APPENDIX B: DATA AND RESULTS APPENDIX – ONLINE

In this section, we describe how we processed the data and show additional results for the various estimation stages. The appendix covers:

1. our method of aggregating the departments into our fourteen categories,
2. our sample selection procedures for the various estimation stages,
3. construction of student choice sets,
4. descriptives on how course grading is related to other outcomes,
5. additional parameters from the motivating regressions on grades and hours studied (Tables III and IV)
6. additional structural parameters (expanding on Table VI),
7. the share of courses taken in each department by unobserved type, and
8. additional parameters from the regressions of average grades and workload on enrollment and instructor characteristics (expanding on Table X).

B.1. *Aggregation of departments*

In Table B.1 we show the aggregation of departments into our fourteen categories. We partitioned departments into these categories by first grouping departments by their school organization. UK consists of the Colleges of Agriculture, Arts and Sciences, Business and Economics, Communication and Information, Design, Education, Engineering, and Fine Arts. Within the colleges, departments were further grouped based partly on shared core requirements and cross-listed coursework. Finally, some departments were manually extracted (e.g., Psychology has its own category) or inserted into a category (e.g., all fine arts departments were subsumed under Communications), mostly due to department size.

B.2. *Sample selection*

We now describe our sample selection rules for the various stages of estimation. We restrict courses to those that have enrollment of at least 15 undergraduates. This cuts the 2,026 classes observed in the population to 1,084. The total number of individual–course observations resulting from this cut is 58,081 with 16,190 unique students. We then remove specialized classes that would result from taking a second course in a sequence, as the decision process is very different for these courses. The restriction we impose is that at

TABLE B.1

AGGREGATION OF DEPARTMENTS

Category	Departments
Agriculture	Ag. Biotechnology, Ag. Economics, Ag. Ed, Ag. General, Animal & Food Sciences, Biosystems & Ag. Engineering, Environmental Studies, Forestry, Landscape Architecture, Plant Pathology, Plant & Soil Sciences, Sustainable Ag.
Regional Studies	Appalachian Studies, Family Sciences, Gender & Women's Studies, Hispanic Studies, Latin American Studies
Communications	Arts Admin, Comm., Comm. & Info Studies, Fine Arts – Music, Theatre Arts, Schl of Journalism & Telecomm, Schl of Art & Visual Studies, Schl of Interior Design
Education & Health	Allied Health Ed & Research, Comm Disorders, Community & Leader Dev, Dept of Gerontology, Dietetics & Nutrition, Early Child, Spec Ed, Rehab, Ed, Ed Curriculum & Instr, Ed Policy Studies & Eval, Ed, Schl & Counsel Psych, Health Sci Ed, Kinesiology – Health Promotion, Lib & Info Sci, Nursing, Public Health, STEM Ed, Social Work
Engineering	Chem. & Materials Engineering, Civil Engineering, Com. Sci., Electrical & Com. Engineering, Engineering, Mech. Engineering, Mining Engineering, Schl of Architecture
Languages	Linguistics, Modern & Classical Languages, Philosophy
English	English
Biology	Biology, Entomology
Mathematics	Mathematics, Statistics
Chem & Physics	Chemistry, Earth & Environmental Sciences, Physics & Astronomy
Psychology	Psychology
Social Sciences	Anthropology, Geography, History, Pol. Sci., Schl of Human Env. Sci., Sociology
Mgmt. & Mkting	Aerospace Studies, Department of Mgmt., Dept of Mkt & Supply Chain, Merchand, Apparel & Textiles, Mil Sci & Leadership
Econ., Fin., Acct.	Accountancy, Economics, Dept of Finance & Quantitative Methods

Note: STEM departments are in bold.

least 99 students had the course in their choice set and that less than 50% of those who had the course in their choice set took the course. Imposing this restriction results in 1,003 courses chosen by 16,079 unique students. This represents our baseline data for the choices of courses and grades.

There is an additional restriction imposed in the grade estimation. Namely, there are 18 courses where all students received the exact same grade, accounting for 518 individual–course observations or less than 1% of enrollments in the baseline data. The courses are still part of our course choice problem but are not used in the estimation of grades. Instead, the expected grades for students in these courses is set to what it is in the data, 4.0, with γ for these courses set to 0.

Estimates of the grade parameters show an additional 7 courses where the estimate of γ is less than 0.01 (estimates of γ are constrained to be greater than zero). For these courses, the factors yielding high grades are fundamentally different from those of other courses in the same department. These courses account for 224 individual–course observations or less than 0.5% of enrollments in the baseline data. For the purposes of estimating study times (where one of the inputs is $\ln(\gamma)$) and the professor estimation (where γ is a choice), we do not use these courses. For our counterfactuals, we fix the grading policies of these courses to what we observe in the data.

For the study effort analysis, observations are at the course–cohort level with an initial sample of 2,395 course–cohort evaluations. In principle, there could have been 4,012 observations if there were a student from each cohort in the class who also filled out a course evaluation. The 2,395 is then the result of some courses either not having students in a particular cohort or having students in a particular cohort where none filled out the course evaluation.

We implement a number of additional restrictions on the sample for the study effort analysis. The cohort of the student in the evaluation data is based on the students' self reports, while in the administrative data, it is based on our calculations given the academic records of the student. We define the response rate for the course–cohort as the number of course–cohort observations in the evaluation data divided by course–cohort enrollment in the registrar data. Because we want the average characteristics for a particular course–cohort from the registrar data to match the characteristics of those who filled out the evaluations, we restrict our analysis to course–cohorts where the response rate on the evaluations is between

70% and 101%. Imposing this restriction reduces our number of course-cohort observations to 866. Further removing courses with γ_js less that 0.01 results in a final sample of 850 course-cohort observations.

