What do course offerings imply about university preferences?

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Abstract

This paper develops a framework for analyzing university course offerings. Course offerings affect student utilities and course choices. As such, course offerings implicitly trade off the number of students choosing courses in each field and total student utility. Marginal effects of offering different courses can quantify the implicit tradeoffs between student utility and field enrollments. At a sample university, the marginal effect of business and occupational spending on student utility is 23% lower than the effect of humanities and arts spending. This implies course offerings implicitly sacrifice student utility to move students from humanities and arts to business and occupational courses.

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

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is the "Bennett hypothesis", which predicts that universities will respond to federal tuition subsidies by increasing their tuition.[1]

This paper advances our understanding of how universities make decisions 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.[2] As such, these budget allocation decisions have potentially lifelong effects on students.

To analyze how universities allocate their instruction budget, 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. 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 humanities and arts courses has large effects on student utility relative to costs but offering additional STEM sections has small effects on student utility relative to costs. In this scenario, reallocating marginal dollars from STEM to humanities and arts would increase student utility; furthermore, it would decrease STEM enrollment and increase humanities and arts enrollment. The differences in marginal effects per dollar would then imply that observed course offerings are

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

[2]For a recent review article, see Altonji et al. (2012)

implicitly sacrificing student utility to draw students out of humanities and arts 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 course choice model with Ackerberg and Rysman (2005) crowding effects and type specific unobserved heterogeneity in preferences for fields. In this model, 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. 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. Furthermore, allowing for type-specific unobserved heterogeneity addresses the concern that the university may tailor its course offerings in response to student characteristics that are not included in my data. Finally, 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 2012-13. 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.[3] Because the median young American completes some college but does not obtain a 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.[4] Second,

[3]Source: National Center for Education Statistics

[4]Estimates 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.

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.[5] 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 significantly across academic fields. A marginal dollar spent offering more sections of introductory business and occupational courses produces 23% less student utility than a marginal dollar spent offering additional introductory humanities and arts sections. This implies that observed course offerings implicitly sacrifice significant student utility to draw students out of introductory humanities and arts courses and into introductory business and occupational courses.

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 tenure-track faculty fixed and only reallocate the budget for adjunct instructors.[6] This analysis reveals that reallocating the adjunct instructor budget to maximize student utility would reduce adjunct instructed STEM offerings by 88% and roughly double adjunct instructed humanities and arts course sections.

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.[7]

One counterfactual examines a scenario in which all students' observed measures of baseline preparation are increased by one-tenth of a standard deviation. This is meant to

[5] Compensation 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)

[6] 44.7% of all course sections are taught by adjunct instructors.

[7] As before, to avoid forecasting too far out of sample, I hold the allocation of tenure-track faculty fixed.

simulate a policy such as the Georgia HOPE scholarship program that increased the in-state retention of better prepared students (Cornwell et al., 2006). Because more prepared students are generally more interested in STEM, this would lead to a 0.8% 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 4.6% increase in total introductory STEM sections. This makes STEM even more attractive resulting in an 5.1% total increase in introductory STEM enrollment. In other words, ignoring the university's response leads to understating effects on STEM enrollment by 4.3 percentage points. A second counterfactual shows that a 5% reduction in the cost of hiring a STEM adjunct instructor would lead to a 12.6% increase in total sections of introductory STEM courses and a 8.9% 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 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 that 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.[8] One branch of this literature focuses on estimating the effects of university choices and inputs on student outcomes. This includes studies of "cohort crowding" effects that 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 that estimates the effects of university tuition on student outcomes (Deming and Walters, 2018; 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 that

[8]Notable contributions not mentioned in the body include but are not limited to: Andrews and Stange (2019); Bhattacharya et al. (2017); Carrell and West (2010); Cellini (2009, 2010); Dinerstein et al. (2014); Hoffmann and Oreopoulos (2009); Hoxby (1997); Jacob et al. (2018); Pope and Pope (2009, 2014); Russell (2021); Tabakovic and Wollmann (2019)

develop general equilibrium models of competition in the higher education market (Cook, 2020; 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.

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 and discusses 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 is to use estimates of the marginal effects of offering additional course sections in each field on student utility and the marginal costs of offering additional sections in each field to assess whether the marginal return on instruction spending differs across fields. Differences in these marginal effects per dollar across fields reveal an implicit willingness to sacrifice student utility to increase enrollment in certain fields.

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.[9] 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 $\mathbf{d}_t = \begin{bmatrix} d_{t1} & \cdots & d_{tF} \end{bmatrix}$.

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

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 $V_t(\mathbf{d}_t)$ are continuously differentiable in $\mathbf{d}_t$.[10] In Section 3, I specify a course choice model with Ackerberg and Rysman (2005) crowding effects in which enrollments and utilities depend on course offerings as desired; however, a wide class of demand models will provide these relationships.

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:

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

Without loss of generality, I normalize $\theta = 1$ and $\gamma_F = 0$.[11] With this structure and normalizations, γ_f measures the amount of student utility that 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.

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:

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

where E_t is a semester specific endowment and $C(\cdot)$ is a smooth function.[12]

[10] Note 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.

[11] Normalizing $\gamma_F = 0$ 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 2.3. Normalizing $\theta = 1$ is without loss of generality because the scale of the university's payoff is not determined.

[12] I 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.

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

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

In this setting, 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 that implicitly favor certain fields as a result of path dependence.

Fundamentally, γ_f represent wedges between the marginal benefits of offering additional courses in terms of student utility and the marginal costs of offering these courses. The first stage of my analysis will be to estimate these wedges and interpret them 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.

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 counter-factual analyses that incorporate university responses into predictions.

2.2 Solving for implied preferences

To solve for implied preference parameters γ_f, I first derive the first order conditions that characterize an interior solution to the university's problem stated in Equation (3). These first order conditions are:

$$\left(\frac{1}{c_{tf_1}}\right)\left[\frac{\partial V_t\left(\mathbf{d}_t^\star\right)}{\partial d_{tf_1}} + \sum_{f'=1}^{F-1} \gamma_{f'} \left(\frac{\partial n_{tf'}\left(\mathbf{d}_t^\star\right)}{\partial d_{tf_1}}\right)\right] = \left(\frac{1}{c_{tf_2}}\right)\left[\frac{\partial V_t\left(\mathbf{d}_t^\star\right)}{\partial d_{tf_2}} + \sum_{f'=1}^{F-1} \gamma_{f'} \left(\frac{\partial n_{tf'}\left(\mathbf{d}_t^\star\right)}{\partial d_{tf_2}}\right)\right] \quad \forall f_1, f_2 \tag{4}$$

where

$$c_{tf} = \frac{\partial C\left(\mathbf{d}_t^\star\right)}{\partial d_{tf}} \tag{5}$$

