



WARWICK BUSINESS SCHOOL
THE UNIVERSITY OF WARWICK

Masters Programmes

Dissertation Cover Sheet

Degree Course: MSc Business Analytics

Student ID Number: 2036451

Title: Using Unstructured Data to Discover Service Quality Dimensions of UK

Universities: An Application of Structural Topic Modelling

Dissertation Code: IB93Y0

Submission Deadline: 14th September 2021

Word Count: 9999

Number of Pages: 94

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Using Unstructured Data to Discover Service Quality Dimensions of UK Universities: An Application of Structural Topic Modelling

By

Simeon Rumyannikov

A dissertation submitted in partial fulfilment for the degree of MSc in Business Analytics at Warwick Business School – University of Warwick.

Executive Summary

Student Satisfaction is increasingly regarded as a crucial metric of university performance. It plays a critical role in league tables and new government sponsored ratings such as the Teaching Excellence and Student Outcomes Framework (TEF). In customer satisfaction literature, satisfaction is seen as a function of service quality. Service quality is regarded as multi-dimensional since individual aspects of a service add up to create an overall perception of quality. Typically, to measure service quality dimensions, the expectation-experience gap model of SERVQUAL is used. Similarly, in universities, satisfaction surveys are largely comprised of Likert scale questions concerning specific service aspects. However, these methods, utilising structured data, are usually limited by prior knowledge. Indeed, whilst multiple aspects of student satisfaction have been uncovered by previous research, such as the quality of teaching, it is still unclear what the dominating dimensions are. Therefore, in this dissertation unstructured textual data is used to enhance understanding of university service quality dimensions. Analysis of unstructured data is traditionally hard to scale as it involves human coding. This problem is addressed by utilising statistical models of text. Specifically, Structural Topic Modelling (STM), an advanced version of Latent Dirichlet Allocation (LDA), is used to analyse online reviews of university students to uncover new dimensions of university service qualities. Combining structured data with topic proportions obtained from modelling unstructured data results in information gain in multinomial regression analysis with student satisfaction as the target variable.

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1. Introduction and Background

Universities provide almost half a million jobs, making higher education one of the most significant industries in the UK's largely service based economy. Historical reputation aided UK universities in attracting students and maintaining their dominant position. However, post financial crisis austerity alongside the ideas of New Public Management which emerged in the 1980's, put pressure on the sector to be more competitive. Examples of such policies include the removal of limits on the number of students enrolling in universities and the introduction of tuition fees. Furthermore, in 2015, universities had to comply with the consumer protection law (Burgess, Senior & Moores, 2018). This meant that students were now customers in the eye of the law. Due to these changes students now see themselves as customers and expect a high-quality experience (Bell & Brooks, 2018). This trend has led to a higher focus on student satisfaction amongst institutions and researchers.

League tables, used by prospective students to evaluate available options, often use student satisfaction as a measure. This has been linked to the number of applications by Gibbons, Neumayer & Perkins, (2015). More importantly, student satisfaction positively effects word of mouth which is a significant factor in university choice. Therefore, a competitive edge can be attained by increasing student satisfaction. Commonly this is done by improving service quality, which leads to higher satisfaction amongst customers (Angelova & Zekiri, 2011; Cronin & Taylor 1992). However, to improve service quality, an understanding of service quality dimensions and their impact on satisfaction is required. This understanding will enable management teams to allocate resources effectively.

Figuring out what makes up a satisfactory student experience is not a trivial task. Multiple university aspects have been linked to student satisfaction with variable degrees of evidence. Mostly, surveys are used to identify areas of improvement. Yet students are often reluctant to complete them. Thus, using available data to its utmost potential is key. Another challenge is analysing responses at scale. An annual survey of a large university can yield thousands of responses. Analysing unstructured data in a survey is a particularly labour-intensive process requiring human coding. Roberts et al. (2014) argue that this encourages a reliance on Likert scales or multiple-choice questions rather than open ended questions. In non-open-ended surveys, questions and quality aspects must be predetermined by researchers based on prior theoretical understanding, which is often incomplete. Open-ended surveys suffer from similar problems because human coding is reliant on pre-determined scope and expectations (Roberts et al., 2014). Additionally, results are dependent on the ability and biases of individual

coders. This makes comparison of numerical estimates across coders challenging. Overall, unstructured data is hard to transform into actionable managerial insights.

Using automated methods, such as statistical topic models, makes it possible to uncover topics discussed frequently in the text. Analysts can then examine these to determine what meaningful topics have in the context of student satisfaction and dimensions of service quality. This insight can then be used directly to enact change. Additionally, researchers can modify existing survey tools such as Likert scales to examine newly detected issues. Statistical modelling can be done comparatively quickly, using free and open source tools such as RStudio. This is more cost effective than human coders, which enables more complex analysis. Thus, data from past surveys can be included to enable temporal comparison. Such analysis can provide management with insight as to what issues are more salient this year in comparison to other years. The main advantage however is that using topic modelling empowers researchers to ask more open-ended questions in student satisfaction surveys. This will allow students to use their own frame of thought, one which might not appear intuitive to the designer of the survey.

To demonstrate the validity of this approach this study uses a dataset of student online reviews. With the rise of social media, online reviews increasingly drive purchase behaviour (CITE). Although research in the area of electronic word of mouth (eWOM) with respect to universities is lacking, it is reasonable to assume that prospective students look to forums and online reviews for feedback and that it does affect choice in some way. This view is corroborated by the fact that universities invest increasing amounts of effort into social media channels (Le et al., 2019). Furthermore, establishing strong brand presence does boost recruitment efforts which indicates that students do look at online resources in their selection process (CITE). Thus, analysing online reviews not only showcases the methodology proposed but can generate direct insight into specific service features salient in eWOM. An extra step is taken to examine the difference between scores from online reviews and figures from surveys. Finally, analysing online reviews enables this study to examine the service quality dimensions across the UK wide student body with the added benefit of a large sample size. Therefore, the results presented here are more general and have higher statistical significance in comparison to extant literature focused on a small sample of universities. This is advantageous from a theoretical point of view as the results can be used to guide future research more confidently in the field.

1.1 Intended Aim

The aim of this dissertation is to uncover service quality dimensions from online reviews. To fulfil this goal topic modelling is used. Structured Topic Model (STM), a variant of LDA, will be applied to user generated content (UGC) scraped from a forum focused on UK universities. Topics will be analysed and labelled to capture the semantic meaning of its words. After labelling topics, they will be compared to existing known attributes of student satisfaction in the literature. Information gains from using unstructured data will be evaluated using logistic regression. The connection between available meta data and topic prevalence will be examined. Practically, the results of this experimental study will be of use to management teams at universities who wish to improve satisfaction amongst its students. These finding will also be of interest to researchers in the field of student satisfaction. The methods used in this dissertation can be extended to internal surveys conducted by universities, thereby helping unlock the full potential of open-ended questions and achieving greater increases in satisfaction for the money spent.

1.2 Research Questions

This dissertation has two questions:

Q1: Is it possible to uncover interpretable service quality dimensions from unstructured data, such as online reviews, and link these to the overall review score? How do uncovered topics vary in relation to structured data? Can topic modelling capture the temporal changes?

Q2: Will using unstructured data result in information gain when modelling satisfaction scores?

1.3 Dissertation Outline

Having discussed the motivations and background, **Part Two** gives an overview of literature. **Part Three** outlines all data acquisition, pre-processing, and modelling steps. Results are presented in **Part Four** and summarised in **Part Five**.

2. Literature Review

2.1.1 Methods of Measuring Student Satisfaction and Service Quality

Student satisfaction has been measured in several ways in extant literature. A simple 'yes' or 'no' question asking students to rate their overall satisfaction has been frequently used (Elliott et. al, 2002). This score is designed to capture the overall satisfaction of the student by effectively aggregating multiple dimensions. However, this results in information loss. One solution is to use a multi-attribute rating scale. Nowadays multi-dimensional customer satisfaction surveys (CSS) are widespread within universities and are used in most studies (Gruber et. al., 2010; Gibson, 2010). These allow students to rate individual service quality dimensions. In addition to the main questions of interest, surveys typically also include additional corroborating questions, such as whether a student would recommend a program to others (Gibson, 2010). In such surveys, categories or dimensions must be determined in advance based on prior understanding.

In the UK, the biggest survey of student satisfaction is the UK's annual National Student Satisfaction Survey (NSS) introduced in 2005. Commissioned by the Office for Students (OfS) the results are published on the Discover Uni website. Every year almost half a million final year students are invited to take part. In addition to the main yes or no question, the NSS assesses satisfaction across 7 dimensions through 23 Likert-scale questions. The findings of this survey are used in league tables (Locke et al., 2008). Findings from NSS evaluations are particularly relevant to this work since they are UK wide, have a large sample, and cover multiple years. In 2021 the OfS was forced to add additional questions related to the handling of the COVID pandemic. This highlights the problem of relying on pre-defined categories. Non-adaptive, static tool are not able to capture dynamic

Another framework which assumes that service quality is a multi-dimensional construct is the SERVQUAL expectation-experience gap model introduced by Parasuraman et al. (1985, 1988). Widely used, this model has been applied across a range of industries and customised when needed as per the original vision of Parasuraman et al. (1988). It has also been utilised in understanding student satisfaction (Gibson, 2010; Hartwig & Billert, 2018). This framework, when interpreted in the context of student satisfaction, attempts to capture the difference between the students' initial expectations and perceptions upon graduation. Hartwig & Billert, (2018) note that this operationalisation of service quality is not necessarily accurate. The authors argue that students are not likely to have clear expectations. They, therefore, conclude that a purely performance focused approach is more suited. Indeed, as Verhoef et al. (2009)

argue expectations are often shaped by the social environment. This is particularly relevant in the UKs higher education context; students come from different backgrounds and spend multiple years together. Hartwig & Billert, (2018) propose their own customization of the SERVQUAL model, using a host of dimensions identified from previous research. However, the fundamental problem remains. Even when multiple categories are present, preselection constraints remain. This results in information loss when the customers' dimensions of concern are not present in the survey.

2.1.2 University Service Quality Dimensions identified in Literature

Some studies show that teaching and academic prowess of a university are the chief drivers of satisfaction (Elliot, 2002; Wiers et al., 2002). On the contrary others show that non-academic features prevail (Letcher & Neves, 2010). In a multi-year survey study of Australian universities Grebennikov & Shah (2013) find that outside of classroom experience also plays a key role in students judgments. Thomas, & Galambos (2004) show that pre-enrolment opinions affect satisfaction. Expectations also appear to be important (Appleton-Knapp & Krentler, 2006). The complexity of what drives student satisfaction is apparent when Fielding et. al. (2010) note how student satisfaction exhibits consistent variability between different subjects in UK's NSS. These finding are confirmed by Hewson (2011). In analysis of NSS data Lenton (2015) finds that student-staff ratio and student employability has a major impact on student satisfaction whilst expenditure per student has no effect. Gibson (2010) carries out a comprehensive overview of prior literature and identifies academic variables to be most significant whilst non-academic attributes also appear import albeit with less evidence in support. Particularly, 'customer focus' is seen to have a positive effect. Similarly, a ten year analysis of UKs NSS survey data by Burgess, Senior & Moores, (2018) indicates that best predictors of student satisfaction are 'Teaching Quality' and 'Organisation & Management'. However, the authors conclude that the survey fails to capture all aspects of student satisfaction and suggest their own additions to the conceptual framework.

Dimension	Keywords	Literature Sample
Teaching	Feedback, Student/Staff Ratio, Quality, Passion, Helpfulness, Friendliness	Elliot, 2002; Wiers et al., 2002, Thomas, & Galambos (2004), Burgess, Senior & Moores, (2018) Lenton (2015)
Community	Atmosphere, Environment, Safety	Elliott, & Shin (2002). Grebennikov & Shah (2013)
Expectations	Pre-enrolment opinion	Thomas, & Galambos (2004), Appleton-Knapp & Krentler, 2006
Student Support	Logistics, Accessibility, Responsiveness	Thomas, & Galambos (2004),
Transformative / Skills Developed	Technical Skills, Socials Skills, Moral Awareness, Confidences, Intellectual Growth	Thomas, & Galambos (2004), Lomas (2007), Watty (2005), Zachariah (2007)
Facilities	Library, IT, Accommodation	Thomas, & Galambos (2004),
Courses and Classes	Range of Modules, Curriculum, Subject, Faculty	Elliot, 2002, Elliott, & Shin (2002), Fielding et. al. (2010), DeShields et al. (2015)
Administration	Organisation, Management	Burgess, Senior & Moores, (2018)

Table 1: Summary of Service Quality Dimensions identified in literature

2.2 STM and Service Quality Dimensions

As discussed, the main limitation in current approaches to measuring service quality is the pre-selection of dimensions in surveys which stems from an overreliance on structured data. Korfiatis et al. (2016) argues that review content can be directly linked to the dimensions that have been most influential in the customers overall rating and attitude. Using topic modelling it is possible to extract these dimensions from unstructured data, thereby solving the problem of preselection. This argument can be extended to include responses to open ended survey questions.

Topic modelling is an unsupervised machine learning approach which is designed to discover latent semantic structures within a set of documents, such as reviews. This enables

researchers to gain new insights from a corpus of unlabelled text. Numerous studies have been conducted using topic modelling and STM to uncover and identify latent topics across different fields. Customer satisfaction dimensions have been explored using topic modelling applied to online reviews with encouraging results (Tirunillai and Tellis 2014; Xiang et al. 2016; Guo, Barnes, and Jia 2017; Korfiatis et al. 2019; Lucini et al. 2020). No study exists that applies topic modelling to analysis of student reviews. Text mining appears to be a novel approach in this area with little work done except for few studies which use sentiment analysis.

The use of STM to model open ended survey responses was conducted by Roberts et al. (2014) using labelled data from the American National Election Study. The authors find there is correlation between themes used by human coders and topics discovered by STM. Additionally, topic modelling divided broad topics into more nuanced ones, generating greater insight. The authors also find that STM established a link between topics and covariates in a similar way to human coders. Furthermore, using the STM to measure relationships between metadata and topics, results in a continuous measure for each document. The authors argue that continuous measures produce better insight over simple categorization done by human coding. Another observation made by Roberts et al. (2014) is that topic modelling fails to identify predetermined categories because they do not appear frequently in the corpus. However, this is not necessarily a problem since the absence of such topics in the corpus is indicative of their low importance.

Topic models are mixed member models. A topic consists of multiple words and each word can also be part of multiple topics. Each word is assigned a probability of belonging to a given topic. Similarly, each document is assumed to contain multiple topics whilst each topic is present in multiple documents. The basic and widely used topic modelling approach is the Latent Dirichlet Allocation model (LDA; Blei et al., 2003). A critical assumption of this model is that topics are independent and uncorrelated. This assumption is unrealistic since certain topics are closer to each other and share common words. For example, economic and political topics are more likely to share common words compared to the topics of food and economics. To solve this issue, Correlated Topic Model (CTM; Blei and Lafferty 2007) was introduced.

Topic modelling assumes that during the process of writing a document, topics are drawn from a prior distribution. In LDA topic prevalence was dictated by Dirichlet distributions with alpha and beta parameters set by analysts. In effect, LDA assumes that authors are equally likely to discuss a given topic. However, because this exchangeability assumption often fails in practice several context specific models were designed (Roberts et al., 2016). STM (Roberts, Stewart, and Airolid 2013; Roberts et al. 2013) innovates on extant models by enabling the

use of arbitrary metadata in the generative process. Users can specify topical prevalence and topical content parameters which are used to estimate the probability of a topic being drawn. Thus, the distribution of topics across documents is dependent on covariates. Besides solving the original problem, this enables analysts to uncover new topics and quantify their relationship to the meta data (Roberts et al., 2019). This is particularly useful in the case of survey data, which typically contains lots of metadata. Similarly in this study, STM is used to examine how topics vary with different covariates. A further advantage of this approach is that by adding time as a covariate may help capture the changing meaning of words across time (Bail, 2018).

STM is a generative model. The generative process needs to be defined and parameters estimated as the model runs. Following Roberts et al., (2019) assume that a corpus is made up of D documents, $d \in (1, \dots, D)$. Words in document d are indexes as $n \in (1, \dots, N_d)$. Corpus vocabulary is defined as $v \in (1, \dots, V)$. Consequently, each word is denoted as w_{dn} . Number of topics is set by the researcher as k .

For each document d , given a metadata $p \times 1$ vector χ_d , a $k \times 1$ vector of topic proportions θ_d needs to be obtained. This done through a linear transformation with a matrix of weights y . Initial matrix values are drawn from a Half-Cauchy(1,1) prior. During the estimation process, these values are learned and replaced with actual parameter values. This prior ensures that the weights of unimportant metadata will tend to zero, preventing overfitting. Vector $\chi_d \gamma$ is set as the mean for a logistic-normal generalised linear models which is used to draw the final theta values.

$$\vec{\theta}_d | X_d \gamma, \Sigma \sim \text{LogisticNormal}(\mu = X_d \gamma, \Sigma)$$

Next, the probability of a word generated by a given topic is obtained by using the baseline log frequency word distribution in the corpus (m) which is a $v \times 1$ vector. Deviations from this baseline are modelled by topic-specific parameter κ_k , the covariate group deviation κ_{g_d} and the interaction between the two $\kappa_i = (\kappa_{g_d})$. As:

$$\beta_{d,k} \propto \exp(m + \kappa_k + \kappa_{g_d} + \kappa_{i=(kg_d)})$$

Next, each word in a document $n \in (1, \dots, N_d)$ is assigned to a topic, based on the document-specific distribution over the set topics, specified as:

$$z_{d,n} | \vec{\theta}_d \sim \text{Multinomial}(\vec{\theta})$$

Given the selected topic, the probability of word from that topic is:

$$w_{d,n} | z_{d,n}, \beta_d, k = z \sim \text{Multinomial}(\beta_{d,k=z})$$

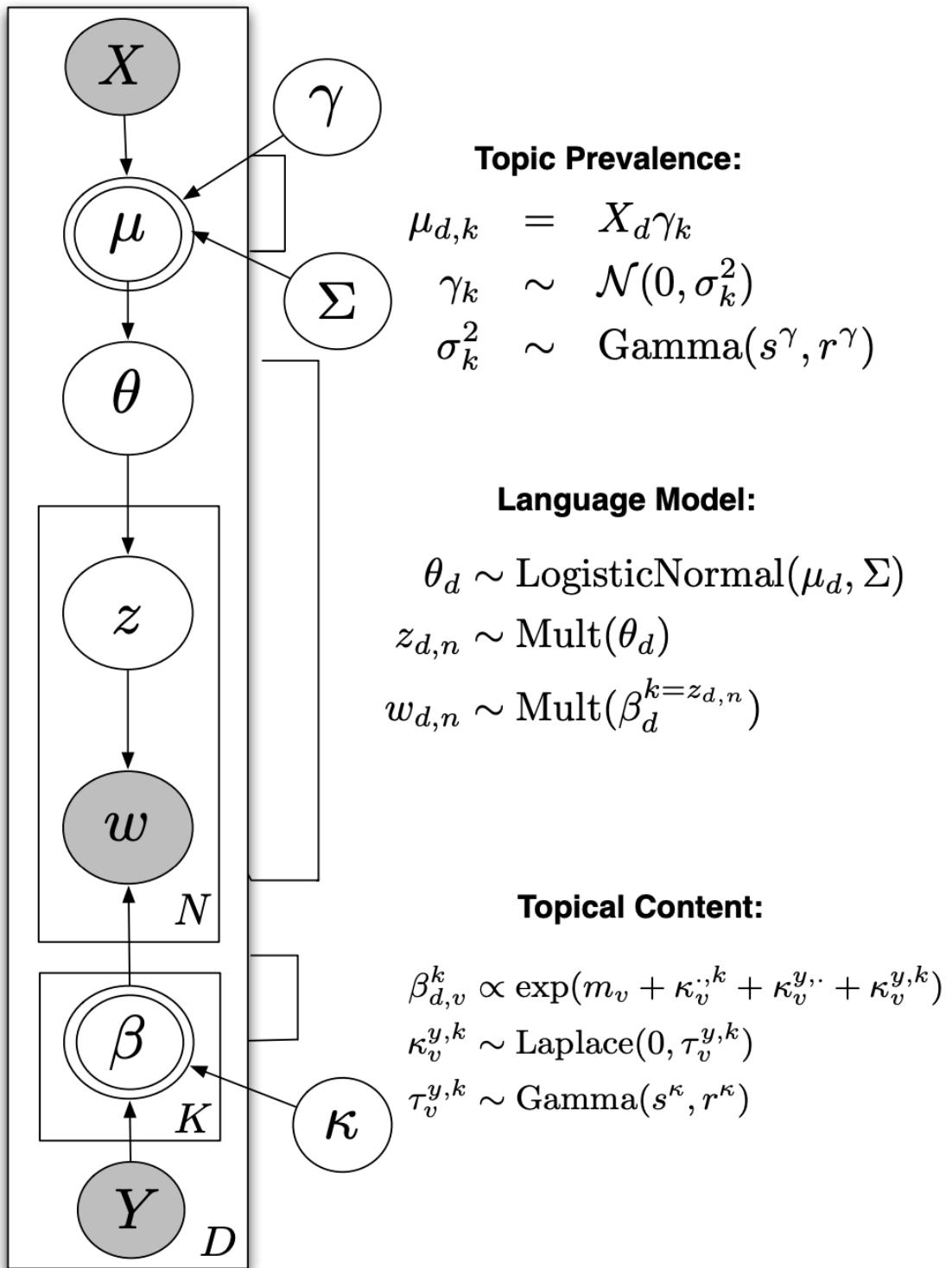


Figure 1: Plate Diagram for STM (Robers et al. 2013).

3. Methodology

3.1 Data Source Choice

The two biggest websites with university reviews are studentcrowd.com and whatuni.com. Both websites offer a league table of universities, based on verified student reviews. However, the latter was chosen because it provides data across a wider period and offers more meta data. Specifically, whatuni.com allows students to enter the course they are enrolled in. This is advantageous, as courses have been linked to satisfaction in the literature. Additionally, the overall format of the review is similar to that of a survey which combines open ended questions with Likert scales. Given the goal of this study to demonstrate the effectiveness of STM in analysing survey responses, reviews at whatuni.com are more appropriate.

3.2 Data Description

Data was scraped from whatuni.com. Not all reviews are scraped as in early 2021 the website underwent a change in questions. All reviews before this date are scraped ($N=138,788$). Resulting dataset covers the years 2013-2020 fully. Single reviews in 2012 and 2009 are removed.

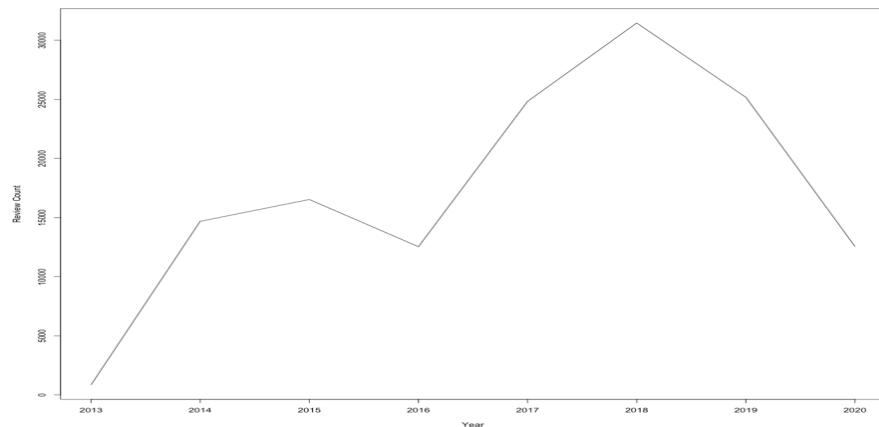


Figure 2: Time Series of Review Counts in corpus.

Students give an overall score for each university and an open-ended response to the prompt “*tell us about your university experience so far*”. Scores are based on an ordinal categorical scale from 1 to 5. Similarly, students provide a rating and textual review across several other service quality dimensions. Additional categories, some of which are optional include: Job Prospects, Course and Lectures, Students’ Union, Accommodation, Facilities, Local Life,

Sport and Societies, Student Support. See **Figure 3** for an example response. See **Table 2** for a descriptive statistics.

Kingston University
Fine Art BA (Hons)

OVERALL UNIVERSITY RATING ★★★★★

Tell us about your overall university experience so far.
I loved being a part of Kingston University and being able to live here for 3 years. My expectations were definitely met. I have come out the other side more educated, a professional ready to go into the work force and continue to be creative in all I do.

JOB PROSPECTS ★★★★★

How does your uni make efforts to increase your employability (careers department, work placements, transferable skills)?
You can go into so many jobs after this degree as the transferable skills are so important to life. Collaboration, independent work and time-management. Also the dissertation on your last year pushes you to new limits.

COURSE AND LECTURERS ★★★★★

What do you like most and least about the way your course(s) are taught?
Contact hours are so important to this course. The tutors are helpful and informative.

How many contact hours per week do you have?
2

STUDENTS' UNION ★★★★★

What do you think of your Students' Union in terms of student representation and facilities?
Your voice will be heard.

ACCOMMODATION ★★★★★

What do you think about the safety, condition, location and cost of your accommodation?
Good housing, it is very expensive but worth it. We have been robbed so you do have to be careful even in this safe area.

UNI FACILITIES ★★★★★

How good are your university's facilities?
Beautiful buildings, next to a river and parks are local. The libraries are great making and working spaces. The studios are one of my homes.

Figure 2: Review sample from whatuni.com. Name of university, course, date, ratings, and review texts were scraped.

Rating Type	Mean	SD
Overall	4.328	0.933
Job Prospects	4.234	0.938
Course and Lecturers	4.073	0.933
Local Life	4.186	1.000
Societies & Sports	4.128	1.042
Facilities	4.208	0.925
Students' Union	4.000	1.109

Table 2: Descriptive Statistics (N=138,788)

Initial sample contained 138,788 reviews of which 98% are English. The dataset contains reviews corresponding to 302 higher education institutions. However, not all are well

represented (see **Figure 3** for review distribution). To enhance the statistical power of the study, removing universities with small number of reviews is necessary. After filtering by number of reviews per university, 132 universities remain. See **Appendix Table 1**.

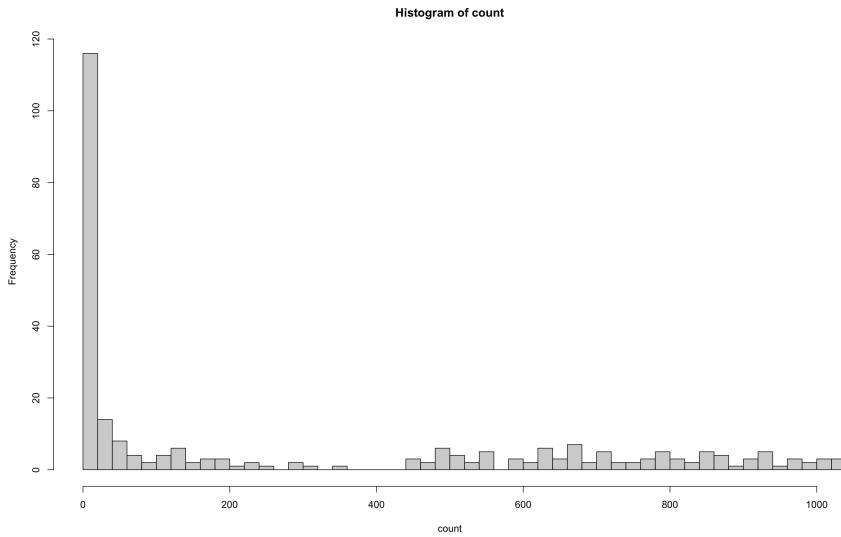


Figure 3: Number of reviews per university.

3.2 Text Data Pre-processing

Firstly, data was cleaned with all non-text features such as emojis removed. Non-English reviews were also removed as topic modelling will not be able to deal with multiple languages due to the different distributions of words in a language. Non-English reviews compromise less than 6% of the corpus. It is assumed that internal university surveys will be conducted in English. Since topic modelling assumes that each document contains multiple topics, short reviews with less than thirty words were removed. In practice, survey designers can specify a minimum word count to avoid removing survey responses. After this step the corpus contains 34,579 reviews.

Next, text was tokenized, Part-of-Speech (POS) tagged and lemmatized using the **udpipe** package (Wijffels, 2020). Critically, POS is conducted before stop-word removal. Common stop-words provide grammatical information which helps the tagger identify parts of speech. POS tagging enables filtering by the word's role in a sentence. Following Korfiatis et al. (2019) nouns, adjectives and adverbs were retained as those best describe university features. However, in the next iteration of modelling, verbs were also used as those were found to carry meaning. For example, the words “pushed”, “push”, and “challenged” emerged with positive adjectives, indicating that students appreciate challenging content. Lemmatization helped

reduce the overall word count further by grouping together words with identical roots. Unlike stemming, which can in fact be seen as a rules-based approximation of lemmatization, lemmatization uses the context in which the word appears to reduce it to its base (Grimmer and Stewart, 2013). Although stemming and lemmatization is regarded as a default approach there is evidence to suggest it does not add value to topic modelling and can even degrade performance (Schofield and Mimno, 2016). Therefore, both approaches are considered.

General language stop-words were removed, using the SMART and NLTK lists, as well as domain specific stop-words. Custom stop-words included university names, city names and the word university itself. Further terms such as “university”, “uni” and “experience” were removed. These do not provide any additional information as it is already known that every review concerns itself with the student’s university experience. Removing stop-words before modelling is seen as a default step in the literature designed to reduce noise in results. However, there is evidence to suggest that removing stop-words prior to topic modelling does not improve topic modelling effectiveness or interpretability compared to removing them after modelling (Schofield, Magnusson & Mimno, 2017). Nonetheless, removing stop words does not negatively impact modelling either. Furthermore, removing sparse terms does reduce computational time and resources. Therefore, this study takes the more practical approach of removing stop-words. Words which appeared less than 5 times were also removed. Infrequent words are unlikely to be discriminating according to Grimmer and Stewart (2013). In other words, they are regarded as too infrequent to affect the final allocations of topics, as topics by their definition are general. This procedure is inspired by Zipf’s law (Banks, 2018).

Another important step involved dealing with n-grams. Typically, n-grams need to be identified with TF-IDF or domain knowledge and tokenized. The corpus contains multiple n-grams which have identical individual tokens present within them. Most prominent ones are student-union, international-students, mature-students. Because of the overlap in tokens, STM groups together all these terms (union, international, mature, student) in one topic. This is not particularly sensible from a theoretical standpoint. Therefore, all are identified and tokenised.

Finally, review text was spell checked. Named entities, such as ‘covid’, ‘lockdown’, and ‘Tesco’, were identified as mistakes but were kept. Most frequent mistakes were manually corrected whilst less frequent mistakes were removed. This approach balances efficiency with accuracy. To remove parsing errors tokens smaller than three characters and larger than seventeen were removed. Care was taken to not remove potentially important short tokens such as “su”, short for student union and “cv” short for resumes.

3.2 Additional Metadata and Feature Engineering

Using insight from extant literature, public data is used to generate additional features. This enables us to quantify the additional information gain from using unstructured data, on top of structural data already shown to influence satisfaction. Additionally, this enables the examination of a broader range of meta data in relation to the dimensions uncovered. Following Lenton (2015) dummy variables are used to encode whether a university belongs to Russel Group, MillionPlus, Alliance Group, the unofficial post-1992 group as well as university location. A number of these were found to be significant predictors of overall student satisfaction in UKs NSS. See **Figure 3** for frequencies.

University Group	Frequency
Russel	24
Million Plus	18
Alliance	11
Post 1992	29

Table 3: Frequency summery of university groups in the pre-processed dataset.

