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I Feel Like Shooting Myself in the Face after taking this God-forsaken Class: The Effects of RateMyProfessors.com on University Course Registration

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Abstract

This study examines the effects of RateMyProfessors.com professor ratings on student decisions related to the Fall 2012 course registration period. Statistical techniques including ordinary least squares regression and survival analysis are employed to model course registration. We operate within an applied economic framework in which the supply and demand for course section seating capacity do not fully equalize due to various physical constraints as well as the existence of imperfect information. By further understanding the factors underpinning student decision making, university departmental management is better able to estimate changes in student demand. RateMyProfessors.com reported measures of overall quality, easiness, and attractiveness are determined to be positively related, in varying magnitude, to course enrollment.

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Keywords: Higher Education, Enrollment

1 Introduction

Each month, more than 4 million college students logon to RateMyProfessors.com (RMP) to research various universities and each institution's individual professors. The controversial website provides college students with reviews of more than 8,000 colleges and universities and their combined more than 1.7 million professors throughout the United States, Canada, and the United Kingdom [1]. On the site, students can rate

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academic professionals and universities based on a variety of subjective categories and post user-generated comments about their overall experience in courses they have taken.

RMP encourages users, who self-select onto the site, to rate professors on a scale of one to five based on the instructor's "helpfulness," "clarity," and "easiness." The site further allows users to interpret the attractiveness of their professor by indicating on a binary scale the "hotness" of the instructor. These data are then displayed on each professor's corresponding university's RMP webpage and are available for users of the site to view free of charge.

RMP's staff moderates user comments for indecency and provides limited controls, such as requiring users of the site to establish an account with a unique username and password in order to submit rating data to discourage irresponsible posting. However, it is hard to distinguish with any measure of reliability if students who post ratings on the site represent a valid sample of classroom attendees or simply reflect the upper and lower bounds of student satisfaction with classes. In other words, the majority of ratings may only reflect the attitudes of students who praise and adore their professors on one end of the spectrum and students who bear grudges against them on the opposite end. Regardless of the reliability of the techniques employed by RMP, the site's analytics of more than 4 million page views per month provides some evidence that at least some students view the data published by RMP and may consider it when selecting courses. This rate of usage raises two important questions of research: Do students significantly utilize RMP as a measure of preference when selecting courses, and, if so, what steps can universities take to ensure more reliable information concerning teacher performance is available to students?

2 Preliminary Notes

2.2 Literature

Research on the relationship between RMP's influence on student preferences for certain professors and the methodology a student employs when selecting college courses is limited in its scope and generally relates to correlation studies between ratings on RMP and end-of-semester student evaluations of teaching (SET). Many universities have a long tradition of utilizing SET data to construct methods to improve classroom instruction and make decisions regarding faculty promotions and tenure considerations [2]. Coladarci and Kornfield summarize literature which provides evidence of the validity of SET data in most institutions and model the relationship between SET data and ratings posted on RMP [3]. The authors' model finds positive, but somewhat weak correlations between a professor's "overall" and "easiness" values on RMP and comparable responses to questions on SET surveys. Their research concludes two policy implications: (1) Institutions should encourage more students to engage in *responsible* posting on RMP; (2) Universities should consider making SET data public as it would make better quality information available to students. Although publicizing SET data is largely a contentious subject among academic professionals, as some faculty members may object to such a policy out of privacy concerns, Coladarci and Kornfield argue:

"[P]rivacy is a thing of the past in the age of RMP, MySpace, and the like. Moreover, by not making SET data available to students, the negative consequence is greater still:

Students will rely on what is publically available. In light of our results, this inevitably will mischaracterize the true standing of many instructors as measured by formal student evaluations of teaching."

Additional research demonstrates strong positive correlations between a professor's overall quality score on RMP and their individual "easiness" and "hotness" indexes and casts doubt on the reliability of RMP's "overall" rating as an accurate measure of faculty effectiveness [4]. A separate study shows that professors perceived as attractive not only generate higher overall scores on RMP but also receive higher SET evaluations [5].

A recent study from the University of Wisconsin Oshkosh found limited evidence that students utilize RMP data when selecting sections [6]. Burnett utilized the campus' Fall 2012 enrollment data and finds evidence to support that RMP's "easiness" score and time of day a class is held helps explain enrollment patterns, while RMP's "overall," "clarity," and "hot" ratings have little effect. However, her study presents a model that fails to account for many other considerations students may have when selecting courses.

