

What do course offerings imply about university preferences?

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Abstract

University decisions can have lasting effects on students in the labor market; however, little is known about how these decisions are made. This paper develops a new framework for empirically analyzing course offerings at a sample university. The framework is based on the idea that course offerings directly affect student utilities and the probabilities that students choose courses in a given field. As such, administrators deciding which courses to offer are always implicitly trading off the number of students choosing courses in each field and total student utility. By measuring the marginal effects of offering additional sections of courses in each field on field enrollments and student utility, one can quantify these implicit tradeoffs between student utility and field enrollments. In my empirical application, I find that a marginal dollar of spending on social science course sections produces 2.5 times as much student utility as a marginal dollar of spending on business or occupational course sections at a sample university. From this, I conclude the university is implicitly sacrificing student utility to draw students out of social science courses and into business or occupational courses. If this is intentional, then the university has a preference for business and occupational enrollment which may affect how their course offerings respond to changes in policies or student composition. Counterfactual analyses show that ignoring these responses can lead to understating the effects of changes in student composition on field enrollments by a factor of three.

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1 Introduction

Universities are very important social institutions—they help students acquire human capital that is valuable to them individually and to society more broadly. However, universities are not passive parties in the production of human capital; they are active entities that choose their inputs to maximize their objective functions subject to constraints. If university objective functions are not aligned with those of policymakers, then universities may respond to policy changes in ways that dampen their effectiveness. A well-studied example of this is the “Bennett hypothesis” which predicts that universities will respond to federal tuition subsidies by increasing their tuition.¹

While certain aspects of university behaviors have received significant attention, there is still a great deal we do not know about the “supply side” of higher education. Substantial literature exists analyzing how universities set tuition and admission policies in competition with one another and in response to various policies; however, very little evidence exists on how universities allocate their budgets internally.² Do they spend marginal dollars on faculty or facilities? Extra-curriculars or instruction? Dormitories or dining halls? These decisions determine whether marginal public dollars are actually producing public goods. Furthermore, they provide a window into what universities value and whether these values are aligned with policymakers.

This paper advances our understanding of how universities allocate resources by empirically analyzing how a university allocates its budget for instruction across academic fields. How a university spends its budget for instruction determines how many sections of different courses are available to students. This directly affects the courses students choose and the utility they derive from these choices. Course choices determine a student’s field of specialization and copious amounts of evidence shows field of specialization has lasting effects on students in the labor market.³ As such, these budget allocation decisions have potentially lifelong effects on students.

Universities are complicated entities with many unobserved constraints; moreover, as with other public or non-profit entities, the structure of a university’s objective is unclear.⁴

¹See Gibbs and Marksteiner (2016); Cellini and Goldin (2014); Long (2004); Singell and Stone (2007); Turner (2017).

²For studies of tuition and admission policies, see Andrews and Stange (2016); Bhattacharya et al. (2017); Cellini (2009, 2010); Epple et al. (2006, 2013); Fu (2014) and the Bennett hypothesis papers listed in the previous footnote. A notable exception is Jacob et al. (2015) which examines university spending on consumption amenities.

³For a recent review article, see Altonji et al. (2012)

⁴For profit universities are probably profit maximizing but they represent a relatively small share of the higher education market comprising only 3% of total enrollment (Turner, 2012). For studies on the objectives of non-profit entities, see Glaeser (2003); Sloan (2000).

For this reason, empirical studies that aim to understand university behaviors typically focus on estimating specific effects using reduced form frameworks that limit assumptions about university constraints and objectives.⁵ While these studies provide important insights, there is additional value in developing structural models of universities as these would provide a richer understanding of university behaviors and would allow for counterfactual policy analyses that incorporate university responses into predictions. For example, while reduced form tests of the Bennett hypothesis convincingly estimate the share of marginal subsidies captured by tuition increases, a structural analysis of the Bennett hypothesis could solve for optimal subsidies given anticipated university responses.

To advance towards a structural model of university behavior while acknowledging the limits of strong functional form assumptions, this paper develops a dual-purpose model. If correctly specified, the model can be used for full counterfactual analyses that incorporate university responses; however, even if aspects of the full model are misspecified, estimates of model parameters still yield interesting information about university behaviors. This provides a useful bridge between more credible (but narrower) reduced form results and more interesting (but more speculative) structural results.

The framework measures the tradeoffs between total student utility and field enrollments that are implied by observed course offerings. These implied tradeoffs can either be treated as the preference parameters of an objective function for a university that values total student utility and field enrollments in a full structural model, or they can be directly interpreted as a measure of the misalignment between student preferences and observed course offerings if the full model is misspecified.

The central principle of the framework is that offering more course sections in a field costs the university money but adds variety of choices within that field. This additional variety increases total student utility and increases expected enrollment in that field by making the field as a whole relatively more attractive. As such, any reallocation of resources across fields changes the expected number of students choosing courses in each field and total student utility. If one can estimate the marginal effects of offering additional course sections in each field on field enrollments and total student utility as well as the marginal costs of offerings additional sections, then one can construct the tradeoffs between student utility and field enrollments that are implied by observed course offerings.

For example, suppose offering additional sections of social science courses has large effects on student utility relative to costs but offering additional STEM sections has small

⁵Notable exceptions include Epple et al. (2006), Epple et al. (2013), and Fu (2014). These papers develop general equilibrium models of the higher education market which explain observed variation in tuition, admission rates, student characteristics, and other measures across schools. My paper uses microdata to analyze the choices of a specific university.

effects on student utility relative to costs. In this scenario, reallocating marginal dollars from STEM to social science would increase student utility; furthermore, it would decrease STEM enrollment and increase social science enrollment. The differences in marginal effects per dollar would then imply that observed course offerings are implicitly sacrificing student utility to draw students out of social science courses and into STEM courses. This insight would inform policymakers that marginal appropriations for instruction would be spent offering disproportionately many STEM courses relative to what would maximize total student utility. If this conflicts with the policymaker's objective function, they could use the full model to solve for taxes and subsidies on courses which induce the university to offer courses preferred by the policymaker.

To estimate the crucial marginal effects of offering additional course sections on field enrollments and total student utility, I propose using a nested logit course choice model with panel data of course choices under different sets of offered courses. To recover the marginal costs of offering additional sections, I propose estimating a simple linear cost equation with data on course costs and characteristics. In a nested logit course choice model with panel data, marginal effects of offering additional course sections are identified by the relationship between the relative number of sections offered in a field and the share of students choosing courses in that field across semesters. If semesters with relatively more sections in a field also have a higher share of students in that field, then adding sections has large marginal effects on student utility and field enrollments. Conversely, if there is little relationship between the relative number of sections and enrollment shares, then adding sections has small marginal effects on student utility and field enrollments. As such, this choice structure provides a transparent and intuitive mapping from empirical variation to identifying marginal effects.

The main identifying assumption underlying this mapping is that the university is not changing its course offerings in response to changes in unobserved student preferences for fields. My data include detailed information on student scores and demographics allowing me to condition on almost all baseline student information that the university stores. Moreover, at the university I study, there do not appear to be trends in course offerings which indicate responses to unmet demand in previous semesters. As such, I argue concerns about the identifying exogeneity assumption should be limited.

I use my framework to analyze the introductory course offerings of the University of Central Arkansas in Fall and Spring academic semesters of academic years 2004-05 through 2009-10. University of Central Arkansas (UCA) is a particularly interesting subject for two reasons: First, UCA is a large public four year university with a 45% six year graduation rate.⁶ Because the median young American completes some college but does not obtain a

⁶Source: National Center for Education Statistics

degree, and because 45% of all full-time equivalent higher education enrollment is at public four year institutions, a public four year university with a 45% graduation rate is somewhat representative of the post secondary education experience of a median American.⁷ Second, UCA is a teaching focused university where 82% of student hours of instruction are provided by instructors who receive at least 95% of their compensation for teaching.⁸ This makes the analysis more credible by reducing concerns that course offerings are cross-subsidizing research. Furthermore, course offering decisions are especially pertinent at teaching focused institutions making an analysis of course offerings by a teaching focused university especially revealing.

In the first stage of my analysis, I find that the effects of marginal dollars of spending on total student utility vary widely across academic fields. A marginal dollar spent offering more sections of introductory social science courses produces 2.5 times as much student utility as a marginal dollar spent offering additional introductory business or occupational sections. This implies that observed course offerings implicitly sacrifice significant student utility to draw students out of introductory social science courses and into introductory business and occupational courses. These conclusions require reliable estimates of marginal effects and marginal costs but do not rely on the full structural model of the university's course offerings and student course choices.

Next, I analyze the importance of these implied tradeoffs by comparing observed course offerings to cost-equivalent course offerings that would have maximized total student utility. To avoid forecasting too far out of sample, I hold the allocation of faculty on long-term contracts fixed and only reallocate the budget for adjunct instructors on single-semester contracts.⁹ This analysis reveals that reallocating the adjunct instructor budget to maximize student utility would remove all adjunct instructed sections of introductory STEM and business and occupational courses and would quadruple the number of adjunct instructed

⁷Estimates from the 2015 Current Population Survey show that of individuals 25-34 years old residing in the United States, 9.5% did not complete high school, 25.5% completed high school only, 18.5% completed some college but did not complete a degree, 10.4% completed an associates degree only, 25.2% completed a bachelor's degree only, and 10.9% completed an advanced degree (Ryan and Bauman, 2016). Full time equivalent enrollment statistics are author's calculation using IPEDS for academic year 2016-2017.

⁸Compensation for teaching is determined by how many credit hours an instructor teaches relative to the definition of a full-time instructor at UCA. See Appendix A for additional details. UCA's teaching focus is also 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. (Board, 2011)

⁹Adjunct instructors on single-semester contracts are those whose contracts need to be renewed every semester. 11.4% of all course sections are taught by adjunct instructors on single-semester contracts.

sections of introductory social science courses. This helps quantify the misalignment between student preferences and observed course offerings.

Finally, I build a two-sided structural model of a university and students and treat estimates of implied tradeoffs as parameters of the university's objective function. The university in this model values total student utility but also values the number of students choosing courses in each field either for paternalistic reasons, to internalize externalities, or for other unspecified reasons. I use this model to analyze how course offerings would change in various counterfactual scenarios and how this would affect field enrollments. Again, to avoid forecasting too far out of sample, I hold the allocation of faculty on long-term contracts fixed.

One counterfactual examines a scenario in which all students' observed measures of baseline preparation are increased by one-third of a standard deviation. Because more prepared students are generally more interested in STEM, this would lead to a 3.7% increase in introductory STEM enrollment even if course offerings were held fixed. However, the university responds to the increase in STEM interest by offering more sections of adjunct instructed introductory STEM courses resulting in a 8.25% increase in total introductory STEM sections. This makes STEM even more attractive resulting in an 11.0% total increase in introductory STEM enrollment. In other words, ignoring the university's response leads to understating effects on STEM enrollment by approximately a factor of three. A second counterfactual shows that a 5% reduction in the cost of hiring a STEM adjunct instructor would lead to a 8.34% increase in total sections of introductory STEM courses and a 6.2% increase in overall enrollment in introductory STEM courses.

Although a full analysis of mechanisms is beyond the scope of this paper, I conclude with a brief discussion of why UCA might favor STEM and business and occupational enrollment. To preview, existing literature shows—and naïve regressions in my data suggest—that STEM and business and occupational courses have higher labor market returns but involve more student effort than other courses. If students are myopic or have incomplete information about heterogeneous labor market returns, UCA's preference for STEM and business and occupational enrollment may reflect paternalistic behavior which maximizes student welfare in the long run. Alternatively, if higher labor market returns also imply larger social externalities, UCA's preference for STEM and business and occupational enrollment may reflect a desire to maximize social welfare more broadly.

This paper relates to a growing literature on the supply side of higher education which analyzes the role of universities in education production.¹⁰ One branch of this literature

¹⁰Notable contributions not mentioned in the body include but are not limited to: Andrews and Stange (2016); Bhattacharya et al. (2017); Carrell and West (2010); Cellini (2009, 2010); Dinerstein et al. (2014);

focuses on estimating the effects of university choices and inputs on student outcomes. This includes studies of “cohort crowding” effects which estimate the effects of aggregate institutional spending on student outcomes (Bound and Turner, 2007; Bound et al., 2010, 2012; Dynarski, 2008; Turner, 2004) and complementary work which estimates the effects of university tuition on student outcomes (Deming and Walters, 2017; Hemelt and Marcotte, 2011; Kane, 1995). Other studies in this branch of supply side higher education literature estimate the effects of instructor characteristics on student outcomes (Bettinger and Long, 2005, 2010; De Vlieger et al., 2017; Figlio et al., 2015). A second branch of this literature aims to form a better understanding of how universities make decisions. This includes studies which develop general equilibrium models of competition in the higher education market (Epple et al., 2006, 2013; Fu, 2014) as well as tests of the aforementioned “Bennett hypothesis” (Gibbs and Marksteiner, 2016; Cellini and Goldin, 2014; Long, 2004; Singell and Stone, 2007; Turner, 2017).

The main goal of this analysis is to contribute to the second branch of literature by analyzing how a university allocates its budget for instruction. To my knowledge, this paper is the first to analyze this important decision. Moreover, this paper also contributes to the second branch of literature by providing the first estimates of a model of university choices using micro-level data. This deepens our understanding of how universities make decisions and allows for counterfactual policy analyses that incorporate university responses into predictions. Tangentially, this paper also contributes to the first branch of supply side literature by providing the first analysis of the effects of course offerings on student course choices and utilities.

As the first analysis of course offering decisions and the first estimation of a university model with micro data, this paper faces many challenges some of which are left for future research. For example, for transparency and tractability, I use a simple model of student demand for courses which abstracts from forward looking behavior and choices of course bundles. Second, I do not observe section capacity constraints which prevents me from including these constraints on demand. Finally, although I provide suggestive evidence on mechanisms in Section 7, I do not explicitly model the underlying reasons why the university might favor enrollment in certain fields. Future work may build upon my analysis by addressing these and other limitations.

The remainder of the paper proceeds as follows: Section 2 introduces a framework for analyzing how universities choose course offerings, Section 3 presents a framework for predicting how student choices are influenced by course offerings, Section 4 describes the data

Hoffmann and Oreopoulos (2009); Hoxby (1997); Jacob et al. (2015); Pope and Pope (2009, 2014); Tabakovic and Wollmann (2016)

and discusses the empirical specifications used for estimation, Section 5 discusses estimates of implied tradeoffs, Section 6 discusses additional results and counterfactual predictions, Section 7 provides suggestive evidence as to why the university might favor enrollment in certain fields, Section 8 concludes.

2 Theoretical Framework: University

In this section, I introduce a general framework for analyzing course offerings at a university. The main idea of the framework is as follows: Suppose one has a model for student demand in which the number of sections offered in each field affects the expected number of students choosing courses in each field and the expected utility students derive from their choices.¹¹ Then one can use this model of student demand to compare the marginal effects per dollar of offering additional sections in one field on total student utility to the same marginal effects per dollar for other fields. Differences in these marginal effects per dollar across fields reveal an implicit willingness to sacrifice student utility to increase enrollment in certain fields. Under relatively lenient assumptions, one can interpret estimates of the implied tradeoffs between total student utility and field enrollments as a measure of the misalignment between student preferences and observed course offerings. Alternatively, under stronger assumptions, one can treat these implicit tradeoffs as structural preference parameters in a two-sided model of a university deciding which courses to offer and students choosing courses from the set of available alternatives.

2.1 University’s course offerings

To begin, let $t \in [1, T]$ index academic semesters and let $f \in [1, F]$ index academic fields.¹² Let d_{tf} represent the number of sections of introductory field f courses offered in semester t and collect these offerings into a single vector $\mathbf{d}_t = [d_{t1} \ \cdots \ d_{tF}]$.

Now suppose one has a model for student demand for introductory courses in which the number of course sections offered in each field \mathbf{d}_t affects the expected number of students choosing courses in each field and the total expected utility students derive from their choices. Let $n_{tf}(\mathbf{d}_t)$ represent the university’s expectation for total enrollment in introductory courses in field f in semester t , let $V_t(\mathbf{d}_t)$ represent the university’s expectation for total student utility from introductory course choices in semester t , and assume both $n_{tf}(\mathbf{d}_t)$ and $V_t(\mathbf{d}_t)$

¹¹A wide class of demand models will exhibit these properties, Sections 3 and 4 outline the specific nested logit demand model that I use in my empirical application.

¹²In the empirical application, fields are STEM, social science, humanities and arts, and business and occupational. See Appendix A for field definitions.

are continuously differentiable in \mathbf{d}_t .¹³

In Sections 3 and 4, I specify a nested logit course choice model in which enrollments and utilities depend on course offerings as desired; however, a wide class of demand models will provide these relationships. Intuitively, the links between course offerings and enrollments and utilities in these models comes from the effects of variety within fields. When a new section of a field f course is added, some students will find this section to be a particularly good match either in terms of content, instructor, meeting time, or other factors. This will induce some students to switch across fields into the new section which increases enrollment in field f . Because all switching students prefer the new section to previously available alternatives, this also increases total student utility. As such, any demand model in which students value individual section characteristics will exhibit the desired properties.

Now suppose the university's payoff from offering courses \mathbf{d}_t is a linear combination of total student utility $V_t(\mathbf{d}_t)$ and field enrollments $n_{tf}(\mathbf{d}_t)$ as follows:

$$\Pi_t(\mathbf{d}_t) = \theta V_t(\mathbf{d}_t) + \sum_{f=1}^F \gamma_f n_{tf}(\mathbf{d}_t) \quad (1)$$

Without loss of generality, I normalize $\theta = 1$ and $\gamma_F = 0$.¹⁴ With this structure and normalizations, the university is indifferent between course offerings which yield the following two outcomes:

	Outcome 1	Outcome 2
V_t	V	$V - \gamma_f$
n_{tf}	n_1	$n_1 + 1$
n_{tF}	n_2	$n_2 - 1$

As such, γ_f measures the amount of student utility which the university is implicitly willing to sacrifice to draw one student out of a field F course and into a field f course in expectation.

