA is 30, the median is 28.

5 Model Predictions, Estimation Strategy, and Identification

Since I only observe data at the school-level, all model predicted moments must be aggregated to the school-level in order to be matched to the observed data. I follow Petrin (2002) in using demographic-level micro-shares (demographic-specific market shares) to aid in estimation, in addition to matching the school market shares. Only new degree/certificate-seeking student enrollment is used towards calculating market shares[25]. The set of data moments I match include school market shares and school dropout rate, as well as moments involving school demographic-specific market shares and school grant and loan function components as described in (9).

[25] Community colleges are known to attract students who only enroll to attend a few classes but not necessarily with the objective of obtaining a degree or certificate. These students are not considered degree/certificate-seeking and are not included in my sample.

5.1 Model Predictions

School j's predicted market share is computed as the weighted average of its predicted market share in each CBSA within its service area, where the weights are the market sizes M_c of the CBSAs c. More specifically,

$$s_j = \frac{\Sigma_{c \in j} M_c \int\int s_{ij}(X, \delta, \theta_{1i}) d\hat{G}(famincpp_i|\theta_{1i}) dF_c(\theta_{1i})}{\Sigma_{c \in j} M_c} \tag{18}$$

where s_{ij} is as defined in (14) and $\theta_{1i} \equiv \{\beta_i, \sigma_{\epsilon i}, \sigma_Y, \bar{\nu}_\tau, \gamma_1, \gamma_2, \gamma_3, \lambda_1, \lambda_2\}$. The inner integral is taken over the empirical distribution of family income adjusted by family size $famincpp$ for individual i given his observed demographics[26]. The outer integral is taken over β_i which is a deterministic function of individuals' observed demographics. $F_c(\theta_{1i})$ is the distribution of observed demographics in CBSA c.

School j's predicted demographic-specific market share for demographic z is computed the same way as its predicted market share except the market sizes are restricted to those of demographic z and the distributions $\hat{G}(famincpp_i|\theta_{1i}, z)$ and $F_c(\theta_{1i}|z)$ are specific to demographic group z; i.e.,

$$s_j^z = \frac{\Sigma_{c \in j} M_c^z \int\int s_{ij}(X, \delta, \theta_{1i}) d\hat{G}(famincpp_i|\theta_{1i}, z) dF_c(\theta_{1i}|z)}{\Sigma_{c \in j} M_c^z} \tag{19}$$

where M_c^z is the market size of demographic group z in CBSA c.

School j's predicted dropout rate is computed as the weighted average of j's predicted dropout rate at the CBSA-level, where the CBSA-level dropout rate is calculated taking into account selection as only those who attend school j can contribute to its dropout rate

[26] The observed demographics are race: black/non-black, sex, and age 18-24, 25-44.

and different individuals have different dropout probabilities.[27] Therefore, school j's model predicted dropout rate is

$$d_j = \frac{\Sigma_{c \in j} M_c \int \int \int d_{ij}(X, \theta_{2i}) dS_j(\theta_{1i}) d\hat{G}(famincpp_i|\theta_{1i}) dF_c(\theta_{1i})}{\Sigma_{c \in j} M_c} \tag{20}$$

where d_{ij} is the actual dropout rate as defined in (17), the inner integral is integrating over the distribution of students enrolled in school j in order to control for selection, and $\theta_{2i} \equiv \{\beta_i, \sigma_{\epsilon i}, \sigma_Y, \nu_j, \gamma_1, \gamma_2, \gamma_3, \lambda_1, \lambda_2\}$. The only difference between θ_{1i} and θ_{2i} is that the former contains $\bar{\nu}_\tau$ whereas the latter contains ν_j. Recall that the enrollment decision is made based in $\bar{\nu}_\tau$ whereas the dropout decision is made based on ν_j.

School j's grant and loan function components taken to data are the five components described in (9); i.e., $pr(g_{ij}^p > 0)$, $E(g_{ij}^p|g_{ij}^p > 0)$, $E(g_{ij}^{np})$, $pr(l_{ij} > 0)$, and $E(l_{ij}|l_{ij} > 0)$. The school-level model prediction for each of these components is computed in the same way as the dropout rate, taking into account selection. For example, the model predicted proportion of school j's students with Pell grants is

$$pr(g_j^p > 0) = \frac{\Sigma_{c \in j} M_c \int \int \int pr(g_{ij}^p > 0) dS_j(\theta_{1i}) d\hat{G}(famincpp_i|\theta_{1i}) dF_c(\theta_{1i})}{\Sigma_{c \in j} M_c} \tag{21}$$

where $pr(g_{ij}^p > 0)$ is defined in (9).

[27] The dropout rate here refers to the actual dropout rate and not the perceived dropout rate.

5.2 Estimation Strategy

I estimate this model using GMM by supplementing school-level moments with demographic micromoments following Petrin (2002). The first set of data moments I match are school market shares and school dropout rates. Matching these moments amounts to solving for the vector of flow utilities students derive from enrolling in schools $\delta(\theta_1)$ and the vector of post-graduation quality indices $\nu(\theta_1)$ such that the following equalities hold

$$\begin{aligned} s_j(X, \delta, \theta_1) - s_j^* = 0, \quad j = 1, ..., J \\ d_j(X, \delta, \theta_1, \nu) - d_j^* = 0, \quad j = 1, ..., J \end{aligned} \tag{22}$$

where $s_j(X, \delta, \theta_1)$ is as in (18) and $d_j(X, \delta, \theta_1, \nu)$ is as in (20), and s^* and d^* are the observed school market shares and school dropout rates, respectively. The existence and uniqueness of $\delta(\theta_1)$ and $\nu(\theta_1)$ are proven in Berry (1994) under some mild regularity conditions.

The second set of data moments I match, M_j^*, include demographic-specific market shares and grant and loan function components; let $M_j(X, \delta, \theta_1)$ denote the model-predicted analog for M_j^*

$$M_j(X, \delta, \theta_1) = [s_j^z \, \forall z, pr(g_j^p > 0), E(g_j^p | g_j^p > 0), E(g_j^{np}), pr(l_j > 0), E(l_j | l_j > 0)] \tag{23}$$

For these moments I minimize the prediction error

$$\varepsilon_j(X, \delta, \theta_1) = M_j(X, \delta, \theta_1) - M_j^* \tag{24}$$

If the model captures the underlying data-generating process, then at the true parameter values δ^*, θ_1^*

$$E(\varepsilon_j | X, \delta^*, \theta_1^*) = 0 \tag{25}$$

Consequently, let Z_j be a vector of instruments that are independent of the prediction error, then Z_j is uncorrelated with ε_j at the true parameter values. Hence, I use

$$G(X, \delta, \theta_1) = E(Z_j \otimes \varepsilon_j(X, \delta, \theta_1)) \tag{26}$$

as GMM moments and denote its sample analog as

$$G_J(X, \delta, \theta_1) = \frac{1}{J} \sum_{j=1}^{J} Z_j \otimes \varepsilon_j(X, \delta, \theta_1). \tag{27}$$

The GMM minimization problem is

$$\begin{aligned}
& min_{\theta_1} \, G(\theta_1)' W^{-1} G(\theta_1) \\
& s.t. \quad \delta: \quad s_j(X, \delta, \theta_1) = s_j^* \quad j = 1, ..., J \\
& \qquad \quad \nu: \quad d_j(X, \delta, \theta_1, \nu) = d_j^* \quad j = 1, ..., J, \\
& \qquad \quad \bar{\nu}_\tau: \quad \bar{\nu}_\tau = \frac{1}{|\tau|} \Sigma_{j \in \tau} \nu_j \quad \forall \tau
\end{aligned} \tag{28}$$

The inner loop ensures that the vector of flow utilities students derive while in school δ matches the predicted market shares to the observed market shares, and the vector of post-graduation quality indices ν matches the predicted (actual) dropout rates to the observed dropout rates[28].

