What do classroom spending decisions reveal about university preferences?

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Abstract

Every semester, a university decides which undergraduate courses to offer and how much to spend on instructors for these courses. These choices determine how efficiently resources from governments, donors, and families are used to benefit students; however, very little is known about how universities make these decisions. In this paper, I develop methods for understanding how universities make these classroom spending decisions. My methods focus on comparing the university's preferences to the preferences of enrolled students. I apply my methods to administrative data from the University of Central Arkansas (UCA) and find that UCA has institutional preferences for decreasing enrollment in introductory business courses and increasing enrollments in introductory humanities and STEM courses. These institutional preferences lead UCA to make classroom spending decisions which are not aligned with student preferences. One counter-factual simulation shows a revenue neutral tax and subsidy policy which reduces the cost of offering introductory business courses and increases the cost of offering other introductory courses can induce UCA to offer courses that maximize student welfare. A second counter-factual simulation shows UCA could achieve the same student welfare at 38.5% of original costs in the absence of contractual constraints.

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1 Introduction

Every semester, a university decides which courses to offer and how much to spend on instructors for these courses. These classroom spending decisions have important implications for students as they may affect the courses students choose, the welfare they receive from these choices, and other potential outcomes. This paper asks: Can researchers reveal a university's preferences for these student outcomes by observing their classroom spending decisions?

Preferences are fundamental to all economic analyses; however, very little evidence exists on the preferences of universities.[1] This is surprising because universities are very important social institutions. There is abundant evidence that post-secondary outcomes have lasting effects on students in the labor market.[2] Furthermore, there is growing evidence that institutional choices have important effects on post-secondary outcomes.[3] Largely due to the value of undergraduate education in the labor market, large sums are spent on undergraduate education every year. In 2011, spending on post-secondary education comprised 2.7% of the United States gross domestic product (OECD, 2014). A better understanding of university preferences could be used to devise policies which lead universities to make decisions which benefit students and save money for taxpayers, families, and donors.

In this paper, I develop several tools for inferring university preferences from classroom spending decisions. I begin by developing a theoretical framework for analyzing classroom spending decisions. The framework casts these spending decisions as a sequential game between universities and students. In the first stage, universities observe constraints and the composition of the student body and decide which courses to offer and how much to spend on instructors for offered courses. In the second stage, students observe course offerings and spending on instruction and choose courses to maximize their utility. In a classical rational choice framework, the utility students achieve from these choices can be directly interpreted as a measure of welfare.[4] This framework thus provides a link between classroom spending decisions and outcomes which may enter university objectives such as student course choices and welfare.

[1] Two notable exceptions are Bhattacharya, Kanaya, and Stevens (2015) and Turner (2014).

[2] See Altonji, Blom, and Meghir (2012) and Oreopoulos and Petronijevic (2013) for reviews.

[3] Ahn, Arcidiacono, Hopson, and Thomas (2015) and Stinebrickner and Stinebrickner (2014) argue that grading policies affect specialization decisions of students. Figlio, Shapiro, and Soter (forthcoming) and Bettinger and Long (2010; 2015) provide mixed results about the effects of instructor characteristics on specialization decisions of students.

[4] There are many alternative settings where choice value does not fully capture welfare. For example, if students are myopic or uninformed choice value is an incomplete measure of welfare. Future research may adapt my theoretical framework to incorporate alternative measures of student welfare or other student outcomes.

I use this theoretical framework to develop three methods for inferring university preferences from observed classroom spending decisions. First, I propose a method for statistically testing whether classroom spending decisions maximize student welfare. To develop this test, I derive the tangency conditions which characterize the spending decisions of a university which maximizes total student welfare giving equal weight to all students. I then show estimates of a course choice model and observed data on spending on instruction can be used to statistically test whether these tangency conditions hold for an observed university. If they do not hold, I reject the hypothesis that the observed university is maximizing total student welfare.

Next, I develop two methods for estimating preference parameters of a more general structure for university objectives. The structure allows the university to value total student welfare and the type of courses students choose. University preferences for the type of courses students choose may arise because the university it trying to internalize social externalities, because certain courses increase alumni donations, because university administrators have personal preferences for certain fields, or for many other possible reasons. In all cases, these institutional preferences result in classroom spending decisions which are not aligned with student preferences.[5]

The first estimation method relates to a university's intensive margin decision of how much to spend on instructors for offered courses. First, I derive the tangency conditions which define how much this university would spend on instructors for offered courses. I then propose a variance minimization routine which solves for the parameter values which come closest to satisfying these tangency conditions. These parameter estimates thus represent the values which best explain how much a university is observed spending on instructors for different courses. Intuitively, this method measures positive (negative) institutional preferences for course types by identifying courses where the marginal value of spending on instruction is low (high) from the perspective of students. This indicates the university is over (under) investing in instruction in these courses.

The second estimation approach focuses on the university's extensive margin decision of which courses to offer. I propose a maximum likelihood estimator which solves for the parameter values which best explain why observed course offerings were preferred to all other feasible course offerings. Intuitively, this method measures positive (negative) institutional preferences for course types by identifying course types which are offered more (less) than student preferences and market costs would suggest. The two alternative methods employ

[5]In Methodological Appendix F, I extend the structure to include welfare weights which allow the university to favor some students more than others. Whether institutional preferences increase or decrease total student welfare is beyond the scope of this paper.

different empirical variation and have complementary strengths and weaknesses providing researchers with multiple tools for analysis.

I apply my inference methods using administrative data from the University of Central Arkansas. University of Central Arkansas (UCA) is a large public university in central Arkansas whose primary focus is teaching.[6] UCA's teaching focus makes analyzing the preferences underlying its classroom spending decisions especially interesting. The administrative data include information on all offered courses and information on the instructors teaching these courses between 1993 and 2013. Furthermore, the data include demographic information and full academic records for all students enrolled between 2004 and 2013. Importantly, the data include instructor salaries and fraction of salaries paid for teaching. This allows me to connect costs of instruction to choices and outcomes of students—a crucial link for inferring university preferences from observed classroom spending decisions.

The first stage of my empirical analysis is to estimate a multinomial choice model of students choosing courses. These estimates measure student preferences for course characteristics and estimate how much the desirability of a course increases when it is taught by a higher salaried instructor. To avoid issues of unobserved choice set heterogeneity, my analysis focuses on choices of introductory courses.[7] Estimates show introductory humanities courses are most popular with first year students while introductory business courses are most popular with sophomores, juniors and seniors. The estimates also show that students with higher ACT scores are relatively more attracted to introductory STEM courses. This corroborates existing literature which finds that initial preparation is an important determinant of whether a student pursues a STEM education (Arcidiacono, 2004; Stinebrickner and Stinebrickner, 2014). Finally, the estimates show that higher salaried instructors generally increase an introductory course's desirability but only to a small degree. This finding has important implications for universities: it implies that the vast amounts of resources spent hiring higher salaried instructors has relatively small effects on student course choices and student welfare.

The second stage of my analysis is to estimate university preference parameters taking student parameters as given. Using my maximum likelihood estimation method, I find UCA has institutional preferences for decreasing enrollment in introductory business courses and

[6] UCA's teaching focus is apparent in their vision statement:

> The University of Central Arkansas aspires to be a premier learner-focused public university, a nationally recognized leader for its continuous record of excellence in undergraduate and graduate education, scholarly and creative endeavors, and engagement with local, national, and global communities (UCA Board of Trustees, 2011).

[7] Many advanced courses have prerequisite restrictions implying they are only in the choice sets of students who have satisfied these pre-requisites.

increasing enrollments in introductory humanities and STEM courses.[8] This suggests UCA over invests in introductory STEM and humanities courses and under invests in introductory business courses relative to a university that is purely maximizing student welfare.

To place these estimates in context and to examine university behaviors under alternative constraints, I also develop a Marginal Improvement Algorithm (MIA) for simulating classroom spending decisions under alternative preferences and constraints (Chade and Smith, 2006). A university's choice set is typically so large that it is intractable to solve its true maximization problem. The MIA reduces dimensionality by breaking the full maximization problem into a series of smaller maximization problems where the objective of each problem is to maximize marginal improvements to the university's payoff.

I use the MIA to examine two counter-factual simulations: First, I solve for counterfactual course offering costs which lead UCA to offer courses which maximize student welfare. The simulation shows decreasing the minimum cost of offering business courses and increasing the minimum cost of offering other introductory courses prices out UCA's preferences for course types and induces UCA to offer courses which are in line with student preferences. These counterfactual costs which maximize student welfare can be achieved with a revenue neutral tax and subsidy policy.

Second, I simulate course offerings and excess spending decisions which produce welfare efficiently in the absence of contractual constraints. This simulation shows UCA could achieve the same student welfare at 38.5% of original costs in the absence of contractual constraints. These savings are achieved by vastly reducing spending on instruction and by changing the course composition to include more introductory business and social sciences courses and fewer introductory STEM and humanities courses. While these scenarios may be undesirable for other reasons, it is useful to see how a revenue neutral policy could be used to benefit students and it is striking to see that students could receive the same benefit at drastically lower costs with changes in instructors and course composition.

Two papers which use observed behaviors to make inferences about university preferences are Bhattacharya, Kanaya, and Stevens (2015) and Turner (2014). Bhattacharya, Kanaya, and Stevens (2015) examines the admissions decisions of a selective British university and finds the university has lower admission thresholds for female and private school applicants. This suggests the university is interested in increasing the number of female and private school students in attendance. Turner (2014) examines the financial aid decisions of US colleges and finds schools are willing to pay an additional $284 to have less privileged students attend their institution. This suggests the university is interested in increasing the number

[8] I do not use the variance minimization method in my empirical application due to a lack of identifying variation in the data.

of less privileged students matriculating at their institution. My analysis uses completely different observed behaviors to infer preferences and thus complements these other works nicely.

The remainder of this paper proceeds as follows: Section 2 presents the theoretical framework for analyzing classroom spending decisions, Section 3 describes the Arkansas Department of Higher Education administrative data used in my empirical application, Section 4 presents the methods for inferring university preferences from classroom spending decisions, Section 5 describes my empirical analysis and presents estimates of student and university parameters, Section 6 describes the Marginal Improvement Algorithm and reports classroom spending decisions under counter-factual preferences and constraints, and Section 7 concludes.

2 Theoretical Framework for Inferring University preferences

In this section, I present a theoretical framework for analyzing how universities make classroom spending decisions and the implications of these decisions for students. The framework describes the setting as a sequential game between a university and students. In the first stage, the university chooses which courses to offer and how much to spend on instruction in these courses to maximize their expected payoff subject to budget and contract constraints. In the second stage, students observe the university's decisions, choose one course to maximize their utility, and derive welfare from this choice. This provides a direct link between classroom spending decisions and student course choices and welfare. In Section 4, I show how this link can be used to reveal university preferences over these student outcomes using data on observed classroom spending decisions.

2.1 Primitives

Index students by $i = 1, \ldots, N$ and potential courses by $j = 1, \ldots, J$. When specified, academic semesters are indexed by $t = 1, \ldots T$. However, most of my analysis considers a static setting of one academic semester; therefore, semester subscripts are generally suppressed.

Suppose a university has an endowment E to spend on undergraduate instructors. The university chooses spending on instruction c_j for every potential course $j \in J$ subject to the budget constraint $\sum_{j=1}^{J} c_j \leq E$. If spending exceeds a course specific minimum cost m_j, an instructor is hired and the course is offered; otherwise, the course is not offered. Let $\mathbf{d} \subset J$

denote the set of offered courses. Formally:

$$j \in \mathbf{d} \; iff \; c_j \geq m_j \tag{1}$$

Define excess spending e_j as spending on instruction which exceeds minimum costs

$$e_j = \begin{cases} c_j - m_j & c_j > m_j \\ 0 & c_j \leq m_j \end{cases} \tag{2}$$

and let $\mathbf{e} = \begin{bmatrix} e_1 & \cdots & e_J \end{bmatrix}'$ represent the full vector of excess spending decisions.

Spending in excess of fixed cost may change unobserved instructor quality I_j following:

$$I_j = \begin{cases} \phi_j\left(e_j\right) & e_j > 0 \\ 0 & e_j = 0 \end{cases} \tag{3}$$

where the quality of a baseline instructor in course j is normalized to zero. Excess spending may increase instructor quality either because these funds are used to hire a more talented instructor or because increases in compensation motivate the same instructor to perform better. I assume the production function $\phi_j(\cdot)$ is differentiable but allow it to vary across courses.

Universities often negotiate long term contracts with instructors which limit the institution's capacity to make short run classroom spending decisions. To correctly reveal university preferences from classroom spending decisions in one semester, it is crucial to identify which decisions were made to maximize an objective and which were made to satisfy preexisting contracts. TO incorporate these short term contracts, let $K \subset J$ denote the subset of potential courses which must be offered by contract. If $j \in K$, then j must be included in every feasible offering vector $\mathbf{d}$ and e_j is set by contract.

2.2 Student Utility

Suppose student utility from enrolling in course j depends on student characteristics X_i, course characteristics Z_j (possibly including expected class size), and unobserved instructor quality I_j following a general additively separable structure:

$$U_{ij} = u_{ij}\left(Z_j\left(\mathbf{e}, \mathbf{d}\right), \, I_j, \, X_i\right) + \epsilon_{ij} \tag{4}$$

where ϵ_{ij} is assumed to follow a Generalized Extreme Value (GEV) distribution (McFadden, 1978) and the deterministic utility function $u_{ij}(\cdot)$ is differentiable in I_j and is allowed to vary across individuals and courses.

If student utility depends on expected class size, course offering and excess spending decisions affect the utility of each course indirectly through their effects on expected class sizes.[9] To emphasize the importance of these general equilibrium effects, the dependence of Z_j on decision vectors $\mathbf{e}$ and $\mathbf{d}$ is made explicit.

In this framework, student choice value is given by:

$$V_i(\mathbf{e}, \mathbf{d}) = \max_{j \in \mathbf{d}} \{u_{ij}(Z_j(\mathbf{e}, \mathbf{d}), \phi_j(e_j), X_i) + \epsilon_{ij}\} \tag{5}$$

For clarity, I consider a simplified setting where all offered courses are included in every student's choice set. This framework can easily be extended to accommodate observed choice set heterogeneity arising from prerequisite restrictions or other mechanisms. For simplicity, I also use a standard multinomial choice framework in which students choose exactly one course. For a course choice model which allows students to choose multiple courses at once, see Ahn, Arcidiacono, Hopson, and Thomas (2015).

2.3 Timing

University and student decisions proceed as follows:

1. The university observes all parameters, minimum costs m_j for every potential course $j \in J$, observed student characteristics for every enrolled student i, and observed course characteristics for every potential course $j \in J$.

2. The university observes the set of contracted courses K and predetermined excess spending levels in these courses.

3. The university makes a two-tiered decision:

   (a) The university decides which courses to offer by choosing the offering vector $\mathbf{d}$ where $K \subset \mathbf{d}$

   (b) The university chooses excess spending e_j for non-contract offered courses $j \in \mathbf{d} \backslash K$

[9] Using expected class size is equivalent to assuming each student's idiosyncratic preferences are private information. Bayer and Timmins (2007) use an alternative justification for integrating out idiosyncratic prefences which is to assume there is a continuum of individuals with different unobserved preferences for each vector of observed characteristics.

4. Students observe $\mathbf{d}$, $\mathbf{e}$, observed student characteristics for every enrolled student i, observed course characteristics for every offered course, and their own idiosyncratic preferences for offered courses, and choose one offered course to maximize their utility.[10]

2.4 University's Problem

Denote the university's expected payoff from choosing offering vector $\mathbf{d}$ and excess spending vector $\mathbf{e}$ as $\mathbb{E}\left[\Pi \,|\, \mathbf{e}, \mathbf{d}\right]$.[11] The university's problem is to choose a spending vector $\mathbf{c} = \begin{bmatrix} c_1 & \cdots & c_J \end{bmatrix}'$ to maximize the expected value of this payoff subject to a budget constraint and contractual constraints. Formally:

$$\mathbf{c}^{\star} = \text{argmax}_{\mathbf{c}} \left\{\mathbb{E}\left[\Pi \,|\, \mathbf{e}, \mathbf{d}\right]\right\} \quad \text{s.t.} \sum_{j=1}^{J} c_j \leq E, \tag{6}$$

At a solution to the university's problem, all non-contracted courses where spending exceeds fixed cost must satisfy the following tangency conditions:

$$\frac{d\mathbb{E}\left[\Pi \,|\, \mathbf{e}, \mathbf{d}\right]}{de_j} = \frac{d\mathbb{E}\left[\Pi \,|\, \mathbf{e}, \mathbf{d}\right]}{de_{j'}} \tag{7}$$

$$\forall j, j' \in \mathbf{d} \backslash K \, \text{s.t.} \, c_j > m_j \, \text{and} \, c_{j'} > m_{j'}$$

Intuitively, the tangency conditions described in Equation 7 impose that the marginal payoff of an additional dollar of spending must be equal across all non-contract courses where spending exceeds the minimum cost. Importantly, the tangency conditions do not apply to courses where the university only pays the minimum cost at a solution or courses where excess spending is determined by contract.