All degrees were classified into undergraduate vs postgraduate. This variable has been linked to variability in satisfaction, particularly that related to academia. 81.5% of degrees in the post-processed dataset are undergraduate degrees.

Due to variety of courses present in the market the original dataset contains 10,094 uniquely named courses. Following the Lenton (2015) courses are grouped to reduce dimensionality (see **Table 4**).

Subject Area	Percentage (%)
Biological sciences	22.4
Art and design	15.7
Business and administration	11.4
Law and criminology	9.9
Mathematical Sciences	9.8
Social Sciences	9.1
Psychology	8.9
Management	7.6
Educational Studies	6.7
Environmental and geography studies	5.3
Computing	4.4
History	3.6
Economics	1.7

Table 4: Course groupings. Percentage indicates the proportion of courses belonging to the category.

To establish links between service quality dimensions and ranking, Teaching Excellence and Student Outcomes Framework (TEF) ratings are sourced. TEF is a newly implemented measure designed to reflect quality of teaching, student outcomes and satisfaction. This rating has 4 categories: Gold, Silver, Bronze and Provisional. This study aims to explore whether TEF can capture the quality dimensions it represents.

3.3 Application of STM

To conduct topic modelling **stm** package in R developed by Roberts et al., (2019) is used.

3.3.1 Data Processing

Using the **textProcessor** and **prepDocuments** functions data is formatted in preparation for **stm**. Infrequent terms are trimmed further by removing one percent of least common terms. All documents are re-indexed if documents are deleted and metadata removed ensuring data remains correctly formatted (Roberts et al., 2019).

3.3.2 Topic Prevalence and Topic Content Parameters

The corpus used in this study has multiple pieces of meta data: date of review, multiple ratings, university name, course, and university features. All are used as topic prevalence parameters. It is implicitly assumed that topics differ in quantity across time and different satisfaction levels.

Other variables have been linked in existing literature to student satisfaction and may influence topic prevalence. Risk of overfitting is negated by the prior which pushes the weights of non-influential parameters to zero. The prevalence equation is specified as:

$$\begin{aligned} Prevalence_i = & \sum_{s=1}^5 \beta_{1s} RevScore_i^s + \sum_{u=1}^{132} \beta_{2u} Uni_i^u + \sum_{l=1}^5 \beta_{3l} Loc_i^l + \sum_{s=1}^{12} \beta_{4s} Sub_i^s + \sum_{r=1}^5 \beta_5 TEF_i^r \\ & + \sum_{g=1}^5 \beta_7 Group_i^g + \beta_8(Date_i) + \beta_8(Undergraduate_i) + \beta_8(Campus_i) \end{aligned}$$

Where $RevScore_i$ is the factor score given by the student from one to five. Uni_i^u is one of the 132 universities in the dataset. Loc_i^l is the location of the university, with l represent London, England, Scotland, Wales, or NI. Sub_i^s is one of the 13 subject areas (see Table 4). TEF_i^r is the TEF rating category with r being one of None, Silver, Gold, Bronze or Base. Group is the group to which a university belongs (see **Table 3**). $Campus_i$ is a dummy variable representing if a university is a campus university. $Undergraduate_i$ is a dummy variable indicating if the student is undergraduate. $Date_i$ is the date of the review.

3.3.3 Other Parameters

As recommended by Roberts et al., (2019) Spectral Initialisation is used. Maximum number of iterations is set to 150 which is enough for all models to converge. Other parameters are kept at default values.

3.3.4 K Selection, Model Evaluation and Model Selection

The most important decision in topic modelling is selecting the number of topics to estimate during modelling. There is no automatic method for doing so. Nonetheless, several metrics exist to guide researchers in selecting an appropriate K. A number of these are implemented in the **stm** package in the warper function, **searchK**.

A popular measure is held-out log-likelihood, which is the probability of held-out documents given a trained model. A higher score indicates greater fit. This is implemented as specified by Wallach et al. (2009) in **stm** (Roberts et al., 2019). However, by conducting word and topic intrusion tests Cheng et al. (2009) find that models with high held out likelihood have less semantic meaning to humans. The authors note that predictive power makes the topics less

interpretable. Since the goal of this study is to uncover interpretable dimensions of service quality, less emphasis is placed on this measure. Additionally, the authors of **stm** package implement the dispersion of residuals metric as designed by Taddy (2012). However, little research outside of the original paper corroborates its usefulness.

The most promising measure is semantic coherence. Formulated by Mimno et al. (2011) it correlates well with human judgment according to the authors. Coherence increases when the most likely words in a topic occur together (Roberts et al., 2019). If $D(v_i, v_j)$ is the number of times word v_i and v_j co-occur together in the same document then semantic coherence of topic k is defined as:

$$C_k = \sum_{i=2}^M \sum_{j=1}^{i-1} \log \left(\frac{D(v_i, v_j) + 1}{D(v_j)} \right)$$

Where M is a vector of most likely words in the topic.

As Roberts et al., (2014) note semantic coherence can be high with low K as topics with topics consisting of frequent words. Thus, in this study small values of K, below ten, are not investigated. This approach is in line with current research on student satisfaction, which shows that the number of dimensions is numerous. Nikolenko et. al (2017) find that semantic coherence, is effective at identifying topics which are not coherent. However, the authors also note that it is not able to distinguish between topics that are genuinely coherent from a human perspective and topics which consist of highly frequent words which often co-occur. Therefore, human input on topic coherence is still a requirement. Although Grimmerand & King (2011) have not used semantic coherence specifically they also advocate for a balance of human and algorithmic evaluation. These findings are in line with those of Cheng et al. (2009) who advocate the use of intrusion tests in the validation pipeline. Meanwhile Roberts et al. (2019) advocate using exclusivity in combination with semantic coherence.

In this study search K is used for values between 10 and 60 to detect candidate K values. Topic models are fitted using the **selectModel** function. The best model is selected for given value of K based on the semantic coherence vs exclusivity plot. Models are qualitatively evaluated when uncertainty exists.

3.3.5 Topic Summarization and Topic Labelling

Once the model is estimated, topics need to be labelled. Typically, topics are summarised by looking at the top N most frequent or most probable words in the topic. These are not always meaningful according to Roberts et al. (2014) and can be incoherent (Bischof and Airoldi, 2012). Building on previous insight on the value of exclusivity by Bischof and Airoldi (2012), Roberts, Stewart and Airoldi (2013) propose the frequency exclusivity measure (FREX). This seeks to balance the probability of a word appearing in a topic with its exclusivity by finding the harmonic mean of the two (Roberts et al., 2014). Lift score has also been used successfully in Taddy (2012).

3.3.6 Topic Validation

Grimmer and Stewart (2013) outline several principles researchers should adhere to when using automatic text analysis. Validation is one of them, specifically validation by human coders. However, the authors note that creating coding schemes is difficult because it is time consuming and can be ambiguous. Song et al., (2020) also demonstrate the failings of human annotators and call for a more methodological approach. Word intrusion tests outlined by Cheng et al. (2009) solve these problems by presenting coders with a simple task. The task is to identify a foreign word in a set of most frequent words in a topic. When no such foreign word is identifiable coders select words randomly indicating low coherence in the given topic. Another task proposed Cheng et al. (2009) is topic intrusion. Given an example document and several topics, with their top terms, a human coder is required to select the intruder topic. Chan and Sältzer (2020) implement word intrusion and topic intrusion tests described by Cheng et al. in their **oolong** package.

Topic intrusion tests aren't used in this study as they are time consuming compared to word intrusion tests. Another issue with topic intrusion tests, particularly to how they are implanted in the **oolong** package, is that they require the coder to select the intruder topic from five options. This is hard to do when reviews are shorter and only few topics are clearly detectable by humans. Therefore, a human coder often fails to distinguish between low proportion topics. However, topic modelling works best on longer texts in the first place. Thus, it can be argued, that topic intrusion tests accurately reflect that.

4. Results

4.1 Choosing the optimal number of topics

To select K the function **SearchK** is run two times. First, it is run for values between 10 and 60 with a step of 5. Search space is narrowed each time. This done by observing semantic coherence, held-out likelihood, and residuals. A huge jump in semantic coherence and held-out likelihood is detected. Residuals and lower bound values decrease substantially (see **Figure 3**). This is interpreted as a sign of optimal K. Next, search is narrowed and **SearchK** is run for values between 30 and 50 with a step of 1. Shift appears to be around the number of topics equal to 44 (see **Figure 4**). Values of 45 and 44 are investigated manually. 44 is selected for further analysis.

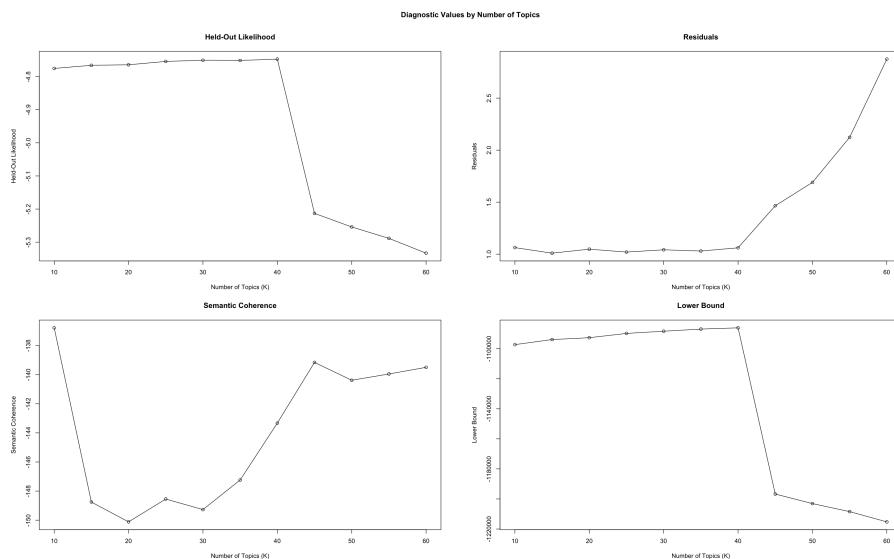


Figure 4: Search K between values of 60 and 10 with a step of 5. Visible shoulder between values of K 40 and 50.

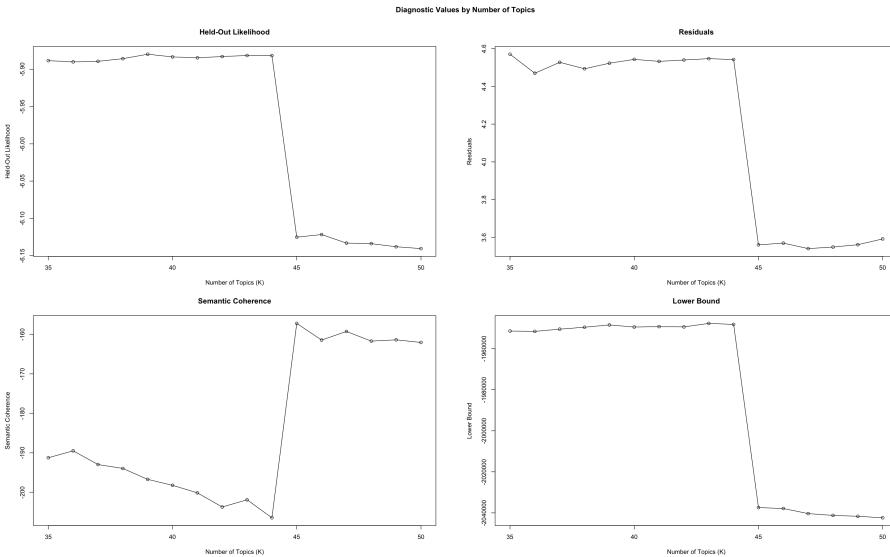


Figure 5: Search K for values of K between 30 and 50. Visible shift at K=44.

4.2 Model Optimisation: Semantic Coherence and Exclusivity

After K is selected, candidate models are drawn as described in the methodology. To select the best model, candidate models are visually evaluated using a semantic coherence vs exclusivity plot. Topics for each model are marked with a coloured point. Numbers represent the average exclusivity/coherence for the corresponding topic. The goal is to maximise both measures. Suboptimal models are those which have both lower exclusivity and lower semantic coherence. Nonetheless, a trade-off must usually be made when selecting the model.

Most models are similar, as points along the exclusivity / semantic coherence structure are clustered together closely. However, model 10 stands out as most of its topics are high in exclusivity but low in semantic coherence. Given the discussion presented in the methodology section this model is dropped outright. Models 2, 4, 5, 6, 7 are sub-par along all axis compared to 9, 8, 3 1. Model 8 is selected as the final model as it appears to achieve greater performance in semantic coherence compared to 9 and 1 whilst retaining similar levels of exclusivity.

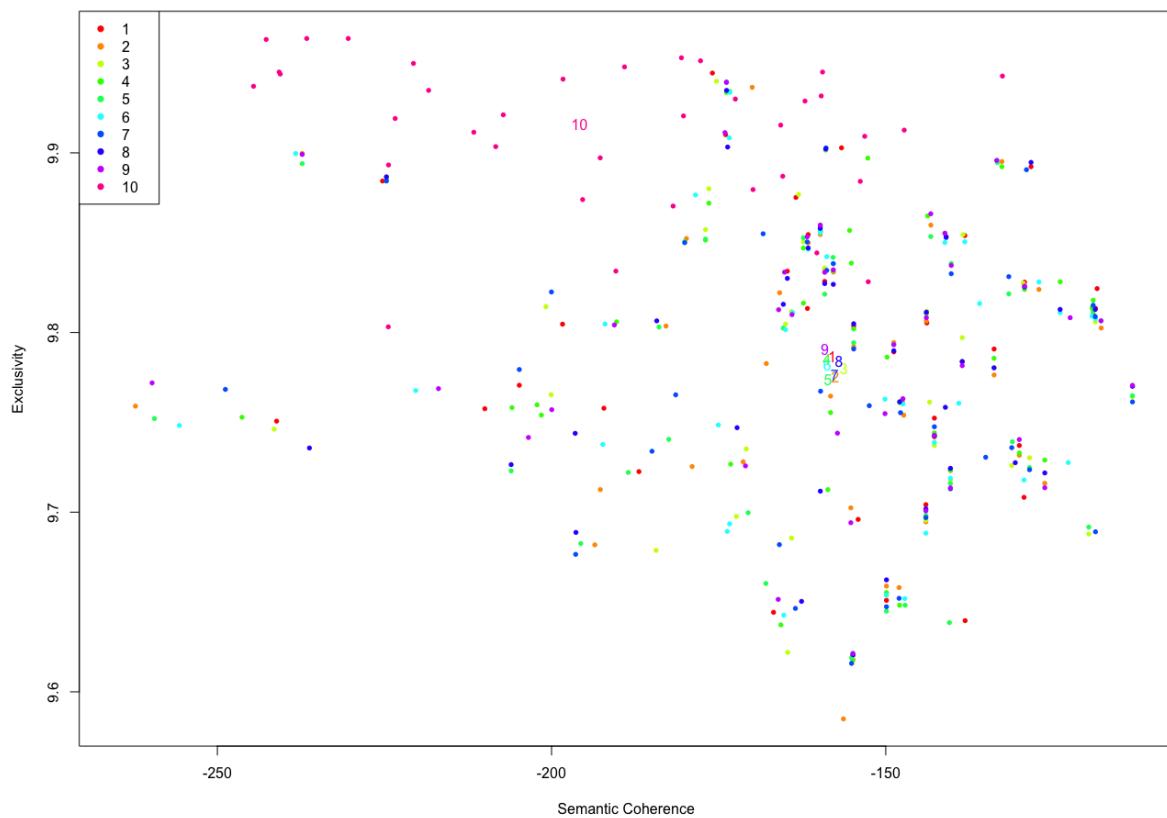


Figure 12: Topics of top 10 models using exclusivity vs semantic coherence.

4.3 Topic Validation

The **oolong** package is used to conduct word intrusion tests for optimally selected models. As recommended by Chan and Sältzer (2020) at least 3 human coders are used. Given that the test presents 5 words with 1 correct answer, it can be expected that if the model were completely nonsense, coders would achieve a performance of around 20%. This is equivalent to a random guess.

Precision (%)	
Coder 1	71.89
Coder 2	68.24
Coder 3	58.94
Average:	66.36

Table 5: Results of Topic Intrusion Tests.

In both cases precision is higher than 20% indicating that the model has validity and coders do not select words randomly.

During the tests it was noted that adjectives are particularly hard to identify as intruders unless there is a positive adjective in a topic full of negative ones. This is because adjectives are meaningless without a corresponding noun. This could lower the precision score for an otherwise coherent model. In the contexts of the test adjectives are like stop words. Nonetheless adjectives are useful because they allow researchers to gauge the sentiment of a topic. Taking inspiration from Schofield, Magnusson & Mimno (2017) who recommend the use of post processing techniques to deal with stop-words, this study suggests that an optimal approach could be to temporarily remove adjectives before conducting the oolong test. However, this could invalidate the statistical validity of the test by introducing bias. This investigation is beyond the scope of this paper and is left to be explored in future research.

4.4 Topic Labelling

Labelling is conducted by evaluating the top words in each topic sorted by 4 measures: FREX, Highest Probability, Score and Lift. FREX is the more nuanced of the four as it seeks to balance between exclusivity of words and their frequency. It is commonly used in practice and recommended by Roberts et al (2019). Therefore, higher emphasis is placed on it. See **Table 6** for top 6 FREX terms. See **Appendix B** for all measures.

Number	Topic Label	Proportion	FREX Words
32	Staff Friendliness	4.80	friendly,helpful,staff,environment,supportive,easy
18	Societies and Sport	4.24	society,sport,involved,join,activity,range
25	Challenge	4.09	friend,meet,lear,challenge,comfort,reward
8	Social/Academic Balance	3.56	life,balance,social,universiy,mixture,memroy
11	Mature Students	3.54	student,advice,fellow,mature,exchange,diverse
12	Lectures and Seminars	3.26	lecture,seminar,lecturer,content,enthusiastic,slide
5	Graduating and Sad to Leave	3.17	love,graduate,sad,imagine,leave,miss
13	Friends	3.16	enjoy,mate,load,throughly,tiring,flat
20	Confidence in Skills Gained	3.02	future,skill,career,gain,knowledge,expand
15	Opportunities and Prospects	3.02	offer,opportunity,abroad,prospects,job,prospect
1	Community	2.82	feel,community,comfortable,sense,feeling,homely
4	Academic Support	2.81	academic,support,guidance,term,potential,receive
33	Academic-Facilities	2.80	library,access,resource,service,facility,equipment
40	Town Transport Links	2.50	town,close,walk,shop,beach,bus
10	Negative Aspects	2.45	waste,terrible,awful,worst,poor,mark
7	Settling In	2.43	start, settle, easier, quickly, begin, adjust
38	Non-Academic facilities	2.41	accommodation,private,gym,food,su,cheaper
21	Home vs Uni Lifestyle	2.40	live,home,move,lifestyle,family,independence
31	Costs	2.23	pay,care,reason,cost,improvement,majority
16	Independent Learning	2.13	learn,learning,alot,independent,subject,curve
43	Degree Completion	2.08	degree,stay,wait,moment,finish,master
19	Bad Semester/Module	2.06	semester,module,bad,pass,grade,final
3	Parties	2.01	night,event,fresher,party,hold,union
35	Issue Resolution Experience	2.00	positive,issue,deal,communication,negative,regard
29	Modern Facilities	1.99	excellent,perfect,beautiful,outstanding,modern,fabulous
28	Personal Tutor	1.95	tutor,personal,talk,workshop,professional,idea
2	Freshers Week	1.95	amazing,incredible,lovely,ill,incredibly,equally
37	Personal Growth	1.88	person,grow,academically,personally,confident,individual
14	Choice Reflection	1.85	happy,choose,glad,decision,regret,pleased
24	Uni Rank and Reputation	1.84	fantastic,country,unique,history,culture,engineering
42	Communication and Classes	1.79	class,teacher,attend,understand,question,lesson
9	Workload	1.75	expect,busy,hand,fault,manage,amount
41	Workload and Mental Health	1.70	stressful,struggle,assignment,stress,health,mental
23	Learning Experience	1.60	fun,exciting,engage,super,bore,weather
22	Undergrad vs Postgraduate	1.57	level,undergraduate,advise,ensure,succeed,postgraduate
6	Will Recommend	1.54	recommend,brilliant,highly,apply,fab,lead
26	Choice Reflection & Memories	1.52	forward,continue,rest,proud,journey,grateful
34	Positive Adjectives	1.49	pretty,focus,awesome,stuff,compare,decent
36	Challenge	1.41	hard,encourage,explore,push,challenging,zone
17	Placement	1.40	placement,practical,session,practice,relevant,nurse
27	International Friends	1.04	world,huge,honestly,friendship,form,freedom
44	Commitment	1.00	enjoyable,mix,create,effort,stuck,commit
39	Discovery	0.91	fast,meeting,masive,strong,add,discover
30	Expectations	0.81	expectation,visit,realise,cover,arrive,wise

Table 6: Labelled topics with top 6 FREX terms. Ranked by Proportion.

In line with existing theoretical knowledge, topics Lectures and Seminars (Topic #12), Staff Friendliness (Topic #32), Communication and Classes (Topic #42) and Learning Experience (Topic #23), which fall under the teaching category, occupy a substantial portion of reviews. Importantly, staff friendliness ranks higher than lectures and seminars suggesting that quality of interpersonal interaction has a high impact on satisfaction. Topics Academic Support (Topic #4), Personal Tutor (Topic #28), Settling In (Topic #7) relate to the well known dimension of Student Support. Similarly, Topics Academics Facilities (Topic #33), Non-Academic Facilities (Topic #38) and Modern Facilities (Topic #29), confirm that facilities provided are an important dimension of university service quality. Several topics explicitly focus on challenges and being pushed outside of the comfort zone: Challenge (Topic #25 & Topic #36) and Personal Growth (Topic #37). These correspond to transformative dimension of university education.

In contrast to most of extant literature many topics related to social aspects of university life dominate online reviews. Seven of top ten topics can be regarded as social. These include Social/Academic Balance (Topic #8), Societies and Sport (Topic #18), Community (Topic #1), Freshers Week (Topic #13), and Friends (Topic #14). Therefore, social aspects are a key service quality dimension of UK universities. The topic Independent Learning (Topic #16) also appears unique in the context of current literature. Perhaps because of the quite unique style of higher education in the UK. Unlike elsewhere, UK universities offer students the opportunity to study in their own time rather than through many of contact hours.

Most topics are positive because most reviews in the corpus are positive. However, a few topics are distinctly negative. This includes Workload and Mental Health (Topic #41), Negative Aspects (Topic #10) and Bad Semester/Module (Topic #19). One dimension absent from the model, yet identified in the literature, is administration and organisation. Whilst it is possible that students do not care about this dimension, it is more likely that administration is considered as a given, and only talked about when things go bad. This is supported by the fact that the main negative topic, Negative Aspects (Topic #10), contains many words related to organisation and administration. These include exam, timetable, unorganized.

4.5 Topic Correlations

Topic correlations are calculated and used to examine the consistency and interpretability of findings. According to Roberts et al. (2019) if topics correlate, they are likely to occur in the same document.

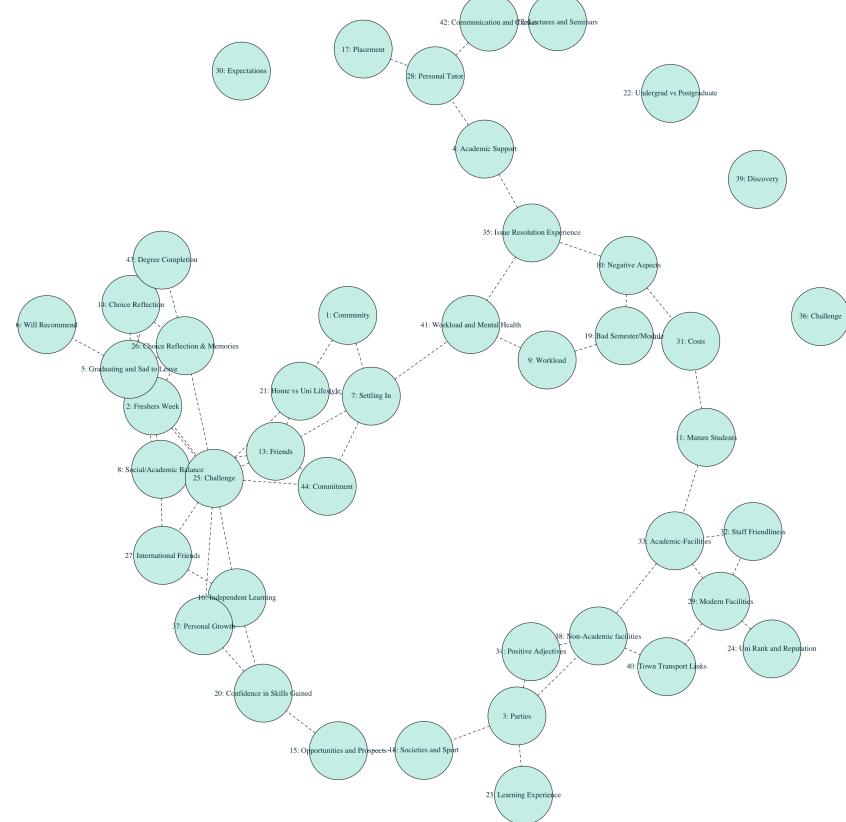
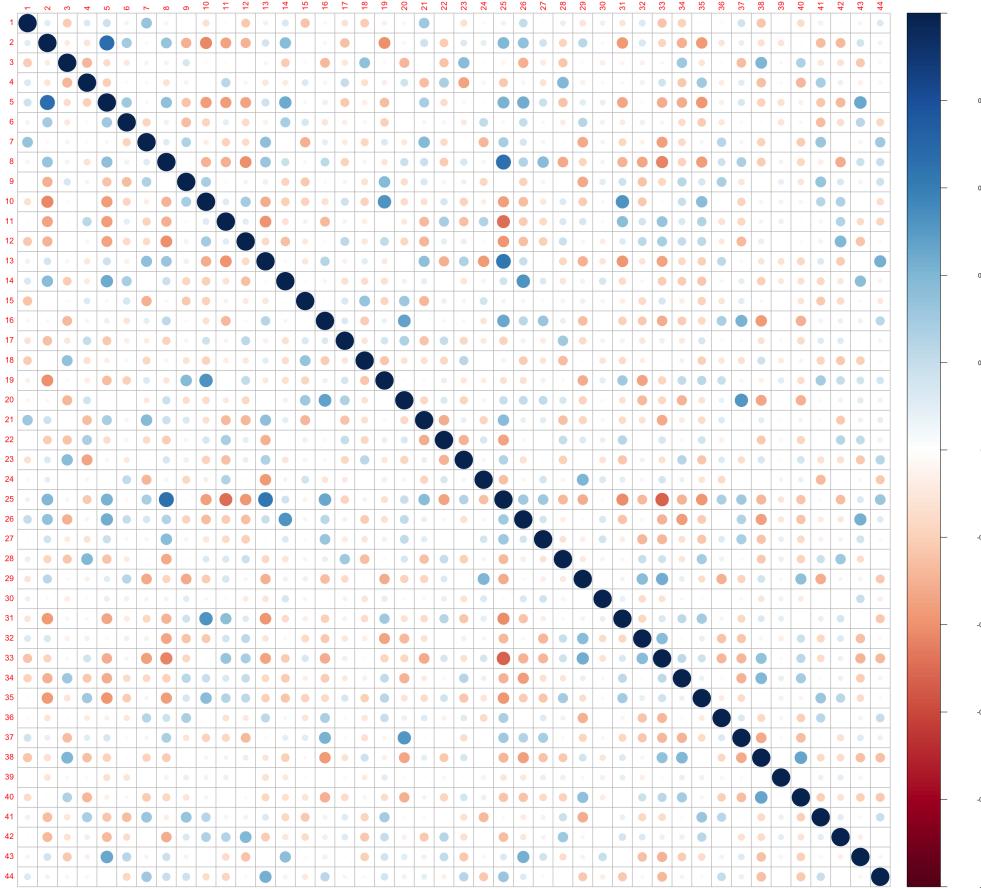


Figure 21: Topic Correlations. Nodes represent topics, whilst vertices represent correlation above 30%.

Independent Learning (Topic #16) is linked to Personal Growth (Topic #37) and Confidence in Skills Gained (Topic #20). Personal Growth (Topic #37) is also correlated with topic of Challenge (Topic #25). Since the correlation amongst these topics is positive, it appears that the feeling of personal growth is connected to that of feeling challenged. Similarly, students who felt challenged during their studies and engaged in independent learning, believe they have gained sufficient skills for life and employment. Challenge (Topic #25) is positively correlated with Social/Academic Balance (Topic #8), Choice Reflection (Topic #14) and Friends (Topic #13). This indicates that unlike the second challenge topic (Topic #36), Topic #25 has a social element to it. This social element is likely linked to positive transformative effects of education, such as the acquisition of confidence. Several negative topics seem to co-occur together; Costs (Topic #36), Negative Aspects (Topic #10), Workload and Mental Health (Topic #41), Bad Semester/Module (Topic #19) and Issue Resolution Experience (Topic #35). Additionally, Issue Resolution Experience is linked to Academic Support (Topic #4). This suggests that improving student support mechanisms could help reduce negative impact of issues arising during course of study.

4.6 Relationship between Topics and Metadata

Given the model chosen in the previous stage of analysis, the relationship between topics and covariates can be estimated using linear regression with topic-proportions as the outcome variable. The regression equation is specified the same way as the prevalence equation. Method of composition facilitates estimation of uncertainty. Plots generated that show the changing in topic proportion between values of interest. Were the number of groups is large a representative sample is presented. For full results see **Appendix C**.

4.6.1 Overall Rating

Figure 6 shows the marginal effects of ratings on topics discussed. The further away a topic is from the centre dotted line, the larger the marginal effect is. For example, the topic Freshers Week (Topic #2) is more probable when the overall rating is high. In contrast, the topic Negative Aspects (Topic #10) is more probable when the review rating is low. Similarly, topics of Mental Health, Workload (Topic #41), Costs (Topic #31) and Issue Resolutions (Topic #35) are more likely at lower ratings. Given the negative sentiment of these topics, this is not

surprising. Additionally, this indicates that universities should work to improve student support services. Interestingly, topics of Personal Growth (Topic #37) and Challenge (Topic #25) are both more likely to occur at higher ratings. This suggests that students recognise the transformative power of education and do not simply want high grades for no effort. Unsurprisingly, topics of positive sentiment, expressing sadness upon graduation (Topic #5) and reflection on choice (Topic #14) are linked to positive ratings.