[28] Imposing the rational expectation assumption $\bar{\nu}_\tau = \frac{1}{|\tau|} \Sigma_{j \in \tau} \nu_j \; \forall \tau$ within the innerloop requires solving a system of 2J equations in δ_j and ν_j simultaneously since $s_j(X, \delta, \theta_1)$ is a function of ν_j through $\bar{\nu}_\tau$. Due to the functional forms of $s_j(X, \delta, \theta_1)$ and $d_j(X, \delta, \theta_1, \nu)$, this system of 2J equations and 2J unknowns does not

I use two-step efficient GMM following Hansen (1982) to find the optimal weighting matrix

$$W^{-1} = E(G(\hat{\theta}_1)G(\hat{\theta}_1)')^{-1} \tag{29}$$

where $\hat{\theta}_1$ is a consistent estimate θ_1. The asymptotic distribution of the two-step efficient GMM estimator is

$$\begin{aligned} &\sqrt{J}(\theta_1^{GMM} - \theta_1^*) \sim N(0, \Omega) \\ where \quad &\Omega = [\frac{\partial G(\theta_1^*)}{\partial \theta_1}' W^{-1} \frac{\partial G(\theta_1^*)}{\partial \theta_1}]^{-1} \end{aligned} \tag{30}$$

5.3 Identification

I parameterize α_i and β_i to be deterministic functions of observed demographics z; i.e.,

$$\begin{aligned} \alpha_i &= \sum_z \alpha_z * 1(i \in z), \\ \beta_i &= \sum_z \beta_z * 1(i \in z), \end{aligned} \tag{31}$$

therefore, these parameters are identified by the relationship between tuition and school characteristics and demographic-specific market shares. Since individuals' choice sets are delineated by CBSA's and there are 852 CBSA's in my sample, the variation of school

have a unique solution. To remedy this problem, I impose the constraint $\bar{\nu}_\tau = \frac{1}{|\tau|}\Sigma_{j\in\tau}\nu_j$ $\forall\tau$in the outerloop (in the GMM objective function) by punishing the difference between $\bar{\nu}_\tau$ and $\frac{1}{|\tau|}\Sigma_{j\in\tau}\nu_j$. More specifically, my GMM objective function becomes $G(\theta_1)'W^{-1}G(\theta_1) + \lambda(\bar{\nu}_\tau - \frac{1}{|\tau|}\Sigma_{j\in\tau}\nu_j)^2$, where λ is a positive constant that is large relative to $G(\theta_1)'W^{-1}G(\theta_1)$ and acts like a Lagrange multiplier. This way, $\bar{\nu}_\tau$ is estimated in the outerloop whereas δ_j's and ν_j's are estimated in the innerloop given the value of $\bar{\nu}_\tau$ from the previous iteration of the outerloop. Doing so allows me to solve the system of J shares equations for δ_j's first, given the value of $\bar{\nu}_\tau$ from the previous iteration of the outer loop, since enrollment decisions are made based on $\bar{\nu}_\tau$ rather than ν_j's. Then I solve the system of dropout rate equations for ν_j's given δ_j's. Each of these systems of J equations and J unknowns has a unique solution.

choices and demographic distributions among different CBSA's help identify the price and preference parameters for tuition and school characteristics. Note that because α_i and β_i are i-specific and estimated in the outer loop whereas the quality indices δ_j and ν_j are school-specific and computed in the inner loop, each iteration of α_i and β_i are chosen given δ_j and ν_j from the inner loop calculations, hence precluding the need of instruments for potentially endogenous variables such as tuition. In other words, when using the demographic-specific micromoments to identify α_i and β_i, the unobserved characteristics δ_j and ν_j can be treated as observed by the econometrician since they are computed from the school market shares and the school dropout rates.

The grant and loan function parameters $\{\gamma_1, \gamma_2, \gamma_3, \lambda_1, \lambda_2\}$ are identified by matching model predicted grant and loan function components to their data counterparts. The vector of flow utilities from enrollment δ explains the variation in market shares between schools that have the same observables and the same dropout rates. The vector of post-graduation quality indices ν explains the variation in dropout rates between schools with the same shares and the same observables. The ex-ante perceived post-graduation quality indices $\bar{\nu}_\tau$'s are identified by the constraint that they should equal $\frac{1}{|\tau|}\Sigma_{j\in\tau}\nu_j, \forall\tau$. Finally, σ_Y is identified by the relationship between dropout rate and observables.

6 Empirical Specification

In estimating the model, I follow the standard in estimating dynamic models by fixing the discount rate r; I set the discount rate to 12%, which is the annual interest rate on private student loans. In comparison, the annual interest rate on federal student loans is set to that of Direct Unsubsidized Loans, 6.8%. Loan repayment is assumed to follow the standard 10 year fixed payment repayment plan where individuals pay a constant amount each month for 10 years[29].

I include the following elements in the vector of observed school characteristics X_j: a constant term, $s =$ per-student instructional spending, s*1(for$-$profit)= per-student instructional spending interacted for with for-profit indicator, $e =$ per-student non-instructional spending, 1(offer online courses), 1(offer <1 year certificate programs), 1(offer associate degree programs), 1(offer 2-4 year certificate programs), 1(offer 2-4 year certificate programs)*1(for-profit), 1(offer beauty programs), 1(offer allied health programs), 1(offer business programs), 1(offer business programs)*1(for-profit), total # of programs offered, average urbanization level in percentage terms of the counties in which school j has campuses, average urbanization level in percentage terms of the counties in which school j has campuses interacted with for-profit indicator, 1(for-profit). This combination was determined to be the best in explaining variations in demographic-specific market shares in multinomial logit regressions, the results of which are not included.

