Determinants of Competition and Student Demand in Higher Education: Evidence from Australia

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Abstract

How consumers make their choices and how firms compete are the central questions for many markets. Despite the importance of college education choices, the evidence of how college markets function and what is the role of government interventions is limited. In this paper, we use an appealing setup and detailed administrative data from Australian college admission system to shed light these questions. Using variation in tuition charges and government subsidies due to changes in government priority majors, we find that students show low price sensitivity. Furthermore, we document that university programs display signs of strategic responses to monetary incentives by adjusting the admission requirements. To study alternative price regulations in college markets, we estimate a structural model of student application decisions and competition of college programs. Our findings suggest that student tuition charges and college revenues have an important effect on the number of admitted students and their distribution across programs.

Keywords: college market, admission mechanism, government regulations

JEL classification: I22, I23, I28, L3

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1 Introduction

Markets for education have attracted considerable attention in economic literature because of the long-lasting effect on economic and social well-being associated with educational opportunities and choices. Furthermore, education is closely linked to a variety of outcomes in society such as political participation, health, unemployment, and crime (Chetty, Friedman, & Rockoff, 2014).

Most of the attention of the literature, however, focused on school education. The main feature of college admission is that applicants can be ranked in terms of their "quality" signaled by test scores.[1] In addition, colleges strategically act to select the pool of students based on a number of criteria including ability signals. In contrast to a school setup where most applicants tend to agree on preferred schools, college programs differ not only in the prestige of colleges but also majors and specializations. This implies that preferences for college programs might be more disperse (Abdulkadiroglu & Sönmez, 2003).

Because of considerable heterogeneity of candidates, colleges might compete with each other to attract a specific subset (Roth, Shorrer, et al., 2015). In addition, although pricing mechanisms are not used in school choice, it is an indispensable part of college markets. The literature studying college markets and related policies has not reached a consensus regarding the determinants of demand in college markets. Furthermore, it lacks conclusive evidence of how colleges compete. Despite active policy debates about regulations in college markets and student finance, we also have limited evidence of the effect of government interventions and optimal design of policies (Bachas, 2017).

This papers analyses how students make college decisions and how university programs compete for students. To study these questions, we use a set-up of the Australian college admission system. It resembles a structure of semi-centralized college admission systems in several countries such as Sweden, Ireland, and the UK, which are currently a subject to active policy debates.[2] It also has a number of particularly appealing institutional features for our study.

Firstly, the admission mechanism encourages truthful revelation of students' preferences by submitting a rank-ordered list (ROL) of programs. However, since the size of ROL is limited to be maximum of 9 programs, it might provide incentives to take into account admission probabilities and "misreport" true program ranking for those who are interested in more programs (Fack, Grenet, & He, 2017; Agarwal & Somaini, 2018). However, more than a half of students do not submit maximum allowed nine programs, which suggests that the length of lists is enough

[1] School choice mechanisms grant priorities based on the distance to a school or socioeconomic background. However, schools do not usually actively select students based on the test scores from previous levels of education and other ability signals.

[2] For examples, see http://www.matching-in-practice.eu/higher-education-in-uk/

to list all the programs of interest for many students.[3] Despite the fact that misrepresentation of preferences should not play a crucial role, we adopt a conservative strategy and use a subpopulation of those who did not submit all 9 programs in estimation where truthfulness of ROLs is crucial.[4]

Secondly, students in our setting have a clear signal of their abilities used by programs to make admission decisions. All school graduates in Australia take a sequence of exams. The results of these tests are aggregated to ATAR score.[5] This score represents percentile in the overall distribution of test results and is used by colleges as the main screening device.

Thirdly, the Australian government has control over tuition fees by setting them on the major-based level. Tuition charges are often only adjusted for inflation. However, because of national major priorities, which has been repeatedly changing over time, there are a number of considerable changes unrelated to inflation adjustment. The government also pays per-student subsidies directly to colleges. These government contributions are also major-based and vary depending on national priorities but are often unrelated to student tuition charges. Such changes in priorities provide two distinct plausibly exogenous sources of variation in tuition charges and college revenues and hence, allow overcoming a price endogeneity problem.[6] Furthermore, since government-induced changes are sometimes changed differently than student prices, it also enables us to separately identify college behavioral parameters.

We use detailed administrative data from the college admission clearinghouse for the New South Wales and Australian Capital Territory. The admission center collects students' ranked order application lists and relevant information for admission decisions. Colleges decide whether to give an offer to a student who has applied and send decisions to the admission center. We observe detailed data on students' submitted rankings and ATAR scores which to a large extent determine the admission decisions of colleges. We also observe detailed data on college programs such as campus location, college affiliation, program name, major and various levels of major and specialization.

The data also contain a key college program decision outcome - admission cutoff or a minimum ATAR score that resulted in an offer in a given year. It allows students who apply the next application year to assess the chances to be admitted to a program with a given test score. However, the ATAR cutoff provides a noisy signal of an admission outcome. It does not ultimately

[3]Furthermore, given the complexity of choosing the ranking with 9 programs, the admission center allows submitting only 5 programs from 2018 admission year.

[4]Note that the fact that a student has submitted 9 programs does not imply that she is interested in more than 9 programs. In this case, she also should truthfully submit her program preferences.

[5]ATAR is an abbreviation for Aggregated Tertiary Admission Rank.

[6]By price endogeneity here we mean that if colleges select prices, it does not allow directly recovering student responsiveness to prices and usually prices have to be instrumented for this purpose.

determine whether a student will actually be admitted since programs might admit students who have lower ATAR because of other merits. Programs can also change cutoffs every year.

We start off by providing evidence on how students respond to changes in tuition charges. Using the exogenous price changes, we find that an increase in student price by 1000 AUD results in 0.0003 lower probability of listing the program first in the ranking and 0.000025 overall in the list. This is a fairly low price response. We also find that raising the ATAR cutoff results in 0.000014 lower likelihood of the program to be listed first and 0.000016 to be listed at all. It suggests that a cutoff has a very small effect, which expected since if students submit preferences truthfully, admission probabilities should not impact the decisions.

Next, we proceed to studying the responses of colleges. We find that most programs respond to higher revenues by lowering down cutoffs by on average 0.0005 as a result of a revenue increase by 1000 AUD. The effect, however, is very heterogeneous, which might suggest differences in college preferences and the presence of strategic motives.

We build a model that combines a student's application decision and college programs' choice of admission cutoffs. A student problem in a raw form is a ranked choice of 9 programs out of approximately a thousand programs offered each year. At the first stage, students choose a subset of programs of interest out of the whole set of offered programs. This step is motivated to a large extent by the presence of non-full ROLs, which suggests that for many students choice sets do not contain the whole set of offered programs. At the second stage, students rank programs of interest and submit the resulted list.

Knowing student preferences, college programs choose admission cutoffs to maximize their utility. We assume that the utility consists of two components: total revenues and average quality of admitted students represented by the average ATAR of enrolled students. In this case, the cutoff choice is aimed at balancing these two components. For example, a decrease in a cutoff leads to a higher expected number of admitted students and hence, higher revenues but lower average ATAR since it requires admitting low ATAR students. The average ATAR component can be viewed as a proxy for reputation related to admitting higher-performing students.

An outcome of a program not only depends on own choices but also on choices of competitors. However, because of a large number of programs available each year, estimating a full game is not feasible.[7] In addition, different competitors might provide a different level of threat given the differences in the degree of substitutability between programs.[8] Therefore, we use an approach to estimating the model by constructing expectations about competitors response as a function of

[7]A number of programs vary slightly over time.

[8]For example, Arts and Medicine programs might not be substitutes for each other compared to other Arts and Medicine programs, correspondingly

government-set prices as relevant state variables. This approach mimics the formation of beliefs about competitors' strategic responses when the set of competitors is large.[9]

We use the model to study a number of counterfactual regulations to understand responses of the college market to alternative financial conditions. More precisely, we simulate market outcomes under both changes in revenues per student while keeping student prices constant, and prices faced by students while keeping college revenues constant. We find that both policies would result in considerable responses by colleges in the form of adjusting admission requirements. As a result, it changes enrollment patterns and composition of admitted students. In contrast, changes in student prices lead to students' responses because of a threat that students substitute to another program. As a result, colleges attempt to compensate for the loss of students by lowering the admission cutoff. Since it would also result in lower overall quality of a student pool, some colleges do not respond to such changes either because of strong preferences for quality of admission pool or because of relative price insensitivity of students who tend to be interested in the program.

Related Literature. This paper contributes to a number of strands in the literature. Firstly, we augment the literature by providing additional evidence of the determinants of applicant decisions in college markets. A number of papers including Hastings, Neilson, and Zimmerman (2013), Kirkeboen, Leuven, and Mogstad (2016) and Wiswall and Zafar (2014) conclude an important role of major in program choices. Furthermore, Bordon and Fu (2015) suggest potential gains from postponing major decisions given a potential major-ability mismatch due to uncertainty. In addition, Avery, Glickman, Hoxby, and Matrick (2012) show that apart from majors, the reputation of college has an important effect on the decisions. Our findings suggest the important role of both major and university affiliation. We propose a novel two-stage model that not only allows estimating preferences when students face a large number of programs but also imposes a more realistic structure that supports the evidence that many students are interested in a very limited set of programs.[10]

[9] This approach can be viewed as similar to the idea behind estimating dynamic games proposed in Bajari, Benkard, and Levin (2007)

[10] A number of papers study whether students can make complicated ranking decisions. Calsamiglia, Haeringer, and Klijn (2010) find that restrictions of the portfolio size have an important effect on how individuals make the decisions. At the same time, Arcidiacono, Hotz, and Kang (2012) show that although the perception of abilities and expectation of future earnings are important determinants of college-major choice, student choices are considerably affected by a sizable forecast error. Kapor, Neilson, and Zimmerman (2018) conclude an important role of admission probability prediction error in the school choice. As a result, the authors argue that such behavioral limitations should be taken into account while designing a matching mechanism. Artemov, Che, and He (2017) also find that student might not behave fully optimal using data from another Australian admission center in Victoria. Similar evidence that students cannot optimally structure application lists are found by

We also contribute to the literature studying competition among educational entities, which predominantly focuses on competition at the school level. The literature has documented the effect of school choice programs on market entry (Hsieh & Urquiola, 2006; Epple & Romano, 2008; Bordon, Fu, Gazmuri, & Houde, 2016) and an important role of cream-skimming of students that might have an ambiguous effect on the market welfare because of a business-stealing effect. Education market policies are also found to be closely related to student performance and outcomes (Neilson, 2013; Böhlmark & Lindahl, 2015).

While the literature on school competition is active, less evidence is available for college markets. A number of theoretical papers studied decentralized college markets. Chade, Lewis, and Smith (2014) develop a model of decentralized college admission with students' heterogeneity. The results of the model suggest that in a setup with student portfolio applications, colleges can utilize a number of competition strategies including toughness or discrimination in admission requirements. Avery and Levin (2010) show that early college admission is a mechanism used by colleges to screen student preferences for a specific program. Che and Koh (2016) presents a model that incorporates strategic screening by colleges. More precisely, colleges target high-quality students who are likely to be overlooked by competitors. As a result, given multi-dimensional quality of students, colleges have incentives to put more weight on college-specific performance measures such as essays to avoid direct competition.

Empirical literature studying college competition is, however, very limited. Arcidiacono (2005) finds an important effect of admission rules and financial terms on educational outcomes. Fu (2014) argues that heterogeneity of students' preferences for colleges is an important determinant of market outcomes. It also implies that expanding the supply of colleges would not necessarily lead to higher enrollment. As a result, tuition fees and restricted supply are not found to be an important obstacle to an expansion of college attendance. The findings also suggest that competition on both tuition fees and admission requirement might lead to adverse consequences for the overall welfare. We contribute to this strand of the literature by providing evidence on how students respond to changes in tuition charges and how it affects competition among colleges. Furthermore, in our counterfactual analysis, we document how colleges would respond to changes in revenues and prices that students pay. As a result, it allows isolating the effects of sensitivity of student demand from the supply responses by university programs. In addition, it also enables us to understand how colleges use admission requirements as a strategic variable in the absence of control over prices.

This paper is organized as follows. Section 2 describes data and institutional details. Section 3 presents evidence of the students' and colleges' behavioral responses to government regulations.

Shorrer and Sóvágó (2018).

Section 4 describes a structural model of student decision and college competition. Section 5 simulates counterfactual policies and discusses their impact. Section 6 concludes.