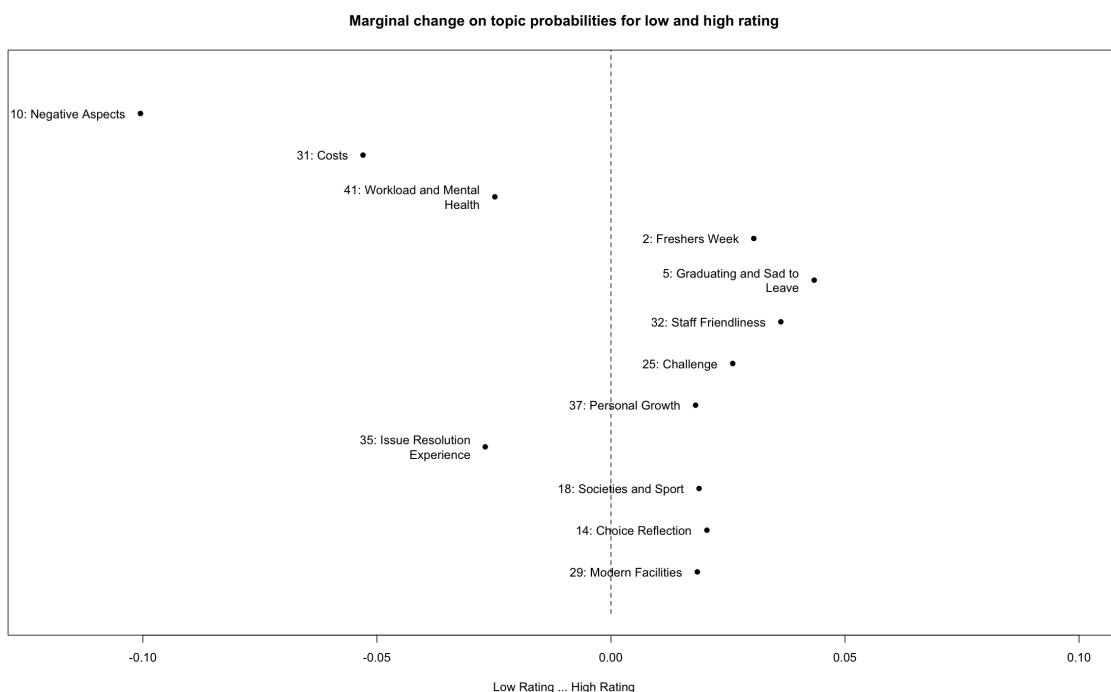
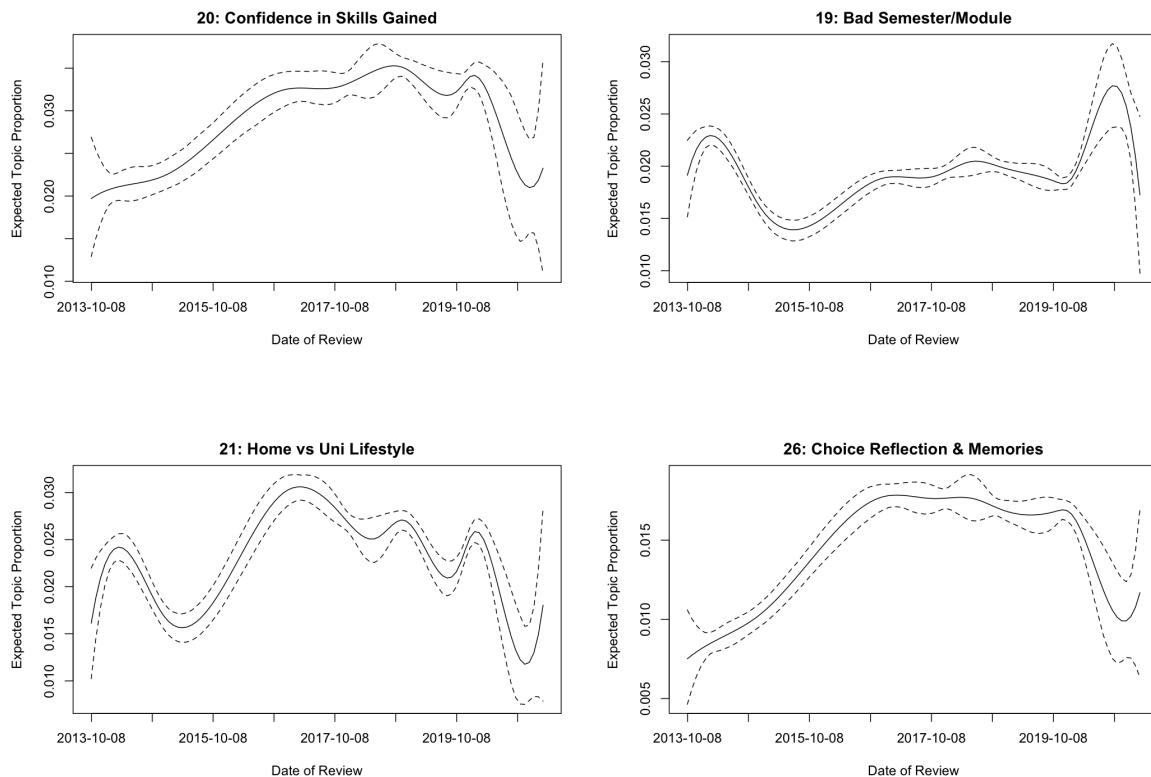


Figure 6 : Marginal Effect of Ratings on Expected Topics Discussed.

4.6.2 Temporal

Expected topic proportions across time are plotted from the date of the first review to the date of the last review. Whilst topics proportions are generally stable, several topics experienced a dramatic shift in prevalence starting from early 2020. This corresponds with the start of the Covid-19 pandemic and the beginning of lockdown measures. For example, there is less discussion of sports/societies (Topic #18), university vs home lifestyle (Topic #21). and community (Topic #1). This is not a surprise since students must stay at home and cannot engage with the community on campus. There is a sharp rise in discussions surrounding costs (Topic #31) which overlaps with a decline in expressions of confidence in skills gained by studying at university (Topic #20). Thus, students do not believe that online education provides

the same level of skills and knowledge. However, the fact that tuition fees remain the same likely means that students no longer regard education to be the same value for money as in pre pandemic years. This has led to discussions surrounding costs. Indeed, wide calls for tuition fee refunds and reduction led to petitions in support for these policies gaining over 300,000 and 500,000 signatures respectively (Hall, 2021; Jeffreys, 2021). The topic of Mental Health (Topic #41) has been rising in salience prior to the pandemic which corresponds to the fivefold increase in disclosed mental health conditions over the period from 2007 to 2017 in the UK (Gunnell, 2018). This topic also experienced an uptick in expected topic proportion during the pandemic, indicating an escalation in mental health crisis due to the pandemic. Overall negative experiences are also on the rise (Topic #19 and Topic #10). This rise in negative sentiment is in line with finding from the NSS, which reports that satisfaction has gone down significantly during this period. Average satisfaction was 75% nationwide in 2021 compared to 83% percent in 2020. In fact, this is the lowest rating of satisfaction recorded. Additionally, the survey participation rates have gone down, which itself can be regarded as an implicit measure of satisfaction. The fact that the topic model can capture broad trends and sudden shifts is a sign of its validity and usefulness. Fluctuations in topic proportion reflect documented, real-life changes. This means that universities can create systems of continuous feedback monitoring which will help them dynamically maintain and sustainably improve on feedback levels despite changes in the strategic landscape.



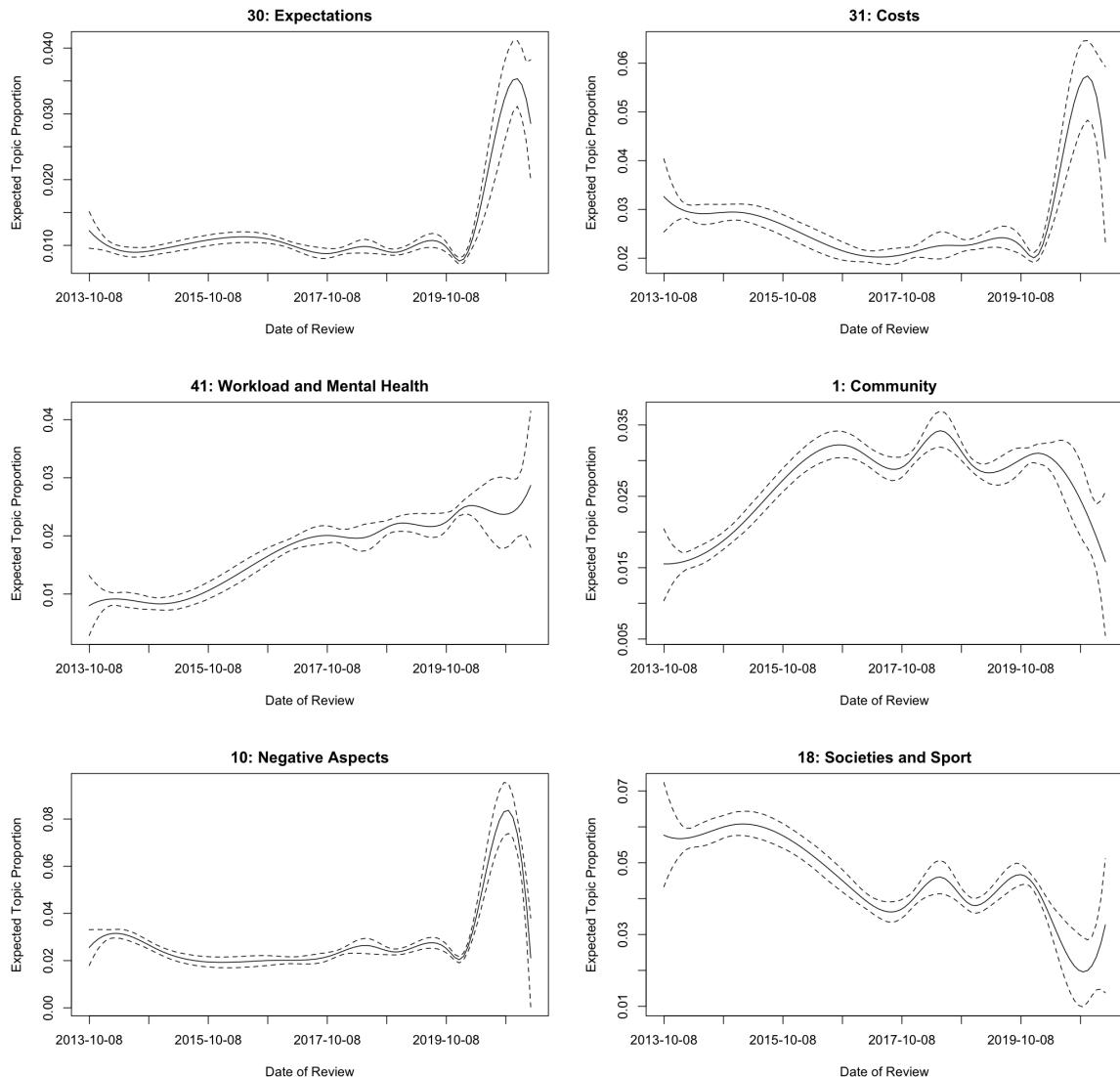


Figure 7: Change Expected Topic Proportions Across Time

In some cases, the initial shifts are followed by a reversal in around the end of 2020. However, because the last review in the corpus is from February 2021 there is not enough data to make a definite statement on how to interpret this trend. Whilst it could be a reversal to the mean, it could simply be the product of spline smoothing.

4.6.3 University Groups

Consistent with expectations, students at Russel Group universities value the universities rank and reputation (Topic #24). Students also believe that these universities offer good opportunities and prospects (Topic #15). Societies and Sports (Topic #18) are more likely to be discussed at Russel Group Universities compared to non-Russel Group ones. This

coincides with discussions of Non-Academic Facilities (Topic #38) and Modern Facilities (Topic #29). Thus, it appears that Russel Group Universities invest more in facilities, including non-academic ones. Possibly, this is a result of their financially more stable position. Negative Aspects (Topic #10) are more likely to be discussed in all groups, which possibly reflects the fact that students going to high end universities are more concerned with value for money. Placements (Topic #17) are more likely to be discussed in Alliance Group students, which is to be expect given the groups emphasis on technical subjects an sandwich courses. Curiously, Costs (Topic #31) appear to be more frequently discussed in all groups but the Alliance group. However, due to the small number of Alliance universities, it is difficult to make conclusive remarks.

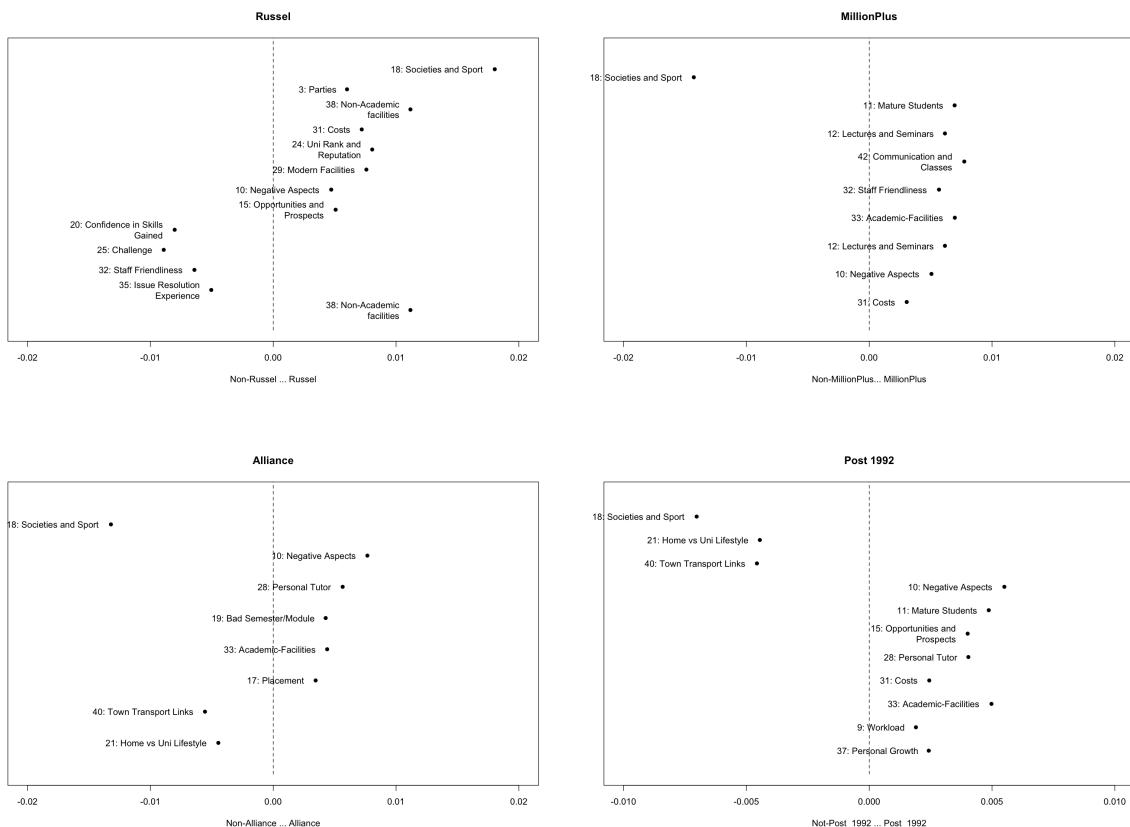
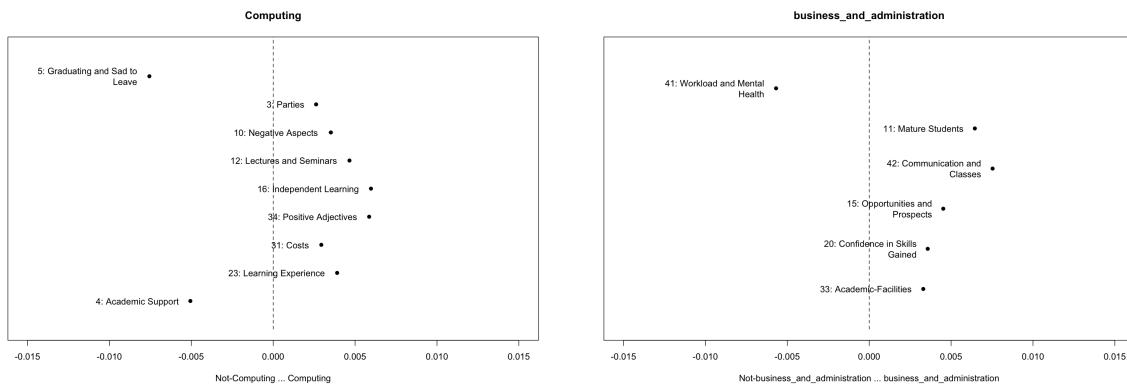


Figure 8: Marginal Effects of Group Status on Expected Topic Proportions

4.6.4 Course Groups

Importantly, significant variation in topic prevalence appears across different subject areas even though they are grouped in few broad categories. This is consistent with findings from analysis of UKs NSS data by Lenton (2015) and Fielding et. al. (2010). Although topics vary substantially it is possible to spot some aspects which verify the validity of the model and

confirm that subject level topic variations are consistent. For example, the topic Placement (Topic #17) dominates reviews in Biological Sciences, which includes medical sciences, a large component of which includes practical placements. In contrast, placements are less likely to be discussed in environmental studies and language studies. A limitation of this study is that subject groups are defined with little connection to departmental structures, because department structures vary wildly. In practice, universities should include department information in the prevalence formula which would allow analysts to examine variation amongst departments. This would produce more interpretable and actionable results. Moreover, given that certain subjects have high levels of satisfaction, if universities want to improve satisfaction amongst these courses, targeted policies and targeted monitoring of salient issues is needed.



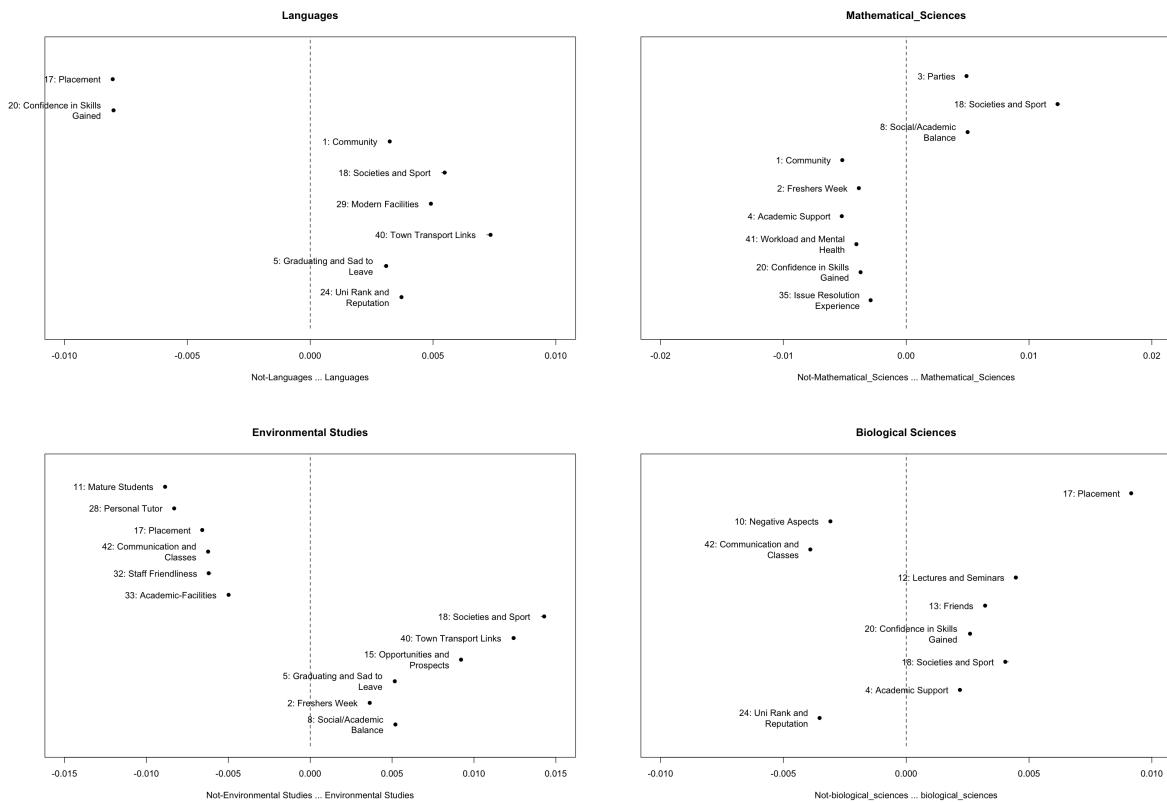


Figure 9: Representative Sample of Subject Area Effect on Topic Proportions

4.6.5 Undergraduate vs Postgraduate

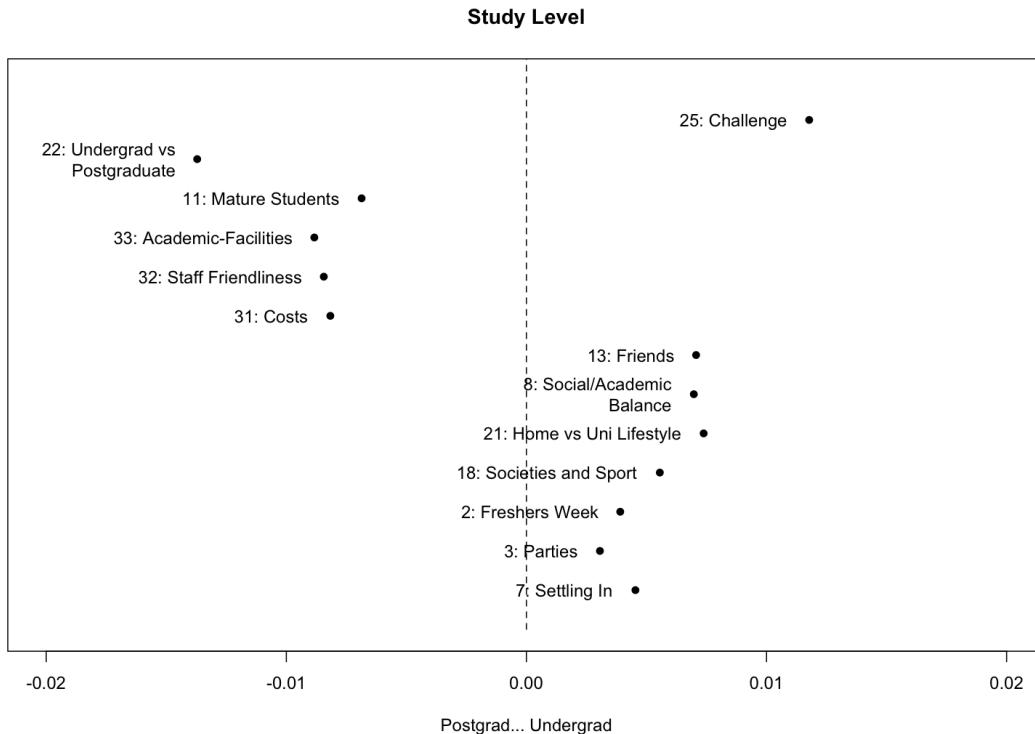


Figure 10: Postgraduate vs Undergraduate marginal effect on topics discussed

In line with existing literature, postgraduate students pay attention more to academic aspects. This is evidenced by the fact that undergraduates more frequently discuss Societies and Sport (Topic #18), Freshers Week (Topic #2), Parties (Topic #3) and Social/Academic Balance (Topic #8). Undergraduates seek to exit their comfort zone and discover themselves through social experiences such as taking up new sports and joining societies. This notion is supported by Topic #25. Postgraduates face higher costs which is reflected in the fact that they more frequently discuss costs (Topic #31). Postgraduates compare their current experience to their undergraduate experience as seen by the higher prevalence of Topic #22. Similarly, Topic #11, which focuses on mature students, is primarily the domain of postgraduates. This reflects the fact that mature students are more likely to be postgraduate students. Understanding that quality dimensions differ amongst graduate and undergraduate students can help universities to create a better experience for both by facilitating more stimulating social experiences for undergraduates whilst providing graduates with the necessary facilities and academic support to pursue more advanced research.

4.6.6 Campus vs non-Campus

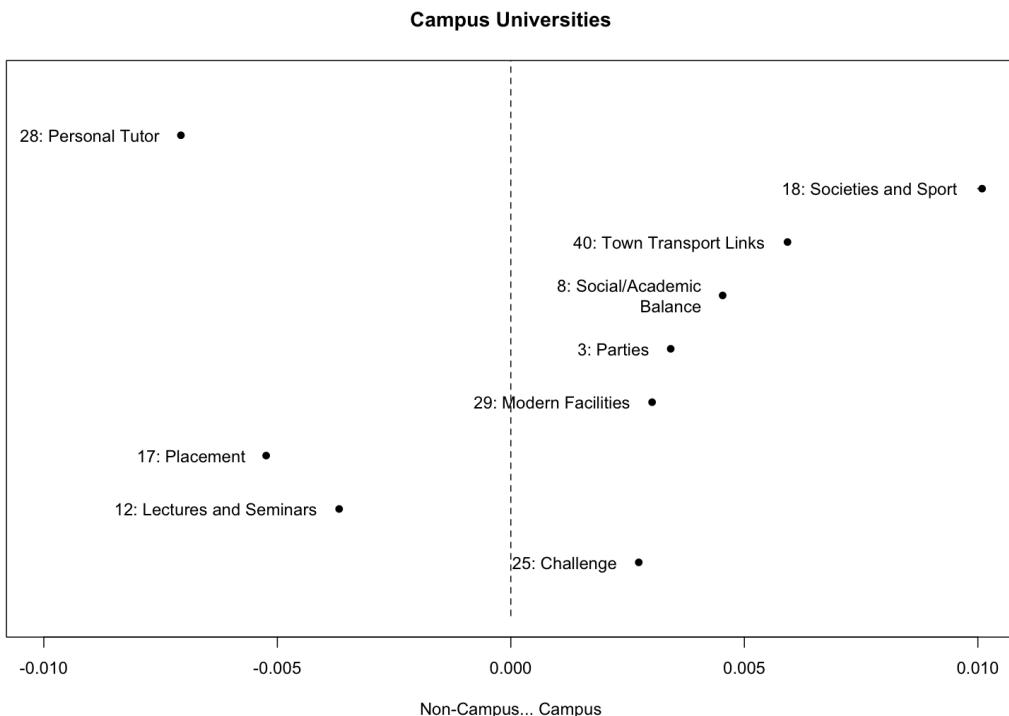


Figure 11: Marginal Effect on Expected Topic Proportions if University is a Campus University

Topic #18, Societies and Sport, has a higher prevalence at campus universities. This indicates that campus universities, unlike those in the cities, often have access to more land and can provide non-academic facilities, such as football pitches, more cost effectively. Campus universities should take full advantage of this feature and position their overall brand accordingly. Similarly, city universities should focus on their own strengths, perhaps emphasising academic expertise and quality of teaching. This will ensure that students expectations are well aligned with reality, and they are not disappointed.

Usurprisingly, Transport links (Topic #40) are important to students who live outside town at campus universities. Given that campus universities are often located in smaller towns and are largest employer in the area they have significant relations with local officials. Universities could leverage these contacts to negotiate bus routes from campus. This can be combined with their own shuttle buses, accommodation, and parking spots.

4.6.7 Location

Although countrywide comparisons do not appear to be useful, the marginal effects of London match expectations. Generally lower satisfaction at London universities is reflected in the fact that Negative Aspects (Topic #10) are more salient whilst the positive topic Sad to Graduate (Topic #5) less salient. Positive topics, related to social aspects, such as Friends (#13) and Social/Academic Balance (#8) are less prevalent. This suggests a focus on academia. As already uncovered, social aspects, such as sports and societies, are important quality dimensions. Therefore, London universities can achieve a competitive advantage if they figure out a strategy to enhance their position on this dimension whilst retaining their academic excellence. Higher living costs compared to the rest of UK lead to discussion on costs (Topic #31). With London being a megapolis, students have access to top notch facilities, both academic and non-academic (Topic #33 and Topic #38), and many opportunities (Topic #31). Students also do not have to worry about transport links which is reflected in Topic #40. Note, these findings are consistent with findings discussed in the previous section. London, however, seems to magnify the negative effects of cities and comes with an additional set of disadvantages and advantages. This again confirms the fact that the model presented here is internally consistent.

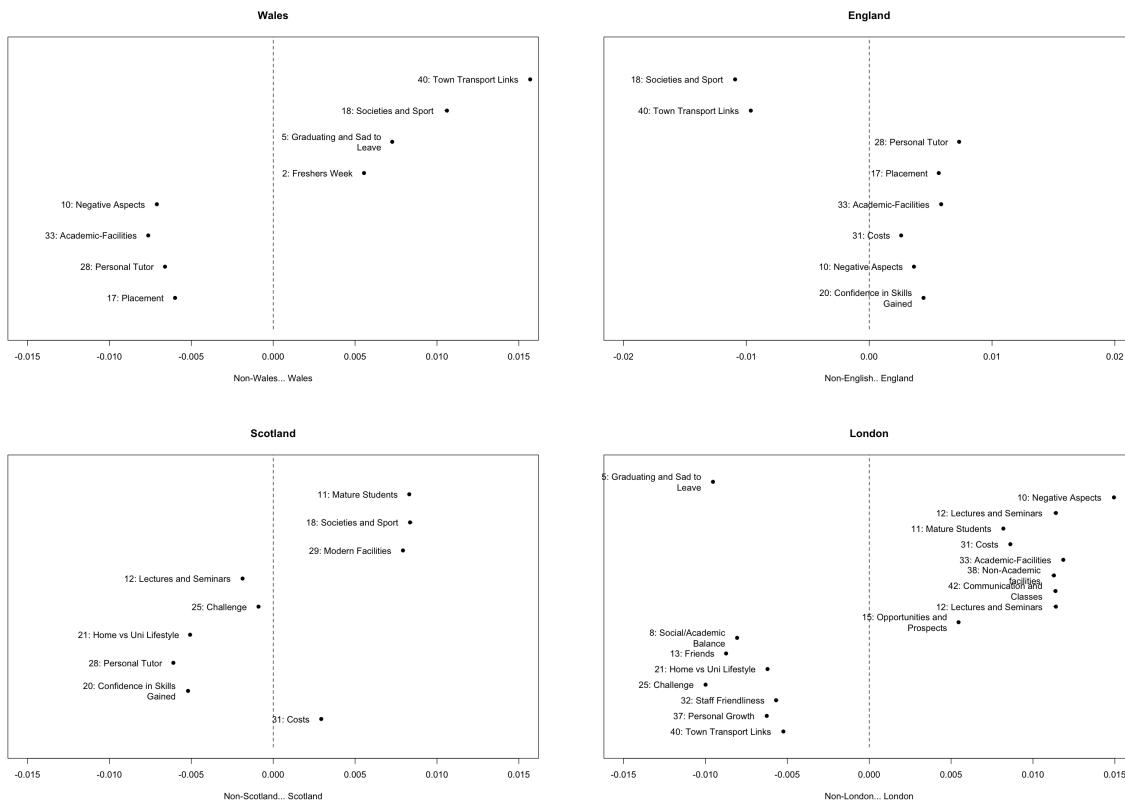
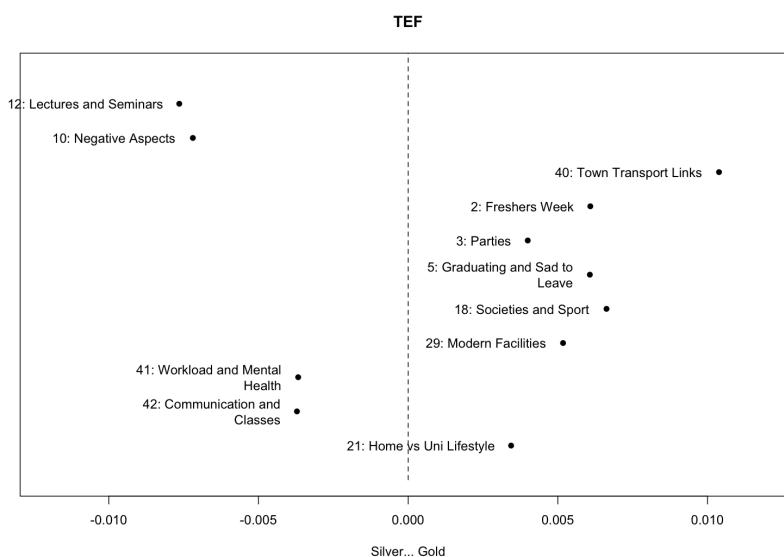


Figure 12: Marginal Effect of Location on Expected Topic Proportions

4.6.8 TEF

The TEF framework was introduced by the government in 2017 with the aim of capturing teaching quality and satisfaction. However, it has been criticised as arbitrary and not reflective of quality of education. Here, these claims are briefly examined by looking at unstructured data. Due to the small sample size of Bronze rated universities, Silver is compared to Gold.