For the ex-ante expected post-graduation quality indices $\bar{\nu}_\tau$, I allow τ to take two values, $\tau = L, H$, which correspond to low dropout rates (below the median), and high dropout rates (above the median) respectively. Finally, for the demographic-specific market shares, I include the market shares of the following demographic groups: female, male, black, non-black, ages 18-24, ages ≥25, black female, black male, females ages 18-24, males ages 18-24, females ages ≥25, males ages ≥25.[30] I allow each demographic group (female, male, black,

[29] I assume that students do not engage in strategic default; i.e., students take out loans with the intention of paying it back in full and on time. This is a reasonable assumption since federal student loans cannot be discharged in bankruptcy and missed payments will be garnered from wage/tax-refunds. Also defaulting in student loans is detrimental to individuals' credit ratings and ability to take out loans or obtain credit for other purposes.

[30] These are the demographic groups that are reported in IPEDS's enrollment data.

non-black, ages 18-24, ages $\geq$25) to have its own price and preference parameters, α_i and β_i, and omit the reference group. My model has a total of 131 parameters, not including nuisance parameters δ_j and ν_j.

7 Model Fit and Estimation Results

The model fits the data fairly well. Tables 6-10 present the model fit for the grant and loan components as specified in (9). Tables 11 and 12 present the model fit for demographic-specific market shares by school type. Recall that the school market shares and dropout rates are matched perfectly with school fixed effects δ_j's and ν_j's.

7.1 Grant and Loan Parameters

The estimated parameters and standard errors for the grant and loan functions are shown in tables 13 and 14. Financial aid parameters are generally in line with the reduced form results in that for-profit colleges students are systematically more likely to receive federal student financial aid, and, to a lesser degree, receive higher amounts. These results are consistent with the fact that for-profit colleges are known to advertise the amount of financial aid their students receive and provide hands-on assistance to students on their federal student financial aid applications, which have been shown to be very effective in increasing federal student financial aid uptake (Bettinger, Long, Sanbonmatsu, 2012)[31]. Note that the advantage for-profit college students have over peer college students show up mostly in the probability of obtaining (need-based) Pell grants rather than the amount received[32].

[31]Community colleges do not make the same efforts in providing support to students with regard to obtaining financial aid.

[32]Pell grants are need based and the amount awarded is based on tuition and family income, whereas unsubsidized federal student loans are not need-based and students are free to borrow up to the maximum

This result assuages concerns about selection on unobserved income; if conditional on observables, poorer students were selecting into for-profit colleges rather than peer colleges, then we would also expect to see for-profit college students being awarded higher amounts of the need-based Pell grant conditional on receiving it relative to peer college students. Instead, my results indicate that, conditional on tuition and family income, for-profit college Pell grant recipients are only awarded slightly higher Pell grants than their peer college counterparts (5.9%), which means that any selection on unobservables is minimal [33]. In contrast, model estimates show that for-profit college students systematically receive less non-Pell grants[34]. This is most likely due to the fact that for-profit colleges rarely give out institutional grants and may not be eligible for some local and state grants.

To illustrate the magnitude of the difference in the financial aid prospects of for-profit college students and peer college students, consider an individual with family income (adjusted by family size) of $12,000, who is deciding between attending a for-profit college with an annual tuition of $4,000 or a peer college with the same tuition. If the individual choose to attend the for-profit college rather than the peer college, he/she would be 77% more likely to receive Pell grants and 63% more likely to take out federal student loans; conditional on receiving Pell grants, he/she would be awarded $230 more, and conditional on taking out federal student loans, he/she would take out $781 more; but he/she would receive $808 less in non-Pell grants. In expectation, this individual would receive $1,028 more in financial aid

amount.

[33]Assisting students on applying for need-based Pell grants would increase their probability on applying for and receiving Pell grants but not the amount awarded conditional on applying and receiving it. On the other hand, since students are free borrow federal student loans up to the maximum amount and for-profit colleges have a direct hand in the application process, for-profit colleges can easily persuade their students to take out a higher amount (for example, by filling out students' financial aid applications for them) in order to lower out-of-pocket costs and offset the brunt of their tuition.

[34]Non-Pell grants consist of institutional grants and local and state grants.

if he/she were to attend the for-profit college rather than the peer college with the same tuition. This number quantifies the magnitude by which for-profit colleges are gaming federal student financial aid to offset their high tuition.

7.2 Preference Parameters

Tables 15, 16, and 17 present estimated price sensitivity parameters α_i and preference parameters β_i for school characteristics X_j . In order to capture heterogeneous preferences, I allow each demographic group to have its own price sensitivity and preference parameters and omit the reference group. My estimates reveal that there exist significant variations in preferences for school characteristics between demographic groups. First, comparing the constant term across demographics reveal that females, blacks, and older students are less inclined to attend college than males, non-blacks, and younger students, respectively. But the coefficients on the for-profit college indicator variable show that the former demographic groups have a stronger preference for for-profit colleges than the latter demographic groups. This is consistent with what has been documented in the existing literature regarding the demographics that for-profit colleges target. Also, it is interesting to note that although for-profit schools and peer schools offer the same programs, they appear to have comparative advantages in different areas. My estimates show that students prefer to attend for-profit colleges for 2-4 years certificate programs whereas they prefer to attend peer colleges for business programs. Furthermore, I find that an additional dollar spent on instructions by for-profit colleges is more effective in attracting new enrollment than an additional dollar spent by peer colleges on instructions. This result somewhat counters the criticism that for-profit colleges are spending less on instructions and hence are providing lower quality education. My parameter estimates reveal that, from the students' perspective, the higher "effectiveness" of for-profit colleges' instructional spending is sufficient to compensate for the difference in instructional expenditure between the two types of colleges. So at least from the prospective students' point of view, for-profit colleges are not providing inferior to peer colleges in terms of their instructional expenditures[35]. Higher effectiveness of for-profit colleges' instructional spending may be explained by the fact that for-profit colleges are known to employ mostly part-time instructors in order to cut cost whereas peer colleges hire mostly full-time instructors.

Preference parameters also show that all demographic groups prefer schools with online offerings to those without[36]. Another way for schools to offer convenience is through having more urban locations. The negative coefficients in front % urban indicate that students do not like more urban campuses. Although urban campuses may be more convenient, campuses located in cities are also more space constrained. Given that most schools already offer online programs, the convenience offered by an urban campus is somewhat redundant and may be overshadowed by the disutility from being space constraint.

Estimates of price sensitivity parameters α_i reveal that females, blacks, and older students are much less sensitive to price than males, non-blacks, and younger students, respectively[37]. Lower price sensitive would also explain why these demographic groups are more

[35]Because I do not have post-graduation earnings data, I cannot assess the effectiveness of for-profit colleges' instructional expenditure in term of its effect on students post-graduating labor market performance. Fortunately, since I'm mainly interested in students' college choice and dropout behavior, this information is not

[36]By the 2009-2010 school year most schools have already began offering online courses. Therefore, the coefficient in front of online offerings indicator variable may be different if this model had been estimated using data from a couple of years earlier when only a small portion of schools had adopted distance learning. Moreover, the online coefficient may be different if I were able to observe the extensiveness of each school's online offerings.