2 Data and Institutional Environment

2.1 College Admission System

The Australian college admission system is divided into regional admission centers. Each territory has a clearinghouse that accepts applications and matches students to college programs. In this paper, we focus on University Admission Center for New South Wales and the Australian Capital Territory (UAC).[11]

To apply for colleges, applicants submit a ranked ordered list (ROL) of programs within the admission system. During the period covered by our data from 2004 to 2017, students could submit ROLs with a maximum of nine university programs.[12] The admission procedure resembles the Deferred Acceptance mechanism in the sense that it provides incentives to truthfully submit the ROL. More precisely, each candidate has to submit a ROL before the deadline and pay application fees.[13] After the application deadline, student preferences are transmitted to the colleges in the order of ranking meaning that programs ranked higher will be contacted on behalf of a student earlier. If the student does not receive an offer from a preferred program, the next program in the list is contacted. Despite this sequential structure, the UAC clearly states that:

> *"If you're not selected for your first preference, you'll be considered equally with all other eligible applicants for your second preference and so on. Your chance of being selected for a course is not decreased because you placed it as a lower order preference. Similarly, you won't be selected for a course just because you entered that course as*

[11]It is possible that students apply to several admission centers. In this case, we do not observe the whole market. However, the ATAR scores are calculated by the admission center based on the test results of 10 subjects. Therefore, the ATAR in one admission center might differ from other admission centers if a student decides to apply outside of her region. For the purpose of our study, it does not pose any threats since the presence of other admission centers only affects students' outside option. Furthermore, the presence of other admission centers should not affect competition among universities since they are only competing directly with the universities in the same region based on the admission requirements.

[12]Currently students can submit up to five programs.

[13]Candidates submit the list of programs earlier than September and can costlessly change them until the admission decisions in January. Students are monetarily incentivized to submit early applications to encourage thorough decision. To encourage early applications, application fees are reduced to 70 AUD for submission before the end of September in contrast to 200 AUD for later application.

a higher order preference." (source: UAC website)[14]

It means that despite the sequential admission process similar to the Boston mechanism, student performance measures determine whether she is admitted to the program but not the position in a ranking. As UAC suggests, an optimally-behaving student should rank programs in order of preferences without taking into account admission probabilities. However, the restrictions on a number of programs in a list might provide incentives to deviate from a truthful strategy for those students who are interested in more than nine programs. In the presence of restrictions on the size of ROLs, students who are interested in more than nine programs might find it worthwhile to include programs that are ranked below top nine programs in terms of preference but which provide higher admission probabilities. Such incentives might result in ROLs that do not necessarily represent ordering in terms of preferences. We discuss the implications later in the paper when analyzing student application decisions.

As mentioned in the previous paragraph, the main determinant of admission decisions is the ATAR score. High school graduates sit a number of exams in core subjects. The results of these exams are aggregated and normalized to represent percentiles of student performance distribution. It means that the ATAR score is in the range between 0 and 100. Although the ATAR score is the key factor in admission decisions, programs might also take into account additional admission criteria such as personal statement, questionnaire, portfolio, audition, interview or tests.[15] To form beliefs about admission probabilities students use test score cutoffs from previous admission years. These cutoffs denote the lowest test score that resulted in an offer in the previous application period.[16] However, students are warned that although these cutoffs provide a strong signal, they might change next application period and, moreover, should be irrelevant for the optimal choice.

The vast majority of programs, which are also a focus of the analysis in this paper, are Commonwealth-Supported Place (CSP) courses. The CSP courses have tuition fees, which are partly covered by the government. It means that total tuition charges received by college programs are partly paid by students and the remaining share is paid by the government. Both price components are regulated by the government, which sets total revenues per student and student fees.[17] These tuitions and contributions are set on a major level ("band"). The government has

[14] For more details see https://www.uac.edu.au/future-applicants/how-to-apply-for-uni/selecting-your-course-preferences .

[15] As mentioned above, despite the fact that ATAR is argued to be a dominant student selection indicator, Che and Koh (2016) show that these additional selection criteria are used to screen students and avoid direct competition.

[16] Very few institutions indicate a guaranteed ATAR, which is the score that will lead to admission without any uncertainty.

[17] More precisely, government regulations are formulated in the form of maximum tuition fees that can be

repeatedly changed the priority majors, which resulted in considerable and plausibly exogenous changes in overall charges or/and government contributions. The term exogenous here refers to the fact that changes in priorities stem from government preferences for majors, potentially driven by expected labor supply needs in various fields. As a result, these changes are exogenous to current demand and supply forces, which would be a typical concern with market interactions data where firms make strategic price decisions. The next subsection describes the data and illustrates this price variation over time across majors.

2.2 Data

We use data from the University Admission Center for New South Wales and the Australian Capital Territory (UAC). The data cover 2004 - 2017 admission years and contain submitted ROLs and student ATAR scores, which, as discussed before, to a large extent determine college admission decisions. We also observe a set of program characteristics including university, campus location and various levels of major allocations and specialization. In addition, the data provide the information about the lowest ATAR which led to an offer in a given year and called *cutoff*.

Table 1: Summary Statistics of Student Population

	ROL size < 9	ROL size $= 9$	Full Sample
	(1)	(2)	(3)
ATAR, *mean*	72.6	74.09	73.21
Cutoff, *list mean*	78.95	79.75	79.38
Student Price, *list mean AUD*	7029.76	6970.02	6997.81
Government Contribution, *list mean AUD*	9312.39	9177.58	9240.29
N. of Majors, *median*	3	5	4
N. of Universities, *median*	3	4	3
N	316 307	220 752	537 059

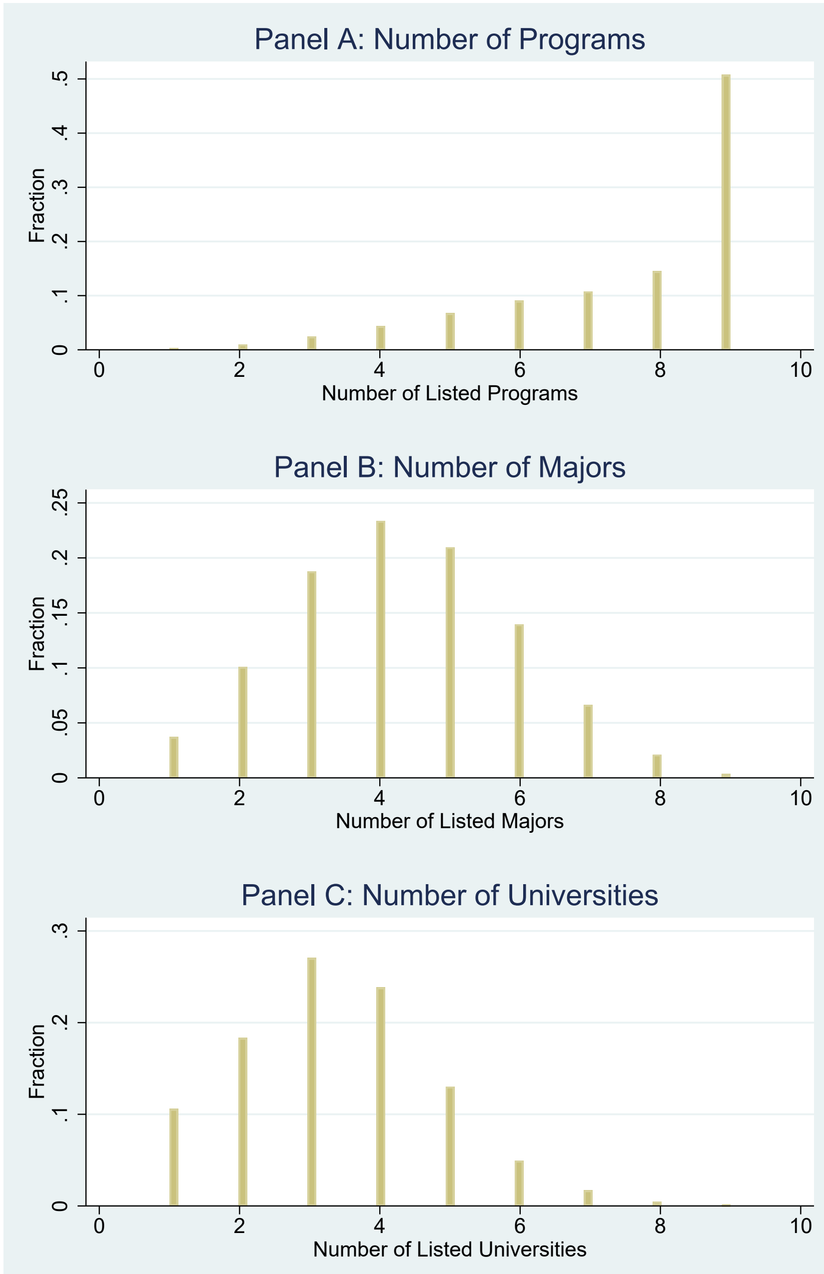
Notes: Table presents descriptive statistics of a population of students pooled over admissions years 2004 - 2017. Column (1) presents statistics of students, who submitted a list containing less than a maximum allowed program to which we refer as truthful lists. Column (2) describes students who have submitted full application lists containing 9 programs. Column (3) presents statistics for the whole population of students.

charged by a college. However, colleges predominantly set tuition charges at the cap (Cardak, Bowden, & Bahtsevanoglou, 2016). Therefore, in this paper, we consider government price regulations as being binding. This can be viewed as a sort of tacit collusion outcome in a pricing game.

Table 1 presents main descriptive characteristics of a student population. We separately provide summary statistics for students who have not reached the maximum allowed number of programs in the ROL and those who exhausted all list positions. The distinction between these groups of students plays a central role in the identification of student preferences discussed later. Therefore, it is important to consider differences in these two groups at least in terms of observables. In our sample, 59% of students across all years have not submitted full ROLs. Those students who submitted full application lists have 1.4 points higher ATAR. The courses they apply for have slightly higher cutoffs on average. At the same time, programs chosen by students who exhaust all list places are slightly cheaper in terms of tuition charges paid by students and attract on average $160 less of government contributions. It might mean that those who submitted 9 programs included safe options in the list and did not rank programs in the descending order of desirability. Finally, students, who submit full rankings have a median number of majors and universities in the list being 5 and 4 while a median number of considered universities and majors among those who have not submitted a full list is 3. These differences can be considered mechanical since individuals with longer lists are more likely to have more diverse rankings.

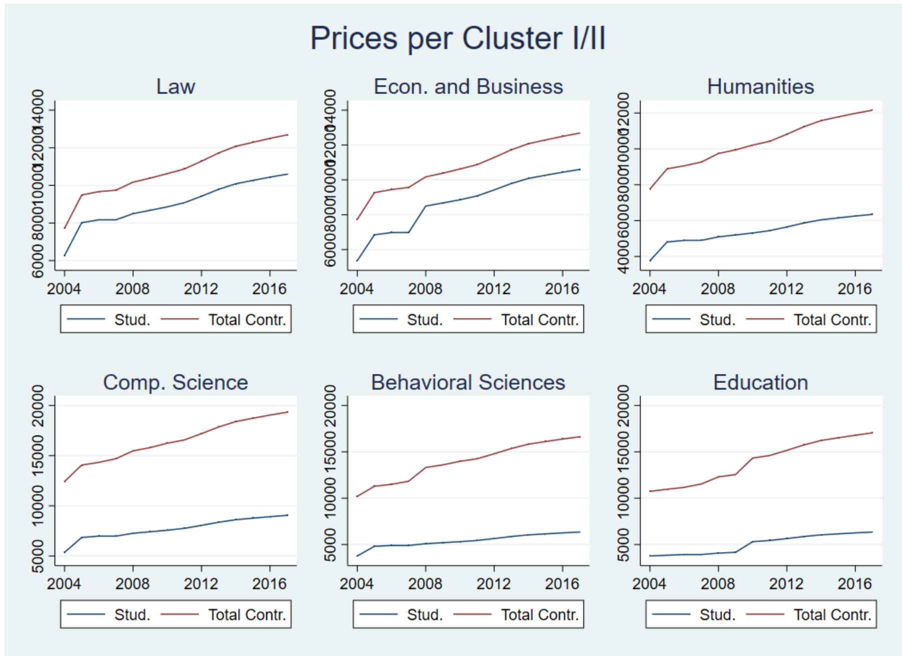
Figure 1 describes distributions of a size of submitted lists as well as a number of majors and universities included in the portfolio. Panel A demonstrates that submitting a full ranking is the most popular choice but is observed in only 41% of cases. Approximately 2% of students submit only one program and around 3% submit two programs. Shares of those who submit from five to eight programs each amount to 10%. The Figure also suggests that most students have fairly diverse preferences in terms of majors and universities. More precisely, the vast majority of students' ROLs contain between 2 and 6 majors included in a list. A similar pattern is observed for universities with most students having 3 different universities listed in their portfolio.

