



The Bottom Line

Shall We Chat? A Statistical Case Study of Chat Reference Utilization Jiebei Luo,

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1 Introduction

Chat reference service has witnessed a rapid growth at academic libraries in the past decade. The debate regarding this virtual reference tool's legitimacy has never stopped since its emergence. The findings and conclusions from numerous prior studies of online chat service are mixed. Tenopir (2004) believed that chat reference filled an important niche that other virtual reference tools, such as phone calls and emails, were not able to address. In a systematic review of researches on live chat service based on 59 studies through 1995-2010, Matteson, Salamon and Brewster (2011) concluded that chat reference was well received and gained high user satisfaction rate. Yet, voluminous studies (e.g., Coffman and Arret, 2004; Radford and Kern, 2006; Naylor, Stoffel and van der Laan, 2008; Applegate, 2008; Mu et al., 2011; Bravender, Lyon and Molaro, 2011) have also questioned the legitimacy of this reference tool because of its low usage rate (compared to its high maintaining cost). According to a study by Radford and Kern (2006) on the discontinuation of nine chat reference services, low volume was one of the primary reasons for library managers to discontinue their chat reference services.

"To chat or not to chat?" In 2016, four years after the introduction of chat reference as a new reference service, the Lucy Scribner Library in Skidmore College decided to conduct an in-depth study of chat volume by adopting a series of statistical analyses. In this case study, two statistical tools, namely, a difference-in-differences approach and a simple moving average time series analysis were employed to evaluate the performance of online chat. In particular, our study aimed to assess the short-term and long-term impact of chat reference on other reference services, particularly on research-related face-to-face reference questions, and shed light on the legitimacy of chat reference in our library based on the statistical evidence.

The findings in this case study will be of value to libraries with a similar scale and institutional features that are also interested in evaluating their chat reference usage, especially the impact brought by chat (as a new reference tool) on the traditional face-to-face reference. In addition, with basic statistical knowledge and proficiency in Microsoft Excel, the methodology adopted in this case study can be

potentially applied by librarians to other similar volume-based library assessment projects without purchasing specialized statistical software or hiring outside consultants.

2 Literature Review

2.1 Chat reference assessment in academic libraries

Assessment projects conducted in academic libraries are structured and interactive processes that seek to not only evaluate whether patrons' information needs are met but also identify areas for further improvement. Assessment on reference transactions generally involves analyzing reference volumes, conducting cost/benefit analysis, and assessing the quality of reference services, among which, the evaluation of chat reference is by far the most studied aspect in the past decade (McLaughlin, 2011).

Early attempts in the literature focus on establishing standards and providing guidelines in assessing the quality of chat reference. Lankes, Gross, and McClure (2003) proposed six quality standards with an emphasis on incorporating the strategic priorities and available resources of the libraries. Ward (2004) suggested that in addition to accuracy and courtesy, the completeness of chat transactions should also be taken into consideration in the quality assessment of chat reference. Luo (2008) provided a comprehensive evaluation framework for libraries to design their own assessment programs for chat reference.

According to Yang and Dalal's (2015) study on web-based reference services, 47.5% of the academic libraries in a sample of 362 institutions provide online chat as one of their digital reference services. With the popularity of online chat, chat reference is further investigated by librarians and practitioners alike from different library settings who aim to provide better reference services to their patrons. Within the existing body of literature, chat transcript content study and user analysis form the two major perspectives in evaluating chat reference in the past decade. By far, endeavors taken by librarians in chat content studies can be generally categorized into chat transaction analysis (e.g., Maness, 2008) and classification of chat queries (e.g., Morais and Sampson, 2010; Logan and Lewis, 2011; Armann-Keown, Cooke and Matheson, 2015; Cabaniss, 2015; Maloney and Kemp, 2015). On the user side, there are also a number of studies on users' expectations and satisfaction evaluation (e.g., Kwon and Gregory, 2007) as

well as search behavior analysis (e.g., Naylor, Stoffel and van der Laan, 2008; Chow and Croxton, 2012). Moreover, there has been a growing interest in chat reference studies to examine the inner connections between chat content and its users (e.g., Radford, 2006; Rawson et al., 2012) and relate to other research areas in library studies, especially on the comparison between online chat and other virtual reference services (VRS). Wikoff (2008) documented librarians' transitions from chat to emails when working under time pressure. In Chow and Croxton's (2014) usability study of five virtual reference tools (i.e., online chat, email, telephone, text messaging and Skype), they concluded that user preference and satisfaction were highly correlated with the overall usability of reference services, and online chat had the highest rating.