[37]The price coefficient is positive because in the empirical specification there is a negative sign in front of price.

willing to attend expensive for-profit colleges. Table 19 provides the average own price elasticity of demand by school type and demographics. As expected from the price sensitivity parameters, females have lower price elasticity than males, blacks have lower price elasticity than non-blacks, and older students have lower price elasticity than younger students. But for-profit colleges on average have much higher price elasticity than peer colleges due to the fact that for-profit colleges are much more expensive and that their students are much closer to the federal student financial aid ceiling than those of peer colleges.

7.3 Other Parameters

The other parameters I estimate include σ_Y, ν_L, and ν_H, δ_j, and ν_j, and they are reported in table 18. The uncertainty surrounding the return to college is captured by σ_Y and this is set to be common across all demographic groups due to data constraints. ν_L and ν_H are the ex-ante expected post-graduation quality indices. As expected, the group of colleges with low dropout rates L has a higher perceived quality index than the group with high dropout rates H. Recall that δ_j is the flow utility students derive from enrolling in school j that captures factors such as the ease of applying and students' in-school experience. On the other hand, ν_j is school j's post-graduation quality index that captures the variation in graduation rates across schools that is not explained by the observables. I find that for-profit colleges on average have lower δ_j but much higher ν_j than peer colleges. The former result implies that, on average, peer colleges provide a better in-school experience to students than for-profit colleges. The latter result indicate that students view for-profit colleges as better than peer colleges in providing higher graduation rates and higher post-graduation earnings, conditional on observables. This mirrors the reduced form estimates shown in table 5.

Figure 2 illustrates the distribution of utilities students derive from each school's observed characteristics and unobserved quality $X_j\beta_i + \nu_j$ by school type; for each school, β_i is integrated over the distribution of demographics in that school's service area. Recall that $X_j\beta_i + \nu_j$ is the mean return to attending school j for individual i, including both pecuniary and non-pecuniary payoffs. On average, the mean return to a for-profit college education 0.6290 is higher than that of a peer college education -5.8783, but for-profit colleges are more variable in their mean returns (standard deviation = 7.9148)than peer colleges (standard deviation = 5.6834).

8 Counterfactual Analyses

I use my parameter estimates to conduct the following counterfactual experiments: 1) restrict for-profit college students' access to federal student financial aid in terms of Pell grants and federal student loans; 2) close down all for-profit colleges.

8.1 Restrict for-profit college students' access to federal student financial aid

To understand the implications of the recently proposed regulation aimed towards for-profit colleges, I conduct a counterfactual simulation where students would not be eligible for any Pell grants or federal student loans if they choose to attend a for-profit college (they are still eligible for Pell grants or federal student loans if they attend peer colleges). I find that this regulation would be successful in steering students away from for-profit colleges as intended by policy makers for it would induce a 74% decrease in for-profit college enrollment. However, of those who sort out of for-profit colleges only 23% will substitute toward a peer college, which translates into a 15% drop in the total enrollment in the market for postsecondary vocational training.

In table 20, I decompose the effect of this regulation on enrollment by $faminpp$ (annual family income per person) and demographic groups (age, race, gender). Doing so separates the enrollment response driven by the income effect from that driven by preferences (recall that different demographic groups are allowed to have different preference parameters). Each cell contains three entries that characterize the response of a particular demographic and $faminpp$ combination; the first entry is the percent change in for-profit enrollment induced by the regulation; the second entry is the percent of those who sorted out of for-profit colleges that switched to peer colleges; and the third entry is the percent change in total enrollment. For example, for female students with $famincpp = \$10,000$, the regulation would result in 64.3% decrease in the for-profit college enrollment of this group; of those who left for-profit college, only 6.3% would switch to a peer college; and overall, this group would suffer a 17.9% decrease in total vocational college enrollment.

Fixing $famincpp$ and comparing the first entry of each cell (percent change in for-profit college enrollment) across demographic groups in table 20 reveals that females are more reluctant to leave for-profit colleges than males, blacks are more reluctant to leave for-profit colleges than non-blacks, and older students are more reluctant to leave for-profit colleges than younger students. This difference is attributed to stronger preference for for-profit colleges by some demographic groups than others since fixing $famincpp$ eliminates the income effect. Conducting the same comparison for the second entry of each cell (percent of those who sort out of for-profit colleges that would switch to peer colleges) reveals that of those who sort out of for-profit colleges, blacks are less inclined to substitute to peer colleges than non-blacks and older students are less inclined to substitute to peer colleges than younger students. This finding implies that peer colleges are more attractive to some demographics than others. Finally, comparing the last entry of each cell (percent change in total vocational college enrollment) across demographic groups conditional on $famincpp$ reveals that this regulation would hurt females more than males, blacks more than non-blacks, and older students more than younger students, in terms of incurring a higher percent drop in vocational college enrollment. Making the same comparison across $famincpp$ while controlling for demographics reveals that this regulation would result in a larger decline in college enrollment among lower-income students. Differential impact across demographic groups and income level may call into question the fairness of this regulation as certain disadvantaged populations suffer more from this policy than others groups.

Another outcome of interest that is affected by this regulation is students' dropout rate. Taking away federal student financial aid from for-profit college students causes them to become more credit constrained, hence making for-profit colleges effectively more expensive[38]. Therefore, it would take a higher realization of postgraduation payoff to justify the cost of continuing with college and graduating in the second period. Restricting federal student financial aid to for-profit colleges students also affect their dropout rate by pushing some to switch to other schools that may less suitable for them. In particular, those sorting into peer schools would suffer an increase in dropout rates because peer schools on average are not as good at graduating students as for-profit colleges conditional on observables. Counterfactual simulations reveal that those who would switch from a for-profit college to a peer college

[38]The model presented in this paper is a partial equilibrium model and does not account for potential responses, such as tuition adjustment, on the part of the school. However, I contend that the partial equilibrium setting offers a good approximation of reality as all past instances of for-profit colleges losing Title IV funding have resulted in school closure rather than tuition adjustment. Therefore, it seems that tuition adjustment would not be the expected response to the proposed regulation.

as a result of this regulation on average sustain a 24 percentage points increase dropout probability. This increase is the result of mismatch and of the fact that peer colleges on average have higher dropout rates than for-profit colleges conditional on observables. I also find that those who would switch from a for-profit college to a different for-profit college on average sustain a 20 percentage point increase in dropout probability. This increase is due to both mismatch and becoming more credit constraint post-policy change. Finally, those who would stay in the same for-profit colleges on average sustain a 6 percentage point increase in dropout probability. This increase is solely because these students are now more credit constrained. Therefore, even those who do not exit the vocational college market at the college choice stage (period 1) would sort out of the market at a higher rate in the dropout stage (period 2).