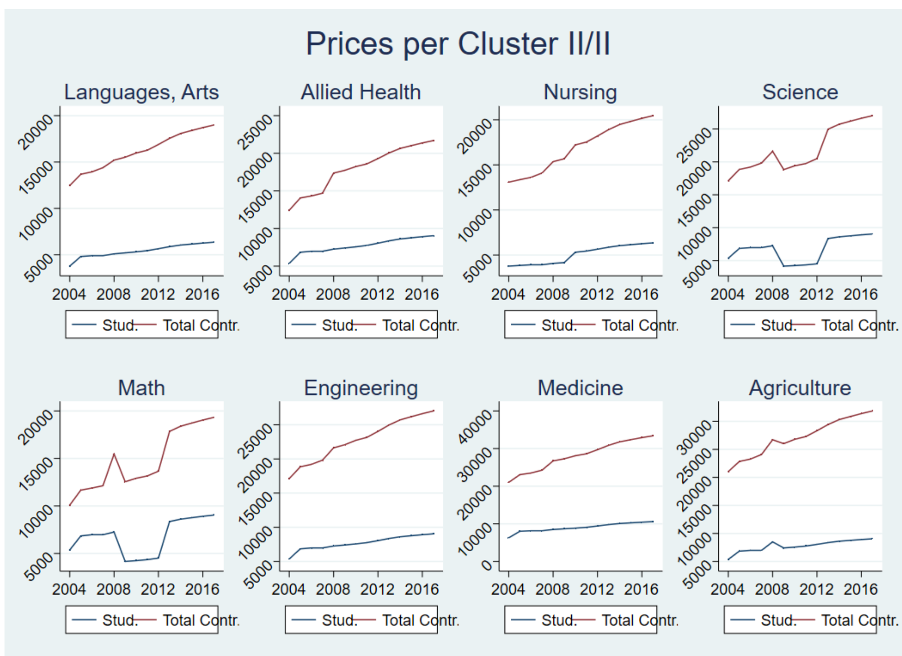
Figure 1: Distribution of a Number of Listed Programs



Notes: Figure illustrates a distribution of a number of programs (Panel A), majors (Panel B) and universities (Panel C) included in the ROLs pooled over admission years from 2004 to 2017. A maximum number of programs and hence, universities and majors one can submit is nine.

Figure 2: Tuition Fees and Government Contributions





Notes: Figure illustrates variation in student tuition charges and government contributions paid to universities for each student.

There are two important price variations leveraged in this paper that are displayed in Figure

2. First, apart from changes in prices due to inflation adjustment, student tuition charges jump because of major-based priority changes depicted by the blue line. We group majors according to the tuition bands. It leads to 14 major categories, namely Law, Economics and Business, Humanities, Computer Science, Behavioral Sciences, Education, Languages and Arts, Allied Health, Nursing, Science, Math, Engineering, Medicine and Agriculture. These broad major groups account for a price variation observed over time. The examples of such major-based price variation due to priority changes are 2005 for Law, 2005 and 2006 for Economics and Business. One can observe similar jumps for nearly all other majors at some point in time within the period under consideration. These changes are important for the identification of student price sensitivity.

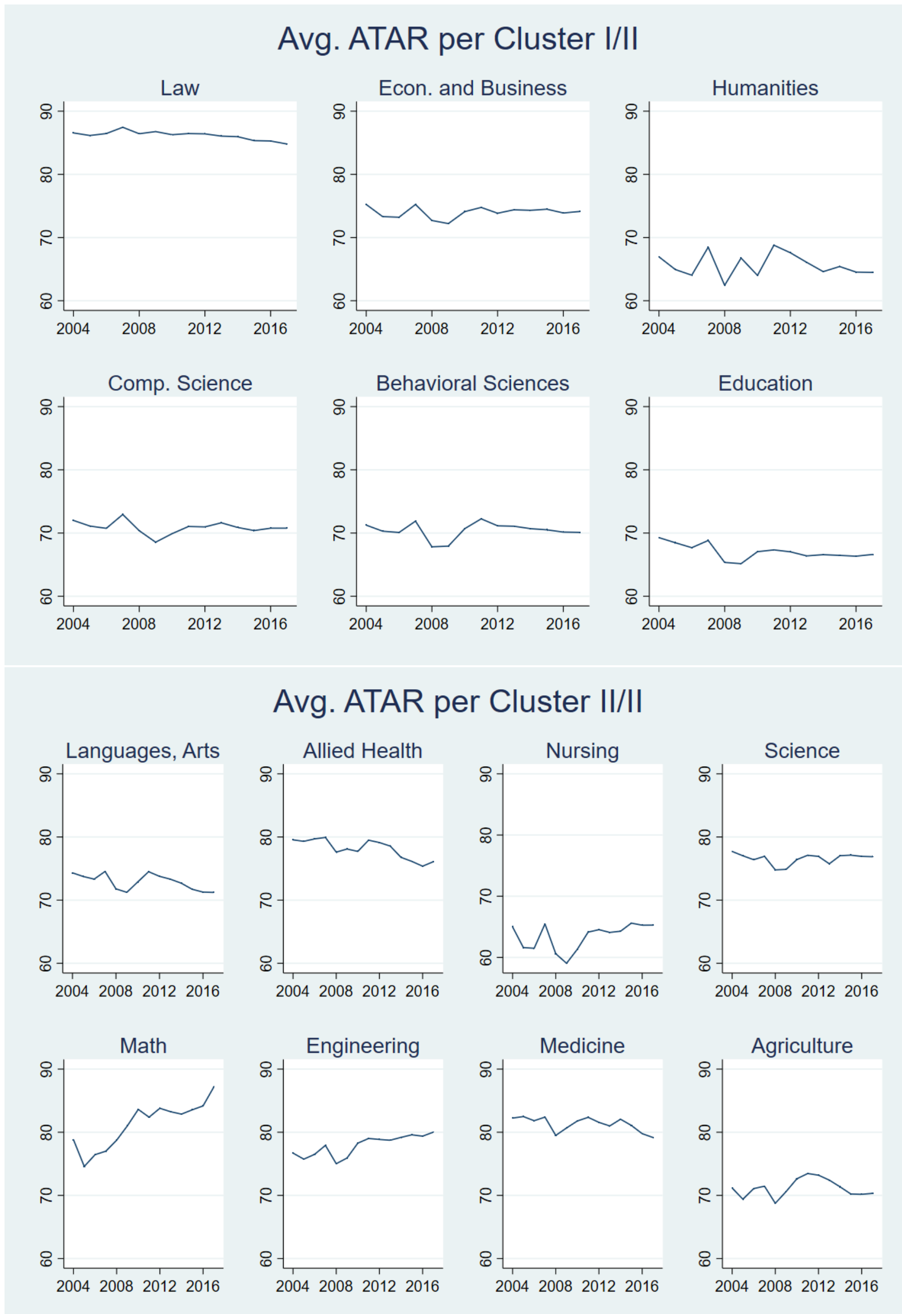
Another valuable source of variation comes from changes in government contributions, which lead to a separate variation in total per-student college revenues, which is a sum of student tuitions and government subsidies. The remainder of the paper will explore the behavior of both students and colleges. The presence of student price changes is useful to identify student preference parameters but have limited use for separate identification of programs' preferences since colleges internalize potential student responses to prices. In this case, the identification would heavily rely on the functional form assumptions. Therefore, additional variation from changes in contributions is required. As the Figure shows, overall per student revenues are closely linked to student prices but in some cases varied separately. The examples of such cases are Allied Health in 2006, Nursing in 2010 and Engineering in 2006.

In the next section, we examine how the college market responded to government regulation and changes in financial incentives.

3 Behavioral Responses in College Markets

In this section, we present the evidence of how a college market responds to changes in government priorities for majors, which leads to the variation in tuition charges and revenues per student. We start by exploring changes in the average ATAR of applicants by major, which is a level at which financial terms vary. The evidence is presented in Figure 3.

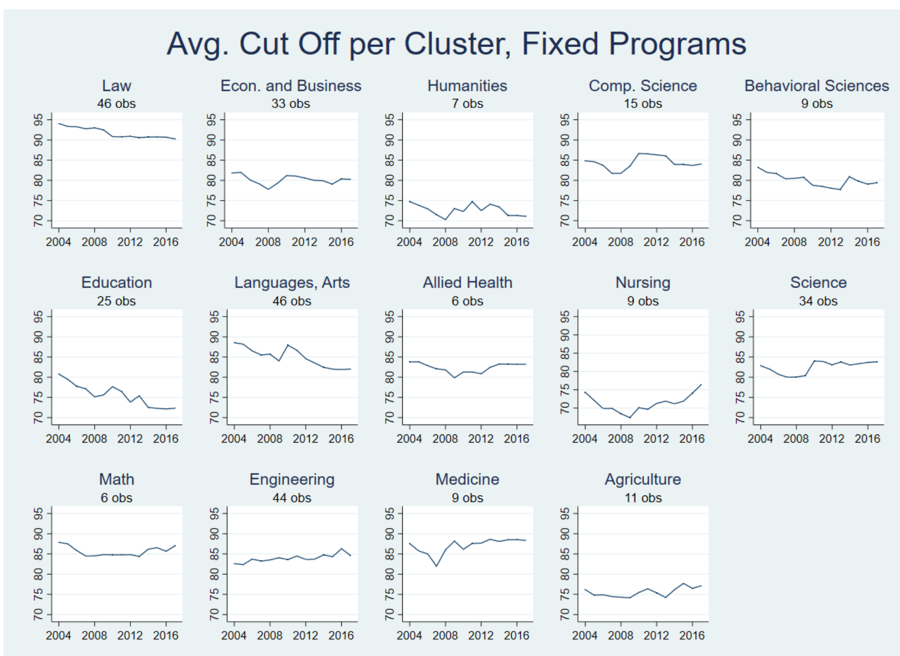
Figure 3: Average ATAR by Major



Notes: Figure illustrates the variation in mean applicants' ATAR by majors based on which government regulates prices.

The Figure suggests that average ATAR among applicants who included programs from a given major varied considerably over time. Note that ATAR represents quantiles, which means that it should display relative attractiveness for students with various performance levels. Law programs tend to constantly attract high-performing students without experiencing significant price fluctuations. ATAR composition in other programs varied considerably over time and cannot be explained solely by changes in prices since most of the time price changes are a result of inflation adjustment. On average, programs in Nursing and Humanities attract students with the lowest average ATAR. All other majors attract students with average ATAR score between 70 and 80. Math tends to attract more high-performing students over time and it reaches Law in terms of the popularity among top-performing students. A sudden rise in popularity of Math coincides with Math being a priority program, which considerably reduced tuition charges paid by students from 2009 to 2013. There might be two forces contributing to such patterns. Firstly, lower tuition charges attract more high-quality students, who might be also more price-sensitive. At the same time, Math programs also receive lower total revenues per student, which implies that they have incentives to reduce the number of students by introducing more stringent admission rules.

Figure 4: Average Cut-off by Major

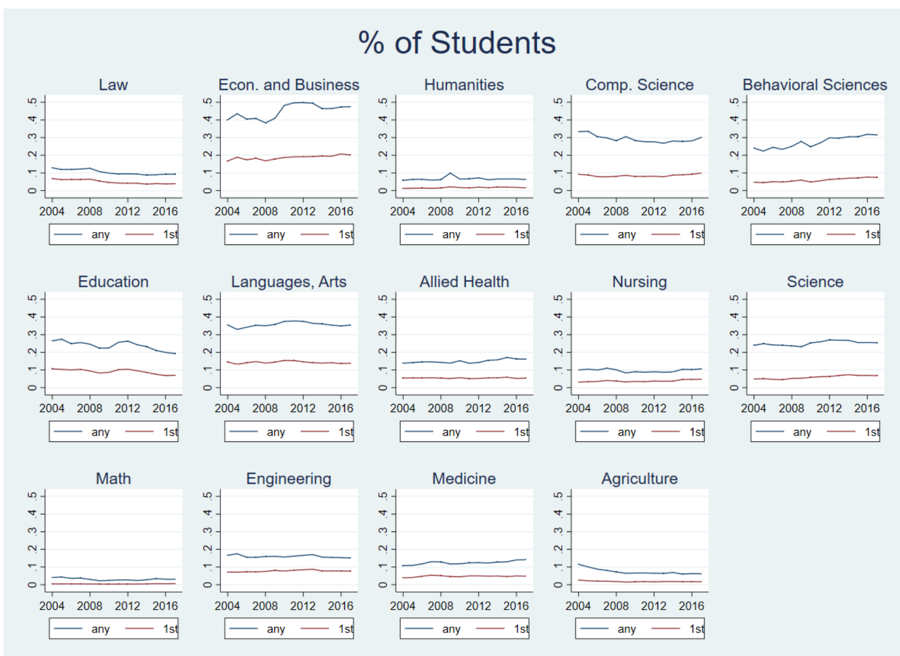


Notes: Figure illustrates a variation in average cutoff in each major group from 2004 to 2017. This evidence includes only those programs, which were available during the entire period under consideration to isolate variation coming from entry and exit.