Besides seeking connections within VRS, researchers have also extended their interests to exploring the inter-relationship between the traditional face-to-face reference and VRS. For instance, in order to address the strength and weakness of different reference media, Desai (2003) compared the questions posed through their instant messenger (IM) tool (Morris Messenger) with questions from reference desk against patrons' willingness to return after using these two reference services. In a later study, Desai and Graves (2006) further analyzed the transcripts from chat service in an academic library and concluded that although traditional instructions provided through IM service were practical and welcomed by students, librarians should still seek to develop corresponding standards and framework appropriate for this new reference form in order to provide high quality reference services. In a case study conducted at Washington State University, Pullman, Nicol and Crook (2013) first incorporated the volume information of chat reference along with face-to-face reference into one evaluation framework as they committed more resources to their VRS. Yet, to our knowledge, no quantitative study has been conducted so far to investigate the possible impact brought by a new reference tool, such as online chat, on the traditional face-to-face reference services.

2.2 Methodology for reference assessment

A variety of quantitative and statistical methods have been applied to evaluate different aspects of reference services. Major topics considered include staffing needs (e.g., Murgai, 2006; Ryan, 2008; Applegate, 2008) and forecasting reference desk traffic flows (e.g., Murgai and Ahmadi, 2007; Ahmadi et

al., 2008; Dubnjakovic, 2012). Statistical methods employed in these studies include comparisons of means (e.g., Ryan, 2008), chi-squared residual analysis (e.g., Murgai, 2006; Applegate, 2008), multivariate regressions (e.g., Murgai and Ahmadi, 2007; Dubnjakovic, 2012), and time series analysis (e.g., Ahmadi et al., 2008). Although in-depth qualitative assessment has been adopted in much of the existing research on chat reference, quantitative analysis of chat volume in academic libraries with statistical methods employed in other reference fields has rarely been conducted.

In this study, we examined the (causal) impact of chat reference in both the short term and long term, using a difference-in-differences method (for short-term analysis) and a simple moving average time series analysis (for long-term analysis). To our knowledge, this paper is the first quantitative study to investigate the impact of chat reference on other reference services. The research question is particularly relevant given the continuing decline in the overall reference volume as documented in many previous studies (e.g., Zabel, 2005; Applegate, 2008; Solorzano, 2013; Stevens, 2013). Our study offers statistical evidence regarding how the existing reference services (mainly research-related face-to-face reference) have been affected by chat reference and provides implications on how adjustments can be made to the current reference staffing arrangement.

Meanwhile, our study makes two additional contributions toward methodology. Firstly, this paper is the first to apply the difference-in-differences approach in the field of library science. The difference-in-differences approach is an intuitive and easy-to-implement method that has been extensively employed to study the causal impact of policy interventions in the social sciences. Secondly, while studies such as Ahmadi et al. (2008) introduced sophisticated time series methods to assess the effectiveness of reference programs, the implementation of their methodology often requires invoking specialized statistical packages such as SPSS. This could make it difficult for practitioners to generalize and apply the methods to other settings. On the other hand, statistical methods employed in this case study can be implemented in Microsoft Excel by librarians with basic proficiency in Excel. This means that a wider range of academic libraries are able to follow the analytical procedures outlined in this study to assess the effectiveness of their chat reference, or other aspects of daily library operations with similar data structures.

3 Background and Data Collection

3.1 Background

Skidmore College is a four-year, private, coeducational liberal arts college located in upstate New York.¹ As the only library on campus, the Lucy Scribner Library provides reference services to students, faculty and its community members on course related questions, research projects and other general inqueries. Currently, there are eight full-time subject librarians and one part-time reference librarian offering reference service.² The chat reference in the Scribner Library started in the Fall 2012 semester, and our librarians have been staffing online chat during their reference shifts since its implementation.

3.2 Data collection

3.2.1 Reference transactions (excluding chat reference)

Starting in the Fall 2011 semester, the Lucy Scribner Library adopted Google Forms to record reference transactions during librarians' reference shifts. The entries are automatically saved in the linked Google Spreadsheet. As presented in Table 1, each reference record contains the timestamp, question asked, type of reference, type of question, time duration, gender of the patron, and further action (optional).

[Insert Table 1 here]

3.2.2 Chat reference transactions

Chat transactions are recorded and managed by LibraryH3lp (https://libraryh3lp.com/). Records can be viewed and downloaded from the LibraryH3lp administrator dashboard by either designating a single date or specifying a date range (see Table 2). Question type information is manually added by reviewing every downloaded chat transcript. Chat data are then restructured according to the master reference transaction record (see Table 1) and merged together. Table 3 provides a snapshot of the merged master data sample. As summarized in Table 4, a total of 7,712 reference transactions were

¹ "About Skidmore College," accessed on April 30, 2016. https://www.skidmore.edu/about/more.php

² The reference hours are: Monday to Thursday: 11am-10pm, and Sunday: 6pm-10pm.

collected in the data pool for this case study, including 3,416 (44.29%) research questions and 4,296 (55.71%) non-research questions.