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

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:

$$\mathbf{dn}^{\star} \times \Gamma = \mathbf{dV}^{\star} \tag{6}$$

where

$$\begin{aligned}
\underset{(F,F-1)}{\mathbf{dn_t}^{\star}}(f_1, f_2) &= \left(\frac{1}{c_{tf_1}}\right)\left(\frac{\partial n_{tf_2}(\mathbf{d_t^{\star}})}{\partial d_{tf_1}}\right) - \left(\frac{1}{c_{tF}}\right)\left(\frac{\partial n_{tf_2}(\mathbf{d_t^{\star}})}{\partial d_{tF}}\right) \\
\underset{(F\times T,F-1)}{\mathbf{dn}^{\star}} &= \begin{bmatrix}\mathbf{dn_1^{\star}} & \cdots & \mathbf{dn_T^{\star}}\end{bmatrix}' \\
\underset{(F,1)}{\mathbf{dV_t^{\star}}}(f) &= \left(\frac{1}{c_{tF}}\right)\left(\frac{\partial V_t(\mathbf{d_t^{\star}})}{\partial d_{tF}}\right) - \left(\frac{1}{c_{tf}}\right)\left(\frac{\partial V_t(\mathbf{d_t^{\star}})}{\partial d_{tf}}\right) \\
\underset{(F\times T,1)}{\mathbf{dV}^{\star}} &= \begin{bmatrix}\mathbf{dV_1^{\star}} & \cdots & \mathbf{dV_T^{\star}}\end{bmatrix}' \\
\underset{(F-1,1)}{\Gamma(f)} &= \gamma_f
\end{aligned}$$

This system of equations can then be inverted to derive the following expression for implied preference parameters $\mathbf{\Gamma}$ as a function of marginal effects and costs:

$$\Gamma = (\mathbf{dn}^{\star})^{+}(\mathbf{dV}^{\star}) \tag{7}$$

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.

2.3 Discussion

To directly interpret estimates of γ_f as measures of the misalignment between student preferences and observed course offerings, one only needs credible estimates of local marginal costs $\frac{\partial C(\mathbf{d}_t^{\star})}{\partial d_{tf}}$ and local marginal effects $\frac{\partial n_{tf'}(\mathbf{d_t^{\star}})}{\partial d_{tf}}$ and $\frac{\partial V_t(\mathbf{d_t^{\star}})}{\partial d_{tf}}$. The student demand model does not need to be globally credible and the university's problem can be misspecified. However, if one wishes to use Equation (3) as a structural model of university decisions in counterfactual analyses, the student demand model must be globally credible and the university's problem must be correctly specified.

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. To partially address this concern, I restrict the university in my counterfactual analyses so it can only reallocate its spending on adjunct (non tenure-track) instructors.[13] 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 it assumes introductory course offerings do not affect the number of students enrolled at the university. Prospective students may have systematically different preferences from enrolled students if other parties, such as parents, have greater influence on enrollment decisions. As such, the effects of course offerings on enrollment may be qualitatively different from the effects on student utility. While it would be interesting to study enrollment responses to course offerings, my data are not well suited for such an analysis. Because of this restriction, a higher value for γ_f could reflect a belief that field f course offerings are more relevant to prospective students than enrolled students.

A final 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, this would require dynamic models of student demand and university course offerings.

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. As such, some level of abstraction from within field course offerings is probably necessary. Furthermore, although the question of how universities match instructors to courses is interesting, an analysis available upon request found that instructor characteristics have negligible effects on student course choices at UCA. 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.

[13] 44.7% of all course sections are taught by adjunct instructors.

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. In this section, I propose estimating these crucial marginal effects using a course choice model with Ackerberg and Rysman (2005) crowding effects and type specific unobserved heterogeneity in preferences for fields.

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 $\mathbf{d}_t$.[14] Furthermore, let $j \in [1, J]$ index specific introductory course sections, let $i \in [1, N]$ index students, and let $r \in [1, R_{it}]$ index observations of students choosing courses in a particular semester.[15] Finally, to allow for type specific unobserved heterogeneity in preferences for fields, assume students belong to one of S unobserved types, index types with $s \in [1, S]$, and let τ_{is} indicate whether student i is unobserved type s (Heckman and Singer, 1984).

Assume that the utility of student i who is type s from choosing introductory course section j belonging to field f depends on observed student characteristics and unobserved student type X_{ist} and unobserved preferences ϵ_{irtj}:

$$U_{irstj} = X_{ist}\beta_f + \epsilon_{irtj} \tag{8}$$

I assume the university knows X_{ist}, β_f, and the distribution of ϵ_{irtj} but does not observe individual realizations of ϵ_{irtj}. An important restriction in Equation (8) is that the deterministic component of utility $X_{ist}\beta_f$ 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.

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

[15] For 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 3.3.

To allow for crowding in the unobserved characteristic space within fields, I follow Ackerberg and Rysman (2005) and assume unobserved preferences for field f course sections depend on the number of sections offered in that field and independent Type 1 Extreme Value preference shocks η_{irtj} as follows:

$$\epsilon_{irtj} = \delta_f \log\left(d_{tf}\right) + \eta_{irtj} \tag{9}$$

The δ_f "crowding" parameters, which are typically between -1 and 0, capture the extent to which successive field f course sections are increasingly similar in terms of unobserved characteristics.[16] This crucial feature ensures that marginal effects reflect empirical variation rather than functional form assumptions. In this setting, this error structure is equivalent to a nested logit structure where nests are defined by academic field.[17]

With this structure, the probability that student i who is type s chooses one specific introductory course section in field f in semester t can be expressed as:

$$P_{istf} = \frac{d_{tf}^{\delta_f} \exp\left(X_{ist}\beta_f\right)}{\sum_{f'=1}^{F} d_{tf'}^{1+\delta_{f'}} \exp\left(X_{ist}\beta_{f'}\right)} \tag{10}$$

3.2 Student outcomes

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

$$\begin{aligned} n_{tf}\left(\mathbf{d}_t\right) &= \sum_{i=1}^{N}\sum_{s=1}^{S} \tau_{is} d_{tf} P_{istf} \\ &= \sum_{i=1}^{N}\sum_{s=1}^{S} \tau_{is} \left[\frac{d_{tf}^{1+\delta_f} \exp\left(X_{ist}\beta_f\right)}{\sum_{f'=1}^{F} d_{tf'}^{1+\delta_{f'}} \exp\left(X_{ist}\beta_{f'}\right)}\right] \end{aligned} \tag{11}$$

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

$$\begin{aligned} V_t\left(\mathbf{d}_t\right) &= \sum_{i=1}^{N}\sum_{s=1}^{S} \tau_{is} \mathbb{E}\left[\max\left\{U_{isjt}\right\} \mid \mathbf{d}_t\right] \\ &= \sum_{i=1}^{N}\sum_{s=1}^{S} \tau_{is} \left\{\log\left(\sum_{f=1}^{F} d_{tf}^{1+\delta_f} \exp\left(X_{ist}\beta_f\right)\right) + c\right\} \end{aligned} \tag{12}$$

[16] If $\delta_f > 0$, variety effects are greater than variety effects in a multinomial logit model. If $\delta_f < -1$, additional sections in field f decrease student utility and field f enrollment.