The university payoff parameters γ_f could reflect a variety of underlying mechanisms. They could reflect true preference parameters rooted in paternalistic beliefs about which courses best serve students' long term interest or social beliefs about which courses produce the most public goods; however, they could also reflect institutional frictions within the university which implicitly favor certain fields as a result of path dependence. The first stage

¹³Note that \mathbf{d}_t is a vector of discrete variables and thus derivatives with respect \mathbf{d}_t are not defined; however, at large universities such as the one I study, the number of introductory course sections in each field is large enough that approximating course offerings as a continuous variable is reasonable.

¹⁴Normalizing $\gamma_F = 0$ is without loss of generality as long as total enrollment $\sum_{f=1}^F n_{tf}(\mathbf{d}_t)$ is the same for all \mathbf{d}_t . This implies \mathbf{d}_t cannot affect the number of students enrolled at the school or the share choosing introductory courses. I discuss this limitation and others in Section 2.4. Normalizing $\theta = 1$ is without loss of generality because the scale of the university's payoff is not determined.

of my analysis will be to estimate γ_f and interpret these estimates as interesting measures of the misalignment between student preferences and observed course offerings. I argue that this “implied preference” interpretation is interesting and valid even if the misalignment results from institutional frictions or other non-intentional mechanisms. As such, this interpretation holds even when Equation (1) is not the university’s true objective function. The second stage of my analysis assumes the misalignment was intentional and treats Equation (1) as a true university objective function in a two-sided model of a university and students. The second analysis requires strong assumptions about university objectives and constraints but allows for a deeper understanding of university behaviors and for counterfactual analyses which incorporate university responses into predictions.

Finally, suppose the university faces a semester specific budget constraint which states that the cost of offering \mathbf{d}_t cannot exceed an endowment. Specifically, I assume:

$$C(\mathbf{d}_t, \psi) \leq E_t \tag{2}$$

where E_t is a semester specific endowment, $C(\cdot)$ is a smooth function, and ψ are parameters to be estimated.¹⁵

The university’s course offering problem in semester t is then given by:

$$\mathbf{d}_t^* = \operatorname{argmax}_{\mathbf{d}_t} \left\{ V_t(\mathbf{d}_t) + \sum_{f=1}^{F-1} \left(\gamma_f n_{tf}(\mathbf{d}_t) \right) \right\} \left(\text{s.t. } C(\mathbf{d}_t, \psi) \leq E_t \right) \tag{3}$$

2.2 Illustration of implied tradeoffs

In the following subsection, I will derive the first order conditions characterizing the solution to Equation (3) and demonstrate how these can be used to recover implied preference parameters γ_f . In this subsection, I will illustrate the strategy for recovering γ_f graphically in a simplified setting with only two fields ($F = 2$) and one academic semester ($T = 1$).

Figure 1 graphs the set of feasible outcomes which can be achieved given the university’s budget constraint, indifference curves for several hypothetical values of γ_1 , and optimal course offerings given the set of feasible outcomes and values of γ_1 . The horizontal axis measures the expected number of students choosing courses in field 1 and the vertical axis measures total expected student utility.¹⁶ The solid semi-circle represents a production possibilities

¹⁵I assume endowments E_t are set exogenously through a process which is unrelated to course offerings \mathbf{d}_t . If offering additional courses in field f has a positive (negative) effect on E_t then I would be ignoring a positive (negative) marginal value to the university of offering additional courses in field f . This would lead to estimates which overstate (understate) implied preferences for enrollment in field f .

¹⁶Since there are only two fields in this example, the expected number of students choosing courses in field 2 is the complement $n_2 = N - n_1$ and thus can be ignored without loss of generality.

frontier (PPF) of all possible (n_1, V) outcomes which could be achieved given the university's budget constraint. Dashed line segments represent potential university indifference curves with payoffs increasing in the direction of the arrows.

In this illustration, University A has horizontal indifference curves implying it is not willing to sacrifice any student utility to change field enrollments ($\gamma_1^A = 0$). Given the PPF representing all feasible outcomes, University A chooses to operate at point A —unsurprisingly, this is the feasible outcome which yields the most student utility. Comparatively, University B (C) has downward (upward) sloping indifference curves implying it is willing to sacrifice some student utility to increase (decrease) the expected number of students choosing courses in field 1. Given the PPF, University B (C) chooses to operate at point B (C) which yields less student utility but more (fewer) students choosing courses in field 1 relative to point A .

Suppose the observed university is offering courses which produce outcome B : The goal of this paper is to determine what value of γ_1^B best characterizes the implied tradeoff between student utility and field enrollments at outcome B . This is equivalent to computing the derivative of the PPF—or marginal rate of transformation (MRT)—at point B . Figure 2 zooms in on the choice of University B to illustrate this derivative. Conceptually, the marginal rate of transformation at point B is given by the instantaneous change in total expected student utility relative to the instantaneous change in the expected number of students choosing courses in field 1 as the university marginally reallocates funds from field 1 to field 2. Denote the instantaneous increase in total expected student utility at point B by dV_B . This is given by the marginal gain in utility from spending more in field 2 minus the utility lost by spending less in field 1. In notation:

$$dV_B = \frac{\left(\frac{\partial V}{\partial d_2} \middle|_H \right)}{\left(\frac{\partial C}{\partial d_2} \middle|_H \right)} - \frac{\left(\frac{\partial V}{\partial d_1} \middle|_H \right)}{\left(\frac{\partial C}{\partial d_1} \middle|_H \right)} \quad (4)$$

dV_B is positive since point B has more field 1 course sections than the utility maximizing bundle implying that replacing some of these field 1 sections with field 2 sections will increase total student utility.

Next, denote the instantaneous change in the expected number of students choosing courses in field 1 by dn_{1B} . This combines both the marginal effect of making field 1 less attractive by offering fewer field 1 courses and the effect of making field 2 more attractive

by offering more field 2 courses. In notation:

$$dn_{1B} = \frac{\left(\frac{\partial n_1}{\partial d_2} \middle|_F\right)}{\left(\frac{\partial C}{\partial d_2} \middle|_F\right)} \left(- \frac{\left(\frac{\partial n_1}{\partial d_1} \middle|_F\right)}{\left(\frac{\partial C}{\partial d_1} \middle|_F\right)} \right) \left(\right) \quad (5)$$

dn_{1B} is always negative since replacing field 1 courses with field 2 courses always makes field 1 relatively less attractive.

Combining both shows that the marginal rate of transformation at point B is given by:

$$\begin{aligned} MRT_B &= \frac{dV_B}{dn_{1B}} \\ &= \frac{\left(\frac{\partial C}{\partial d_2} \middle|_F\right)^{-1} \left(\frac{\partial V}{\partial d_2} \middle|_F\right) \left(- \left(\frac{\partial C}{\partial d_1} \middle|_F\right)^{-1} \left(\frac{\partial V}{\partial d_1} \middle|_F\right) \right)}{\left(\frac{\partial C}{\partial d_2} \middle|_F\right)^{-1} \left(\frac{\partial n_1}{\partial d_2} \middle|_F\right) \left(- \left(\frac{\partial C}{\partial d_1} \middle|_F\right)^{-1} \left(\frac{\partial n_1}{\partial d_1} \middle|_F\right) \right)} \end{aligned} \quad (6)$$

Therefore, the tradeoff between total student utility and field enrollments implied by observed course offerings is given by $\gamma_1^B = MRT_B$. This illustrates how marginal effects of offering additional course sections and marginal costs of offering additional sections can be used to solve for implicit tradeoffs between student utility and field enrollments in a simplified setting with only two fields ($F = 2$) and one academic semester ($T = 1$).

2.3 Formal derivation of implied tradeoffs

To extend the analysis to F academic fields and T semesters, I first derive the first order conditions which characterize an interior solution to the university's problem stated in Equation (3). These first order conditions are:

$$\left(\frac{1}{c_{tf_1}}\right) \left[\left(\frac{\partial V_t(\mathbf{d}_t^*)}{\partial d_{tf_1}}\right) + \sum_{f'=1}^{F-1} c_{f'} \left(\frac{\partial n_{tf'}(\mathbf{d}_t^*)}{\partial d_{tf_1}}\right) \right] = \left(\frac{1}{c_{tf_2}}\right) \left[\left(\frac{\partial V_t(\mathbf{d}_t^*)}{\partial d_{tf_2}}\right) + \sum_{f'=1}^{F-1} c_{f'} \left(\frac{\partial n_{tf'}(\mathbf{d}_t^*)}{\partial d_{tf_2}}\right) \right] \quad (\forall f_1, f_2) \quad (7)$$

where

$$c_{tf} = \frac{\partial C(\mathbf{d}_t^*, \psi)}{\partial d_{tf}} \quad (8)$$

is the marginal cost of offering additional course sections in field f at observed course offerings \mathbf{d}_t^* .

Intuitively, these conditions state that the net marginal benefit of offering an additional course section relative to the cost of offering this section must be the same across all academic

fields. If this were not the case, the university could improve its payoff by reallocating funds away from fields with low returns to fields with high returns. Net marginal benefit includes both benefit from increasing total student utility and net benefit (cost) from drawing students into more (less) implicitly favored fields.

Rearranging and stacking fields and semesters yields:

$$\mathbf{dn}^* \times \Gamma = \mathbf{dV}^* \quad (9)$$

where

$$\begin{aligned} \mathbf{dn}_{(F, F-1)}^* (f_1, f_2) &= \begin{pmatrix} 1 \\ c_{tf_1} \end{pmatrix} \begin{pmatrix} \frac{\partial n_{tf_2}(\mathbf{d}_t^*)}{\partial d_{tf_1}} \end{pmatrix} - \begin{pmatrix} 1 \\ c_{tF} \end{pmatrix} \begin{pmatrix} \frac{\partial n_{tf_2}(\mathbf{d}_t^*)}{\partial d_{tF}} \end{pmatrix} \begin{pmatrix} \\ \\ \\ \end{pmatrix} \\ \mathbf{dn}_{(F \times T, F-1)}^* &= \begin{bmatrix} \mathbf{dn}_1^* \\ \vdots \\ \mathbf{dn}_T^* \end{bmatrix} \begin{pmatrix} \\ \\ \\ \end{pmatrix} \\ \mathbf{dV}_{(F, 1)}^* (f) &= \begin{pmatrix} 1 \\ c_{tF} \end{pmatrix} \begin{pmatrix} \frac{\partial V_t(\mathbf{d}_t^*)}{\partial d_{tF}} \end{pmatrix} - \begin{pmatrix} 1 \\ c_{tf} \end{pmatrix} \begin{pmatrix} \frac{\partial V_t(\mathbf{d}_t^*)}{\partial d_{tf}} \end{pmatrix} \begin{pmatrix} \\ \\ \\ \end{pmatrix} \\ \mathbf{dV}_{(F \times T, 1)}^* &= \begin{bmatrix} \mathbf{dV}_1^* \\ \vdots \\ \mathbf{dV}_T^* \end{bmatrix} \begin{pmatrix} \\ \\ \\ \end{pmatrix} \\ \Gamma_{(F-1, 1)}(f) &= \gamma_f \end{aligned}$$

This system of equations can then be inverted to derive the following expression for implied preference parameters Γ as a function of marginal effects and costs:

$$\Gamma = (\mathbf{dn}^*)^+ (\mathbf{dV}^*) \quad (10)$$

where M^+ denotes the pseudo-inverse of M .

This illustrates how estimates of marginal effects and costs of offering additional course sections at observed course offerings can be used to measure the tradeoffs between total student utility and field enrollments implied by observed course offerings. These tradeoffs can either be interpreted directly under relatively lenient assumptions as measures of the misalignment between student preferences and observed course offerings; or alternatively, they can be treated as structural preference parameters in a two-sided model of university course offerings and the implications for students under stronger assumptions.

2.4 Discussion

Subsection 2.3 shows that implied preference parameters γ_f can be obtained from marginal effects of offering additional course sections on field enrollments, marginal effects of offering additional sections on total student utility, and marginal costs of offering additional sections. In this subsection, I discuss how to use and interpret estimates of γ_f under various assumptions and extensions of this framework which may be pursued in future research.

First, I argue that estimates of γ_f are interesting measures of the misalignment between student preferences and observed course offerings and that one can interpret them as such even if the university's problem in Equation (3) is misspecified. If one has credible estimates of the local marginal costs $\frac{\partial C(\mathbf{d}_t^*, \psi)}{\partial d_{t,f}}$ for all fields, then one can measure how marginally reallocating dollars across any pair of fields would change observed course offerings. Furthermore, if one has credible estimates of the local marginal effects $\frac{\partial n_{t,f'}(\mathbf{d}_t^*)}{\partial d_{t,f}}$ and $\frac{\partial V_t(\mathbf{d}_t^*)}{\partial d_{t,f}}$ for all fields, then one can predict how these changes in observed course offerings would affect total student utility and field enrollments. As such, if marginally reallocating dollars from field f to field F would increase student utility and draw students out of field f and into field F in expectation, then one can quantify how much student utility observed courses are implicitly sacrificing to prevent students from moving out of field f courses and into field F courses. This is precisely what is measured by γ_f .

Therefore, without asserting why observed course offerings were chosen by a university, one can still produce an interesting measure of the misalignment between student preferences and the course offerings that were chosen. To be clear, obtaining credible estimates of local marginal effects and local marginal costs will require assumptions about costs and student demand which will be discussed in subsequent sections. However, this narrow interpretation of γ_f does not require the university's objective function and constraints to be correctly specified as long as marginal cost estimates are correct.

In addition to directly interpreting estimates of γ_f as measures of the misalignment between student preferences and observed course offerings, one can also treat Equation (3) as a full structural model of a university's course offering decision. This interpretation requires stronger assumptions: First, the structural interpretation requires assuming that marginal effects and marginal costs can be constructed globally rather than locally in neighborhoods around observed course offerings. Second, and most importantly, the structural interpretation requires assuming that the objective structure and constraints in the university's problem specified in Equation (3) are correct. There are many potential objective structures which could rationalize observed course offerings and these different structures will generally yield differing predictions under counterfactual policies. As such, the predictions of this particular structure will only be correct if this structure is a good approximation of the uni-

versity's true objective structure. While this is certainly a strong assumption, the structural interpretation gives a deeper understanding into how universities make decisions and allows for counterfactual policy analyses which incorporate university responses in predictions.

One shortcoming of Equation (3) as a structural model of university behavior is that it almost certainly overstates how quickly a university can respond to changes in student demand, costs, or education policies. Equation (3) posits a single decision maker who has preference parameters γ_f , observes state variables in semester t , and chooses course offerings in semester t without friction. In reality, universities are large institutions with complicated leadership structures where decisions probably require substantial deliberations and compromises between interested parties. This likely generates significant friction that is not captured by Equation (3).

To partially address this concern, I restrict the university in my counterfactual analyses so it can only reallocate its spending on adjunct instructors on single-semester contracts.¹⁷ This provides a coarse measure of institutional friction and prevents my counterfactuals from predicting too far out of sample. Still, extensions that handle institutional friction more carefully would likely yield improved predictions.

Another shortcoming of Equation (3) is that this model abstracts from closely related decisions such as how many advanced courses to offer in each field, which introductory courses to offer within fields, and how to match instructors to courses. One direct consequence of abstracting from advanced course offering decisions is that this necessitates assuming introductory course offerings do not affect students' decisions of whether to take advanced or introductory courses. In theory, one could extend this framework to include advanced courses; however, because advanced courses in a field must follow introductory courses in that field, one would need a dynamic model of student demand and a dynamic model of university choices that captures the return on enrollment in introductory courses in terms of expected future enrollment in related advanced courses. I leave this extension for future work.

While one could use this framework with a less aggregated definition of field if desired, it seems infeasible to model a university's choice of how many sections to offer for every potential course in a semester. The universe of potential courses is quite large implying that the set of potential course offering vectors likely suffers from the curse of dimensionality. As such, some level of abstraction from within field course offerings is probably necessary.

Finally, although the question of how universities match instructors to courses is interesting, empirical evidence suggests instructor characteristics have small effects on student

¹⁷Adjunct instructors on single-semester contracts are those whose contracts need to be renewed every semester. 11.4% of all course sections are taught by adjunct instructors on single-semester contracts.

demand for courses at the university I study. In Appendix B, I extend the university’s model to allow the university to choose how much to spend on the instructor’s salary for each course. Instructor salary is clearly the most salient instructor characteristic from the university’s standpoint; furthermore, at a teaching focused university such as University of Central Arkansas, one would expect higher paid instructors to have characteristics which make them more attractive to students. However, in Appendix B, I find that the elasticities of enrollment with respect to instructor salaries range from .02 to .16. In other words, the university could spend twice as much hiring more desirable STEM instructors and this would increase STEM enrollment by at most 16%. Comparatively, the elasticities of enrollment with respect to offering additional course sections range from .32 to .50. This suggests students are generally more responsive to course variety than instructor characteristics. While future work analyzing how instructors are matched to courses would be interesting; I abstract from these choices to focus on the course offering decisions that are more relevant at the university I study.

3 Theoretical Framework: Students

In Section 2, I demonstrated how estimates of marginal effects and marginal costs of offering additional course sections in each field can be used to measure a university’s implied preferences for total student utility and field enrollments. The framework assumes the researcher has a model for student demand which can be used to estimate the marginal effects of offering additional course sections in each field on field enrollments and total student utility.

In this section, I propose estimating these crucial marginal effects using a nested logit course choice model with panel data of course choices under different sets of offered courses. The advantage of a nested logit model in this setting is that the relationship between empirical variation and these marginal effects is simple and transparent. Under the assumption that the university is not changing its course offerings in response to unobserved student preferences for fields, the nested logit model identifies marginal effects from the relationship between the relative number of course sections offered in a field and the share of students choosing courses in that field across semesters.