2.2 Methodology

If students indeed select sections based on preferences for professors garnered from RMP, then it is important to distinguish if a professors "helpfulness" and "clarity" ratings influence their decisions to a greater magnitude than factors such as "easiness" and "hotness." If the former is the case, then there exists little cause for alarm. However, if the latter holds true, then the implications could be negative: the university will produce graduates who potentially sacrifice quality educations in favor of the path of least resistance.

Many factors potentially dictate student enrollment patterns. Our model's null hypothesis assumes that the supply of available seats will match the demand for seats given that administrative expectations of the demand for seating capacity perfectly predict the future, homogeneity of professors, and no unavoidable constraints such as faculty availability, lumpiness[5] in course section sizes, availability of suitable classrooms during peak hours etc. In other words, observing that a section fills quickly does not by itself imply that a professor or course is popular. It could mean that the demand for the course was under-estimated or that some constraint on time, space, or faculty availability was binding.

We test this initial assumption by employing two different statistical techniques on a cross-sectional dataset comprised of Armstrong State University's (ASU) Fall 2012 course offerings, following the close of the university's mandatory advisement period. First, employing ordinary least squares (OLS), we estimate the behavior of enrollment patterns as follows:

$$E_i = \alpha + \beta X + \lambda Y + \delta Z + \psi U + \varepsilon \qquad (1)$$

where E_i represents the ratio of students enrolled in an individual course to the university-imposed capacity of students allowed in the course (the percent of

[5]By lumpiness we mean that an additional section will not be created for a small number of students. If every class has a capacity of forty students and forty-two wish to take the course, supply cannot exactly meet demand because sections come in "lumps."

capacity filled). The subsequent vectors on the right hand side of the equation control for university space constraints, faculty constraints and clairvoyance failures of department heads, individual perceived quality of a particular course's professor, and transaction costs incurred by individual students during the registration period. Each vector gives way to a variety of individual independent variables intended to control for known departures from the initial assumption that classes will fill identically under conditions of perfect information, homogeneous professors, non-lumpy inputs, and no space constraints. We define these variables in Table 1.

One potential flaw in an OLS approach is that each course observed contains a maximum student capacity that might be exceeded if such capacity restrictions were not imposed and, thus, poses downward-bias pressure on the entirety of the

Table 1: Independent Variable Categories

Space Constraints (X)	
Core type	Specific classes in varying categories all students are required to take such as English Composition or U.S. History. Any class that fulfills "Core A" through "Core E" is flagged as such with a dummy variable.
Time of day	The hour in which the course begins (8 a.m. to 7 p.m.) recorded as a series of binary terms.
Clairvoyance (Y)	
Departments	A dummy variable term that captures the specific department responsible for scheduling the observed section.
Quality (Z)	
Helpful	Each course instructor's respective RMP "Helpfulness" rating
Clarity	Each course instructor's respective RMP "clarity" rating
Easy	Each course instructor's respective RMP "easiness" rating.
Hot	Whether or not RMP rated the course's instructor as "hot."
Urgency (U)	
Total Cap	The total amount of seats available for multiple sections of the same course.

model. For example, an economics section that reaches its capacity will force students initially interested in taking it to substitute an alternate course in its place. The student may select the substituted course based *less* on our model's variables of interest and more so on more limited choices that are less in alignment with the student's actual preferences. However, this bias should be minimized because of the date (see data collection methods' section) of the cross section.

Consequently, to provide better evidence for the effects of our variables of interest, we also employ a Cox proportional hazards survival model using the same independent variables as our OLS approach [7]. Unlike an OLS approach which observes a snapshot of data, a hazard model allows us to explicitly control for time by using the number of days each section spent below 100 percent of capacity as the dependent variable, while censoring those observations that never reach their capacity within the observation period. Hazard models allow our results to automatically minimize biases that can occur when observing long registration periods during which each section can be considered constantly at risk of filling completely. Static models inherently fail to control for such risk [8].

2.2.1 Space Constraints

Space constraints are perhaps the greatest obstacle university department heads face when scheduling each semester's course load. ASU breaks its core curricula into five specific categories—A through E—in order to prescribe courses required for all students enrolled at the university. Such courses include subjects in the languages, mathematics, social and natural sciences, and ethics disciplines. Certain core classes, such as college algebra and freshman English composition are anticipated as more popular among incoming freshmen than upper-classmen. Also many students tend to devote a large part of their freshman and sophomore years completing state mandated graduation requirements.