For the professor estimation, we do not use courses where γ is less than 0.01. We also do not use courses that hit their capacity constraint, as the professor maximization problem is different when the capacity constraint binds. This reduces our number of courses to 951.

B.3. *Construction of students' choice sets*

We account for administrative and academic rules and students' academic histories to construct accurate class choice sets for students:

1. Academic history: We drop classes that the student completed over the prior seven semesters (fall 2008–spring 2011) unless he or she is in the class in fall 2012.
2. Class prerequisites: We compile lists of prerequisite classes (from the UK Undergraduate Bulletin) for every course. We use the student's academic history and close the choice set unless all prerequisites are met. If a student is in a class without having completed all requirements, we assume an exemption was granted by the instructor.
3. AP exams: Students can bypass introductory courses in some subjects (from the UK Undergraduate Bulletin) with a score of 3 or above on the corresponding AP exam.
4. Room capacity: We have timestamps for all classes that students registered for. Using data on room capacity, we find the timestamp of when/if the class reaches capacity. We compare this time stamp to the first observed time stamp for the student. If the student's first timestamp is after the class's timestamp, the class is not in the choice set.

Table B.2 shows the average share of STEM and non-STEM classes available by cohort after the imposition of each restriction. Restriction 1 implies that for seniors, almost 10% (5%) of courses in STEM (non-STEM) are closed, which is reflective of more demand for STEM courses. Restriction 2 substantively restricts the choice set, especially for STEM. Overall, almost 40% (20%) of STEM (non-STEM) courses are closed due to students either not meeting prerequisites or having already completed the course. The changes to the choice set from AP exams (Restriction 3) or capacity constraints (Restriction 4) are marginal.

TABLE B.2

SHARE OF COURSES AVAILABLE BY COHORT/STEM CLASSIFICATION UNDER CHOICE SET RESTRICTIONS

Restriction	Freshmen	Sophomores	Juniors	Seniors	Overall
STEM departments					
(1)	1.000	0.953	0.921	0.906	0.946
(2)	0.550	0.541	0.552	0.555	0.550
(3)	0.562	0.547	0.556	0.558	0.556
(4)	0.556	0.546	0.555	0.557	0.554
non-STEM departments					
(1)	1.000	0.974	0.962	0.952	0.972
(2)	0.802	0.785	0.790	0.789	0.792
(3)	0.804	0.787	0.791	0.790	0.793
(4)	0.800	0.786	0.790	0.789	0.792

Note: (1) removes courses already taken. (2) removes courses where prerequisites are not met based on transcripts. (3) adds courses for which the prerequisites were met by AP exams. (4) removes courses where capacity constraints are met and adds courses where the student enrolled in the course despite not meeting the prerequisites.

B.4. *Characteristics of classes with above and below median grades*

Table B.3 compares classes with above median average grades to classes with below median average grades. Higher grades are associated with being a non-tenure track instructor as well as with being female. The latter could be due in part to STEM classes giving lower grades. Courses with high grades are also somewhat more likely to receive positive student evaluations. In our structural model, we handle the fact that higher grades may be correlated with other factors that drive student demand by directly including many of these variables in our estimating equations, modeling the professor behavior explicitly, and including course-level fixed effects to account for other student non-grade preferences.

B.5. *Additional parameters from the motivating regressions*

In Table B.4 we show estimates of the department indicator variables from Tables III and IV. The grade regression results show that the coefficients are lowest for STEM classes plus English and Psychology. For example, in the first column with the entire sample, there is a gap of over 0.8 grade points between the highest-grading department (Education & Health)

TABLE B.3

CHARACTERISTICS OF HIGH VS. LOW GRADE CLASSES

		High Grades	Low Grades
Faculty Rank	Full / Assoc. / Assist. / Lecturer	0.13 / 0.16 / 0.13 / 0.58	0.20 / 0.20 / 0.15 / 0.45
	Female Professor	0.48	0.34
Class Eval	Presents effectively	3.44 (0.40)	3.23 (0.46)
Class Eval	Stimulates interest	3.37 (0.39)	3.11 (0.43)
Class Eval	Stimulates further reading	3.25 (0.40)	2.97 (0.50)
	STEM Dept.	0.20	0.47

Note: Fall 2012 University of Kentucky courses with enrollments of 15 or more students; Classes divided at the median grade: 3.16. Standard deviations in parentheses. Class evaluation questions use a 5-point Likert scale.

and lowest-grading department (Chemistry & Physics). The second set of columns shows that the Engineering and Chemistry & Physics departments have the highest coefficients for hours of study.

B.6. *Additional structural parameters and standard errors*

In Table B.5 we show the full set of student preference parameters (see Table VI for a subset of the parameters). The parameters not discussed in the body of text also follow the expected patterns. The more courses opened up by a class (ln Open Class), the more appealing the class is for sophomores and even more so for freshmen. For junior and seniors, courses that fill requirements for their declared majors are associated with higher utilities, as are upper-level classes in general.