3 Data for Inferring University Preferences

I will apply my methods for inferring university preferences using administrative data from University of Central Arkansas (UCA). University of Central Arkansas is a large public teaching focused university located in central Arkansas. The administrative data include information on all offered courses and information on the instructors teaching these courses for all courses offered between 1993 and 2013. Importantly, these course and instructor data

[10] If class size does not affect utility, students do not need to observe characteristics of other students.

[11] Expectations are taken over idiosyncratic shocks to student course preferences which are not observed by the university.

include instructor salaries and fraction of salaries paid for teaching.[12] Furthermore, the data include demographic information and full academic records for all students who were enrolled between 2004 and 2013. These detailed course and student data allow me to connect costs of instruction to choices and outcomes of students—a crucial link for inferring university preferences from observed classroom spending decisions.

Generally speaking, the inference methods presented in this article involve revealing student preferences from student course choices given offered courses and revealing university preferences from classroom spending decisions given anticipated responses of students. To reveal student preferences, data must include student characteristics, characteristics of offered courses, and student choices given available alternatives. Importantly, characteristics of offered courses must include excess spending on instruction e_j to directly link the university's excess spending decisions to student choices. To reveal university preferences given student preferences, data must include information on preexisting contracts which constrain short run decisions, minimum costs of offering courses m_j, and characteristics of all potential courses in J.

Using the administrative data, I directly observe student characteristics, characteristics of offered courses other than excess spending on instruction, and student choices given available alternatives.[13] Important components of the theoretical framework which are not directly observed and must be estimated from data are excess spending on instruction e_j, minimum costs of offering courses m_j, and characteristics of potential courses which are not offered.

With limited assumptions, total spending on instruction c_j can be constructed for every offered course using observed data on instructor salaries and fraction of salaries paid for teaching.[14] To estimate minimum costs m_j using c_j, I assume minimum costs are the same for all introductory courses in the same academic field. I then estimate these minimums as the fifth percentile of the distribution of c_j for introductory courses in a specific field.[15]

[12] The observed measure of fraction of salary paid for teaching is based on the number of credit hours an instructor teaches relative to UCA's definition of a full time instructor (Arkansas Department of Higher Education, 2012). At a university where faculty have multiple duties this definition may not accurately reflect fraction of salary paid for instruction. At UCA, 96% of all student course observations are in courses taught by instructors who earn at least 95% of their salary from instruction. This implies almost all of UCA's instruction is provided by full time instructors meaning this observed measure of fraction of salary paid for instruction provides little variation.

[13] Observed student characteristics used in my analysis are race, cohort, and ACT test scores. Observed course characteristics used in my analysis (other than excess spending on instruction) are academic field and difficulty level. Possible academic fields are: STEM, humanities and arts, social science, occupation, and business. Possible difficulty levels are: introductory and advanced. Only introductory courses are included in my empirical analysis.

[14] In many cases, instructors will be paid one salary to teach multiple courses. In these cases, I allocate an instructor's teaching salary to specific courses based on the number of credit hours each course is worth.

[15] I use the fifth percentile instead of the sample minimums to reduce sensitivity to outliers with unrealistically low values for c_j.

Excess spending on instruction e_j is then defined using Equation (2).

To construct characteristics of potential introductory courses which are not offered I assume introductory courses are fully defined by academic fields and that infinitely many potential introductory courses exist in every field. This implies non-offered introductory STEM courses have the same minimum cost and intrinsic popularity as offered introductory STEM courses and that the university can always offer additional introductory STEM courses. This provides a computationally simple method for constructing characteristics of non-offered courses; however, this approach has important limitations: First, it ignores unobserved heterogeneity in the desirability and cost of courses. One may expect non-offered courses to be unobservably worse—from the perspective of the university—than observationally equivalent observed courses. Second, the assumption that infinitely many potential introductory courses exist in every field is clearly unrealistic. At a certain point, recruiting costs and facility constraints will limit the number of introductory courses a university can offer in any given field.[16]

4 Methods for Inferring University Preferences

In this section, I present various methods for making empirical inferences about university preferences. First, I propose a method for statistically testing whether classroom spending decisions maximize student welfare. To develop this test, I derive the tangency conditions which characterize the excess spending decisions of a university which maximizes total student welfare giving equal weight to all students. I then show estimates of a course choice model and observed data on spending on instruction can be used to statistically test whether these tangency conditions hold for an observed university. If they do not hold, I reject the hypothesis that the observed university is maximizing total student welfare.

Next, I develop two methods for estimating preference parameters of a more general structure for university objectives. The structure allows the university to value total student welfare and the type of courses students choose. The first estimation method relates to a university's intensive margin decision of how much to spend on instructors for offered courses. First, I derive the tangency conditions which define how much this university would spend on instructors for offered courses. I then propose a variance minimization routine which solves for the parameter values which come closest to satisfying these tangency conditions. These parameter estimates thus represent the values which best explain observed excess spending

[16] An alternative approach for constructing the characteristics of non-offered courses uses panel data to define the set of potential courses J as all courses which were ever offered in any semester present in the panel. While it would be computationally challenging, this approach could theoretically estimate unobserved course attributes for every course in J.

decisions. Intuitively, this method measures positive (negative) institutional preferences for course types by identifying courses where the marginal value of spending on instruction is low (high) from the perspective of students. This indicates the university is over (under) investing in instruction in these courses.

The second estimation approach focuses on the university's extensive margin decision of which courses to offer. I propose a maximum likelihood estimator which solves for the parameter values which best explain why observed course offerings were preferred to all other feasible course offerings. Intuitively, this method measures positive (negative) institutional preferences for course types by identifying course types which are offered more (less) than student preferences and market costs would suggest. The two alternative methods employ different empirical variation and have complementary strengths and weaknesses providing researchers with multiple tools for analysis.

In Section 4, I perform an empirical application of the maximum likelihood estimation method described in Subsection 4.3 using administrative data from the University of Central Arkansas (UCA). Methods described in Subsections 4.1 and 4.2 were found to be inappropriate at UCA due to a lack of identifying variation; however, these methods may be applicable in alternative settings.

4.1 Are excess spending decisions consistent with utilitarian student welfare maximization?

In this subsection, I examine the special case of a university whose goal is to maximize student welfare giving equal weight to all students. I refer to this baseline school as a utilitarian student welfare maximizing (U-SWM) university. I derive the tangency conditions described in Equation (7) for this university and show how observed data on spending on instruction and estimates of a student course choice model can be used to statistically test whether observed spending decisions satisfy the tangency conditions of this U-SWM university. This is equivalent to testing whether the incentives of an observed university are aligned with its students. I begin by describing the statistical test for the baseline setting in which students only value fixed course characteristics and instructor quality. Following this, I describe the statistical test in the general equilibrium setting in which students also value class size. Finally, I show how panel data can be used to reduce reliance on functional form assumptions about student utility. I conclude with a short discussion of these methods.

4.1.1 Statistical test of U-SWM without class size effects

A U-SWM university's payoff from decision vectors $\mathbf{d}$ and $\mathbf{e}$ is the sum of choice values over all students. The U-SWM problem is then given by:

$$\mathbf{c}^{\star} \quad = \quad \mathrm{argmax}_{\mathbf{c}} \left\{ \sum_{i=1}^{N} \mathbb{E}\left[V_i\left(\mathbf{e},\mathbf{d}\right)\right] \right\} \quad \text{s.t.} \sum_{j=1}^{J} c_j \leq E \tag{8}$$

Because student preference shocks are assumed to follow a GEV distribution, a convenient property can be used to simplify the tangency conditions for a U-SWM university. For any θ_j which affects deterministic utility in course j , $\frac{d\mathbb{E}[V_i(\mathbf{e},\mathbf{d})]}{d\theta_j} = \left(\frac{du_{ij}}{d\theta_j}\right) P_{ij}\left(\mathbf{e},\mathbf{d}\right)$ where $P_{ij}\left(\mathbf{e},\mathbf{d}\right)$ is the probability individual i chooses course j given excess spending vector $\mathbf{e}$ and offering vector $\mathbf{d}$.[17] This property implies the U-SWM version of the general tangency conditions given in Equation (7) is given by :

$$\sum_{i=1}^{N} \left(\frac{\partial u_{ij}}{\partial I_j}\right)\left(\frac{\partial \phi_j}{\partial e_j}\right) P_{ij}\left(\mathbf{e},\mathbf{d}\right) = \sum_{i=1}^{N} \left(\frac{\partial u_{ij'}}{\partial I_{j'}}\right)\left(\frac{\partial \phi_{j'}}{\partial e_{j'}}\right) P_{ij'}\left(\mathbf{e},\mathbf{d}\right) \tag{9}$$

$$\forall j, j' \in \mathbf{d} \backslash K \,\text{s.t.}\, c_j > m_j \,\text{and}\, c_{j'} > m_{j'}$$

As before, note the tangency conditions only relate the marginal values of spending across non-contract courses where spending exceeds minimum costs.

With functional form assumptions on the structure of $u_{ij}(\cdot)$ and $\phi_j(\cdot)$ and distribution of ϵ_{ij}, researchers can estimate the parameters of a multinomial course choice model in which students choose one course to maximize utility defined in Equation (4). The parameters of this choice model can then be used to construct estimates of the tangency condition components $\left(\frac{\partial u_{ij}}{\partial I_j}\right)$, $\left(\frac{\partial \phi_j}{\partial e_j}\right)$, and $P_{ij}\left(\mathbf{e},\mathbf{d}\right)$ for all students i and offered courses $j \in \mathbf{d}$

These estimates can be used to form test statistics which are the empirical analogs of the tangency conditions:

$$\hat{t}_{jj'} = \left\{ \sum_{i=1}^{N} \left(\frac{\partial \hat{u}_{ij}}{\partial I_j}\right)\left(\frac{\partial \hat{\phi}_j}{\partial e_j}\right) \hat{P}_{ij}\left(\mathbf{e},\mathbf{d}\right) \right\} - \left\{ \sum_{i=1}^{N} \left(\frac{\partial \hat{u}_{ij'}}{\partial I_{j'}}\right)\left(\frac{\partial \hat{\phi}_{j'}}{\partial e_{j'}}\right) \hat{P}_{ij'}\left(\mathbf{e},\mathbf{d}\right) \right\} \tag{10}$$

For the observed spending vector to be consistent with the goal of maximizing student welfare, $\hat{t}_{jj'}$ must be statistically indistinguishable from zero for every course pair $j, j' \in \mathbf{d} \backslash K$ for which $c_j > m_j$, and $c_{j'} > m_{j'}$. If $\hat{t}_{jj'}$ is statistically positive (negative), it implies the welfare return on an additional dollar of spending is significantly higher (lower) in course j

[17] $P_{ij}\left(\mathbf{e},\mathbf{d}\right) = 0$ if course j is not offered.

relative to course j'. This would be inconsistent with the goal of maximizing student welfare because welfare could be increased by marginally increasing (reducing) spending in course j and reducing (increasing) spending in course j'. Formally, the testing procedure is as follows:

$$\begin{aligned} H_0 &: \text{Excess spending decisions maximize student welfare} \\ H_a &: \text{Excess spending decisions do not maximize student welfare} \end{aligned}$$

Testing procedure:

1. Identify the set of courses $\tilde{J} = \{j \in \mathbf{d} \backslash K \mid c_j > m_j\}$.
2. Use a bootstrap algorithm to estimate the distribution of the $\frac{\tilde{J}[\tilde{J}-1]}{2}$ dimensional random vector $\hat{\mathbf{t}} = \begin{bmatrix} \hat{t}_{12} & \ldots & \hat{t}_{\tilde{J}-1\tilde{J}} \end{bmatrix}$.[18]
3. Test the joint hypothesis: $H_0 : \hat{t}_{jj'} = 0$ for all pairs of offered courses $j, j' \in \tilde{J}$.

To implement the first step of this procedure, researchers can use observed data on c_j and estimates of m_j obtained as described in Subsection **??**. To reduce sensitivity to estimation error in $\hat{m}_j$, researchers may use a stricter set: $\tilde{J}_\delta = \{j \in \mathbf{d} \backslash K \mid c_j > m_j + \delta\}$where $\delta > 0$. Choosing a large δ guarantees that spending exceeds minimum costs implying the tangency conditions must bind. However, as δ increases, the set of courses shrinks which reduces power to reject the null hypothesis.

4.1.2 Statistical test of U-SWM with class size effects

When class size affects choice utility, excess spending in course j has direct effects on choice utility for course j but also has indirect effects on choice utility for all courses through changes in class sizes. These general equilibrium effects make simplifying the general tangency conditions in Equation 7 somewhat more difficult. A general version of the GEV property used previously is helpful: For any θ affecting deterministic utility in any course, $\frac{d\mathbb{E}[V_i(\mathbf{e},\mathbf{d})]}{d\theta} = \sum_{j\in\mathbf{d}} \left(\frac{du_{ij}}{d\theta}\right) P_{ij}(\mathbf{e},\mathbf{d})$. This yields the following general equilibrium U-SWM tangency conditions:

$$\sum_{i=1}^{N} \sum_{k \in J_i(\mathbf{d})} \left(\frac{du_{ik}}{de_j}\right) P_{ik}(\mathbf{e}, \mathbf{d}) = \sum_{i=1}^{N} \sum_{k \in J_i(\mathbf{d})} \left(\frac{du_{ik}}{de_{j'}}\right) P_{ik}(\mathbf{e}, \mathbf{d}) \tag{11}$$

[18] In theory, one could derive the true asymptotic distribution of $\hat{\mathbf{t}}$ since this random vector is a function of a maximum likelihood estimator which is asymptotically multivariate normal. However, the function is extremely complicated even for very simple utility structures which makes this derivation impractical.

$$\forall j, j' \in \mathbf{d} \backslash K \, \text{s.t.} \, c_j > m_j \, \text{and} \, c_{j'} > m_{j'}$$

where

$$\frac{du_{ik}}{de_j} = \begin{cases} \frac{\partial u_{ij}}{\partial I_j}\frac{\partial \phi_j}{\partial e_j} + \frac{\partial u_{ij}}{\partial \tilde{n}_j}\frac{d\tilde{n}_j}{de_j} & k = j \\ \frac{\partial u_{ik}}{\partial \tilde{n}_k}\frac{d\tilde{n}_k}{de_j} & k \neq j \end{cases} \tag{12}$$

Estimates of the parameters of a general equilibrium course choice model can be used to estimate the tangency condition components $P_{ik}(\mathbf{e}, \mathbf{d})$, $\frac{\partial u_{ij}}{\partial I_j}\frac{\partial \phi_j}{\partial e_j}$, and $\frac{\partial u_{ik}}{\partial \tilde{n}_k}$; however, they cannot be used to directly construct the effects of spending on class sizes given by $\frac{d\tilde{n}_k(\mathbf{e},\mathbf{d})}{de_j}$.[19] These are complicated effects because they depend on the effects of spending on course utility and these effects depend on the effects of spending on class sizes. In Methodological Appendix A, I show how this recursive relationship can be unraveled to yield a closed form expression when ϵ_{ij} follows a type 1 extreme value distribution.

As before, these estimates can be used to construct test statistics which are the empirical analogs of the general equilibrium tangency conditions:

$$\hat{t}_{jj'} = \sum_{i=1}^{N}\sum_{k\in\mathbf{d}}\left(\widehat{\frac{du_{ik}}{de_j}}\right)\hat{P}_{ik}(\mathbf{e},\mathbf{d}) - \sum_{i=1}^{N}\left(\sum_{k\in\mathbf{d}}\left(\widehat{\frac{du_{ik}}{de_{j'}}}\right)\hat{P}_{ik}(\mathbf{e},\mathbf{d})\right) \tag{13}$$

These test statistics can then be used to test whether observed spending is consistent with the goal of utilitarian student welfare maximization following the same procedure described in Subsection 4.1.1.