To explore additional forces that might affect the composition of students, Figure 4 describes changes in admission cutoffs by major over time. Cutoffs have an effect on applicants compositions through a signal of the score that one has to have to be admitted. The first important observation is that Math programs did not considerably raise admission cutoffs, which implies that an upward trend in the average applicant ATAR must be attributed to price sensitivity rather than the programs' actions. At the same time, such majors as Medicine and Allied Health display co-movement patterns in cutoffs and an average applicants' ATAR.

To further exploit the patterns of student decisions, Figure 5 shows how the share of students who included major either into the list or ranked first varied over time. The evidence suggests that Business and Economics is the most popular major meaning that around 40% of students included courses from this major in the list and around 15% ranked a course first. Majors that usually attract high average ATAR, such as Math and Law, are among the least popular. It implies that high average ATAR is achieved by attracting top-performing students. In addition to Economics and Business, popular programs are Computer Sciences, Language and Arts, Education and Science.

Figure 5: Market Shares by Majors



Notes: Figure demonstrates market shares by majors. The red line denotes the percentage of students who ranked the program first. A blue line corresponds to a share of students who included at least one program from a given major to the list. Note that in the latter case, market shares should not sum up to one.

In the remainder of this section we explore more systematically how a college market responds to exogenous changes in financial incentives created by reversal of government major priorities.

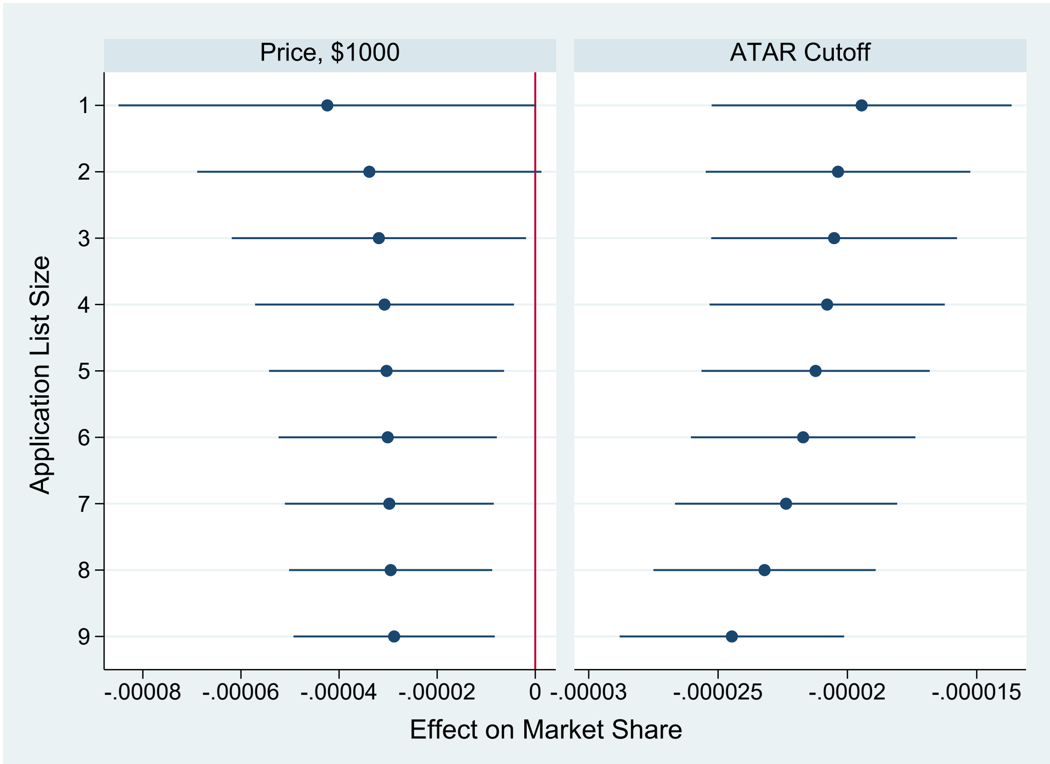
More precisely, we look at how tuition charges affect the decision to apply to a given program. We estimate the following regression:

$$Y_{it} = \beta_0 + \beta_1 \cdot p_{it} + \beta_2 \cdot c_{it} + \gamma_i + \varepsilon_{it} \tag{1}$$

where p_{it} - price paid by students; c_{it} - program cutoff; γ_i - course fixed effects; Y_{it} - market share outcomes, which include a share of students who rank a programs among first k programs.

Figure 6 demonstrates the coefficients from equation (1). The left panel presents the coefficient β_1 for different k, whereas the right panel plots the coefficient β_2. Standard errors are presented at the 95% confidence level and clustered on a program level. Y-axis denotes home many ranks are included in the outcome market share variable (k). For example, the upper coefficient on the left panel shows how student price affects a share of students who ranked the program first, whereas the bottom coefficient on the left panel illustrates the effect on a share of students who included a program at all.

Figure 6: Effect of Tuition Charges and Admission Probabilities on Application Decisions



Notes: Figure demonstrates coefficients from equation (1). Standard errors are clustered on a program level. The left panel presents price coefficient and the right panel corresponds to the cutoff coefficient. The vertical axis shows estimates for different size of the list varying from one, which corresponds to listing the program first, to 9 which would correspond to including the program at all in the list.

Overall, the results suggest that student decisions are moderately sensitive to prices and admission cutoffs. The left panel suggests that price has the most significant effect on the share of students who rank a program first. The coefficients for other market shares are constant around 0.00003 meaning that an increase in tuition charges by 1000 AUD decreases the share of students who include the program in the list by 0.00003. The effect on listing first is around 0.00004. A stronger effect is expected since students mostly care about the program listed first. The reason is that most students are admitted to the first program in their list (Cardak et al., 2016).

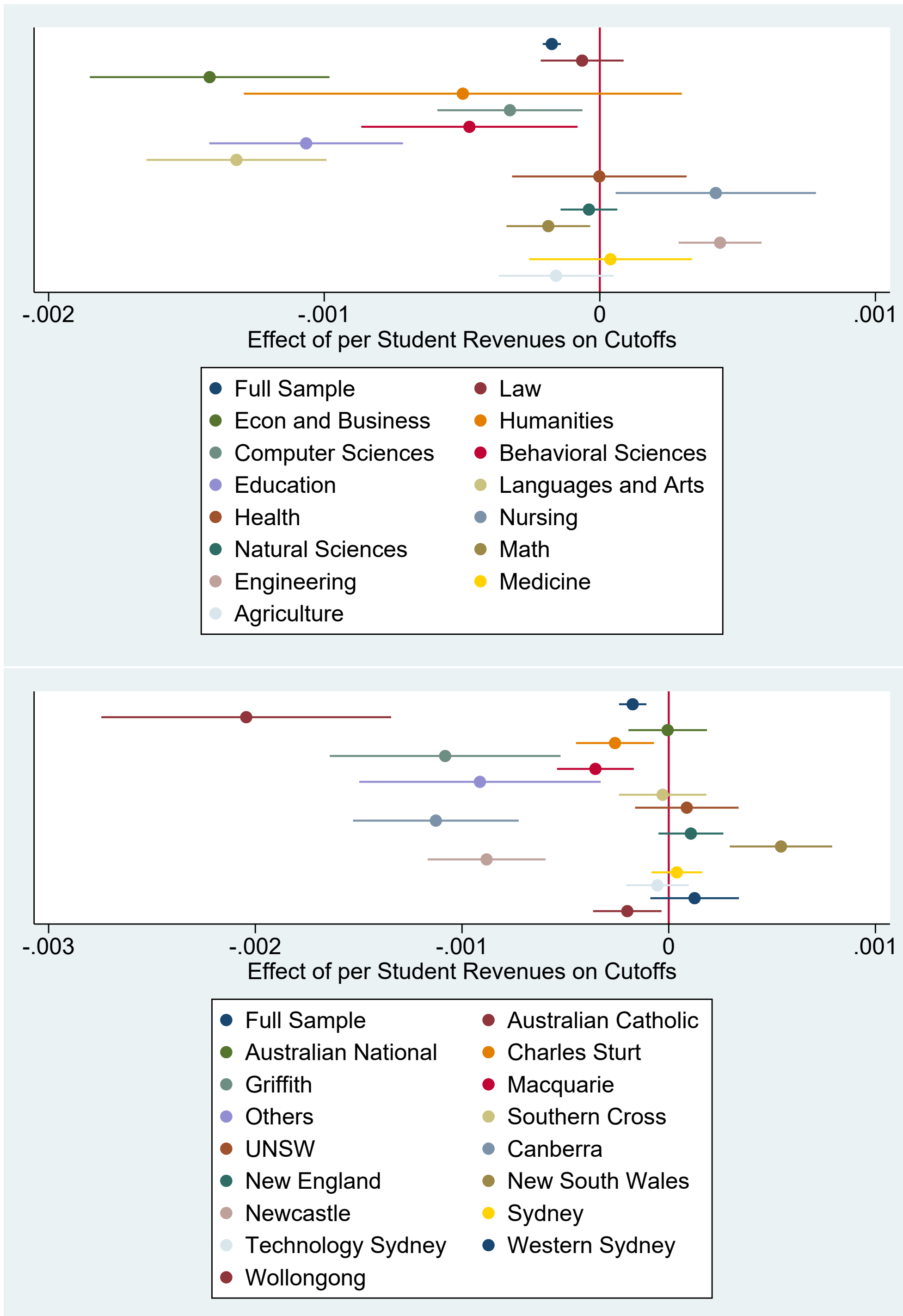
The effect of program cutoffs on a market share is opposite to what is observed for price effects. The highest negative effect of admission requirement is observed for being listed at all in the list. Such a pattern is also in line with the logic of student ranking formation. Given that the list may include up to nine programs and many students do not submit full lists, the programs ranked at the top should not be affected by admission probabilities. The reason is that students are not bounded by the list size should rank programs in the order of preferences disregarding the admission probabilities. The effect on being ranked from 1st to 6th place is around -0.00002. The coefficient gradually goes down and reaches -0.000025 for being included in the list at all. A stronger effect of admission requirements at the bottom of the list suggests that strategic incentives start playing a role in the form of inclusion safe option at the bottom of the list. However, given a small difference in the effect at the bottom of the list and at the top, it is reasonable to believe that the size of the list is long enough to reveal preferences in the order of preferences. It might mean that an overall significant but small effect of cutoffs on market share comes from a signal about the quality of the match and peer effect rather than a strategic portfolio choice.

To investigate the effect of financial incentives on college behavior, we study how colleges respond to changes in per student revenues, which consists of price paid by a student and a government contribution. We estimate the following regression:

$$Y_{it} = \alpha_0 + \alpha_1 \cdot r_{it} + \gamma_i + \varepsilon_{it} \tag{2}$$

where r_{it} - per student revenues; γ_i - program fixed effects.

Figure 7: Effect of Per Student Revenues on Admission Requirement



Notes: Figure presents estimates of α_1 from (2) estimated separately by major (upper figure) and university (lower figure). Standard errors are clustered on a program level.

We estimate this regression separately by major and then by the university to understand the heterogeneity of the responses. The results are presented in Figures 7. The upper part of Figure 7 shows that for most majors, an increase in revenues per student results in less strict admission requirements, which is in line with the existence of a trade-off between financial incentives and benefits of admitting better students. A significant and positive effect, which contradicts previous logic is observed for Nursing and Math, which usually attract low and high ATAR students, correspondingly. The effect for Law, which is another major that constantly attracts the highest performing students and imposes the strictest admission requirements, is statistically insignificant. The effect using the whole sample is negative.