TABLE B.4

REDUCED-FORM REGRESSIONS OF DEPARTMENT GRADE AND STUDY HOURS PARAMETERS

	Grades				Study Hours			
Department	All Classes	Upper Level	STEM	non-STEM	All Classes	Electives	STEM	non-STEM
Regional Std.	0.014(0.031)	0.099(0.054)		0.024(0.029)	0.192(0.084)	0.650(0.134)		0.188(0.079)
Communication	0.244(0.025)	0.210(0.035)		0.223(0.023)	0.182(0.085)	0.422(0.151)		0.194(0.080)
Ed&Health	0.341(0.026)	0.421(0.034)		0.368(0.025)	-0.100(0.082)	0.382(0.177)		-0.093(0.077)
Engineering	-0.161(0.029)	-0.156(0.042)			0.767(0.092)	0.812(0.196)		
Language	0.104(0.027)	0.036(0.042)		0.085(0.025)	0.094(0.074)	0.512(0.115)		0.085(0.070)
English	-0.102(0.034)	-0.170(0.053)		-0.096(0.032)	0.269(0.090)	0.621(0.132)		0.269(0.085)
Biology	-0.408(0.028)	-0.213(0.043)	-0.370(0.031)		0.263(0.137)	0.372(0.201)	-0.437(0.177)	
Math	-0.353(0.026)	-0.350(0.058)	-0.277(0.025)		0.487(0.108)	0.544(0.280)	-0.305(0.125)	
Chem.&Phys.	-0.487(0.027)	-0.286(0.092)	-0.424(0.026)		0.364(0.110)	0.167(0.184)	-0.434(0.148)	
Psychology	-0.212(0.030)	-0.286(0.092)		-0.203(0.029)	0.310(0.154)	0.781(0.206)		0.315(0.146)
Social Science	-0.022(0.025)	0.057(0.036)		-0.054(0.024)	0.123(0.075)	0.608(0.121)		0.125(0.071)
Mgmt.&Mkting	0.249(0.031)	0.363(0.036)		0.259(0.028)	-0.144(0.107)	0.443(0.196)		-0.134(0.101)
Econ,Fin.,Acct	-0.143(0.027)	0.051(0.036)	0.008(0.025)		0.235(0.096)	0.597(0.184)	-0.514(0.127)	

Note: STEM departments are in bold. Agriculture is the excluded department for all cases except only; Engineering is the excluded category in the STEM-only specifications. Standard errors are in parentheses.

TABLE B.5

COMPLETE TABLE – ESTIMATES OF PREFERENCE PARAMETERS

	E(grades)		Fem x E(grade)		Fem x Fem Prof							
All Cohorts x	0.927	(0.006)	0.257	(0.009)	0.141	(0.007)			No. of Classes in Dept. Last Year			
	Req. Class		ln Open Classes		STEM Class		Fem x STEM Class		One		More than One	
Freshmen x	3.006	(0.021)	0.476	(0.004)	0.469	(0.018)	-0.046	(0.025)	—		—	
Sophomores x	1.510	(0.021)	0.388	(0.004)	0.422	(0.016)	-0.145	(0.023)	0.212	(0.014)	0.832	(0.014)
	Major Req. (A)		Major Req. (B)		Upper-Lev. Class							
Upperclassmen x	3.558	(0.008)	2.091	(0.017)	1.861	(0.007)						

	Female		ACT read		ACT Math		HS GPA		Type 3		Type 2	
Regional Studies	-0.091	(0.027)	-0.231	(0.021)	-0.062	(0.024)	-0.057	(0.022)	-1.580	(0.072)	-1.555	(0.032)
Communications	-0.401	(0.022)	-0.247	(0.016)	0.036	(0.018)	-0.090	(0.016)	-0.987	(0.043)	-1.484	(0.022)
Education & Health	0.139	(0.023)	-0.336	(0.018)	0.010	(0.020)	0.075	(0.017)	-1.227	(0.047)	-2.063	(0.026)
Engineering	-0.897	(0.032)	-0.275	(0.020)	0.494	(0.021)	0.048	(0.020)	-0.802	(0.060)	-1.237	(0.028)
Languages	-0.159	(0.024)	-0.116	(0.018)	0.042	(0.020)	-0.154	(0.018)	-1.383	(0.055)	-1.471	(0.026)
English	0.127	(0.029)	0.024	(0.023)	-0.208	(0.025)	0.051	(0.023)	-0.430	(0.073)	-1.580	(0.036)
Biology	0.504	(0.026)	-0.238	(0.019)	0.033	(0.021)	-0.136	(0.019)	-0.688	(0.056)	-1.176	(0.028)
Math	-0.133	(0.026)	-0.154	(0.017)	-0.193	(0.019)	-0.200	(0.017)	-1.265	(0.049)	-1.095	(0.024)
Chem. & Physics	0.069	(0.026)	-0.177	(0.017)	0.143	(0.019)	-0.178	(0.017)	-1.051	(0.050)	-1.131	(0.025)
Psychology	0.162	(0.025)	-0.375	(0.020)	0.047	(0.023)	-0.202	(0.019)	-0.816	(0.055)	-1.066	(0.029)
Social Sciences	-0.350	(0.022)	-0.175	(0.016)	-0.010	(0.018)	-0.182	(0.016)	-0.966	(0.044)	-1.247	(0.021)
Mgmt. & Mkting	-0.049	(0.028)	-0.243	(0.021)	0.138	(0.023)	-0.081	(0.021)	-1.392	(0.075)	-1.551	(0.033)
Econ., Fin., Acct.	-0.378	(0.026)	-0.295	(0.018)	0.131	(0.020)	-0.040	(0.018)	-1.760	(0.061)	-1.477	(0.026)

Note: "Major Req. (A)" refers to whether the course was required for the major; "Major Req. (B)" refers to whether the course was one of two or more required for the major.

B.7. *Share of courses taken in each department by unobserved type*

In Table B.6 we show how types are distributed across departments. The order of the rows is given by the ranking on the ratio of the type 1 (high-ability) share to the type 3 (low-ability) share, implying positive selection into courses listed in the first few rows.