3.1 Student choices

As before, let $t \in [1, T]$ index academic semesters, let $f \in [1, F]$ index academic fields, let d_{tf} represent the number of sections of introductory field f courses offered in semester t , and

collect these offerings into a single vector $\mathbf{d}_t = [d_{t1} \ \cdots \ d_{tF}]$.¹⁸ Furthermore, let $i \in [1, N]$ index observations of students choosing introductory courses and let $j \in [1, J]$ index specific introductory course sections.¹⁹

Assume that student observation i 's stochastic utility from choosing introductory course section j belonging to field f can be additively separated into a field-specific deterministic component and a section-specific stochastic component as follows:

$$U_{itj} = v(X_{it}, \beta_f) + \epsilon_{itj} \quad (11)$$

where X_{it} are observed student characteristics, β_f are utility parameters, $v(\cdot)$ is a smooth function, and ϵ_{itj} are stochastic preference shocks.

I assume the university knows $v(X_{it}, \beta_f)$ and the distribution of ϵ_{itj} but does not observe individual realizations of ϵ_{itj} . An important restriction in Equation (11) is that the deterministic component of utility $v(X_{it}, \beta_f)$ does not vary within field f . This restriction implies that marginal effects of offering additional sections of introductory courses in field f on expected student outcomes are the same regardless of which course within field f receives an additional section. This is central to the methodology because identification of university preference parameters γ_f requires marginal effects of offering additional course sections at the field level. If deterministic utilities vary within fields, either the university model in Section 2 needs to be extended to model course offering decisions within fields or the researcher needs to make a somewhat arbitrary decision about which courses within a field are marginal. To avoid such a decision, I exclude observed course section characteristics such as sub-field, instructor characteristics, and meeting time. These factors influence the unobserved preference shocks ϵ_{itj} which are assumed to be known by students but not observed by the university.

I assume stochastic preference shocks ϵ_{ijt} are drawn from a Type 1 Extreme Value distribution with a nesting structure in which nests are defined by academic fields. This implies stochastic preference shocks can be additively decomposed into a field specific component ψ_{ift} and an idiosyncratic section specific component η_{ijt} scaled by a field-specific constant λ_f :

$$\epsilon_{ijt} = \psi_{ift} + \lambda_f \eta_{ijt} \quad (12)$$

where η_{ijt} are iid draws from a Type 1 Extreme Value distribution, ψ_{ift} and η_{ijt} are independent, and ψ_{ift} is drawn from a conjugate distribution derived in Cardell (1997). I will show

¹⁸In the empirical application, fields are STEM, social science, humanities and arts, and business and occupational. See Appendix A for field definitions.

¹⁹For simplicity, I treat choices of multiple courses in the same semester by the same student as independent observations. I discuss this limitation and others in Section 3.5.

that in a panel data setting, this nesting structure implies that marginal effects of offering additional sections of introductory courses on total student utility and field enrollments are identified by the empirical relationship between the relative number of sections offered in a field and the share of students choosing courses in that field across semesters.

With this structure, the probability that student i chooses one specific introductory course section in field f in semester t is given by:

$$P_{itf} = \frac{\exp\left(\frac{v(X_{it}, \beta_f)}{\rho_f}\right) \left[\sum_{j \in f} \exp\left(\frac{v(X_{it}, \beta_f)}{\rho_f}\right)\right]^{\rho_f - 1}}{\sum_{f'=1}^F \left[\sum_{j \in f'} \exp\left(\frac{v(X_{it}, \beta_{f'})}{\rho_{f'}}\right)\right]^{\rho_{f'}}} \quad (13)$$

$\rho_f \in (0, 1]$ is a nesting parameter which measures the degree of independence in unobserved preferences ϵ_{ijt} for sections within field f . When $\rho_f = 1$, variance in ψ_{ift} is zero so that unobserved preferences are iid draws from a Type 1 Extreme Value distribution and choice probabilities are equivalent to those in multinomial logit. When $\rho_f \rightarrow 0$, the scalar λ_f approaches zero so that unobserved preferences are equal for all sections within field f (Train, 2009). Allowing ρ_f to vary across fields implies that the extent to which sections are similar or dissimilar within fields is allowed to vary across fields. This is an important mechanism for capturing heterogeneous marginal effects of offering additional sections across fields.

With this structure, choice probabilities simplify to:

$$P_{itf} = \frac{d_{tf}^{\rho_f - 1} \exp(v(X_{it}, \beta_f))}{\sum_{f'=1}^F d_{tf'}^{\rho_{f'}} \exp(v(X_{it}, \beta_{f'}))} \quad (14)$$

Before proceeding, note that the general additively separable structure in Equation (11) nests dynamic discrete choice structures which are commonly used in models of student choice as long as the future value term depends only on the field of a course and does not vary across semesters.²⁰ Specifically, one could parametrize deterministic utility as:

$$v(X_{it}, \beta_f) = u(X_{it}, \beta_f^1) + \delta \mathbb{E}[V' | X_{it}, \beta_f^2] \quad (15)$$

where $u(X_{it}, \beta_f^1)$ represents the flow utility associated with introductory courses in field f and $\delta \mathbb{E}[V' | X_{it}, \beta_f^2]$ represents the discounted expected next period value associated with choosing an introductory course in field f this period. The expected next period value of

²⁰For papers using dynamic discrete choice models of student choice, see Arcidiacono (2004, 2005); Bordon and Fu (2015); Stinebrickner and Stinebrickner (2014a).

choosing an introductory course in field f could reflect the option value of being able to take advanced courses in field f in the future, the future labor market value of coursework in field f , or any other future return associated with introductory coursework in field f . Since my goal is only to obtain estimates of the marginal effects of offering additional introductory course sections on field enrollments and total student utility, my empirical specification will be a simple static structure which identifies these marginal effects from empirical variation in a clear and transparent manner. However, if desired, the general framework can accommodate richer models of student choice.

3.2 Student outcomes

With this framework for student demand, I can now define the total student utility and field enrollment outcomes which entered into the university's objective function in Equation (1). First, expected enrollment in introductory field f courses in semester t is given by:

$$\begin{aligned} n_{tf}(\mathbf{d}_t) &= \sum_{i=1}^N d_{tf} P_{itf} \\ &= \sum_{i=1}^N \left(\frac{d_{tf}^{\rho_f} \exp(v(X_{it}, \beta_f))}{\sum_{f'=1}^F d_{tf'}^{\rho_{f'}} \exp(v(X_{it}, \beta_{f'}))} \right) \left(\right) \end{aligned} \quad (16)$$

Second, total expected student utility from introductory courses in semester t is given by:

$$\begin{aligned} V_t(\mathbf{d}_t) &= \sum_{i=1}^N \mathbb{E}[\max\{U_{ijt}\} | \mathbf{d}_t] \\ &= \sum_{i=1}^N \left(\log \sum_{f=1}^F \left(d_{tf}^{\rho_f} \exp(v(X_{it}, \beta_f)) \right) + c \right) \left(\right) \end{aligned} \quad (17)$$

where $c \approx 0.5772$ is the Euler-Mascheroni constant. As required by the university model, both outcomes depend closely on course offerings \mathbf{d}_t .

However, as shown in Section 2, it is not these outcome formulas *per se* which are useful for measuring implied tradeoffs; rather, it is the marginal effects of course offerings on these outcomes. These marginal effects are given by:²¹

$$\frac{\partial V_t(\mathbf{d}_t)}{\partial d_{tf}} = \sum_{i=1}^N \left(\rho_f P_{itf} \right) \quad (18)$$

²¹Note that d_{tf} is actually a discrete variable and thus these derivatives are not defined; however, the number of introductory course sections in each field is large enough that approximating it as a continuous variable is reasonable.

$$\frac{\partial n_{tf'}(\mathbf{d}_t)}{\partial d_{tf}} = \begin{cases} \sum_{i=1}^N \rho_f P_{itf} (1 - d_{tf} P_{itf}) & f' = f \\ \sum_{i=1}^N \rho_f d_{tf'} P_{itf} P_{itf'} & f' \neq f \end{cases} \quad (19)$$

These formulas illustrate the important roles of the nesting parameters ρ_f in determining the marginal effects of offering additional sections of introductory courses on outcomes. Equation (18) shows that marginal effects on total student utility are increasing in ρ_f . This makes sense because larger values for ρ_f imply more independence in unobserved preferences for sections within field f . This greater independence means that additional sections provide more valuable variety.

Similarly, Equation (19) shows that larger values for ρ_f yield more positive own-field marginal effects on enrollment and more negative cross-field effects on enrollment.²² Once again, this makes sense because greater independence implies that additional sections are less similar to other sections within the same field and thus will induce more students to switch fields in expectation.

3.3 Identification of marginal effects

As shown in Section 2, the marginal effects of offering additional sections in each field defined in the previous subsection play a crucial role in measuring the tradeoffs between total student utility and field enrollments implied by offered courses. Given the central role of these marginal effects in driving the main conclusions of this paper, it is important to understand how these effects are identified from the data.

Equations (18) and (19) show that in this framework, marginal effects depend on choice probabilities P_{itf} , introductory course offerings d_{tf} , and nesting parameters ρ_f . Choice probabilities are conditional moments and are thus non-parametrically identified from the data. Furthermore, introductory course offerings are directly observed. As such, the crucial parameters driving marginal effects are the nesting parameters ρ_f . In this subsection, I show that nesting parameters are identified by the empirical relationship between the relative number of course sections offered in a field and the share of students choosing courses in that field across semesters.

To show identification of ρ_f , choose a sub-population of students with observed characteristics $X_{it} = X$ and restrict to two academic semesters t_1 and t_2 and two academic fields f_1 and f_2 which are chosen so that $d_{t_1 f_2} = d_{t_2 f_2}$ but $d_{t_1 f_1} \neq d_{t_2 f_1}$. This isolates panel variation in field f_1 course offerings holding fixed field f_2 offerings.

Let Φ_{tf} denote the probability that one of these students chooses any introductory

²²Because $d_{tf} P_{itf}$ is the probability that student i chooses any course in field f and is thus less than one, the own-field effect on enrollment is always positive.

course in field f in semester t . These probabilities are given by:

$$\Phi_{tf} = \frac{d_{tf}^{\rho_f} \exp(X\beta_f)}{\sum_{f'=1}^F d_{tf'}^{\rho_{f'}} \exp(X\beta_{f'})} \quad (20)$$

and the natural logarithms of these probabilities are:

$$\ln(\Phi_{tf}) = \rho_f \ln(d_{tf}) + X\beta_f - \ln \left[\sum_{f'=1}^F d_{tf'}^{\rho_{f'}} \exp(X\beta_{f'}) \right] \quad (21)$$

The difference in log probabilities across the two academic fields within semester t is then given by:

$$\ln \left(\frac{\Phi_{tf_1}}{\Phi_{tf_2}} \right) = \rho_{f_1} \ln(d_{tf_1}) - \rho_{f_2} \ln(d_{tf_2}) + (X\beta_{f_1} - X\beta_{f_2}) \quad (22)$$

Furthermore, the difference in this difference across the two academic semesters is given by:

$$\ln \left(\frac{\Phi_{t_1 f_1}}{\Phi_{t_1 f_2}} \right) - \ln \left(\frac{\Phi_{t_2 f_1}}{\Phi_{t_2 f_2}} \right) = \rho_{f_1} [\ln(d_{t_1 f_1}) - \ln(d_{t_2 f_1})] - \rho_{f_2} [\ln(d_{t_1 f_2}) - \ln(d_{t_2 f_2})] \quad (23)$$

$$= \rho_{f_1} [\ln(d_{t_1 f_1}) - \ln(d_{t_2 f_1})] \quad (24)$$

where the second equality holds because $d_{t_1 f_2} = d_{t_2 f_2}$.

Rearranging yields:

$$\rho_{f_1} = \frac{\ln \left(\frac{\Phi_{t_1 f_1}}{\Phi_{t_2 f_1}} \right) - \ln \left(\frac{\Phi_{t_1 f_2}}{\Phi_{t_2 f_2}} \right)}{\ln(d_{t_1 f_1}) - \ln(d_{t_2 f_1})} \quad (25)$$

This illustrates that ρ_f is identified by the empirical relationship between the relative number of course sections offered in each field and the relative probability of choosing any course in that field. For example, if $d_{t_1 f_1} > d_{t_2 f_1}$, then ρ_{f_1} will be close to one if field choice probabilities in field f_1 increase significantly more than field choice probabilities in field f_2 and will be close to zero if field choice probabilities in field f_1 do not increase relative to field choice probabilities in field f_2 . This makes sense because larger values for ρ_{f_1} imply more independence in unobserved preferences within field f_1 . If there is more independence in unobserved preferences, then offering additional sections in field f_1 provides attractive variety which induces more students to choose courses in this field. Conversely, if unobserved preferences are largely determined by field then offering additional sections in field f_1 does not add variety and will not induce more students to choose courses in this field.

Another way to see how ρ_f is identified from empirical variation is to note that this nested logit choice model yields the same choice probabilities—and is thus equivalent to—an

Ackerberg and Rysman (2005) crowding framework. Specifically, assume utility is defined as in Equation (11) but that stochastic preference shocks are given by:

$$\epsilon_{ijt}^{AR} = \delta_f \log(d_{tf}) + \eta_{ijt} \quad (26)$$

where η_{ijt} are independent draws from a Type 1 Extreme Value distribution and δ_f are parameters to be estimated.

In this setting, δ_f measures field specific “crowding” of the unobserved characteristic space. If δ_f is zero, then the number of options available in field f does not change the unobserved desirability of new sections. However, if δ_f is significantly negative, then new sections in field f will provide less option value when there are already many options available in that field. In estimation, $\log(d_{tf})$ is simply included as a time-varying field characteristic implying that δ_f is identified from the relationship between course offerings and field choice probabilities across semesters (Ackerberg and Rysman, 2005). With this structure, choice probabilities are given by:

$$P_{itf}^{AR} = \frac{\exp(v(X_{it}, \beta_f) + \delta_f \log(d_{tf}))}{\sum_{f'=1}^F d_{tf'} \exp(v(X_{it}, \beta_{f'}) + \delta_{f'} \log(d_{tf'}))} \quad (27)$$

It is straightforward to show that this is equivalent to the expression in Equation (14) when $\delta_f = \rho_f - 1$ implying that the variation which identifies the crowding parameters δ_f in an Ackerberg and Rysman (2005) framework is equivalent to the variation which identifies the (shifted) nesting parameters $\rho_f - 1$ in my nested logit framework.

3.4 Threats to identification

The Ackerberg and Rysman (2005) representation of student demand presented in the preceding subsection also makes it easier to see that the main identifying assumption necessary to recover δ_f (or equivalently, $\rho_f - 1$) is that introductory course offerings d_{tf} must be independent of preference shocks η_{ijt} . In words, this assumption means the university cannot consider unobserved student preferences when deciding how many sections of introductory courses to offer in each field. Two violations of this assumption seem most plausible: First, the university may use pre-registration information to cancel unpopular courses or offer additional sections of popular ones.²³ Second, the university may forecast trends in field

²³The university I study posts preliminary Fall (Spring) course offerings by March (October) of the preceding Spring (Fall) semester at which point currently enrolled students can pre-register for courses. While the stated justification for pre-registration is to allow students to plan ahead, the university is not precluded from changing course offerings in response to pre-registration information (UCA, 2006).

preferences across semesters either by anticipating general trends in student preferences or by noticing which courses in preceding semesters were over- or under-subscribed. Because the structure assumes field preferences β_f are fixed across semesters, these trends will be subsumed into η_{ijt} thus any response of the university to these trends will cause misspecification.²⁴

Both of these scenarios suggest there could be positive correlation between introductory course offerings d_{tf} and preference shocks η_{ijt} . Because this is a non-linear model, one cannot rigorously sign biases in parameter estimates by signing correlation between unobserved shocks and endogenous variables. With this caveat, the intuition of bias signing in linear models may still be useful when interpreted with sufficient caution. In an analogous linear model, positive correlation between d_{tf} and η_{ijt} (and a negative crowding parameter δ_f) would imply that estimates of δ_f are biased towards zero (and estimates of ρ_f are biased towards one). Intuitively, if relatively more sections are offered in field f in semesters where students are unobservably more interested in field f , the model will incorrectly conclude that the additional sections attracted the additional enrollment. The model will then incorrectly infer that the new sections provided meaningful variety and thus must have largely independent unobserved characteristics (ρ_f close to one / δ_f close to zero).

However, upward bias in estimates of ρ_f will only confound estimates of γ_f if the bias is disproportionately large in certain fields. Specifically, suppose there is multiplicative bias in estimates of ρ_f so that

$$\hat{\rho}_f = \phi \rho_f \tag{28}$$

It is straightforward to show that this multiplicative bias in estimates of ρ_f leads to multiplicative bias in estimates of marginal effects at observed course offerings as follows:²⁵

$$\frac{\partial \hat{V}_t(\mathbf{d}_t^*)}{\partial d_{tf}} = \phi \frac{\partial V_t(\mathbf{d}_t^*)}{\partial d_{tf}} \tag{29}$$

$$\frac{\partial \hat{n}_{tf}(\mathbf{d}_t^*)}{\partial d_{tf'}} = \phi \frac{\partial n_{tf}(\mathbf{d}_t^*)}{\partial d_{tf'}} \tag{30}$$

This leads to multiplicative bias in estimates of stacked vectors of marginal effects \mathbf{dn}_T^* and

²⁴In theory, one could allow for some degree of time variation in preferences β_f ; however, any time variation in field enrollments that is captured by variation in β_f can no longer be explained by variation in course offerings. In the extreme case, if β_f were semester specific, then all variation in n_{tf} across semesters would be captured by semester specific β_f . As such, allowing for time variation in β_f reduces identifying variation for ρ_f . I will show that there are no detectable trends in field preferences suggesting it is better to assume β_f is fixed to preserve variation for identifying ρ_f .

²⁵Note that this type of misspecification will also affect estimates of choice probabilities P_{itf} which also influence marginal effects; however, because these choice probabilities are conditional moments of observed data, one should expect the estimates to be relatively robust to misspecification.