**Figure 13: Marginal Effect of TEF Rating on Expected Topic Proportions**

Negative Aspects (Topic #10), Workload and Mental Health Issues (Topic #41) are more often discussed by students attending a TEF Silver ranked university. At the same time positive topic Sad to Graduate (Topic #5) is amongst the topics more often discussed by students at TEF Gold Universities. This is consistent with claims by TEF. Lectures and Seminars (Topic #12), Communication and Classes (Topic #42) is also discussed by TEF Silver students. However, the expectation is that these would be more salient amongst students TEF Gold ranked university. This suggests and inconsistency in TEFs ability to capture variability.

4.7 Predictive Model Validation and Assessing Information gain from unstructured data through regression

Another way of validating a topic model is by assessing its explanatory power. Additionally, this will allow us to quantify the information gain from integrating unstructured data into

analysis. Since the dependent variable, the overall rating given by a student in a review, is a factor variable, Logistic Regression is used. A base model is specified using all available structured data. Assessing all topics is beyond the scope of this dissertation, hence, a number of topics which were found to be meaningful are selected. Topic proportions are used as independent variables in addition to other metadata.

All topics are found to have a statistically significant impact on predicting the overall score. Relative likelihood of the advanced model is calculated compared to the base model. A likelihood ratio test is conducted to quantify information gained. The null hypothesis is that both models fit the data equally well and thus the nested model is preferable. The chi-squared value yielded is 3887 with a p value of 2.2e-16 which is statistically significant. Therefore, null hypothesis is rejected, and the model with topic proportions is preferable.

Variables	Base Model	Advanced Model
Undergrad	0.035*** (0.011)	-0.001 (0.010)
Job Prospects Rating	0.160*** (0.005)	0.140*** (0.005)
Course and Lecturers Rating	0.263*** (0.006)	0.224*** (0.005)
Student Support Rating	0.213*** (0.005)	0.185*** (0.005)
Uni Facilities Rating	0.135*** (0.005)	0.114*** (0.005)
Local Life Rating	0.097*** (0.005)	0.087*** (0.004)
Societies and sports Rating	0.102*** (0.005)	0.082*** (0.004)
Russel	0.015 (0.016)	0.003 (0.015)
Post 1992	-0.024* (0.013)	0.014 (0.016)
Alliance	-0.009 (0.018)	-0.024** (0.012)
MillionPlus	-0.033* (0.017)	-0.037* (0.012)
Economics	0.042 (0.030)	0.064** (0.028)
History	0.021 (0.023)	0.008 (0.021)
Computing	-0.017 (0.021)	-0.025 (0.019)
Management	-0.011 (0.017)	-0.003 (0.016)
Psychology	0.007 (0.016)	0.019 (0.015)
Social Sciences	0.018 (0.015)	0.036*** (0.014)
Mathematical Sciences	0.022 (0.017)	0.003 (0.015)
Biological Sciences	0.034** (0.013)	0.048*** (0.012)
Environmental Studies	0.071*** (0.019)	0.086*** (0.018)
Law and Criminology	0.016 (0.016)	0.025* (0.015)
Languages	0.045** (0.019)	0.077*** (0.017)
Educational and Eeographical Studies	0.038** (0.018)	0.044*** (0.017)
Art and Design	0.016 (0.014)	0.041*** (0.013)
Business and Administration	0.011 (0.016)	-0.030** (0.015)
Campus University	0.027*** (0.010)	0.016* (0.009)
England	0.099 (0.103)	0.105 (0.096)
London	-0.033 (0.021)	-0.004 (0.019)
Wales	0.127 (0.104)	0.095 (0.096)
Scotland	0.110 (0.104)	0.111 (0.096)
TEF Gold	0.004 (0.017)	-0.028* (0.015)
TEF Silver	-0.020 (0.016)	-0.034* (0.017)
TEF None	-0.018 (0.019)	-0.049*** (0.015)
Topic 8 (Academic/Social Balance)		2.477*** (0.224)
Topic 18 (Societies and Sport)		4.616*** (0.189)
Topic 25 (Challenge)		0.720*** (0.084)
Topic 32 (Staff Friendliness)		4.518*** (0.122)
Topic 41 (Workload and Mental Health)		5.854*** (0.207)
Topic 37 (Personal Growth)		3.494*** (0.174)
AIC	43788.72	39954.12
LL	-21880.36	-19936.47
Chisq		3887.01***

Figure 14: Regression Results. N = 24,168 for both models after reviews with no ratings were removed.

4.8 Mapping University Service Quality Dimensions: Perceptual Map

To achieve a better understanding of how universities position themselves with respect to identified quality dimensions, correspondence analysis is conducted on topic proportions extracted from the STM model. Results are used to plot a perceptual map. Calculating mean values of dimensions for each university gives its position with respect to the service quality dimension axis. Top ten topics are used. The top two principal components capture 60% of the variance. Analysing all dimensions and university groups is outside of the scope of the study, so London universities are selected.

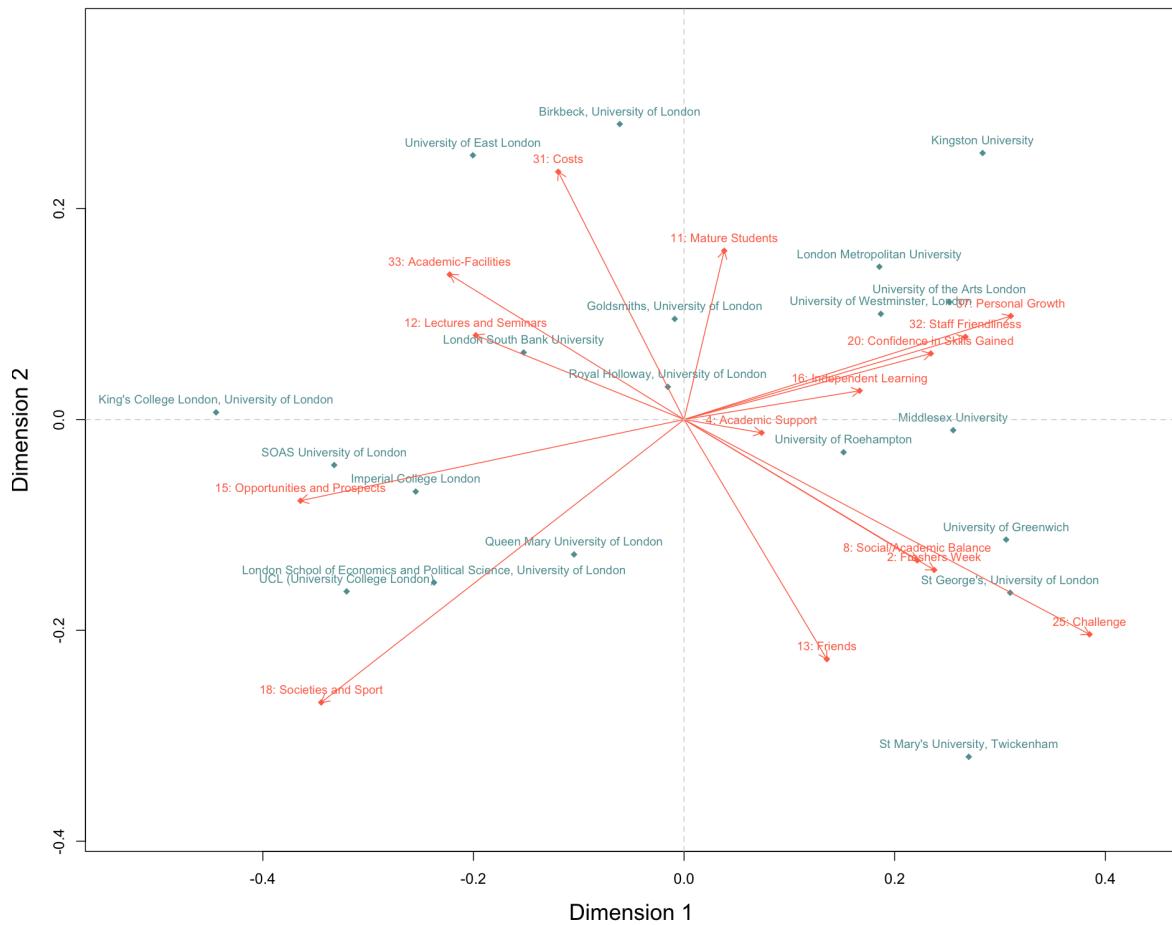


Figure 15: London Universities positioned along the uncovered service quality dimensions. Dimension one explains 43% of variance whilst dimension two explains 17% of variance.

Elite London universities, such as LSE, KCL, UC and Imperial position themselves along the opportunity and prospects axis. The costs dimension is orthogonal to opportunities and prospects. Thus, it appears that students who attend these universities likely consider current costs to be worth it for future returns. In other words, they provide value for money. These universities also have a high loading on the Societies and Sports axis which also appears to be related to the dimension of opportunities. Likely this is because many societies are academic in nature and provide great avenues for knowledge acquisition and networking. This is especially true in London, where access to speakers and businesses is better than anywhere else in the UK. Other universities, who perhaps have less reputation, focus on providing a better experience through academic support, friendly staff, and social activities. Overall, they succeed at creating a more balanced experience as evidenced by high loading on the social/academic balance, friends and fresher's, week dimensions. At the same time, they can provide a transformative experience that challenges students, fosters personal growth, and gives them confidences in the skills gained. From previous sections, it is apparent this approach generally creates more satisfied students.

5. Conclusion

5.1 Contributions

The intended aim of this dissertation is twofold; to discover dimensions of university service quality by analysing online reviews and link these to existing quantitative data used previous research. In fulfilling this goal, the application of topic modelling to open ended survey questions in combination with Likert style questions and available metadata of survey participants, is demonstrated. Previous research uses quantitative data and Likert scale-based questions to assess student satisfactions. In contrast, this dissertation is the first to focus on the use automated statistical methods to analyse unstructured data to understand student satisfaction. The advantage of this approach is made clear quantitatively through regression analysis and qualitatively by examining the topic solution with existing data.

44 topics were extracted from unstructured data. Most of topics were linked to service quality dimensions already identified in previous research, which verifies the validity of our approach and findings. Most of the identified quality dimension point towards concrete aspects of the university experiences, such as access to transport. A significant contribution of this study is the discovery of two new, UK specific, dimensions: Societies and Sports, Independent Learning.

Societies and Sports is closely linked to the dimension of community identified by previous literature. However, this study regards it as a distinct dimension due to its large proportion. In fact, the expected topic proportion attributed to the topic of Societies and Sports is larger than the topic Community. Additionally, Sports and Societies is orthogonal to community and other social quality dimensions identified. Content wise, community is a topic that refers to the general atmosphere on campus, whilst sports and societies refers to concrete activities that students partake in. This means that a university might have a great community and friendly environment without having many active societies. Thus, this distinction is practical when viewed from a managerial perspective. Furthermore, this topic that stands out in terms of its strong relationship with metadata on several dimensions (see Figured 5 and 6).

Independent learning appears to be a dimension highly relevant to UK's education system, which places a high focus on independent learning. Theoretically, it is hard to link to any dimensions identified in the literature. Therefore, more examination is needed as to what drives students to put more effort in their spare time into studying. It is reasonable, for example, that enthusiastic teachers could be a factor. Access to facilities, such as a library,

could also have an effect. Perhaps universities could adopt policies that empower students to peruse independent learning to greater effect. This dimension needs to be explored and quantified in future research.

5.2 Implications

This work is of interest to management at universities. By following the methodology demonstrated here and implementing Structural Topic Model to analyse responses to open ended questions in internal surveys, universities will be able to achieve a competitive advantage. Firstly, topic modelling enables the discovery of salient, previously unknown, issues. These can then be explored more thoroughly and quantified in future surveys with targeted questions. Secondly, by utilising both unstructured data and structured data universities can examine the relationship between topics and metadata. Particularly, examining temporal changes in topic salience can help understand whether a policy had the intended effect and continually monitor further impacts. Finally, the results of this study, due to its large UK wide sample, can be used directly to guide policy or future research at individual institutions. For example, given the large proportion of reviews focused on social aspects such as societies, universities should consider supporting those directly rather than delegating this task to student unions. Arguably, providing annual grants to societies is cheaper than building new facilities, yet based on the results of this study could have a disproportionate effect on satisfaction. Currently, most surveys such as the NSS ignore this aspect of university life entirely, which perhaps is the reason that students choose to express their opinions in online forums instead. Other identified quality dimensions also point towards concrete aspects of the university experiences, such as access to transport which can also be used to guide decision making. To conclude, investing into salient aspects can have a higher marginal return on investment in terms of increasing student satisfaction.

5.3 Limitations

The primary limitation of this dissertation is the focus on the overall review text field response rather than the multiple fields available. In part this is because of the limitation of the **stm** package. Currently it limits the number of content covariates. This makes combining text from multiple fields a non-trivial task with multiple options available. Option 1, concatenate all text and set prevalence covariates depending on which field the text comes from. Option 2, concatenate all text and set a content covariate as a factor variable. Option 3, run separate models for each open-ended question. Whilst it is unclear how consistent results from option

1 and 2 will be, option 3 is most expensive. Therefore, future research should be done to evaluate these options. Improving the implementation of the **stm** to enhance support for multiple content covariates could be of interest to researchers in the field of Statistical Software. Nonetheless, despite this limitation the model presented, this study uncovered all but one, quality dimensions present in the literature. This implies that just one open ended question could be enough to generate significant insight. This is encouraging because it is difficult to convince people to complete surveys, so shorter is better. A limitation of using online reviews is that the sample is likely non-random. Self-selection bias exists. Therefore, online reviews are not representative. Nonetheless, this is a problem that affects surveys too and is not exclusive to online review. For example, Hewson (2011) identifies this problem in the NSS.

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Appendix A

List of Universities and Frequency of Reviews

University	Frequency
Swansea University	2095
University of Hull	1809
Edge Hill University	1680
Northumbria University, Newcastle	1676
University of Glasgow	1469
Bangor University	1409
Nottingham Trent University	1077
University of Chester	999
Loughborough University	788
Aberystwyth University	754
University of Worcester	729
Leeds Arts University	652
Teesside University, Middlesbrough	616
University of Sunderland	515
University of Plymouth	485
University of East Anglia UEA	456
University of Cumbria	455
University of Lincoln	450
The University of Law	371
University of Strathclyde	369
University of Portsmouth	366
Lancaster University	363
University of Exeter	350
University of Bradford	277
Hartpury University	275
University of Gloucestershire	274
University of South Wales	274
University of York	272
University of Hertfordshire	269
University of Kent	258
Arts University Bournemouth	255
Brunel University London	255
Harper Adams University	238
University of Stirling	231
University of Wales Trinity Saint David	230
Buckinghamshire New University	223
Birmingham City University	211
Liverpool Hope University	210
Keele University	207
Coventry University	206
Middlesex University	202
Sheffield Hallam University	197
Leeds Trinity University	193
University of Westminster, London	190
University of Leeds	187

University	Frequency
Canterbury Christ Church University	181
University of Suffolk	179
University of Greenwich	178
London Metropolitan University	169
Bournemouth University	166
Falmouth University	166
University of Buckingham	156
University of Southampton	153
Aston University, Birmingham	148
University of Salford	148
King's College London, University of London	144
BIMM Institute	143
University of Brighton	141
University of Sheffield	136
Anglia Ruskin University	130
University of Surrey	126
University of Warwick	125
University of Liverpool	124
Royal Agricultural University	123
University of Derby	117
University of Chichester	114
Solent University (Southampton)	111
University of Huddersfield	109
Liverpool John Moores University	106
Goldsmiths, University of London	103
University of Sussex	103
Edinburgh Napier University	94
Bristol, University of the West of England	93
Leeds Beckett University	93
Oxford Brookes University	91
University of Essex	88
Manchester Metropolitan University	87
Queen Margaret University, Edinburgh	86
University of Nottingham	85
Glasgow Caledonian University	84
Durham University	82
Cardiff University	78
Glyndwr University, Wrexham	77
Queen Mary University of London	76
University for the Creative Arts	72
University of Leicester	72
University of Winchester	72
Heriot-Watt University	71
University of Bath	71
Newcastle University	68

University	Frequency
University of Manchester	68
Staffordshire University	66
University of Edinburgh	66
St George's, University of London	64
UCL (University College London)	64
University of Central Lancashire	60
University of Wolverhampton	60
Royal Holloway, University of London	59
University of East London	59
York St John University	59
University College Birmingham	57
SOAS University of London	54
Newman University, Birmingham	50
University of Reading	50
University of the Arts London	50
University of Northampton	47
University of Roehampton	45
De Montfort University	43
London South Bank University	42
University of Birmingham	42
University of Dundee	42
Plymouth Marjon University	38
London School of Economics and Political Science, University of London	37
University of Cambridge	36
University of St Andrews	36
Norwich University of the Arts	35
University of Bolton	35
University of Bristol	33
Bath Spa University	31
University of Bedfordshire	31
Imperial College London	30
Ulster University	30
Abertay University	29
St Mary's University, Twickenham	28
University of Aberdeen	23
Birkbeck, University of London	18
Kingston University	17
Queen's University Belfast	15
Robert Gordon University	15
Cardiff Metropolitan University	12
University of the West of Scotland	4
University of Oxford	1

Appendix B

Top 7 terms ranked by highest probability, FREX, Lift and Score.

Topic 1 Top Words:

Highest Prob: feel, community, comfortable, safe, sense, fit, lucky
 FREX: feel, community, comfortable, sense, feeling, homely, belong
 Lift: belong, supported, comfortable, feeling, community, sense, feel
 Score: feel, community, comfortable, welcomed, safe, sense, fit

Topic 2 Top Words:

Highest Prob: amazing, lovely, incredible, incredibly, ill, include, exceptional
 FREX: amazing, incredible, lovely, ill, incredibly, equally, ton
 Lift: ill, incredible, amazing, lovely, incredibly, include, rarely
 Score: amazing, lovely, incredible, ill, incredibly, include, exceptional

Topic 3 Top Words:

Highest Prob: night, event, week, union, fresher, run, drink
 FREX: night, event, fresher, party, hold, union, hang
 Lift: alcohol, drinking, hang, party, ball, evening, event
 Score: night, event, union, week, fresher, alcohol, drink

Topic 4 Top Words:

Highest Prob: support, academic, term, aspect, receive, guidance, network
 FREX: academic, support, guidance, term, potential, receive, aspect
 Lift: encouragement, academic, dyslexia, support, guidance, potential, commitment
 Score: support, academic, term, aspect, receive, dyslexia, guidance

Topic 5 Top Words:

Highest Prob: love, leave, graduate, miss, minute, imagine, sad
 FREX: love, graduate, sad, imagine, leave, miss, outdoor
 Lift: outdoor, love, sad, imagine, bubble, graduate, miss
 Score: love, leave, outdoor, sad, graduate, minute, miss

Topic 6 Top Words:

Highest Prob: recommend, brilliant, highly, apply, fab, leed, sign
 FREX: recommend, brilliant, highly, apply, fab, leed, possibly
 Lift: lecturers, possibly, recommend, strongly, apply, brilliant, fab
 Score: recommend, brilliant, highly, apply, lecturers, leed, fab

Topic 7 Top Words:

Highest Prob: start, difficult, settle, month, easier, quickly, flatmate
 FREX: start, settle, easier, quickly, begin, adjust, beginning
 Lift: adapt, daunt, easier, finde, homesickness, nervous, routine
 Score: start, settle, difficult, shock, easier, quickly, month

Topic 8 Top Words:

Highest Prob: life, social, change, balance, memory, forget, universiy
 FREX: life, balance, social, universiy, mixture, memory, hardest
 Lift: mixture, universiy, balance, life, social, cherish, hardest
 Score: life, social, change, mixture, balance, memory, forget

Topic 9 Top Words:

Highest Prob: expect, amount, manage, busy, hand, happen, fault
 FREX: expect, busy, hand, fault, manage, amount, happen
 Lift: alright, busy, deep, expect, fault, hand, happen
 Score: expect, necessarily, amount, manage, busy, hand, happen

Topic 10 Top Words:

Highest Prob: hour, contact, poor, exam, leave, structure, timetable
 FREX: waste, terrible, awful, worst, poor, mark, timetable
 Lift: marking, total, unorganized, actual, awful, bother, cancel

Topic 11 Top Words:

Highest Prob: student, advice, mature, diverse, background, type, faculty
 FREX: student, advice, fellow, mature, exchange, diverse, faculty
 Lift: exchange, fellow, national, accommodate, student, cultural, advice
 Score: student, mature, advice, national, diverse, fellow, faculty

Topic 12 Top Words:

Highest Prob: lecturer, lecture, teach, content, feedback, information, seminar
 FREX: lecture, seminar, lecturer, content, enthusiastic, slide, lab
 Lift: lecture, enthusiasm, record, revision, seminar, engaging, slide
 Score: lecture, lecturer, slide, teach, seminar, content, feedback

Topic 13 Top Words:

Highest Prob: enjoy, load, flat, mate, highlight, manageable, throughly
 FREX: enjoy, mate, load, throughly, tiring, flat, manageable
 Lift: throughly, tiring, mate, enjoy, manageable, load, flat
 Score: enjoy, load, tiring, flat, mate, manageable, highlight

Topic 14 Top Words:

Highest Prob: happy, choose, glad, decision, regret, decide, pleased
 FREX: happy, choose, glad, decision, regret, pleased, happier
 Lift: everyday, choose, decision, firm, glad, happier, happy
 Score: choose, happy, glad, decision, regret, everyday, decide

Topic 15 Top Words:

Highest Prob: opportunity, offer, job, plenty, chance, field, trip
 FREX: offer, opportunity, abroad, prospects, job, prospect, advantage
 Lift: advantage, internship, search, opportunity, abroad, cv, prospect
 Score: opportunity, offer, job, plenty, search, prospects, chance

Topic 16 Top Words:

Highest Prob: learn, subject, independent, learning, passionate, alot, adult
 FREX: learn, learning, alot, independent, subject, curve, overcome
 Lift: curve, learn, alot, independent, learning, overcome, subject
 Score: learn, independent, subject, curve, learning, passionate, alot

Topic 17 Top Words:

Highest Prob: placement, practical, industry, base, organise, session, require
 FREX: placement, practical, session, practice, relevant, nurse, industry
 Lift: clinical, company, fashion, nursing, practice, purpose, relevant
 Score: placement, practical, industry, occasion, session, practice, organise

Topic 18 Top Words:

Highest Prob: society, club, sport, involved, join, activity, range
 FREX: society, sport, involved, join, activity, range, wide
 Lift: committee, extra-curricular, rugby, sporting, sport, curricular, football
 Score: society, club, sport, join, curricular, involved, activity

Topic 19 Top Words:

Highest Prob: module, bad, real, final, grade, semester, plan
 FREX: semester, module, bad, pass, grade, final, fine
 Lift: bag, means, semester, count, mixed, havent, vari
 Score: bad, module, means, grade, final, real, semester

Topic 20 Top Words:

Highest Prob: future, skill, career, improve, gain, knowledge, prepare
 FREX: future, skill, career, gain, knowledge, expand, path
 Lift: career, gain, knowledge, skill, boost, expand, future
 Score: skill, future, career, gain, knowledge, improve, confidence

Topic 21 Top Words:

Highest Prob: live, home, move, family, house, independence, lifestyle
 FREX: live, home, move, lifestyle, family, independence, housemate
 Lift: live, move, sick, home, lifestyle, closer, housemate
 Score: live, home, move, sick, family, independence, house

Topic 22 Top Words:

Highest Prob: teaching, level, ready, undergraduate, advise, ensure, succeed
 FREX: level, undergraduate, advise, ensure, succeed, postgraduate, teaching
 Lift: aim, academics, advise, approach, current, ensure, level
 Score: teaching, desire, level, undergraduate, postgraduate, ready, undergrad

Topic 23 Top Words:

Highest Prob: fun, engage, nightlife, exciting, size, project, super
 FREX: fun, exciting, engage, super, bore, weather, size
 Lift: bore, clubbing, exciting, fun, lots, suite, super
 Score: fun, nightlife, engage, suite, exciting, size, super

Topic 24 Top Words:

Highest Prob: fantastic, department, country, culture, completely, opinion, matter
 FREX: fantastic, country, unique, history, culture, engineering, universities
 Lift: tailor, engineering, fantastic, feature, history, prestigious, unique
 Score: fantastic, rank, department, country, culture, history, opinion

Topic 25 Top Words:

Highest Prob: friend, meet, challenge, learner, step, share, reward
 FREX: friend, meet, learner, challenge, comfort, reward, step
 Lift: comfort, friend, meet, reward, learner, challenge, embrace
 Score: friend, meet, comfort, challenge, learner, reward, step

Topic 26 Top Words:

Highest Prob: choice, forward, extremely, continue, rest, proud, journey
 FREX: forward, continue, rest, proud, journey, grateful, excited
 Lift: continue, anticipate, forward, journey, proud, rest, strive
 Score: forward, choice, memorable, extremely, continue, rest, proud

Topic 27 Top Words:

Highest Prob: world, huge, honestly, friendship, form, freedom, style
 FREX: world, huge, honestly, friendship, form, freedom, style
 Lift: form, friendship, huge, independently, difference, freedom, fresh
 Score: world, sixth, honestly, huge, form, friendship, freedom

Topic 28 Top Words:

Highest Prob: tutor, personal, talk, professional, understanding, workshop, idea
 FREX: tutor, personal, talk, workshop, professional, idea, understanding
 Lift: technician, touch, tutor, personal, talk, statement, workshop
 Score: tutor, personal, statement, talk, professional, workshop, understanding

Topic 29 Top Words:

Highest Prob: excellent, beautiful, location, wonderful, perfect, building, top
 FREX: excellent, perfect, beautiful, outstanding, modern, fabulous, equip
 Lift: grounds, perfect, excellent, notch, outstanding, pleasure, modern
 Score: excellent, beautiful, location, notch, building, perfect, wonderful

Topic 30 Top Words:

Highest Prob: expectation, visit, realise, cover, arrive, wise, forever
 FREX: expectation, visit, realise, cover, arrive, wise, forever
 Lift: apprehensive, cover, expectation, flexibility, forever, fulfil, overwhelm
 Score: exceed, expectation, visit, cover, forever, realise, arrive

Topic 31 Top Words:

Highest Prob: money, quality, pay, care, research, spend, reason
 FREX: pay, care, reason, cost, improvement, majority, fee
 Lift: actively, attract, deserve, fund, afford, award, cost
 Score: money, pay, league, care, quality, research, cost

Topic 32 Top Words:

Highest Prob: staff, friendly, helpful, nice, easy, supportive, environment
 FREX: friendly, helpful, staff, environment, supportive, easy, welcoming
 Lift: navigate, helpful, friendly, approachable, welcoming, environment, supportive
 Score: friendly, staff, helpful, nice, easy, supportive, navigate

Topic 33 Top Words:

Highest Prob: facility, provide, library, service, access, resource, include
 FREX: library, access, resource, service, facility, equipment, provide
 Lift: computers, source, access, availability, equipment, impressive, library
 Score: facility, library, provide, service, access, resource, source

Topic 34 Top Words:

Highest Prob: pretty, free, focus, system, awesome, stuff, compare
 FREX: pretty, focus, awesome, stuff, compare, decent, satisfied
 Lift: focus, awesome, bigger, compare, fill, politics, satisfied
 Score: pretty, combine, free, awesome, focus, system, stuff

Topic 35 Top Words:

Highest Prob: positive, issue, lack, deal, email, communication, negative
 FREX: positive, issue, deal, communication, negative, regard, listen
 Lift: assistance, query, resolve, address, comment, issue, minor
 Score: issue, positive, resolve, lack, email, parking, communication

Topic 36 Top Words:

Highest Prob: hard, worth, encourage, explore, push, challenging, zone
 FREX: hard, encourage, explore, push, challenging, zone, motivate
 Lift: illustration, push, wider, worthwhile, zone, challenging, encourage
 Score: hard, zone, worth, encourage, push, challenging, explore

Topic 37 Top Words:

Highest Prob: person, develop, grow, academically, achieve, personally, confident
 FREX: person, grow, academically, personally, confident, individual, socially
 Lift: immensely, professionally, shape, shy, grow, person, character
 Score: person, grow, develop, academically, confident, professionally, achieve

Topic 38 Top Words:

Highest Prob: accommodation, su, hall, food, expensive, option, cheap
 FREX: accommodation, private, gym, food, su, cheaper, clean
 Lift: candy, canteen, accommodation, cater, cheaper, gym, halls
 Score: accommodation, su, hall, food, expensive, candy, cheap

Topic 39 Top Words:

Highest Prob: short, fast, meeting, massive, strong, add, period
 FREX: fast, meeting, massive, strong, add, discover, mention
 Lift: additionally, dynamic, importantly, integrate, pace, regular, relate
 Score: mention, fast, meeting, short, strong, massive, discover

Topic 40 Top Words:

Highest Prob: town, close, walk, bar, shop, beach, travel
 FREX: town, close, walk, shop, beach, bus, local
 Lift: walking, convenient, handy, relaxing, station, street, quiet
 Score: town, close, station, shop, beach, walk, bus

Topic 41 Top Words:

Highest Prob: stressful, struggle, assignment, stress, health, mental, workload
 FREX: stressful, struggle, assignment, stress, health, mental, workload
 Lift: cope, depression, health, roller, stress, deadline, disability
 Score: mental, stressful, struggle, health, assignment, stress, workload

Topic 42 Top Words:

Highest Prob: class, teacher, attend, understand, question, lesson, speak
 FREX: class, teacher, attend, understand, question, lesson, speak
 Lift: understand, answer, attend, classmate, concept, english, lesson
 Score: class, teacher, attend, understand, concept, question, lesson