TABLE B.6

SHARE OF COURSES TAKEN IN EACH DEPARTMENT BY UNOBSERVED TYPE

	Type 1 (High Ability)	Type 2 (Medium Ability)	Type 3 (Low Ability)
Econ., Fin., Acct.	0.0944	0.0614	0.0415
Management & Marketing	0.0477	0.0278	0.0230
Regional Studies	0.0383	0.0319	0.0279
Biology	0.0656	0.0540	0.0478
Engineering	0.0643	0.0543	0.0471
Chem. & Physics	0.0985	0.0916	0.0803
Languages	0.0691	0.0622	0.0669
Math	0.1165	0.1291	0.1137
English	0.0237	0.0222	0.0236
Psychology	0.0502	0.0496	0.0530
Social Sciences	0.1092	0.1277	0.1360
Communications	0.1211	0.1547	0.1612
Education & Health	0.0889	0.0573	0.1269
Agriculture	0.0126	0.0763	0.0511

Note: The shares of each type are 64.1%, 29.5%, and 6.4% respectively. STEM departments are in bold. The order is given by the ranking on the ratio of the type 1 (high-ability) share to the type 3 (low-ability) share.

B.8. *Additional regression parameters relating course demand to average grades and workloads*

In Table B.7 we show the full set of professor parameters (see Table X for a subset of the parameters).

APPENDIX C: METHODS APPENDIX – ONLINE

This appendix provides additional details regarding our empirical methods:

TABLE B.7

COMPLETE TABLE – RELATING COURSE DEMAND TO GRADES AND WORKLOADS

	Average Grades				γ			
	OLS		IV		OLS		IV	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Constant	3.418	(0.091)	4.375	(0.097)	0.124	(0.021)	-0.109	(0.022)
Ln Enroll	-0.066	(0.020)	-0.352	(0.023)	0.007	(0.004)	0.077	(0.005)
Grad. Student	-0.057	(0.044)	-0.045	(0.042)	0.006	(0.010)	0.003	(0.010)
Lecturer	-0.016	(0.043)	0.111	(0.041)	0.015	(0.010)	-0.016	(0.009)
Asst. Prof.	-0.136	(0.049)	-0.079	(0.047)	0.040	(0.011)	0.027	(0.011)
Tenured Prof.	-0.091	(0.040)	-0.030	(0.039)	0.018	(0.009)	0.003	(0.009)
Female Prof.	0.102	(0.030)	0.123	(0.029)	0.008	(0.007)	0.003	(0.007)
Female Prof. X STEM	-0.023	(0.062)	-0.065	(0.059)	-0.020	(0.014)	-0.010	(0.013)
Upper-Level Class	0.084	(0.034)	-0.016	(0.032)	0.009	(0.008)	0.033	(0.007)
Upper-Level Class X STEM	0.088	(0.065)	-0.013	(0.062)	0.035	(0.015)	0.060	(0.014)
Regional Studies	0.051	(0.075)	0.028	(0.071)	0.061	(0.017)	0.066	(0.016)
Communications	0.086	(0.062)	0.110	(0.059)	0.020	(0.014)	0.014	(0.013)
Education & Health	0.225	(0.068)	0.275	(0.064)	-0.009	(0.015)	-0.022	(0.015)
Engineering	-0.127	(0.079)	-0.011	(0.075)	0.267	(0.018)	0.238	(0.017)
Language	-0.024	(0.068)	-0.031	(0.065)	0.036	(0.015)	0.037	(0.015)
English	-0.123	(0.082)	-0.171	(0.078)	0.053	(0.019)	0.065	(0.018)
Biology	-0.276	(0.105)	0.109	(0.102)	0.146	(0.024)	0.052	(0.023)
Math	-0.396	(0.073)	-0.209	(0.070)	0.120	(0.016)	0.074	(0.016)
Chem. & Physics	-0.287	(0.085)	-0.037	(0.082)	0.071	(0.019)	0.011	(0.019)
Psychology	-0.145	(0.098)	0.069	(0.094)	0.095	(0.022)	0.043	(0.021)
Social Science	-0.180	(0.064)	-0.111	(0.061)	0.020	(0.015)	0.003	(0.014)
Mgmt. & Mkting	0.213	(0.087)	0.339	(0.083)	-0.022	(0.020)	-0.052	(0.019)
Econ., Fin., Acct.	-0.278	(0.091)	-0.018	(0.088)	0.070	(0.021)	0.007	(0.020)

Note: The analysis is at the course level. The estimates are from 951 courses where $\gamma_j > 0$ and the course capacity constraint does not bind.

1. our modified EM algorithm for recovering the parameters of the grade process and conditional probabilities of a student being each unobserved type,
2. the fixed point algorithm we use when estimating the structural utility parameters of the students,

3. and our method of solving for counterfactual choice probabilities in the presence of capacity constraints.