[Insert Table 2 here]

[Insert Table 3 here]

[Insert Table 4 here]

4 Methodology

4.1 Short-term analysis: the difference-in-differences method

The difference-in-differences method is a statistical technique widely employed in social science studies for analyzing the causal impact of policy interventions. For example, in a seminal paper, Card and Krueger (1994) utilized the difference-in-differences method to study the impact of a minimum wage increase on local employment levels.

The simplest form of the difference-in-differences method considers a policy intervention (treatment) and compares the outcomes of two groups over two time periods, t_1 and t_2 , i.e., before and after the policy intervention. One group (the treatment group, or TG) is not exposed to the treatment in the first period (t_1), but is affected in the second period (t_2). The other group (the control group, or CG) is not exposed to the treatment in either period. The difference-in-differences estimator calculation can be summarized in three steps as follows:

Null hypothesis H_0 : the treatment group is not affected by the treatment

Step 1 – compute the differences within control group (CG): $\Delta \bar{Y}_{CG} = \bar{Y}_{CG,t_2} - \bar{Y}_{CG,t_1}$

Step 2 – compute the differences within treatment group (TG): $\Delta \bar{Y}_{TG} = \bar{Y}_{TG,t_2} - \bar{Y}_{TG,t_3}$

Step 3 – compute the difference-in-differences estimator between CG and TG:

$$\beta_{diff-in-diffs} = \Delta \bar{Y}_{TG} - \Delta \bar{Y}_{CG}$$

The advantage of applying the difference-in-differences method is that the calculation can not only eliminate the within-group pre-treatment differences but also remove the between-group biases. In particular, the between-group biases can possibly be caused by permanent differences between the treatment and control groups, and the within-group pre-treatment differences may result from the biases over time due to time trends (as illustrated in Figure 1). In this study, the implementation of chat reference in the Fall 2012 semester is regarded as the treatment (i.e., the policy intervention). By eliminating the influence of overall declining trend of reference volume (i.e., the within-group pre-treatment differences) and differences in volumes between different reference services (i.e., the between-group biases), the difference-in-differences method well suits the characteristics of the reference volume data in our study.

[Insert Figure 1 here]

After the difference-in-differences estimator ($\beta_{dif-in-diffs}$) is obtained, a test of statistical significance is performed to assess the strength of the evidence against the null hypothesis (H_0). Here, we follow a standard t-test procedure employed in previous related studies, such as Enger (2009). Specifically, if the test statistic is greater than the established thresholds, we can conclude that there is evidence to reject the null hypothesis and favor the alternative hypothesis that the treatment group is affected by the treatment (i.e., the face-to-face reference volume is affected by the implementation of chat reference). Table 5 summarizes the procedures to calculate and test the differences within the treatment and control groups as well as the difference-in-differences estimator under the null hypothesis (H_0) that the face-to-face reference (research) volume is not affected by the implementation of chat reference service.³

[Insert Table 5 here]

4.2 Long-term analysis: moving average process

 $^{^{3} \}text{ Similar to Enger (2009), the standard deviation is given by: } SD_{TG} = \sqrt{\frac{SD_{TG,t_{1}}^{2}}{n_{1}} + \frac{SD_{TG,t_{2}}^{2}}{n_{2}}} \text{ and } SD_{CG} = \sqrt{\frac{SD_{CG,t_{1}}^{2}}{n_{1}} + \frac{SD_{CG,t_{2}}^{2}}{n_{2}}}; \text{ Test statistic is given by: } \mu_{dif-in-difs} = \frac{\beta_{\text{dif-in-difs}}}{\sqrt{\frac{SD_{TG,t_{1}}^{2}}{n_{1}} + \frac{SD_{TG,t_{2}}^{2}}{n_{2}} + \frac{SD_{CG,t_{1}}^{2}}{n_{1}} + \frac{SD_{CG,t_{2}}^{2}}{n_{2}}}}.$

A simple time series analysis using a moving average process is adopted to further investigate the long-term impact of chat reference by focusing on the trends of different reference services since chat's implementation. Despite its wide applications in many fields of the social sciences, time series analysis has only been employed in limited occasions in library science studies.⁴ More importantly, due to the seasonal and frequently fluctuating nature of reference desk visits in a typical academic library, time series method can be particularly useful in our application.