\mathbf{dV}_T^* . However, these stacked vectors appear on opposite sides of the university’s system of first order conditions in Equation (9) implying that constant multiplicative bias in estimates of ρ_f divides out of the university’s first order conditions.

This suggests correlation between introductory course offerings and unobserved preferences will only confound estimation of γ_f if it is stronger in some fields relative to others. I will argue that the presence of detailed baseline student characteristics and the lack of trends in introductory course offerings imply that concerns about the exogeneity of \mathbf{d}_t should be limited; however, it is encouraging to know that correlation between course offerings and unobserved student preferences will only affect estimates of γ_f if the correlations are stronger in certain fields relative to others.

3.5 Discussion

In addition to the endogeneity concern discussed previously, this general framework for student demand possesses several important limitations: First, the framework does not have a mechanism for incorporating section capacity constraints. As most universities, UCA places constraints on the number of students who can enroll in particular course sections. This implies that for sections where the capacity constraint is reached, true student demand may be substantially greater than constrained demand. Unfortunately, data on capacity constraints are not available; however, even with data on constraints, methodological advances would likely be required to incorporate these in demand estimation.²⁶ I leave both the data and methodological advances for future work. Omitting capacity constraints leads to understating demand for certain course sections; if disproportionately many of these sections are in field f , this may lead to understating the marginal effects of offering additional sections in field f and thus overstating the university’s implied preference for enrollment in field f .

A second limitation is that the framework does not incorporate class size externalities. Although most of the literature on class size externalities has focused on primary school, one may suspect that college students also value small class sizes with more instructor interaction.²⁷ Incorporating class size externalities would be a nice extension as these effects would provide a richer mechanism through which offering additional course can affect student choices and utility. Including these effects requires two main extensions: First, marginal

²⁶Conlon and Mortimer (2013) uses vending machine data to estimate demand in a setting where items can be sold out. However, they observe vending machine inventory every four hours yielding substantial observed variation in item availability. To use their methods in a course choice model, one would need enrollment timestamps or other information to identify which students had the option to enroll in a section which eventually became constrained.

²⁷For example, see Angrist and Lavy (1999); Hoxby (2000); Krueger (2003). An exception which examines the effects of class size in higher education is Kokkelenberg et al. (2008).

effects in Equations (18) and (19) must be reformulated to incorporate the general equilibrium effects of reducing class sizes in all pre-existing sections. A previous draft of this paper available upon request provides guidance. Second, a strategy must be developed to handle potential correlation between class size and unobserved student preferences η_{ijt} . Here, empirical models with agglomeration/crowding externalities from urban and environmental economics may prove useful (Bayer and Timmins, 2007).

Finally, this framework assumes students choose individual course sections independently rather than complementary bundles of sections. One issue with this is technical: For a student who chooses a section of Econ 101 and a section of Math 55 in semester t , independent choice interprets these choices to mean that the Econ 101 section was preferred to all other sections including the Math 55 section; and that, irrationally, the Math 55 section was also preferred to all other sections including the Econ 101 section. Ahn et al. (2019) introduces a bundled choice estimator that addresses this issue; however, the Ahn et al. (2019) approach greatly increases computational burden and complicates the equations for enrollment, total utility, and marginal effects. Moreover, the approach yields only modestly different choice parameter estimates when the number of choices is large as in my setting. As such, I prefer the independent choice specification for transparency and tractability.

The larger issue with independent choice is that it ignores portfolio effects from choosing a diverse bundle of courses which complement one another. Gentzkow (2007) analyzes news consumption in a bundled choice framework with portfolio effects. In addition to greatly increasing computational burden, the Gentzkow (2007) method is not well-suited for my analysis for two primary reasons: First, in my setting, the number of feasible bundles is large enough that estimating bundle specific portfolio effects is impractical without strong restrictions. More importantly, the Gentzkow (2007) method assigns independent type 1 extreme value unobserved preferences for bundles rather than underlying choices. This implies that if a new choice is added, new independent preferences are introduced for every feasible bundle that includes this new choice. This substantially overstates the amount of variety introduced by this new choice. Given that a crucial step in my methodology is measuring the utility effects of offering additional course sections, this characteristic is undesirable.

Although my student demand framework abstracts from capacity constraints, class size effects, and bundled choice, the framework has the advantage of being simple and providing a transparent link between empirical variations and conclusions under familiar assumptions that can be readily scrutinized. As such, I view this demand framework as an appropriate starting point from which future research may build upon.

4 Data, descriptive statistics, and empirical specifications

The framework introduced previously calls for panel data of offered introductory courses, student characteristics, and student course choices as well as data for estimating the marginal costs of offering additional sections of introductory courses. To this end, I employ administrative data from the University of Central Arkansas (UCA). UCA is a large public teaching focused university located in central Arkansas. Table 1 provides background statistics on UCA. The statistics show UCA is a less selective mid-sized university with a six year graduation rate which is below the national average.²⁸ Furthermore, almost all students at UCA are full-time, 24 and under, and from the state of Arkansas.

These administrative data include demographic information, admissions information, and full academic transcripts for all students who were enrolled between the 2004-05 and 2011-12 academic years and information on all offered course sections and the instructors teaching these sections for all sections offered between the 1994-95 and 2011-12 academic years. I combine these to create a sub-sample of student information and course information from the 2004-05 to the 2009-10 academic years. After excluding required writing courses, required oral communication courses, required health courses, and other special courses, the sample includes 25,056 unique UCA undergraduates and 258,662 observations of students choosing introductory courses.²⁹

These administrative data are ideal for this study for two reasons: First, the data on student choices and characteristics together with information on course offerings allows me to analyze how students make choices given a set of alternatives. Crucially, the panel structure of these data allows me to analyze how choices change when course offerings change providing useful empirical variation for identifying the marginal effects of changing course offerings. Second, the data include information on instructor salaries, teaching loads, and contract

²⁸The national average six year graduation rate is 59.4% (Ginder et al., 2017).

²⁹Required writing, oral communication, and health courses are specific courses which almost all students take during their Freshmen year. I exclude these courses because students are choosing these courses to satisfy a requirement rather than to maximize utility. Including these courses would lead me to overstate the desirability of fields associated with these courses. I also exclude first year seminar courses (which are only available to freshmen and can only be taken once), English as a second language courses, military science courses, and courses worth fewer than three credit hours (which are predominantly labs associated with other courses, music lessons, and exercise classes). In addition to writing, oral communication, and health courses, UCA also has general education requirements in fine arts, American history and government, humanities, mathematics, natural sciences, behavioral and social sciences, and world cultural traditions. These requirements can be satisfied with many different courses and are often completed in later years. Furthermore, many of these courses also satisfy major specific requirements. I include these courses because many students are choosing these courses to maximize utility. For more information, please see the UCA course bulletin (UCA, 2006).

characteristics which allows me to estimate the implied cost of offering course sections with different characteristics and to constrain counterfactuals so that the university can only reallocate its instruction budget for adjunct instructors on single-semester contracts.

An important empirical decision which must be made to conduct the analysis described in Sections 2 and 3 is whether to use courses (Econ 101), course-instructor pairs (Econ 101 taught by Prof. Smith), or course sections (Econ 101 taught by Prof. Smith at 9AM on Tuesdays and Thursdays) as the unit of analysis j . In Section 2, j represents a unit that presents a marginal cost to the university. In Section 3, j represents a unit that provides meaningful choice variety to students. In this paper, I use course sections—defined by a course number, instructor, and meeting time—as the unit of analysis j . Arguments can certainly be made in favor of alternative choices; however, I feel course sections are the most appropriate unit because they present the most direct cost to the university. When defining full-time instructors and computing each instructor’s share of full-time, UCA uses course sections rather than courses as the relevant unit (ADHE, 2011). This choice reflects the fact that although there are fixed preparation costs, instruction and grading time are substantial costs which roughly vary by number of sections. Because my focus is on the decisions of a university, I choose the unit of analysis which presents the most direct cost to the university.

Using course sections as the unit of analysis j implies that variety across j arises from differences in course content, instructor, and meeting time. One may argue that another section of an existing course taught by the same instructor but at a different time provides trivial choice variety to students. However, I would argue that if the university is willing to effectively “pay” an instructor to teach an additional section, it must be because the university implicitly values this additional section and the goal of this study is to infer what the university implicitly values. Moreover, as discussed in Section 3, empirical variation determines the estimated choice variety of additional sections and estimates discussed in Section 5 show additional sections provide significant choice variety.

4.1 Descriptive statistics

For my main empirical analysis, I will be analyzing introductory course offerings and student choices across four academic fields: STEM, social science, humanities and arts, and business and occupational. Before proceeding to the main analysis, Table 2 compares several relevant statistics across introductory courses in these fields. The statistics show that social science is the largest field in terms of courses, sections, and student enrollment. STEM is second in terms of course sections and student enrollment but has relatively fewer courses suggesting offerings in this field may be more homogenous. Humanities and arts is third largest in terms

of course sections and student enrollment followed by business and occupational.

Statistics on average introductory enrollment per section show that on average there are 34.1 students in social science sections, 29.2 students in humanities and arts sections, and 26.6 students in both STEM sections and business and occupational sections. These differences suggest there is substantial variation in the average desirability of introductory courses in different fields. Furthermore, the cost statistics show that social science sections have the lowest implied instruction costs at all quartiles of the cost distributions. The low average costs and large average class sizes in social sciences do not necessarily imply that marginally reallocating resources from STEM to social sciences would increase total student utility; however, they do provide suggestive evidence that there could be some misalignment between student preferences and observed course offerings.

The remaining statistics in Table 2 describe how observed student characteristics affect course choices. The statistics show that students choosing introductory STEM courses have higher ACT scores and high school GPA than students choosing introductory courses in other fields on average. Students choosing business and occupational courses have high GPA but less remarkable ACT scores and students choosing social science or humanities and arts courses are comparable in terms of these measures of baseline preparation. The statistics also show that students choosing introductory business and occupational courses are less likely to be women or freshmen but more likely to be sophomores, juniors, or seniors.

In Subsection 3.3, I showed that the crucial nesting parameters ρ_f are identified by the empirical relationship between introductory course offerings and introductory field enrollments across semesters. Table 3 reports the number of introductory courses and sections offered in each field by semester as well as each field's share of total sections and total introductory enrollment by semester to illustrate this identifying variation. The statistics show that the share of STEM sections varies from 28% - 31% across semesters, the share of social science sections varies from 34% - 37% across semesters, the share of humanities and arts sections varies from 21% - 25%, and the share of business and occupational sections varies from 12% - 14%. The extent to which enrollment shares move in concert with these fluctuations in section shares helps identify the nesting parameters ρ_f .

As discussed previously, this identification argument relies on the assumption that course offerings are uncorrelated with the unobserved components of student preferences. While this assumption is fundamentally untestable, one can investigate whether there appear to be broad trends in preferences and course offerings that would cause endogeneity as discussed in Subsection 3.3. A perusal of Table 3 suggests such trends are not present in these data. Section shares and enrollment shares fluctuate from year to year in a manner that appears random suggesting that estimates of nesting parameters are not confounded by

correlated trends in preferences and course offerings.

4.2 Empirical specifications

In Sections 2 and 3, I developed a theoretical framework for measuring implied tradeoffs between total student utility and field enrollments under a general additively separable course utility function and a general course cost function. In this subsection, I discuss the exact specifications I use in my empirical application.

As discussed previously, these marginal effects are identified by the empirical relationship between course offerings and field enrollments across semesters. As such, for tractability, and to preserve the transparent link between empirical variation and results, I employ the following simple linear structure for the deterministic component of utility:

$$U_{itj} = X_{it}\beta_f + \epsilon_{itj} \quad (31)$$

where X_{it} includes ACT scores, high school GPA, and indicators for gender and year in school. Notice that Equation (31) does not include any observed course section characteristics other than academic field. As discussed previously, omitting within field characteristics is necessary to ensure that marginal effects of offering additional course sections are defined at the field level.

To estimate the marginal costs of offering additional sections of introductory courses, I assume that the implicit cost of hiring an instructor to teach course section j can be additively separated into a field specific effect ψ_f , an instructor rank specific effect ξ_r where r indexes instructor rank, and an idiosyncratic component v_j as follows:³⁰

$$C_j = \psi_f + \xi_r + v_j \quad (32)$$

I then assume that the marginal cost of adding or removing one introductory course section in field f' is given by the expected cost of hiring an adjunct instructor on a single-semester

³⁰Possible instructor ranks are: tenured, tenure-track, on a long term contract but ineligible for tenure, and adjunct instructors on single-semester contracts. Allowing costs to differ by instructor rank suggests instructor rank should also enter into student utility. Appendix B suggests instructor compensation (which is highly related to rank) has little effect on student utility so I exclude these effects for clarity. See Appendix A for a detailed description of how I use data on instructor salaries, contract details, and teaching histories to construct the implicit cost of hiring an instructor to teach course section j C_j .

contract to teach an introductory course section in field f' .³¹ In notation,

$$c_f = \mathbb{E}[C_j \mid f = f', r = \text{single semester}] \quad (33)$$

The idea is that if a university wants to add or subtract a section in field f in semester t , it is generally simpler and more cost effective to do this by hiring or firing an adjunct instructor on a single-semester contract.³² As such, costs of hiring adjunct instructors represent better estimates of marginal costs than average costs within a field.

As discussed in Subsection 2.4, the interpretation of γ_f as implied local tradeoffs only requires estimates of marginal costs which are valid in a neighborhood around observed course offerings. Conversely, treating γ_f as structural parameters requires assuming marginal costs can be estimated globally. Notice that Equation (33) assumes the marginal cost of offering an additional course section in field f is independent of the number of sections offered in field f . This is consistent with a framework in which UCA is a wage-taker in the market for adjunct instructors; however, this assumption may still be violated at hypothetical course offerings which are far away from observed offerings. While this does not affect the implied local tradeoff interpretation of γ_f , it may affect counterfactual analyses in which predicted counterfactual offerings are far away from observed offerings.

Another limitation of this cost framework is that it ignores facility costs, material costs, and other non-instructor costs. To see how ignoring these non-instructor costs affects my analysis, suppose there is general downward multiplicative bias in my estimates of marginal costs given by:

$$\hat{c}_f = \pi_f c_f \quad (34)$$

where $\pi_f \in (0, 1)$. If π_f is equal across fields, then there is multiplicative bias in both \mathbf{dn}^* and \mathbf{dV}^* which divides out in Equation (9). Therefore, estimates of γ_f are robust to ignoring non-instructor costs if these costs are proportional to instructor costs. If $\pi_f < \pi_{f'}$ for all $f' \neq f$ then I am understating the relative marginal cost of adding sections in field f . This leads to downward bias in estimates of the implied local preference for enrollment in field f γ_f .

Finally, readers may notice a disagreement between the cost equation (32) and the utility specification (31) because instructor rank affects costs but not utility. This is by no means a necessary exclusion restriction—instructor rank can be included in both or in

³¹Adjunct instructors on single-semester contracts are those whose contracts need to be renewed every semester. 11.4% of all course sections are taught by adjunct instructors on single-semester contracts.

³²Research universities may find it optimal to subtract a course by giving a tenured or tenure-track instructor a teaching reduction which allows her to produce more research. This is less likely to be true at a teaching-focused university such as UCA.

neither if desired.³³ I made this empirical choice because rank has large effects on instructor costs but small effects on student demand. Table 4 shows large effects of rank on salary but a supplemental analysis in Appendix B shows that salary—which is closely related to rank—has minor effects on demand. As such, I include rank in the cost regression to better capture cost variation but exclude rank from the demand model for power.

5 Effects of course offerings and implied preferences

This section reports the first set of results for my analysis of the introductory course offerings at the University of Central Arkansas (UCA) in Fall and Spring academic semesters of academic years 2004-05 through 2009-10. I begin by reporting estimates of primitive student preference parameters and cost parameters. I then use these primitive parameters to construct local marginal effects of offering additional sections of introductory courses on total student utility, marginal effects relative to marginal costs, and implied preference parameters γ_f . Results show that an additional dollar of spending offering introductory social science sections produces 2.5 times as much student utility as an additional dollar of spending on introductory business or occupational sections. This implies the university is implicitly sacrificing significant student utility to draw students out of social science courses and into business and occupational courses.

Results in this section require only credible estimates of local marginal costs and effects of offering additional course sections. As such, these results are robust to misspecification of the university’s objective function or constraints. The following section discusses results which rely on the full two-sided structural model.

5.1 Student preference parameters and cost parameters

As discussed in Section 2, the fundamental elements needed to measure implied preference parameters γ_f are local marginal effects of offering additional course sections on total student utility, local marginal effects of offering additional sections on field enrollments, and local marginal costs of offering additional sections.

Table 4 reports estimates of the cost regression described in Equation 32 which will be used to compute marginal costs. Results show that conditional on instructor rank, costs are highest for introductory STEM courses followed by business and occupational, humanities and arts, and social science. Results also show that conditional on field, adjunct instruc-

³³If instructor rank is included in student utility, marginal effects must reflect the effects of offering additional sections taught by adjunct instructors on single-semester contracts.

tors cost \$5,595 per section less than tenured instructors and \$3,132 per section less than instructors who are on long term contracts but are not eligible for tenure. Because adjunct instructor is the omitted rank category—and because the regression does not include a constant—coefficients on field indicators measure the expected cost of hiring an adjunct instructor to teach an introductory course section in each field. As discussed previously, I use these adjunct instructor costs as my estimate of the marginal cost of adding or subtracting a course section in a given field.

Table 5 reports estimates of student preference parameters from the nested logit course choice model which will be used to measure the marginal effects of offering additional course sections. The estimates imply a first year male student with average ACT scores and HS GPA is most attracted to introductory social sciences courses followed by humanities or arts, STEM, and business or occupational. First year female students with average scores and grades have the same relative preferences over fields for introductory courses; however, the magnitudes suggest first year female students are relatively more attracted to social science courses and less interested in business or occupational courses than their male counterparts. While introductory business courses are quite unpopular with freshmen, they are relatively more popular with advanced students. In fact, male sophomores, juniors, and seniors with average scores and grades prefer introductory business courses to introductory courses in all other fields.