C.1. *Modified EM algorithm*

We first describe our estimation procedure in the presence of unobserved heterogeneity. First, consider the parameters of the grade process and the course choices. With unobserved heterogeneity, we now need to make an assumption on the distribution of η_{ij}, the residual in the grade equation. We assume that the error is distributed $N(0,\sigma_\eta)$. In theory, one could use the structural choice likelihood in Equation (23) to capture the likelihood of making observed course choices; however, maximizing Equation (23) at every iteration of the EM algorithm is computationally infeasible. Instead, we construct an alternative course choice likelihood function based on a flexible analog of the structural model. For the reduced-form choice problem, we abstract from the bundling of courses, treating each course choice as its own decision problem. To facilitate computation, at points, we break down the problem into the probability of taking a course from department k and then the probability choosing the specific course j:

$$p_{ijk} = p_{ik} p_{ij|k}$$

We specify the reduced-form payoff of taking class j as:

$$v_{ij} = (\phi_1^* + w_i \phi_2^*) g_{ij}(\gamma_j^N, \theta_{j(k)}^N, X_i) + \delta_{0j}^* + w_i \delta_{1j}^* + Z_{1i} \delta_{2k(j)}^* + Z_{2ij} \delta_3^* + \epsilon_{ij}^* \tag{35}$$

where $g_{ij}(\cdot)$ represents the expected grade of student i in course j and ϵ_{ij}^* is assumed to follow a nested logit structure with nesting at the department level characterized by ν. The full set of choice parameters is then $\varphi = \{\phi^*, \delta^*, \nu\}$. Note that although we will not be interpreting the estimates of φ, the structure of utility in Equation (35) is very similar to the structure in Equation (9).[30] This ensures that the conditional type probabilities from this specification are appropriate for classifying students for the estimation of Equation (9).

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[30] The structure of utility in Equation (35) differs from the structure in Equation (9) in three ways: First, Equation (35) does not subtract γ_j from expected grades. Second, Equation (35) assumes nested logit preference shocks, while Equation (9) assumes independent Type 1 extreme value errors. Finally, Equation (35) assumes that contemporaneous choices are independent, while Equation (9) models students choosing bundles of courses simultaneously.

Let φ represent the parameters of this flexible choice process. The integrated log likelihood is then:

$$\sum_i \ln \left(\sum_{s=1}^{S} \pi_s \mathcal{L}_{igs}\left(\theta, \gamma\right) \mathcal{L}_{ics}\left(\varphi\right) \right) \tag{36}$$

where $\mathcal{L}_{igs}\left(\theta, \gamma\right)$ and $\mathcal{L}_{ics}\left(\varphi\right)$ are the grade and course choice likelihoods, respectively, conditional on i being of type s.

We iterate on the following steps until convergence, where the mth step follows:

1. Given the parameters of the grade equation and choice process at step $m-1$, $\{\theta^{(m-1)}, \gamma^{(m-1)}\}$ and $\{\varphi^{(m-1)}\}$ and the estimate of $\pi^{(m-1)}$, calculate the conditional probability of i being of type s using Bayes's rule:

$$q_{is}^{(m)} = \frac{\pi_s^{(m)} \mathcal{L}_{igs}\left(\theta^{(m-1)}, \gamma^{(m-1)}\right) \mathcal{L}_{ics}\left(\varphi^{(m-1)}\right)}{\sum_{s'} \pi_{s'}^{(m)} \mathcal{L}_{igs'}\left(\theta^{(m-1)}, \gamma^{(m-1)}\right) \mathcal{L}_{ics'}\left(\varphi^{(m-1)}\right)} \tag{37}$$

2. Update $\pi_s^{(m)}$ using $\left(\sum_{i=1}^{N} q_{is}^{(m)}\right)/N$.
3. Using the $q_{is}^{(m)}$s as weights, obtain $\{\theta^{(m)}, \gamma^{(m)}, \varphi^{(m)}\}$ by maximizing:

$$\sum_i \sum_s q_{is}^{(m)} \left(\ln\left[\mathcal{L}_{igs}\left(\theta, \gamma\right)\right] + \ln\left[\mathcal{L}_{ics}\left(\varphi\right)\right]\right) \tag{38}$$

To facilitate computation, the maximization step (step 3) is conducted in stages. Denote as $f(g_{ij}, \gamma_j^N, \theta_{k(j)}^N)$ the likelihood of observing g_{ij} given the parameters γ_j^N and $\theta_{k(j)}^N$. Denote as $\varphi(!A)$ φ absent the Ath component. Finally, denote as d_{ij} an indicator for whether i chose course j, as d_{ijk} an indicator for whether i chose course j in department k, and as d_{ik} an indicator for whether i's choice was in department k. Maximization then proceeds as follows:

1. For each department $k \in K$, taking φ as given, choose γ_j^N and θ_k^N to maximize:

$$\sum_i \sum_{j \in k} d_{ijk} \left(\ln[f(g_{ij}, \gamma_j^N, \theta_k^N)] + \ln[p_{ij|k}(\gamma_j^N, \theta_k^N, \varphi)] \right) \tag{39}$$

2. Taking γ_j^N, θ_k^N, and $\varphi(!\phi^*, !\delta_3^*)$ as given, choose ϕ^* and δ_3^* to maximize:

$$\sum_i \sum_j d_{ij} \ln \left[p_{ijk} \left(\gamma_j^N, \theta_k^N, \varphi(!\phi^*, !\delta_3^*), \phi^*, \delta_3^* \right) \right] \tag{40}$$

3. For each department $k \in K$, taking γ_j^N, θ_k^N, and $\varphi(!\delta_0^*)$ as given, choose δ_{0j}^* (relative to one course in each department) to maximize:

$$\sum_i \sum_{j \in k} d_{ijk} \ln \left[p_{ij|k} \left(\gamma_j^N, \theta_k^N, \varphi(!\delta_{0j}^*), \delta_{0j}^* \right) \right] \tag{41}$$

4. Taking γ_j^N, θ_k^N, and $\varphi(!\delta_1^*, !\delta_2^*, !\nu)$ as given, choose $\delta_{1j(k)}^*$, $\delta_{2j(k)}^*$, and ν to maximize:[31]

$$\sum_i \sum_k d_{ik} \ln \left[p_{ik} \left(\gamma_j^N, \theta_k^N, \varphi(!\delta_1^*, !\delta_2^*, !\nu), \delta_1^*, \delta_2^*, \nu \right) \right] \tag{42}$$

The advantage of this sequential strategy is that it limits the number of parameters being estimated at each stage and limits the number of times that the 1,003 choice probabilities are calculated for each individual. Further, when the 1,003 choice probabilities are calculated within the maximization routine at step 2, the number of parameters over which we are maximizing is limited.