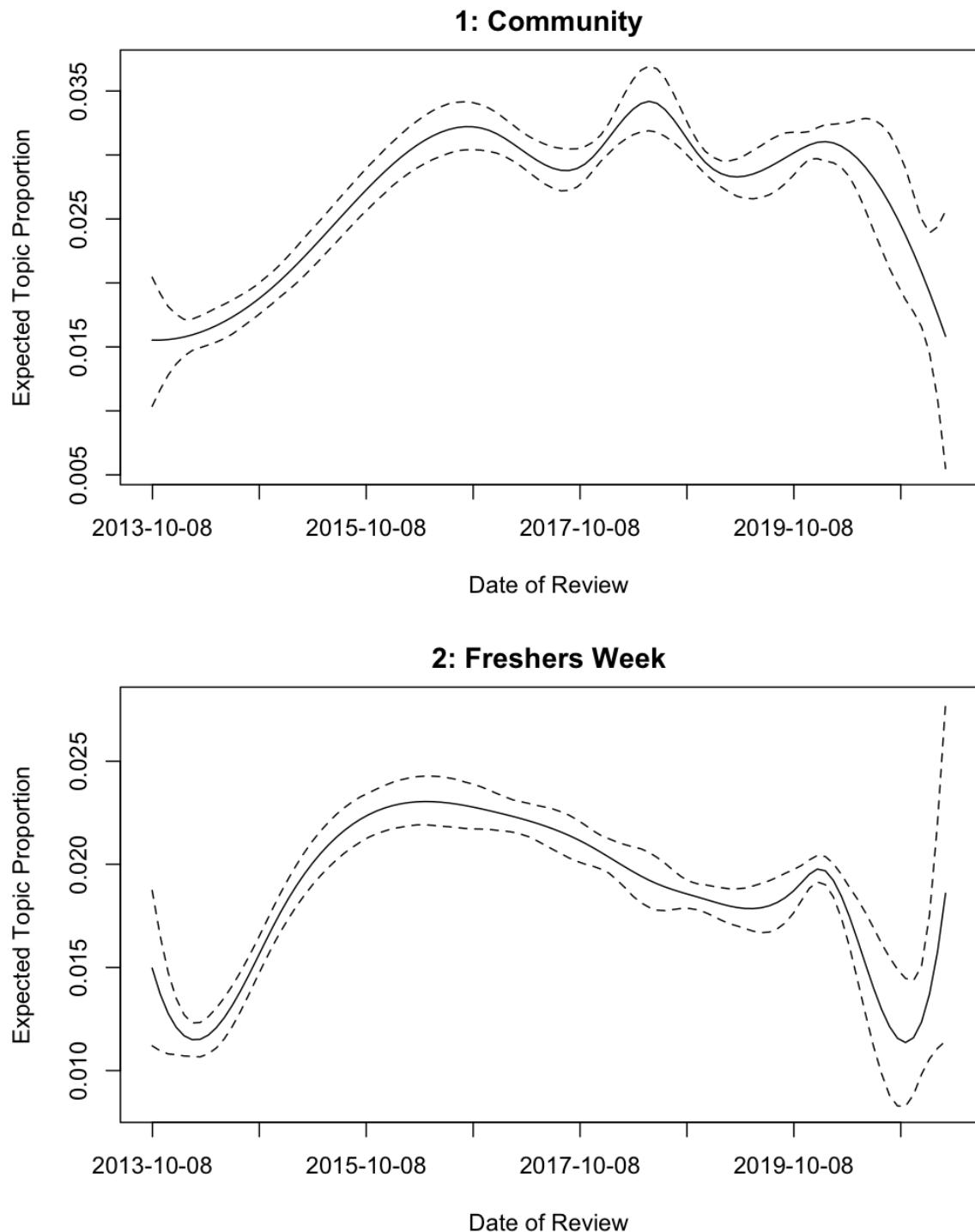
Topic 43 Top Words:

Highest Prob: degree, stay, absolutely, wait, complete, moment, finish
 FREX: degree, stay, wait, moment, finish, master, st
 Lift: disappointment, finish, master, masters, stay, rd, st
 Score: degree, absolutely, stay, wait, master, disappointment, complete

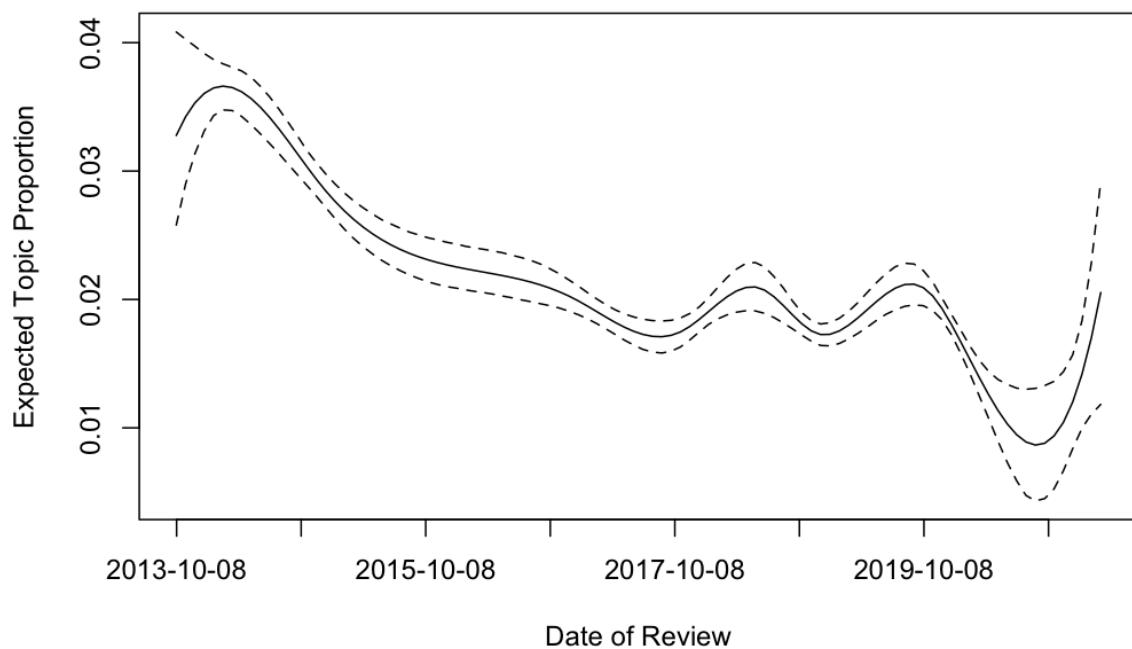
Topic 44 Top Words:

Highest Prob: enjoyable, spend, effort, mix, create, past, specific
 FREX: enjoyable, mix, create, effort, stuck, commit, past
 Lift: commit, enjoyable, stuck, mix, create, past, addition
 Score: enjoyable, commit, effort, spend, mix, create, past

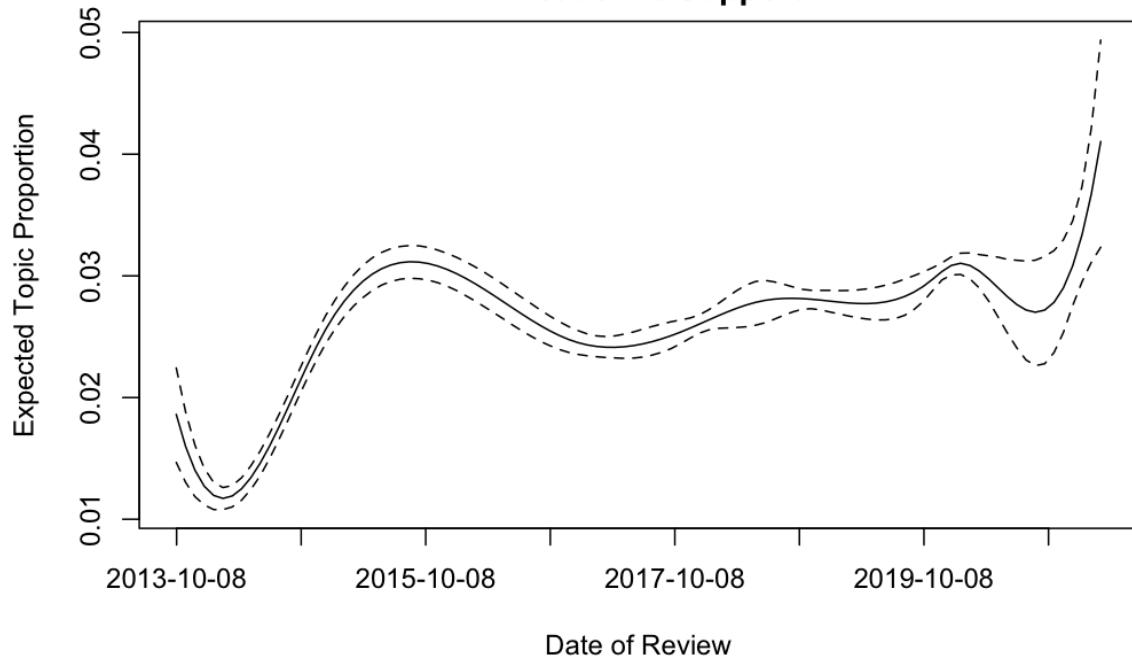
Appendix C



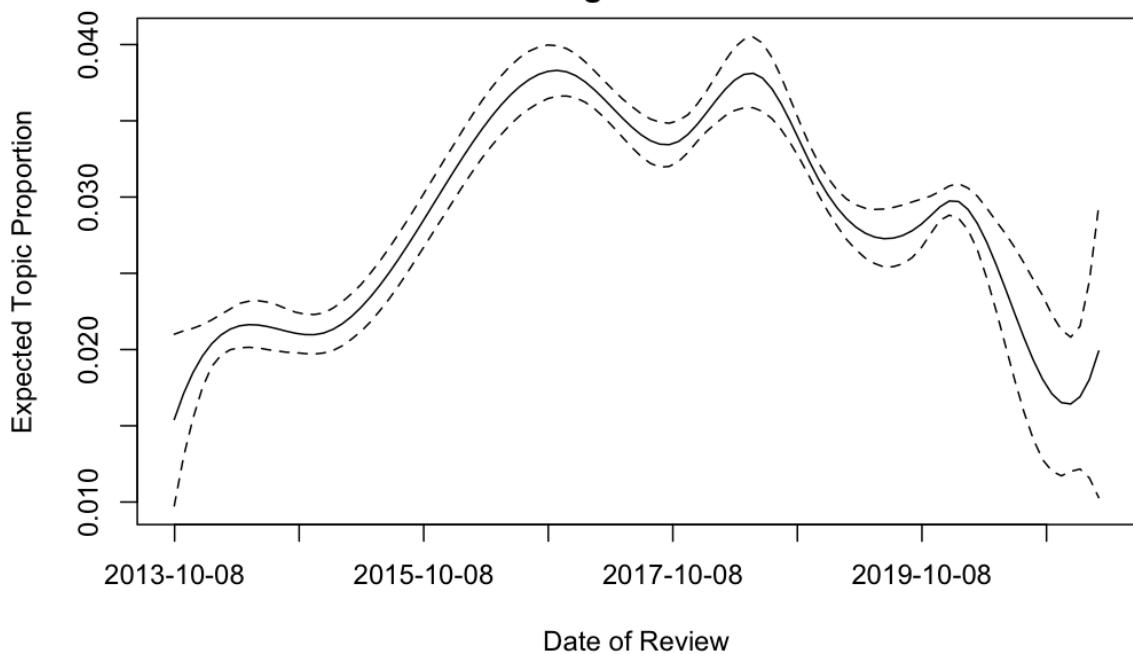
3: Parties



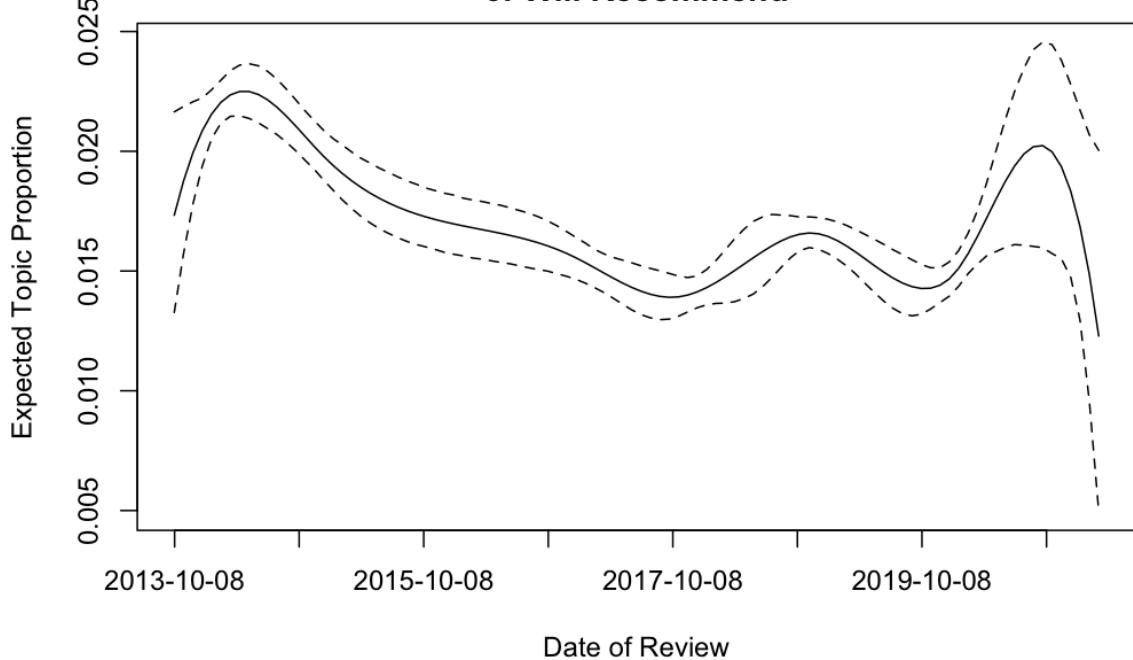
4: Academic Support



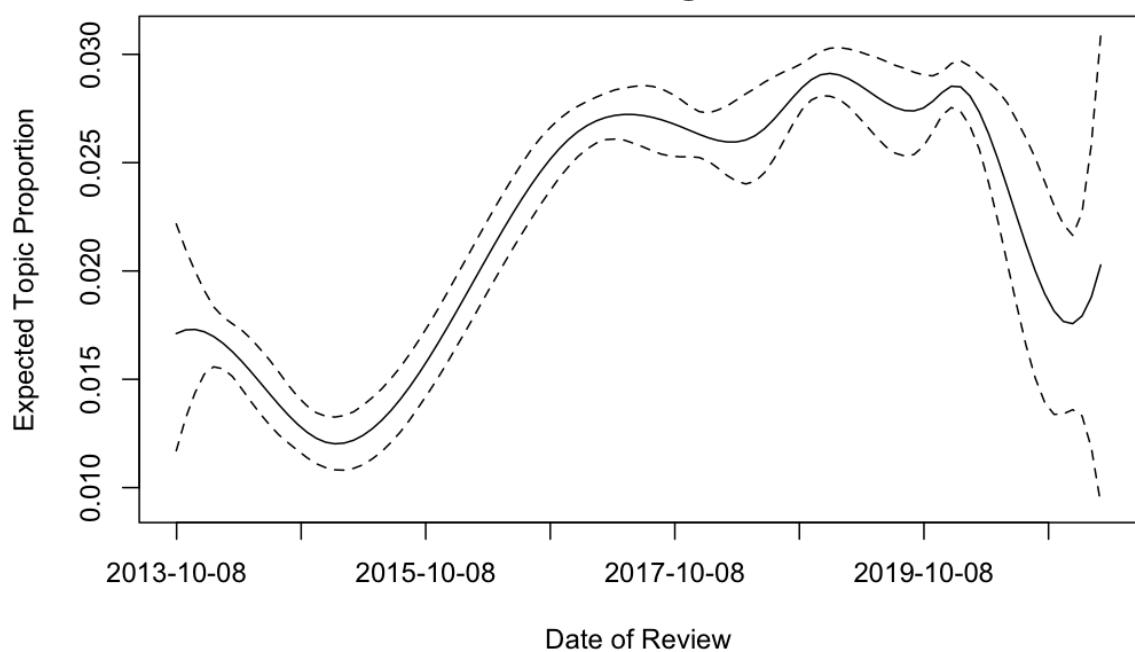
5: Graduating and Sad to Leave



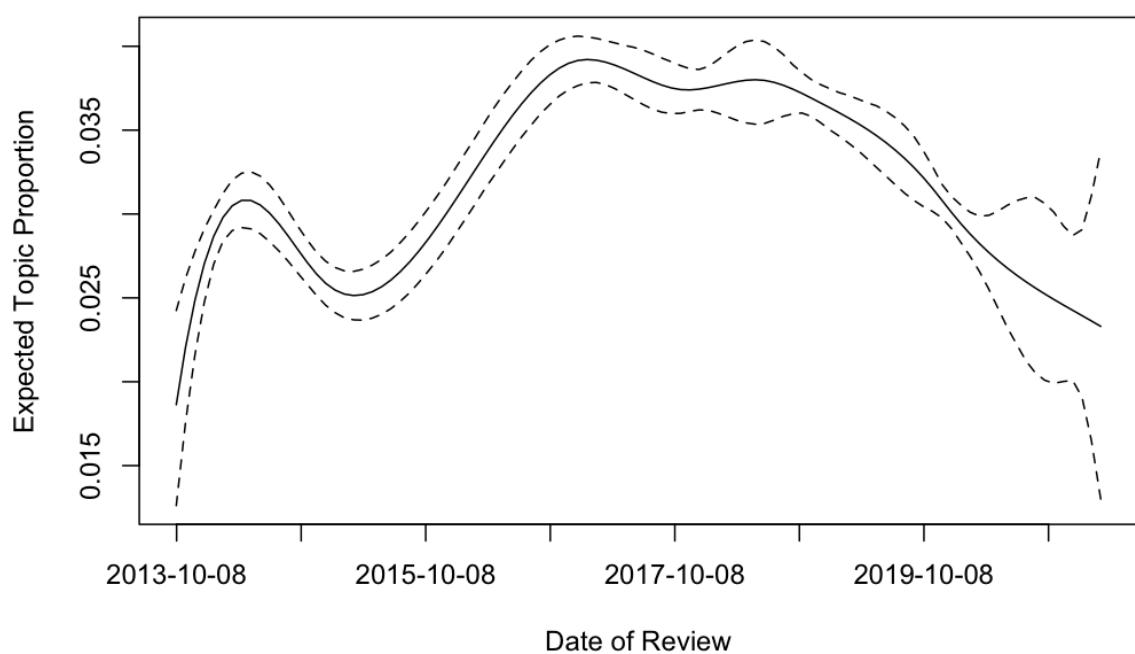
6: Will Recommend

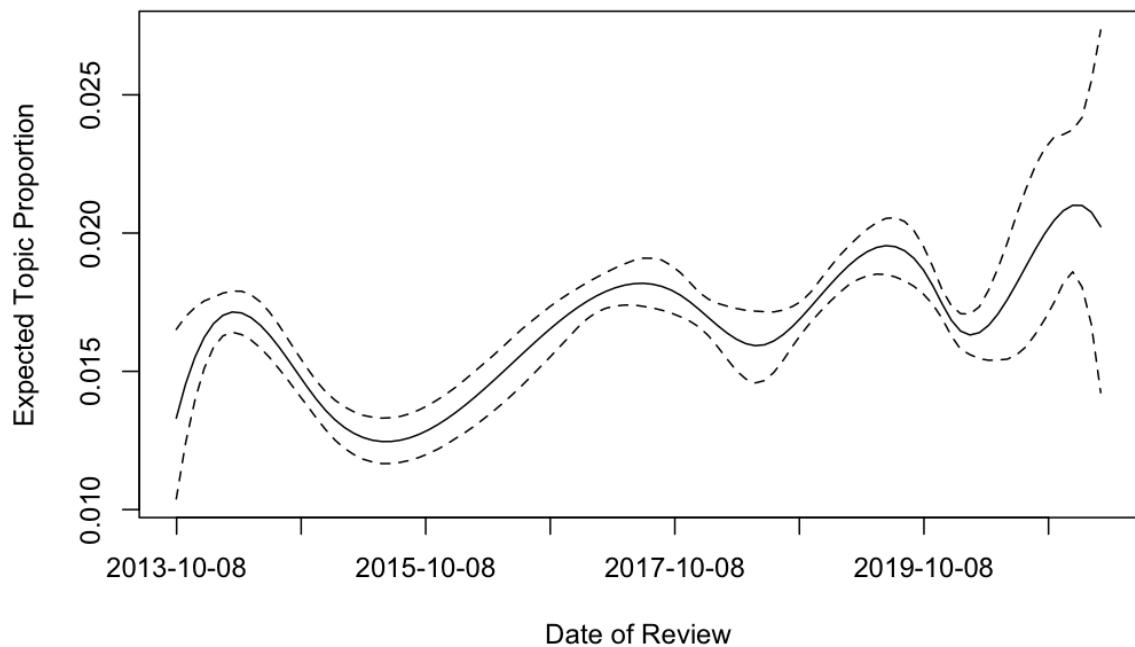
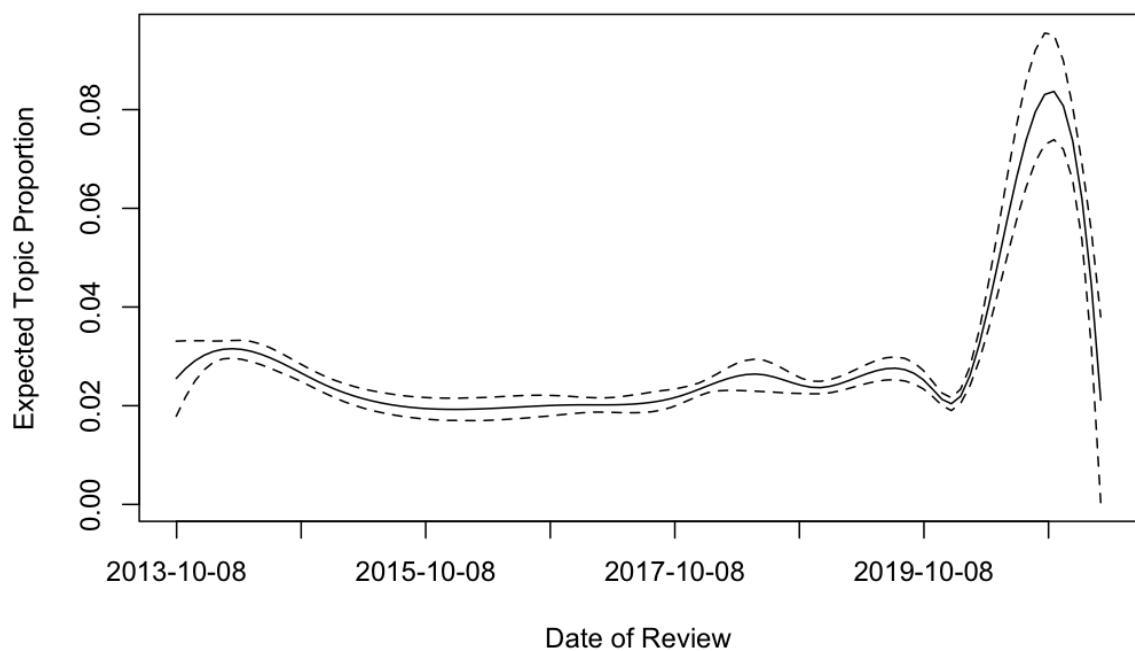