The estimates also imply students with conditionally higher ACT scores are relatively more likely to enroll in STEM or humanities or arts courses while students with conditionally higher high school GPA are relatively more likely to enroll in STEM or business or occupational courses. The finding that students with higher ACT scores and high school GPA are relatively more likely to enroll in 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, 2014b).

Finally, estimates of the nesting parameters are in the middle range varying from 0.461 to 0.680. This implies unobserved preferences for course sections within the same field are neither fully independent nor perfectly identical. This shows that new sections are sufficiently different from existing sections within the same field to provide students with meaningful choice variety; however, it also shows that assuming independence within fields would lead to grossly overstating the effects of offering additional sections on student choices and utilities. Furthermore, the estimates suggest there is substantial heterogeneity in crowding across fields implying that allowing for heterogeneous crowding is important when comparing marginal effects across academic fields.

5.2 Marginal effects, marginal effects per dollar, and implied preferences

Table 6 uses estimates of the student course choice model and the cost regression to construct marginal effects and to measure implied tradeoffs between total student utility and field enrollments. To begin, column 1 uses estimates of student preference parameters to construct the local marginal effects of offering additional sections of introductory courses on total student utility. For expositional purposes, these are averaged across semesters and reported relative to effects of offering additional sections of introductory business or occupational courses. In notation, column 1 reports:

$$\frac{1}{T} \sum_{t=1}^T \left(\frac{\partial V_t(\mathbf{d}_t)}{\partial d_{tf}} \right) / \frac{1}{T} \sum_{t=1}^T \left(\frac{\partial V_t(\mathbf{d}_t)}{\partial d_{tBus-Occ}} \right) \quad (35)$$

Stars report whether relative effects in field f are significantly greater than one (implying field f effects are significantly greater than business and occupational effects).

Results show that on average, an additional humanities or arts section produces 1.541 times as much student utility as an additional business or occupational section, an additional social science section produces 1.533 times as much student utility as an additional business or occupational section, and an additional STEM section produces 1.484 times as much student utility as an additional business or occupational section.

While the figures in column (1) show significant differences in the marginal benefits of additional sections of introductory courses in terms of total student utility, they do not account for differences in the marginal costs of these sections. Results in Table 4 showed that differences in costs are sizable implying that ignoring these differences would lead to incorrect conclusions. To account for these differences, column 2 reports local marginal effects divided by marginal cost. Once again, these are averaged across semesters and reported relative to effects of offering additional introductory business or occupational sections. In notation, column 2 reports:³⁴

$$\frac{1}{T} \sum_{t=1}^T \frac{1}{c_f} \frac{\partial V_t(\mathbf{d}_t)}{\partial d_{tf}} / \frac{1}{T} \sum_{t=1}^T \left(\frac{1}{c_f} \frac{\partial V_t(\mathbf{d}_t)}{\partial d_{tBus-Occ}} \right) \quad (36)$$

Results show that on average, an additional dollar spent offering social science sections produces 2.533 times as much student utility as an additional dollar spent offering business or occupational sections, an additional dollar spent offering humanities or arts sections pro-

³⁴As before, average marginal effects per dollar are reported relative to the average effect per dollar of offering an additional introductory business or occupational section which is normalized to one and stars report whether effects per dollar in other fields are significantly greater than one.

duces 2.249 times as much student utility as an additional dollar spent offering business or occupational sections, and an additional dollar spent offering STEM sections produces 1.365 times as much student utility as an additional dollar spent offering business or occupational sections.

These differences show that marginally reallocating spending from business and occupational sections to social science sections would increase total student utility; however, doing so would decrease variety in business and occupational sections and increase variety in social science sections which would decrease business and occupational enrollment and increase social science enrollment in expectation. Since spending was not reallocated from business and occupational sections to social science sections despite the potential for increasing student utility, observed course offerings are implicitly sacrificing some student utility to keep students from switching from business and occupational courses to social science courses in expectation. This reveals an implicit willingness to sacrifice student utility to draw students out of social science courses and into business and occupational courses.

Column 3 reports estimates of γ_f to precisely quantify these implicit tradeoffs. The omitted field is social science; therefore, estimates for field f report how much total student utility the university is implicitly sacrificing to move one student out of an introductory social science course and into an introductory course in field f in expectation. Results show that the university is implicitly sacrificing 0.086 units of student utility to move a student from social science to humanities and arts, 0.611 units of student utility to move a student from social science to STEM, and 1.114 units of student utility to move a student from social science to business or occupational. By showing that observed course offerings are implicitly sacrificing significant student utility to change field enrollments, these estimates quantify the extent to which student preferences and observed course offerings are misaligned.

The interpretation of estimates of γ_f as implicit tradeoffs and measures of misalignment holds even when the university's problem is misspecified and/or when the student model holds only in a neighborhood around observed course offerings. However, quantifying these tradeoffs in terms of units of total student utility makes them difficult to interpret and measures of these implicit tradeoffs alone cannot be used for policy analysis. In the following section, I report results which require stronger assumptions but provide additional interpretation and predictions for policy analysis.

6 Interpretation and Policy Counterfactuals

The preceding section used estimates of local marginal costs and local marginal effects of offering additional course sections to measure the tradeoffs between total student utility and

field enrollments which are implied by observed course offerings. Under relatively lenient assumptions, these tradeoffs can be interpreted as a measure of the misalignment between student preferences and observed course offerings. In this section, I treat these implied tradeoffs as the university's structural preference parameters in a two-sided model of a university choosing course offerings and students choosing courses from the set of available alternatives. While this requires assuming that the university's problem and student choice model are both correctly specified, it allows me to provide additional intuitive ways to quantify misalignment between student preferences and observed course offerings and to conduct counterfactual policy analyses which incorporate university responses.

6.1 Utility maximizing course offerings and equivalent costs

To further quantify the misalignment between student preferences and observed course offerings, columns (1) - (5) of Table 7 compare average observed course offerings and field enrollments to cost-equivalent offerings and enrollments which would have maximized total student utility. Columns (1) - (3) report averages across semesters of the number of introductory course sections taught by instructors on long term contracts in each field, the number of introductory course sections taught by adjunct instructors on single-semester contracts in each field, and enrollment in introductory courses by field. Columns (4) and (5) then examine how adjunct instructed offerings and enrollments would change if the portion of the budget allocated to pay adjunct instructors were reallocated to maximize total student utility holding contracted offerings in column (1) fixed.³⁵ Stars indicate where columns (4) and (5) are statistically different from columns (2) and (3) respectively.

Results suggest the utility maximizing allocation of the adjunct instructor budget for introductory courses contains no STEM sections, no business or occupational sections, approximately the same number of humanities and arts sections, and four times as many social science sections. The large increase in social science sections reflects the finding in Table 6 that marginal spending on social science courses produces student utility more efficiently than spending in other fields. Column (5) predicts that offering the utility maximizing adjunct instructed courses would increase overall introductory social science enrollment by 11.65% and decrease overall introductory STEM and business and occupational enrollment by 13.74% and 5.96% respectively.

³⁵There are several reasons to reallocate the budget for adjunct instructors only: First, this mechanically restricts counterfactual course offerings to remain relatively close to observed offerings where I am more confident in the predictive power of the estimated student choice model; second, this represents a realistic picture of what could be achieved in the short run since instructors on long term contracts can only be released when those contracts expire; third, the model provides no mechanism for explaining why the university hires instructors of different ranks and thus is not well equipped to predict hiring decisions across ranks.

To provide an additional intuitive way to measure the misalignment between student preferences and observed course offerings, column (6) of Table 7 reports how much costs of adjunct instructors would need to change to induce a utility maximizing university to offer the adjunct instructed sections reported in column (2). I refer to these as the “equivalent costs” of $\hat{\gamma}_f$ since going from observed costs to equivalent costs with a utility maximizing objective would have the same effect on course offerings as going from a utility maximizing objective to an objective characterized by $\hat{\gamma}_f$ holding costs fixed at observed costs. Figure 3 illustrates the idea with one semester and two fields: The observed production possibilities frontier is PPF and the outcomes associated with observed course offerings are given by B . The goal is to solve for counterfactual costs which yield a production possibilities frontier PPF' which makes it so that a utility maximizing university with indifference curves given by Π^{SUM} would offer courses which achieve outcomes B . Intuitively, I infer these equivalent costs by solving for costs which make it so that a utility maximizing university’s first order conditions are satisfied at observed course offerings. This means solving for costs which imply that marginal effects per dollar of offering additional course sections on total student utility are equal across fields at observed course offerings. Details are reported in Appendix C.

Results suggest that inducing a utility maximizing university to offer observed courses would require a 45.62% increase in the cost of hiring a social science adjunct instructor, a 24.99% increase in the cost of hiring a humanities or arts adjunct instructor, a 17.01% decrease in the cost of hiring a STEM adjunct instructor, and a 41.99% decrease in the cost of hiring a business and occupational adjunct instructor. This shows that the estimated preference parameters $\hat{\gamma}_f$ have the same effects on course offerings as substantial increases in social science and humanities and arts costs and substantial decreases in business and occupational and STEM costs.

6.2 Counterfactual analyses with university responses

As mentioned previously, one of the primary reasons for moving towards structural models of university behaviors is the capacity to conduct counterfactual policy analyses which incorporate university responses into predictions. In general, universities are not passive parties in the production of human capital but rather active entities which allocate their resources to maximize their objectives subject to constraints. While predicting university responses requires strong assumptions, counterfactual policy analyses which assume university inputs remain fixed are arguably making even stronger assumptions.

To illustrate the value of my two-sided model, and for higher education models which

incorporate supply-side responses more generally, this subsection performs several counterfactual analyses which both include university responses and exclude university responses for comparison. To begin, I restate the university’s problem with an additional clarification that total student utility V_t and enrollment in each field n_{tf} depend on the set of all observed student characteristics in semester t denoted by $\mathbf{X}_t = \{X_{it}\}_{i=1}^N$

$$\mathbf{d}_t^* = \operatorname{argmax}_{\mathbf{d}_t} \left\{ V_t(\mathbf{d}_t; \mathbf{X}_t) + \sum_{f=1}^{F-1} \gamma_f n_{tf}(\mathbf{d}_t; \mathbf{X}_t) \right\} \left(\text{s.t. } C(\mathbf{d}_t, \psi) \leq E_t \right) \quad (37)$$

For counterfactual analyses which incorporate university responses, I proceed in two steps. First, I solve for a counterfactual $\tilde{\mathbf{d}}_t$ which solves (37) given either counterfactual student characteristics $\tilde{\mathbf{X}}_t$ or counterfactual cost parameters $\tilde{\psi}$. These represent the courses the university would offer in a counterfactual scenario in which either student characteristics or course costs are changed. Second, I calculate counterfactual field enrollments \tilde{n}_{tf} given counterfactual student characteristics $\tilde{\mathbf{X}}_t$ and counterfactual course offerings $\tilde{\mathbf{d}}_t$ using Equation (16). For counterfactual analyses which ignore university responses, I calculate field enrollments given counterfactual student characteristics $\tilde{\mathbf{X}}_t$ but observed course offerings \mathbf{d}_t . The first order conditions characterizing the solution to Equation (37) are complicated non-linear functions of course offerings \mathbf{d}_t . As such, it is unclear whether a closed form expression for \mathbf{d}_t^* exists. Instead of deriving a closed form expression for \mathbf{d}_t^* , I solve for \mathbf{d}_t^* directly using numerical constrained maximization methods.

Tables 8 and 9 predict introductory course offerings and introductory field enrollments in several counterfactual scenarios.³⁶ To enhance the credibility of these predictions, I make two choices: First, I choose counterfactual scenarios which are relatively close to the observed scenario to increase confidence in the ability of my model to predict university and student choices. Second, as in Table 7, I only allow the university to reallocate the portion of its budget for introductory courses paid to adjunct instructors on single-semester contracts. This also restricts the counterfactual scenarios to be close to the observed scenario and examines a short run scenario in which inputs which are costly to vary are held fixed.

Given the policy interest in increasing specialization in STEM, one interesting counterfactual scenario to consider is one in which the state subsidizes STEM instructors to increase STEM course offerings and enrollments. To evaluate the effectiveness of such a subsidy, my first counterfactual predicts adjunct instructed introductory course offerings and

³⁶Tables 8 and 9 also report predicted introductory course offerings and introductory field enrollments in the observed state in row 1. Stars in rows 2 and beyond indicate whether predictions in counterfactual scenarios are statistically different from predictions in the observed state. Reported figures of averages of predictions across all academic semesters.

introductory field enrollments under a subsidy which reduces the cost of hiring a STEM adjunct instructor by 5%. Row 2 of Table 8 shows that this subsidy would increase the number of adjunct instructed STEM sections by 49.15% and reduce offerings in other fields. Furthermore, row 2 of Table 9 shows that this increase in STEM offerings would lead to a 6.22% increase in overall STEM enrollment with additional students coming mostly from social science and humanities and arts courses. The subsidy would cost \$252.87 per adjunct instructed section implying a total cost of \$13,498.23 or 4.18% of spending on adjunct instructed introductory courses.

Another interesting scenario to consider is one in which UCA begins attracting higher ability students. From Table 5, we know that higher ability students are generally more interested in STEM suggesting that UCA might respond to a higher ability student body by offering more STEM courses and thus making the STEM field even more attractive. To analyze this scenario, my second counterfactual predicts adjunct instructed introductory course offerings and introductory field enrollments if all student ACT scores and high school GPAs were increased by one-third of a standard deviation holding fixed other student characteristics.³⁷ Row 3 of Table 8 shows that increasing student abilities would increase the number of adjunct instructed STEM sections by 48.62% and reduce offerings in other fields. To see how field enrollments would change with higher ability students, row 3 of Table 9 first predicts field enrollments in a partial equilibrium where student characteristics are changed but course offerings remain fixed. Results show that attracting higher ability students would increase introductory STEM enrollment by 3.68% without any response in course offerings. Row 4 of Table 9 incorporates the changes in adjunct instructed course offerings and shows that the total effect of attracting higher ability students is a 10.97% increase in introductory STEM enrollment. This illustrates the importance of incorporating university responses into counterfactual policy analyses; ignoring changes in course offerings leads to understating increases in STEM enrollment by approximately a factor of three.

A final scenario to consider is one in which the gender composition of students at UCA changes. Results in Table 5 suggest men and women do not have wildly different field preferences so I choose an extreme counterfactual setting in which all male students are given female field preferences for illustrative purposes. Row 4 of Table 8 shows that if all students had female preferences, UCA would offer 2.4 times as many adjunct instructed social science sections, 54.86% more adjunct instructed humanities and arts sections, 32.69% fewer adjunct instructed STEM sections, and would virtually eliminate adjunct instructed business and

³⁷These predictions assume that student field preferences depend on absolute abilities rather than abilities relative to the student body. If field preferences depend on relative abilities then increasing the abilities of all students will have no effect on field preferences and thus no effect on course offerings.

occupational sections. Once again, to separate out the direct effects of changes in students characteristics and the indirect effects of changes in course offerings, row 5 of Table 9 predicts field enrollments in partial equilibrium without changes in course offerings and row 6 of Table 9 predicts field enrollments in general equilibrium with university responses. Results show that stronger female preferences for introductory social science courses imply that giving all students female preferences leads to a 4.71% increase in introductory social science enrollment without any change in course offerings. Incorporating the effects of the increase in adjunct instructed introductory social science sections leads to a total predicted increase in introductory social science enrollment of 8.68%. Once again, ignoring the indirect effects of changes in course offerings leads to significantly understating changes in field enrollments.

7 Suggestive Evidence on Mechanisms

Natural questions arising from the analysis in this paper are: “Why might a university be willing to sacrifice student utility to increase STEM and business and occupational enrollment? Are these tradeoffs beneficial for students and society in the long run or do they reflect selfish interests of the university?” For the most part, I leave these larger questions for future research; however, this section will briefly conclude by discussing literature and presenting suggestive evidence which gives clues as to why UCA might prefer STEM and business and occupational enrollment. To preview, I argue that STEM and business and occupational courses have higher future labor market returns but also higher present psychic costs. As such, a university may favor STEM and business and occupational courses either to paternalistically induce myopic students to make decisions in their best long term interests, or to internalize larger social externalities generated by higher earning graduates.

First, there is ample evidence that STEM and business and occupational degrees have larger labor market returns than degrees in other fields. In a recent review article, Altonji et al. (2012) summarizes the relative returns to different majors: “Engineering consistently commands a high premium, usually followed by business and science. Humanities, social sciences, and education are further behind.” Interestingly, this ordering of relative returns closely matches the ordering of UCA’s preferences reported in Table 6.

To supplement the findings of Altonji et al. (2012) with suggestive evidence on relative returns at UCA, column 1 of Table 8 reports results from a naïve regression of annual earnings on field of major for workers who earn Bachelor’s degrees from UCA. Data on earnings are from Arkansas state unemployment insurance tax filings and include earnings from all employers who pay Arkansas state unemployment insurance taxes (excludes self-employed individuals, federal employees, and all employers outside Arkansas). The sample

for this regression is all students who earn Bachelor's degrees between the 1993-94 and 2003-04 academic years and report positive earnings eight years after graduating.³⁸ The regression controls for ACT scores, high school GPA, gender, and graduation year but should still be considered naïve because there are certainly other omitted factors which are related to both final major and earnings.

Results of this naïve earnings regression suggest earnings are 42.8% higher for STEM graduates relative to observationally equivalent Humanities and Arts graduates, 39.1% higher for Business and Occupational graduates relative to Humanities and Arts graduates, and 10.4% higher for Social Science graduates than Humanities and Arts graduates. These differences in earnings across majors are generally consistent with the summary of relative returns given by Altonji et al. (2012).