4.1.3 Statistical test of U-SWM with panel data

One concern with the baseline test described in Subsection 4.1.1 is the results may be sensitive to the functional form of student utility. In this subsection, I develop a complementary panel data test which is more robust to functional form assumptions. The idea behind this test is that the researcher can solve for the return on spending parameters which exactly satisfy the U-SWM first order conditions in a given semester. If the university is U-SWM in every semester then these implied returns should be statistically similar for the same course in different semesters. In this subsection only, academic semesters are indexed by $t = 1, \ldots, T$.

Suppose student utility falls into a general class of models in which utility from enrolling in course j in semester t depends on student characteristics X_{it}, course characteristics Z_{jt}, and excess spending on instruction e_{jt} in the following additively separable manner:

[19] In this general equilibrium setting, class sizes are correlated with unobserved course attributes by construction. To estimate parameters of such a general equilibrium choice model, researchers may adapt the iterative instrumental variables approach described in Bayer and Timmins (2007).

$$U_{ijt} = \theta_j \ln e_{jt} + \psi_{ijt}\left(Z_{jt},\, X_{it}\right) + \epsilon_{ijt} \tag{14}$$

where ϵ_{ijt} is assumed to follow a Generalized Extreme Value distribution (McFadden, 1978) and the deterministic utility function $\psi_{ijt}\left(\cdot\right)$ is allowed to vary across individuals, courses, and semesters. While this class is generally quite flexible it places some restrictions on how spending on instruction affects utility. Most notably, although returns on spending are allowed to vary across courses they are not allowed to vary across individuals. Additionally, this structure imposes that concavity is generated by the natural logarithm function.

For this class of utility structures, the tangency conditions describing a U-SWM university's solution are:

$$\frac{\sum_{i=1}^{N_t} \theta_j P_{ijt}\left(\mathbf{e_t}, \mathbf{d_t}\right)}{e_{jt}} = \frac{\sum_{i=1}^{N_t} \theta_{j'} P_{ij't}\left(\mathbf{e_t}, \mathbf{d_t}\right)}{e_{j't}} \tag{15}$$

$$\forall j, j' \in \mathbf{d}\backslash K \text{ s.t. } c_j > m_j \text{ and } c_{j'} > m_{j'}$$

Rearranging yields:

$$\frac{\theta_j}{\theta_{j'}} = \left(\frac{e_{jt}}{e_{j't}}\right)\left(\frac{\sum_{i=1}^{N_t} P_{ij't}\left(\mathbf{e_t}, \mathbf{d_t}\right)}{\sum_{i=1}^{N_t} P_{ijt}\left(\mathbf{e_t}, \mathbf{d_t}\right)}\right) \tag{16}$$

$$\forall j, j' \in \mathbf{d}\backslash K \text{ s.t. } c_j > m_j \text{ and } c_{j'} > m_{j'}$$

Notice the left hand side of this expression is invariant across semesters. This implies that if the U-SWM first order conditions are satisfied in both semesters t and t' then the following conditions must hold:

$$\left(\frac{e_{jt}}{e_{j't}}\right)\left(\frac{\tilde{n}_{j't}\left(\mathbf{e_t}, \mathbf{d_t}\right)}{\tilde{n}_{jt}\left(\mathbf{e_t}, \mathbf{d_t}\right)}\right) = \left(\frac{e_{jt'}}{e_{j't'}}\right)\left(\frac{\tilde{n}_{j't'}\left(\mathbf{e_{t'}}, \mathbf{d_{t'}}\right)}{\tilde{n}_{jt'}\left(\mathbf{e_{t'}}, \mathbf{d_{t'}}\right)}\right) \tag{17}$$

$$\forall j, j' \in \mathbf{d}\backslash K \text{ s.t. } \min\left\{c_{jt}, c_{jt'}\right\} > m_j \text{ and } \min\left\{c_{j't}, c_{j't'}\right\} > m_{j'}$$

where $\tilde{n}_{jt}\left(\mathbf{e_t}, \mathbf{d_t}\right) = \sum_{i=1}^{N} P_{ijt}\left(\mathbf{e_t}, \mathbf{d_t}\right)$ is expected enrollment in course j in semester t given decision vectors $\mathbf{e_t}$ and $\mathbf{d_t}$. Intuitively, this panel condition states that a U-SWM university responds to changes in relative intrinsic popularity by spending more in courses which are becoming more popular.

The benefit of the panel condition given in Equation (17) is it depends on excess spending e_{jt} and equilibrium choice probabilities $P_{ijt}\left(\mathbf{e_t}, \mathbf{d_t}\right)$ but does not depend on other parameters. Because no specific parameters are required to construct (17), researchers may conduct this test using flexible reduced form utility structures which are robust to functional form assumptions.[20]

As before, estimates of equilibrium choice probabilities and observed data can be used to construct the empirical analogs of (17):

$$\hat{t}_{jj',tt'} = \left(\frac{e_{jt}}{e_{j't}}\right)\left(\frac{\hat{\hat{n}}_{j't}\left(\mathbf{e_t},\mathbf{d_t}\right)}{\hat{\hat{n}}_{jt}\left(\mathbf{e_t},\mathbf{d_t}\right)}\right) - \left(\frac{e_{jt'}}{e_{j't'}}\right)\left(\frac{\hat{\hat{n}}_{j't'}\left(\mathbf{e_{t'}},\mathbf{d_{t'}}\right)}{\hat{\hat{n}}_{jt'}\left(\mathbf{e_{t'}},\mathbf{d_{t'}}\right)}\right) \tag{18}$$

These test statistics can then be used to test whether observed spending is consistent with the goal of utilitarian student welfare maximization following the same procedure described in Subsection 4.1.1.

4.1.4 Discussion of tangency condition inference methods

The tangency condition inference methods have several strengths: First, they provide a clear statistical test of whether observed behavior is consistent with utilitarian student welfare maximization. The methods test a specific structure of university objectives—rather than imposing a structure and estimating parameters assuming that structure is true—and they handle sampling error in estimates of student choice parameters appropriately. Furthermore, the trio of a baseline test, general equilibrium test, and panel data test offers researchers several inference tools which apply to a variety of settings and can be used to assess the robustness of results.

While these inference methods are desirable for their clarity and rigor, the tradeoff is they only offer narrow inferences about university preferences. Specifically, the tests can only reject or fail to reject that observed spending is consistent with utilitarian student welfare maximization. If the null hypothesis of U-SWM is rejected, these methods do not offer a preferable alternative. In subsequent sections, I introduce and discuss complementary inference methods for estimating university preference parameters of a more general objective structure.

The other limitation of these methods is that statistical power depends on the size of $\tilde{J}_\delta$. $\tilde{J}_\delta$ contains non-contract courses where spending on instruction exceeds minimum costs. In many settings—including UCA—compensation for instructors hired on short term contracts almost always represents the minimum cost of instruction. This results in a $\tilde{J}_\delta$ which is too small for meaningful analysis.

[20] Estimates of $P_{ijt}\left(\mathbf{e_t},\mathbf{d_t}\right)$ must approximate how the university believes individual i will choose courses. As such, researchers should avoid using student data which is not observed by the university or utility structures which are impractical.

4.2 What university preferences best explain observed spending decisions

The preceding subsection demonstrates how estimates of student choice parameters and minimum course costs can be used to test whether observed spending decisions are consistent with student welfare maximization. While these tests are a useful place to start, they can only reject or fail to reject that spending maximizes student welfare. If welfare maximization is rejected, it would be useful to understand the alternative motives which are driving classroom spending decisions.

In this subsection, I present methods for estimating preference parameters of a more general structure for university objectives. The structure allows the university to value total student welfare and the type of courses students choose. First, I derive the tangency conditions which define how much this university would spend on instructors for offered courses. I then propose a variance minimization routine which solves for the parameter values which come closest to satisfying these tangency conditions. These parameter estimates thus represent the values which best explain observed excess spending decisions. Intuitively, this method measures positive (negative) institutional preferences for course types by identifying courses where the marginal value of spending on instruction is low (high) from the perspective of students. This indicates the university is over (under) investing in instruction in these courses.

With this more general objective structure, university expected payoffs are an additively separable function of total student welfare and institutional preferences for the type of courses students choose.[21] Formally

$$\mathbb{E}\left[\Pi \,|\, \mathbf{e}, \mathbf{d}\right] = \sum_{i=1}^{N} \mathbb{E}\left[V_i \,|\, \mathbf{e}, \mathbf{d}\right] + \sum_{j=1}^{J} \gamma_j \tilde{n}_j\left(\mathbf{e}, \mathbf{d}\right) \tag{19}$$

where $\sum_{i=1}^{N} \mathbb{E}\left[V_i \,|\, \mathbf{e}, \mathbf{d}\right]$ represents expected total student welfare given university choices for $\mathbf{d}$ and $\mathbf{e}$, $\tilde{n}_j\left(\mathbf{e}, \mathbf{d}\right)$ represents the expected number of students choosing course j given university choices for $\mathbf{d}$ and $\mathbf{e}$, and γ_j represent institutional preferences for students choosing j. University preferences γ_j may exist because the university it trying to internalize social externalities, because certain courses increase alumni donations, because university administrators have personal preferences for certain fields, or for many other possible reasons. In all cases, these institutional preferences result in classroom spending decisions which are not aligned with student preferences. The objective of this method—and my paper more

[21] In Methodological Appendix F, I extend the structure to include welfare weights which allow the university to favor some students more than others.

generally—is to estimate γ_j to reveal university preferences which drive classroom spending decisions and thus have consequences for student course choices and welfare.

The university's problem is then given by:

$$\mathbf{c}^{\star} \;=\; \text{argmax}_{\mathbf{c}} \left\{ \sum_{i=1}^{N} \mathbb{E}\left[V_i \,|\, \mathbf{e}, \mathbf{d}\right] + \sum_{j=1}^{J} \gamma_j \tilde{n}_j \left(\mathbf{e}, \mathbf{d}\right) \right\} \quad \text{s.t.} \sum_{j=1}^{J} c_j \leq E \tag{20}$$

With this structure, the university's tangency conditions are given by:

$$\frac{d\mathbb{E}\left[\Pi \,|\, \mathbf{e}, \mathbf{d}\right]}{de_j} \;=\; \frac{d\mathbb{E}\left[\Pi \,|\, \mathbf{e}, \mathbf{d}\right]}{de_{j'}} \tag{21}$$

$$\forall j, j' \in \mathbf{d} \backslash K \,\text{s.t.}\, c_j > m_j \,\text{and}\, c_{j'} > m_{j'}$$

In the baseline setting where students do not value class sizes, $\frac{d\mathbb{E}[\Pi \,|\, \mathbf{e}, \mathbf{d}]}{de_j}$ is given by:

$$\frac{d\mathbb{E}\left[\Pi \,|\, \mathbf{e}, \mathbf{d}\right]}{de_j} = \sum_{i=1}^{N} \left(\frac{\partial u_{ij}}{\partial I_j}\right) \left(\frac{\partial \phi_j}{\partial e_j}\right) P_{ij}\left(\mathbf{e}, \mathbf{d}\right) + \sum_{k=1}^{J} \gamma_k \left(\frac{\partial \tilde{n}_k}{\partial e_j}\right) \tag{22}$$

With functional form assumptions on the structure of $u_{ij}(\cdot)$ and $\phi_j(\cdot)$ and distribution of ϵ_{ij}, researchers can use estimates of a multinomial course choice model to construct $\left(\frac{\partial u_{ij}}{\partial I_j}\right)$, $\left(\frac{\partial \phi_j}{\partial e_j}\right)$, $P_{ij}\left(\mathbf{e}, \mathbf{d}\right)$, and $\left(\frac{\partial \tilde{n}_k}{\partial e_j}\right)$ for all students i and offered courses j s.t. $d_j = 1$.

In a general equilibrium setting where class size affects choice utility, $\frac{d\mathbb{E}[\Pi \,|\, \mathbf{e}, \mathbf{d}]}{de_j}$ is given by:

$$\frac{d\mathbb{E}\left[\Pi \,|\, \mathbf{e}, \mathbf{d}\right]}{de_j} = \left\{ \sum_{i=1}^{N} \sum_{k \in \mathbf{d}} \left(\frac{du_{ik}}{de_j}\right) P_{ik} \right\} + \sum_{k=1}^{J} \gamma_k \left(\frac{d\tilde{n}_k}{de_j}\right) \tag{23}$$

With functional form assumptions on the structure of $u_{ij}(\cdot)$ and $\phi_j(\cdot)$ and distribution of ϵ_{ij}, researchers can construct $\frac{du_{ik}}{de_j}$ and $\frac{d\tilde{n}_k}{de_j}$ with estimates of a general equilibrium sorting model.[22]

To identify preference parameters which best explain observed spending, I propose solving for values of γ_j which come closest to satisfying these tangency conditions at observed spending levels. For a single academic semester, the university's excess spending tangency conditions state that the marginal returns $\frac{d\mathbb{E}[\Pi \,|\, \mathbf{e}, \mathbf{d}]}{de_j}$ must be equal for all courses where spending exceeds fixed costs. To solve for the parameter values which come closest to satisfying this condition at observed spending levels, I propose solving

[22] In this general equilibrium setting, class sizes are correlated with unobserved course attributes by construction. To estimate parameters of such a general equilibrium choice model, researchers may adapt the iterative instrumental variables approach described in Bayer and Timmins (2007).

$$\hat{\gamma} = \text{argmin}_{\gamma} \left\{ \text{Var}_{j \in \mathbf{d} \backslash K \text{ s.t. } c_j > m_j} \left(\frac{d\mathbb{E}\left[\Pi \,|\, \gamma, \tilde{\mathbf{e}}, \tilde{\mathbf{d}} \right]}{de_j} \right) \right\} \tag{24}$$

where $\tilde{\mathbf{e}}$ and $\tilde{\mathbf{d}}$ represent observed excess spending. If the tangency conditions are satisfied for all pairs of courses $j, j' \in \mathbf{d} \backslash K$ for which $c_j > m_j$, and $c_{j'} > m_{j'}$then this objective variance is exactly zero. As such, the parameter values γ which minimize this variance represent university preferences which best explain observed excess spending decisions.

As in Subsection 4.1, this inference method requires identifying the set of courses $\tilde{J} = \{j \in \mathbf{d} \backslash K \,|\, c_j > m_j\}$. As before, researchers may use a stricter set:

$$\tilde{J}_\delta = \{j \in \mathbf{d} \backslash K \,|\, c_j > m_j + \delta\} \tag{25}$$

where $\delta > 0$ to reduce sensitivity to error in estimates of m_j. Choosing a large δ guarantees that spending exceeds minimum costs implying the tangency conditions must bind. However, as δ increases, the set of courses shrinks which reduces precision in estimates of γ.

4.2.1 Identification and estimation

For identification and estimation, it is necessary to place some restrictions on γ_j. In my empirical application, I restrict γ_j to be equivalent within academic fields.[23] In Methodological Appendix B, I show this restriction means γ_j are over-identified as long as the number of course types is less than the total number of courses $j \in \mathbf{d} \backslash K$ such that $c_j > m_j$. Intuitively, identification of γ_j comes from differences in the marginal effects of excess spending across academic fields. For instance, if student parameter estimates imply increasing spending in STEM courses has larger effects on student welfare than increasing spending in humanities courses this implies the university is over-spending in humanities courses and under-spending in STEM courses. This reveals an institutional preference for drawing students out of STEM and into humanities courses.

The fact that γ_j are over-identified provides a useful over-identification test of functional form assumptions. If all functional form assumptions are correct, the objective variance:

$$\text{Var}_{j \in \mathbf{d} \backslash K \text{ s.t. } c_j > m_j} \left(\frac{d\mathbb{E}\left[\Pi \,|\, \gamma, \tilde{\mathbf{e}}, \tilde{\mathbf{d}} \right]}{de_j} \right) \tag{26}$$

should be exactly zero at true parameter values γ_j. If the objective variance is statistically

[23] Academic fields are STEM, humanities and arts, business, social science, and occupational.

positive at estimates of γ_j, we can jointly reject the structures of student utility and university objectives. As with any over-identification test, failure to reject the null hypothesis does not validate the model structure.