8.2 Close down all for-profit colleges

In the second counterfactual experiment, I simulate a world in which for-profit colleges do not exist. Although this experiment is less realistic, it sheds light on the role that for-profit colleges play in market for postsecondary vocational training. Closing down all for-profit colleges would lead to a 22% drop in total enrollment in the market for postsecondary vocational training. Only 18% of those who would otherwise attend for-profit colleges would switched to peer colleges. This result validates the claim that for-profit colleges are indeed serving a niche student population that does not find peer colleges to be a reasonable substitute. In other words, for-profit colleges are not stealing students away from peer colleges but rather are targeting those who would not attend college otherwise.

I further decompose the enrollment response by demographics and $famincpp$ (family income adjusted by family size) in table 21, where the first entry of each cell is the percent change in total enrollment of a given demographic and $famincpp$ combination, and the second entry is the percent of for-profit college students who switched to peer colleges. Fixing $famincpp$ and comparing the first entry of each cell across demographics reveals that closing down for-profit colleges induces a much larger drop in female college enrollment than male college enrollment, a much larger drop in black college enrollment than non-black college enrollment, and a much larger drop in older students college enrollment than younger students college enrollment. Fixing a demographic group and comparing percent change in total enrollment across income levels reveals that lower-income students suffer a larger decline in college enrollment than higher-income students as the result of closing down for-profit colleges. I conclude from these findings that the niche population for-profit colleges serve is more likely to be female, black, older, and lower-income relative to those who would be willing to attend peer colleges.

9 Conclusion

The for-profit college industry is a subject of continuing debate among policy makers, but most of the dialogue thus far have been focused on the flaws of these institutions such as higher tuition, higher dependence on federal student financial aid, and higher federal student loan default rates. This paper examines the debate over for-profit colleges from a different angle, by understanding the role that these institutions play the market for vocational training relative to their main competitors (peer colleges). Model estimates and counterfactual experiments show that for-profit colleges are in fact targeting a niche student population that would not otherwise attend peer colleges. In other words, for-profit colleges are successfully attracting students who otherwise would not attend college to the higher education arena. Preference estimates exhibit significant heterogeneity across demographics. I find that for-profit colleges cater to a student population that is more likely to be female, black, older, and lower income compared to those who would be willing to attend peer colleges. Counterfactual simulation shows that although regulating for-profit colleges by restricting their students' access to federal student financial aid would be successful in steering students away from these schools as intended, an unintended consequence of the regulation is that most of the students sorting out of for-profit colleges would not be substituting to peer colleges but rather to the outside option of no college. Therefore, an undesirable side effect of this regulation is that it would significantly depress college enrollment among the demographics that for-profit colleges target. Another undesirable side effect of this regulation is that for those who do substitute to peer colleges as a result of the proposed regulation, they would drop out of school at a much higher rate than they would have in the absence of the regulation due to mismatch.

My findings shed light on several factors that attract students to for-profit colleges over peer colleges. Model estimates show that for-profit colleges and peer colleges are differentiated beyond their program offerings and tuition. First, I find that for-profit colleges and peer colleges have comparative advantages in different programs. Whereas students prefer peer college for business programs, they prefer for-profit colleges for 2-4 year certificate programs. Second, I find that even though for-profit colleges spend less on student instructions they are more effective with their instructional spending than peer colleges, sufficiently so to compensate for the difference in instructional spending between the two types of colleges[39].

[39] Effectiveness here is evaluated in terms the utility instructional spending brings to students at the college choice stage and while students are in school. Recall that post-graduation outcome data is not

And finally, I find that students view for-profit colleges as better at graduating their students and offering higher postgraduation payoffs than peer colleges, controlling for observables. Higher graduation rate is particularly important in the market for vocational training where most of the jobs students pursue post-graduation require the relevant degree or certification. Beyond these differences, there remains a large utility gain attributed enrolling in for-profit colleges for some demographics that cannot be decomposed into observables; therefore, a more detailed analysis into the difference between for-profit and peer colleges is warranted and planned for future research.

The findings of this paper illustrate deficiencies in the current system of peer colleges and identify a few areas in which peer colleges can improve in order to appeal to a wider spectrum of prospective students. Counterfactual analyses indicate that simply regulating for-profit colleges without making any changes to peer colleges would marginalize a niche student population that currently does not find peer colleges to be a reasonable alternative; hence this regulation would induce a sizable population to opt out of the college option. A more judicious policy would be to couple the regulation of for-profit colleges with efforts to improve the current system of peer colleges. As more data become available, including post-graduation earnings data, the model presented in this paper can also be used to compare the cost of educating the population of for-profit college students to the economic benefit of doing so.

available so effectiveness should not be interpreted in terms of labor market earnings.

Figures and Tables

Figure 1: Flow of students in and out of a school in years t and $t+1$

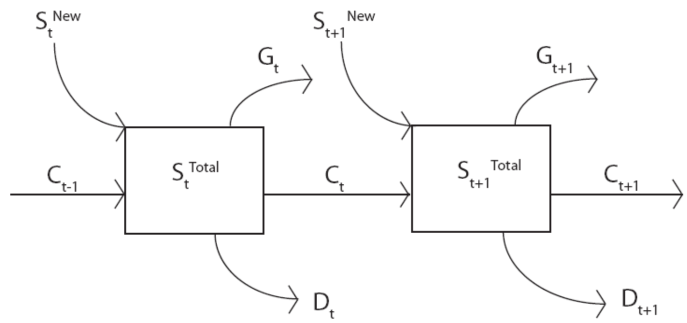

Table 1: Descriptive statistics of school financial and demographics

	unweighted		weighted by #stdts	
Average	for-profit	peer	for-profit	peer
pr(Pell>0)	0.642	0.451	0.610	0.391
E(Pell | Pell>0)	$4,089	$3,712	$4,094	$3,711
E(non-Pell)	$762	$1,243	$840	$872
pr(loan>0)	0.678	0.285	0.764	0.237
E(loan | loan>0)	$6,674	$4,245	$8,177	$4,656
tuition	$7,503	$3,735	$8,684	$2,769
tuition−grant−loan	-$836	-$855	-$1,021	-$871
per-stdt instr exp	$2,507	$3,509	$1,920	$3,007
per-stdt non-instr exp	$4,443	$4,310	$5,097	$3,449