A concern with the results in column 1 is that non-random selection into the sub-sample which reports earnings could bias results. In this setting, graduates could be absent from the earnings data either because they are unemployed for the entire year, out of the labor force, working in an excluded sector within Arkansas, or working outside of Arkansas. In this sample, 36.7% of graduates do not report earnings eight years after graduating implying this selection is substantial.

Because there are many possible reasons for absence, it is difficult to even hypothesize how the unobserved characteristics of earners might differ from those of non-earners making it challenging to argue about the signs and magnitudes of biases in column 1. Still, to better understand non-random selection into the earners sub-sample, column 2 of Table 8 reports results from a linear probability model which predicts whether an individual reports earnings eight years after graduating as a function of field of major and controls. Results suggest graduates with Business or Occupational majors and graduates with Social Science majors are more likely to report earnings than observationally equivalent graduates with Humanities or STEM majors. While this selection is non-trivial, it seems unlikely that this selection explains the large differences in column 1. As such, these naïve regressions generally support existing evidence which concludes that STEM and business and occupational degrees have larger labor market returns than degrees in other fields.

There is also existing literature which suggests STEM coursework may involve higher psychic costs to students. Numerous studies find that grading policies in STEM courses are harsher than in other fields (Sabot and Wakeman-Linn, 1991; Thomas, 2019; Johnson, 2003; Stinebrickner and Stinebrickner, 2014b). One reason why harsher grading policies imply higher psychic costs is that fewer students will expect to reach the upper bounding A grade at which point the marginal benefit of effort must diminish. Furthermore, there may be

³⁸I exclude degree-earners who complete multiple degrees or majors (4.2% of degree earners).

direct psychic costs associated with receiving lower grades. Relatedly, existing literature also finds that STEM courses are associated with higher study times than courses in other fields (Brint et al., 2012; Stinebrickner and Stinebrickner, 2014b). If one assumes an hour of studying is equally costly across fields, this implies STEM courses involve higher psychic costs than other coursework.

Once again, to supplement these findings, columns 1 and 2 of Table 9 contain naïve regressions relating grade outcomes to course field at UCA. The sample for these regressions—which closely mirrors the sample in my main analysis—is all grades earned in introductory courses in Fall and Spring academic semesters between the 2005-06 and 2011-12 academic years.³⁹ The regressions control for ACT scores, high school GPA, gender, and student level but should once again be considered naïve because there may be omitted factors which are related to both course field and grade outcomes.

Column 1 of Table 9 reports estimates of a linear probability model which predicts whether a student earns the maximum grade of A. In this sample, 25.3% of earned grades are an A implying a substantial number of students reach the upper bounding grade where return on effort must diminish. Results suggest observationally equivalent students are 13.1 percentage points less likely to earn an A in an introductory STEM course relative to an introductory humanities or arts course. Column 2 of Table 9 reports estimates of a censored regression which predicts grade points as a function of course field and controls.⁴⁰ The censored feature accounts for the fact that many students receive the maximum grade of A.⁴¹ Results suggest observationally equivalent students should expect to earn 0.600 fewer grade points in STEM courses relative to Humanities or Arts courses, 0.292 fewer points in Social Science courses relative to Humanities or Arts courses, and 0.192 fewer points in Business or Occupational courses relative to Humanities or Arts courses. In this sample, the standard deviation in grade points is 1.224 grade points implying these differences are substantial relative to the overall variation in grades. These results are consistent with existing literature which finds that grading policies are harshest in STEM courses.

A similar selection concern with the results in columns 1 and 2 of Table 9 is that some students withdraw from courses before earning grades. Withdrawals appear on a student's transcript but do not count towards her grade point average; as such, withdrawals probably mean poor expected performance but it is unclear exactly how poor (ADHE, 2011). In this sample, 9.7% of observations are withdrawals implying the confounding effects of this

³⁹I exclude 2.1% of observations which have bad grade data.

⁴⁰Letter grades are assigned to numeric grade point values using the Arkansas Department of Higher Education's metric (A=4, B=3, C=2, D=1, F=0) (ADHE, 2011).

⁴¹Specifications which ignore censoring (available upon request) produce the same ordering of fields but with smaller differences across fields.

selection could be non-trivial. To evaluate this selection, column 3 of Table 9 reports results from a linear probability model which predicts whether an observation is a withdrawal as a function of field of major and other controls. Results suggest observationally equivalent students are most likely to withdraw from STEM courses and least likely to withdraw from Humanities and Arts courses. If students generally withdraw when they expect to earn grades that are lower than their observed covariates imply, this suggests the results in column 2 understate the differences between STEM and Humanities and Arts grades.

To summarize, existing literature shows—and naïve regressions in my data suggest—that STEM and business and occupational courses have higher labor market returns and that STEM courses also have larger present psychic costs. These findings provide some clues as to why UCA might prefer STEM and business and occupational enrollment. First, if students are myopic or lack information about future labor market returns, a paternalistic university may offer additional STEM and business and occupational courses to induce more students to complete courses with high labor market returns. In this setting, the university’s offerings may maximize some notion of long term student welfare but not short term choice utility.

Existing literature supports the idea that students may be myopic or lack information about future labor market returns. For myopic behavior, Spear (2000) discusses neurological reasons why adolescents focus more on immediate costs than future gains relative to adults and Oreopoulos (2007) provides evidence that high school students ignore or heavily discount future consequences when deciding to drop out of school. For incomplete information, Wiswall and Zafar (2014) find that providing students with information about average labor market outcomes by major leads students to update their beliefs about their own labor market outcomes and the probabilities that they will complete each major. This supports the idea that paternalism may underlie UCA’s preference for STEM and business and occupational enrollment.

Alternatively, if STEM education has larger social externalities than coursework in other fields, UCA may be offering additional STEM courses to maximize social welfare more broadly. One mechanical reason why producing additional STEM graduates may have larger social externalities is that higher earning STEM graduates probably pay more in taxes.⁴² Estimates in column 1 of Table 8 imply that a male STEM graduate with average ACT scores and high school GPA who graduates in 2001 earns \$46,028 in 2009 while an observationally

⁴²The argument that producing additional STEM and business and occupational majors increases total tax take only holds in a human capital framework in which STEM and business and occupational degrees make workers more productive so that producing more of these majors increases total productivity. In an alternative signaling framework where degrees only signal underlying abilities without increasing productivities, effects of additional STEM and business and occupational majors on total productivity are ambiguous.

equivalent humanities or arts graduate earns \$28,941 in 2009.⁴³ If these individuals have no dependents, itemized deductions, or tax credits, the STEM graduate pays \$7,106 in federal income tax and \$2,349 in Arkansas state income tax while the humanities or arts graduate pays \$3,749 in federal income tax and \$1,189 in Arkansas state income tax.⁴⁴ This likely understates the difference in contributions to state coffers as higher income STEM graduates probably also pay more in state sales taxes and other state and local taxes.⁴⁵

Furthermore, although empirical evidence on heterogeneous social returns to higher education by field is thin, theoretical models of education externalities typically assume externalities arise because individuals learn from one another (Moretti, 2004; Lucas, 1988; Jovanovic and Rob, 1989; Glaeser, 1999). Since STEM degrees have more labor market value for individuals, it seems natural to assume that interactions with STEM graduates yield more valuable learning spillovers than interactions with other graduates. This suggests UCA’s preference for STEM enrollment may be an attempt to increase the social externalities produced by their graduates.

Moreover, a preference for STEM enrollment is in line with recent federal and state initiatives to induce more students to complete STEM degrees (PCAST, 2012; Chapman, 2014). The justifications for these initiatives were to “retain [the United States’] historical preeminence in science and technology” (PCAST, 2012) and to “[lay] the foundation for a truly world-class workforce” (Chapman, 2014). Implicit in both justifications is the notion that the high productivity of STEM graduates generates social externalities which justify intervention.

While my analysis does not directly imply that UCA’s implicit preferences for STEM and business and occupational enrollment are driven by paternalistic or socially conscious motivations, the evidence in this section does suggest that these preferences would be qualitatively consistent with paternalistic or socially conscious behavior. Future research may delve deeper into the mechanisms underlying university preferences for certain fields.

8 Conclusion

In 1973, Daniel Bell described the university as “the axial institution of post-industrial society” (Bell, 1973). This is more true today than it was over four decades ago. Despite this, there is still a great deal we do not know regarding how universities make decisions and the implications of these decisions for students. These knowledge gaps limit our understanding

⁴³Units are nominal dollars in 2009.

⁴⁴See IRS (2009) and ADFA (2009a) for federal and state marginal tax rates in 2009.

⁴⁵In 2009, Arkansas had a 6% general sales tax and a 3% sales tax on food and food ingredients (ADFA, 2009b).

of the “axial institution” and prevent higher education policymakers from choosing policies which correctly anticipate university responses.

To advance our understanding of the “supply side” of higher education, this paper proposed a new framework for analyzing course offerings at a university. Course offering decisions may affect the long term labor market outcomes of students and provide a useful window into what a university values. The main idea of the framework is that offering additional sections of courses in a field provides more variety of choices within that field making the field relatively more attractive to students and increasing total student utility in expectation. As such, any marginal reallocation of resources across fields will have effects on both expected field enrollments and total expected student utility.

One can use models of student demand and instructor costs to measure the marginal effects of spending increases in each field on total student utility. Fields with the smallest marginal effects on total student utility have more sections than the hypothetical offerings which would have maximized student utility. Since more sections means more variety of choices and thus more enrollment, differences in marginal returns imply observed course offerings are implicitly sacrificing student utility to increase enrollment in certain fields. Estimates of these implied tradeoffs can either be interpreted directly as a measure of the misalignment between student preferences and offered courses or they can be treated as university preference parameters in a two-sided model of a university offering courses and students choosing courses from the set of offered alternatives.

I use my framework to analyze introductory course offerings at the University of Central Arkansas (UCA) and find that UCA is implicitly sacrificing student utility to draw students out of social science courses and into STEM and business and occupational courses. The misalignment is so large that if one were to reallocate the portion of the introductory course budget paid to adjunct instructors on single-semester contracts to maximize total student utility, one would eliminate all adjunct-instructed introductory STEM and business and occupational course sections and offer four times as many adjunct-instructed introductory social science sections. To quantify the misalignment in another way, I show that a utility maximizing university would only offer the observed composition of courses if social science adjunct instructors were 45.6% costlier and business and occupational adjunct instructors were 42.0% cheaper.

Finally, to illustrate the value of the two-sided model, and for higher education models which incorporate supply-side responses more generally, I perform a number of simulations which predict course offerings and student outcomes in counterfactual scenarios. To avoid forecasting too far out of sample, I hold the allocation of faculty on long-term contracts fixed and only reallocate the budget for adjunct instructors on single-semester contracts.

One notable counterfactual increases all observed measures of student preparation by one third of a standard deviation. Even without a university response, this would increase introductory STEM enrollment by 3.7% because more prepared students are more interested in STEM. Incorporating how the university responds to this increase in STEM demand by hiring more STEM adjunct instructors yields a 11% total increase in introductory STEM enrollment. In other words, ignoring the university's response leads to understating effects on STEM enrollment by approximately a factor of three.

To my knowledge, this is the first analysis of course offerings at a university and the first attempt to estimate a two-sided model of a university and students with microdata. As such, the analysis must come with important caveats and there is substantial room for subsequent extensions. First, although the static nested logit model I use for student demand provides a transparent and intuitive mapping from empirical variation to identifying marginal effects, this model abstracts from many factors which affect student choices and makes a crucial assumption about the exogeneity of course offerings. If course offerings are related to unobserved student demand, marginal effects are likely overstated. If effects are disproportionately overstated in certain fields, then estimates of implied preferences will be biased downwards in these fields. Future work may build deeper models of student demand or exploit quasi-experimental variation in course offerings to enhance the credibility of results.

Furthermore, while my simple model of university course offering decisions benefits from transparency and tractability, it abstracts from closely related choices made by the university and incorporates bureaucratic friction and other university constraints in a very limited fashion. The limited role of bureaucratic friction and other constraints probably means that my counterfactuals overstate university responses. Moreover, while my analysis quantifies how much student utility a university is willing to sacrifice to increase STEM and business and occupational enrollment, I can offer only suggestive evidence as to why the university prefers these fields. A future analysis which includes more fundamental outcomes in the university's payoff function could provide more conclusive inferences on why a university might prefer certain fields. These extensions and others will broaden our understanding of the higher education market and may lead to more informed policies which benefit students, families, and taxpayers.

Appendix A: Data Appendix

Definitions

STEM: Biology; Chemistry; Computer Science; Mathematics; Physics and Astronomy.

Social Science: Family and Consumer Sciences; Geography; History; Political Science; Psychology and Counseling; Sociology; World Languages, Literatures, and Cultures.

Humanities and Arts: Art; Communication; English; Mass Communication and Theater; Music; Philosophy and Religion; Writing.

Business and Occupational: Accounting; Economics, Finance, Insurance, and Risk; Education; Elementary, Literacy, and Special Education; Health Sciences; Kinesiology and Physical Education; Management Information Systems; Marketing and Management; Nursing; Occupational Therapy

Long term contracts: Tenured instructors, tenure-track instructors, and instructors who teach on a recurring contractual basis but are ineligible for tenure. See ADHE (2011) for further information.

Short term contracts: Instructors with a non-recurring appointment where funding is temporary and there is no guarantee of a continuing appointment and graduate student instructors. See ADHE (2011) for further information.

Instructor costs

To compute the implicit cost of hiring an instructor to teach course section j C_j , I use information on instructor salaries, contract details, and teaching histories. Instructor salaries are typically paid for multiple services across multiple semesters so one must make assumptions regarding what share of an instructor's total salary is paid for a specific section. Generally speaking, this method uses credit hours to allocate an instructor's total salary to specific sections. I make use of the following information: how much the instructor is paid for an entire contract, a contract identifier which indicates which semesters are covered by the same contract, the number of credit hours that a full time instructor teaches, a numeric measure of what share of full time each instructor is, and the credit hour value of each course section.

The first step is to calculate the number of credit hours each instructor would be teaching in each semester if they were only paid to teach. This involves multiplying the share of full time measure by the number of credit hours that a full time instructor teaches. For example, if an instructor has a 50% part time contract and a full time instructor teaches 12 credit hours per semester, then this instructor would teach 6 credit hours if she were only paid to teach. The second step is to sum these teaching only credit hours across all semesters covered by the same contract. This represents the total number of credit hours the instructor would teach in each contract if they were only paid to teach. The third step is to divide instructor salary for each contract by this measure of total contract teaching

only credit hours. This yields a measure of salary per credit hour for each contract which can be interpreted as an instructor wage. Finally, multiplying this salary per credit hour measure by the credit hour value of each course section yields the instructor salary paid for each course.

Importantly, this method ensures that faculty members who are paid for activities other than teaching are not assigned inflated “wages” despite having high salaries relative to the number of credit hours they teach. To see this, suppose the 50% part time instructor from the previous example only teaches a three credit hour course and receives the rest of her compensation for administrative duties. If she is on a one semester contract with a salary of \$60,000, her salary per credit hour of teaching is:

$$\frac{\$60,000}{6\text{hrs}} = 10,000 \frac{\$}{\text{hr}}$$

Dividing by 6—the credit hours she would teach if she were only paid to teach—rather than 3—the credit hours she actually taught—ensures that her pay for administrative activities does not inflate the true cost of hiring her to teach.

Appendix B: Intensive margin of instruction spending

The body of this article assumes instruction spending only affects students through the number of course sections offered. However, if higher paid instructors are more attractive to students, universities could also influence student choices and utility by spending more on instructors. There can be both budget allocation decisions on the extensive margin—how many course sections to offer in each field—and budget allocation decisions on the intensive margin—how much to pay instructors in each section—which are made by the university and directly affect student outcomes.

In this appendix, I modify the model presented in Section 2 to include both intensive and extensive margin spending decisions and discuss alternative methods for recovering university preference parameters in this setting.⁴⁶ Following this, I present evidence which suggests intensive margin spending has minor effects on student choices at UCA and justify my decision to abstract from intensive margin spending decisions in the analysis.

⁴⁶An earlier draft of this paper (available upon request) contains a more detailed discussion of this model and these estimation methods.

Theoretical model with intensive margin spending decisions

To incorporate intensive margin spending, in this Appendix only, let c_{jt} represent spending on instruction in course section j in semester t , let m_f represent the minimum cost of offering a section in field f , and let e_{jt} represent spending in excess of this minimum which may affect the desirability of section j . For sections taught by instructors on long term contracts, c_{jt} must be paid to honor these contracts. For the share of the budget that remains after all existing contracts are honored, a section in field f is offered if and only if $c_{jt} \geq m_f$.

To allow for the possibility that excess spending affects the desirability of a section, modify student utility in Equation (31) to be:⁴⁷

$$U_{ijt} = X_{it}\beta_f + \theta \log(e_{jt} + 1) + \epsilon_{ijt} \quad (38)$$

The parameter θ measures the extent to which higher paid instructors make sections more attractive to students.

For simplicity, assume ϵ_{ijt} are iid draws from a type 1 extreme value distribution. Similar to Section 3.2, total expected student utility in semester t , the expected number of students choosing courses in field f in semester t , and the effects of both extensive margin spending and intensive margin spending on both of these outcomes can be defined as a function of model parameters and observed data. The effects of intensive margin spending on total expected student utility in semester t and on the expected number of students choosing courses in field f in semester t are given by:⁴⁸

$$\frac{\partial V_t(\mathbf{d}_t, \mathbf{e}_t)}{\partial e_{jt}} = \sum_{i=1}^N P_{itj} \left(\frac{\theta}{e_{jt} + 1} \right) \left(\quad \right) \quad (39)$$

$$\frac{\partial n_{tf}(\mathbf{d}_t, \mathbf{e}_t)}{\partial e_{jt}} = \begin{cases} \sum_{i=1}^N \left\{ \left(\frac{\theta}{e_{jt}+1} \right) \left(P_{itj} (1 - P_{itj}) - \sum_{j' \in f \setminus j} \left(\frac{\theta}{e_{jt}+1} \right) P_{itj} P_{itj'} \right) \right\} & (j \in f) \\ - \sum_{i=1}^N \sum_{j' \in f} \left(\frac{\theta}{e_{jt}+1} \right) P_{itj} P_{itj'} & (j \notin f) \end{cases} \quad (40)$$

where \mathbf{e}_t is a vector containing all excess spending decisions, \mathbf{d}_t is a vector containing all offered courses, and P_{itj} is the probability that student i chooses course j in semester t . As one might expect, these equations illustrate the crucial role of the parameter θ in determining the effects of intensive margin spending on student outcomes.