4.2.2 Discussion of marginal return variance minimizing inference methods

The strength of the variance minimizing methods described in this subsection is that they provide estimates of preference parameters for an objective structure which is more general than utilitarian student welfare maximization. Specifically, they quantify institutional preferences over the type of courses students choose. These institutional preferences measure the extent to which student and university preferences are not aligned.

The main limitation of these methods is that the set $\tilde{J}_\delta$ may be too small to conduct inference with sufficient power. $\tilde{J}_\delta$ contains non-contract courses where spending on instruction exceeds minimum costs. In many settings—including UCA—compensation for instructors hired on short term contracts almost always represents the minimum cost of instruction. This results in a $\tilde{J}_\delta$ which is too small for meaningful analysis.

4.3 What university preferences best explain observed course offerings?

In the preceding subsection, I presented an algorithm for estimating university preference parameters by solving for parameter values which best explain observed excess spending decisions in non-contract courses. One shortcoming of this method is it relies on variation from non-contract courses with positive excess spending. This will be a small set of courses if salaries for non-contract instructors are at the bottom of the pay distribution as is often the case.

In this subsection, I propose complementary methods which estimate university preference parameters which best explain observed course offering and excess spending decisions. Intuitively, this method solves for the parameter values which maximize the likelihood that observed course offerings are preferred to all feasible alternatives.

To illustrate these methods more concretely, note that it is often possible to combine the university's conditions given by Equation (21) with the budget constraint to solve for the optimal excess spending vector for each offering vector.[24] Denote these optimal excess spending vectors as: $\mathbf{e}(\mathbf{d})^{\star}$. The university's problem can then be restated to focus on

[24]See Methodological Appendix C for an illustration.

extensive margin decisions:

$$\mathbf{d}^{\star} \;=\; \operatorname{argmax}_{\mathbf{d}}\left\{\mathbb{E}\left[\Pi \,|\, \mathbf{e}\left(\mathbf{d}\right)^{\star}, \mathbf{d}; \gamma\right]\right\} \text{ s.t. } \sum_{j=1}^{J} d_j m_j \leq E \tag{27}$$

If the objective structure is correct, the observed offering vector $\hat{\mathbf{d}}$ is the optimal vector $\mathbf{d}^{\star}$ and the observed excess spending vector $\hat{\mathbf{e}}$ is the optimal spending vector given the optimal offering vector $\mathbf{e}\left(\mathbf{d}^{\star}\right)^{\star}$ and the true parameter values γ.

This implies that the observed decision vectors $\hat{\mathbf{d}}$ and $\hat{\mathbf{e}}$ must provide the highest university payoff at the true parameter values γ if the objective structure is correct. Formally,

$$\mathbb{E}\left[\Pi \,|\, \hat{\mathbf{e}}, \hat{\mathbf{d}}; \gamma\right] \geq \mathbb{E}\left[\Pi \,|\, \mathbf{e}\left(\mathbf{d}\right)^{\star}, \mathbf{d}; \gamma\right] \tag{28}$$

$$\forall \mathbf{d} \text{ s.t. } \sum_{j=1}^{J} d_j f_j \leq E \text{ and } K \subset \mathbf{d}$$

at the true parameter values γ.

This suggests one method for estimating γ: Choose the values of γ which maximize the number of times the observed decision vector yields a higher payoff than an alternative feasible vector. Formally,

$$\hat{\gamma} = \operatorname{argmax}_{\gamma}\left\{\sum_{\mathbf{d}\in\mathbf{D}(E)} \mathbf{1}\left\{\mathbb{E}\left[\Pi \,|\, \hat{\mathbf{e}}, \hat{\mathbf{d}}; \gamma\right] > \mathbb{E}\left[\Pi \,|\, \mathbf{e}\left(\mathbf{d}\right)^{\star}, \mathbf{d}; \gamma\right]\right\}\right\} \tag{29}$$

where $\mathbf{D}\left(E\right) = \left\{\mathbf{d} \,|\, \sum_{j=1}^{J} d_j f_j \leq E \text{ and } K \subset \mathbf{d}\right\}$ is the set of feasible offering vectors given endowment E. Importantly, every feasible set of offered courses must contain the courses K which are set by preexisting contracts.

It is theoretically possible to point identify γ when the set $\mathbf{D}\left(E\right)$ generates a connected space of welfare and class size outcomes in a neighborhood around the outcomes generated by the observed choices $\hat{\mathbf{d}}$ and $\hat{\mathbf{e}}$. In this case, there is at most one point in the parameter space at which observed choices $\hat{\mathbf{d}}$ and $\hat{\mathbf{e}}$ yield a higher payoff than all feasible alternatives in $\mathbf{D}\left(E\right)$. This is clearly illogical because it requires the set $\mathbf{D}\left(E\right)$ to be infinitely large; however, this illustrates how increasing the number of feasible alternatives in $\mathbf{D}\left(E\right)$ shrinks the parameter subspace in which observed choices $\hat{\mathbf{d}}$ and $\hat{\mathbf{e}}$ yield a higher payoff than all feasible alternatives.

To provide a unique solution with a finite number of alternatives in $\mathbf{D}\left(E\right)$, I propose treating expected payoffs as quantities which are measured with error and solving the stochastic analog of (29). Suppose true expected payoffs are given by:

$$\mathbb{E}\left[\Pi \mid \mathbf{e}\left(\mathbf{d}\right)^{\star}, \mathbf{d}; \gamma\right] = \hat{\Pi}\left(\mathbf{e}\left(\mathbf{d}\right)^{\star}, \mathbf{d}, \gamma\right) + \zeta_{\mathbf{d}} \tag{30}$$

where $\hat{\Pi}\left(\mathbf{e}\left(\mathbf{d}\right)^{\star}, \mathbf{d}, \gamma\right)$ is observed up to values for γ and $\zeta_{\mathbf{d}}$ is an unobserved error term. In practice, welfare and class size outcomes will be estimated using estimates of a student choice model. As such, a theoretical justification for including $\zeta_{\mathbf{d}}$ is the presence of standard sampling error in estimates of these outcomes. The stochastic analog of (29) is then given by:

$$\hat{\gamma} = \operatorname{argmax}_{\gamma}\left\{\Pr\left(\hat{\Pi}\left(\hat{\mathbf{e}}, \hat{\mathbf{d}}, \gamma\right) + \zeta_{\mathbf{d}} \geq \hat{\Pi}\left(\mathbf{e}\left(\mathbf{d}\right)^{\star}, \mathbf{d}, \gamma\right) + \zeta_{\mathbf{d}}\, \forall \mathbf{d} \in \mathbf{D}\left(E\right)\right)\right\} \tag{31}$$

Because the term in braces is a probability, (31) represents a a maximum likelihood estimator for γ. Intuitively, the estimator solves for the parameter values which maximize the likelihood that observed classroom spending decisions are preferred to all feasible alternatives.

Implementing (31) requires an assumption about the distribution of the error term $\zeta_{\mathbf{d}}$. In my empirical application, I assume $\zeta_{\mathbf{d}}$ follows a type 1 extreme value distribution. This yields the following likelihood function:

$$\mathscr{L}\left(\hat{\mathbf{d}}; \gamma\right) = \frac{\exp\left(\hat{\Pi}\left(\hat{\mathbf{e}}, \hat{\mathbf{d}}, \gamma\right)\right)}{\sum_{\mathbf{d} \in \mathbf{D}(E)} \exp\left(\hat{\Pi}\left(\mathbf{e}\left(\mathbf{d}\right)^{\star}, \mathbf{d}, \gamma\right)\right)} \tag{32}$$

If researchers have access to panel data, the likelihood function given by (32) can be adapted to include multiple semesters of classroom spending decisions. Let $\hat{\mathbf{d}}_t$ and $\hat{\mathbf{e}}_t$ represent observed decisions in period t and let $\mathbf{D}_t\left(E_t\right)$ represent the set of feasible offerings in semester t. With T semesters of observed classroom spending decisions, the likelihood function is given by:

$$\mathscr{L}\left(\hat{\mathbf{d}}_t; \gamma\right) = \prod_{t=1}^{T}\left[\frac{\exp\left(\hat{\Pi}\left(\hat{\mathbf{e}}_t, \hat{\mathbf{d}}_t, \gamma\right)\right)}{\sum_{\mathbf{d} \in \mathbf{D}_t(E_t)} \exp\left(\hat{\Pi}\left(\mathbf{e}\left(\mathbf{d}\right)^{\star}, \mathbf{d}, \gamma\right)\right)}\right] \tag{33}$$

With panel data, this estimator converges to the true parameter values as T increases and as the size of $\mathbf{D}_t\left(E_t\right)$ increases. When T increases, the estimator approaches true values because there are a larger number of choices which must be explained by parameter values. This is akin to increasing the number of individuals in a standard discrete choice framework. When the size of $\mathbf{D}_t\left(E_t\right)$ increases, the estimator approaches true values because each semester's decision is more difficult to explain. For the theoretical estimator in (29), increasing the number of feasible alternatives shrinks the parameter subspace in which observed choices

$\hat{\mathbf{d}}$ and $\hat{\mathbf{e}}$ yield a higher payoff than all feasible alternatives. For the stochastic maximum likelihood estimator in (32), increasing the number of feasible alternatives reduces reliance on specific realizations of the error terms for generating a unique solution. Simulation results which demonstrate the effectiveness of this estimator are compiled in Methodological Appendix D.

4.3.1 Identification and estimation

As in Subsection 4.2.1, it is necessary to place some restrictions on γ_j. In my empirical application, I restrict γ_j to be equivalent within academic fields.[25] Intuitively, identification of γ_j comes from the share of courses offered by the observed university relative to the welfare maximizing composition of courses. For instance, if student parameter estimates imply students would prefer a university which offered more STEM and fewer humanities courses this implies the observed university is offering too many humanities courses and too few STEM courses. This reveals an institutional preference for drawing students out of STEM and into humanities courses.

One challenge with implementing the estimation algorithm described in this subsection is that the set of feasible vectors $\mathbf{D}(E)$ may be so large that summing over all $\mathbf{d} \in \mathbf{D}(E)$ is impractical. To address this, researchers can use a subset of $\mathbf{D}(E)$ rather than the full set. In this case, the estimator chooses parameter values which make the observed offering vector yield a higher payoff than a subset of alternative feasible vectors. This provides a computationally feasible algorithm at the cost of modest efficiency losses.

As before, this method also comes with a useful specification test. If all functional form assumptions are correct, the observed offering vector $\hat{\mathbf{d}}$ should yield a higher payoff than all alternative offering vectors at true student and university parameter values. If there are a significant number of alternatives which are preferred to $\hat{\mathbf{d}}$ at parameter estimates we can jointly reject the university objective structure and other functional form assumptions. Once again, failure to reject the null hypothesis does not validate the model structure.

4.3.2 Discussion of best offering vector methods

The strength of the variance minimizing methods described in this subsection is that they provide estimates of preference parameters for an objective structure which is more general than utilitarian student welfare maximization. Specifically, they quantify institutional preferences over the type of courses students choose. These institutional preferences measure the extent to which student and university preferences are not aligned.

[25] Academic fields are STEM, humanities and arts, business, social science, and occupational.

The main disadvantage of these methods is that they depend on the characteristics of non-offered courses. As discussed in Section 3, researchers rarely observe non-offered courses; this implies that strong assumptions about non-offered courses are required to implement this method. Researchers can somewhat address this issue by using a subset of $\mathbf{D}(E)$ which only contains offering vectors which are deemed reasonable. Furthermore, these methods are very sensitive to estimates of minimum costs m_j because these estimates determine which offering vectors are feasible and how much residual money is left for excess spending. Any error in estimates of m_j may lead to spurious conclusions about university preference parameters.

5 Empirical Application

In this section, I describe estimation details and present estimates of student and university preference parameters. Student preference parameters are estimated using a nested logit course choice model where nests are defined by academic fields. Estimates show introductory humanities courses are most popular with first year students while introductory business courses are most popular with sophomores, juniors and seniors. The estimates also show students with higher ACT scores are relatively more attracted to introductory STEM courses. Finally, the estimates suggest higher salaried instructors generally increase an introductory course's desirability but only to a small degree.

University parameters are estimated using the maximum likelihood estimator presented in Subsection 4.3 using student parameter estimates as inputs.[26] Estimates suggest UCA has institutional preferences for decreasing enrollment in introductory business courses and increasing enrollments in introductory humanities and STEM courses. This suggests UCA over invests in introductory STEM and humanities courses and under invests in introductory business courses relative to a university that is purely maximizing student welfare.

5.1 Estimation Details

In the sequential game between a university and students described in Section 2, university decisions about which courses to offer and how much to spend on instructors hinge on how the university expects students to respond to these decisions. As such, it is crucial to obtain credible estimates of how student course choices depend on the set of offered courses and spending on instructors for these courses.

To obtain these estimates, I use a multinomial nested logit model of student course choices

[26] I do not use the variance minimization method in my empirical application due to a lack of identifying variation in the data.

where nests are defined by academic fields.[27] The nesting structure relaxes the independence of irrelevant alternatives assumption by allowing for correlation in unobserved preferences for courses of the same field. To avoid issues of unobserved heterogeneity in choice sets, I focus on introductory course choices only and assume that all introductory courses are in the choice sets of all enrolled students.[28] As such, the estimation method should be viewed as a conditional nested logit in which students choose which introductory courses to take conditional on already choosing to take some introductory course.

In this analysis, I consider the baseline setting in which class sizes do not affect the desirability of a course. Future research may employ a general equilibrium framework in which class size affects course desirability.

5.1.1 Student utility, choice probabilities, and expected welfare

I assume the deterministic utility of introductory course j for student i depends on observed student characteristics X_i and excess spending on instruction in course j e_j as:

$$u_{ij}\left(e_j\right) = X_i \beta_{f(j)} + \theta_{f(j)} \ln\left(e_j + 1\right) \tag{34}$$

where $f\left(j\right)$ indicates the academic field of introductory course j. The logarithmic structure is included to make the marginal utility of excess spending diminish as spending increases.[29] X_i includes gender and ACT scores to capture heterogeneous preferences for academic fields by gender and initial preparation. Furthermore, X_i includes cohort dummy variables to allow for changes in relative preferences for introductory courses of different fields over the course of college.

I assume stochastic utility is given by deterministic utility with an additively separable error:

$$U_{ij}\left(e_j\right) = u_{ij} + \epsilon_{ij} \tag{35}$$

where ϵ_{ij} follows a nested logit structure in which nests are defined by academic fields.

With this structure, the probability student i chooses introductory course j conditional

[27] See McFadden (1978). Academic fields are: STEM, social science, humanities and arts, occupational, and business.

[28] Many advanced courses have prerequisite restrictions implying they are only in the choice sets of students who have satisfied these pre-requisites.

[29] I add 1 to excess spending to make the marginal utility of excess spending finite over the entire support of excess spending: $e_j \in [0, \infty)$.

on choosing an introductory course is given by:

$$P_{ij}\left(\mathbf{e},\mathbf{d}\right)=\frac{\exp\left(\frac{u_{ij}}{\rho}\right)\left[\sum_{j'\in f(j)}\exp\left(\frac{u_{ij'}}{\rho}\right)\right]^{\rho-1}}{\sum_{f=1}^{F}\left[\sum_{j'\in f}\exp\left(\frac{u_{ij'}}{\rho}\right)\right]^{\rho}} \tag{36}$$

where ρ is the nesting parameter.[30] Furthermore, with this structure, student i's expected welfare from her choice of which introductory course to take is given by:

$$\mathbb{E}\left[V_i\,|\,\mathbf{e},\mathbf{d}\right]=\ln\left\{\sum_{f=1}^{F}\left[\sum_{j'\in f}\exp\left(\frac{u_{ij'}}{\rho}\right)\right]^{\rho}\right\}+\gamma \tag{37}$$

where γ is the Euler-Mascheroni constant. Importantly, choice probabilities and expected welfare both depend on the university's choice of which courses to offer $\mathbf{d}$ and how much to spend in excess of minimum costs to increase instructor quality $\mathbf{e}$.