The lower part of Figure 7 presents results by universities. The effect is also negative and significant for most universities. The universities that deviate from this pattern are Wollongong and New England Universities.

The evidence presented in this section was intended to shed light on how the college market responds to financial regulation. We find that tuition charges affect application decisions. This effect is especially pronounced for the probability of listing the program first, which is the most important choice given a high probability of being matched to. At the same time, we find that students internalize the ATAR cutoff that might signal the quality of the match between a program and a student. We observe mixed evidence of programs' responses to changes in revenues per student. One potential explanation is that colleges should also internalize potential responses from competitors. The model described in the next section attempts to describe forces that supposedly determine college market equilibria and will be used to study the effect of alternative college market regulations.

4 Structural Model of College Market

4.1 Student Choice Model

4.1.1 Model

In this section, we present the model of student choice. There are a number of institutional features that motivate modeling choices. Firstly, there are many programs from which students choose and rank up to nine programs. This poses two problems for the estimation of student preferences. Firstly, a naive approach to a problem requires solving a problem of finding an optimal composition of programs out of up to 1000 programs available each year. It is a burdensome computational problem and is unrealistic to assume that students actually solve it. Another important feature of the institutional environment is the presence of choice restrictions meaning that a student cannot submit more than nine choices. It poses a threat to identification of preferences from the observed ROLs (Agarwal & Somaini, 2018). The intuition is that such restrictions might result in the inclusion of programs that are ranked beyond nine programs to ensure admission to at least a low-risk program if it is preferred to an outside option.[18] Despite the fact that we are taking a defensive approach to student preference estimation, a number of theoretical papers concluded that a question of misreporting in large markets might not be important.[19]

Our model has two features that are aimed at addressing these concerns. Firstly, since the main threat to recovering student preferences arises from the restrictions on the size of the ROLs, we estimate student preferences using a subset of those who did not include all 9 programs in the list. These students should submit all the programs of interest in the descending order of desirability.

We also make an assumption that a restricted choice list is the only reasons why students would submit non-truthful application lists and it is exogenous to other preference parameters. Previous literature has documented a number of alternative sources of preferences misrepresentation such as "skipping the impossible" (Fack et al., 2017). We disregard these concerns since a student model will be used as the first stage for a program competition model. We believe that this level of abstraction is sufficient for this purpose.

We assume that students who have submitted less than nine programs are only interested in these programs meaning that other programs are not better than being not admitted at all. To decide on the optimal ranking, a student has to rank only programs from the choice set. We assume that the probability of being in a choice set of a student is a function of student ATAR, university, and major:

$$P\left[j \in S_i\right] = \frac{\exp(\alpha' Z_{ij})}{1+\exp(\alpha' Z_{ij})} \tag{3}$$

where Z_{ij} contains a constant, university FE, major FE and interaction terms of university and major FE with student ATAR.

After a student has drawn a set of programs of interest, she ranks them according to utility. We assume that a student has the following utility function of being admitted to a program j

[18] An outside option is not being admitted, which might differ among students and is not necessarily an undesirable outcome.

[19] Kojima and Pathak (2009) show that a share of students who misrepresent their preferences approaches zero in a market with many participants under the student-optimal stable mechanism. Azevedo and Budish (2018) proposes a concept of strategy-proofness in the large instead of just strategy-proofness. It is shown that when the mechanism "prices" are treated by an applicant as exogenous to her choice, truthful reporting is a dominant strategy.

from a choice set S:

$$U_{ij} = \beta' X_i + \varepsilon_{ij} \tag{4}$$

where X_i is a vector of program characteristics that include price, major and university; ε_{ij} is an error term distributed as Type 1 extreme value.

A probability that a student ranks a program j higher than all programs in a choice set S is:

$$P(U_j > U_k, \quad \forall k \in S_i) = \frac{\exp(\beta' X_j)}{\sum_{k \in S_i} \exp(\beta' X_k)} \tag{5}$$

A practical advantage of this two-stage model is that we can treat the observed submitted ROL as a realization of a random draw of programs into and then as a ranking problem of considerably reduced choice set. It means that in the case of a student who did not submit nine programs, we can treat the set of observed ranked programs as an entire choice set.

The key object from the student model used in the estimation of college preferences is a probability that a student i chooses a program j if she satisfies the admission requirements. This probability is a composition of a probability that a program j is in the choice set of a student i, a probability that a program j is ranked above all other programs in the choice list S_i and that a student satisfies admission requirements of program j as well as all other programs in a choice set.

$$P_{ij} = \frac{P[j \in S_i] \cdot \mathbb{1}[ATAR_i > \xi_j] \cdot \exp(\beta X_j)}{\sum_{k \in S_i} P[k \in S_i] \cdot \mathbb{1}[ATAR_i > \xi_k] \cdot \exp(\beta X_k)} \tag{6}$$

Equation (6) is a composition of equations (4) and (5). More precisely, the formula expresses the probability of being ranked first by a student i taking into account the probabilities that each program is in the choice list of a student i and that a student satisfied the test score admission requirements for the programs of interest.

4.1.2 Estimation

Given this two-stage structure of the model, we estimate the vectors of parameters α and β separately. As discussed above, since restricted choice lists raise concerns about truthfulness of submitted ROLs, we use a sub-sample of students who have listed less than nine programs in their applications to estimate student preferences. An important assumption is that preferences obtained from the chosen sub-sample are generalizable to the remaining part of the student population. One important note is that not all students who submitted all nine programs necessarily deviate from a truthful ranking of programs. The reason is that those who have exactly nine programs in their choice set also do not have incentives to misrepresent the ranking. However, since it is impossible to disentangle those who manipulate the ranking from those who truthfully rank the programs, we use a subset of those who rank strictly less than nine programs.

We firstly estimate a logit model whether a student i included a program j in the application portfolio using maximum likelihood based on equation (4):

$$\log L = \sum_i \sum_i y_{ij} \cdot \log\left(P\left[j \in S_i\right]\right) + (1 - y_{ij}) \cdot \log\left(1 - P\left[j \in S_i\right]\right) \tag{7}$$

Using only actual observed ranking data, we estimate a ranked-order logit model based on equation (5). The probability of observing a given ranking of the programs from the choice set is:

$$P_i\left[\{r = j\}_{r=1}^{R}\right] = \prod_{r=1}^{R} \frac{\exp(\beta' X_j)}{\sum k \in S^r \exp(\beta' X_k)} \tag{8}$$

where r is a given place in ranking; S^r is a choice set after excluding programs that were included in the rank at the position above r. More precisely, for $r = 1$, S^r is an initial set S. For $r = 2$, S^r is the same as S but excluding the program that was ranked first.

Equation (5) leads to a simple ranked ordered logit model.

4.2 College Market

4.2.1 Model

In this section we describe a model of college program choice of admission requirements in the form of ATAR cutoffs, ξ. The model attempts to capture key features of competition for students among colleges. We assume that colleges' decisions are affected by total revenues and quality of admitted pool of students in the form of the average ATAR score. Therefore, a college program j chooses a cutoff ξ_j that maximizes the following utility function:

$$V_j = \left[\alpha \cdot (D(\xi_j, \psi_j) \cdot R_j)^r + (1 - \alpha) \cdot AT\bar{A}T(\xi_j, \psi_j)^r\right]^{\frac{1}{r}} \tag{9}$$

where $D(\xi_j, \psi_j)$ is an expected number of admitted students for program j as a function of own cutoff ξ_j and expected cutoffs of all other programs presented on the market except j, ψ_j; R_j - per student government-regulated revenues that vary across majors over time; $AT\bar{A}R(\xi_j)$ average expected ATAR of admitted students.

An important clarification regarding the chosen functional form of colleges' utility is that although share parameters α mean weight on revenues compared to average ATAR, the scale of the parameter depends on the scales of components. In other words, one component in the utility function is total revenues in thousands of Australian dollars that has a support of any positive number, whereas the average quality of student pool has support from 0 to 100. It implies that coefficients α partly reflect scale differences and partly actual weights in the utility function. A parameter r is bounded above by 1, where revenues and quality of a student pool are perfect complements. If r goes to $-\infty$, these components become perfect substitutes. $r = 0$ is a special case which leads to a Cobb-Douglas function. Although the Cobb-Douglas function might seem an appealing functional form choice, it exhibits an undesirable property. Because of the multiplicative form of revenues consisting of demand and per student revenues, the latter has no effect on the cutoff choice. It can be shown by constructing the first order condition of the Cobb-Douglas production function version. The component R^{α} would simply play a role of the technology component and hence would not affect the cutoff decision. This property is undesirable and unrealistic with respect to the goal of the model and the main variation that allows identifying the parameters of the model. Therefore, a more general CES utility function is chosen.

The expected number of enrolled students follows from the equation (6) and can be expressed:

$$D(\xi_j, \psi_j) = \int_{\xi_j}^{100} P_{ij}(\eta, \psi_j) \cdot dF(\eta) \tag{10}$$

Equation (10) suggests that the expected demand is just a sum over probabilities that program j is in the list and is ranked first across students who meet the ATAR requirements ξ_j. One important limitation of our data is that although we observe each year cutoffs for each program, we do not observe actual admission and enrollment decisions. It means that despite the fact that we, for example, know that a minimum cutoff was 70, it implies that no students with ATAR 70 were admitted but from that, it does not follow that all students with ATAR higher than 70 were admitted. Therefore, we have to make an assumption that if a program gives an offer to a student with ATAR ζ, it must offer a place also to all students with an ATAR score above ζ. A need for this assumption can be viewed as a consequence of the measurement error. Deviations from the published cutoffs might come from colleges taking into account other minor factors not captured by the ATAR score such as essays or extracurricular activities. Since the UAC website and anecdotal evidence suggests that ATAR is the main determinant of the admission decisions, we believe that measurement error should not play a crucial role.

Expected ATAR of admitted students is defined as follows:

$$A\bar{T}AT(\xi_j) = \frac{\int_{\xi_j}^{100} P_{ij}(\eta, \psi_j) \cdot \eta \cdot dF(\eta)}{\int_{\xi_j}^{100} P_{ij}(\eta, \psi_j) \cdot dF(\eta)} \tag{11}$$

One of the components of enrollment probability from equation (6) is a probability that a student i meets the admission requirement of all other college programs in the admission year. This is where ψ_j plays an important role by denoting cutoff decisions of all other colleges on the market. This element introduces a competition channel. It means that when deciding on the cutoff, college programs have to internalize the probability that each student will be offered a place by all competitors if applies. The fact that each application year contains slightly less than 1000 programs and around 40 000 students makes the problem of finding a Nash equilibrium of the game highly multidimensional and problematic to solve. Furthermore, solving the game once will not be enough since the game has to be solved repeatedly to find a set of college program behavioral parameters. Therefore, we impose the following equilibrium concept, which we refer to as the Large College Market Equilibrium (LCME):

Definition 1. *Large College Market Equilibrium (LCME):*

1. *College programs have beliefs about cutoff responses of other colleges to market state variables. These beliefs are based on previously observed changes in per student revenues $\psi(\mathbb{R})$, where $\mathbb{R}$ is a collection of all per student revenues on the market.*

2. *Each program chooses the cutoff that maximizes utility function (9) given beliefs about the behavior of competitors defined by a function $\psi(\mathbb{R})$.*

Such a definition of a market equilibrium has a number of convenient and, in our view, realistic features. Firstly, college programs compete on the same market over many years and, most likely, have extensive information about the strategic behavior of competitors. It motivates the idea that when making its own strategic decision and knowing changes in market prices, they can use a basic inference model to predict the responses of the competitors. Apart from being realistic, this assumption also allows overcoming computational burden of solving this model, which otherwise would require looping over all possible strategies of all competitor to find a Nash equilibrium in a market with many players.