With these marginal effects, one can construct the set of intensive margin university

⁴⁷The log function is used to ensure diminishing marginal returns to avoid a corner solution in which the university spends its entire discretionary instruction budget on a single course. I add 1 to ensure marginal effects of excess spending are finite over the entire support of excess spending.

⁴⁸Other equations are straightforward to derive and are omitted for brevity.

first order conditions analogous to the extensive margin conditions given by Equation (7):

$$\frac{\partial V_t(\mathbf{d}_t, \mathbf{e}_t)}{\partial e_{j_1 t}} + \sum_{f'=1}^{F-1} \gamma_{f'} \left(\frac{\partial n_{tf'}(\mathbf{d}_t, \mathbf{e}_t)}{\partial e_{j_1 t}} \right) \left(\frac{\partial V_t(\mathbf{d}_t, \mathbf{e}_t)}{\partial e_{j_2 t}} + \sum_{f'=1}^{F-1} \gamma_{f'} \left(\frac{\partial n_{tf'}(\mathbf{d}_t, \mathbf{e}_t)}{\partial e_{j_2 t}} \right) \right) \left(\forall j_1, j_2 \right) \quad (41)$$

As in Section 2.3, this system can be rearranged to solve for the university preference parameters which best explain why observed intensive margin spending decisions were preferred to all feasible alternative decisions.

The intuition underlying this method is analogous to the intuition behind the extensive margin methods discussed in the body: If the university were purely trying to maximize total student utility, it would choose excess spending levels so that the marginal effect of increasing excess spending on total student utility is the same across all course sections. If the university is consistently overpaying instructors in a certain field relative to the allocation which maximizes student utility, it must be that the university is trying to draw more students into this field thus revealing an institutional preference to increase the number of students in this field.

Effects of intensive and extensive margin spending

I chose to abstract from intensive margin spending decisions in my analysis because empirical evidence suggests intensive margin spending has much smaller effects on student choices than extensive margin spending. Panel A of Table A1 reports estimates of the elasticity of enrollment with respect to spending on instructors estimated with several specifications of the regression:

$$\log(S_{jt}) = \tilde{\theta} \log(c_{jt}) + \xi_k + \eta_{jt} \quad (42)$$

where S_{jt} is the number of students enrolled in section j in semester t and ξ_k is a course number fixed effect (e.g. ECON 101). Specification 2 suggests the elasticity of enrollment with respect to instructor salary could be as large as 0.162 for sections taught by adjunct instructors on single-semester contracts. This would imply that doubling spending on instruction for all adjunct instructed field f sections but keeping other course characteristics fixed would increase adjunct instructed field f enrollment by 16.2%. However, specification 4 suggests this moderately large estimate is driven by a small number of very small course sections. When I exclude 45 course observations with five or fewer students, the elasticity drops to 0.0534. This suggests doubling spending on field f adjunct instructors but keeping other course characteristics fixed only increases adjunct instructed field f enrollment by 5.34%. Elasticities for all instructor contract types (columns 1 and 3) suggest similarly small

effects.

While it is not the focus of this paper, I should note that this finding is in line with existing literature which finds that higher paid instructors have small or zero effects on student outcomes at universities (Bettinger and Long, 2010; Figlio et al., 2015).

Comparatively, Panel B of Table A1 reports estimates of elasticities of enrollment with respect to spending on course offerings computed using estimates of the nested logit course choice model, observed adjunct instructed course offerings, and estimates of costs of hiring adjunct instructors.⁴⁹ Estimates of these elasticities range from 0.3229 in social science to 0.4999 in humanities and arts. This suggests that doubling the number of adjunct instructed field f course sections offered to students increases adjunct instructed field f enrollment by 32.29 - 49.99%.

The large differences between intensive margin elasticities and extensive margin elasticities suggest UCA can increase total student utility more and attract more students into desirable fields by spending marginal dollars offering additional course sections rather than increasing spending on instruction. This implies that no values for γ_f can rationalize both observed intensive and observed extensive margin spending decisions at UCA. Furthermore, the small effects of intensive margin spending suggest variation in spending on instruction at UCA exists for some reason other than influencing student choices and utility. For this reason, I focus on extensive margin decisions which have significant effects on student choices and utility at UCA. Future research may seek to better explain variation in spending on instruction.

Appendix C: Solving for equivalent costs

In this appendix, I describe my method for estimating the equivalent costs reported in Column 6 of Table 7. The goal of this exercise is to solve for counterfactual costs of hiring adjunct instructors which come closest to inducing a utility maximizing university to offer observed adjunct instructed courses.

⁴⁹Specifically, the formula is:

$$\epsilon_{tf} = \frac{\partial n_{tf}(\mathbf{d}_t)}{\partial d_{tf}} \times \frac{d_{tf}^N}{n_{tf}^N(\mathbf{d}_t)} \quad (43)$$

where d_{tf}^N is the number of field f course sections taught by adjunct instructors in semester t and $n_{tf}^N(\mathbf{d}_t)$ is observed enrollment in adjunct instructed field f course sections in semester t . Figures in Panel B of Table A1 are field specific averages of elasticities across academic semesters.

A utility maximizing university's problem is given by:

$$\mathbf{d}_t^{\text{SUM}} = \operatorname{argmax}_{\mathbf{d}_t} \{V_t(\mathbf{d}_t)\} \quad \text{s.t.} \quad \sum_{f=1}^F \left(d_{tf}^N c_f \leq E_t^N \right) \quad (44)$$

where c_f is the cost of hiring an adjunct instructor to teach a field f course section, d_{tf}^N is the number of adjunct instructed field f course sections offered in semester t , and E_t^N is the residual share of the semester t instruction budget which is paid to adjunct instructors on single-semester contracts. This equation is similar to Equation 3 except that it excludes the implied preference terms $\gamma_f n_{tf}$, it uses the empirical linear budget constraint, and it imposes the counterfactual restriction that the university can only reallocate the portion of its budget paid to adjunct instructors on single-semester contracts. The goal of the equivalent cost exercise is then to solve for equivalent costs \tilde{c}_f which imply that the solutions to Equation (44) are as close as possible to observed course offerings.

To solve for equivalent costs \tilde{c}_f , note that the system of first order conditions characterizing a solution to (44) if adjunct instructor costs are given by \tilde{c}_f is:

$$\left(\frac{1}{\tilde{c}_{f_1}} \right) \left[\frac{\partial V_t(\mathbf{d}_t^*)}{\partial d_{tf_1}} \right] = \left(\frac{1}{\tilde{c}_{f_2}} \right) \left[\frac{\partial V_t(\mathbf{d}_t^*)}{\partial d_{tf_2}} \right] \quad \left(\forall f_1, f_2 \right) \quad (45)$$

$$\sum_{f=1}^F \left(d_{tf}^N \tilde{c}_f = E_t^N \right) \quad (46)$$

Because this university's objective is to maximize total student utility, optimal course offerings simply equate marginal utility per dollar of additional course offerings across all academic fields.

Rearranging and stacking fields and semesters yields:

$$(\mathbf{M}^1 + \mathbf{M}^2) \tilde{\mathbf{c}} = \mathbf{ME} \quad (47)$$

where

$$\mathbf{M}_t^1(f_1, f_2) = \left(\frac{\partial V_t(\mathbf{d}_t)}{\partial d_{tf_1}} \right) \left(\frac{d_{tf_2}}{d_{tF}} \right) \left(\begin{array}{c} \mathbf{M}_1^1 \\ \vdots \\ \mathbf{M}_T^1 \end{array} \right) \left(\begin{array}{c} \vdots \\ \vdots \\ \vdots \end{array} \right)$$

$$\mathbf{M}_{((F-1) \times T, F-1)}^1 = \left[\begin{array}{c} \mathbf{M}_1^1 \\ \vdots \\ \mathbf{M}_T^1 \end{array} \right] \left(\begin{array}{c} \vdots \\ \vdots \\ \vdots \end{array} \right)$$

$$\begin{aligned}
\mathbf{M}_t^2 (f_1, f_2) &= \begin{cases} \frac{\partial V_t(\mathbf{d}_t)}{\partial d_{tF}} & f_1 = f_2 \\ 0 & f_1 \neq f_2 \end{cases} \\
\mathbf{M}^2_{((F-1) \times T, F-1)} &= \begin{bmatrix} \mathbf{M}_1^2 \\ \vdots \\ \mathbf{M}_T^2 \end{bmatrix} \\
\tilde{\mathbf{c}}_{(F-1,1)}(f) &= \tilde{c}_f \\
\mathbf{ME}_t (f)_{(F-1,1)} &= \left(\frac{\partial V_t(\mathbf{d}_t)}{\partial d_{tF}} \right) \left(\frac{\partial \mathcal{L}_t^N}{\partial d_{tF}} \right) \\
\mathbf{ME}_{((F-1) \times T, 1)} &= \begin{bmatrix} \mathbf{ME}_1 \\ \vdots \\ \mathbf{ME}_T \end{bmatrix}
\end{aligned}$$

This system of equations can then be inverted to derive the following expression for equivalent costs:

$$\tilde{\mathbf{c}} = (\mathbf{M}^1 + \mathbf{M}^2)^+ \mathbf{ME} \tag{48}$$

where M^+ denotes the pseudo-inverse of M .

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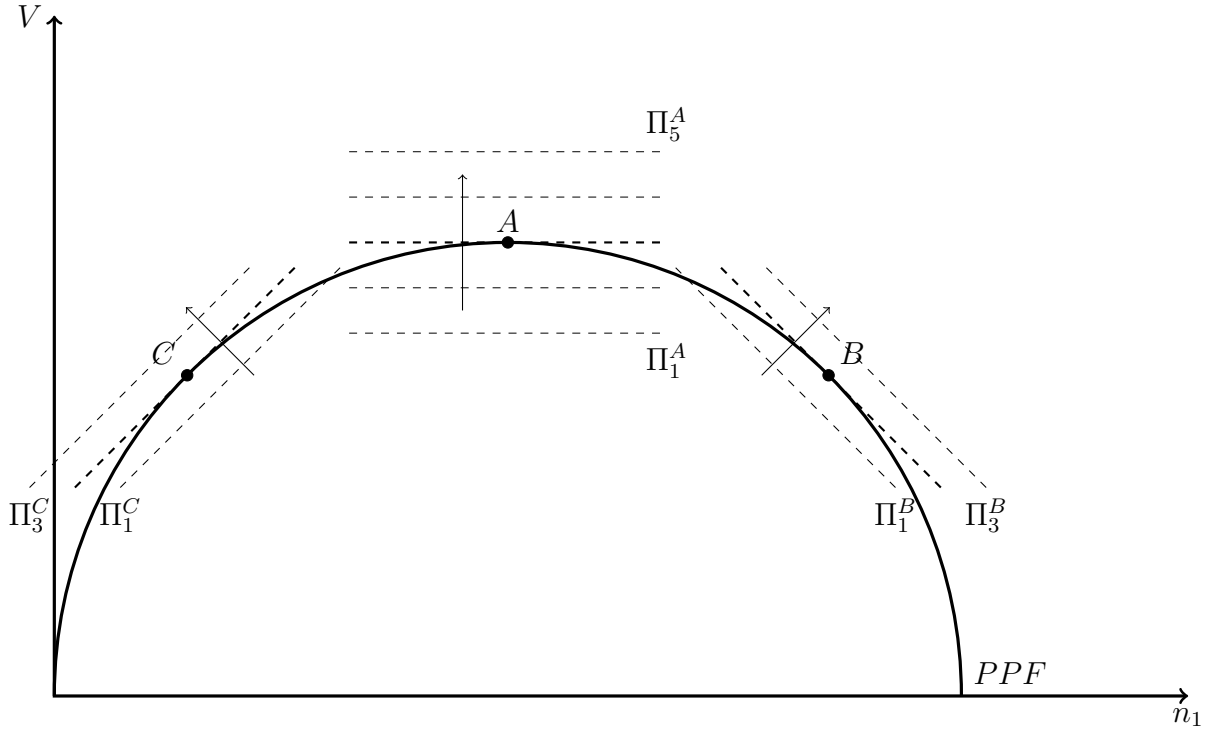
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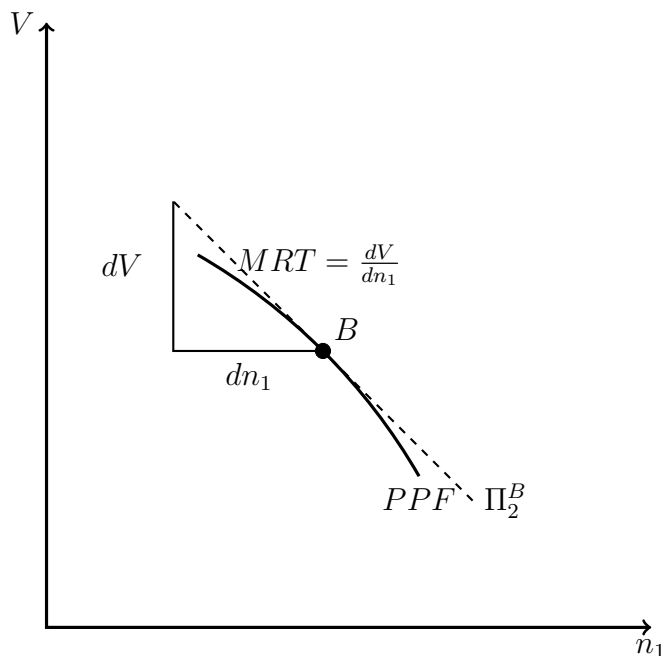
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Figure 1: Optimal Course Offerings



The vertical axis is total expected student utility. The horizontal axis is expected number of students choosing courses in field 1 (the expected number of students choosing courses in field 2 is the complement). The solid semi-circle is a production possibilities frontier representing the frontier of outcomes which can be achieved given the university's constraints. Dashed line segments represent potential university indifference curves with payoffs increasing in the direction of the arrows. University A only values total expected student utility ($\gamma_1^A = 0$) and offers courses to achieve outcome A. University B has institutional preferences to increase the expected number of students choosing courses in field 1 ($\gamma_1^B > 0$) and offers courses to achieve outcome B. University C has institutional preferences to decrease the expected number of students choosing courses in field 1 ($\gamma_1^C < 0$) and offers courses to achieve outcome C.

Figure 2: Revealed Institutional Preferences



This is Figure 1 zoomed in to focus on the tangency condition of university B. The derivative of the PPF at point B, or marginal rate of transformation (MRT), is given by the instantaneous change in total expected student utility relative to the instantaneous change in the expected number of students choosing courses in field 1 as the university marginally reallocates funds from field 1 to field 2. The instantaneous change in total expected student utility is given by the marginal effect per dollar of offering an addition field 2 section on total expected student utility minus the marginal effect per dollar of offering an addition field 1 section:

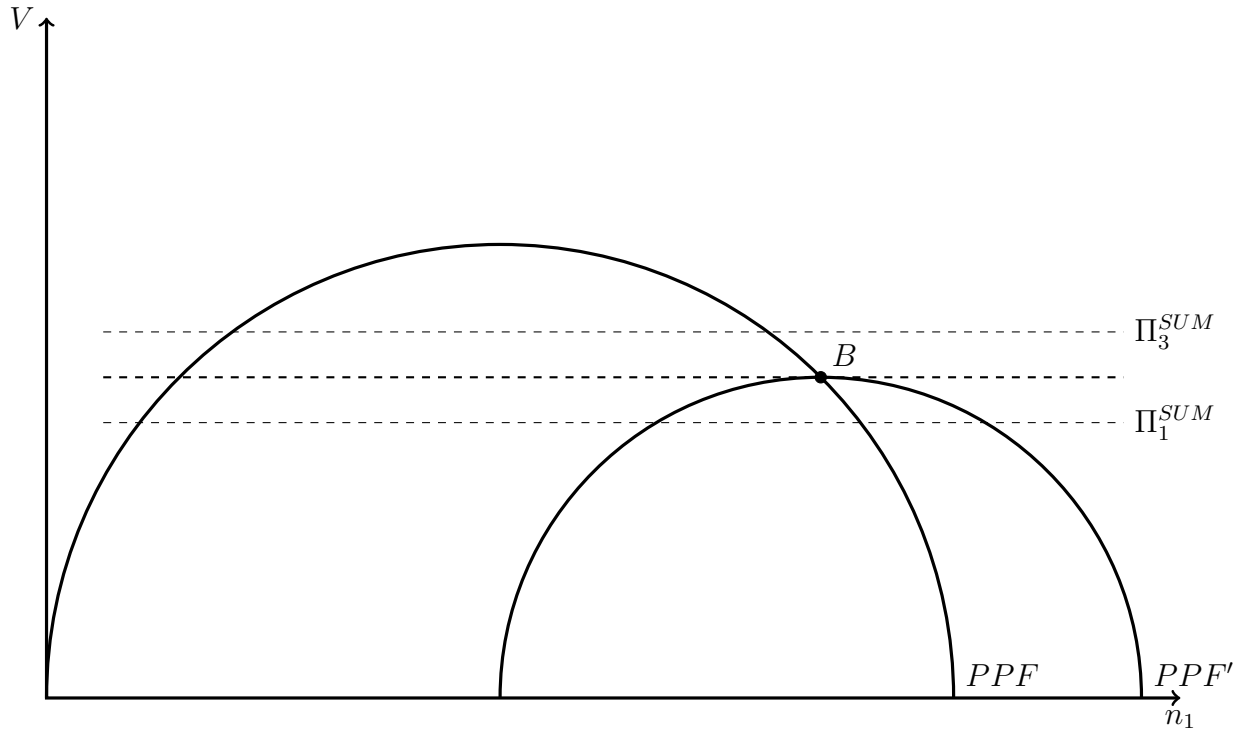
$$dV = \left(\frac{1}{c_2^N}\right) \left(\frac{\partial V}{\partial d_2}\right) - \left(\frac{1}{c_1^N}\right) \left(\frac{\partial V}{\partial d_1}\right) \left($$

The instantaneous change in the expected number of students choosing courses in field 1 is given by the marginal effect per dollar of offering an addition field 2 section on the expected number of students choosing courses in field 1 minus the marginal effect per dollar of offering an addition field 1 section on the expected number of students choosing courses in field 1.

$$dn_1 = \left(\frac{1}{c_2^N}\right) \left(\frac{\partial n_1}{\partial d_2}\right) - \left(\frac{1}{c_1^N}\right) \left(\frac{\partial n_1}{\partial d_1}\right) \left($$

This graphically demonstrates how marginal effects of spending can be used to solve for the slope of the indifference curves which rationalize why point B was optimal for this university.