To build intuition, we consider modeling the reference traffic since the implementation of chat reference (i.e., the Fall 2012 semester) as a simple first-order moving average process, MA(1).⁵ Generally speaking, a moving average process essentially represents, as its name suggests, a weighted average (with uneven weights) of the current and past random shocks (i.e., seasonality and irregularities). In our application, the reference question frequency at any given time can be viewed as a result of a series of observed and unobserved random shocks, e.g., time of the semester, librarians on duty, difficulty of professors' assignments, weather conditions, etc. The first-order moving average process then takes a moving average of such shocks from both the current and past period. More formally, the number of reference questions received at any given time can be expressed as:

$$Y_t = \mathcal{E}_t + \beta_1 \mathcal{E}_{t-1}, \qquad t = 1, 2, \dots$$

where Y_t is the number of reference questions at time t; \mathcal{E}_t includes observed and unobserved shocks that may explain reference question frequencies in period t; \mathcal{E}_{t-1} represents the observed and unobserved shocks from previous period t-1; β_1 is the moving average coefficient. The estimated β_1 is thus the focus of the analysis because it signals whether the frequency of reference questions is increasing or decreasing over time, after taking into account the seasonal nature of reference visits.

⁴ See Jeong and Kim (2010) for a complete review of library science studies that employ time series methods.

⁵ In practice, to accommodate the seasonality of the outcome variable, one may want to use higher order moving average processes, e.g. MA(4). While the assumptions and derivations will be more complicated, the implementation of the estimation procedure in Microsoft Excel spreadsheets is still similar to MA(1).

In practice, the moving average process can be implemented in Microsoft Excel by computing the average of the observations in the most recent periods and using it to forecast the outcome in the next period. Moving from the current period to the next period, the computed average replaces the oldest observation. By continuing this iteration process, the short-term irregularities can thus be smoothed out. In other words, the computation of the moving average process can be expressed as:

$$\hat{Y}_i = \frac{y_t + y_{t-1} + \dots + y_{t-N+1}}{N}$$
 $i = 1, 2 \dots N$

N is chosen based on the seasonality of reference traffic, which typically involves a cycle of every four academic months, or a semester.⁶ Thus, the moving average process in our study is essentially a MA(4) process. Similar to the difference-in-differences analysis, a standard procedure of testing the resulting coefficients against the relevant test statistic thresholds is processed to ensure that the results are statistically significant against the null hypothesis. A step-by-step guide of the estimation procedures with sample Excel spreadsheets is provided in Appendix 1.1-1.3.

5 Empirical Results

5.1 Short-term impact

5.1.1 Data range

Given that our focus is to investigate how the introduction of chat reference affects the usage volume of the traditional face-to-face reference (research), the implementation of chat reference is considered as the treatment and face-to-face reference (research) is set as the treatment group in our difference-in-differences analysis. The supplies reference volume (e.g., inquiries about staples and paper clips) is selected as the control group, because the question volume in this subgroup is presumably least likely to be affected by virtual reference. Next, with regard to the sampling period, the 2011-2012 Academic Year (covering the Fall 2011 and Spring 2012 semesters) is selected as the "before" period (t_I),

⁶ Alternatively, one could follow a procedure outlined in Lawrence (2009), which involves experimenting with different levels of N until one finds the level that minimizes the mean squared error (MSE).

and the "after" period (t_2) is the 2012-2013 Academic Year (covering the Fall 2012 and Spring 2013 semesters). The relevant data are first reorganized in an Excel master spreadsheet as shown in Table 3. A pivot table based on the processed transaction record is then created in a new spreadsheet. The number of reference questions for different subgroups (e.g., supplies, face-to-face (research)) across the two time periods can be quickly obtained via a pivot table calculation.

5.1.2 Findings

Table 6 presents the key results of the difference-in-differences estimator calculation based on the procedures outlined in Table 5.

[Insert Table 6 here]

As shown in Table 6, the pre- and post- difference within the treatment group (face-to-face (research) question) is -1.02. The negative sign indicates a declining trend in the face-to-face reference (research) volume, and the magnitude of 1.02 suggests that between period t_I (the 2011-2012 Academic Year) and t_2 (the 2012-2013 Academic Year), the average research questions encountered at the reference desk dropped by 1.02 questions (per reference day). On the other hand, the corresponding change in the control group (supplies) is 0.24, which suggests a slight growth of the supplies-related questions received between the two time periods. Given that the treatment and control groups are compared under the same circumstances (e.g., the overall declining trend of reference service needs, weather conditions, etc.), if the two groups were not affected by the introduction of chat reference, the difference-in-differences outcome would be subtle and not statistically significant. However, the estimated difference-in-differences coefficient that we obtained in the analysis is -1.26, suggesting that, on average, research-related face-to-face reference volume declined by 1.26 questions (per reference day) after the implementation of chat service in its first academic year. This is a sizable decline, given that the average number of total reference questions per reference day is 4.36 prior to the implementation of chat.