We parametrize the beliefs about a competitor k cutoff as follows:

$$\psi_{t,k}(\mathbb{R}) = \left(\gamma_0 + \sum_{m=1}^{M} \gamma_m R_m + \gamma_\psi \psi_{t-1,k} \right) \cdot \sum_{n=1}^{M} \mathbb{1}[m_k = n] \cdot \delta_n \tag{12}$$

The formulation in equation (12) means that colleges have linear beliefs about competitors' cutoffs, which depend on a previous observed cutoff $\psi_{t-1,k}$ and revenues in each major $m \in M$. The component $\sum_{n=1}^{M} \mathbb{1}[m_k = n] \cdot \delta_n$ means that all the coefficients in the linear prediction function vary over majors themselves.[20]

4.2.2 Estimation

We estimate the model using Generalized Method of Moments. We match equally spaced 50 percentiles of the cutoffs distribution. We find parameters by minimizing the following criterion function:

$$\theta^* = \arg\min(m - \hat{m}(\alpha, r))' W (m - \hat{m}(\alpha, r)) \tag{13}$$

where m is a vector of data moments; $\hat{m}(\alpha, r)$ - vector of parameters generated by the model; W - weighting matrix.[21]

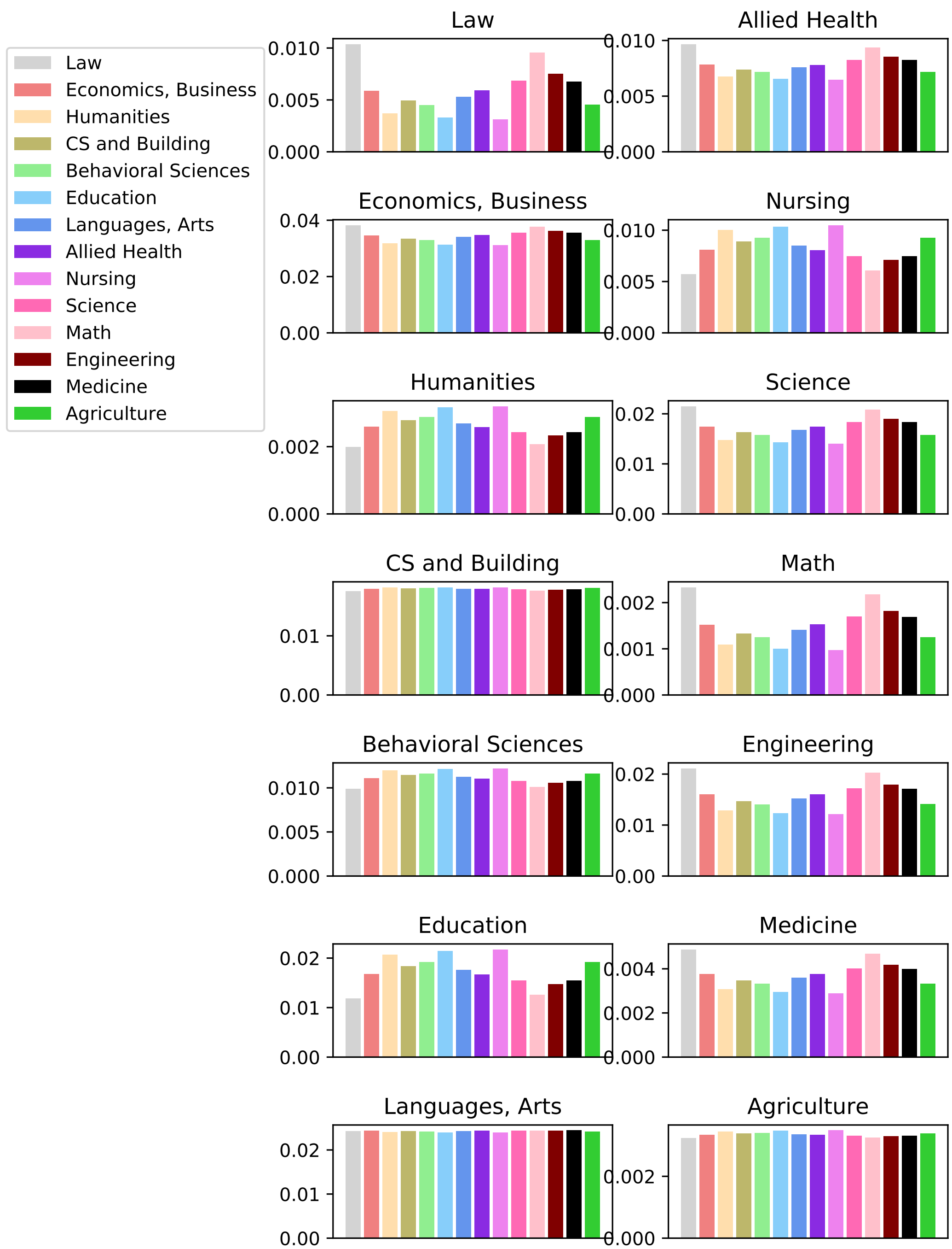
4.3 Results

This section presents the main results of the structural model outlined in this section. We start with the results of the student decision model. Tables 3 and 4 in Appendix present parameter estimates. In this section, instead, we present substitution patterns that stem from the model estimates. Figure 8 describes substitution patterns across majors while Figure 9 illustrates substitution patterns across universities. More precisely, each of the figures denotes price elasticity averaged over majors or universities.

[20]Note that a linear form might result in predicted cutoffs being outside of the support $[0, 100]$. In this case, we substitute the value outside of the support with a closest bound of the support.

[21]We use an identity matrix. To obtain standard errors, we use bootstrap with 100 draws with replacement.

Figure 8: Demand Substitution across Majors



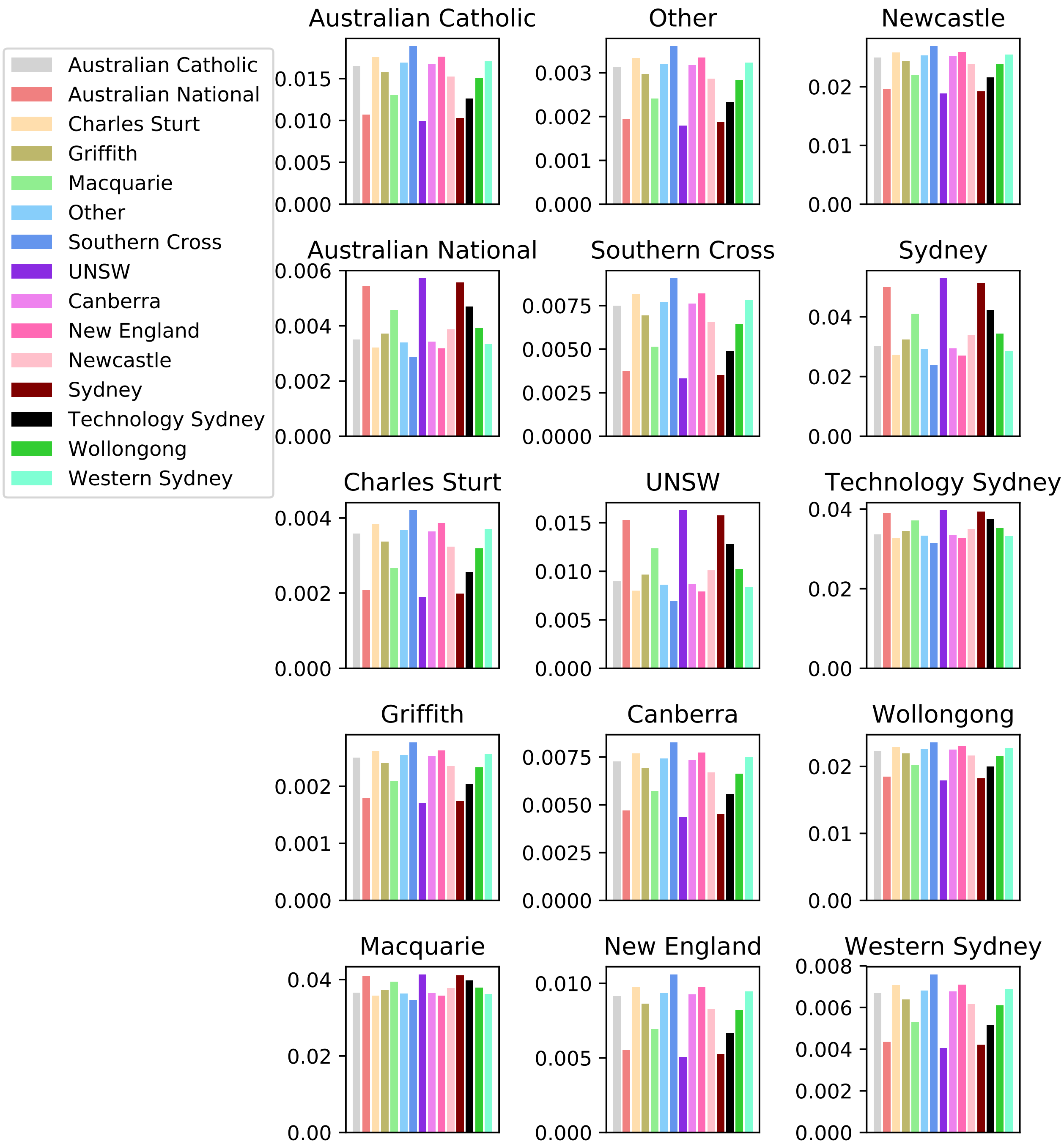
Notes: Figure presents estimates of elasticities by majors. Each box contains a number of bars for each major. Each bar denotes the percentage of students who would switch to a given major if a price for a program increases by 1%

Figure 8 presents subplots for each major in which each bar denotes a percentage of students who switch to a program in the corresponding major if a price for a given program increases by one percent. For example, the upper left bar for Law programs shows that if a price for a Law program increases by one percent, most of the switchers (0.1% of demand) would choose another Law program. The next popular choice would be Math (0.08% of demand). Other majors with a dominant "self-substitution" pattern are Nursing and Education. Languages and Arts, Agriculture and Computer Science, and Building have evenly distributed substitution patterns across all majors. Law is the most popular major to switch to. For example, in addition to being a dominant substitution option for itself, it is also the most popular for Allied Health, Economics and Business, Science, Math, Engineering and Medicine programs. Nursing is also a popular substitution option, especially for Humanities, Nursing, Behavioral Sciences, and Education. Overall, the Figure suggests that students have very heterogeneous preferences for majors since an increase in prices is predicted to result in an application to programs from different majors. These results are intuitive and follow directly from the fact that many students tend to be interested in many majors simultaneously and include them in the application lists.

Apart from the substitution patterns, overall elasticity to price changes differs across majors. The highest elasticity is observed for Economics and Business, Languages and Arts and Computer Science and Building. Agriculture, Math, and Medicine are among price inelastic majors.

Figure 9 demonstrates similar evidence across universities. In contrast to the previous case, preferences over universities are more salient meaning that none of the universities have uniformly distributed cross-elasticities among other colleges. In most of the cases, the University of New South Wales or Southern Cross Universities are main switching option. Students prefer to switch to programs from the same university for Australian National University, Southern Cross University and University of New South Wales. Universities with the most elastic demand are Australian Catholic University, Macquarie University, University of Sydney, University of Newcastle, University of Technology Sydney and the University of Wollongong.

Figure 9: Demand Substitution across Universities



Notes: Figure presents estimates of elasticities by universities. Each box contains a number of bars for each university. Each bar denotes the percentage of students that would switch to a given university if a price for a program increases by 1%

The second step of the model is estimation in programs' preferences that together with preferences of students determine the outcomes of the market. Recall that parameters that explain college cutoffs in the model are share parameter of the CES production function (α), which is a weight that colleges put on a specific component of the utility function and a parameter r that expresses the degree of substitution between revenues and the expected quality of admitted students. In the main specification presented in the paper, we allow all these parameters to be university-specific for sufficient heterogeneity in the model.[22] Table 2 presents parameters of the model.

Although absolute values of α parameters in the model are hard to interpret, relative comparison is possible. The parameters suggest that programs from Australian Catholic University and Charles Sturt University (all campuses) place the highest weight on financial gains compared all other programs. In contrast, programs from the University of Sydney, University of New South Wales and Macquarie University have a strong focus on the overall quality of students when making admission decisions. These parameters suggest that most prestigious universities in the region focus on quality of the admitted pool, which might signal an important role of reputation, whereas less prestigious colleges react more to price changes. The model estimated in this paper is static in the sense that decisions of colleges are only determined by current market conditions and programs do not internalize the impact of a decision on future outcomes through, for example, reputation. Therefore, we do not explore this question in more details in this paper. Overall, we find significant heterogeneity in α parameters across universities. It not only reflects different preferences for monetary gains but possibly differences in cost structures as a result of being affiliated to different universities.

[22]The reason is that key variation in the model that allows identifying parameters of interest is the variation in subsidies and prices across majors.