7: Settling In

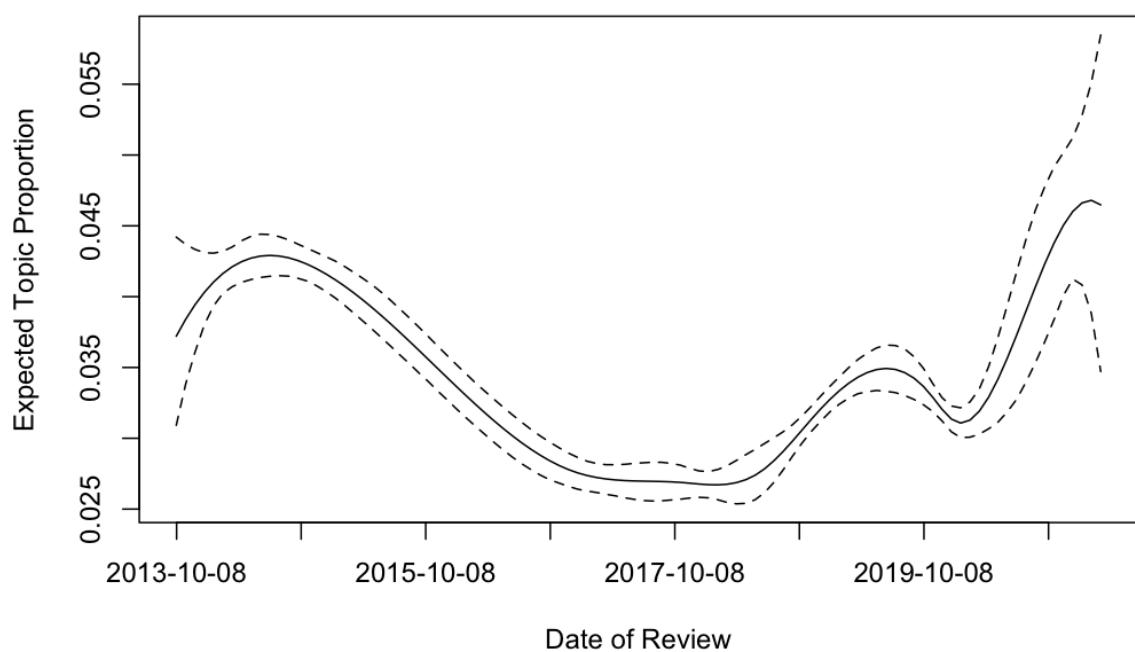


8: Social/Academic Balance

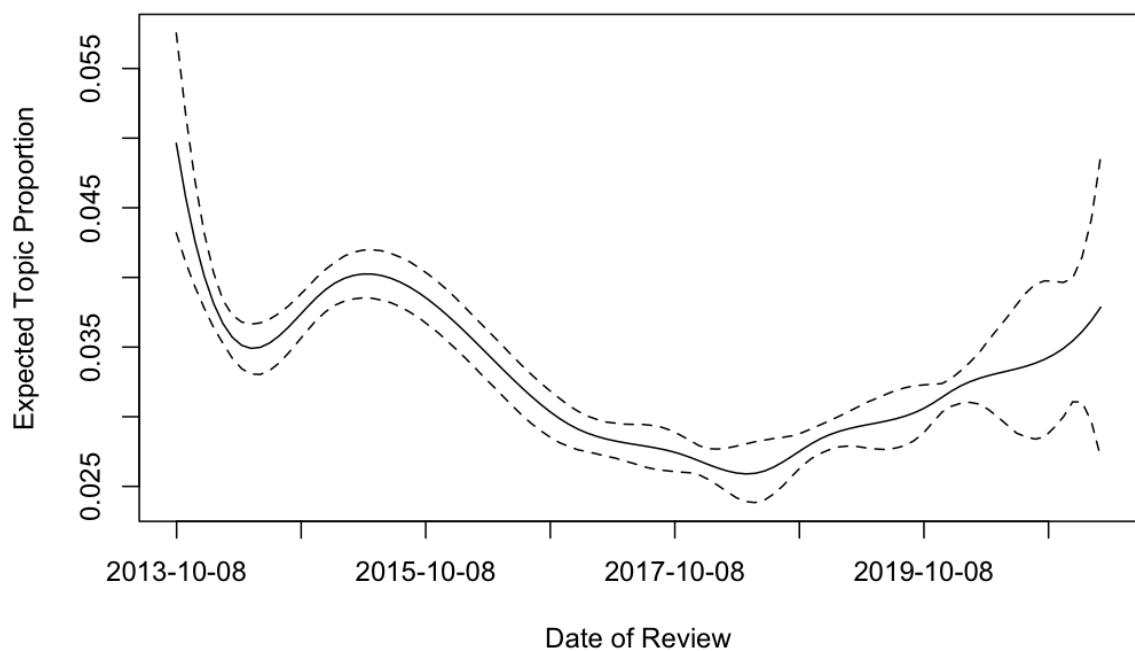


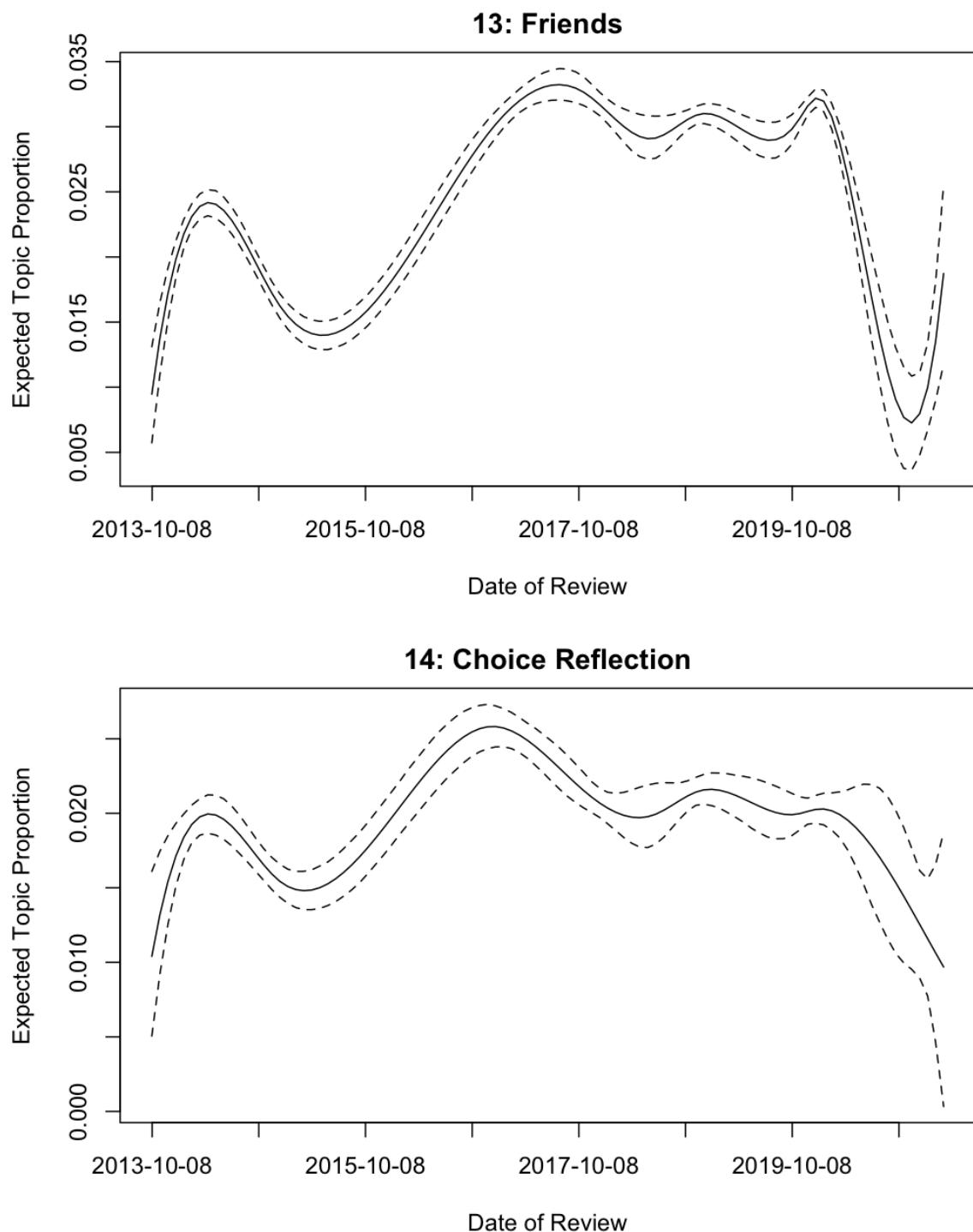
9: Workload**10: Negative Aspects**

11: Mature Students

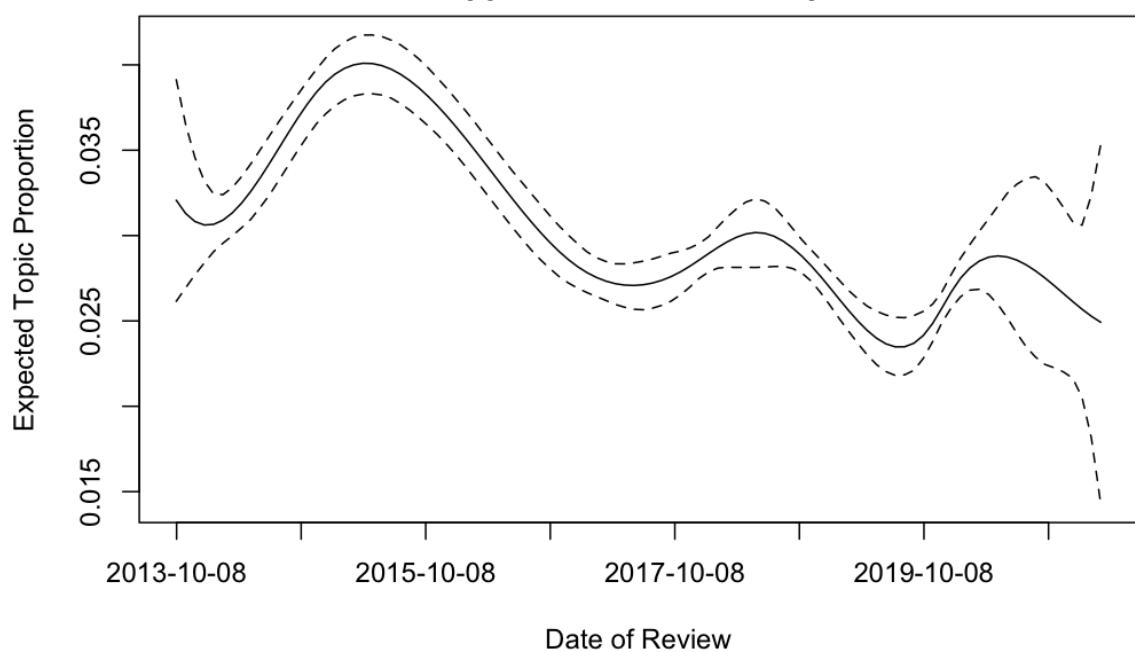


12: Lectures and Seminars

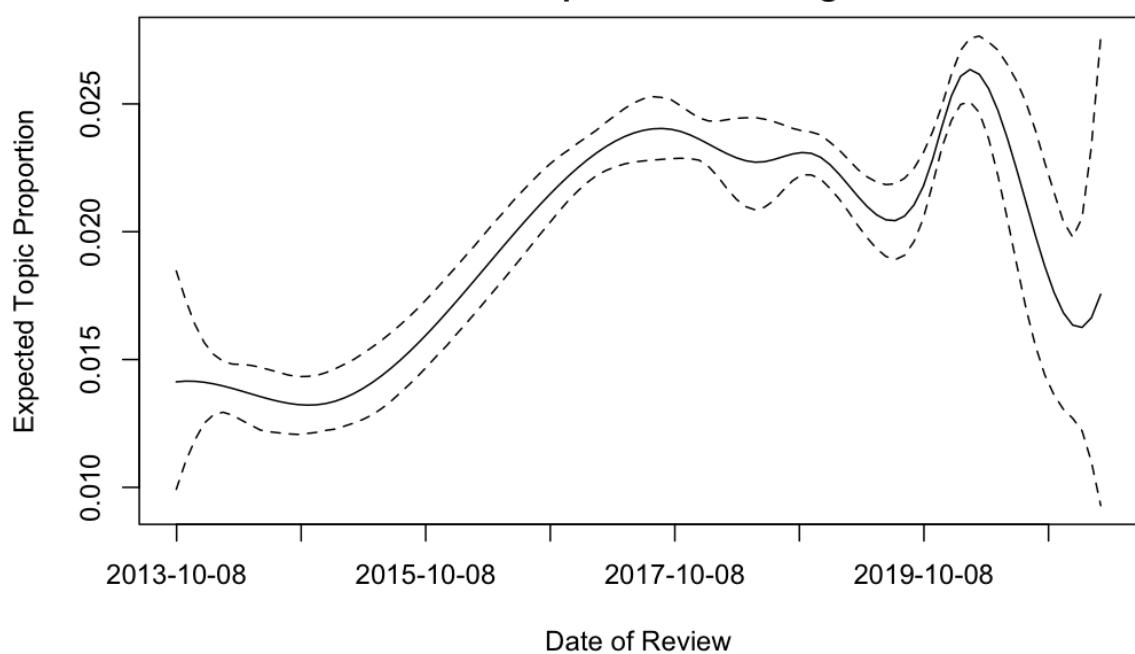




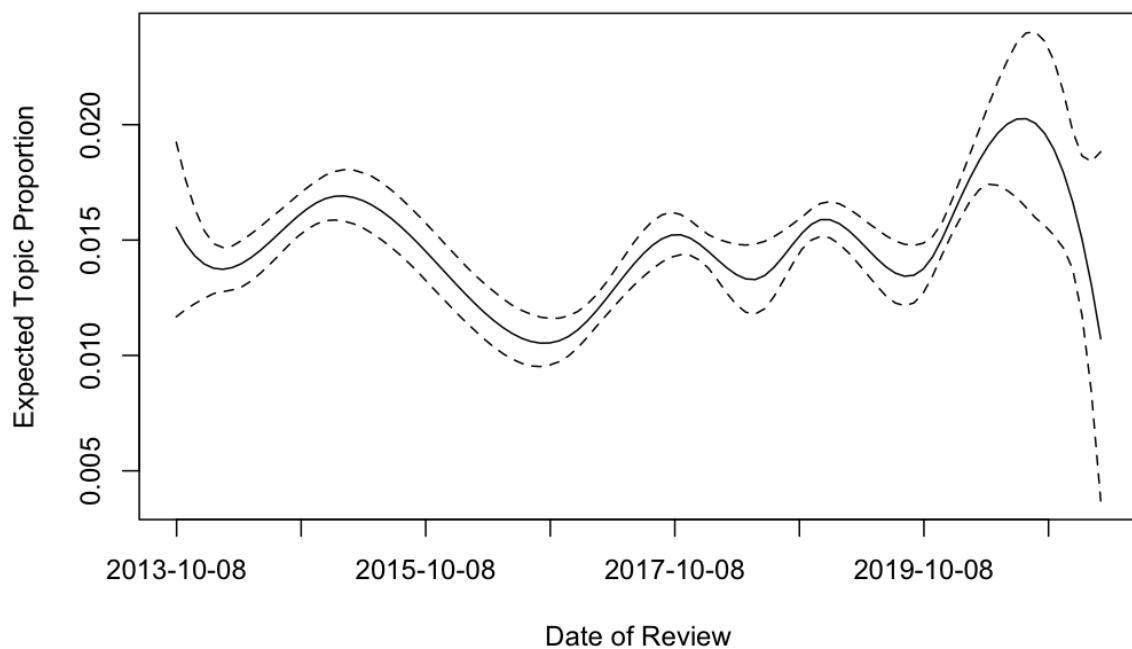
15: Opportunities and Prospects



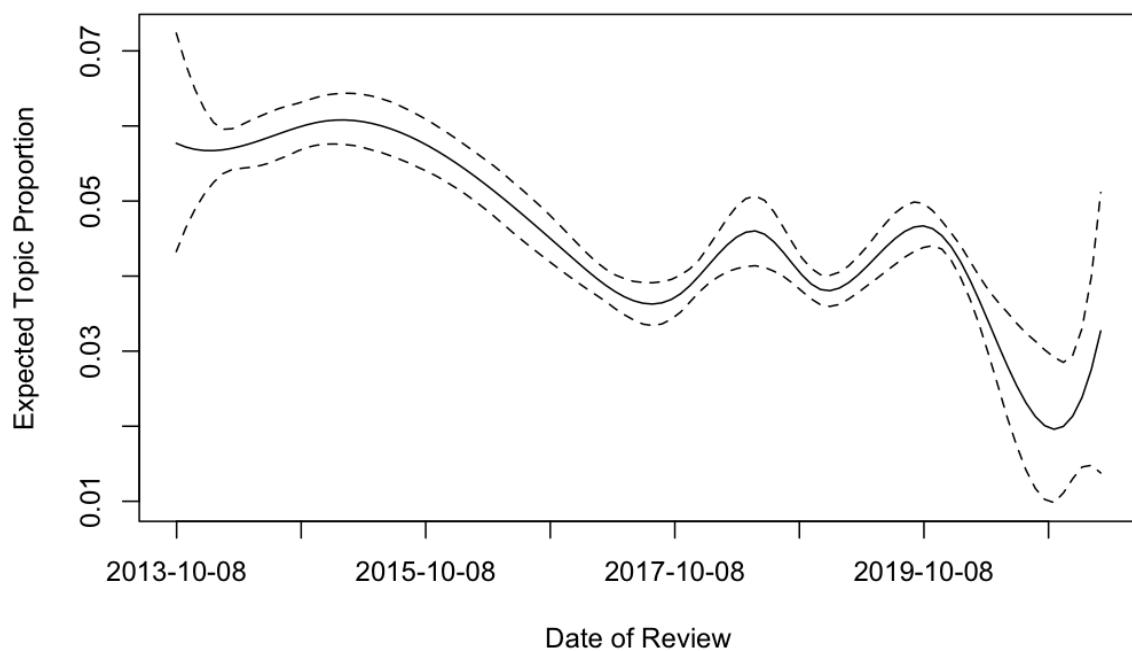
16: Independent Learning



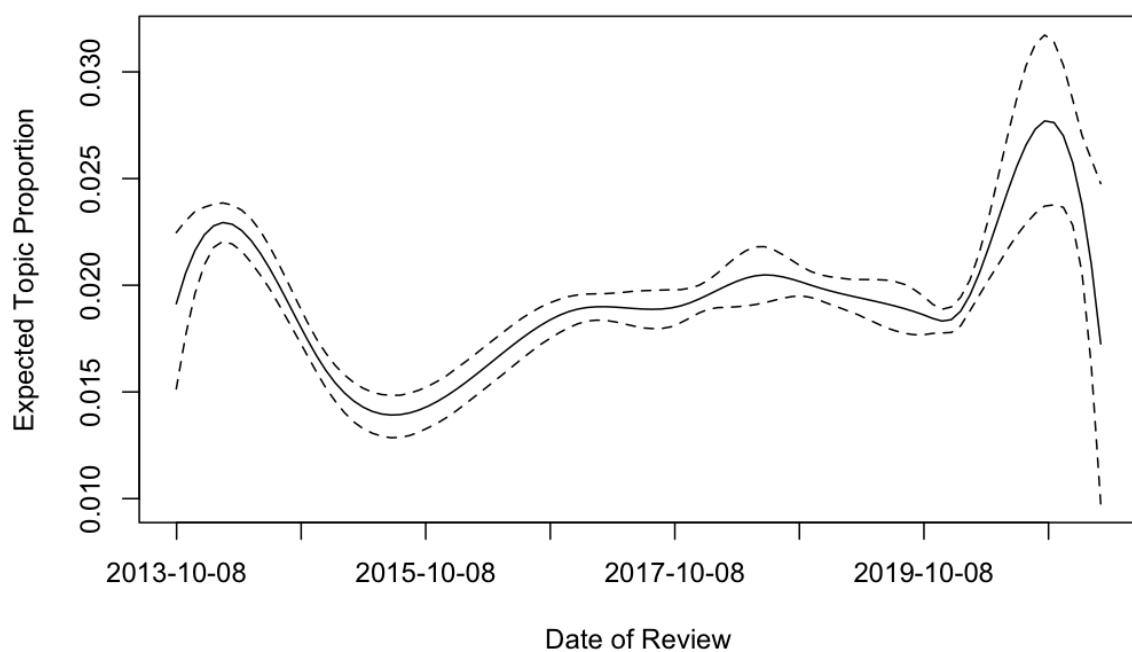
17: Placement



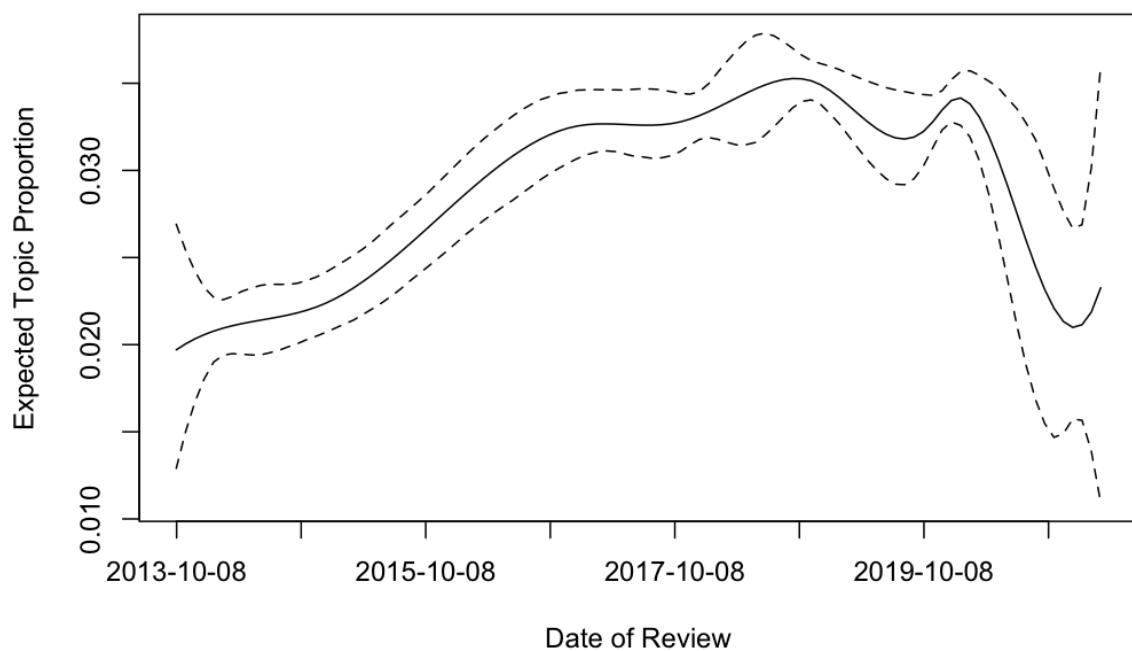
18: Societies and Sport



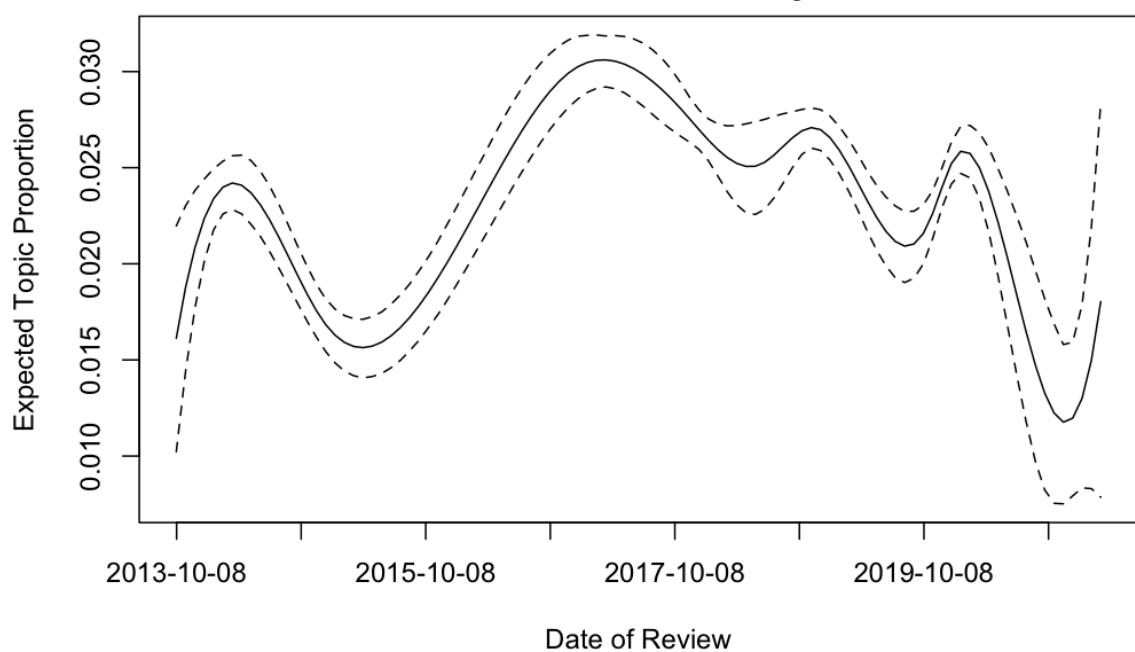
19: Bad Semester/Module



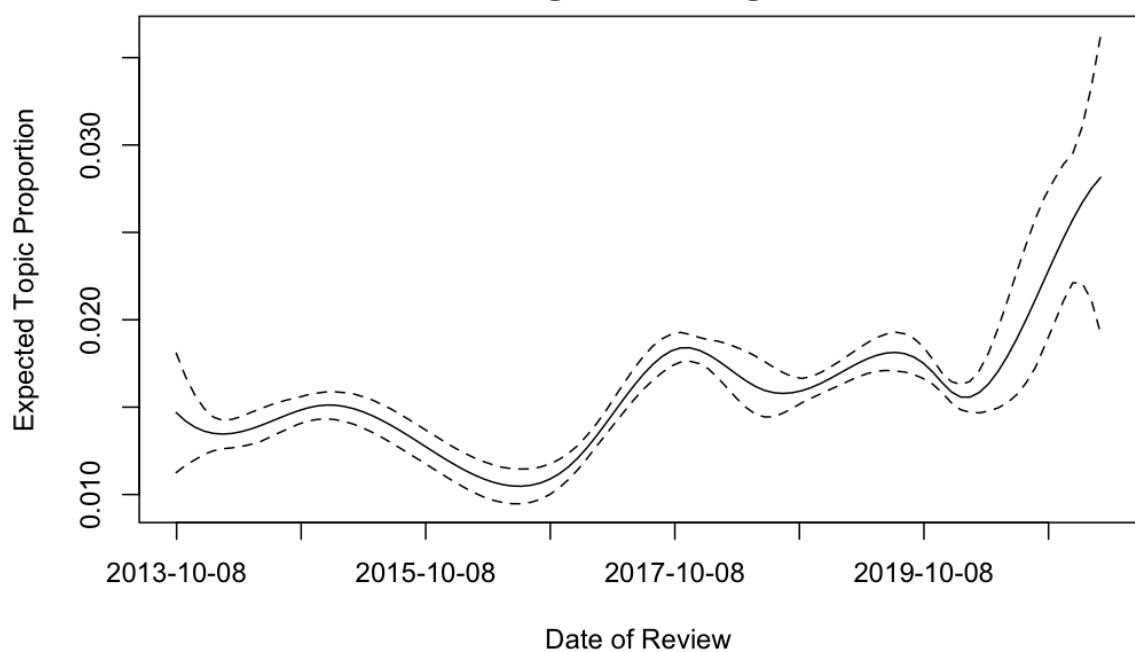
20: Confidence in Skills Gained



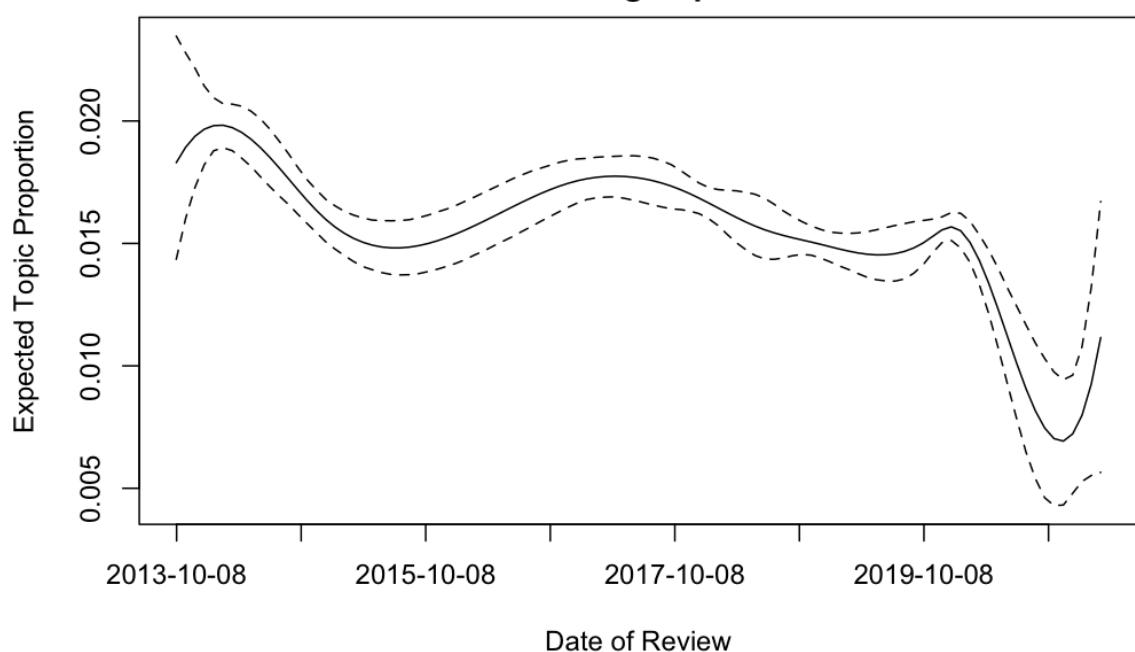
21: Home vs Uni Lifestyle



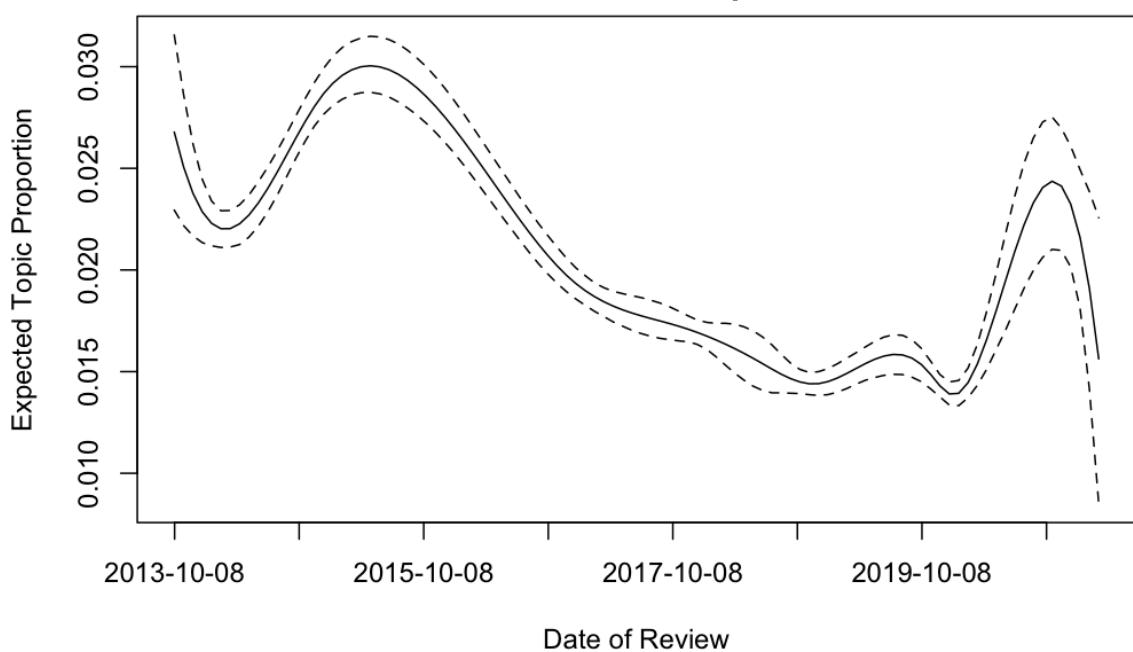
22: Undergrad vs Postgraduate



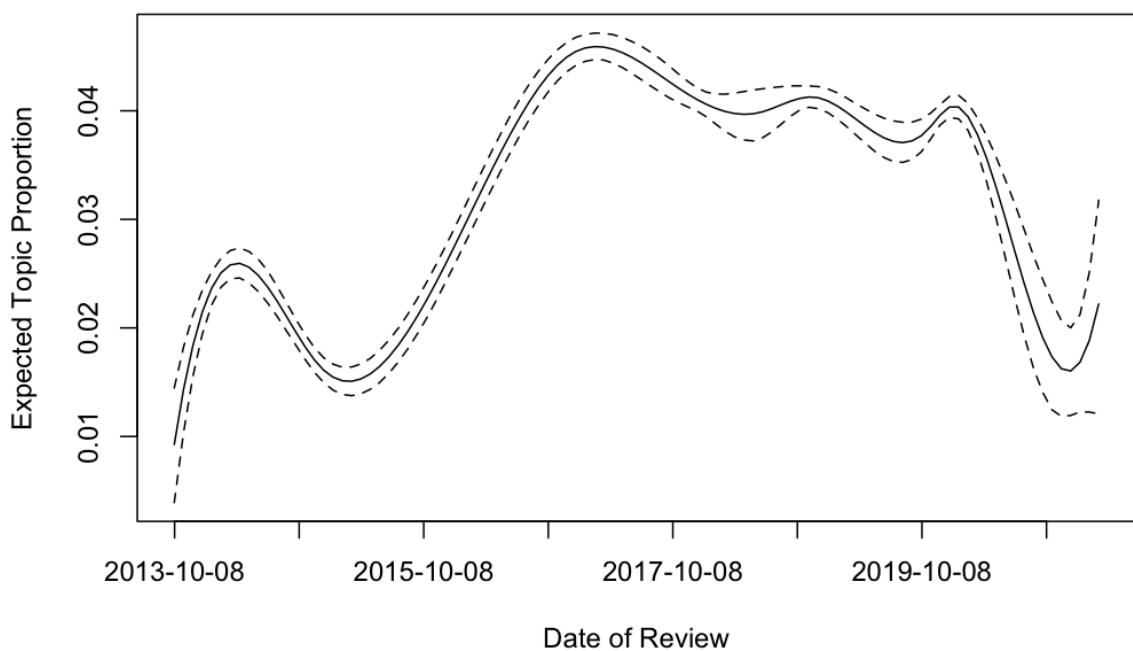
23: Learning Experience



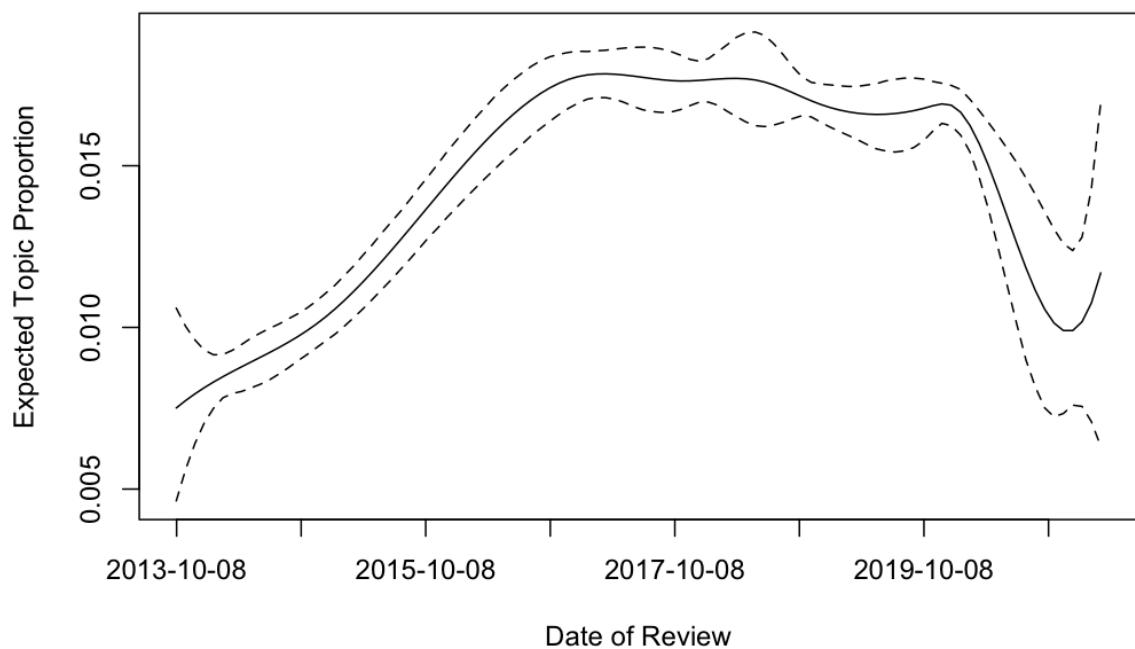
24: Uni Rank and Reputation