Another consideration is that incoming freshmen tend to register later in the enrollment window than current students, and since a new student's acceptance to the university is sporadic, we expect their enrollment behaviors to occur in less predictable waves and often closer to the start of the semester; our hazard model should serve as a better indicator of such behavior. An additional physical constraint stems from courses in science disciplines. These sections often require lab space that is more limited than larger lecture halls and scheduling is limited by the availability of these rooms. While one would typically expect the available space for labs to eventually converge on the demand for that type of space, the constraint on the number of science labs was common knowledge at the time of the data collection. To further account for limited space, we also control for the hour of the day during which each observed section is taught. Since all students have heterogeneous preferences—some students may prefer sections that start early so they can work in the afternoon, while others might like to sleep in and take afternoon classes—we offer no speculation of the effect of the time of day on enrollment.

2.2.2 Clairvoyance

Our department variables act as controls for the university department responsible for scheduling each individual section. Varying experience and luck of department heads at guessing the quantity of seats demanded in each course when laying out the schedule, as well as departmental staffing issues, may both have a tendency to deviate the model's results from our underlying assumption that with perfect information, (among other things) classes would fill equally.

2.2.3 Urgency

We include the total cap variable in the urgency vector as a transaction-cost control for how prudent a student might find it to enroll in a course early in the registration period. For example, if a specific course has more than one section—each with varying capacities—then a student may find it unnecessary to register early. Therefore, we anticipate a section with higher total caps to reflect lower enrollment rates.

2.2.4 Quality

The RMP reported measures of professor helpfulness, clarity, easiness and attractiveness may influence students to substitute between sections or courses in order to find a higher quality professor, gain an easy 'A,' or draw some measure of utility from a physically attractive professor. Core classes and upper level inter-major electives are common examples of course types that may be strongly affected by varying perceptions of professor quality. This measure may have significantly varied impacts between courses in the core and courses that are more geared toward specific majors for two reasons: The first being courses in the core have much more flexibility in choice of professor than do major-related courses; secondly, major-related courses might tend to suffer from an inherent bias, being as they are generally more difficult than core classes, despite ratings produced by RMP.

To account for such varying effects between course types, we categorize our observations into separate model specifications to gauge quality ratings on specific course types. The first utilizes all course observations in the dataset. In an effort to isolate quality effects on heterogeneous course types, the second and third models subdivide observations into core and non-core observations respectfully, and eliminates observations in which any degree track explicitly required the course and no substitutable section was offered—that is, courses in which any particular student had no choice in professor and simply required the student to enroll in the section out of necessity.

We expect all of our quality variables to have an observable positive effect on course enrollment. Although we expect “helpfulness,” “clarity,” and “easiness” to influence course choice, we expect the latter to have a greater impact on courses characterized as part of ASU’s core curriculum. We offer no alternative hypothesis on the effect of “hotness.”

2.3 Data Collection Methods

Our course-specific data are collected from Armstrong State University’s (ASU) student registration portal. Data used in the OLS model represents ASU’s total enrollment as of April 22, 2013—the Monday following the end of the university’s mandatory advisement period. We specifically observe this date for two reasons: (1) all current students at the university had at least one weekend to register, and (2) doing so will allow for the observation of quality variable effects, while minimizing biases caused by students selecting sections based on limited choice. Data for our hazard model differs from our OLS data in that the number of days for the course to fill completely is tracked as well as whether the course ever filled to its capacity.

ASU is a relatively small public university located in Savannah, GA consisting of approximately 7500 students with a focus on undergraduate level Liberal Arts, Science, and Medical training. 91 percent of the university’s students are undergraduates, 65 percent of whom are enrolled full-time. Females make up 66 percent of the university population and 87 percent of students are Georgia residents. The average enrollee’s age was 24.3 years at the time of this study[10].