Once the algorithm has converged, we have consistent estimates of $\{\theta, \gamma, \varphi\}$ and the conditional probabilities of a student being of each type. We can use the estimates of q_{is} as weights to form the average type probabilities of students of year in school l in class j to then estimate the parameters of the study process in (20). Finally, we use the estimates of q_{is} as weights in estimating the structural choice parameters using (23).

C.2. *Fixed-point algorithm*

We now describe our fixed-point algorithm used in each calculation of the student choice likelihood. Let $\tilde{\Theta} = \{\delta_{1k(j)}, \delta_{2k(j)}, \delta_3, \phi_0, \phi_1\}$ represent choice parameters other than δ_{0j}, let S_j^d represent the share of students choosing course j in the data, and let $S_j\left(\delta_{0j}, \tilde{\Theta}\right)$ represent the predicted share of students choosing course j as a function of δ_{0j} and other choice parameters. Given a new guess of $\tilde{\Theta}$, we use the δ_{0j}s from the previous guess $\delta_{0j}^0(\tilde{\Theta})$

[31] At this step, we also recover the δ_{0j}^*s for the normalized courses in each department from step 3.

and calculate $S_j\left(\delta^0_{0j}, \tilde{\Theta}\right)$. The mth iteration of the fixed-point problem updates δ^m_{0j} using:

$$\delta^m_{0j} = \delta^{m-1}_{0j} + \ln\left[S^d_j\right] - \ln\left[S_j\left(\delta^{m-1}, \tilde{\Theta}\right)\right] \tag{43}$$

Given the δ^m_{0j}, we update $S_j\left(\delta^m_{0j}, \tilde{\Theta}\right)$. These steps are repeated until the predicted and actual enrollment shares are arbitrarily close.

C.3. *Counterfactuals in the presence of capacity constraints*

Embedded within each counterfactual are each student's conditional choice probabilities. To ensure that capacity constraints are not exceeded, we work backward based on the registration ordering given by the timestamps (see Section B.3). We proceed in the following manner for each student n, where n refers to the ordering based on the student's timestamp:

1. Calculate the choice probabilities for student n over the courses where the student has met the prerequisites and where the course is not already filled.
2. If adding the choice probabilities to the probabilities of the previous $n-1$ students does not cause any of the classes to exceed the course capacity, proceed to the next student.
3. If one or more of the courses exceeds capacity in step 2, identify the class where adding n's probability causes the capacity constraint to be exceeded by the greatest amount. Label this excess capacity c and the choice probability p. Note that $c < p$, as the course previously had open space.
4. Assign the probability that the course identified in step 3 is in n's choice set as $1 - \frac{c}{p}$. Take the choice probabilities when this course is in the choice set, multiply them by $1 - \frac{c}{p}$, and add them to the number of enrollees in each course. This ensures that the identified course will be exactly filled. Repeat step 1 for student n, taking into account that all probabilities from the new choice set will be multiplied by $\frac{c}{p}$ and where the identified course is no longer in n's choice set.

The algorithm ensures that any capacity-constrained courses are exactly filled, with filled courses no longer available to individuals with later timestamps.

APPENDIX D: EXTENDING THE SUPPLY-SIDE MODEL TO INCLUDE PROFESSOR EFFORT – ONLINE

In this section, we extend our model of professor choices to include efforts exerted to affect enrollment directly. In the section, we

1. show how effort affects the course payoffs,
2. show how professor effort is measured,
3. show how the extension affects the modeling and estimation of the professor's objective function,
4. present estimates of the parameters of the professor's objective function and the equilibrium counterfactuals with the extended model, and

We extend our model to allow professors to directly influence demand for courses by exerting effort, in addition to setting grading parameters. We decompose the course fixed effect in the student's utility function, δ_{0j}, into intrinsic demand, δ^*_{0j}, and the effort of the professor, τ_j:

$$\delta_{0j} = \rho\tau_j + \delta^*_{0j} \tag{44}$$

where ρ measures how professor effort translates into course utility. Two major complications arise in extending the model. First, clean measures of professor effort are difficult to obtain from administrative data. We use student responses from the evaluation data and purge potentially contaminating endogenous effects to arrive at a viable measure. Second, we do not have a way to recover ρ. As a result, we estimate the model under different assumed values of ρ.

D.1. *Measuring Professor Effort*

Outside of a time-use survey or rigidly prescribed schedules (for example, unionized manufacturing jobs), it is often difficult to gather data on worker effort. For professors, whose time could have multiple uses (for example, data analysis or writing an article/book could yield benefits for both research and teaching), even direct measures of inputs become problematic. Instead, we use information about students' receptivity to the professor's teaching to capture a measure of the professor's effort, τ. Of the twenty questions in the evaluations, we focus on three with students answering on a five-point Likert scale:

TABLE D.1

CORRELATION AMONG CLASS EVALUATION AND GRADES THAT STUDENTS EXPECT TO RECEIVE

	Expected Grade	Q09	Q13	Q19	(Q09+Q13+Q19)/3
Expected Grade	1.0000				
Q09	0.2132	1.0000			
Q13	0.2392	0.7364	1.0000		
Q19	0.2192	0.5878	0.7387	1.0000	
(Q09+Q13+Q19)/3	0.2518	0.8575	0.9291	0.8818	1.0000

Note: Expected Grades are grades that students expect to receive (as indicated on class evaluations). Questions receive responses on the evaluation on a 5-point Likert scale and are worded as follows: Did the instructor (1) present the material effectively – Q09, (2) stimulate interest in the subject – Q13, and (3) stimulate you to read further beyond the class – Q19?