[17] Nesting parameters ρ_f are equivalent to $\delta_f + 1$. See Appendix B for a proof of this equivalence.

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* that are useful for measuring implied tradeoffs; rather, it is the marginal effects of course offerings on these outcomes. These marginal effects are given by:[18]

$$\frac{\partial V_t(\mathbf{d}_t)}{\partial d_{tf}} = \sum_{i=1}^{N} \sum_{s=1}^{S} \tau_{is}(1+\delta_f) P_{istf} \tag{13}$$

$$\frac{\partial n_{tf'}(\mathbf{d}_t)}{\partial d_{tf}} = \begin{cases} \sum_{i=1}^{N} \sum_{s=1}^{S} \tau_{is}(1+\delta_f) P_{istf}(1-d_{tf}P_{istf}) & f'=f \\ -\sum_{i=1}^{N} \sum_{s=1}^{S} \tau_{is}(1+\delta_f) d_{tf'} P_{istf} P_{istf'} & f' \neq f \end{cases} \tag{14}$$

These formulas illustrate the important roles of the crowding parameters δ_f in determining the marginal effects of offering additional sections of introductory courses on outcomes. Equation (13) shows that marginal effects on total student utility increase as δ_f approaches zero. This makes sense because less crowding in the unobserved characteristic space implies that additional sections provide more valuable variety.

Similarly, Equation (14) shows that δ_f has increasing own-field marginal effects on enrollment and decreasing cross-field effects on enrollment.[19] Once again, this makes sense because less crowding implies that additional sections will induce more students to switch fields in expectation.

Because these crowding parameters play a crucial role in determining the marginal effects that will be used to infer implied preferences γ_f, it is important to understand how these parameters are identified from the data. Substituting Equation (9) into Equation (8), one sees that δ_f is identified by the relationship between relative course offerings in field f and the share of students choosing courses in field f. As such, panel variation in course offerings is critical for producing credible estimates of δ_f (and thus γ_f).

It makes intuitive sense that such variation would be important for measuring marginal effects of additional course offerings. If only one semester of data were available, there would be no empirical variation to assess how additional course offerings affect field enrollments. With multiple semesters, one can see how field enrollments vary when course offerings change. If additional offerings draw many students into a field, marginal offerings must be adding substantial utility. Conversely, if additional offerings do not change field enrollments, the

[18]Note 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.

[19]Because $d_{tf}P_{itf}$ 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.

new courses must be mostly redundant.

Although panel variation in course offerings is the most intuitive source of variation for identifying δ_f, I note that this is not the only source of variation used to estimate δ_f in practice. As discussed in Berry et al. (2004), variation in observed student characteristics and unobserved student types also plays an important role in identifying substitution parameters such as δ_f. Intuitively, this variation helps identify δ_f because these characteristics place students at varying distances from points of indifference between alternatives. This implies that the number of additional sections in field f needed to change a student's choice differs across students providing useful variation for identifying δ_f.

3.3 Discussion

The main identifying assumption necessary to recover δ_f is that introductory course offerings d_{tf} must be independent of preference shocks η_{irtj}. 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.[20] Second, the university may forecast trends in field 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_{irtj} thus any response of the university to these trends will cause misspecification.[21]

Both of these scenarios suggest there could be positive correlation between introductory course offerings d_{tf} and preference shocks η_{irtj} that may bias estimates of δ_f towards zero. Because only relative marginal effects matter for inferring university preferences, this will only confound estimates of γ_f if the endogeneity is stronger in certain fields relative to others. Furthermore, 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

[20] The 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).

[21] In 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 δ_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 δ_f.

of $\mathbf{d}_t$ should be limited. Finally, by allowing for type specific unobserved heterogeneity in preferences for fields, I give the university some scope to tailor its course offerings in response to student characteristics that are known to the university but are not included in my data.

In addition to this endogeneity concern, this 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.[22] 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.[23] Class size effects are challenging to include in the demand model because class size will be correlated with any unobserved course section attributes by construction. Bayer and Timmins (2007) propose an iterative IV strategy for addressing this issue. I experimented with this method but found that the instruments lacked power in my setting.[24] As such, I have excluded class size effects from my analysis.

Finally, this framework assumes students choose individual course sections independently rather than complementary bundles of sections. Nevo et al. (2005) and Ahn et al. (2019) introduce methods for estimating models of bundled choice; however, these methods greatly increase computational burden and complicate the equations for enrollment, total utility, and marginal effects. Moreover, these methods typically yield parameter estimates

[22]Conlon 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.

[23]For 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). Alternatively, the university might promote smaller classes to increase student learning. The university in Section 2 values student choices and utilities but not their learning. As such, a larger γ_f may partially reflect a university's belief that smaller classes have greater pedagogical benefits in field f (or that learning in field f is valued more than in other fields).

[24]Details of this analysis are available upon request

similar to those of independent choice models 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 that 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 because it 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.

4 Data, descriptive statistics, and estimation

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 that is below the national average.[25] 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 2012-13 academic years and information on all offered course sections and the instructors teaching these sections for all sections offered between the 1994-95 and 2012-13 academic years. I combine these to create a sub-sample of student information and course information from the 2004-05 to the 2012-13 academic years. After excluding required writing courses, required oral communication courses, required health courses, and other special courses, the sample includes 32,445 unique UCA undergraduates and 359,659 observations of students choosing introductory courses.[26]

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

[26] Required 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

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 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.

An important empirical decision 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 that roughly vary by number of sections. Because my focus is on the decisions of a university, I choose the unit of analysis that 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.

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).