ASU’s total enrollment data includes roughly 1800 sections. These data were carefully scrubbed in order to remove observations with disparate registration motivations that would distort the patterns present for the rest of the university. Courses other than those falling under the colleges of Science and Technology or Liberal Arts were omitted due to the highly structured and career specific natures of degrees such as Nursing where graduation paths are methodologically formulated, leaving students with little flexibility in course choice. Graduate-level courses are omitted from the dataset as well as courses designed as internships, seminars, research studies, freshman orientations, and sections that have maximum caps of ten students or less, as these courses are small in number and are generally filled by students who are specially selected by their professors. Also, classes held at the university's satellite "Liberty Center" campus are removed because of the remote campus' limited choice in curriculum and differing substitutability of professors. Online courses are also removed from the dataset due to absence of values for the time of day variables. Sections with professors who have no RMP rating are removed as well. After these constraints were imposed, 493 total observations remained. These data are described in Table 2. Unlike Burnett, our data set does not immediately eliminate courses with only one section in order to avoid biases created from a lack of choice. Keeping those sections allows us to capture substitution effects between courses. Sections which are likely to fill due to a lack of student choice are otherwise controlled for by flagging courses in which insufficient choice exists. Sections considered to lack choice were those which are required for all students such as English Composition or courses in which only one section exists that are explicitly required by any major-track.

Table 2: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Helpfulness	483	3.95	0.78	1	5
Clarity	483	3.85	0.75	1.4	5
Overall	483	3.88	0.76	1.2	5
Easy	483	3.28	0.77	1	5
Hot	483	0.33	0.47	0	1

Data for the "helpfulness," "clarity," "easiness," and "hotness" variables are transposed from RMP's ASU webpage[11]. Each professor's rating in the four categories is compiled and attached to the appropriate observed section. Consequently, a professor who instructs four courses will subsequently have his or her rating reported in four separate observations. RMP describes its rating system as follows[6]:

Helpfulness - Is this professor approachable, nice and easy to communicate with? How accessible is the professor and is he/she available during office hours or after class for additional help? 5 = Helpful 1 = Useless
Clarity - How well does the professor teach the course material? Were you able to understand the class topics based on the professor's teaching methods and communication style? 5 = Crystal Clear 1 = Confusing
Easiness - Some students may factor in the easiness or difficulty of the professor or course material when selecting a class to take. Is this class an easy A? How much work needs to be done in order to get a good grade? Easiness is rated on a 5 point scale, with 1 being the hardest and 5 being the easiest. Please note this category is NOT included in the Overall Quality rating.
Hotness - Is your professor hot? Hot professors get a red chili pepper. The Hotness rating is NOT included when calculating the Overall Quality rating.

[6]RMP also reports an overall quality score. Given that a professor's "overall quality" is the average of his or her "Helpful" and "clarity" indexes, we omit "overall quality" as a control in favor of the former two indices.

The values employed by the model for the "helpfulness," "clarity," and "easiness" variables utilize the same four-point (1-4) scale derived by RMP. The model operationalizes "hotness" as a binary term with one being "hot," zero otherwise. "Overall" is an RMP-reported average of "Helpful" and "Clarity" scores. Although ratings reported to RMP are similar to Likert-scale responses, RMP itself averages the ratings together and reports them as a continuous number. While we acknowledge that quantifying Likert scales is problematic, the conversion to a continuous score is performed by RMP. Regardless of the potential issue in RMP's method, site users nonetheless observe a continuous number when formulating their perceptions of professor quality. Therefore, treating these scores as continuous data should pose no concern in the context of our models.

ASU breaks core classes into five categories—A, B, C, D, and E—which represent various areas of required disciplines all of the university's students must complete. Some courses are listed by the university as satisfying multiple core areas. Such courses are coded by the primary core area it represents. All core courses are coded with a value of one for the core discipline it reflects, including non-core, and receive a zero otherwise.

The time of day category is recorded as a series of dummy variables, where a one indicates the hour of the day when the course begins. The range of start times is between 8 a.m. and 7 p.m., with 12 p.m. being the omitted relative term. The department under which each section falls was also recorded as a list of binary terms, with English serving as the reference term.

3 Main Results

A complete list of results for both the OLS and survival model can be found in the Appendix. Tables 3 and 4 present truncated versions of the full results. Using an OLS multivariate regression yields estimates of the average marginal impact of each professor quality metric on the percentage of university-imposed seating capacity filled. Three data sets are examined with two model specifications for each and are regressed to observe varying course types. Model 1 utilizes all observations in the dataset. Model 2 limits the observation set to only courses offered as part of ASU's core curriculum in which a student has flexibility in choice. Model 3 examines only those courses that cannot be used to fulfill core requirements in which classes are either not required for any degree-track or classes that are required, but have at least two course sections available taught by different professors. Additionally each model is subdivided into two additional specifications, where "clarity" and "Helpful" indices are replaced in favor of RMP's "overall" score.