5.1.2 Maximum Likelihood Estimation

Let C_{it} represent the number of introductory courses taken by individual i in semester t and index these courses by c. Let y_{itcj} indicate whether individual i chooses introductory course j for choice c in academic semester t. The conditional likelihood that student i chooses her observed introductory course for choice c in academic semester t is given by:

$$\mathscr{L}_{itc}=\prod_{j\in\mathbf{d_t}}P_{ij}\left(\mathbf{e_t},\mathbf{d_t}\right)^{y_{itcj}} \tag{38}$$

where $\mathbf{d}_t$ and $\mathbf{e}_t$ represent course offerings and excess spending in semester t respectively. Taking products over courses within semesters, students, and semesters, the conditional likelihood of observing the observed introductory course choices is given by:[31]

$$\mathscr{L}\left(\mathbf{y};\beta,\theta,\rho\right)=\prod_{t=1}^{T}\prod_{i=1}^{N_t}\prod_{c=1}^{C_{it}}\prod_{j\in\mathbf{d_t}}P_{ij}\left(\mathbf{e_t},\mathbf{d_t};\beta,\theta,\rho\right)^{y_{itcj}} \tag{39}$$

[30] $\rho\in(0,1]$. $1-\rho$ can be viewed as an indication of the correlation in unobserved preferences within the same academic field (McFadden, 1978).

[31] This framework approximates choices by students within academic semesters as C_{it} independent choices. An alternative framework models students as choosing the best bundle of C_{it} courses from all feasible bundles. I abstract from this complication to focus on university preferences. For a choice model in which students choose course bundles, see Ahn, Arcidiacono, Hopson, and Thomas (2015).

The log conditional likelihood is then given by:

$$\ln \mathscr{L}(\mathbf{y}; \beta, \theta, \rho) = \sum_{t=1}^{T} \sum_{i=1}^{N} \sum_{c=1}^{C_{it}} \sum_{j \in \mathbf{d}_t} y_{itcj} \ln P_{ij}(\mathbf{e_t}, \mathbf{d_t}; \beta, \theta, \rho) \tag{40}$$

Estimates of student utility parameters β, θ, and ρ are obtained by numerically solving for the parameter values which maximize this log conditional likelihood.

5.2 Estimates of student utility parameters

Table 2 compiles estimates of the multinomial logit choice model. The estimates imply a first year male student with average ACT scores is most attracted to introductory humanities and arts courses followed by STEM, occupational, social science and business. First year female students with average scores are also most attracted to introductory humanities and arts courses followed by social science, occupational, STEM, and business. While introductory business courses are unpopular with freshmen, they are quite popular with more advanced students. With one exception, male and female sophomores, juniors, and seniors with average ACT scores favor introductory business courses to all other courses. Comparatively, while introductory humanities and arts courses are popular with Freshmen, they are rarely taken by more advanced students—sophomores, juniors and seniors with average ACT scores are least interested in taking introductory humanities and arts courses.

The estimates also imply students with higher ACT scores are relatively more likely to enroll in introductory STEM courses and slightly less likely to enroll in introductory occupational courses. For example, while a first year male student with average ACT scores prefers taking introductory humanities and arts courses, a first year male student whose ACT scores are 1.5 standard deviations above the mean is approximately indifferent between introductory STEM and humanities courses. The finding that students with higher ACT scores are relatively more likely to enroll in introductory STEM courses is consistent with existing literature which shows initial preparation is an important determinant of whether a student pursues a STEM education (Arcidiacono, 2004; Stinebrickner and Stinebrickner, 2014).

The return on excess spending results show that excess spending on instruction has a positive and significant effect on course desirability for all fields except business. However, the magnitudes of these estimates suggest the effects are quite small relative to non-spending preferences for fields. Social science courses appear most sensitive to excess spending but even these coefficients are small. The distribution of $\ln(e_j + 1)$ has mean 7.71 and standard deviation 2.10. This implies first year male students with average ACT scores are approximately indifferent between an introductory social science course with $\ln(e_j + 1)$ that is 3.67 standard deviations above zero and an introductory humanities course with zero excess spending. Put simply, even in the field most sensitive to excess spending it takes large increases in spending to overcome latent differences in preferences.

This finding has important implications for universities. It implies that the vast amounts of resources spent hiring instructors who cost more than minimally qualified teachers has relatively small effects on student course choices and student welfare. To see this more concretely, consider the comparison of three simple hypothetical universities given in Table 3. The baseline university offers one course from each field and hires minimally qualified instructors to teach these courses. This costs \$14,420 and yields 61,829 units of welfare. Now suppose the university has surplus funds and wishes to either increase student welfare or increase enrollment in social science courses. In the "More Courses" alternative, the university spends its additional funds hiring another minimally qualified instructor to teach one additional social science course. Under this alternative, total cost is \$17,124, social science enrollment is 28.3% of total enrollment, and student welfare is 66,282 units. In the "More Spending" alternative, the university spends the same amount of funds hiring a more qualified instructor to teach its one social science course. Under this alternative, total cost is still \$17,124, but social science enrollment is only 24.2% of the total, and student welfare is only 64,509. This implies that even for social science—where excess spending has the largest effects on utility—it is more efficient to increase student welfare or change student course choices by offering additional courses rather than hiring more qualified instructors.

This result provides an interesting complement to existing literature which examines the effects of instructor qualifications on student learning. Figlio, Shapiro, and Soter (2013) use data from Northwestern University and find students learn relatively more from non-tenure track instructors—who generally have lower salaries—than tenure track instructors. Additionally, Bettinger and Long (2010) use data from public four year colleges in Ohio and find non-tenure track instructors make students more likely to take subsequent courses in a field. While my result only applies to introductory courses at University of Central Arkansas, it does corroborate existing literature which suggests the vast amounts of resources universities spend hiring more expensive instructors have small (or possibly negative) effects on the academic experiences of students.

5.3 Estimates of university parameters

Table 4 compiles estimates of university preference parameters obtained using the maximum likelihood estimation procedure discussed in Subsection 4.3.[32] Intuitively, this estimation algorithm solves for parameter values which best explain why observed introductory course offerings were preferred to alternative feasible offering vectors. To be feasible, an alternative offering vector must contain introductory courses which must be offered to honor preexisting contracts and must satisfy the budget constraint.[33]

Recall from Section 4 that university payoffs are modeled as:

$$\mathbb{E}\left[\Pi \mid \mathbf{e}, \mathbf{d}\right] = \sum_{i=1}^{N} \mathbb{E}\left[V_i \mid \mathbf{e}, \mathbf{d}\right] + \sum_{j=1}^{J} \gamma_{f(j)} \tilde{n}_j \left(\mathbf{e}, \mathbf{d}\right) \tag{41}$$

Table 4 contains estimates of $\gamma_{f(j)}$. These parameters represent institutional preferences for the type of courses students choose. If $\gamma_f = 0$ for all f then the university's objective is to maximize total student welfare giving equal weight to all students. Non-zero estimates for γ_f reveal relative institutional preferences for the type of courses students choose. These institutional preferences lead to classroom spending decisions which are not in line with student preferences.

The results in table 4 imply University of Central Arkansas (UCA) values enrollment in humanities and arts courses more than all other fields. After humanities and arts, UCA values STEM enrollment, social science enrollment, occupational enrollment and business enrollment. This implies UCA over-invests in humanities and arts courses and under-invests in business courses relative to a university whose objective is to maximize student welfare.

To directly see UCA's relative preference for humanities and arts enrollment, note that descriptive statistics in Table 1 show humanities courses comprise 31.6% - 34.5% of introductory course spending but only 30.7% - 32.2% of introductory course enrollment. This outsize investment reflects UCA's desire to increase enrollment in introductory humanities courses. Comparatively, business courses comprise only 5.7% - 7.3% of introductory course spending but make up 8.1% - 9.7% of introductory course enrollment. This under investment is consistent with an objective to draw students away from introductory business courses and into other fields.

[32]These are preliminary estimates which assume $\mathbf{e}\left(\mathbf{d}\right)^{\star} = \mathbf{0}$ for all $\mathbf{d}$. Results which use the true $\mathbf{e}\left(\mathbf{d}\right)^{\star}$ are in progress; however, as discussed in Subsection 5.2, estimates of student parameters imply these optimal excess spending levels will always be close to zero. As such, these preliminary estimates should be similar to the final estimates.

[33]As discussed in Subsection 4.3.1, the set of alternative feasible offering vectors is typically unfeasibly large making it necessary to draw a sample of alternative feasible offering vectors. I sample 1000 feasible offering vectors for each academic semester.

Table 4 also includes measures assessing goodness of fit for the model of classroom spending decisions. As discussed in Subsection 4.3.1, model fit can be evaluated by calculating the fraction of alternative feasible offering vectors which are preferred to the chosen vector in the estimated model. If a substantial fraction of alternative feasible offering vectors yield larger university payoffs than the chosen vector then the model is explaining university decisions poorly. The results of this analysis show that at most 0.5% of alternative feasible offerings are preferred to the chosen vector in any given semester. In two of the four semesters, all alternative feasible offerings yield lower university payoffs than the chosen vector. This indicates that the fitted model is explaining university choices remarkably well.

6 Counter-factual Simulations

In Section 5, I presented estimates of university preference parameters which show University of Central Arkansas (UCA) has a relative preference for increasing enrollments in introductory humanities courses and decreasing enrollments in introductory business courses. To place estimates of university parameter values in context and to examine university behaviors under alternative constraints, I develop a Marginal Improvement Algorithm (MIA) for simulating classroom spending decisions under alternative preferences and constraints (Chade and Smith, 2006). A university's choice set is typically so large that it is intractable to solve its true maximization problem. The MIA reduces dimensionality by breaking the full maximization problem into a series of smaller maximization problems where the preference of each problem is to maximize marginal improvements to the university's payoff.

I use the MIA to examine two counterfactual scenarios: First, I solve for counter-factual minimum costs m_j which induce UCA to offer courses which maximize student welfare. The simulation suggests that a revenue neutral tax and subsidy policy which increases the cost of offering introductory humanities, STEM, social science, and occupational courses and decreases the cost of offering business courses leads UCA to offer courses which maximize student welfare. Second, I simulate course offerings and excess spending decisions which produce welfare efficiently in the absence of contractual constraints. This simulation shows UCA could achieve the same student welfare at 38.5% of original costs in the absence of contractual constraints.

6.1 Marginal Improvement Algorithm

This subsection presents a Marginal Improvement Algorithm (Chade and Smith, 2006) for approximating the course offerings and excess spending decisions of a university with a known objective function. Broadly speaking, the algorithm iteratively adds single courses which best complement previously selected courses until the budget constraint is satisfied or no marginal improving courses exist.

To illustrate these methods more concretely, note that it is often possible to combine tangency conditions given by Equation (7) with the budget constraint to solve for the optimal excess spending vector for each offering vector.[34] Denote these optimal excess spending vectors as: $\mathbf{e}(\mathbf{d})^{\star}$. The university's problem can then be restated to focus on extensive margin decisions:

$$\mathbf{d}^{\star} \quad = \quad \operatorname{argmax}_{\mathbf{d}} \left\{ \mathbb{E}\left[\Pi \,|\, \mathbf{e}(\mathbf{d})^{\star}, \mathbf{d}\right] \right\} \ \forall \mathbf{d}\, \text{s.t.} \sum_{j=1}^{J} d_j f_j \leq E \tag{42}$$

Because the offering vector $\mathbf{d}$ is discrete, Lagrange methods cannot be used to characterize properties of the extensive margin solution. Furthermore, because the number of feasible $\mathbf{d}$ is typically very large, directly solving the problem is impractical.[35] To solve for $\mathbf{d}^{\star}$, the Marginal Improvement Algorithm starts by selecting the single course offering which delivers the greatest expected payoff to the university.[36] Denote this course by $j_1^{\star}$. Finding $j_1^{\star}$ requires computing the university's payoff for every potential course. Following this, the algorithm selects the best course to offer alongside $j_1^{\star}$. This entails calculating the university's payoff for every offering vector which includes $j_1^{\star}$ and one other potential course. The algorithm continues adding marginally improving course until marginal effects turn negative or until the constraint $\sum_{j=1}^{J} d_j m_j \leq E$ binds. Technical details on this algorithm are provided in Methodological Appendix E.

6.2 Counter-factual costs which yield welfare maximizing course offerings

Table 5 reports market minimum costs and counterfactual minimum costs m_j which induce UCA to offer courses which maximize student welfare. The counterfactual setting increases minimum costs of offering introductory STEM, humanities, social science, and occupational courses and decreases the minimum costs of offering introductory business courses. These

[34]See Methodological Appendix C for an illustration.

[35]In my empirical application, a conservative lower bound for the number of feasible choices for $\mathbf{d}$ is 2.95×10^{13}.

[36]I describe the algorithm for a setting in which the university has no contractual constraints. To incorporate contractual constraints, the algorithm should start with the set of courses which must be offered by contract. A variation of the algorithm selects courses which yield the greatest marginal improvement per minimum cost. This variation outperforms the standard version in settings where variation in minimum costs is large relative to marginal utilities of excess spending.

counterfactual costs can be achieved with a tax and subsidy policy that is approximately revenue neutral.

Column 1 reports optimal course offerings for a welfare maximizing university with a 1.9 million dollar endowment and no contractual constraints facing market minimum costs estimated from data. The results suggest introductory business and occupational courses yield the best value to students while introductory STEM and humanities courses are less desirable. Column 2 reports offerings for an unconstrained university with the same endowment and minimum costs but with estimated institutional preferences reported in Table 4. These results show UCA's preference for students choosing humanities and STEM courses relative to occupational and business courses lead to many more humanities and STEM course offerings and fewer occupational and business courses.

Column 3 shows the welfare maximizing offerings presented in column 1 will be chosen by a university with estimated institutional preferences under counter-factual minimum costs. The counter-factual costs represent a 87% increase in the minimum cost of introductory humanities courses, a 45% increase for STEM courses, a 32% increase for social science courses, a 14% increase in occupational courses, and a 21% decrease in the minimum cost of introductory business courses.

These counterfactual costs could be achieved with a fixed tax on instruction spending in introductory humanities, STEM, social science, and occupational courses and a fixed subsidy for spending on introductory business courses. The cost of such a policy would be:

$$\tau = \sum_{j \in \mathbf{d}} \left(m_j - m'_j\right) \tag{43}$$

where m_j represents market minimum costs and m'_j represents counterfactual minimum costs. In my application, $\tau = \$2,410$ or 0.12% of the university's endowment making it effectively revenue neutral.

This demonstrates that an approximately revenue neutral tax and subsidy policy which modifies the relative minimum costs of offering different courses can induce UCA to offer courses which maximize student welfare. While such a policy may be impractical or undesirable for other reasons it is interesting to see what counter-factual minimum costs would price out institutional preferences for enrollments in different fields.

6.3 Welfare maximizing classroom spending decisions at University of Central Arkansas

Table 6 compares UCA's observed course offerings in the Fall semester of 2007 to the course offerings which produce welfare efficiently in a scenario with no contractual constraints. The differences are quite striking. In the counterfactual scenario, UCA achieves the same student welfare at 38.5% of original costs. These savings are primarily due to reductions in spending on instruction. As discussed in Section 5, the student utility parameter estimates suggest spending on instruction has relatively small effects on course desirability. Because students place little value on spending on instruction, a counterfactual university which produces welfare efficiently spends 54.5% - 66.5% less on instruction in median courses by field. This saves vast sums of money and only modestly decreases student welfare.

The results also show that UCA could alter its introductory course composition to better serve students. Observed course offerings at UCA include 433 introductory humanities courses, 279 introductory STEM courses, 272 introductory social science courses, 125 introductory occupational courses, and only 65 introductory business courses. Comparatively, the counterfactual welfare maximizing university offers 521 introductory business courses, 518 introductory social science courses, 110 introductory occupational courses, and only 54 introductory humanities courses and 38 introductory STEM courses.

Importantly, although the counter-factual scenario is very different from observed course offerings the total number of courses offered is similar in both scenarios. This suggests the welfare maximizing offerings would not require large changes in facilities which would introduce costs not included in my analysis. While such a vastly different university may be undesirable for other reasons, it is striking to see that students could obtain the same welfare with drastically lower costs and interesting to note what alternative classroom spending decisions achieve these savings.