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 32.6 students in social science sections, 28.2 students in humanities and arts sections, 25.4 students in both STEM sections, and 24.5 students in 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 the second highest ACT scores and high school GPA and students choosing social science and humanities and arts courses have the lowest 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 3.2, I showed that the crucial crowding parameters δ_f are identified by the empirical relationship between the share of course sections offered in each field and field enrollment shares 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.[27] The statistics show that the share of STEM sections varies from 28% - 31% across semesters, the share of

[27]Note that there are generally fewer introductory sections offered in Spring semesters relative to Fall semesters. This across semester variation in total introductory sections is not a source of identifying variation for δ_f. Only the share of sections offered in each field across semesters is a source of identifying variation.

social science sections varies from 34% - 37% across semesters, the share of humanities and arts sections varies from 20% - 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 crowding parameters δ_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. 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 crowding parameters are not confounded by correlated trends in preferences and course offerings.

4.2 Estimation

To estimate the student choice model in the presence of unobserved type specific heterogeneity, I employ the Expectation-Maximization (EM) Algorithm (Dempster et al., 1977). The EM algorithm is an iterative algorithm that uses a student's choices to infer her unobserved type. For instance, suppose unobserved type s has a relative preference for business and occupational classes. If student i chooses many more business and occupational classes over the course of her career at UCA than her observed characteristics would predict, then the algorithm will identify her as more likely to be type s. A full description of the EM algorithm is provided in Appendix B.

In addition to providing estimates of student choice parameters β_f and δ_f, the EM algorithm also yields estimates of conditional type probabilities q_{is}. These measure the probability that student i is type s and can be used in place of τ_{is} in Equations (11)-(14) to integrate out unobserved student types when constructing outcomes and marginal effects. See Appendix B for a formal definition of q_{is}.

In addition to estimating student choice parameters, inferring university preferences also requires estimates of the marginal costs of offering additional sections of introductory courses. To estimate these costs, I compute the average cost of hiring an adjunct instructor to teach a single course section in each field.[28]

[28]Using instructor rank to estimate costs suggests rank should also enter into student utility. An analysis available upon request finds that instructor rank has negligible effects on student utility; as such, I exclude these effects for power and tractability. 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 a single course section.

The idea of using adjunct instructor costs is that if a university wants to add or subtract a section, it is generally simpler and more cost effective to do this by hiring or firing an adjunct instructor rather than a tenure-track instructor.[29] As such, costs of hiring adjunct instructors represent better estimates of marginal costs than average costs within a field.

One limitation of this method is that the marginal cost of offering an additional course section in field f is independent of the number of sections offered in that field. 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 that 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. If these other costs are proportional to adjunct instructor costs, then their omission will not affect the relative marginal costs used to measure implied university preferences. However, if other costs are disproportionately high in field f, this will lead to downward bias in estimates of γ_f.

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). I begin by reporting estimates of primitive student preference 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 business and occupational sections produces 23% less student utility than an additional dollar of spending on introductory humanities and arts sections. This implies the university is implicitly sacrificing significant student utility to draw students out of humanities and arts courses and into business and occupational courses.

5.1 Student preference parameters

Table 4 reports estimates of student preference parameters from the course choice model that will be used to measure the marginal effects of offering additional course sections. Results are for a specification with two unobserved student types and parametric block bootstrapped standard errors are reported in italics.[30] Although student choice parameters are not the

[29] Research 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.

[30] Results with three and four unobserved types, available upon request, are qualitatively similar but noisier. Parametric block bootstrapping samples full student panels of observed independent variables and uses point

focus of this paper, several findings are worth highlighting: First, higher ACT scores and high school GPA make students more likely to choose introductory STEM courses. This is consistent with existing literature that shows initial preparation is an important determinant of whether a student pursues a STEM education (Arcidiacono, 2004; Stinebrickner and Stinebrickner, 2014). Second, women are less interested in business and occupational courses on average; conversely, non-white students and students missing race are more interested in business and occupational courses than their white counterparts. Furthermore, Sophomores, Juniors, and Seniors are much more likely to take business and occupational courses than Freshmen.

Finally, estimates of the crowding parameters δ_f are in the middle range varying from -0.445 to -0.200.[31] This implies there is some crowding in the unobserved characteristic space, but not so much that additional sections do not provide students with meaningful choice variety. 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 and implied preferences

Table 5 uses estimates of the student course choice model 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, I report relative marginal effects averaged across semesters. In notation, column 1 reports:

$$\frac{1}{T}\sum_{t=1}^{T}\frac{\left(\partial V_t(\mathbf{d}_t)/\partial d_{tf}\right)}{\left(\partial V_t(\mathbf{d}_t)/\partial d_{tHum}\right)} \tag{15}$$

Results suggest marginal effects of offering additional course sections are fairly similar across fields. Point estimates suggest effects in social science are 10% smaller than effects in humanities in arts; however, this difference is not statistically significant. However, although marginal effects are similar, column 2 shows that marginal costs vary significantly across fields. Adjunct instructors for business and occupational courses cost 38.5% more than

estimates and the course choice model to simulate unobserved types and choices. This is the recommended procedure for estimating standard errors in models with type specific unobserved heterogeneity (McLachlan and Peel, 2004).

[31]In this setting, crowding parameters generally vary from -1 to 0. δ_f=0 if multinomial logit errors accurately measure variety effects; $\delta_f = -1$ if there are no variety effects from additional course sections. In an equivalent nested logit model, $\delta_f = \rho_f - 1$ where ρ_f are field specific nesting parameters (see Appendix B for a proof). As such, the equivalent nesting parameters would vary from 0.555 to 0.800.

adjunct instructors in social science.

Column 3 combines marginal effects and marginal costs to form the identifying marginal effects per dollar. Once again, I report relative marginal effects per dollar averaged across semesters. Marginal effects per dollar are very similar in humanities and arts and social sciences; however, effects per dollar in STEM and business and occupational are 22% and 23% smaller than effects per dollar in humanities and arts.

These differences show that marginally reallocating spending from business and occupational sections to humanities and arts would increase total student utility; however, doing so would decrease variety in business and occupational sections and increase variety in humanities and arts sections, which would decrease business and occupational enrollment and increase humanities and arts enrollment in expectation. Since spending was not reallocated from business and occupational to humanities and arts 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 humanities and arts. This reveals an implicit willingness to sacrifice student utility to draw students out of humanities and arts courses and into business and occupational courses.

Column 3 reports estimates of γ_f to precisely quantify these implicit tradeoffs. The omitted field is humanities and arts; therefore, estimates for field f report how much total student utility the university is implicitly sacrificing to move one student out of an introductory humanities and arts course and into an introductory course in field f in expectation. Point estimates show the university is implicitly sacrificing 0.27 units of utility to move one student from humanities and arts to STEM and 0.31 units of utility to move one student from humanities and arts to business and occupational. The estimate for STEM is statistically significant but the estimate for business and occupational is at the margins of significance. 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.