Our OLS results appear in Table 3. This analysis reveals "Easiness" to be significant at conventional levels (p-value < 0.1) in all specifications except for model 3. This result implies, as expected, that students will select core classes based on the perceived easiness of the professor much more readily than their non-core, major-related classes. "Clarity," "Helpfulness," and "Hot" fail to achieve significance at the five-percent level in any of our specifications. At first glance it seems as though students are more interested in identifying easy professors in core areas than quality faculty members. However, considering that RMP reports the average of a professor's "Helpfulness" and "Clarity" scores as an "Overall" rating as well, and that rating being the most visible index of performance displayed on the site, breaking the "Overall" RMP rating down into its component parts may actually bias our results.

Table 3: Professor Quality Metrics (OLS Model)

	All		Core		Non-Core	
Model #	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
Overall	---	0.041	---	0.086	---	0.024
	---	(1.78)	---	(2.20)*	---	(0.43)
Clarity	-0.019	---	0.004	---	0.001	---
	(-0.47)	---	(0.05)	---	(0.01)	---
Helpful	0.039	---	0.066	---	0.017	---
	(0.93)	---	(0.96)	---	(0.18)	---
Easiness	0.082	0.074	0.108	0.103	0.050	0.046
	(3.86)**	(3.59)**	(2.94)**	(2.88)**	(1.40)	(1.27)
Hot	0.061	0.050	0.050	0.039	0.060	0.056
	(1.91)	(1.54)	(0.89)	(0.68)	(1.08)	(0.99)
R^2	0.39	0.39	0.43	0.43	0.36	0.36

***, * represent significance at the 1 and 5 percent level respectively.*
Coefficients shown with t-statistics reported in parentheses.
All models use robust errors.

Table 4: Professor Quality Metrics (Cox proportional hazards model)

	All		Core		Non-Core	
Model #	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
Overall	---	1.26	---	1.88	---	1.03
	---	(1.51)	---	(2.37)*	---	(0.09)
Clarity	1.06	---	0.57	---	1.49	---
	(0.20)	---	(-1.09)	---	(0.63)	---
Helpful	1.09	---	2.93	---	0.75	---
	(0.32)	---	(2.06)*	---	(0.65)	---
Easiness	1.32	1.26	1.89	1.84	1.26	1.31
	(2.12)*	(1.74)	(1.80)	(2.63)**	(0.37)	(1.01)
Hot	1.47	1.41	1.70	1.64	2.19	2.29
	(2.32)*	(2.03)*	(1.65)	(1.56)	(2.54)*	(2.66)**

***, * represent significance at the 1 and 5 percent level respectively.*
Hazard ratios shown with z-statistics reported in parentheses.

Table 4 displays the results of our survival model. Each specification is identical to our OLS approach. Greater significance is found in "Helpful" for core classes than was found using OLS. In fact, a one point increase in "Helpful" was found to increase the hazard rate by 193 percent in core classes where students had options. "Clarity" remains insignificant, though its t-score being greater than one and its hazard ratio being well below one lead us to believe that “Overall” is the best measure of an RMP user’s expectations about the professor. Replacing “Clarity” and “Helpful” with “Overall” yields a more believable 88 percent increase in hazard from a one point increase in “Overall.”

Table 5: Correlation

	Clarity	Helpful	Easy	Hot	Overall
Clarity	1				
Helpful	0.29	1			
Easiness	0.52	0.26	1		
Hot	0.35	0.19	0.16	1	
Overall	0.93	0.32	0.57	0.40	1

“Easiness” maintains its positive effect and significance within models 1 and 2. Similar to the OLS model, “Easiness” loses its effect among non-core (major-related) classes, as reflected in model 3. This result makes intuitive sense for two reasons: First, students have personal experience with professors in their own major, so they are less likely to utilize outside information in those choices. Secondly, students may fear that easiness comes at the expense of quality – a tradeoff it is less rational to make for major-related classes.