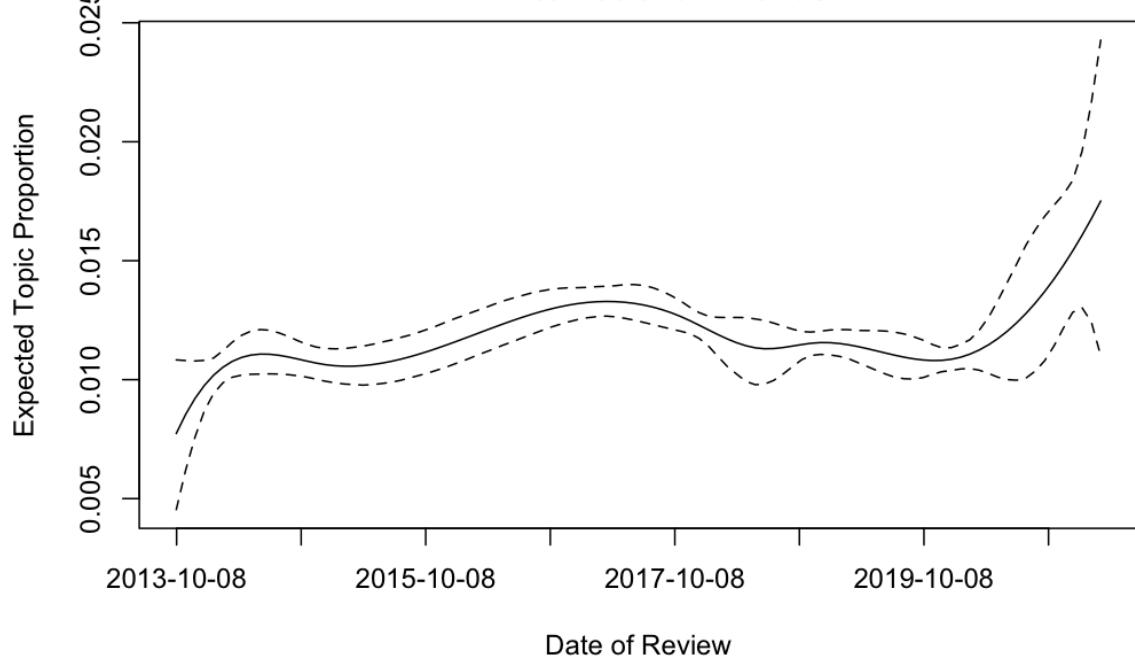
25: Challenge



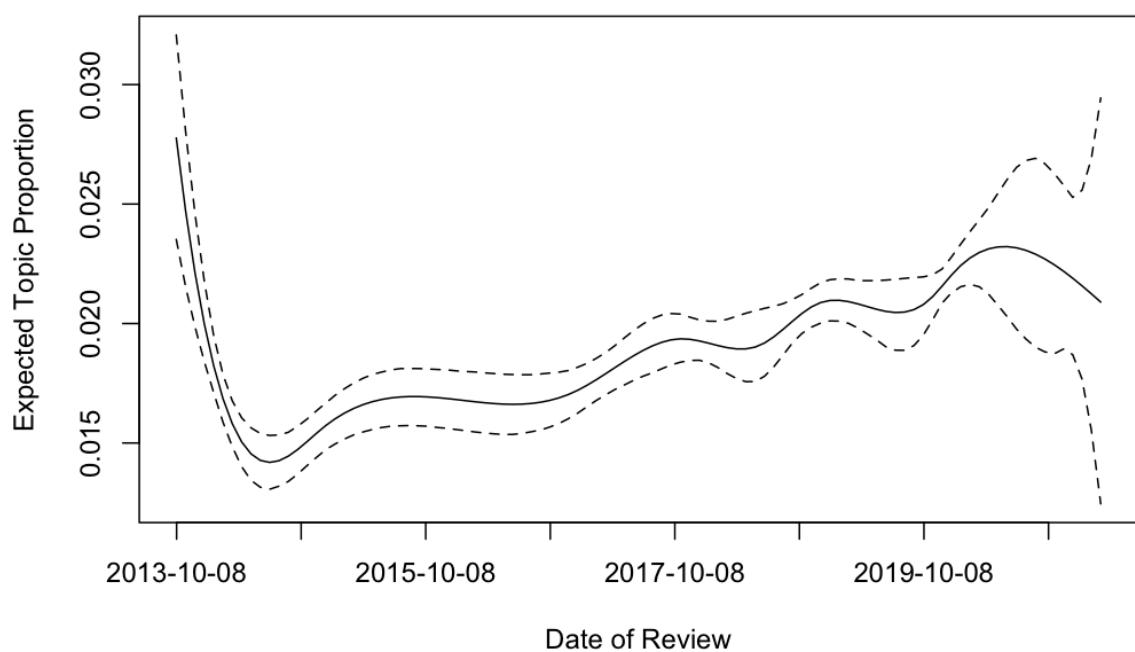
26: Choice Reflection & Memories



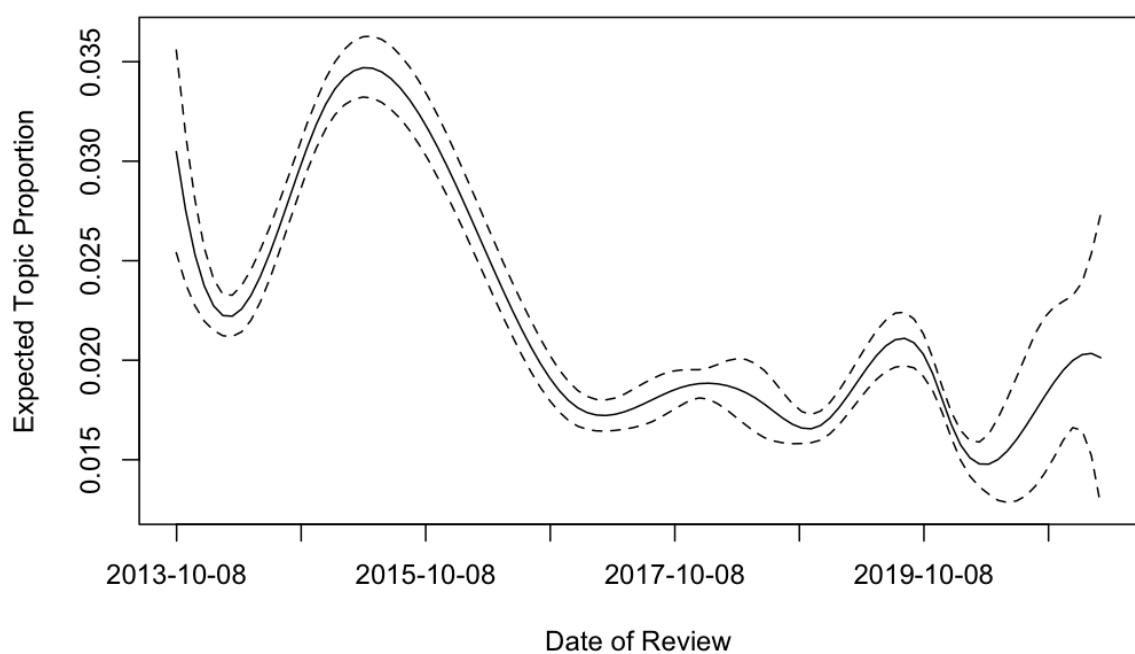
27: International Friends



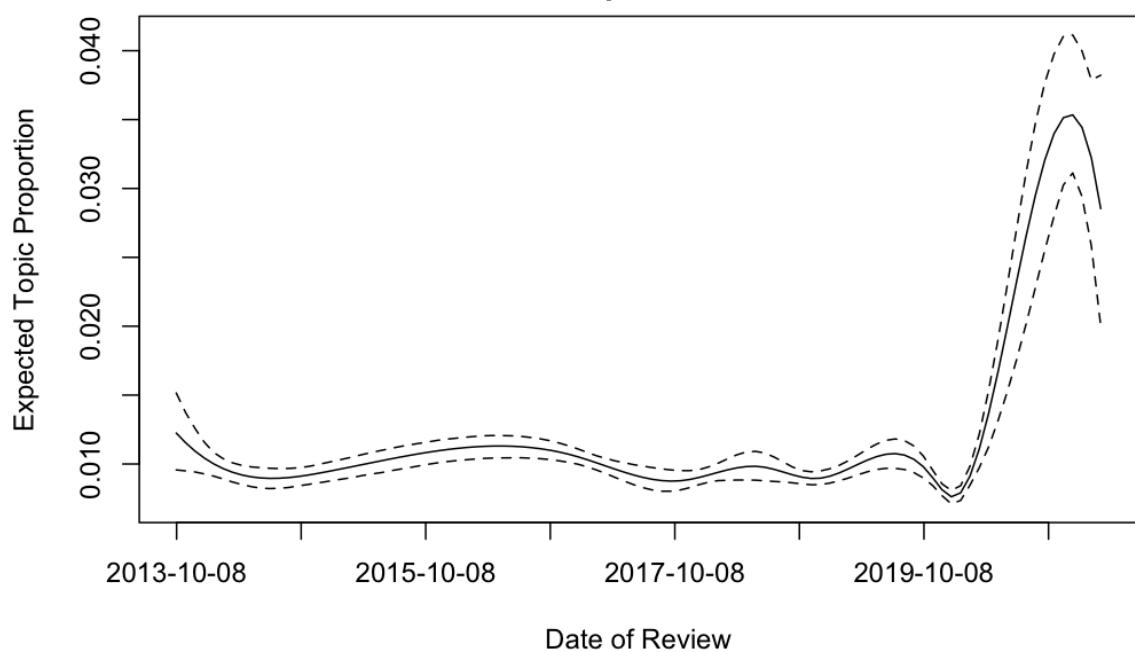
28: Personal Tutor



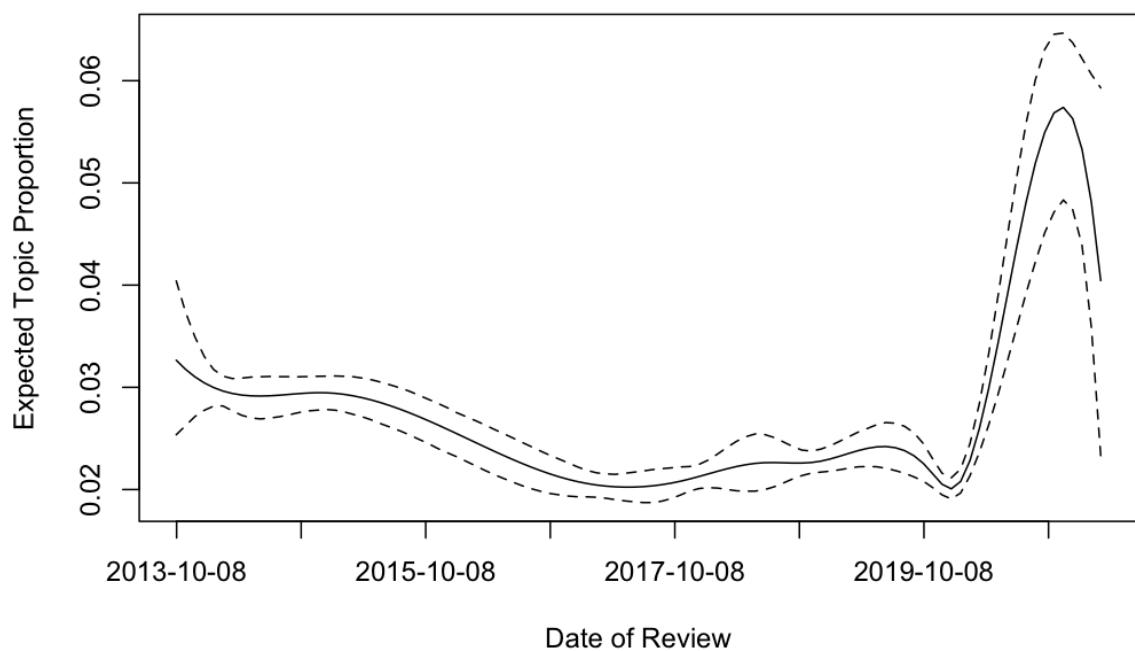
29: Modern Facilities



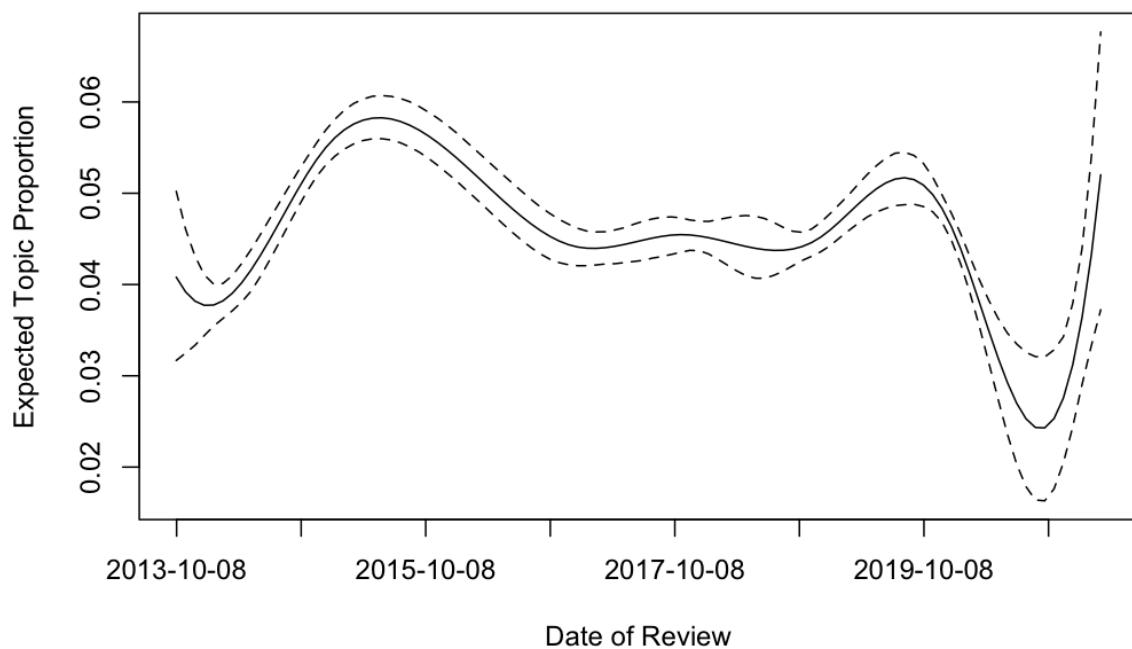
30: Expectations



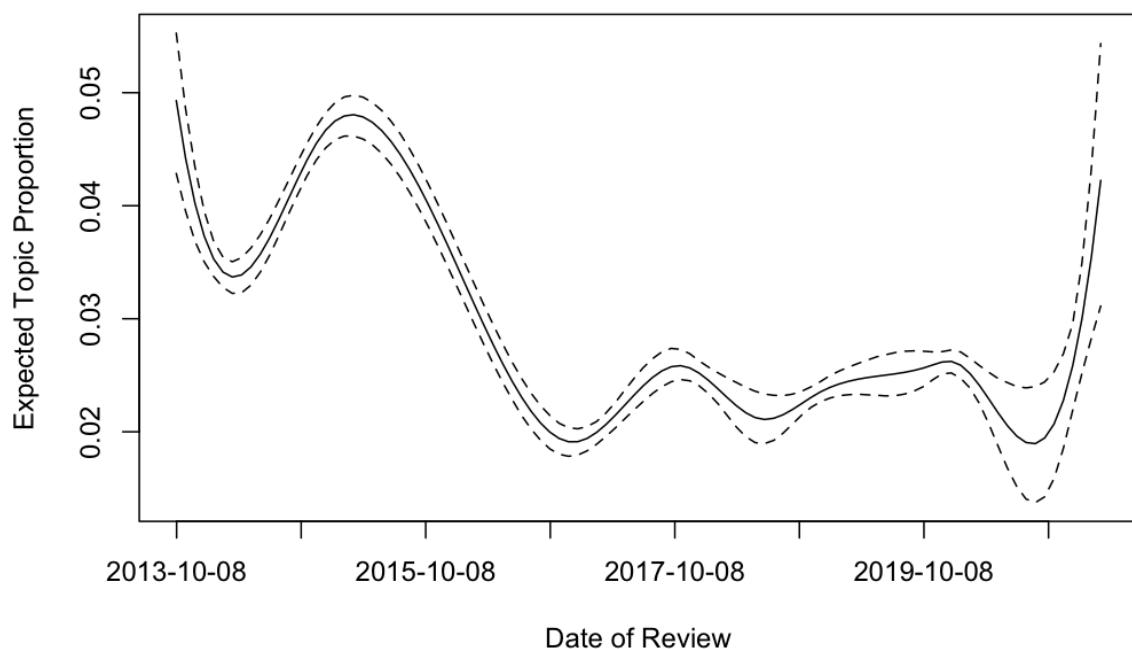
31: Costs



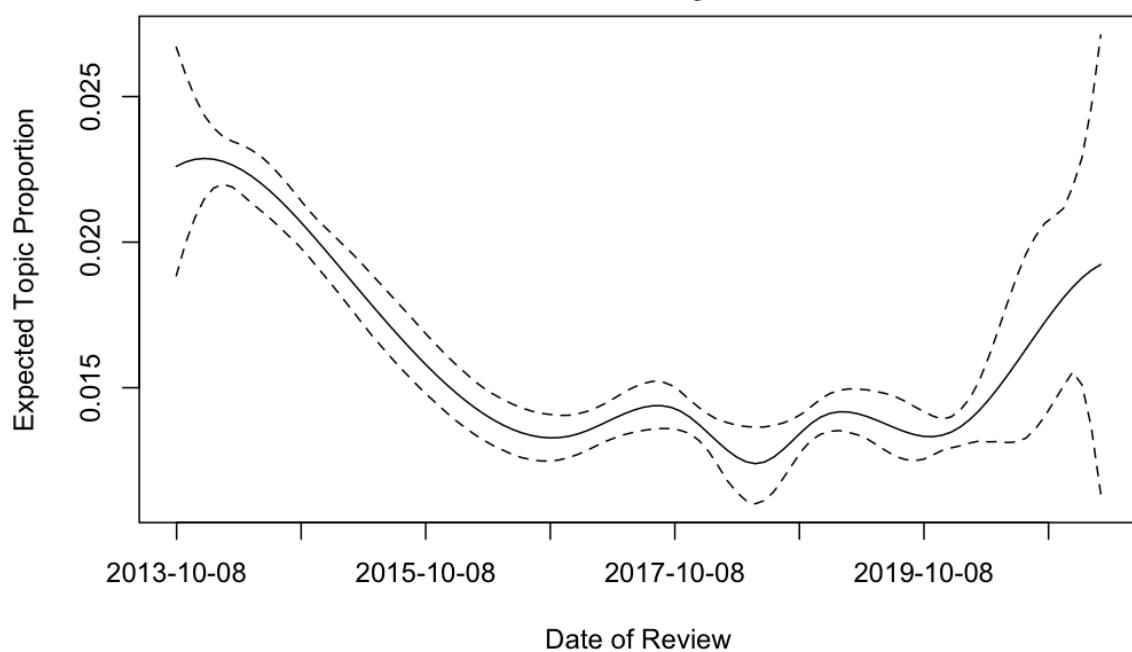
32: Staff Friendliness



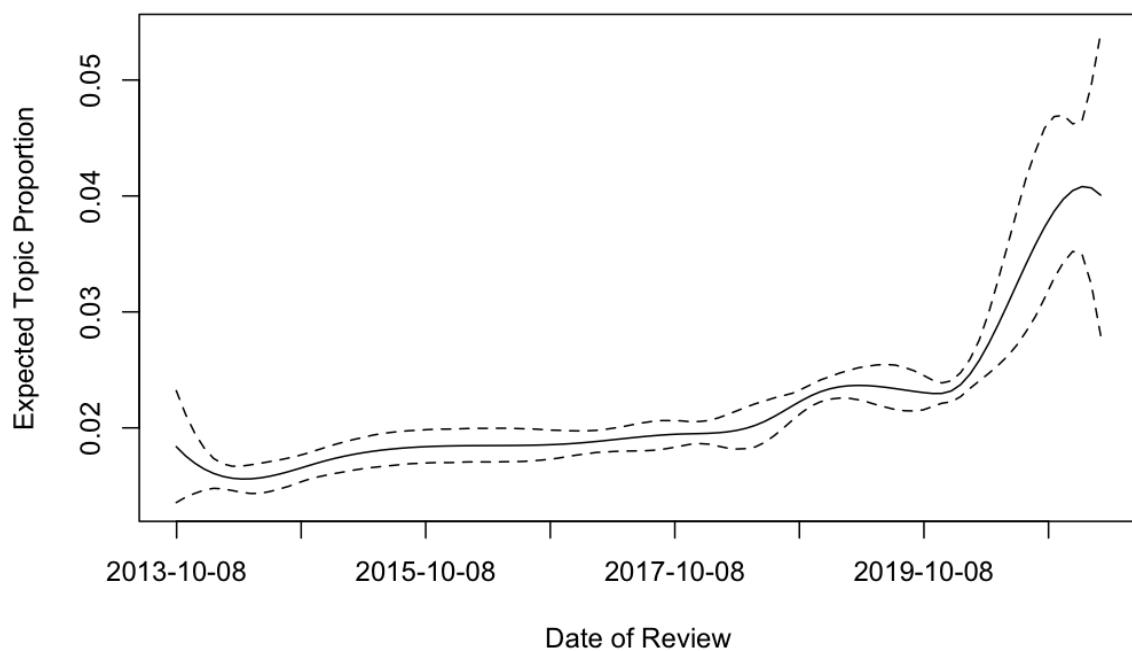
33: Academic-Facilities



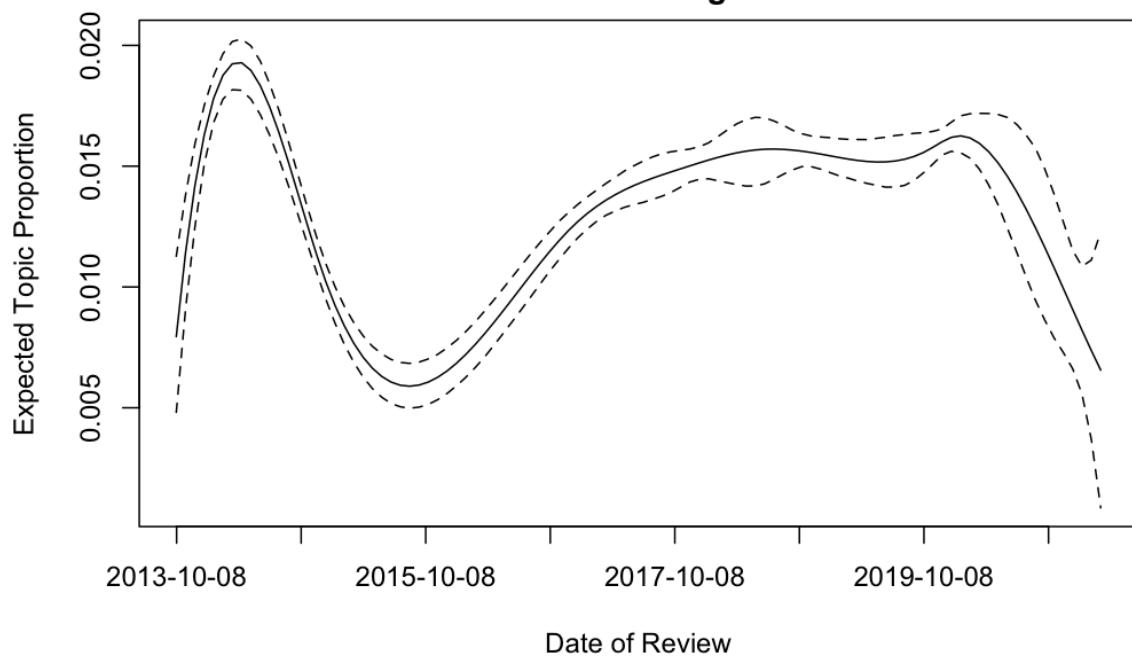
34: Positive Adjectives



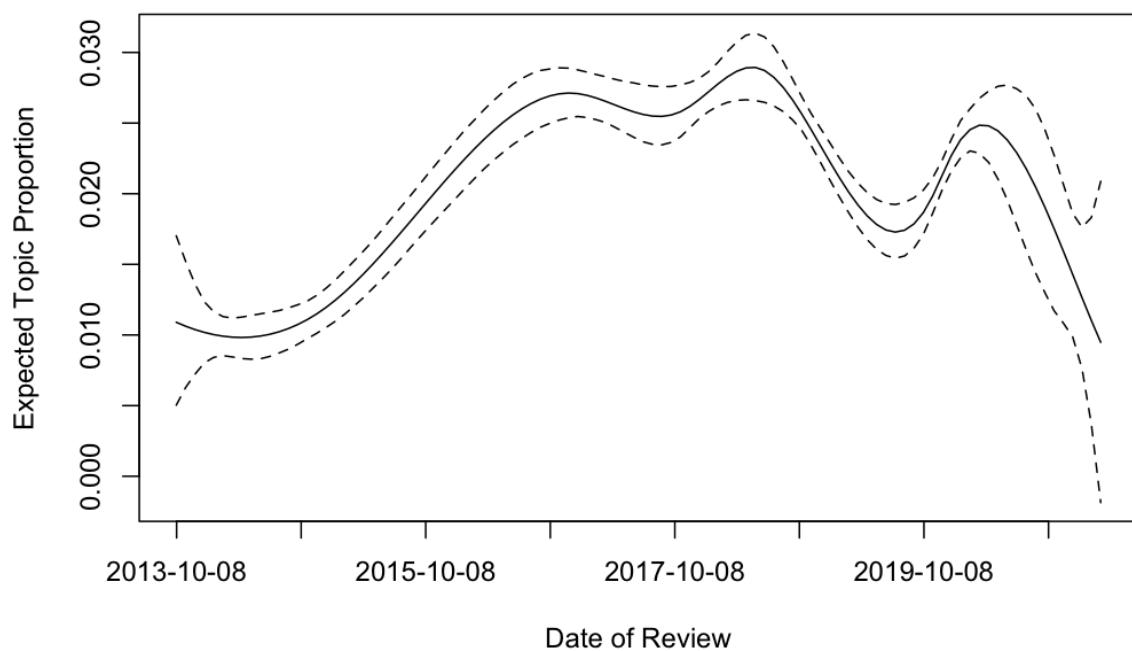
35: Issue Resolution Experience



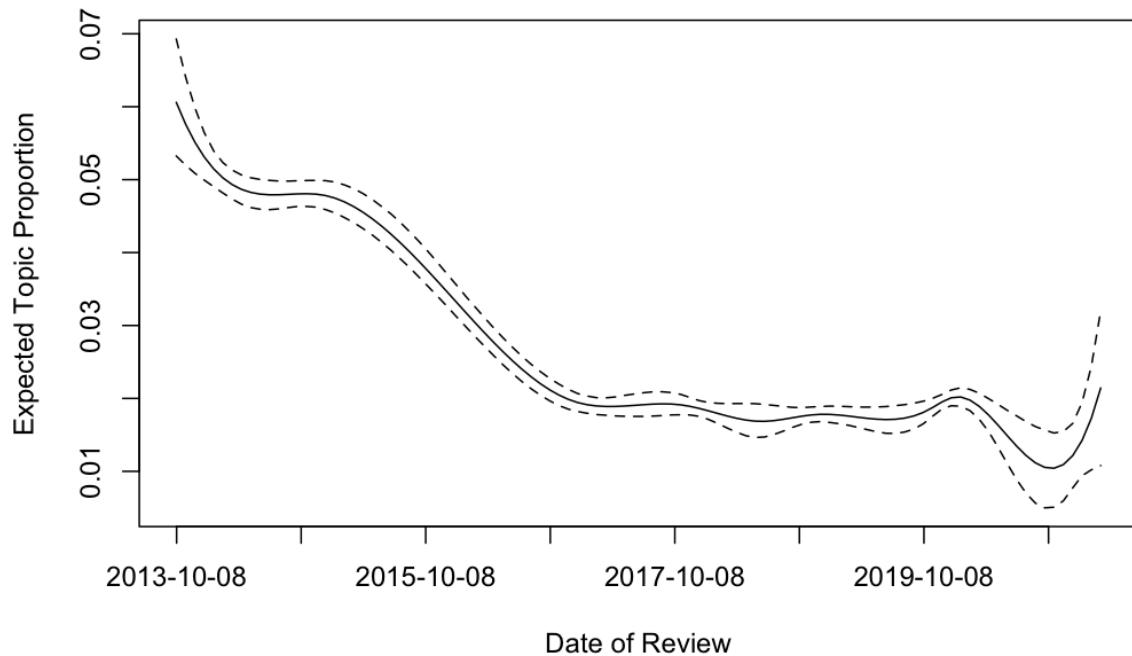
36: Challenge



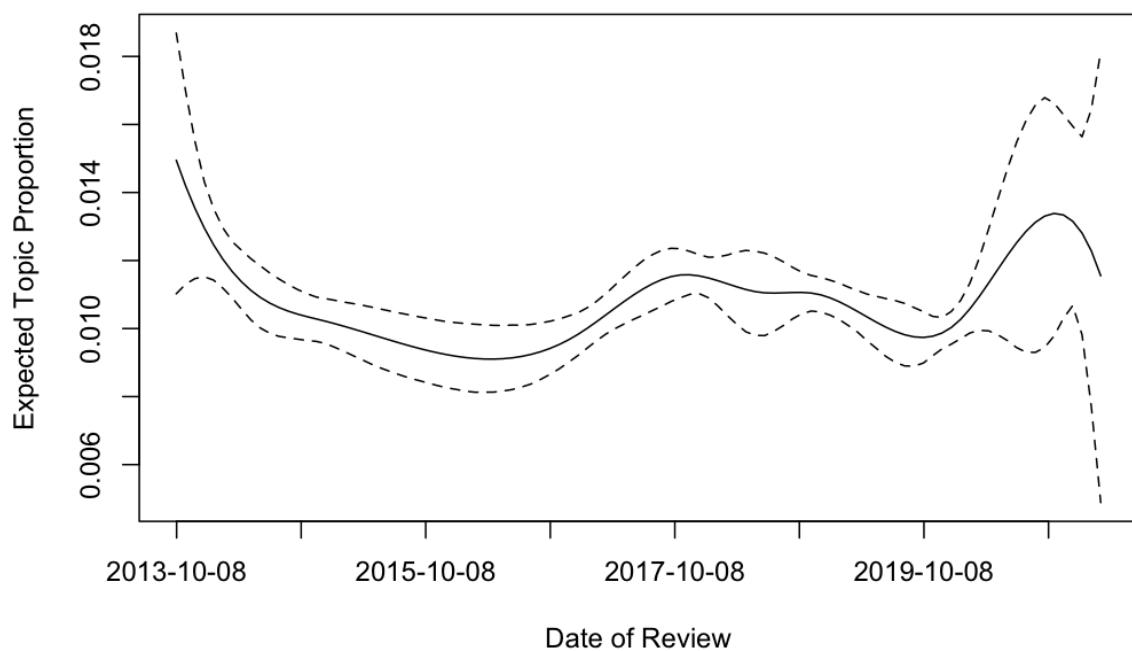
37: Personal Growth



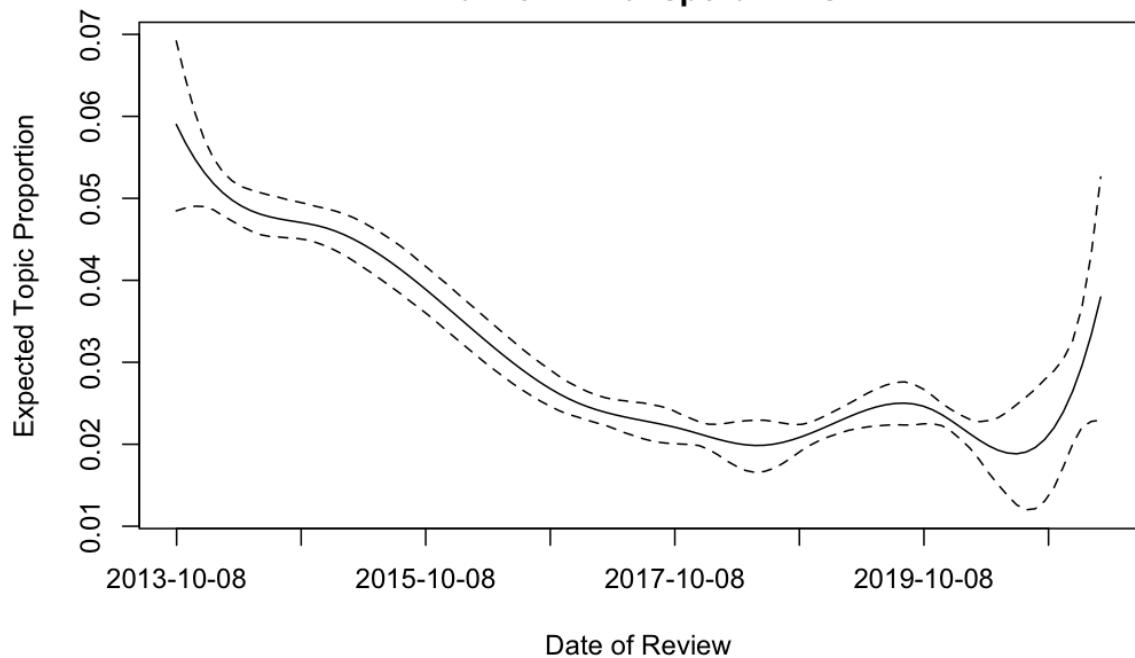
38: Non-Academic facilities



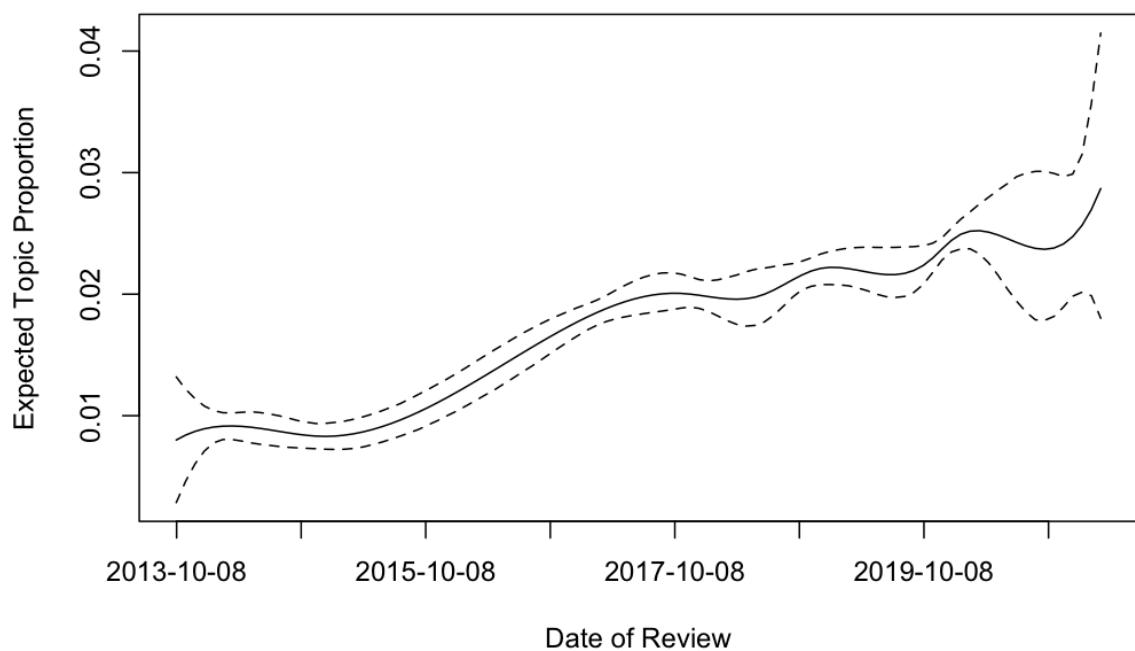
39: Discovery



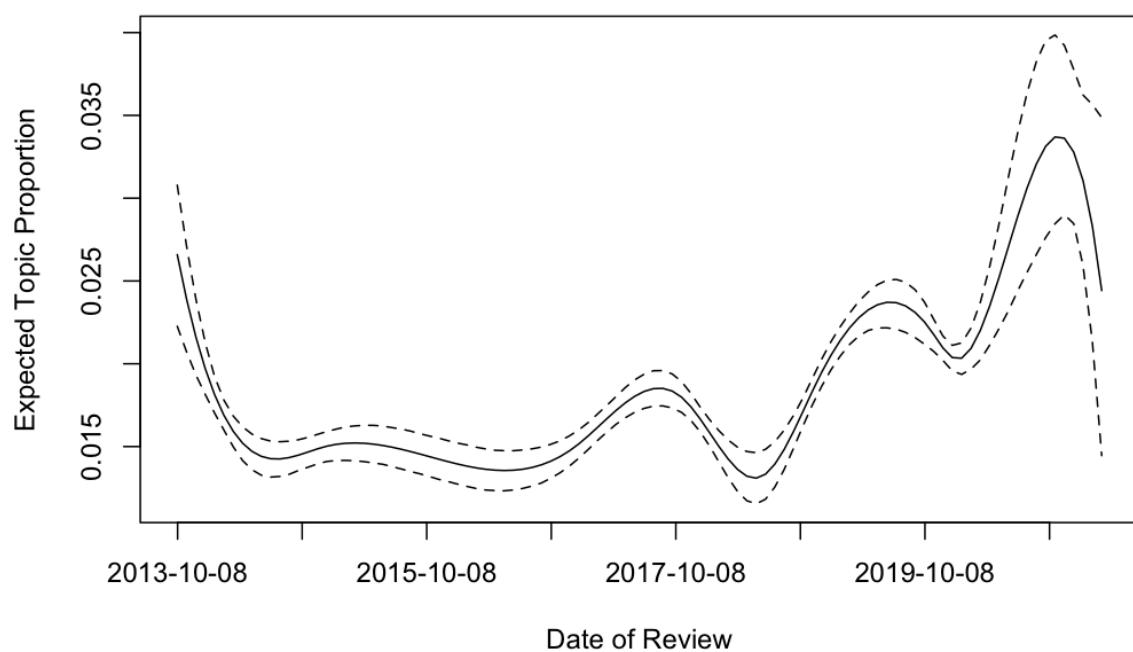
40: Town Transport Links