Figure 3: Equivalent Costs to Make a Utility Maximizing University Offer Observed Courses



PPF' is the production possibilities frontier under “equivalent costs” which would induce a student utility maximizing university to offer courses producing observed allocation B . They are equivalent in the sense that going from preferences characterized by Π^A to preferences characterized by Π^B while holding PPF fixed in Figure 1 has the same effect on course offerings as going from PPF to PPF' while maintaining utility maximizing preferences characterized by Π^{SUM} in this figure.

Table 1: University of Central Arkansas

Institutional Characteristics	
Undergraduates	9,887
Full-time faculty	547
Admission Rate	92%
Yield	44%
ACT 25th pctile	20
ACT 75th pctile	26
6 year graduation rate	45%
Student characteristics	
Full-time	84%
24 and under	90%
In-state	89%
Female	59%
White	66%
Black	18%
Hispanic	5%
Other race	11%

Source: National Center for Education Statistics. Fall, 2015. Yield is the percent of students who choose to enroll conditional on being offered admission. ACT scores are composite scores. Graduation rate is for students pursuing a Bachelor's degree.

Table 2: Field Characteristics at UCA

	STEM	Social Science	Humanities and Arts	Business and Occupational
Avg. intro courses per semester	33.1	64.7	52.6	25.2
Avg. intro sections per semester	210	259	165	88
Avg. intro enrollment per semester	5590	8833	4802	2330
Avg. intro enrollment per section	26.6	34.1	29.2	26.6
Intro section cost (25th pctile)	\$5,766	\$4,566	\$5,184	\$5,168
Intro section cost (Median)	\$8,684	\$6,088	\$6,801	\$7,012
Intro section cost (75th pctile)	\$10,927	\$8,781	\$9,382	\$11,407
Avg. ACT score	24.2	23.7	23.9	23.9
Avg. HS GPA	3.42	3.37	3.36	3.41
Share Female	58.0%	59.8%	57.9%	48.2%
Share Freshmen	43.9%	40.5%	40.2%	11.4%
Share Sophomores	27.9%	31.8%	34.7%	40.6%
Share Juniors	16.9%	18.1%	16.1%	35.5%
Share Seniors	11.2%	9.6%	9.0%	12.5%

Notes: Statistics are for introductory courses at the University of Central Arkansas. “Courses” are defined by a course number (e.g. Econ 101). “Sections” are defined by a course number, instructor and meeting time (e.g. Econ 101 taught by Prof. Jane Doe meeting MWF from 9 - 10:30AM). Section cost is the amount an instructor is implicitly paid to teach a course section. This depends on an instructor’s salary, teaching load, and other responsibilities. Average student scores and demographic proportions treat every instance of a student choosing an introductory course as an observation and compute statistics conditional on the field of the introductory course.

Table 3: Course Offerings and Enrollment Shares

	Semester											
	F04	S05	F05	S06	F06	S07	F07	S08	F08	S09	F09	S10
STEM												
Courses	34	30	33	33	34	32	33	33	33	34	33	35
Sections	194	175	221	179	235	208	248	211	222	207	219	201
Sections (%)	30%	28%	31%	28%	30%	29%	30%	28%	29%	29%	28%	29%
Enrollment (%)	27%	24%	28%	24%	26%	25%	27%	25%	26%	26%	26%	26%
Social Science												
Courses	59	64	65	61	65	64	65	66	66	67	69	65
Sections	227	220	250	231	284	269	297	271	272	270	279	240
Sections (%)	35%	35%	36%	36%	36%	37%	36%	37%	35%	37%	36%	34%
Enrollment (%)	42%	43%	41%	42%	41%	41%	40%	41%	40%	41%	41%	40%
Humanities and Arts												
Courses	47	48	49	52	51	50	55	53	56	54	56	60
Sections	146	146	148	148	169	158	182	172	182	160	187	176
Sections (%)	22%	23%	21%	23%	22%	22%	22%	23%	24%	22%	24%	25%
Enrollment (%)	21%	23%	21%	23%	22%	22%	22%	23%	22%	21%	23%	23%
Business and Occupational												
Courses	26	26	26	24	26	24	25	25	26	24	25	25
Sections	90	81	85	77	95	86	98	87	96	85	91	82
Sections (%)	14%	13%	12%	12%	12%	12%	12%	12%	12%	12%	12%	12%
Enrollment (%)	10%	11%	10%	11%	10%	11%	11%	11%	11%	12%	10%	11%

Notes: Statistics are for the University of Central Arkansas. FXX/SXX indicate fall/spring semester of 20XX. “Courses” are defined by a course number (e.g. Econ 101). “Sections” are defined by a course number, instructor and meeting time (e.g. Econ 101 taught by Prof. Jane Doe meeting MWF from 9 - 10:30AM).

Table 4: Course Section Cost Regression
 Course Section Cost

STEM	5057.4 <i>124.9</i>
Social Science	2816.9 <i>127.1</i>
Humanities and Arts	3191.3 <i>152.2</i>
Business and Occupational	4650.9 <i>198.1</i>
Tenured	5595.1 <i>143.4</i>
Tenure-track	5433.6 <i>161.2</i>
Contracted non-tenure	3132.5 <i>135.0</i>
Single-semester adjunct	<i>omitted</i>
Course Section Observations	8857

Notes: Block bootstrapped standard errors (1000 iterations, sampling course sections) are in italics. Dependent variable is the amount an instructor is implicitly paid to teach a course section. This depends on an instructor's salary, teaching load, and other responsibilities. All course sections are categorized into either STEM, social science, humanities and arts, or business and occupational (the regression does not include a constant). As such, coefficient on STEM indicates that the predicted cost of offering a STEM course section with an adjunct instructor on a single-semester contract is \$5,057.40. Adjunct instructors on single-semester contracts are hired to teach for one semester and have no explicit guarantee that their contracts will be renewed.

Table 5: Student Course Choice Parameters

	STEM	Social Science	Humanities and Arts	Business and Occupational
Intercept	0.473*** <i>0.032</i>	1.344*** <i>0.045</i>	0.543*** <i>0.023</i>	<i>omitted</i>
ACT Z-Score	0.155*** <i>0.013</i>	0.073*** <i>0.012</i>	0.127*** <i>0.014</i>	<i>omitted</i>
Missing ACT	-0.203*** <i>0.029</i>	-0.161*** <i>0.026</i>	-0.233*** <i>0.030</i>	<i>omitted</i>
GPA Z-score	0.003 <i>0.013</i>	-0.093*** <i>0.013</i>	-0.126*** <i>0.015</i>	<i>omitted</i>
Missing GPA	0.089*** <i>0.031</i>	0.162*** <i>0.029</i>	0.180*** <i>0.032</i>	<i>omitted</i>
Female	0.416*** <i>0.024</i>	0.525*** <i>0.021</i>	0.457*** <i>0.025</i>	<i>omitted</i>
Sophomore	-1.737*** <i>0.028</i>	-1.495*** <i>0.026</i>	-1.395*** <i>0.029</i>	<i>omitted</i>
Junior	-2.086*** <i>0.031</i>	-1.923*** <i>0.030</i>	-2.016*** <i>0.034</i>	<i>omitted</i>
Senior	-1.449*** <i>0.040</i>	-1.522*** <i>0.037</i>	-1.561*** <i>0.042</i>	<i>omitted</i>
Nesting Parameter ρ_f	0.680 <i>0.007</i>	0.547 <i>0.011</i>	0.642 <i>0.008</i>	0.461 <i>0.008</i>

Notes: Block bootstrapped standard errors (1000 iterations, sampling student panels) are in italics. *** indicates significantly different from omitted category (normalized to zero) at 1% significance. ACT/GPA Z-scores are scores that have been rescaled to have mean 0 and standard deviation 1 in my observed sample of students.

Table 6: Relative Marginal Effects and Implied Preferences
Relative

	Relative Average Marginal Effect on Total Utility (1)	Average Marginal Effect on Total Utility per Dollar (2)	Implied Preferences (3)
STEM	1.484*** <i>0.033</i>	1.365*** <i>0.059</i>	0.611*** <i>0.041</i>
Social Science	1.533*** <i>0.035</i>	2.533*** <i>0.117</i>	0
Humanities and Arts	1.541*** <i>0.031</i>	2.249*** <i>0.109</i>	0.086*** <i>0.029</i>
Business and Occupational	1	1	1.114*** <i>0.068</i>

Notes: Block bootstrapped standard errors (1000 iterations, sampling student panels for student parameters and course sections for costs) are in italics. Column 1 contains marginal effects of offering an additional course section in the specified field on total expected student utility. These are averaged across academic semesters and reported relative to the effect for a business or occupational course section. Column 2 divides marginal effects by the cost of hiring an adjunct instructor to teach a course section in the specified field. Once again, these are averaged across semesters and reported relative to the effect per dollar for a business or occupational course section. Column 3 reports estimates of implied preference parameters γ_j with social science as the omitted field. Estimates quantify how much student utility the university is implicitly willing to sacrifice to move one student from a social science course to a course in the specified field.

Table 7: Utility Maximizing Course Offerings and Equivalent Costs

	Observed			Utility Maximizing			Equivalent Cost Differences
	(1)	(2)	(3)	(4)	(5)	(6)	
Average Contracted Sections	Average Contracted Sections	Average Adjunct Instructed Sections	Average Field Enrollment	Average Adjunct Instructed Sections	Average Field Enrollment	Equivalent Differences	
STEM	175.08	34.92	5589.75	0.00***	4821.49***	-17.01%***	
Soc Sci	234.58	24.58	8833.33	98.35***	33.45	1.13	
Hum and Arts	150.17	14.33	4801.83	10.52	9862.71***	45.62%***	
Bus and Occ	81.00	6.75	2330.25	14.69	178.39	3.57	
				8.72	4681.97	24.99%***	
				0.00***	169.01	3.18	
				0.00	2191.49***	-41.99%***	
					24.52	2.08	

Notes: Block bootstrapped standard errors (1000 iterations, sampling student panels for student parameters and course sections for costs) are in italics. Columns 1-3 are the observed number of course sections taught by instructors on long term contracts, the observed number of course sections taught by adjunct instructors on single semester contracts, and observed field enrollments averaged across semesters. Column 4 reallocates the residual budget spent on adjunct instructors to maximize total student utility and column 5 reports estimated field enrollments under these utility maximizing offerings. In columns 4 and 5, *** indicates significantly different from observed values at 1% significance. Column 6 reports how much the cost of hiring an adjunct instructor would need to change to induce a utility maximizing university to offer the observed adjunct instructed course sections reported in column 2. In other words, the implied preferences reported in Table 6 have the same effect on course offerings as changing costs by the percentages reported in column 6. In column 6, *** indicates significantly different from zero at 1% significance.

Table 8: Adjunct Instructed Course Offerings in Counterfactual Scenarios

	STEM	Social Science	Humanities and Arts	Business and Occupational
(1) Observed state (predicted)	35.79 <i>0.15</i>	20.55 <i>0.36</i>	12.15 <i>0.24</i>	9.73 <i>0.29</i>
(2) Reduce cost of STEM instructors by 5%	53.38*** <i>0.30</i>	6.31*** <i>0.53</i>	5.00*** <i>0.28</i>	7.03*** <i>0.24</i>
(3) Increase all SAT scores and GPA by 1/3 of a std dev	53.19*** <i>0.60</i>	2.71*** <i>0.57</i>	4.25*** <i>0.54</i>	7.04*** <i>0.42</i>
(4) Make all students female	24.09*** <i>1.95</i>	49.91*** <i>2.39</i>	18.82*** <i>2.04</i>	0.14*** <i>0.12</i>

Notes: Block bootstrapped standard errors (1000 iterations, sampling student panels for student parameters and courses for costs) are in italics. Row 1 is the average number of course sections taught by adjunct instructors on single-semester contracts predicted by the estimated model in the observed state. Rows 2-4 are the average number of course sections taught by adjunct instructors on single-semester contracts in counterfactual states. In rows 2-4, *** indicates significantly different from row 1 at 1% significance.

Table 9: Field Enrollments in Counterfactual Scenarios

	STEM	Social Science	Humanities and Arts	Business and Occupational
(1) Observed state (predicted)	5619.26 36.11	8787.54 43.37	4779.57 29.19	2371.28 26.78
(2) Reduce cost of STEM adjunct by 5%	5968.65*** 37.93	8566.8*** 42.52	4667.73*** 28.86	2354.48 26.23
(3) Increase all SAT scores and GPA by 1/3 of a std dev (PE)	5825.93*** 39.48	8676* 44.91	4749.75 30.54	2305.98* 26.27
(4) Increase all SAT scores and GPA by 1/3 of a std dev (GE)	6235.6*** 46.08	8369.65*** 45.5	4615.37*** 33	2337.03 28.64
(5) Make all students female (PE)	5563.19 40.9	9201.64*** 49.31	4865.66* 36.2	1927.17*** 26.5
(6) Make all students female (GE)	5288.73*** 70.75	9550.23*** 69.65	4884.21 61.13	1834.49*** 26.46

Notes: Block bootstrapped standard errors (1000 iterations, sampling student panels for student parameters and courses for costs) are in italics. Row 1 are average field enrollments predicted by the estimated model in the observed state. Rows 2-6 are average field enrollments in counterfactual states. In rows 2-6, ***/**/* indicates significantly different from row 1 at 1%/5%/10% significance. (PE) indicates that student characteristics are changed but course offerings are held fixed. (GE) indicates that course offerings change in response to counterfactual student characteristics as reported in Table 8.

Table 10: Naive Earnings Regressions

	(1)	(2)
Field of major	Log annual earnings conditional on reporting 8 years after graduating	Reporting earnings 8 years after graduating
STEM	0.428*** (0.0625)	0.00223 (0.0233)
Social Science	0.104** (0.0513)	0.0498** (0.0195)
Humanities	<i>Omitted</i>	<i>Omitted</i>
Business and Occupational	0.391*** (0.0443)	0.0909*** (0.0168)
General / Missing Field	0.283*** (0.0466)	0.125*** (0.0179)
Observations	7,375	11,645
R-squared	0.060	0.013

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Additional controls include ACT scores, high school GPA, gender, and graduation year. Column 2 is a linear probability model. Data are for students who earn Bachelor's degrees between the 1993-1994 and 2003-2004 academic years. 27.5% of degrees cannot be matched to a field and thus are included in the General / Missing Field category. Graduates who complete multiple degrees or majors are excluded (4.2% of degree earners).

Table 11: Naive Grade Regressions

	(1) Earning an A grade conditional on completing	(2) Grade points conditional on completing (Censored Regression)	(3) Withdraw / Incomplete Grade
Field of course			
STEM	-0.131*** (0.00235)	-0.600*** (0.00833)	0.0392*** (0.00157)
Social Science	-0.0671*** (0.00213)	-0.292*** (0.00758)	0.0103*** (0.00143)
Humanities	<i>Omitted</i>	<i>Omitted</i>	<i>Omitted</i>
Business and Occupational	-0.0434*** (0.00306)	-0.192*** (0.0109)	0.0225*** (0.00205)
Observations	258,924	258,924	286,682
R-squared	0.157	N/A	0.025

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Controls include ACT scores, high school GPA, gender, and student level. Columns 1 and 3 are linear probability models. A withdrawal or incomplete is recorded on a student's transcript but does not impact the student's GPA (9.7% of observations). Letter grades are assigned to numeric grade point values using the Arkansas Department of Higher Education's metric (A=4, B=3, C=2, D=1, F=0). 25.3% of grades are an A. Data are for introductory courses in Fall and Spring academic semesters between the 2005-06 and 2011-2012 academic years.

Table A1: Elasticities of enrollment

Panel A: Elasticity with respect to instructor salaries (log-log regression)

	log(Enroll)	log(Enroll)	log(Enroll)	log(Enroll)
log(Instructor Salary)	0.0888*** <i>0.0112</i>	0.162*** <i>0.0388</i>	0.0220*** <i>0.0064</i>	0.0534*** <i>0.0191</i>
Course fixed effects	Yes	Yes	Yes	Yes
Adjunct instructed only	No	Yes	No	Yes
Enrollment>5	No	No	Yes	Yes
Observations	8,556	873	8,280	819
R-squared	0.499	0.564	0.609	0.589

Panel B: Elasticity with respect to spending on course offerings (model based)

	STEM	Soc Sci	Hum and Arts	Bus and Occ
Elasticity	0.4963*** <i>0.0055</i>	0.3229*** <i>0.0064</i>	0.4999*** <i>0.0064</i>	0.3844*** <i>0.0067</i>

Notes: Standard errors in italics. *** denotes p-value for test that coefficient is not equal to zero is $p < .01$. Panel A contains estimates of the elasticities of enrollment with respect to spending on instructor salaries which are estimated using the log-log regression specification given in Equation 41. Panel B contains estimates of the elasticities of enrollment with respect to spending on course offerings which are derived from estimates of the nested logit student choice model.