Table 2: College Model Parameters

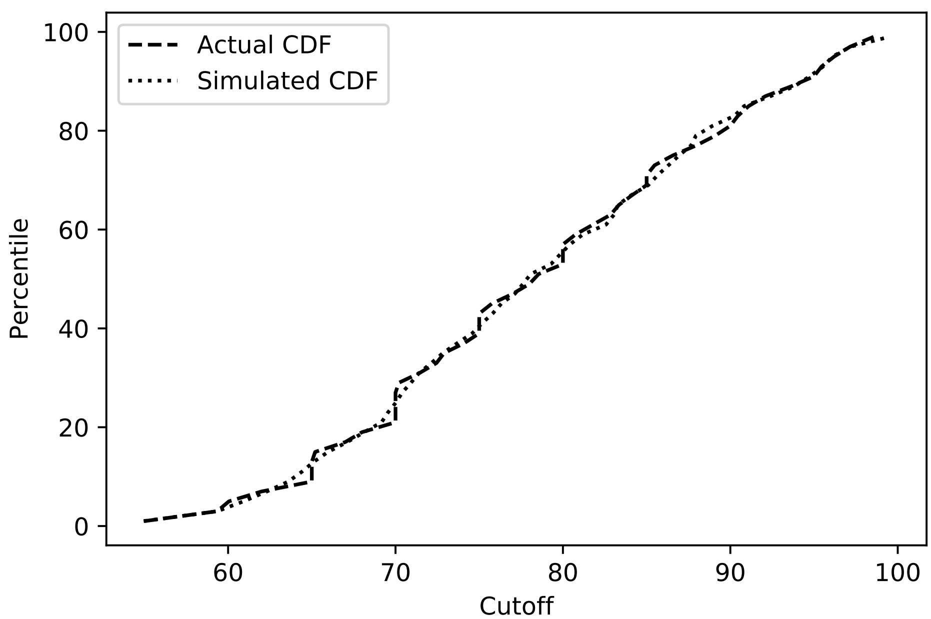
	α	r
Australian Catholic University	0.214397	-0.135049
	(0.00200952)	(0.00210807)
Australian National University	0.173522	-0.037721
	(0.00117618)	(0.00780676)
Charles Sturt University	0.0206467	-0.621324
	(0.00731124)	(0.266071)
Charles Sturt University - Bathurst	0.125085	-0.118208
	(0.00574016)	(0.124865)
Charles Sturt University - Wagga Wagga	0.093215	-0.702761
	(0.0162217)	(0.301881)
Griffith University	0.118947	0.368549
	(0.00215637)	(0.00986394)
Macquarie University	0.0304149	-4.98925
	(0.00736678)	(0.0130811)
Other	0.128765	0.0134385
	(0.00160913)	(0.0224744)
Southern Cross University	0.111901	-0.186905
	(0.000930401)	(0.0366673)
UNSW Australia	0.060354	-0.493937
	(0.00132744)	(0.0814062)
University of Canberra	0.133444	0.217833
	(0.00083535)	(0.0190935)
University of New England	0.0999119	-0.198914
	(0.00079801)	(0.0094933)
University of New South Wales	0.0725893	-0.399736
	(0.00202217)	(0.0378579)
University of Newcastle	0.0932283	0.189342
	(0.000777019)	(0.00274217)
University of Sydney	0.075227	-4.41869
	(0.00720078)	(0.45144)
University of Technology Sydney	0.0853021	-0.0776609
	(0.00132436)	(0.0102248)
University of Western Sydney	0.117248	0.091255
	(0.000384809)	(0.00251997)
University of Wollongong	0.0973293	0.0894362
	(0.00188962)	(0.0392899)
Western Sydney University	0.115891	0.173925
	(0.000479805)	(0.00629672)

Notes: Standard errors presented in parentheses are estimated using bootstrap with 100 draws.

We also find considerable heterogeneity in complementarity of monetary gains and quality of admitted students. Complementarity in this model means that in the event of considerable changes in revenues, colleges cannot fully react by changing admission requirements, which would move average quality of admitted students to the opposite direction. We find that programs in such universities as Australian National University, Griffith University, University of Canberra, University of New England and Western Sydney University show signs of high substitutability between average ATAR of admitted students and revenues, which allows them to react more to price changes. Macquarie University and the University of Sydney display high complementary between financial gains and quality of admitted students.

The model fits the data well, which is presented in Figure 10. We present the model fit results in terms of the moments used in the estimation, which correspond to the CDF of a cutoff distribution.

Figure 10: Model Fit



Notes: Figure demonstrates a model fit in terms of percentiles of a cutoff distribution pooled over all years.

In the next section, we use the model and estimated parameters to study counterfactual policies that affect program revenues and tuition charges.

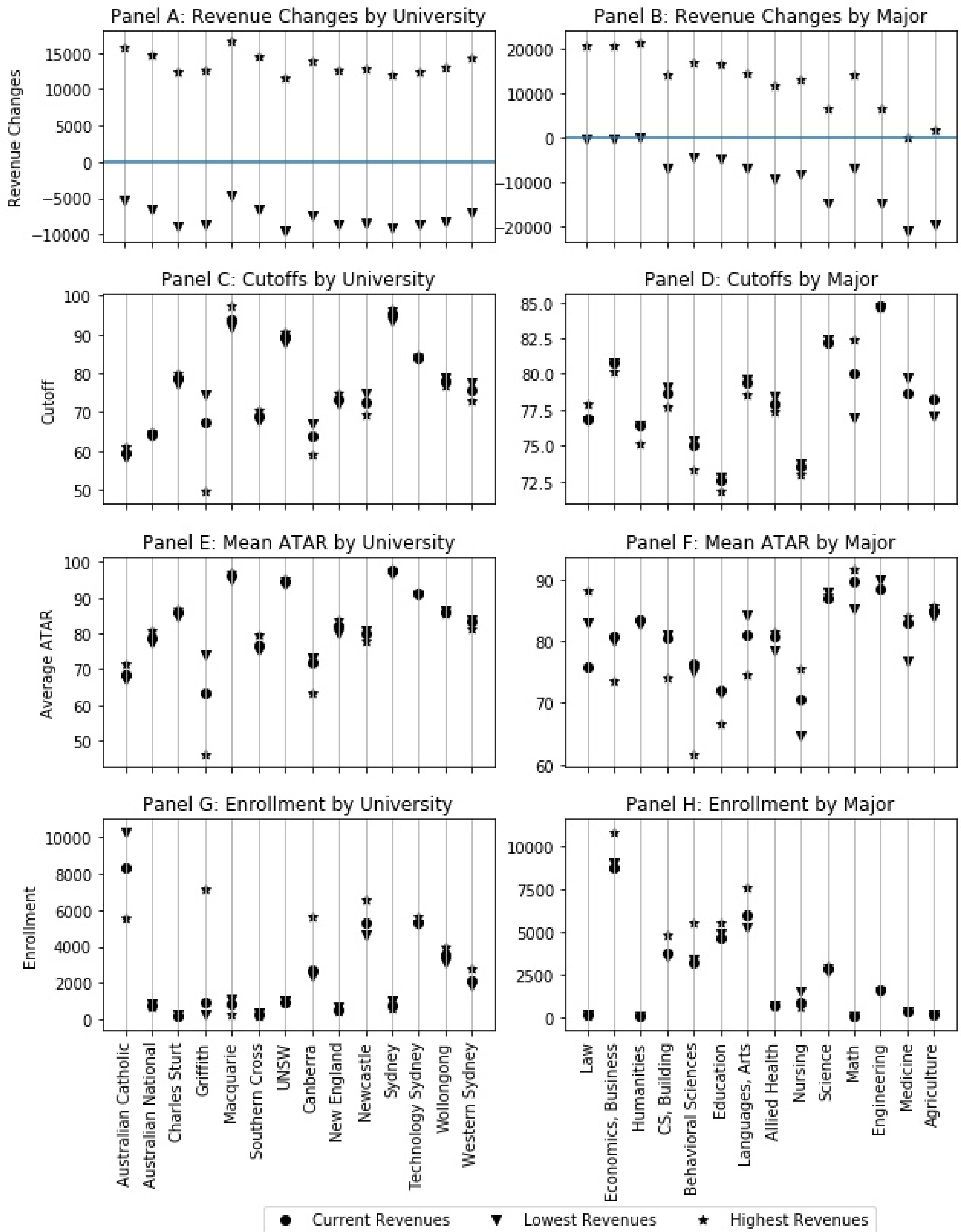
5 The Effect of Financial Regulations in College Markets

In this section, we use the model to study a number of counterfactual regulations in college markets. We study the effect of two types of interventions. Firstly, we simulate counterfactual market outcomes in terms of college admission requirements (cutoffs), enrollment patterns and student composition under different revenues of university programs. Another counterfactual policy concerns changes in student prices while keeping college revenues constant. The choice of counterfactual policies is driven by both, the interest in the effect of financial terms on college market outcomes and credibility of the analysis given the structure of the model. The latter means that an important assumption in the model that significantly restricts the choice of counterfactual policies is a structure of beliefs about competitors' responses. Proposed counterfactual policies fit well into this model since it is intended to capture these patterns. However, another potentially interesting set of counterfactual policies such as the effect of removal of price regulations, which would allow colleges to freely set both prices and cutoffs, is inappropriate for this model. The reason is that the proposed equilibrium concept will not hold not only since changes are too dramatic but also because programs will not have price information to make predictions about competitors' responses. In this case, the model requires a different equilibrium concept which handles a price setting scenario. However, in the absence of variation in the data that would inform parameters responsible for price competition, such counterfactual policies might be an unconvincing extrapolation exercise.

To analyze the effect of counterfactual policies, we focus on the 2017 admission year. We start with the effect of alternative regulations of college revenues. More precisely, we study how admission requirements and enrollment change if revenues of all programs are reduced to the minimum and raised to maximum observed values in 2017. It means that we consider identical revenues per student for all colleges. Figure 11 demonstrates the effect of such changes.

In these counterfactuals, we change revenues from unequally distributed across majors and hence universities to identical. It means that depending on the major affiliation, different programs will face different price changes. We depict actual price changes averaged on university (Panel A) and major levels (Panel B). The only channel how these policy changes affect the market is through changes in admission requirements. Colleges change the admission requirement because they have to re-optimize according to the utility function. In addition, colleges need to adjust cutoffs even if revenues have not been changed because of competitors' responses.

Figure 11: Effect of Changes in College Revenues on Market Outcomes



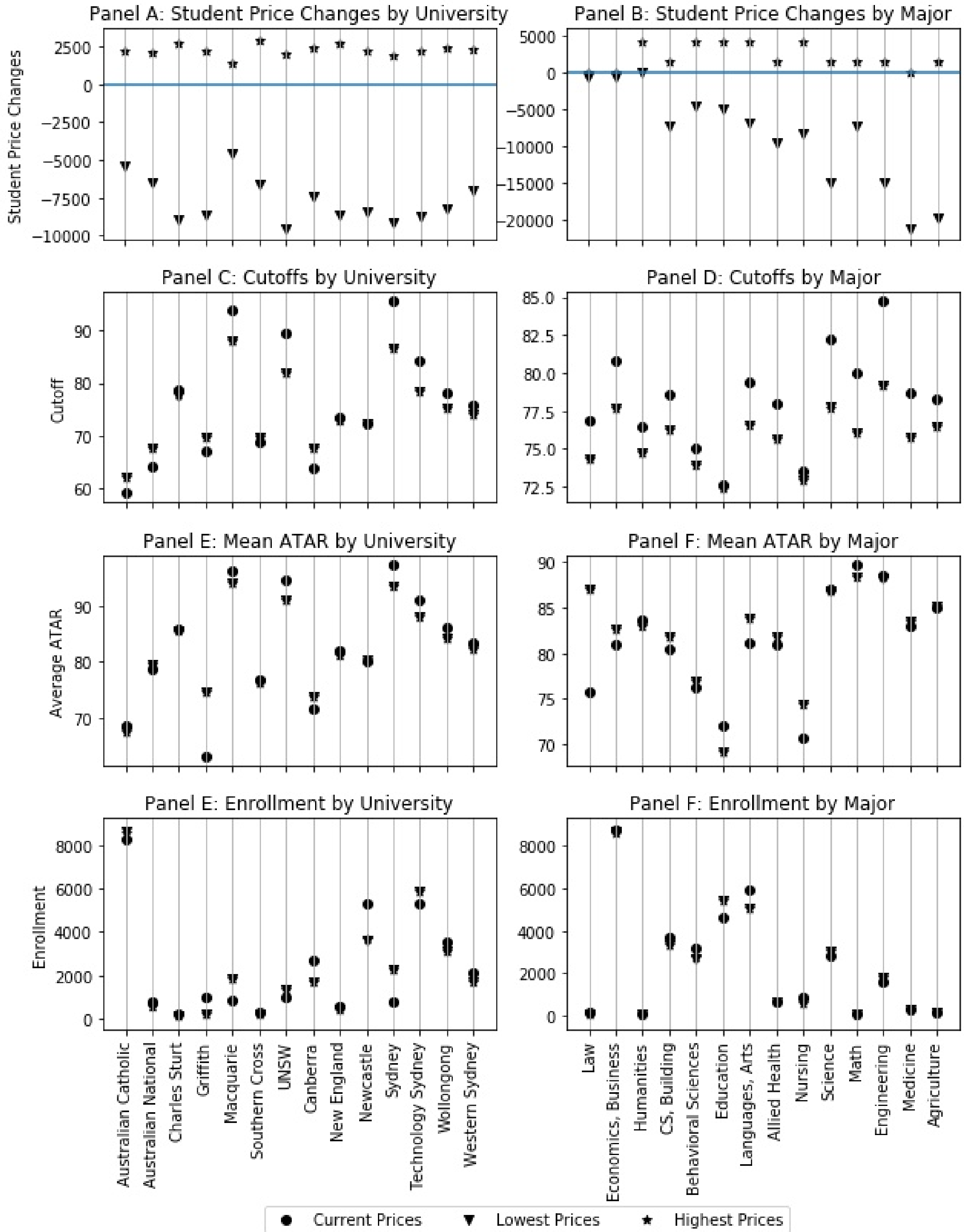
Notes: Panel A and B demonstrate counterfactual changes in financial terms. Panels C and D show how colleges would respond in terms of changing admission requirements. Panels E and F present the market outcomes in terms of resulted average ATARs while G and H in terms of a number of enrolled students.