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 that are implied by 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 that 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 6 compare average observed course offerings and field enrollments to cost-equivalent offerings and enrollments that would have maximized total student utility. Columns (1) - (3) report averages across semesters of the number of introductory course sections taught by tenure-track instructors in each field, the number of introductory course sections taught by adjunct instructors 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 tenure-track offerings in column (1) fixed.[32] 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 would contain much fewer STEM and business and occupational courses sections and much more social science and humanities and arts sections. These differences reflect the finding in Table 5 that marginal humanities and arts and social sciences sections yield more student utility per dollar than marginal STEM and business and occupational sections. Column (5) predicts that utility maximizing adjunct offerings would increase humanities and arts enrollment and social science enrollment by 26% and 10% and decrease STEM and business and occupational enrollment by 28% and 27%.

To provide an additional intuitive way to measure the misalignment between student preferences and observed course offerings, column (6) of Table 6 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 $\hat{\gamma}_f$ with observed costs. Intuitively, I infer these

[32]There 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 tenure-track instructors are generally more difficult to fire; 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.

equivalent costs by solving for costs that make it so a utility maximizing university's first order conditions are satisfied at observed course offerings. This means solving for costs that imply 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 B.

Results suggest that inducing a utility maximizing university to offer observed courses would require a 12.2% increase in the cost of hiring a humanities and arts adjunct instructor, a 9.6% increase in the cost of hiring a social science adjunct instructor, a 9.3% decrease in the cost of hiring a STEM adjunct instructor, and a 12.7% 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 developing models of university behaviors is the capacity to conduct counterfactual policy analyses that incorporate university responses into predictions. In general, universities are not passive parties in the production of human capital but rather active entities that allocate their resources to maximize their objectives subject to constraints. While predicting university responses requires strong assumptions, counterfactual policy analyses that 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 that incorporate supply-side responses more generally, this subsection performs several counterfactual analyses that both include university responses and exclude university responses for comparison. For counterfactual analyses that incorporate university responses, I proceed in two steps. First, I solve for counterfactual course offerings that solve the university's problem given either counterfactual student characteristics or counterfactual cost parameters. Second, I calculate counterfactual field enrollments given counterfactual student characteristics and counterfactual course offerings. For counterfactual analyses that ignore university responses, I calculate field enrollments given counterfactual student characteristics but observed course offerings.[33]

Tables 7 and 8 predict introductory course offerings and introductory field enrollments

[33]The first order conditions characterizing the solution to the university's problem are complicated nonlinear functions of course offerings. As such, it is unclear whether a closed form expression for a solution to the university's problem exists. Instead of deriving a closed form expression, I solve the problem using numerical constrained maximization methods.

in several counterfactual scenarios.[34] To enhance the credibility of these predictions, I make two choices: First, I choose counterfactual scenarios that 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 6, I only allow the university to reallocate the portion of its budget for introductory courses paid to adjunct instructors. This also restricts the counterfactual scenarios to be close to the observed scenario and examines a short run scenario in which inputs that are costly to vary are held fixed.

Given the policy interest in increasing specialization in STEM, one interesting 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 introductory field enrollments under a subsidy that reduces the cost of hiring a STEM adjunct instructor by 5%. Row 2 of Table 7 shows that this subsidy would increase the number of adjunct instructed STEM sections by 32.0% and reduce offerings in other fields. Furthermore, row 2 of Table 8 shows that this increase in STEM offerings would lead to a 8.9% increase in overall STEM enrollment. The subsidy would cost $319.38 per adjunct instructed section implying a total cost of $34,526 or 1.92% of spending on adjunct instructed introductory courses. Because my framework does not account for administrative constraints (aside from the constraint that tenure track instructors cannot be fired), this simulation almost certainly overstates how many STEM sections would be added in response to this subsidy; however, this still provides suggestive evidence that a STEM instructor subsidy could have substantial effects.

Another interesting scenario to consider is one in which UCA begins attracting higher ability students. Cornwell et al. (2006) show evidence that the Georgia HOPE scholarship program increased the SAT scores of students attending public universities in Georgia relative to the national student population. From Table 4, we know that students with higher scores are generally more interested in STEM suggesting that universities might respond to such a change in student composition 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-tenth of a standard deviation. These increases are calibrated to approximately match the effects of the Georgia HOPE scholarship documented

[34]Tables 7 and 8 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 are averages of predictions across all academic semesters.

in Cornwell et al. (2006).[35] Row 3 of Table 7 shows that increasing student abilities would increase the number of adjunct instructed STEM sections by 11.5% and reduce offerings in other fields. To see how field enrollments would change with higher ability students, row 3 of Table 8 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 only 0.8% without any response in course offerings. Row 4 of Table 8 incorporates the changes in adjunct instructed course offerings and shows that the total effect of attracting higher ability students is a 5.1% 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 4.3 percentage points.

A final scenario to consider is one in which the gender composition of students changes, as happened in the US over the course of the 20th century. According to the National Center for Education Statistics, female share of college enrollment increased from 40.4% in 1968 to 57.0% in 2018.[36] To consider how this change might have affected course offerings and field enrollments, I compare UCA in the observed state (where the gender share of 59.0% closely matches the current national share) to a counterfactual state where the gender share matches the 1968 share of 40.4%.

Row 4 of Table 7 shows that with a 1968 gender ratio, UCA would offer 11.8% more adjunct instructed business and occupational sections, 4.3% more adjunct instructed STEM sections, 5.9% fewer adjunct instructed humanities and arts sections, and 8.5% fewer social science 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 8 predicts field enrollments in partial equilibrium without changes in course offerings and row 6 of Table 8 predicts field enrollments in general equilibrium with university responses. Results show that a 1968 gender ratio would increase business and occupational enrollment by 3.5% without any change in course offerings. Incorporating the effects of the increase in adjunct instructed introductory business and occupational sections leads to a total predicted increase in introductory business and occupational enrollment of 8.7%. Once again, ignoring the indirect effects of changes in course offerings leads to significantly understating changes in field enrollments.

[35] Specifically, I use the data in Figure 3 of Cornwell et al. (2006) to conclude that the SAT scores of Freshmen at public universities in Georgia increased 25 points after 1993 versus 8.3 points for high school seniors nationwide. This implies an effect of 16.75 SAT points. This is equivalent to 0.396 ACT points, which represents 0.091 standard deviations in my data.

[36] Source: NCES Table 303.10.: Total fall enrollment in degree-granting postsecondary institutions, by attendance status, sex of student, and control of institution: selected years, 1947 through 2029.

7 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 that gives clues as to why UCA might prefer STEM and business and occupational enrollment.

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.