Figure 2: Distribution of $X_j\beta_i + \nu_j$ by school type

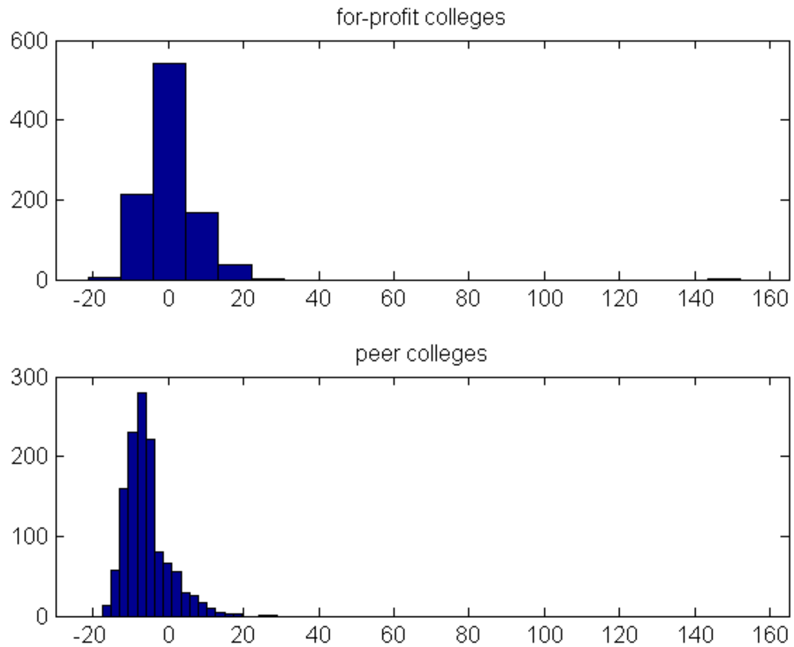

Table 2: Descriptive statistics of enrollment, program offerings and graduation rate

	unweighted		weighted by #stdts	
Average	for-profit	peer	for-profit	peer
enrollment/school (median)	1,668(271)	3,451(2,179)	-	-
%black (median)	25(17)	17(10)	30(32)	17(12)
%female (median)	75(84)	53(53)	64(70)	52(53)
%ages≥25 (median)	48(49)	41(39)	59(61)	38(37)
average (median) #programs	5(4)	38(34)	12(10)	51(54)
program length in yrs (median)	2.0(2.0)	2.4(2.2)	2.8(2.7)	2.4(2.2)
graduation rate % (median)	51(51)	30(25)	35(30)	21(18)

Table 3: School-level reduced form estimates of grant components in (9)

	$log(\frac{pr(Pell_j>0)}{1+pr(Pell_j>0)})$		$log(Pell_j \mid Pell_j>0)$		$log(nonPell_j)$	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
cons	-.6250	.1155	1.1239	.0278	-.6092	.1775
1(for-profit)	.4102	.0546	.0552	.0152	-1.2070	.0875
log(tuition in K)	.2629	.0331	.0221	.0079	.6822	.0461
% black	1.2547	.1042	.0691	.0277	-.3468	.1447
% female	.5577	.0897	.0287	.0282	-.9157	.1665
% 18-24	-.6625	.1411	.2045	.0351	.2285	.2098
Adj. R^2	.3086		.0376		.2003	

[a] All monetary variables in thousands

[b] Dependent variables derived from solving (9) for the observables.

Table 4: School-level reduced form estimates of loan components in (9)

	$log(\frac{pr(Loan_j>0)}{1+pr(Loan_j>0)})$		$log(Loan_j \mid Loan_j>0)$	
	Estimate	S.E.	Estimate	S.E.
cons	-2.192	.1583	1.556	.0488
1(for-profit)	.7445	.0841	.1173	.0248
log(tuition in K)	1.3060	.0546	.2245	.0154
% black	.4619	.1543	-.0902	.0481
% female	.3961	.1285	-.1805	.0439
% 18-24	-.7529	.1825	-.1715	.0546
Adj. R^2	.5382		.2028	

[a] All monetary variables in thousands

[b] Dependent variables derived from solving (9) for the observables.

Table 5: School-level linear probability model of graduation rate

	(1)		(2)		(3)	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
cons	.2021	.0104	.3777	.0296	.4030	.0374
1(for-profit)	.2407	.0119	.0688	.0173	.0733	.0176
tuition (in K)	.0069	.0018	.0091	.0020	.0089	.0020
grant (in K)	.0056	.0025	.0030	.0026	.0048	.0027
loan (in K)	-.0110	.0021	-.0029	.0022	-.0034	.0022
instr. exp (in K)	.0264	.0028	.0157	.0025	.0153	.0025
non-instr. exp (in K)	-.0027	.0020	.0009	.0017	.0007	.0017
1(online)			-.0677	.0154	-.0689	.0153
% urban			-.0006	.0001	-.0004	.0001
# campuses			-.0002	.0004	-.0002	.0004
1(1yr certificates)			.0555	.0093	.0545	.0092
1(1-2yr certificates)			.0384	.0137	.0396	.0136
1(associate deg)			-.1042	.0132	-.1045	.0133
1(2-4yr certificates)			.0349	.0104	.0319	.0105
1(Bachelor's deg)			-.0147	.0151	-.0143	.0151
1(beauty prgms)			-.0235	.0097	-.0192	.0099
1(health prgms)			.0680	.0133	.0695	.0138
1(business prgms)			-.0740	.0150	-.0743	.0150
total# prgrams			-.0008	.0002	-.0009	.0002
% black					-.0788	.0192
% female					-.0207	.0232
% 18-24					-.0212	.0286
Adj. R^2	.2853		.4220		.4267	

[a] All monetary variables in thousands
[b] Dependent variable = graduation rate.
[c] instr. exp = instructional expenditure per student.
[d] non-instr. exp = non-instructional expenditure per student.

Table 6: Model fit for grant and loan components in (9) by school type

	for-profit	peer
$pr(Pell_j > 0)$ (model)	0.641	0.452
$pr(Pell_j > 0)$ (data)	0.642	0.451
$E(Pell_j \mid Pell_j>0)$ (model)	4.075	3.708
$E(Pell_j \mid Pell_j>0)$ (data)	4.089	3.712
$E(nonPell_j)$ (model)	0.770	1.241
$E(nonPell_j)$ (data)	0.762	1.243
$pr(Loan_j > 0)$ (model)	0.678	0.285
$pr(Loan_j > 0)$ (data)	0.678	0.285
$E(Loan_j \mid Loan_j>0)$ (model)	6.678	4.243
$E(Loan_j \mid Loan_j>0)$ (data)	6.674	4.245

[a] All monetary variables in thousands

Table 7: Model fit for grant and loan components in (9) by tuition quartiles

tuition	1st quartile	2nd quartile	3rd quartile	4th quartile
$pr(Pell_j > 0)$ (model)	0.431	0.485	0.597	0.611
$pr(Pell_j > 0)$ (data)	0.429	0.497	0.607	0.605
$E(Pell_j \mid Pell_j>0)$ (model)	3.668	3.740	4.024	4.069
$E(Pell_j \mid Pell_j>0)$ (data)	3.660	3.738	4.028	4.079
$E(nonPell_j)$ (model)	0.709	1.012	0.908	1.578
$E(nonPell_j)$ (data)	0.723	0.925	0.893	1.592
$pr(Loan_j > 0)$ (model)	0.161	0.321	0.621	0.731
$pr(Loan_j > 0)$ (data)	0.158	0.310	0.624	0.734
$E(Loan_j \mid Loan_j>0)$ (model)	3.421	4.184	6.035	7.514
$E(Loan_j \mid Loan_j>0)$ (data)	3.432	4.136	5.981	7.670