7 Conclusion

In 1973, Daniel Bell described the university as "the axial institution of post-industrial society" (Bell, 1974). This is more true today than it was over four decades ago. Despite this, very little is known about how universities make decisions. A better understanding of how universities make decisions could lead to policies which benefit students and reduce financial burdens on taxpayers, families, and donors.

In this paper, I develop tools for revealing university preferences from decisions of which courses to offer and how much to spend on instructors for these courses. The methods include a statistical test of whether classroom spending decisions maximize student welfare and two methods for estimating a university's relative preferences for student welfare and the type of courses students choose. I apply these methods to administrative data from University of Central Arkansas (UCA) and find UCA has institutional preferences for decreasing enrollment in introductory business courses and increasing enrollments in introductory humanities and STEM courses.

In addition to discussing methods for inferring the preferences of an observed university, I also present a method for simulating the classroom spending decisions of a university with alternative preferences or facing counter-factual constraints. I use this method to run two simulations: First, I show that a revenue neutral tax and subsidy policy which reduces the cost of offering introductory business courses and increases the cost of offering other introductory courses can induce UCA to offer courses which maximize student welfare. Second, I show that UCA could achieve the same student welfare at 38.5% of original costs in the absence of contractual constraints. The savings primarily result from hiring less expensive instructors but are also generated by offering more introductory business courses and fewer introductory STEM and humanities courses. While these scenarios may be undesirable for other reasons, it is useful to see how a revenue neutral policy could be used to benefit students and it is striking to see that students could receive the same benefit with drastically lower costs with changes in instructors and course composition.

Future work may build upon my framework and methods in many possible ways. First, empirical applications which allow class size to affect utility and estimate non-utilitarian weights on student welfare should be conducted. I describe methods for these extensions but do not include these features in my empirical application.

Second, my framework and methods could be extended to include a larger set of university decisions. For clarity and tractability, I focus on revealing university preferences from observed classroom spending decisions for non-contract introductory courses. Data on prerequisite restrictions could be used to extend my methods to include non-contract advanced courses. Moreover, a dynamic university model could potentially model decisions of which instructors to hire on long term contracts. Such an analysis may explain why UCA and other schools spend vast amounts of resources hiring more expensive instructors despite evidence that these sums have small effects on student choices and welfare.

Third, my model for student course choices could be expanded to create a richer link between classroom spending decisions and student outcomes. My model for student course choices is static and reduced form. While this is a tractable way to relate classroom spending decisions to student outcomes it has many limitations. My specification assumes students derive utility from spending on instruction. In fact, students derive utility from instructor characteristics which are correlated with spending on instruction. A more structural student choice model which captures the relationship between instructor characteristics and utility could be used to extend the university's problem to a three tier decision where the university chooses which courses to offer, how much to spend on instruction, and what instructor characteristics to rent with these funds. This more structural model would yield a deeper understanding of university decisions and the implications for students.

Furthermore, a richer dynamic model of student course choices could provide a more complete portrait of the relationship between university decisions and student outcomes. For example, a dynamic model which includes major choices, dropout decisions, or labor market outcomes could be used to reveal university preferences for these outcomes. A deeper understanding of institutional preferences could be used to determine whether institutional preferences are socially beneficial phenomena which internalize externalities or whether they are socially detrimental factors which hurt the very students universities exist to serve.

Methodological Appendix A: Expressions for effects of spending on choice probabilities and class sizes in general equilibrium

In this appendix, I derive expressions for the effects of spending on instruction in one course on enrollments in all courses in a general equilibrium setting in which class size affects choice utility. These effects are complicated because spending on instruction has direct effects on own course enrollment through changes in instructor quality but also indirect effects on all course enrollments through changes in class sizes. In this appendix only, I assume idiosyncratic preferences ϵ_{ij} are drawn independently from a type 1 extreme value distribution for tractability.

The effects of excess spending on instruction in course j on expected enrollment in course j' can be written in terms of effects on individual choice probabilities:

$$\frac{d\tilde{n}_{j'}}{de_j} = \sum_{i=1}^{N} \frac{dP_{ij'}}{de_j} \tag{44}$$

The effects of excess spending in course j on probabilities of choosing course j' can be written as the effects of excess spending in course j on choice utility for all courses multiplied by the effects of these choice utilities on the probabilities of choosing course j':

$$\frac{d\tilde{n}_{j'}}{de_j} = \sum_{i=1}^{N} \sum_{k \in \mathbf{d}} \frac{\partial P_{ij'}}{\partial u_{ik}} \frac{du_{ik}}{de_j} \tag{45}$$

where

$$\frac{du_{ik}}{de_j} = \begin{cases} \frac{\partial u_{ij}}{\partial I_j} \frac{\partial \phi_j}{\partial e_j} + \frac{\partial u_{ij}}{\partial \tilde{n}_j} \frac{d\tilde{n}_j}{de_j} & j = k \\ \frac{\partial u_{ik}}{\partial \tilde{n}_k} \frac{d\tilde{n}_k}{de_j} & j \neq k \end{cases} \tag{46}$$

and the type 1 extreme value assumption imples that:

$$\frac{\partial P_{ij'}}{\partial u_{ik}} = \begin{cases} P_{ij'} \left(1 - P_{ij'}\right) & j' = k \\ -P_{ij'} P_{ik} & j' \neq k \end{cases} \tag{47}$$

Equation (45) holds for any multinomial choice model; however, without class size effects the terms $\frac{du_{ik}}{de_j} = 0$ for $j \neq k$. In this setting, these cross course effects are non-zero because spending in course j affects the desirability of course j which affects expected class sizes in all courses.

Combining (45), (46), and (47) yields own spending effects of:

$$\begin{aligned} \frac{d\tilde{n}_j}{de_j} &= \sum_{i=1}^{N} \Bigg[P_{ij} \left(1 - P_{ij}\right) \left[\frac{\partial u_{ij}}{\partial I_j} \frac{\partial \phi_j}{\partial e_j} + \frac{\partial u_{ij}}{\partial \tilde{n}_j} \frac{d\tilde{n}_j}{de_j} \right] \\ &\quad - \sum_{k \in \mathbf{d} \setminus j} P_{ij} P_{ik} \left[\frac{\partial u_{ik}}{\partial \tilde{n}_k} \frac{d\tilde{n}_k}{de_j} \right] \Bigg] \end{aligned} \tag{48}$$

and cross course effects of:

$$\begin{aligned} \frac{d\tilde{n}_{j'}}{de_j} &= \sum_{i=1}^{N} \Bigg[P_{ij'} \left(1 - P_{ij'}\right) \frac{\partial u_{ij'}}{\partial \tilde{n}_{j'}} \frac{d\tilde{n}_{j'}}{de_j} \\ &\quad - P_{ij'} P_{ij} \left[\frac{\partial u_{ij}}{\partial I_j} \frac{\partial \phi_j}{\partial e_j} + \frac{\partial u_{ij}}{\partial \tilde{n}_j} \frac{d\tilde{n}_j}{de_j} \right] \\ &\quad - \sum_{k \in \mathbf{d} \setminus \{j, j'\}} P_{ij'} P_{ik} \left[\frac{\partial u_{ik}}{\partial \tilde{n}_k} \frac{d\tilde{n}_k}{de_j} \right] \Bigg] \end{aligned} \tag{49}$$

where $j \neq j$. In both cases, effects of spending on enrollment depend on the effects of spending on enrollment in all courses. To convert these implicit definitions into explicit solutions for $\frac{d\tilde{n}_{j'}}{de_j}$, rearrange Equation (48) to obtain:

$$\begin{aligned} 0 &= \left[\sum_{i=1}^{N} P_{ij}\left(1-P_{ij}\right)\frac{\partial u_{ij}}{\partial I_j}\frac{\partial \phi_j}{\partial e_j}\right] + \frac{d\tilde{n}_j}{de_j}\left[\left(\sum_{i=1}^{N} P_{ij}\left(1-P_{ij}\right)\frac{\partial u_{ij}}{\partial \tilde{n}_j}\right)-1\right] \\ &\quad - \sum_{k\in\mathbf{d}\backslash j}\frac{d\tilde{n}_k}{de_j}\left[\sum_{i=1}^{N} P_{ij}P_{ik}\frac{\partial u_{ik}}{\partial \tilde{n}_k}\right] \end{aligned} \tag{50}$$

and rearrange Equation (49) to obtain:

$$\begin{aligned} 0 &= \frac{d\tilde{n}_{j'}}{de_j}\left[\left(\sum_{i=1}^{N} P_{ij'}\left(1-P_{ij'}\right)\frac{\partial u_{ij'}}{\partial \tilde{n}_{j'}}\right)-1\right] \\ &\quad - \left[\sum_{i=1}^{N} P_{ij'}P_{ij}\frac{\partial u_{ij}}{\partial I_j}\frac{\partial \phi_j}{\partial e_j}\right] - \frac{d\tilde{n}_j}{de_j}\left[\sum_{i=1}^{N} P_{ij'}P_{ij}\frac{\partial u_{ij}}{\partial \tilde{n}_j}\right] \\ &\quad - \sum_{k\in\mathbf{d}\backslash\{j,j'\}}\frac{d\tilde{n}_k}{de_j}\left[\sum_{i=1}^{N} P_{ij'}P_{ik}\frac{\partial u_{ik}}{\partial \tilde{n}_k}\right] \end{aligned} \tag{51}$$

where $j \neq j'$.

For ease of notation, define:

$$\begin{aligned} A_j &= -\sum_{i=1}^{N} P_{ij}\left(1-P_{ij}\right)\frac{\partial u_{ij}}{\partial I_j}\frac{\partial \phi_j}{\partial e_j} \\ B_j &= \left(\sum_{i=1}^{N} P_{ij}\left(1-P_{ij}\right)\frac{\partial u_{ij}}{\partial \tilde{n}_j}\right)-1 \\ C_{kj} &= -\sum_{i=1}^{N} P_{ij}P_{ik}\frac{\partial u_{ik}}{\partial \tilde{n}_k} \\ E_{jj'} &= \sum_{i=1}^{N} P_{ij'}P_{ij}\frac{\partial u_{ij}}{\partial I_j}\frac{\partial \phi_j}{\partial e_j} \\ F_{jj'} &= -\sum_{i=1}^{N} P_{ij'}P_{ij}\frac{\partial u_{ij}}{\partial \tilde{n}_j} \end{aligned}$$

Index courses in $\mathbf{d}$ from 1 to J. For any $j \in \mathbf{d}$, the system can then be written as:

$$\begin{bmatrix} B_1 & \cdots & F_{j1} & \cdots & C_{J1} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ C_{1j} & \cdots & B_j & \cdots & C_{Jj} \\ \vdots & \ddots & & \ddots & \vdots \\ C_{1J} & \cdots & F_{jJ} & \cdots & B_J \end{bmatrix} \begin{bmatrix} \frac{d\tilde{n}_1}{de_j} \\ \vdots \\ \frac{d\tilde{n}_j}{de_j} \\ \vdots \\ \frac{d\tilde{n}_J}{de_j} \end{bmatrix} = \begin{bmatrix} E_{j1} \\ \vdots \\ A_j \\ \vdots \\ E_{jJ} \end{bmatrix}$$

The first row of the matrix generates Equation (51) where $j' = 1$; the middle row of the matrix generates Equation (50) where $j' = j$; and the bottom row of the matrix generates Equation (51) where $j' = J$. The explicit solution is then given by:

$$\begin{bmatrix} \frac{d\tilde{n}_1}{de_j} \\ \vdots \\ \frac{d\tilde{n}_j}{de_j} \\ \vdots \\ \frac{d\tilde{n}_J}{de_j} \end{bmatrix} = \begin{bmatrix} B_1 & \cdots & F_{j1} & \cdots & C_{J1} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ C_{1j} & \cdots & B_j & \cdots & C_{Jj} \\ \vdots & \ddots & & \ddots & \vdots \\ C_{1J} & \cdots & F_{jJ} & \cdots & B_J \end{bmatrix}^{-1} \begin{bmatrix} E_{j1} \\ \vdots \\ A_j \\ \vdots \\ E_{jJ} \end{bmatrix} \tag{52}$$

With functional form assumptions on the structure of u_{ij}, researchers can estimate a general equilibirum choice model to obtain choice probabilities P_{ij} and marginal effects $\frac{\partial u_{ij}}{\partial \tilde{n}_j}$ and $\frac{\partial u_{ij}}{\partial I_j}\frac{\partial \phi_j}{\partial e_j}$ for all offered courses $j \in \mathbf{d}$. These can be used to construct A_j, B_j, C_{kj}, $E_{jj'}$, and $F_{jj'}$ which in turn can be used to construct $\frac{d\tilde{n}_{j'}}{de_j}$ using Equation (52).

Methodological Appendix B: Identification of γ_f from tangency conditions

In this appendix, I show how the system of tangency conditions given by Equation (23) can be used to identify university preferences for students choosing courses in field f .[37]

Because the total number of enrolled students is fixed, only relative parameters $\{\gamma_f - \gamma_F\}_{f=1}^{F-1}$ are identified. To see this more concretely, combine university payoffs given by Equation (19)

[37] I present an identification argument for the general equilibrium setting in which class size affects choice utility. The baseline setting with no class size effects is a specific case of the general equilibrium setting. As such, identification in the general equilibrium setting implies identification in the baseline setting.

with the constraint $\sum_{j=1}^{J} \tilde{n}_j\left(\mathbf{e},\mathbf{d}\right) = N$ to obtain:

$$\mathbb{E}\left[\Pi \,|\, \mathbf{e},\mathbf{d}\right] = \sum_{i=1}^{N} \mathbb{E}\left[V_i \,|\, \mathbf{e},\mathbf{d}\right] + \sum_{f=1}^{F-1} \gamma_f \left[\sum_{j\in f} \tilde{n}_j\left(\mathbf{e},\mathbf{d}\right)\right] + \gamma_F \left(N - \sum_{f=1}^{F-1}\sum_{j\in f} \tilde{n}_j\left(\mathbf{e},\mathbf{d}\right)\right)$$

Rearranging yields:

$$\mathbb{E}\left[\Pi \,|\, \mathbf{e},\mathbf{d}\right] = \sum_{i=1}^{N} \mathbb{E}\left[V_i \,|\, \mathbf{e},\mathbf{d}\right] + \sum_{f=1}^{F-1} \left(\gamma_f - \gamma_F\right) \left[\sum_{j\in f} \tilde{n}_j\left(\mathbf{e},\mathbf{d}\right)\right] + \gamma_F N$$

The last term $\gamma_F N$ is uninformative because N is fixed across course offerings $\mathbf{d}$ and excess spending vectors $\mathbf{e}$. This demonstrates that relative parameters $\{\gamma_f - \gamma_F\}_{f=1}^{F-1}$ fully characterize university preferences for the courses students choose. As such, without loss of generality I normalize $\gamma_F = 0$.

To identify relative γ_f using the university's tangency conditions, I begin by selecting one non-contract offered course with positive excess spending for each academic field. The tangency conditions imply the marginal effects of excess spending on university payoffs must be the same across these selected courses. I show how this system of tangency conditions can be inverted to solve for the unique values of γ_f which make this true.

For ease of notation, define:

$$\begin{aligned} dW_f &= \sum_{i=1}^{N}\sum_{k\in\mathbf{d}} \left(\frac{du_{ik}}{de_j}\right) P_{ik} \\ dn_{fk} &= \frac{d\tilde{n}_k}{de_j} \end{aligned}$$

where course j is the selected course in academic field f. dW_f represents the marginal effect of excess spending on total student welfare for the selected course in field f while dn_{fk} represents the marginal effect of excess spending on the number of students choosing course k for the selected course in field f .