There is also existing literature that 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, 2014). This also appears to be the case in my setting—the average introductory STEM grade is 2.47 versus 2.80 in humanities and arts. 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 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, 2014). If one assumes an hour of studying is equally costly across fields, this implies STEM courses involve higher psychic costs than other coursework.

Together, existing literature finds 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.[37] In this setting, the university's offerings may maximize some notion of long term

[37] 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.

student welfare but not short term choice utility.

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.[38] 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.

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 of the "axial institution" and prevent higher education policymakers from choosing policies that correctly anticipate university responses.

To advance our understanding of the "supply side" of higher education, this paper

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.

[38] The 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.

proposed a new framework for analyzing course offerings at a university. 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 that 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.

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 and humanities and arts 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 to maximize total student utility, one would reduce adjunct STEM offerings by 88% and more than double adjunct humanities and arts offerings. To quantify the misalignment in another way, I show that a utility maximizing university would only offer the observed composition of courses if humanities and arts adjunct instructors were 12.2% costlier and STEM adjunct instructors were 9.3% cheaper.

Finally, I perform a number of simulations that predict course offerings and student outcomes in counterfactual scenarios. One notable counterfactual increases all observed measures of student preparation by one tenth of a standard deviation. Even without a university response, this would increase introductory STEM enrollment by 0.8% 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 5.1% total increase in introductory STEM enrollment. In other words, ignoring the university's response leads to understating effects on STEM enrollment by 4.3 percentage points.

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 choice 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 that affect student choices and makes a crucial assumption about the exogeneity of course offerings. 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 that 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

Field Definitions

Fields are defined using Classification of Instructional Program (CIP) Codes as follows:

STEM: Biological and Biomedical Sciences (26), Mathematics and Statistics (27), Physical Sciences (40).

Social Science: Area, Ethnic, Cultural and Gender Studies (5), Foreign Languages, Literatures, and Linguistics (16), Family and Consumer Sciences / Human Sciences (19), Psychology (42), Social Sciences (45), History (54).

Humanities and Arts: Communication, Journalism, and Related Programs (9), English Language and Literature / Letters (23), Philosophy and Religious Studies (38), Visual and Performing Arts (50).

Business and Occupational: Computer and Information Sciences and Support Services (11), Education (13), Parks, Recreation, Leisure, and Fitness Studies (31), Health Professions and Related Clinical Sciences (51), Business, Management, Marketing, and Related Support Services (52).

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: Technical Appendix

Equivalence of Crowding and Nesting Models

This subsection shows the equivalence of the Ackerberg and Rysman (2005) crowding model described in Section 3 and a nested logit course choice model with nests defined by academic field. In an analogous nested logit model, probabilities of choosing any course section in field f are given by:

$$P_{istf} = \frac{\exp\left(\frac{X_{ist}\beta_f}{\rho_f}\right)\left[\sum_{j'\in f}\exp\left(\frac{X_{ist}\beta_f}{\rho_f}\right)\right]^{\rho_f-1}}{\sum_{f'=1}^{F}\left[\sum_{j'\in f'}\exp\left(\frac{X_{ist}\beta_{f'}}{\rho_{f'}}\right)\right]^{\rho_{f'}}}$$

These simplify as follows:

$$\begin{aligned}
P_{istf} &= \frac{\exp\left(\frac{X_{ist}\beta_f}{\rho_f}\right)\left[d_{tf}\exp\left(\frac{X_{ist}\beta_f}{\rho_f}\right)\right]^{\rho_f-1}}{\sum_{f'=1}^{F}\left[d_{tf'}\exp\left(\frac{X_{ist}\beta_{f'}}{\rho_{f'}}\right)\right]^{\rho_{f'}}} \\
&= \frac{\exp\left(\frac{X_{ist}\beta_f}{\rho_f}\right)d_{tf}^{\rho_f-1}\left[\exp\left(\frac{X_{ist}\beta_f}{\rho_f}\right)\right]^{\rho_f-1}}{\sum_{f'=1}^{F}d_{tf'}^{\rho_{f'}}\left[\exp\left(\frac{X_{ist}\beta_{f'}}{\rho_{f'}}\right)\right]^{\rho_{f'}}} \\
&= \frac{d_{tf}^{\rho_f-1}\left[\exp\left(\frac{X_{ist}\beta_f}{\rho_f}\right)\right]^{\rho_f}}{\sum_{f'=1}^{F}d_{tf'}^{\rho_{f'}}\left[\exp\left(\frac{X_{ist}\beta_{f'}}{\rho_{f'}}\right)\right]^{\rho_{f'}}} \\
&= \frac{d_{tf}^{\rho_f-1}\exp\left(X_{ist}\beta_f\right)}{\sum_{f'=1}^{F}d_{tf'}^{\rho_{f'}}\exp\left(X_{ist}\beta_{f'}\right)}
\end{aligned}$$

which is equivalent to Equation (10) with $\rho_f = \delta_f + 1$.

Expectation-Maximization (EM) Algorithm

This subsection describes the Expectation-Maximization (EM) Algorithm used to estimate student choice parameters in the presence of type specific unobserved heterogeneity in student preferences for fields. Let y_{irstf} indicate whether observation r of student i in semester t who is type s chooses a field f course section. Furthermore, let $\Theta = \{\beta_f, \rho_f\}_{f=1}^{F}$ contain all student choice parameters. Then the likelihood of observing student i's panel of choices in the state where she is type s as a function of Θ is given by:

$$l_{is}(\Theta) = \prod_{t=1}^{T}\prod_{r=1}^{R_{it}} P_{istf}^{y_{irstf}}$$

Let π_s represent the unconditional probability that a student is type s. The full log-likelihood as a function of Θ would then be:

$$\mathscr{L}(\Theta) = \sum_{i=1}^{N} \ln\left(\sum_{s=1}^{S} \pi_s \left(\prod_{t=1}^{T}\prod_{r=1}^{R_{it}} P_{istf}^{y_{irstf}}\right)\right)$$

In theory, one can estimate student choice parameters using this full log-likelihood function; however, doing so would be computationally burdensome. Instead, define the augmented log-likelihood function

$$Q(\Theta) = \sum_{i=1}^{N}\sum_{s=1}^{S}\sum_{t=1}^{T}\sum_{r=1}^{R_{it}} q_{is} y_{irstf} \ln P_{istf} \tag{16}$$

where q_{is} represent the probability that student i is type s conditional on her observed choices given by:

$$q_{is}(\Theta) = \frac{\pi_s l_{is}}{\sum_{s'=1}^{S} \pi_{s'} l_{is'}} \tag{17}$$

The EM algorithm proceeds by iteratively maximizing Equation (16) to obtain estimates of Θ and using Equation (17) to infer conditional type probabilities given these estimates. Specifically, the algorithm proceeds as follows:

1. Begin with arbitrary guesses for Θ^0 and π_s^0
2. Evaluate Equation (17) at Θ^0 and π_s^0 to obtain q_{is}^0
3. Estimate Θ^1 by maxizing Equation (16) given q_{is}^0. Estimate π_s^1 with the sample average $\pi_s^1 = \frac{1}{N}\sum_{i=1}^{N} q_{is}^0$
4. Return to step 2 using Θ^1 and π_s^1 and iterate until successive estimates of Θ and π_s become arbitrarily close.