[a] All monetary variables in thousands

Table 8: Model fit for grant and loan components in (9) by %black quartiles

% black	1st quartile	2nd quartile	3rd quartile	4th quartile
$pr(Pell_j > 0)$ (model)	0.498	0.492	0.524	0.628
$pr(Pell_j > 0)$ (data)	0.491	0.478	0.517	0.651
$E(Pell_j \mid Pell_j>0)$ (model)	3.845	3.843	3.812	3.968
$E(Pell_j \mid Pell_j>0)$ (data)	3.895	3.804	3.804	3.986
$E(nonPell_j)$ (model)	1.139	1.125	1.031	0.843
$E(nonPell_j)$ (data)	1.142	1.140	1.016	0.836
$pr(Loan_j > 0)$ (model)	0.457	0.425	0.434	0.508
$pr(Loan_j > 0)$ (data)	0.449	0.426	0.444	0.508
$E(Loan_j \mid Loan_j>0)$ (model)	5.357	5.154	5.338	5.301
$E(Loan_j \mid Loan_j>0)$ (data)	5.367	5.297	5.345	5.209

[a] All monetary variables in thousands

Table 9: Model fit for grant and loan components in (9) by %female quartiles

% female	1st quartile	2nd quartile	3rd quartile	4th quartile
$pr(Pell_j > 0)$ (model)	0.475	0.446	0.615	0.640
$pr(Pell_j > 0)$ (data)	0.458	0.450	0.602	0.627
$E(Pell_j \vert Pell_j>0)$ (model)	3.785	3.748	3.846	4.204
$E(Pell_j \vert Pell_j>0)$ (data)	3.761	3.756	3.891	4.096
$E(nonPell_j)$ (model)	1.194	1.105	1.118	0.724
$E(nonPell_j)$ (data)	1.205	1.107	1.203	0.619
$pr(Loan_j > 0)$ (model)	0.403	0.264	0.505	0.658
$pr(Loan_j > 0)$ (data)	0.396	0.265	0.523	0.641
$E(Loan_j \vert Loan_j>0)$ (model)	5.034	4.425	5.653	6.157
$E(Loan_j \vert Loan_j>0)$ (data)	5.063	4.428	5.653	6.075

[a] All monetary variables in thousands

Table 10: Model fit for grant and loan components in (9) by %age 18-24 quartiles

% ages 18-24	1st quartile	2nd quartile	3rd quartile	4th quartile
$pr(Pell_j > 0)$ (model)	0.597	0.578	0.507	0.475
$pr(Pell_j > 0)$ (data)	0.606	0.584	0.497	0.451
$E(Pell_j \vert Pell_j>0)$ (model)	3.801	3.946	3.884	3.889
$E(Pell_j \vert Pell_j>0)$ (data)	3.766	3.937	3.897	3.904
$E(nonPell_j)$ (model)	0.934	0.933	0.928	1.351
$E(nonPell_j)$ (data)	0.924	0.930	0.918	1.362
$pr(Loan_j > 0)$ (model)	0.548	0.462	0.375	0.454
$pr(Loan_j > 0)$ (data)	0.551	0.454	0.374	0.447
$E(Loan_j \vert Loan_j>0)$ (model)	5.716	5.028	5.097	5.410
$E(Loan_j \vert Loan_j>0)$ (data)	5.614	5.078	5.188	5.339

[a] All monetary variables in thousands

Table 11: Model fit for demographic-specific market shares by school type

	model	data
black (for-profit)	0.0029	0.0029
black (peer)	0.0341	0.0346
non-black (for-profit)	0.0022	0.0022
non-black (peer)	0.0315	0.0313
female (for-profit)	0.0033	0.0034
female (peer)	0.0332	0.0330
male (for-profit)	0.0012	0.0012
male (peer)	0.0279	0.0280
age 18-24 (for-profit)	0.0037	0.0038
age 18-24 (peer)	0.0584	0.0586
age $\geq$ 25 (for-profit)	0.0017	0.0017
age $\geq$ 25(peer)	0.0179	0.0176

Table 12: Model fit for demographic-specific market shares by school type

	model	data
black female (for-profit)	0.0044	0.0046
black female (peer)	0.0416	0.0418
black male (for-profit)	0.0018	0.0018
black male (peer)	0.0324	0.0325
non-black female (for-profit)	0.0032	0.0032
non-black female (peer)	0.0343	0.0340
non-black male (for-profit)	0.0012	0.0011
non-black male (peer)	0.0284	0.0288
age 18-24 female (for-profit)	0.0056	0.0057
age 18-24 female (peer)	0.0649	0.0651
age 18-24 male (for-profit)	0.0018	0.0019
age 18-24 male (peer)	0.0525	0.0526
age $\geq$ 25 female (for-profit)	0.0028	0.0025
age $\geq$ 25 female (peer)	0.0224	0.0224
age $\geq$ 25 male (for-profit)	8.9e-4	8.9e-4
age $\geq$ 25 male (peer)	0.0130	0.0131

Table 13: Structural estimates of grant components in (9)

	$pr(Pell_j > 0)$		$E(Pell_j \mid Pell_j > 0)$		$E(nonPell_j)$	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
cons	2.585	0.841	1.316	0.348	-0.283	0.084
1(for-profit)	0.875	0.079	0.059	0.012	-1.001	0.246
log(tuition in K)	0.094	0.024	0.032	0.010	0.647	0.102
log(famincpp)	-1.528	0.440	-0.017	0.003	-0.148	0.034

[a] All monetary variables in thousands
[b] famincpp = family income per person (discounted by family size)

Table 14: Structural estimates of loan components in (9)

	$pr(Loan_j > 0)$		$E(Loan_j \mid Loan_j > 0)$	
	Estimate	S.E.	Estimate	S.E.
cons	-0.914	0.214	1.767	0.450
1(for-profit)	0.741	0.311	0.175	0.069
log(tuition in K)	1.238	0.385	0.218	0.047
log(famincpp)	-0.740	0.100	-0.268	0.130

[a] All monetary variables in thousands
[b] famincpp = family income per person (discounted by family size)

Table 15: Price and preference parameters estimates by demographics: α_i, β_i

	female		male	
	Estimate	S.E.	Estimate	S.E.
cons	-1.699	0.408	-0.725	0.243
α_i	0.023	0.010	0.219	0.020
1(for-profit)	1.690	0.214	-0.911	0.100
s (K)	0.033	0.018	0.003	0.001
s*1(for-profit) (K)	0.090	0.042	0.070	0.028
e (K)	0.045	0.019	0.005	0.004
% campus w online courses	0.303	0.046	0.174	0.011
% urban of campus locations	-0.009	0.002	-0.014	0.012
% urban*1(for-profit)	-0.026	0.006	-0.0003	0.001
total # of prgm	0.021	0.007	0.026	0.005
offer 1yr certificate prgm	0.144	0.071	0.016	0.010
offer Associate degree prgm	0.149	0.003	0.523	0.048
offer 2-4yrs certificate prgm	-0.575	0.097	-0.130	0.110
offer 2-4yrs certificate*1(for-profit)	0.301	0.150	0.772	0.081
1(offer beauty prgm)	0.339	0.061	-0.312	0.079
1(offer health prgm)	0.698	0.250	0.141	0.081
1(offer business prgm)	0.547	0.226	0.797	0.100
1(offer business prgm)*1(for-profit)	-0.379	0.070	-0.112	0.045

[a] All monetary variables in thousands

[b] s = instructional expenditure; e = non-instructional expenditure.