The results suggest that changes in college revenues would result in heterogeneous responses from university programs. Looking at the aggregation by universities, most of the changes in terms of admission cutoffs would come from Griffith University, Macquarie University, University of Canberra and the University of Newcastle. The results suggest that none of the prestigious universities would significantly react by changing admission requirements despite fairly considerable changes in financial incentives. Despite fairly modest responses in terms of admission requirements, some universities will experience sizable changes in enrollment. For example, although programs from Australian Catholic University almost do not adjust cutoffs on average, considerably higher enrollment is expected as a result of reduced revenues and lower by 2000 students in case of higher revenues. The reduction in enrollment comes from the responses of competitors. Considerable changes in the composition of students by ATAR score would only be observed by schools which experienced changes in enrollment.

Results aggregated by majors presented in the right column suggest the absence of such dramatic jumps as in the case of the aggregation by university. Law majors would slightly respond in terms of cutoffs and would not experience considerable demand changes despite the fact that a composition of students will increase under both scenarios. This would happen even for the case of lowering down student prices, which would imply no changes for Law programs. The effect is fully attributed to the responses of other majors and substitution of students to and from Law programs. Economics and Business programs would only experience higher revenues and would lower down cutoffs. It would bring about nearly 2000 more enrolled students but overall lower average ATAR by 18 points. The most considerable changes are observed for Behavioral Sciences in which case a price increase leads to a 3 points lower average cutoff but more than a 15 points lower average cutoff translated into around 1500 more enrolled students. Similar ordinal responses are predicted for CS, Languages and Art, and Education programs. Nearly no changes are expected for Math, Engineering, and Agriculture on average.

Next, we proceed to analyzing the market responses to changes in prices paid by students illustrated in Figure 12.

Figure 12: Effect of Changes in Student Tuition Charges on Market Outcomes



Notes: Panel A and B demonstrate counterfactual changes in financial terms. Panels C and D show how colleges would respond in terms of changing admission requirements. Panels E and F present the market outcomes in terms of resulted average ATARs while G and H in terms of a number of enrolled students.

The reason why programs might have incentives to respond by changing the admission requirements is to compensate students for higher prices and prevent them from switching to competitors. The overall results are very similar while looking at both aggregation levels. Some colleges depending on price changes to adjust cutoffs accordingly. As a result, the overall composition of ATAR and enrollment patterns would stay nearly the same for most programs. Changes would only be observed on the aggregate level for Griffith University, Macquarie University, University of Newcastle and University of Sydney. Enrollment patterns across majors would be very similar to the status quo case. Changes in student composition are observed for Law, Education, Languages and Art, and Nursing.

6 Conclusions

This paper is one of the first attempts to systematically study the determinants of equilibria in college markets. We leverage an appropriate set-up of the Australian higher education system that provides both detailed administrative data and appealing institutional environment that includes variation in set student prices and university revenues.

We provide novel empirical evidence of the effect of government price regulations on market outcomes in the form of student demand for college education and strategic responses of colleges to such regulations. The results suggest that students are relatively price-insensitive. One of the explanations is that pricing is major based. The presence of strong preferences for majors or universities would dominate demand responses to major-based price changes. We observe very heterogeneous responses of colleges to changes in financial incentives.

Upon documenting this evidence, we construct and estimate a student choice and college competition model. Conditionally on student preferences and financial terms, colleges compete with each other by setting the admission requirements. Estimation of the model allows obtaining student preference parameters including price sensitivity as well as major and university preferences. Estimated student preferences, which are in line with the reduced form evidence, show small price sensitivity and strong preferences for major and college affiliation. The results of the model of college competition suggest considerable heterogeneity in preferences, which should be an important channel through which government price interventions affect the market outcomes.

Using the model, we study the effect of changes in financial conditions for students and colleges on the market outcomes in terms of admission requirement and enrollment patterns. We conclude that changes in college revenues would result in changes in admission requirements, which overall would lead to redistribution of enrollment. It forces programs to adjust admission cutoff. These results suggest an important role of financial incentives in college markets.

The main limitation of the study stems from the measurement error in the college admission decisions. Therefore, future work studying student decisions in college markets is required. In addition, the competition model estimated in this paper allows overcoming computational burden associated with the market size. However, given heterogeneity and clustering of the market by majors and universities, a promising approach to estimating the game with many players might be to use a machine learning algorithm to cluster programs in sub-markets where competition is more severe. It would allow reducing the burden of estimating a game on a larger market by substituting it with many smaller markets instead of imposing the assumption about the structure of beliefs about competitors' responses.

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A Appendix

Table 3: Selection in the Choice Set Model

	Parameters	Std. Errors
2.cgroup	7.1896578	(0.1511461)**
3.cgroup	6.9349832	(0.1655056)**
4.cgroup	7.6474777	(0.1524289)**
5.cgroup	7.5656049	(0.1528365)**
6.cgroup	8.5298571	(0.1514722)**
7.cgroup	7.3846193	(0.1517630)**
8.cgroup	5.1977329	(0.1624109)**
9.cgroup	7.8934658	(0.1554531)**
10.cgroup	6.0314418	(0.1554143)**
11.cgroup	1.9132708	(0.2760250)**
12.cgroup	5.7293555	(0.1588721)**
13.cgroup	3.6886528	(0.1746649)**
14.cgroup	6.2491104	(0.1640343)**
15.cgroup	6.5188498	(0.1554640)**
2.cuni	-5.3317243	(0.1557347)**
3.cuni	-1.0660354	(0.1017142)**
4.cuni	-0.9409696	(0.0997257)**
5.cuni	-1.5690692	(0.1092466)**
6.cuni	-1.8020550	(0.1157411)**
7.cuni	-1.2752882	(0.0640810)**
8.cuni	-1.2647041	(0.1134505)**
9.cuni	-0.0409580	(0.0788016)
10.cuni	-5.2752688	(0.1099343)**
11.cuni	-0.7355024	(0.0831773)**
12.cuni	-0.3518560	(0.0766283)**
13.cuni	-3.8243905	(0.0808241)**
14.cuni	-0.0243183	(0.0614077)
15.cuni	-3.9202510	(0.0678565)**
16.cuni	-1.4208890	(0.0629519)**
17.cuni	1.4167146	(0.0561684)**
18.cuni	-0.4225894	(0.0641340)**
19.cuni	-0.7616461	(0.0873632)**
2.cgroup#c.atar	-0.0144630	(0.0011465)**
3.cgroup#c.atar	-0.0390164	(0.0015092)**
4.cgroup#c.atar	-0.0301862	(0.0011817)**
5.cgroup#c.atar	-0.0304977	(0.0011917)**
6.cgroup#c.atar	-0.0413959	(0.0011629)**
7.cgroup#c.atar	-0.0217964	(0.0011623)**
8.cgroup#c.atar	-0.0059246	(0.0013625)**
9.cgroup#c.atar	-0.0421144	(0.0012722)**
10.cgroup#c.atar	-0.0100588	(0.0012338)**
11.cgroup#c.atar	0.0102948	(0.0029390)**
12.cgroup#c.atar	-0.0089671	(0.0012961)**
13.cgroup#c.atar	0.0072755	(0.0015505)**
14.cgroup#c.atar	-0.0302163	(0.0014411)**
15.cgroup#c.atar	-0.0159356	(0.0012583)**
1b.cuni#c.atar	0.0017284	(0.0012910)
2.cuni#c.atar	0.0598063	(0.0020552)**
3.cuni#c.atar	-0.0030499	(0.0017407)
4.cuni#c.atar	-0.0031632	(0.0017211)
5.cuni#c.atar	0.0043798	(0.0017917)*
6.cuni#c.atar	0.0048170	(0.0018591)**
7.cuni#c.atar	0.0314050	(0.0012144)**
8.cuni#c.atar	-0.0042452	(0.0018973)*
9.cuni#c.atar	-0.0102833	(0.0014603)**
10.cuni#c.atar	0.0707664	(0.0015793)**
11.cuni#c.atar	0.0015486	(0.0014743)
12.cuni#c.atar	-0.0014208	(0.0014035)
13.cuni#c.atar	0.0601466	(0.0013325)**
14.cuni#c.atar	0.0121389	(0.0012065)**
15.cuni#c.atar	0.0704902	(0.0012241)**
16.cuni#c.atar	0.0355667	(0.0012030)**
17.cuni#c.atar	-0.0053981	(0.0011704)**
18.cuni#c.atar	0.0145435	(0.0012313)**
Constant	-9.7856088	(0.1554758)**
N	7,606,812	

* $p < 0.05$; ** $p < 0.01$

Notes: Table presents results of the logit model of inclusion a program in a choice set from the equation (3).

Table 4: Program Ranking Model

	rank
price	-0.0035054
	(0.0026431)
2bn.cgroup	0.8296572
	(0.0090693)**
3.cgroup	0.7678708
	(0.0169507)**
4.cgroup	0.9334394
	(0.0106660)**
5.cgroup	1.0280744
	(0.0138866)**
6.cgroup	0.9296877
	(0.0147267)**
7.cgroup	0.8562755
	(0.0136761)**
8.cgroup	0.5711292
	(0.0117139)**
9.cgroup	0.7998642
	(0.0164372)**
10.cgroup	1.1423147
	(0.0120233)**
11.cgroup	1.0189921
	(0.0193433)**
12.cgroup	0.7269325
	(0.0118453)**
13.cgroup	0.7619506
	(0.0120960)**
14.cgroup	1.0301927
	(0.0137471)**
15.cgroup	1.1211195
	(0.0136587)**
2bn.cuni	-0.2571268
	(0.0136588)**
3.cuni	0.0546605
	(0.0167268)**
4.cuni	0.1551681
	(0.0145366)**
5.cuni	0.1396567
	(0.0158576)**
6.cuni	0.1223081
	(0.0163961)**
7.cuni	-0.1601216
	(0.0074258)**
8.cuni	0.3895526
	(0.0162219)**
9.cuni	0.2666595
	(0.0130224)**
10.cuni	-0.5532454
	(0.0094154)**
11.cuni	0.3274917
	(0.0118495)**
12.cuni	0.1370143
	(0.0119731)**
13.cuni	-0.4605595
	(0.0079889)**
14.cuni	-0.1014521
	(0.0092748)**
15.cuni	-0.5339515
	(0.0072696)**
16.cuni	-0.3983852
	(0.0072867)**
17.cuni	0.0540999
	(0.0072434)**
18.cuni	-0.2179875
	(0.0086653)**
19.cuni	-0.0446628
	(0.0121284)**
N	1,508,091

* $p < 0.05$; ** $p < 0.01$

Notes: Table presents results of the rank ordered logit model based on pre-selected into choice set programs.