Solving for equivalent costs

In this subsection, I describe my method for estimating the equivalent costs reported in Column 6 of Table 6. 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.

A utility maximizing university's problem is given by:

$$\mathbf{d_t^{SUM}} = \text{argmax}_{\mathbf{d_t}} \left\{V_t(\mathbf{d}_t)\right\} \quad \text{s.t.} \quad \sum_{f=1}^{F} d_{tf}^N c_f \leq E_t^N \tag{18}$$

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 (18) 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 (18) if adjunct instructor costs are given by $\tilde{c}_f$ is:

$$\left(\frac{1}{\tilde{c}_{f_1}}\right)\left[\frac{\partial V_t\left(\mathbf{d}_t^\star\right)}{\partial d_{tf_1}}\right] = \left(\frac{1}{\tilde{c}_{f_2}}\right)\left[\frac{\partial V_t\left(\mathbf{d}_t^\star\right)}{\partial d_{tf_2}}\right] \quad \forall f_1, f_2 \tag{19}$$

$$\sum_{f=1}^{F} d_{tf}^N \tilde{c}_f = E_t^N \tag{20}$$

Rearranging and stacking semesters yields:

$$\mathbf{M}\tilde{\mathbf{c}} = \mathbf{E} \tag{21}$$

where

$$\underset{(F,F)}{\mathbf{M}_t} = \begin{bmatrix} \frac{-\partial V_t}{\partial d_{tF}} & & & \frac{\partial V_t}{\partial d_{t1}} \\ & \ddots & & \vdots \\ & & \frac{-\partial V_t}{\partial d_{tF}} & \frac{\partial V_t}{\partial d_{tF-1}} \\ d_{t1}^N & \cdots & \cdots & d_{tF}^N \end{bmatrix}$$

$$\underset{(F\times T,F)}{\mathbf{M}} = \begin{bmatrix} \mathbf{M}_1 & \cdots & \mathbf{M}_T \end{bmatrix}'$$

$$\underset{(F,1)}{\mathbf{E}_t} = \begin{bmatrix} \mathbf{0}_{1,F-1} & E_t^N \end{bmatrix}'$$

$$\underset{(F\times T,1)}{\mathbf{E}} = \begin{bmatrix} \mathbf{E}_1 & \cdots & \mathbf{E}_T \end{bmatrix}'$$

$$\underset{(F,1)}{\tilde{\mathbf{c}}}(f) = \tilde{c}_f$$

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

$$\tilde{\mathbf{c}} = \mathbf{M}^+\mathbf{E} \tag{22}$$

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

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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	33.7	65.8	49.5	25.2
Avg. intro sections per semester	204	250	160	87
Avg. intro enrollment per semester	5181	8161	4516	2123
Avg. intro enrollment per section	25.4	32.6	28.2	24.5
Intro section cost (25th pctile)	\$6,000	\$4,566	\$5,034	\$5,441
Intro section cost (Median)	\$8,811	\$6,088	\$6,734	\$7,140
Intro section cost (75th pctile)	\$10,880	\$8,366	\$8,865	\$11,708
Avg. ACT score	24.4	23.7	23.9	24.0
Avg. HS GPA	3.43	3.35	3.34	3.39
Share Female	57.5%	59.5%	58.1%	47.5%
Share Freshmen	43.8%	39.7%	40.3%	11.6%
Share Sophomores	27.9%	31.8%	33.8%	40.6%
Share Juniors	17.1%	18.3%	16.5%	35.0%
Share Seniors	11.2%	10.2%	9.4%	12.7%

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																	
STEM	F04	S05	F05	S06	F06	S07	F07	S08	F08	S09	F09	S10	F10	S11	F11	S12	F12	S13
Courses	34	30	33	33	34	32	33	33	33	34	33	35	34	34	34	36	35	37
Sections	194	175	221	179	233	207	248	211	221	201	219	199	212	184	197	181	206	188
Sections (%)	30%	29%	32%	29%	31%	29%	30%	29%	29%	29%	29%	29%	29%	28%	28%	28%	29%	28%
Enrollment (%)	27%	24%	28%	24%	26%	25%	27%	25%	26%	25%	26%	26%	27%	26%	26%	26%	27%	26%

	Semester																	
Social Science	F04	S05	F05	S06	F06	S07	F07	S08	F08	S09	F09	S10	F10	S11	F11	S12	F12	S13
Courses	59	64	65	60	64	64	65	66	66	67	68	65	66	69	69	69	70	68
Sections	227	220	250	230	275	261	294	267	268	261	274	237	249	236	249	227	248	233
Sections (%)	35%	36%	36%	37%	36%	37%	36%	37%	35%	37%	36%	34%	34%	36%	36%	35%	35%	35%
Enrollment (%)	42%	43%	41%	42%	41%	41%	40%	41%	40%	41%	41%	40%	40%	41%	41%	40%	40%	40%

	Semester																	
Humanities and Arts	F04	S05	F05	S06	F06	S07	F07	S08	F08	S09	F09	S10	F10	S11	F11	S12	F12	S13
Courses	41	43	44	45	48	46	50	49	52	50	50	55	53	51	53	52	53	56
Sections	134	135	142	140	165	153	175	166	177	156	180	171	172	156	169	160	168	166
Sections (%)	21%	22%	20%	22%	22%	22%	21%	23%	23%	22%	24%	25%	24%	24%	24%	25%	24%	25%
Enrollment (%)	21%	23%	21%	23%	22%	23%	22%	23%	23%	22%	23%	24%	23%	22%	23%	23%	23%	24%

	Semester																	
Business and Occupational	F04	S05	F05	S06	F06	S07	F07	S08	F08	S09	F09	S10	F10	S11	F11	S12	F12	S13
Courses	26	26	25	24	25	24	25	25	26	24	25	25	26	25	27	26	25	25
Sections	90	81	84	77	90	85	97	87	96	84	91	80	92	87	84	82	87	86
Sections (%)	14%	13%	12%	12%	12%	12%	12%	12%	13%	12%	12%	12%	13%	13%	12%	13%	12%	13%
Enrollment (%)	10%	11%	10%	11%	10%	11%	11%	11%	11%	12%	10%	10%	10%	11%	10%	11%	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: Student Course Choice Parameters