- Q09: Did the professor present class materials effectively?
- Q13: Did the professor stimulate your interest in the subject?
- Q19: Did the professor stimulate you to read further in the subject beyond the class?

We average these three measures to create a student i's perception of professor effort in course j, $\tau_{ij}^{(1)}$.

There are at least two issues with using this average as a measure of effort. First, as shown in Table D.1, professors who give high grades may receive better evaluations because of the high grades rather than because of the effort exerted by the professor.[32]

We are able to purge the effort measure of grade effects because the evaluation data contain the expected grade of each student filling out the evaluation. Using evaluation data across multiple semesters (fall 2011 to spring 2013), we regress $\tau_{ij}^{(1)}$ on a course fixed effect and dummy variables for each expected grade. The course fixed effect, $\tau_j^{(2)}$, gives us a measure of effort purged of the effect of offering high grades. The results from this regression are given in the top half of Appendix Table D.2 and show that higher expected grades are associated with better evaluations.

The second issue is that, conditional on the same amount of effort, some instructors may be better in the classroom than others. Since we are interested in discretionary effort rather than fixed instructor ability, we purge our effort measure of instructor effects, using multi-

[32]See Insler et al. (2021), Nelson and Lynch (1984), and Zangenehzadeh (1988), who also find this positive relationship.

TABLE D.2

PROFESSOR EFFORT RESIDUALIZATION & REGRESSION OF EFFORT MEASURE ON LOG ENROLLMENT

	Coef.	Std. Err.
Expected Grade:		
A	0.9519	(0.0358)
B	0.7709	(0.0358)
C	0.5336	(0.0361)
D	0.2933	(0.0370)
log(class size)	-0.0901	(0.0082)

Note: The dependent variable in the top half is the average response to questions 9, 11, and 13 from the evaluation data. Regressors include class times semester fixed effects. The dependent variable in the bottom half is the average response to the three evaluation question minus the grade effects estimated in the top half of the table. Regressors include professor and semester fixed effects. Sample size for the top panel is 150,303 and 4,075 for the bottom panel. Both use evaluation data from Fall 2011 to Spring 2013.

ple semesters of the evaluation data. To do so, we collapse the multi-semester data to the class-year-semester level and regress $\tau_j^{(2)}$ on an instructor fixed effect (taking advantage of the panel nature of the data) and log enrollment. The regression results in the bottom half of Appendix Table D.2 show that the coefficient on log enrollment is large and negative, implying that perceived quality of the class is lower when enrollment is high given the same instructor. We then subtract the instructor fixed effect but leave in the effect of log enrollment: effort should be correlated with log enrollment if it is responding to characteristics of the class. We then standardize this variable to have mean zero and standard deviation one. It is this standardized variable that we use for τ_j.

For estimation of the professor model with professor effort, we impose additional restrictions on the sample. Here, we need professors to have at least two measures of effort across fall 2011 to spring 2013, in addition to having one of those measures for our semester of analysis, fall 2012. This reduces our sample to 748 courses.

D.2. *Model Extension and Estimation*

Professors choose their effort level, τ_j, in addition to grading policy parameters β_j and γ_j. The professor has an ideal effort level e_{3j}, which depends on his or her observed and unobserved characteristics. Then, our equilibrium objects, expected grades, probability of student i enrolling in a class, and log enrollments, are now defined as $\overline{G}_j(\beta,\gamma,\tau)$, $P_{ij}(\beta,\gamma,\tau)$, and $\ln[E_j(\beta,\gamma,\tau)]$, respectively. The professor's objective function now has an extra term to maximize:

$$V_j(\beta,\gamma,\tau) = -\left(\ln[E_j(\beta,\gamma,\tau)] - e_{0j}\right)^2 - \lambda_1\left(\overline{G}_j(\beta,\gamma,\tau) - e_{1j}\right)^2 \\ -\lambda_2(\gamma_j - e_{2j})^2 - \lambda_3(\tau_j - e_{3j})^2 \tag{45}$$

where $e_{3j} = W_{3j}\Psi_3 + \varepsilon_{3j}$. Solving for ideal effort proceeds similarly to the procedure in the main model. There is an extra first-order condition:

$$0 = -\left(\ln[E_j(\beta,\gamma,\tau)] - e_{0j}\right)\frac{\partial \ln E_j}{\partial \tau_j} - \lambda_1\left(\overline{G}_j(\beta,\gamma,\tau) - e_{1j}\right)\frac{\partial \overline{G}_j}{\partial \tau_j} - \lambda_3(\tau_j - e_{3j}) \tag{46}$$

In recovering Ψ_0, Ψ_2, and λ_2, we create our instruments with β^0, γ^0, and τ^0.