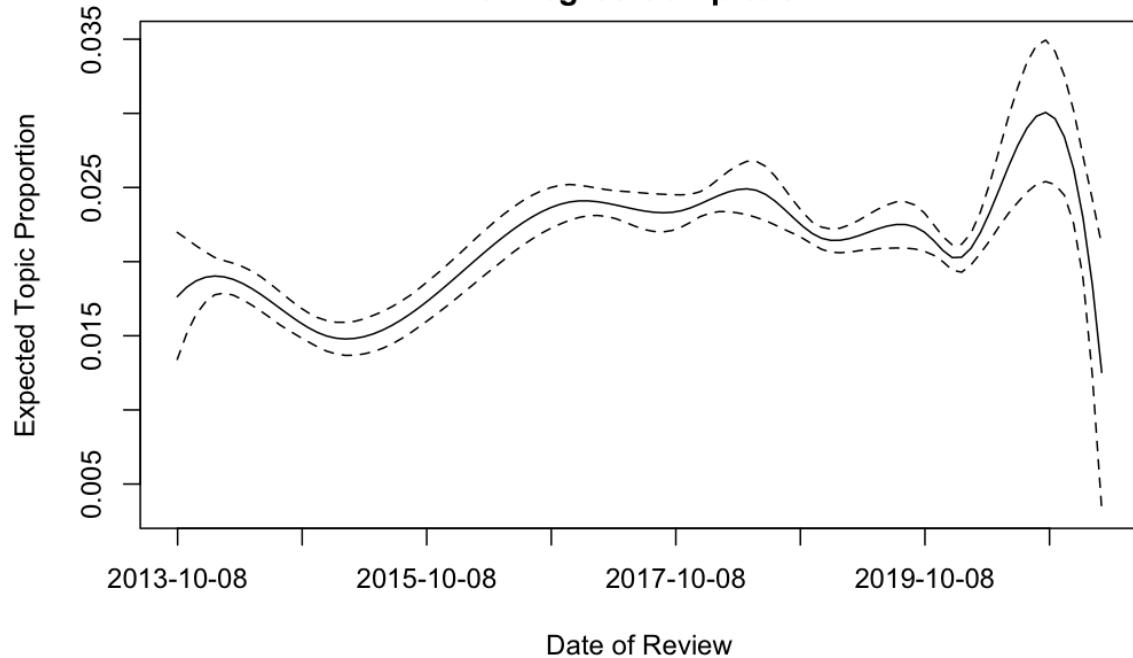
41: Workload and Mental Health

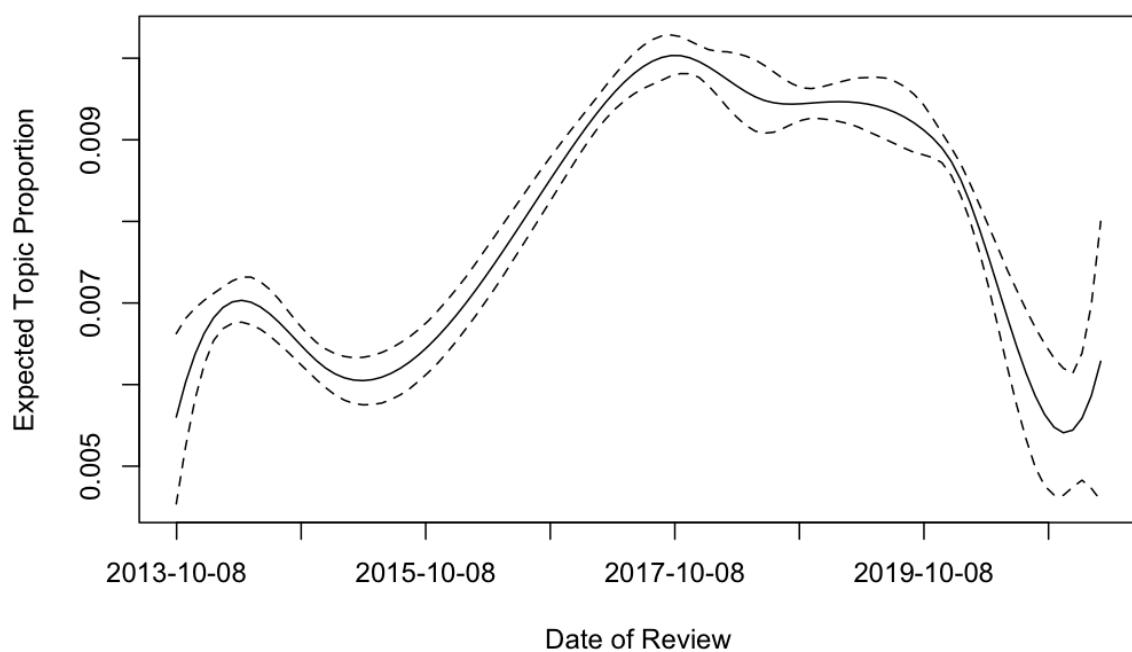
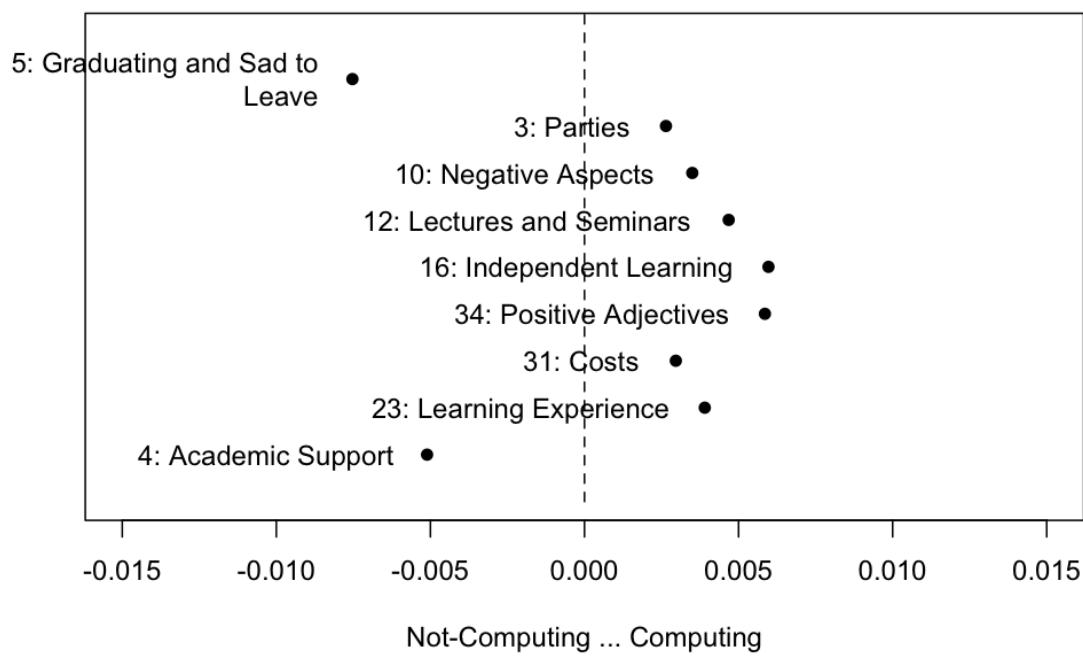


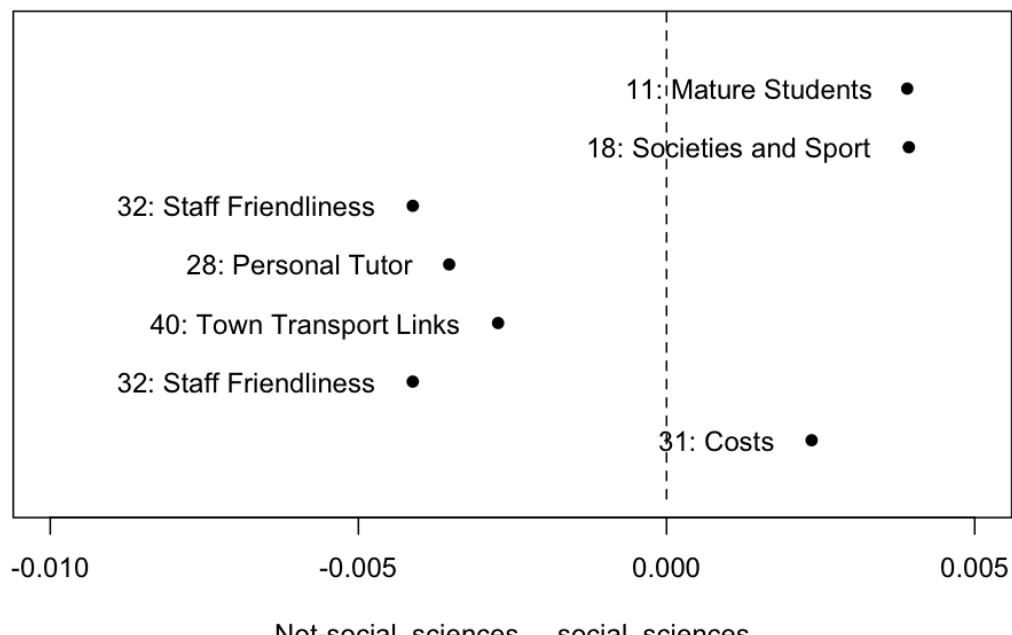
42: Communication and Classes



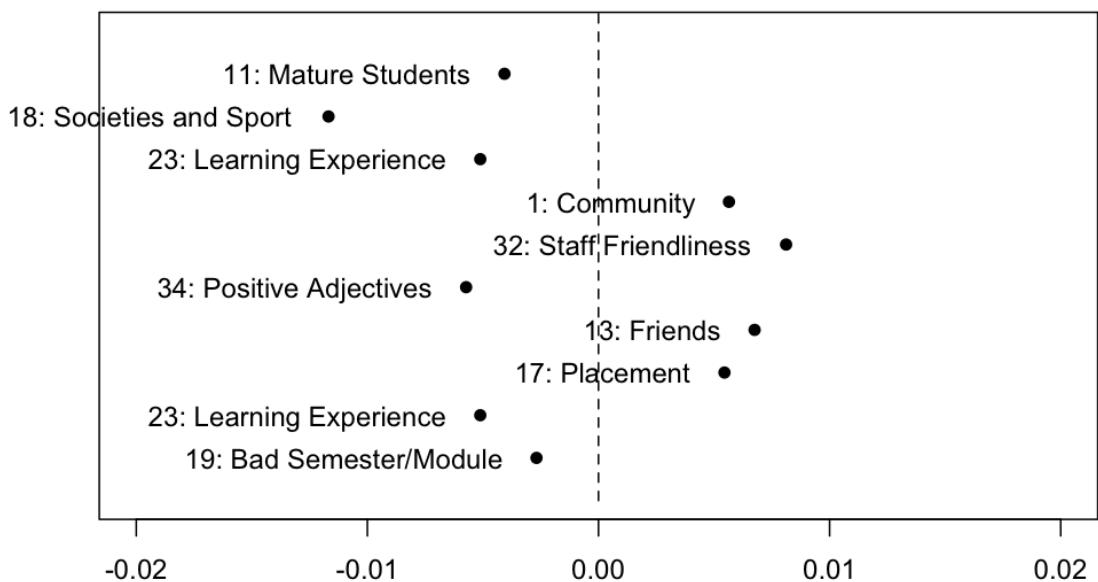
43: Degree Completion



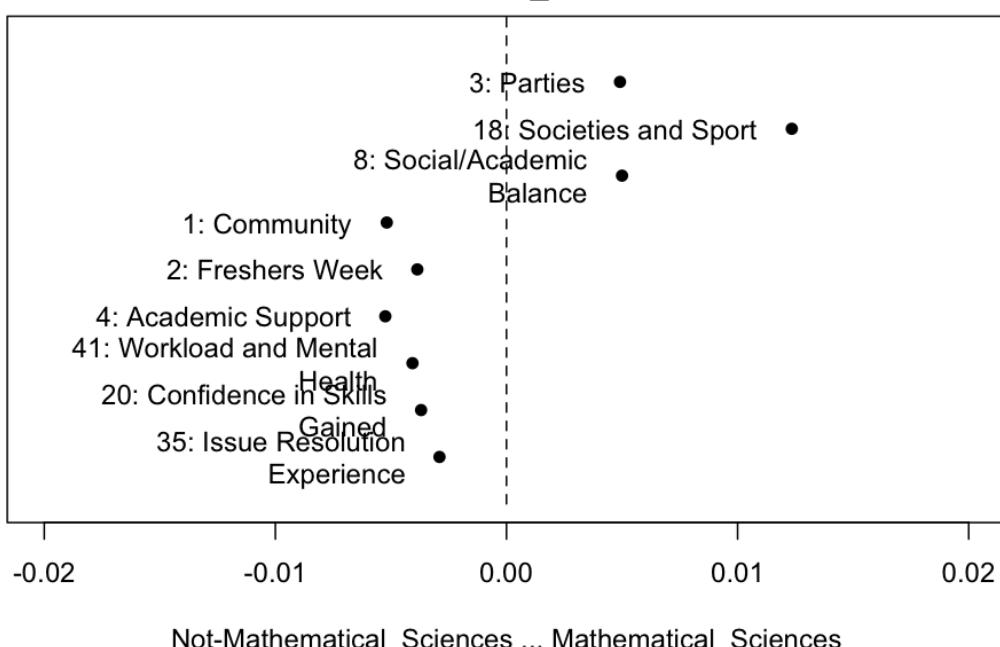
44: Commitment**Computing**

Social Sciences

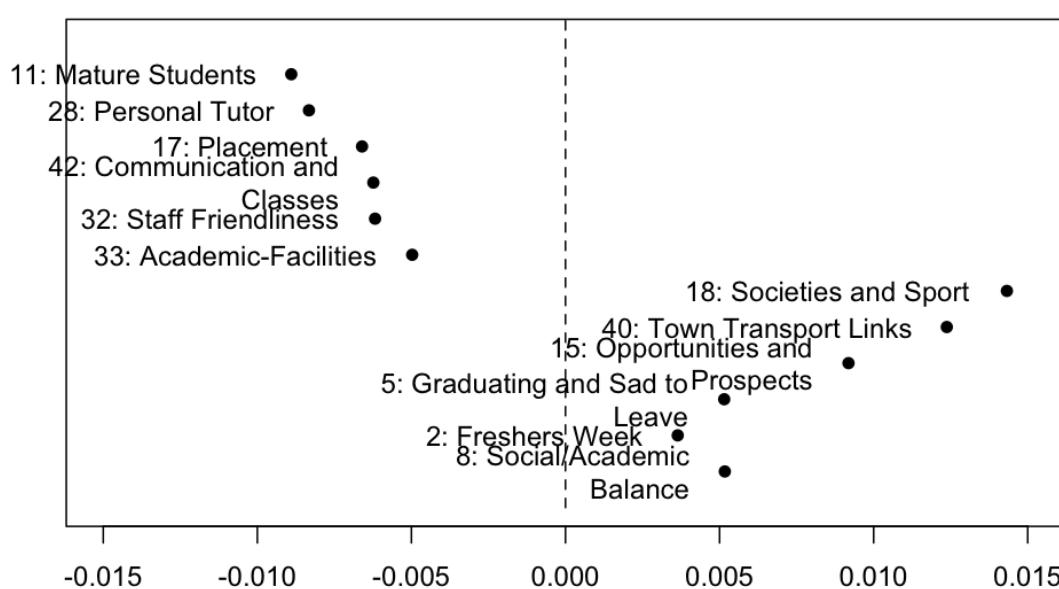
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Educational and Geographical Studies

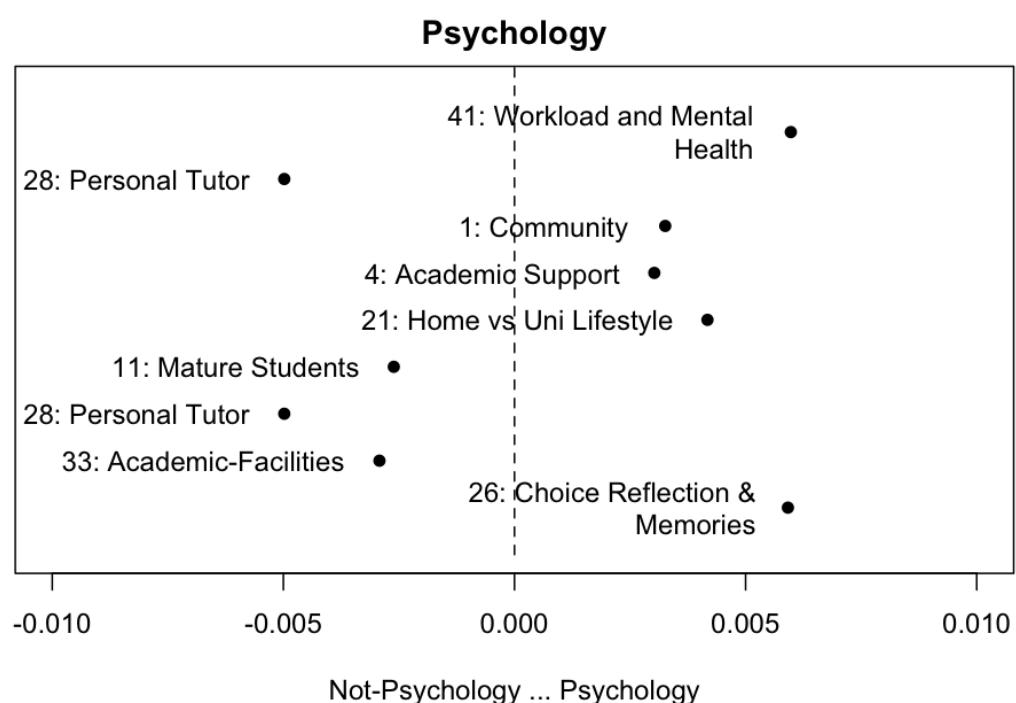
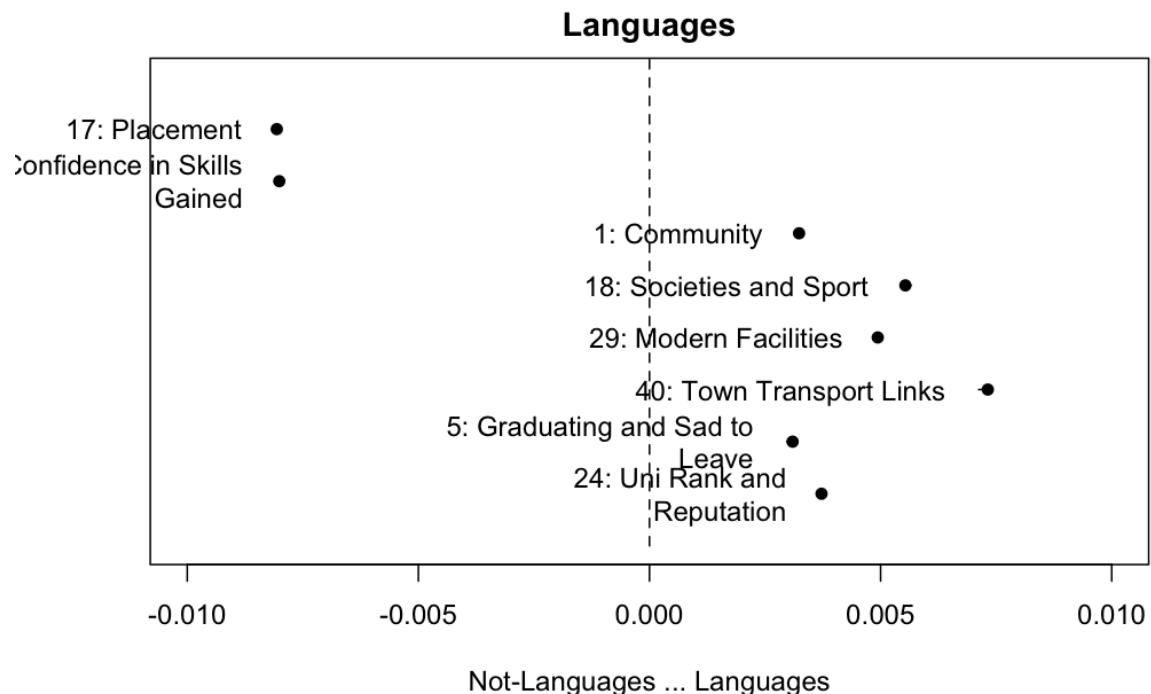
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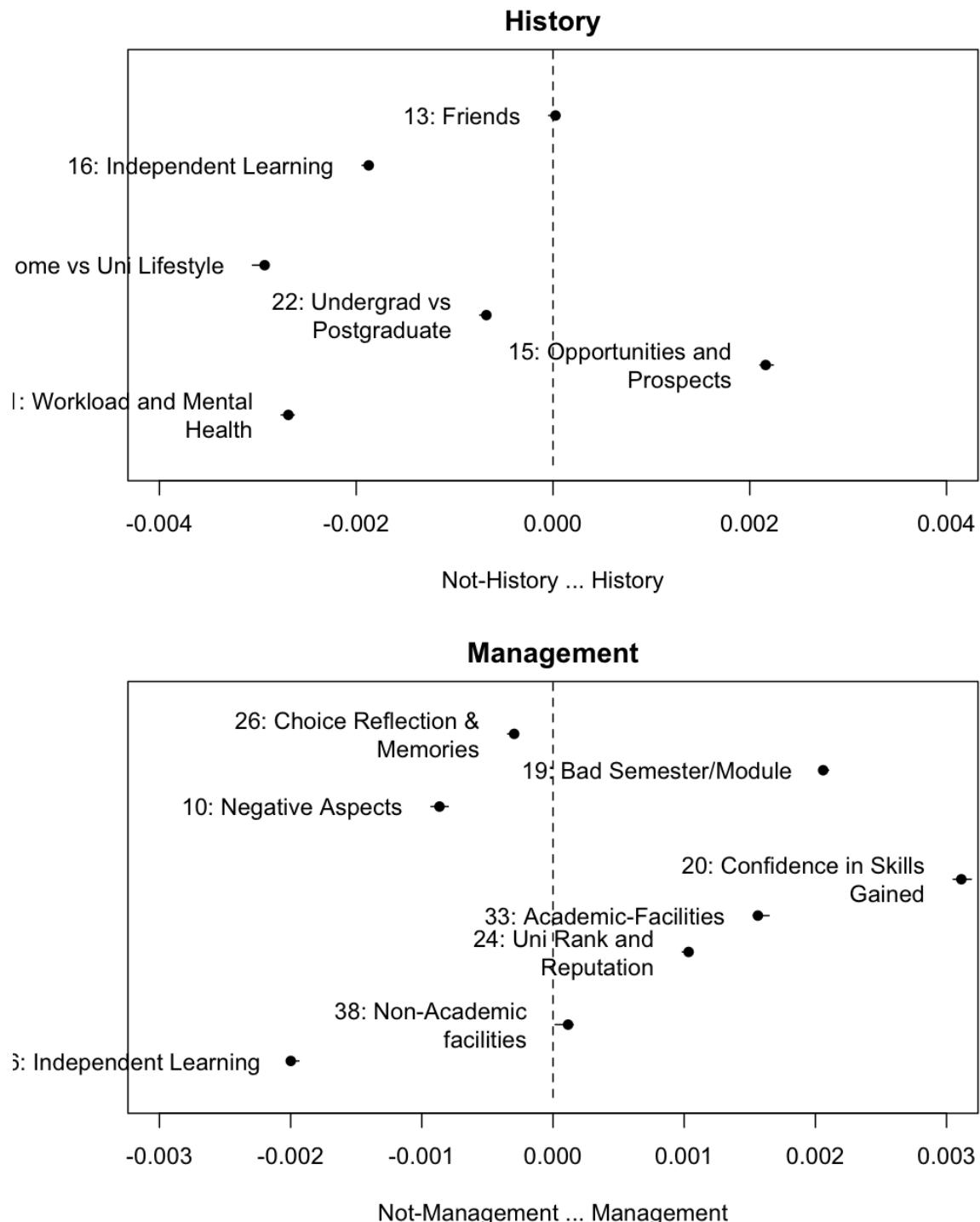
Mathematical_Sciences

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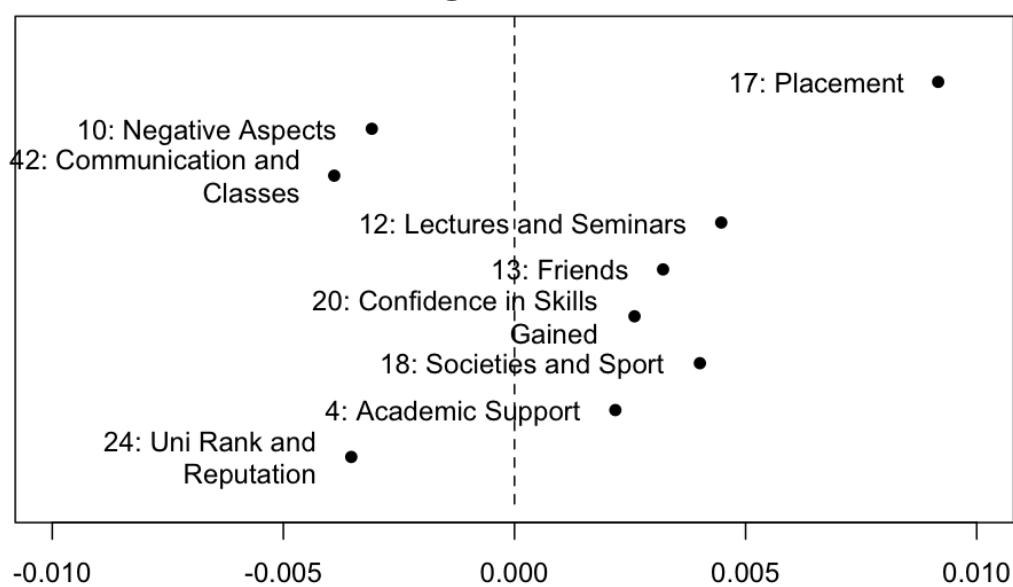
Environmental Studies

Not-Environmental Studies ... Environmental Studies



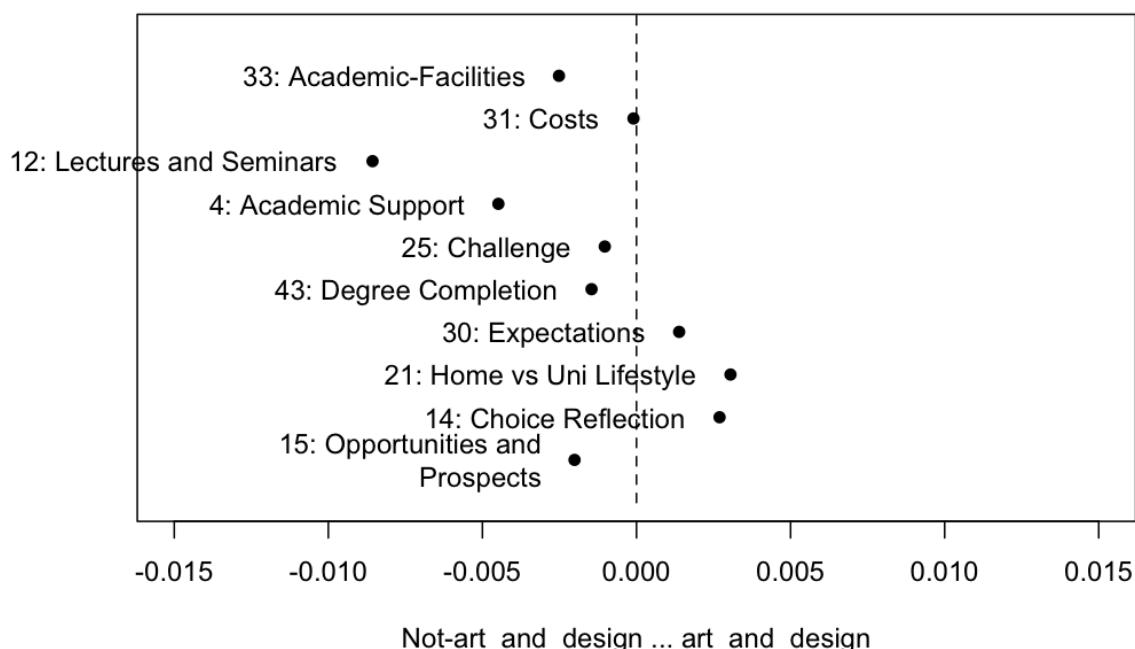


Biological Sciences



Not-biological_sciences ... biological_sciences

Art and Design



Not-art_and_design ... art_and_design