The general equilibrium tangency conditions given by Equations (21) and (23) relating these selected courses can then be represented with the following system of $(F-1)$ equations and $(F-1)$ unknown parameters:

$$\begin{aligned} dW_1 + \sum_{f=1}^{F-1} \gamma_f \left[\sum_{k \in f} dn_{1k} \right] &= dW_F + \sum_{f=1}^{F-1} \gamma_f \left[\sum_{k \in f} dn_{Fk} \right] \\ &\vdots \\ dW_{F-1} + \sum_{f=1}^{F-1} \gamma_f \left[\sum_{k \in f} dn_{F-1k} \right] &= dW_F + \sum_{f=1}^{F-1} \gamma_f \left[\sum_{k \in f} dn_{Fk} \right] \end{aligned}$$

To solve this system, define the matrices and vectors:

$$dn = \begin{bmatrix} \sum_{k \in 1} (dn_{1k} - d_{Fk}) & \cdots & \sum_{k \in F-1} (dn_{1k} - d_{Fk}) \\ \vdots & \ddots & \vdots \\ \sum_{k \in 1} (dn_{F-1k} - d_{Fk}) & \cdots & \sum_{k \in F-1} (dn_{F-1k} - d_{Fk}) \end{bmatrix}$$

$$dW = \begin{bmatrix} dW_F - dW_1 \\ \vdots \\ dW_F - dW_{F-1} \end{bmatrix}$$

$$\gamma = \begin{bmatrix} \gamma_1 \\ \vdots \\ \gamma_{F-1} \end{bmatrix}$$

The system of tangency conditions can then be written as:

$$(dn)\,\gamma = (dW)$$

Assuming there is enough variation to invert dn, γ is identified using:

$$\gamma = (dn)^{-1}\,(dW)$$

This argument demonstrates γ is identified as long as there is at least one non-contract offered course with positive excess spending in each academic field. In all practical cases, there are multiple non-contract offered course with positive excess spending in each academic field. In these cases,γ is over-identified allowing for the over-identification test described in Subsection 4.2.1.

Methodological Appendix C: Optimal Excess Spending Decisions

In this appendix, I present methods for computing $\mathbf{e}(\mathbf{d})^\star$ for several alternative settings and utility structures. In most cases, it is infeasible to solve for $\mathbf{e}(\mathbf{d})^\star$ explicitly; however, it is often possible to define $\mathbf{e}(\mathbf{d})^\star$ implicitly and solve for a fixed point of these implicit definitions using a iterative algorithm.

Example 1: Welfare Maximizing University - no effects of class size

This example solves for $\mathbf{e}(\mathbf{d})^\star$ for a welfare maximizing university in the baseline setting where class size does not effect course utility. Suppose choice utility is given by:

$$U_{ij} = \theta_j \ln(e_j + 1) + \psi_{ij}(Z_j, X_i) + \epsilon_{ij} \tag{53}$$

With this structure, a welfare maximizing university's tangency conditions are given by:

$$\frac{\theta_j \tilde{\mathbf{n}}_j(\mathbf{e})}{e_j + 1} = \frac{\theta_{j'} \tilde{\mathbf{n}}_{j'}(\mathbf{e})}{e_{j'} + 1} \quad \forall j, j' \in \mathbf{d}\, s.t.\, c_j > m_j,\, c_{j'} > m_{j'} \tag{54}$$

and the binding budget constraint is given by:

$$\sum_{j \in \mathbf{d}} (m_j + e_j) = E \tag{55}$$

$\mathbf{e}(\mathbf{d})^\star$ can then be implicitly defined as:

$$e_j(\mathbf{d})^\star = \frac{\left[E + J - \sum_{j=1}^{J} m_j\right] \theta_j \tilde{\mathbf{n}}_j(\mathbf{e})}{\sum_{j'=1}^{J} \theta_{j'} \tilde{\mathbf{n}}_{j'}(\mathbf{e})} - 1 \tag{56}$$

The following iterative algorithm can then be used to solve for a fixed point of this implicit definition:

1. Set initial excess spending values to be uniform across offered courses: $e_j^1 = \frac{E - \sum_{j=1}^{J} m_j}{J}$
2. Compute expected class sizes given initial excess spending values: $\tilde{\mathbf{n}}_j^1 = \tilde{\mathbf{n}}_j(\mathbf{e}^1)$
3. Use Equation (56) to compute new excess spending values: e_j^2
4. Repeat until sequential values of $\mathbf{e}$ become arbitrarily close.

Example 2: General Objective Structure - no effects of class size

This example solves for $\mathbf{e}(\mathbf{d})^{\star}$ for the general university objective structure in the baseline setting where class size does not effect course utility. As before, suppose choice utility is given by:

$$U_{ij} = \theta_j \ln(e_j + 1) + \psi_{ij}(Z_j,\, X_i) + \epsilon_{ij} \tag{57}$$

where ϵ_{ij} follows a type 1 extreme value distribution. With this structure, the university's tangency conditions are given by:

$$\frac{d\mathbb{E}[\Pi \,|\, \mathbf{e}, \mathbf{d}]}{de_j} = \frac{d\mathbb{E}[\Pi \,|\, \mathbf{e}, \mathbf{d}]}{de_{j'}} \quad \forall j, j' \in \mathbf{d}\, s.t.\, c_j > m_j,\, c_{j'} > m_{j'} \tag{58}$$

where

$$\begin{aligned} \frac{d\mathbb{E}[\Pi \,|\, \mathbf{e}, \mathbf{d}]}{de_j} &= \left\{\sum_{i=1}^{N}\left(\frac{\theta_j}{e_j+1}\right)P_{ij}\right\} + \sum_{k\in\mathbf{d}}\gamma_k\left(\frac{\partial\tilde{n}_k}{\partial e_j}\right) \\ &= \left(\frac{\theta_j}{e_j+1}\right)\left[\sum_{i=1}^{N}P_{ij} + \gamma_k\left(\sum_{i=1}^{N}P_{ij}(1-P_{ij})\right)\right] \\ &\quad -\sum_{k\neq j}\left(\frac{\theta_k}{e_k+1}\right)\gamma_k\left(\sum_{i=1}^{N}P_{ik}P_{ij}\right) \end{aligned} \tag{59}$$

and the binding budget constraint is given by:

$$\sum_{j\in\mathbf{d}}(m_j + e_j) = E \tag{60}$$

To simplify notation, I make the following substitutions:

$$\alpha_j(\mathbf{e}) = \sum_{i=1}^{N}P_{ij} + \gamma_j\left(\sum_{i=1}^{N}P_{ij}(1-P_{ij})\right) \tag{61}$$

$$\kappa_j(\mathbf{e}) = (e_j+1)\left[\sum_{k\neq j}\left(\frac{\theta_k}{e_k+1}\right)\gamma_k\left(\sum_{i=1}^{N}P_{ik}P_{ij}\right)\right] \tag{62}$$

This simplifies the first order conditions to:

$$\frac{\theta_j\alpha_j(\mathbf{e}) - \kappa_j(\mathbf{e})}{e_j+1} = \frac{\theta_{j'}\alpha_{j'}(\mathbf{e}) - \kappa_{j'}(\mathbf{e})}{e_{j'}+1} \tag{63}$$

$\mathbf{e}(\mathbf{d})^{\star}$ can then be implicitly defined as:

$$e_j(\mathbf{d})^{\star} = \frac{(\theta_j \alpha_j(\mathbf{e}) - \kappa_j(\mathbf{e}))\left(E + J - \sum_{j=1}^{J} m_j\right)}{\sum_{j'=1}^{J} (\theta_{j'} \alpha_{j'}(\mathbf{e}) - \kappa_{j'}(\mathbf{e}))} - 1 \tag{64}$$

Methodological Appendix D: Testing Maximum Likelihood Estimator on Simulated Data

In this appendix, I present simulation results which demonstrate the effectiveness of the Maximum Likelihood estimator of university preference parameters.

Data Simulation

I consider a hypothetical university observed for T semesters, with N students enrolled in each semester, and J potential courses which may be offered in each semester. Following the empirical specification used in Section 5, courses are grouped into F academic fields.

To simulate the data, I begin by simulating the deterministic utility u_{ij} for every student in each of the J potential courses. For the purpose of this simulation, the structure of student utility is irrelevant as long as sufficient variation across students and course types exists. Following this, I draw D potential course offering vectors. Each feasible offering vector is a $(J \times 1)$ vector which indicates whether each of the J potential courses are offered with this vector. Without loss of generality, I assume the endowment is large enough that all of these simulated offering vectors are feasible. For this simulation, I assume optimal excess spending for each offering vector $\mathbf{e}(\mathbf{d})^{\star}$ is zero for all possible values of university parameters. While this is a simplifying assumption, it is consistent with my empirical setting in which estimated marginal utilities of excess spending are so low that $\mathbf{e}(\mathbf{d})^{\star}$ is always zero.

I use the deterministic utilities to compute expected welfare $\mathbb{E}[V_i(\mathbf{d})]$ for every student and expected class sizes $\tilde{n}_j(\mathbf{d})$ for every potential course for each potential course offering vector. This yields a $(N \times D)$ matrix of expected student welfare and a $(J \times D)$ matrix of expected class sizes for every semester. To maintain consistency with my empirical application, I compute these expected welfare and class sizes using a nested logit structure in which course nests are defined by academic fields.

Importantly, the university's chosen offering vector $\tilde{\mathbf{d}}$ cannot be strictly dominated by other choices over the entire parameter space. Otherwise, it will be impossible to solve for parameter values which make the observed choice preferred to all feasible alternatives. To ensure that $\tilde{\mathbf{d}}$ is not strictly dominated, I simulate potential values for university parameters, compute university payoffs for all offering vectors at these parameter values, and select the offering vectors which yield the highest payoffs in each semester. This guarantees that observed university decisions can be rationalized with some values for university preference parameters. To maintain consistency with my empirical application, the structure for university payoffs in this simulation is:

$$\mathbb{E}\left[\Pi \,|\, \mathbf{e}, \mathbf{d}\right] = \sum_{i=1}^{N} \mathbb{E}\left[V_i \,|\, \mathbf{e}, \mathbf{d}\right] + \sum_{j=1}^{J} \gamma_{g(j)} \tilde{n}_j \left(\mathbf{e}, \mathbf{d}\right) \tag{65}$$

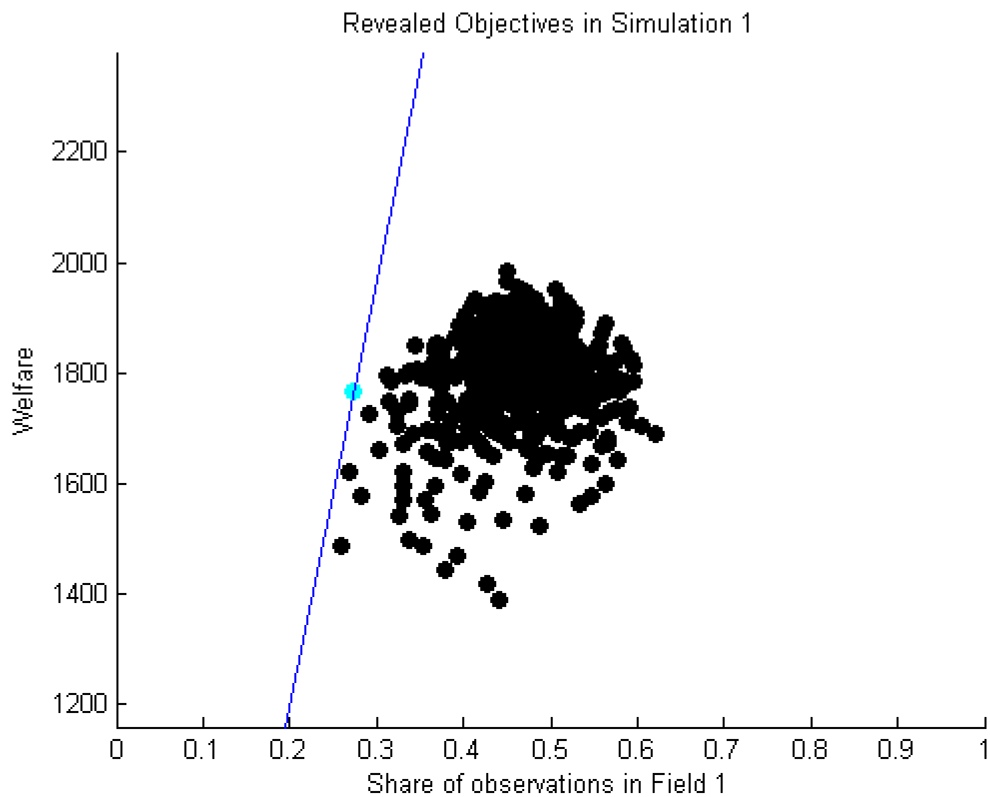
Simulation Results

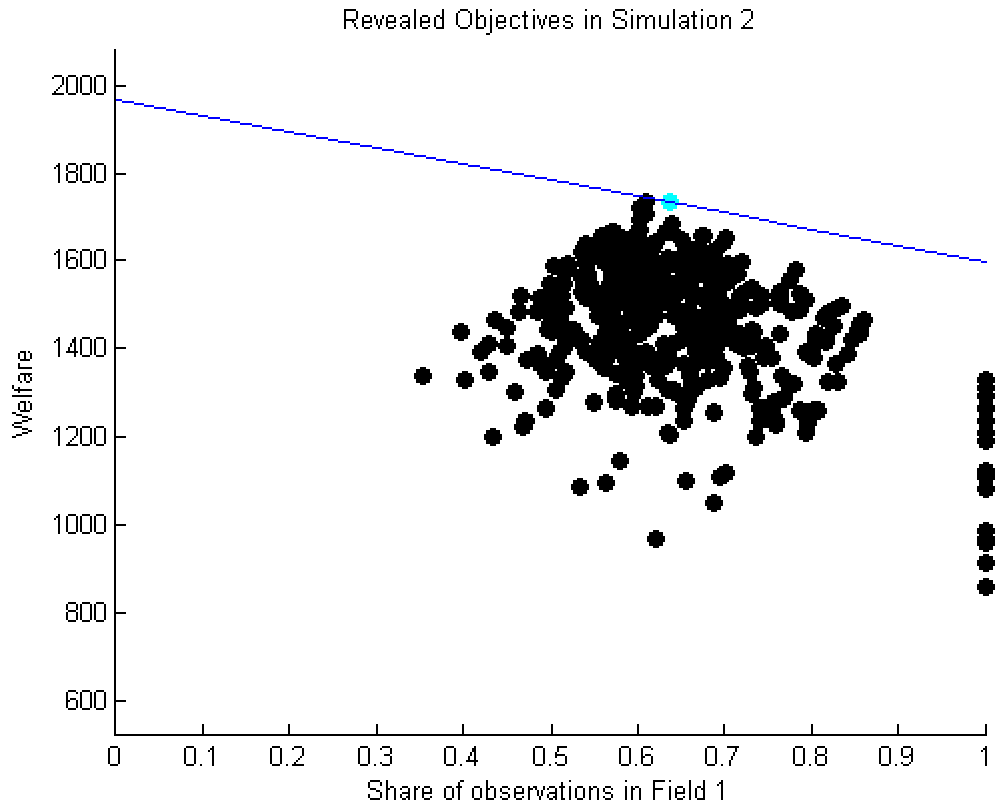
I use the simulated matrices of expected student welfare and expected class sizes to estimate values of $\gamma_{g(j)}$ which best explain why chosen offering vector $\tilde{\mathbf{d}}$ is preferred to all D feasible alternatives using the estimator presented in Subsection 4.3. The maximization problem is solved using numerical maximization techniques built into the software package MAT LAB. To assess performance of the estimator, I perform multiple simulations and report the fraction of feasible alternatives which are preferred to the chosen offering vector at parameter estimates. Sizes used in the simulation are: $T = 2$, $N = 500$, $J = 30$, and $D = 500$. Results compiled in the table below demonstrate the algorithm performs remarkably well at finding parameter values which explain why $\tilde{\mathbf{d}}$ was preferred to feasible alternatives. In half of my simulations, no preferable feasible alternatives exist at parameter estimates. In the other half, the share of feasible alternatives preferred to $\tilde{\mathbf{d}}$ is very small.

	Share of feasible alternatives preferred to $\tilde{\mathbf{d}}$
Simulation 1	0%
Simulation 2	0%
Simulation 3	.1%
Simulation 4	.1%
Simulation 5	0%
Simulation 6	0%
Simulation 7	0%
Simulation 8	.6%
Simulation 9	.3%
Simulation 10	.1%

The below figures illustrate this estimation approach visually. The figures arise from a simplified setting where $T = 1$ and all courses belong to one of two academic fields. In this case, the value of course offering vectors from the perspective of the university can be fully summarized by total welfare and the share of students choosing courses in one field. This allows me to plot all simulated feasible offerings on a graph with share of students choosing one field on the x-axis and total welfare on the y-axis.