To estimate λ_3 and Ψ_3, we take Ψ_0 as given and eliminate λ_1 using using Equations (29) and (46) to solve for τ_j:

$$\tau_j = (1/\lambda_3)C_j\left(\ln[E_j] - \Psi_0\right) + \Psi_3 + \varepsilon_{3j} \tag{47}$$

where C_j is given by:

$$C_j = \left[\frac{\partial \ln[E_j]}{\partial \beta_j}\frac{\partial \overline{G}_j}{\partial \tau_j} \Big/ \frac{\partial \overline{G}_j}{\partial \beta_j}\right] - \frac{\partial \ln[E_j]}{\partial \tau_j} \tag{48}$$

We then instrument for $C_j\left(\ln[E_j] - \Psi_0\right)$ by evaluating C_j and $\ln[E_j]$ at the common grading and effort policies, β^0, γ^0, and τ^0. Recovery of Ψ_1 and λ_1 proceeds as before.

D.3. *Professor preference estimates and equilibrium counterfactuals under different values of ρ*

We estimate the professor preference parameters in this extended model $\rho = 0.05$ and $\rho = 0.2$. Table D.3 shows the estimates of professor preferences (shown in Table XI) at alternate values of ρ. Table D.4 shows the general equilibrium counterfactual results (shown in Table XIV) at alternative values of ρ. Allowing for professor endogenous effort mutes the effects of the grading policy but does so only slightly. For example, at $\rho = 0.2$ average class for STEM courses is 99.5, or about one student less than when professors could not adjust their effort.

TABLE D.3

ESTIMATES OF PROFESSOR PREFERENCES AT ALTERNATIVE ρ VALUES

	$\rho = 0.2$		$\rho = 0.05$		$\rho = 0.2$		$\rho = 0.05$	
	Ideal grade				Ideal workload			
λ	2.933	(0.448)	2.898	(0.434)	48.167	(5.025)	46.874	(4.675)
Constant	2.627	(0.120)	2.619	(0.119)	0.275	(0.038)	0.277	(0.038)
Upper-Level Class	0.436	(0.065)	0.440	(0.065)	-0.074	(0.038)	-0.075	(0.038)
Upper-Level X STEM	-0.050	(0.069)	-0.052	(0.069)	0.073	(0.021)	0.074	(0.021)
Grad. Student	-0.009	(0.050)	-0.008	(0.051)	0.008	(0.014)	0.008	(0.014)
Lecturer	0.112	(0.052)	0.114	(0.053)	-0.012	(0.013)	-0.013	(0.013)
Asst. Prof.	-0.106	(0.054)	-0.105	(0.054)	0.035	(0.015)	0.035	(0.015)
Tenured Prof.	-0.070	(0.047)	-0.069	(0.047)	0.007	(0.012)	0.007	(0.012)
Female Prof.	0.102	(0.032)	0.102	(0.033)	0.002	(0.009)	0.002	(0.009)
Female Prof. X STEM	-0.056	(0.065)	-0.056	(0.065)	-0.002	(0.018)	-0.002	(0.018)
Regional Studies	-0.015	(0.074)	-0.015	(0.074)	0.050	(0.021)	0.050	(0.021)
Communications	0.086	(0.069)	0.087	(0.069)	0.004	(0.019)	0.004	(0.019)
Education & Health	0.218	(0.068)	0.218	(0.069)	-0.011	(0.019)	-0.011	(0.019)
Engineering	-0.043	(0.082)	-0.041	(0.082)	0.206	(0.024)	0.205	(0.024)
Language	-0.057	(0.066)	-0.057	(0.066)	0.042	(0.018)	0.042	(0.018)
English	-0.223	(0.082)	-0.224	(0.082)	0.094	(0.024)	0.094	(0.024)
Biology	0.016	(0.129)	0.022	(0.129)	0.035	(0.031)	0.033	(0.030)
Math	-0.331	(0.081)	-0.328	(0.081)	0.094	(0.021)	0.092	(0.021)
Chem. & Physics	-0.159	(0.106)	-0.156	(0.106)	0.024	(0.026)	0.022	(0.026)
Psychology	-0.023	(0.101)	-0.020	(0.101)	0.055	(0.026)	0.053	(0.026)
Social Science	-0.138	(0.064)	-0.137	(0.064)	0.023	(0.018)	0.023	(0.018)
Mgmt. & Mkting	0.308	(0.088)	0.310	(0.088)	-0.042	(0.024)	-0.043	(0.024)
Econ., Fin., Acct.	-0.075	(0.101)	-0.071	(0.101)	0.008	(0.026)	0.006	(0.026)
	Ideal log enrl				Ideal prof. effort			
λ	1.000		1.000		0.528	(0.073)	0.252	(0.064)
Constant	5.196	(0.662)	5.173	(0.639)	-0.347	(0.061)	-0.179	(0.059)
Upper-Level Class	-1.385	(0.528)	-1.372	(0.511)				

Note: Ideal enrollment λ is normalized to equal 1. The base for rank is "Instructor," who are adjunct instructors contracted by the course/semester. "Lecturers" are offered longer-term contracts and are salaried.

TABLE D.4

COUNTERFACTUAL SCENARIOS IN GENERAL EQUILIBRIUM AT ALTERNATIVE ρ VALUES

		Class Size		STEM Enrollment Share		
	ρ	STEM	Non-STEM	Overall	Female	Male
Baseline		82.6	45.0	41.8%	34.6%	49.5%
Grade Around 3$^{\diamond}$	0	100.6	37.9	50.9%	45.1%	57.2%
	0.05	100.5	37.9	50.9%	44.9%	57.3%
	0.2	99.5	38.3	50.4%	44.4%	56.8%

Note: $\diamond$: "Grade Around 3" adjusts the mean grade in all courses to a B, affecting both men and women. Professors change their grading strategies based on student responses to changes in preferences and abilities for the general equilibrium analysis.