Table 16: Price and preference parameters estimates by demographics: α_i, β_i

	black		non-black	
	Estimate	S.E.	Estimate	S.E.
cons	-2.514	0.460	0.044	0.306
α_i	0.024	0.009	0.348	0.034
1(for-profit)	4.478	1.006	3.154	0.675
s (K)	0.022	0.019	0.022	0.021
s*1(for-profit) (K)	0.086	0.030	0.084	0.039
e (K)	0.038	0.009	0.038	0.010
% campus w online courses	0.065	0.031	0.210	0.014
% urban of campus locations	-0.018	0.036	-0.014	0.001
% urban*1(for-profit)	-0.033	0.019	-0.005	0.004
total # of prgm	0.026	0.005	0.021	0.003
offer 1yr certificate prgm	0.111	0.038	0.135	0.069
offer Associate degree prgm	0.137	0.036	0.257	0.090
offer 2-4yrs certificate prgm	-0.438	0.108	-0.315	0.087
offer 2-4yrs certificate*1(for-profit)	0.401	0.155	0.013	0.026
1(offer beauty prgm)	0.029	0.027	-0.066	0.050
1(offer health prgm)	0.527	0.066	0.467	0.081
1(offer business prgm)	0.581	0.141	0.486	0.060
1(offer business prgm)*1(for-profit)	-0.278	0.074	-0.294	0.090

[a] All monetary variables in thousands

[b] s = instructional expenditure; e = non-instructional expenditure.

Table 17: Price and preference parameters estimates by demographics: α_i, β_i

	age 18-24		age$\geqslant$ 25	
	Estimate	S.E.	Estimate	S.E.
cons	2.673	0.900	-1.673	0.370
α_i	0.257	0.067	0.052	0.010
1(for-profit)	1.389	0.632	1.821	0.551
s (K)	0.017	0.100	0.033	0.010
s*1(for-profit) (K)	0.070	0.030	0.093	0.017
e (K)	0.020	0.002	0.047	0.019
% campus w online courses	0.404	0.148	0.211	0.101
% urban of campus locations	0.008	0.003	-0.029	0.005
% urban*1(for-profit)	-0.015	0.006	-0.016	0.002
total # of prgm	0.021	0.005	0.029	0.005
offer 1yr certificate prgm	0.132	0.026	0.198	0.062
offer Associate degree prgm	0.356	0.105	0.197	0.090
offer 2-4yrs certificate prgm	-0.436	0.046	0.498	0.042
offer 2-4yrs certificate*1(for-profit)	0.665	0.150	0.353	0.103
1(offer beauty prgm)	0.216	0.079	0.049	0.021
1(offer health prgm)	0.258	0.100	0.638	0.095
1(offer business prgm)	0.534	0.135	0.602	0.203
1(offer business prgm)*1(for-profit)	-0.370	0.031	-0.411	0.160

[a] All monetary variables in thousands
[b] s = instructional expenditure; e = non-instructional expenditure.

Table 18: Estimates for other parameters

parameter	estimate	S.E.
σ_Y	6.300	4.010
ν_L	0.929	0.010
ν_H	-8.861	0.394
mean δ_j (for-profit)	-6.003	-
mean δ_j (peer)	-5.317	-
mean ν_j (for-profit)	-3.803	-
mean ν_j (peer)	-12.059	-

Table 19: Average own price elasticity of demand

	for-profit	peer
average	3.204	1.751
average (female)	2.920	1.506
average (male)	4.116	2.196
average (black)	1.571	1.173
average (non-black)	4.034	2.084
average (age 18-24)	3.661	1.968
average (age $\geq$25)	2.855	1.602

Table 20: Restrict for-profit college students' access to federal student financial aid: the entries in each cell are respectively: 1) percent change in for-profit enrollment, 2) percent of those who sorted out of for-profit colleges that switched to peer colleges, 3) percent change in total enrollment.

famincpp	\$6,000	\$8,000	\$10,000	\$12,000	\$14,000
	-79.9	-72.0	-64.3	-57.3	-51.3
Female	14.9	10.2	7.2	6.3	5.5
	-24.7	-22.6	-20.2	-17.9	-15.9
	-91.4	-86.5	-81.0	-75.5	-70.2
Male	16.8	10.2	7.0	5.3	4.4
	-11.8	-11.4	-10.5	-9.5	-8.6
	-51.9	-46.1	-41.2	-37.0	-33.4
Black	7.0	5.8	5.2	4.8	4.5
	-20.6	-19.4	-17.8	-16.2	-14.7
	-94.7	-91.4	-87.4	-83.1	-78.7
Non-black	17.2	11.3	8.3	6.5	5.5
	-18.1	-17.1	-15.5	-13.8	-12.2
	-96.4	-93.7	-90.2	-86.2	-81.8
Age 18-24	25.4	17.0	12.7	10.2	8.7
	-13.7	-13.1	-11.8	-10.4	-9.1
	-72.8	-65.0	-58.1	-52.1	-46.9
Age $\geq$25	5.4	4.3	3.7	3.4	3.2
	-26.0	-23.4	-20.9	-18.6	-16.6

Table 21: Close down all for-profit colleges: the entries in each cell are respectively: 1) percent change in total enrollment 2) percent of for-profit college students who switched to peer colleges

famincpp	\$6,000	\$8,000	\$10,000	\$12,000	\$14,000
Female	-31.5	-31.9	-31.7	-31.4	-31.1
	13.2	8.8	6.7	5.6	5.0
Male	-13.0	-13.3	-13.1	-12.7	-12.3
	15.9	9.5	6.4	4.9	4.1
Black	-40.0	-42.2	-43.3	-43.9	-44.2
	6.3	5.4	4.9	4.6	4.4
Non-black	-19.2	-18.8	-17.8	-16.6	-15.6
	16.8	10.9	7.9	6.2	5.2
Age 18-24	-14.2	-14.0	-13.1	-12.1	-11.1
	25.1	16.8	12.5	10.0	8.5
Age $\geq$25	-35.7	-36.0	-35.9	-35.6	-35.3
	5.3	4.4	4.0	3.7	3.6

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