On the figures, I highlighted the university's chosen offering vector in cyan and plotted the indifference curve implied by estimates of $\gamma_{g(j)}$. Simulation 1 illustrates a university which has a revealed preference for decreasing the share of students choosing courses in Field 1 ($\gamma_1 > 0$) while simulation 2 illustrates a university which has a revealed preferences for increasing the share of students choosing courses in Field 1 ($\gamma_1 < 0$). Notice that in both cases, the slope of the estimated indifference curve indicates that the university achieves the highest possible estimated payoff at the chosen allocation. This indicates that estimates of γ_1 fully explain why the university's chosen course offerings were preferred to all feasible alternatives.





Methodological Appendix E: Marginal Improvement Algorithm for U-SWM Course Offerings

In this appendix, I describe a Marginal Improvement Algorithm (MIA) for solving for the optimal course offerings and excess spending decisions of a university. The algorithm requires that the university's objective as a function of offering vector $\mathbf{d}$ and excess spending vector $\mathbf{e}$ is known. Furthermore, the algorithm requires that the set of feasible courses J and the budget endowment E are observed.

Let $\Pi(\mathbf{d}, \mathbf{e})$ represent the university's course offerings $\mathbf{d}$ and excess spending vector $\mathbf{e}$ and let $\mathbf{e}(\mathbf{d})^{\star}$ represent the university's optimal excess spending vector given course offerings $\mathbf{d}$. Algorithms for deriving $\mathbf{e}(\mathbf{d})^{\star}$ for various structures of student utility and university objectives are presented in Methodological Appendix D. Finally, let $\mathbf{v_j}$ represent the elementary $J \times 1$ vector which contains 1 in entry j and zeros in all other entries. The MIA proceeds as follows:

1. Solve for the best single course to offer alongside contracted courses:

$$j_1^\star = \text{argmax}_{j \in J} \left\{ \Pi\left(\mathbf{v_j}, \mathbf{e}\left(\mathbf{v_j}\right)^\star\right) \right\} \quad \text{s.t.}\, m_j \leq E \tag{66}$$

2. Solve for the best course to offer alongside $j_1^\star$ and contracted courses:

$$j_2^\star = \text{argmax}_{j \in J \setminus j_1^\star} \left\{ \Pi\left(\mathbf{v_j} + \mathbf{v_{j_1^\star}}, \mathbf{e}\left(\mathbf{v_j} + \mathbf{v_{j_1^\star}}\right)^\star\right) \right\} \quad \text{s.t.}\, m_j + m_{j_1^\star} \leq E \tag{67}$$

3. In general, solve for the best $k+1$ courses to offer alongside previously chosen k courses and contracted courses:

$$\begin{aligned} j_{k+1}^\star \quad = \quad & \text{argmax}_{j \in J \setminus \cup_{k'=1}^{k} j_{k'}^\star} \left\{ \Pi\left(\mathbf{v_j} + \sum_{k'=1}^{k} \mathbf{v_{j_{k'}^\star}}, \mathbf{e}\left(\mathbf{v_j} + \sum_{k'=1}^{k} \mathbf{v_{j_{k'}^\star}}\right)^\star\right) \right\} \\ & \text{s.t.}\, m_j + \sum_{k'=1}^{k} m_{j_{k'}^\star} \leq E \end{aligned} \tag{68}$$

The algorithm terminates when either the best additional course decreases the university's objective or when no additional courses can be added without violating the budget constraint. Formally, the algorithm terminates if:

$$\Pi\left(\sum_{k'=1}^{k+1} \mathbf{v_{j_{k'}^\star}}, \mathbf{e}\left(\sum_{k'=1}^{k+1} \mathbf{v_{j_{k'}^\star}}\right)^\star\right) < \Pi\left(\sum_{k'=1}^{k} \mathbf{v_{j_{k'}^\star}}, \mathbf{e}\left(\sum_{k'=1}^{k} \mathbf{v_{j_{k'}^\star}}\right)^\star\right) \tag{69}$$

or if

$$\min_{j \in J \setminus \cup_{k'=1}^{k} j_{k'}^\star} \left\{ m_j + \sum_{k'=1}^{k} m_{j_{k'}^\star} \right\} > E \tag{70}$$

Methodological Appendix F: Non-Utilitarian Welfare Weights

In this appendix, I discuss extending my theoretical framework and inference methods to include non-utilitarian weights on student welfare. This extension can be used to estimate weighting parameters which best explain observed classroom spending decisions. Non-unitary weights reveal institutional preferences for the welfare of some students relative to others.

With welfare weights, the university's payoff given by Equation (19) is modified to:

$$\mathbb{E}\left[\Pi \,|\, \mathbf{e}, \mathbf{d}\right] = \sum_{i=1}^{N} \omega_i \mathbb{E}\left[V_i \,|\, \mathbf{e}, \mathbf{d}\right] + \sum_{j=1}^{J} \gamma_j \tilde{n}_j\left(\mathbf{e}, \mathbf{d}\right) \tag{71}$$

where $\sum_{i=1}^{N} \omega_i = 1$.

For the baseline setting where class size does not affect utility, marginal effects given by Equation (22) are modified to:

$$\frac{d\mathbb{E}\left[\Pi \,|\, \mathbf{e}, \mathbf{d}\right]}{de_j} = \sum_{i=1}^{N} \omega_i \left(\frac{\partial u_{ij}}{\partial I_j}\right) \left(\frac{\partial \phi_j}{\partial e_j}\right) P_{ij}\left(\mathbf{e}, \mathbf{d}\right) + \sum_{k=1}^{J} \gamma_k \left(\frac{\partial \tilde{n}_k}{\partial e_j}\right) \tag{72}$$

For the general equilibrium setting where class size affects choice utility, marginal effects given by Equation (23) are modified to:

$$\frac{d\mathbb{E}\left[\Pi \,|\, \mathbf{e}, \mathbf{d}\right]}{de_j} = \left\{\sum_{i=1}^{N} \sum_{k \in \mathbf{d}} \omega_i \left(\frac{du_{ik}}{de_j}\right) P_{ik}\right\} + \sum_{k=1}^{J} \gamma_k \left(\frac{d\tilde{n}_k}{de_j}\right) \tag{73}$$

The variance minimization estimation problem given by Equation (24) then jointly estimates the parameter values for γ_j and ω_i which minimize the variance in $\frac{d\mathbb{E}[\Pi \,|\, \mathbf{e},\mathbf{d}]}{de_j}$ across non-contract offered courses for which spending on instruction exceeds minimum costs. Formally,

$$(\hat{\gamma}, \hat{\omega}) = \text{argmin}_{(\gamma,\omega)} \left\{ \text{Var}_{j \in \mathbf{d} \setminus K \text{ s.t. } c_j > m_j} \left(\frac{d\mathbb{E}\left[\Pi \,|\, \gamma, \omega, \tilde{\mathbf{e}}, \tilde{\mathbf{d}}\right]}{de_j} \right) \right\} \tag{74}$$

For identification and estimation, it is necessary to group students into types indexed by τ and restrict welfare weights to be the same for all student types $\omega_i = \omega_{\tau(i)}$. With this restriction, relative values of ω_τ and γ_f are over-identified as long as the number of student types plus the number of course types is less than the total number of non-contract courses for which spending on instruction exceeds minimum costs. Intuitively, identification of ω_τ comes from students of type τ concentrating in classes where the university is under (over) investing relative to a U-SWM university. This implies that the university puts less (more) weight on the welfare of type τ students relative to the general student population. Identification of γ_g comes from residual differences in marginal returns on spending which cannot be explained by student weights. For example, if course groups g and group g' have identical student compositions but the marginal returns on spending are higher (lower) in group g it must be that the university values enrollment in group g courses less (more) than enrollment in group g' courses.

The maximum likelihood estimator given by (31) then jointly estimates the parameter values for γ_j and ω_i which maximize the likelihood that observed course offerings yield a greater payoff for the university than all feasible alternatives. Formally,

$$(\hat{\gamma}, \hat{\omega}) = \operatorname{argmax}_{(\gamma,\omega)} \left\{ \Pr\left(\hat{\Pi}\left(\hat{\mathbf{e}}, \hat{\mathbf{d}}, \gamma, \omega \right) + \zeta_{\mathbf{d}} \geq \hat{\Pi}\left(\mathbf{e}\left(\mathbf{d}\right)^{\star}, \mathbf{d}, \gamma, \omega \right) + \zeta_{\mathbf{d}} \, \forall \mathbf{d} \in \mathbf{D}\left(E\right) \right) \right\} \quad (75)$$

where $\hat{\Pi}\left(\hat{\mathbf{e}}, \hat{\mathbf{d}}, \gamma, \omega\right)$ use the modified payoff structure in (71).

Once again, it is necessary to group students into types indexed by τ and restrict welfare weights to be the same for all student types $\omega_i = \omega_{\tau(i)}$. Intuitively, identification of ω_τ comes from differences across student types in preferences for observed offerings $\hat{\mathbf{d}}$—if type τ students prefer $\hat{\mathbf{d}}$ to most alternative offerings but type τ' students do not particularly like $\hat{\mathbf{d}}$ this suggests the university values the welfare of type τ students more than the welfare of type τ' students. Identification of γ_g comes from the composition of courses offered in $\hat{\mathbf{d}}$ relative to the composition of courses in alternative offerings. If $\hat{\mathbf{d}}$ and $\mathbf{d}$ are equivalent from the perspective of students but $\hat{\mathbf{d}}$ offers more type g courses this implies the university values enrollment in type g courses more than other courses.

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Table 1: Course Offerings, Spending, and Course Choices

	Fall, 2007	Spring, 2008	Fall, 2008	Spring, 2009
Introductory course offerings				
STEM	279	242	249	226
Social Sciences	272	245	257	258
Humanities	433	407	418	368
Occupational	125	114	107	99
Business	65	57	61	58
Median spending per introductory course				
STEM	$8,410	$9,098	$8,632	$8,597
Social Sciences	$6,868	$6,354	$6,516	$6,292
Humanities	$6,547	$5,996	$5,802	$5,718
Occupational	$7,266	$6,824	$6,324	$5,531
Business	$9,480	$7,642	$7,391	$7,279
Share of total spending on introductory courses by field				
STEM	26.3%	27.9%	27.6%	28.5%
Social Sciences	21.7%	21.3%	22.2%	24.5%
Humanities	34.1%	33.8%	34.5%	31.6%
Occupational	10.6%	11.3%	9.1%	8.4%
Business	7.3%	5.7%	6.6%	7.0%
Share of total introductory student-course observations by field				
STEM	22.2%	20.9%	21.8%	21.7%
Social Sciences	26.8%	27.0%	27.5%	28.2%
Humanities	31.6%	32.1%	32.2%	30.7%
Occupational	11.3%	11.3%	9.4%	9.6%
Business	8.1%	8.6%	9.2%	9.7%
Total Cost	$9,784,463	$8,369,421	$7,930,221	$7,109,921
Total Courses	1174	1065	1092	1009

Statistics are for University of Central Arkansas. Students include all full time degree seeking undergraduates. Courses include all introductory undergraduate courses. All cost statistics are measured in 2012 dollars.

Table 2: Nested Logit Coefficient Estimates

	STEM	Social Science	Humanities	Occupational	Business
Intercept	0.2754***	0.098***	0.4986***	0.2188***	*omitted*
	0.0090	*0.0091*	*0.0096*	*0.0143*	
Female	0.514***	0.8093***	0.456***	0.6694***	*omitted*
	0.0112	*0.0115*	*0.0128*	*0.0187*	
ACT Z-score	0.1518***	0.0005	-0.0049	-0.0677***	*omitted*
	0.0062	*0.0057*	*0.0094*	*0.0146*	
Missing ACT	-0.222***	-0.055***	-0.1696***	0.0017	*omitted*
	0.0200	*0.0181*	*0.0187*	*0.0253*	
Sophomore	-1.7746***	-1.6281***	-2.3829***	-1.9234***	*omitted*
	0.0191	*0.0173*	*0.0176*	*0.0274*	
Junior	-2.2214***	-2.2204***	-3.2888***	-2.003***	*omitted*
	0.0251	*0.0233*	*0.0257*	*0.0317*	
Senior	-0.933***	-1.1566***	-2.3669***	-0.7185***	*omitted*
	0.0321	*0.0313*	*0.0358*	*0.0397*	
Marginal utility of	0.0218***	0.052***	0.0432***	0.0067***	-0.0021
log spending	*0.0010*	*0.0011*	*0.0012*	*0.0018*	*0.0019*

Nesting parameter estimate: .9032; standard errors in italics. *** denotes p<.01

Results are for a multinomial nested logit model of students choosing introductory courses. Nests are defined by academic fields. Data are from Fall and Spring academic semesters of 2007-08 and 2008-09 at University of Central Arkansas.

Table 3: Adding Courses vs Spending on Instruction

	Baseline	"More courses" Alternative	"More spending" Alternative
Introductory course offerings			
STEM	1	1	1
Social Science	1	2	1
Hum and Arts	1	1	1
Occupational	1	1	1
Business	1	1	1
Spending per course			
STEM	$2,819	$2,819	$2,819
Social Science	$2,704	$2,704	$5,408
Hum and Arts	$2,976	$2,976	$2,976
Occupational	$2,663	$2,663	$2,663
Business	$3,258	$3,258	$3,258
Total Cost	$14,420	$17,124	$17,124
Share of total student-course observations by field			
STEM	16.7%	14.4%	15.3%
Social Science	17.6%	28.3%	24.2%
Hum and Arts	15.4%	13.2%	14.0%
Occupational	18.6%	16.0%	17.0%
Business	31.8%	28.1%	29.5%
Student Welfare	61,829	66,282	64,509

Enrollment shares and total welfare are calculated using estimates of the multinomial nested logit course choice model. Student sample is Fall, 2007 students at University of Central Arkansas

Table 4: University Preferences for the Type of Courses Students Choose

	Preferences for enrollments
STEM	0.778***
	0.038
Social Science	0.651***
	0.031
Humanities and Arts	1.229***
	0.058
Occupational	0.472***
	0.029
Business	*omitted*
Share of alternatives preferred to chosen option	
Fall 2007	0.5%
Spring 2008	0.1%
Fall 2008	0.0%
Spring 2009	0.0%
Alternatives per semester	1000
Number of semesters	4

Standard errors in italics. *** denotes p<.01. Parameters estimated by maximizing likelihood that chosen course offerings are preferred to randomly drawn alternative feasible course offerings. All alternative feasible offerings include contracted courses.

Table 5: Counterfactual costs which yield Welfare Maximizing Course Offerings

	Welfare Maximizing at market costs (1)	Estimated Objective at market costs (2)	Estimated Objective at tax/subsidy costs (3)
		Minimum costs	
	Market costs	Market costs	After tax/subsidy
STEM	$2,819.0	$2,819.0	$4,081.6
Social Science	$2,704.0	$2,704.0	$3,563.9
Humanities	$2,976.0	$2,976.0	$5,560.0
Occupational	$2,663.0	$2,663.0	$3,033.3
Business	$3,258.0	$3,258.0	$2,571.4
		Simulated Optimal Course Offerings	
STEM	34	160	34
Social Science	86	78	86
Humanities	21	423	21
Occupational	171	10	171
Business	338	0	338
Cost of Offerings	$1,947,463	$1,947,430	$1,949,873

All simulations assume no contractual constraints and do not allow for spending in excess of minimum costs. Optimal course offerings are simulated using Marginal Improvement Algorithm taking estimates of university and student parameters as given. Costs of offerings are approximately 20% of UCA's endowment in Fall, 2007

Table 6: Observed and Welfare Maximizing UCA

	Observed	Welfare Maximizing
Introductory course offerings		
STEM	279	38
Social Sciences	272	518
Humanities	433	54
Occupational	125	110
Business	65	521
Median spending per course		
STEM	$8,410	$2,819
Social Sciences	$6,868	$2,704
Humanities	$6,547	$2,976
Occupational	$7,266	$2,663
Business	$9,480	$3,258
Share of students choosing each field		
STEM	22.2%	3.0%
Social Sciences	26.8%	38.7%
Humanities	31.6%	4.5%
Occupational	11.3%	7.9%
Business	8.1%	45.9%
Relative Cost	1	0.385
Relative Welfare	1.000	1.010
Total Courses	1174	1241

Welfare maximizing course offerings are obtained using Marginal Improvement Algorithm. Enrollment shares and total welfare are estimated using estimates of the multinomial nested logit course choice model. Student sample is Fall, 2007 students at University of Central Arkansas