	STEM	Social Science	Humanities and Arts	Business and Occupational
Intercept	1.095**	2.186***	0.934*	*omitted*
	0.478	*0.494*	*0.485*	
ACT Z-Score	0.119***	0.019*	0.073***	*omitted*
	0.010	*0.010*	*0.011*	
Missing ACT	-0.261***	-0.212***	-0.273***	*omitted*
	0.017	*0.015*	*0.017*	
GPA Z-score	0.060***	-0.063***	-0.101***	*omitted*
	0.009	*0.009*	*0.009*	
Missing GPA	0.139***	0.162***	0.202***	*omitted*
	0.019	*0.018*	*0.020*	
Female	0.243***	0.366***	0.305***	*omitted*
	0.014	*0.013*	*0.014*	
Non-White	-0.035*	-0.086***	-0.128***	*omitted*
	0.020	*0.019*	*0.020*	
Missing Race	-0.266***	-0.145***	-0.129***	*omitted*
	0.016	*0.015*	*0.016*	
Sophomore	-1.766***	-1.500***	-1.461***	*omitted*
	0.020	*0.019*	*0.020*	
Junior	-2.162***	-1.962***	-2.099***	*omitted*
	0.021	*0.019*	*0.021*	
Senior	-1.649***	-1.630***	-1.754***	*omitted*
	0.026	*0.025*	*0.026*	
Unobs. Type 2	2.231***	2.163***	2.459***	*omitted*
	0.016	*0.016*	*0.016*	
Crowding Parameters	-0.270***	-0.445***	-0.291***	-0.200*
	0.055	*0.058*	*0.063*	*0.110*

Notes: Parametric block bootstrapped standard errors (300 iterations) are in italics. */**/*** indicate significantly different from omitted category (or from zero for δ_f) at 10%/5%/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 5: Relative Marginal Effects and Implied Preferences

	Average Marginal Effect on Total Utility (1)	Cost of Adjunct Instructors (2)	Average Marginal Effect on Total Utility per Dollar (3)	Implied Preferences (4)
STEM	0.926	$6387.60	0.781***	0.266***
	0.077	*92.61*	*0.065*	*0.084*
Social Science	0.904	$4941.05	0.985	0.024
	0.086	*56.95*	*0.094*	*0.085*
Hum. and Arts	1	$5387.07	1	0
		99.35		
Business and Occ.	0.979	$6845.59	0.771**	0.307
	0.126	*126.96*	*0.099*	*0.189*

Notes: Parametric block bootstrapped standard errors (300 iterations) 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 averages across academic semesters of effects relative to humanities and arts. Column 2 reports average costs of hiring adjunct instructors to teach one course section in each field. Column 3 divides marginal effects by the costs of hiring adjunct instructors. Once again, these are averages across semesters of effects per dollar relative to humanities and arts. Column 4 reports estimates of implied preference parameters γ_j with humanities and arts as the omitted field. Estimates quantify how much student utility the university is implicitly willing to sacrifice to move one student from a humanities and arts course to a course in the specified field.

Table 6: Utility Maximizing Course Offerings and Equivalent Costs

	Observed			**Utility Maximizing**		
	(1) Average Tenure-Track Courses	(2) Average Adjunct Courses	(3) Average Field Enrollment	(4) Average Adjunct Courses	(5) Average Field Enrollment	(6) Equivalent Cost Differences
STEM	125.28	78.94	5181.39	9.26***	3744.78***	-9.3%**
				14.00	*320.56*	*3.7*
Soc Sci	132.33	118.00	8161.22	176.54	8991.03	9.6*%
				45.27	*817.78*	*5.0*
Hum and Arts	100.11	60.17	4515.94	128.90	5697.85	12.2%**
				42.26	*831.46*	*5.8*
Bus and Occ	29.94	56.72	2122.50	25.40**	1547.40**	-12.7%
				14.29	*266.29*	*8.6*

Notes: Parametric block bootstrapped standard errors (300 iterations) are in italics. Columns 1-3 are the observed number of course sections taught by tenure-track instructors, the observed number of course sections taught by adjunct instructors, 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 5%/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 5 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 10%/5% significance.

Table 7: Adjunct Instructed Course Offerings in Counterfactual Scenarios

		STEM	Social Science	Humanities and Arts	Business and Occupational
(1)	Baseline (predicted)	81.91	118.54	56.92	56.12
		0.74	*0.34*	*0.56*	*0.65*
(2)	Reduce cost of STEM adjunct by 5%	108.10***	108.17***	46.79***	52.18***
		5.43	*2.50*	*3.21*	*2.24*
(3)	Increase all SAT scores and GPA by 1/10 of a std dev	91.35***	112.84***	52.28***	55.08
		2.43	*1.28*	*1.64*	*1.15*
(4)	1968 gender ratio	85.43	108.45***	53.57***	62.76***
		1.96	*2.20*	*1.76*	*2.66*

Notes: Parametric block bootstrapped standard errors (300 iterations) are in italics. Row 1 is the average number of course sections taught by adjunct instructors predicted by the estimated model in the observed state. Rows 2-4 are the average number of course sections taught by adjunct instructors in counterfactual states. In rows 2-4, *** indicates significantly different from row 1 at 1% significance.

Table 8: Field Enrollments in Counterfactual Scenarios

		STEM	Social Science	Humanities and Arts	Business and Occupational
(1)	Baseline (predicted)	5219.30	8169.82	4474.81	2117.12
		30.72	*34.09*	*24.17*	*24.89*
(2)	Reduce cost of STEM adjunct by 5%	5684.09***	7978.77***	4265.92***	2052.27***
		145.40	*66.92*	*83.03*	*56.11*
(3)	Increase all SAT scores and GPA by 1/10 of a std dev (PE)	5262.04**	8106.88***	4493.29**	2118.84
		26.35	*33.13*	*22.54*	*19.59*
(4)	Increase all SAT scores and GPA by 1/10 of a std dev (GE)	5484.37***	8029.12***	4367.56***	2100.01**
		70.74	*42.00*	*43.77*	*33.28*
(5)	1968 gender ratio (PE)	5227.20	8055.82***	4507.05***	2190.98***
		26.46	*33.82*	*22.83*	*20.08*
(6)	1968 gender ratio (GE)	5350.94**	7910.82***	4417.95***	2301.34***
		55.24	*59.14*	*44.93*	*69.09*

Notes: Parametric block bootstrapped standard errors (300 iterations) 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% 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 7.