As hypothesized, “Hot” is also found to increase the likelihood that a section fills to capacity. “Hot” gains significance at the 10 percent level or better in all specifications less model 2b. Such results lead us to reject our null hypothesis that RMP has no effect on course choice for students enrolled at Armstrong State University.

Table 6: Two Sample T-tests on Seating Capacity Levels

	High Rated Capacities			Low Rated Capacities			
	Mean	Std Dev	n	Mean	Std Dev	n	p-value
Overall	30.47	13.04	400	29.51	7.74	69	0.40
Easiness	29.33	11.82	287	32.11	13.61	159	0.03
Hot	29.25	13.27	157	30.81	11.91	326	0.21

It may occur that professor hotness and large capacity intro level courses are both caused by some lurking variable such as professor age. To ensure that this sort of bias was not present, we examined the correlations between individual course capacities and all RMP variables. No correlation was found to be over 0.1. Furthermore, the distribution of course capacities was split on high and low values of “Overall,” “Easiness,” and “Hot.” The average capacities of sections with high RMP ratings were then t-tested versus the average capacities of sections with low RMP ratings to search for evidence of a difference in means. Any value greater than three constitutes “High Rated” for “Overall” and “Easiness.” “Low Rated” is any observation with a rating less than three. A high rating for “Hot” is simply all professors rated as hot while a low rating consists of all professors not rated as such. The results of these tests appear in Table 6. The only mean that is statistically different among high and low RMP rated sub-samples is that of “Easiness.” In other words, on average, professors with low “Easiness” ratings in this sample teach courses with larger registration capacities. However, this will only matter if the registration capacity of the class affects how fast its percentage of capacity filled increases. We expect that if this effect exists, it will be minimized by the relatively homogeneous course capacities at ASU. Courses making it through our stipulations for entry into the dataset range between 12 and 100 seats with a mean of 30.30 and a standard deviation of 12.37. It should be reiterated that no courses were removed from our sample for being too large. ASU is simply a small university, and therefore has much smaller variation in its course capacities than large state schools. To further rule out that courses with larger capacities were taking longer to fill as a percentage of capacity, regressions were rerun using the same OLS and Cox models on all 483 observations, but with the seating capacity of each observation as the only independent variable. Neither model achieved a p-value of below 0.5. This result leads us to believe that standardizing our observations by observing a percentage of total capacity filled for each does not bias our results.

4 Conclusion

This study attempted to find evidence that student decisions are significantly influenced by RMP data, and if so to estimate the relative effects of professor easiness, clarity, helpfulness, overall score, and physical attractiveness on registration decisions. While the four million monthly page views the site reports indicate that people are viewing RMP data and significant correlations were found between registration patterns and RMP scores, it is impossible to say with certainty whether, or to what degree, those patterns are caused by RMP because there are other channels through which students gain information about professors. However, even if RMP simply serves as a proxy for student expectations of professor quality, the relative sizing of the effects is valid.

Both models used provide reasonable evidence that students may utilize RMP information to assess the overall quality, easiness, and attractiveness of their professors to aid their registration decisions. Our results suggest that “Overall,” “Hot,” and “Helpful” scores are successful predictors of the natural capacity of a particular section offered during the registration period. Professor quality expectations (especially “Easiness”) seem to matter most as a way for students to resolve their lack of information when choosing professors for core classes where they have the least information on professor quality.

Students appear to utilize both “Overall” and “Easiness” ratings in making their decisions about core classes. While our OLS model estimates a larger effect of “Easiness” than “Overall” consistent with Burnett, that differential disappears in our survival model analysis [6]. It should be noted that our data set only describes the behavior of registrants at Armstrong State University. Future researchers may be inclined to employ survival model analysis across a multiple-institution data set.

Since students will utilize whatever information is available to them—good or bad—when selecting classes, universities should consider releasing SET data in a *more* accessible medium and recommend that professors encourage students to *responsibly* post on RMP in order to increase the validity of the information posted on the website and, thus, make it of greater use. Combined with the potential for RMP to provide students with unreliable, biased information and SET and grade-distribution data being a more accurate—although declining at ASU[7]—indicator of teacher performance, our results strengthen the policy arguments put forth by Coladarci and Kornfield [3].

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[7]ASU has moved from an in-class paper SET collection policy to an online survey process. Ironically, as students now voluntarily self-select to submit SET, the data may also begin reflecting validity concerns similar to RMP.