Following the difference-in-differences estimator calculation, a t-test is performed with a test statistic of -3.51 (test statistic: -1.26/0.36 = -3.51).⁷ In light of the fact that the result is outside the critical value for 1% statistical significance level (i.e., ±2.326), we can conclude that the difference-in-differences coefficient is statistically significant at 1%. Thus, the null hypothesis that face-to-face reference (research) volume is not affected by the implementation of chat reference can be rejected and the alternative that the introduction of chat reference service reduces the usage of research-related face-to-face reference service in the short term is favored. In other words, our result suggests that the face-to-face reference (research) volume saw a significant decline between two periods (-1.26 questions per reference day) due to the impact of chat reference in its first service year. The estimated decline would account for more than one quarter (28.81%) of the face-to-face research questions received at the reference desk per reference day prior to the implementation of chat reference.

5.2 Long-term impact

5.2.1 Data range

Given that the short-term impact brought by chat reference, in order to further examine its influence on face-to-face reference (research) volume in a longer time frame and quantify its evolving trend, a simple moving average time series analysis is adopted in this phase with the same focus on research-related questions. Data adopted in the time series calculation start from the Fall 2012 semester (when chat reference was initially launched) and end in the Fall 2015 semester (which provides the latest reference data available to this study).

Data are processed in the same manner as discussed in Section 5.1.1. As explained in Section 4.2, we adopt a MA(4) moving average process in our analysis since a typical academic semester at Skidmore college spans four months. Thus, in the pivot table, by placing the three data fields (Timestamp, Type of reference and Type of question) in the filter section and applying multiple filters (e.g., IM (in Type of

⁷ Following prior related studies that employ t-test (e.g., Enger, 2009), the test statistic is obtained by dividing the difference-in-differences estimator by the standard deviation (discussed in Footnote 3), i.e., in this case, the test statistic is -1.26/0.36=-3.51.

Reference), research (in Type of Question)), we can derive the data (number of face-to-face research questions per month, number of chat (research) questions per month) for the time series calculation.

Detailed MA(4) time series calculations and visualization procedures are summarized in Appendix 1.1-1.3 which uses chat (research) MA(4) as an example.

5.2.2 Findings

[Insert Table 7 here]

Table 7 summarizes the estimated results from the moving average process based on the estimation procedures outlined in Appendix 1.1-1.3. We can conclude that the volumes of both face-to-face (research) (p-value = 0.0026) and online chat (research) (p-value = 0.0016) reference services experienced significant declines in the sample period, with p-values of 0.0026 and 0.0016, respectively. Such declining trend is also visualized and confirmed in Figure 2 and Figure 3. In addition, as shown in Table 7, the average declining rate (i.e., the intercept value divided by estimated time series coefficient β)⁸ of face-to-face (research) reference volume is -1.63% per academic month and agrees with our librarians' anecdotal observations during their reference shifts as well as the findings in prior related studies. However, what surprises us is that although online chat is considered as a more accessible reference option for patrons and its short-term impact has been established in the difference-in-differences analysis, the average decline rate of chat (research) reference (-2.06%) in the sample time range is actually greater than that of face-to-face (research) reference (-1.63%). This finding may potentially indicate that chat reference did not continue to attract patrons or boost the overall research-related reference usage in the long term (i.e., from the Fall 2012 semester to the Fall 2015 semester).

[Insert Figure 2 here]

[Insert Figure 3 here]

⁸ As shown in Appendix 1.2, intercept value (B26) and estimated time series coefficient β (B27) are obtained in the simple linear regression summary result.

In order to further determine how the share of chat (research) reference evolved in the same period, we use the proportion of chat (research) transactions among all research reference questions (i.e., chat (research) divided by all (research)) as the third outcome variable of interest in the moving average analysis. Results are presented in Table 7. Intriguingly, according to Table 7, the p-value on the change of chat (research) reference's share in all research-related reference questions is 0.416, suggesting that the changing trend of the composition of research-related reference questions is not statistically significant (as illustrated in Figure 4). In other words, although a significant declining trend of the chat (research) reference usage is suggested in the time series analysis and its average declining rate is even greater than that of face-to-face, there is no statistical evidence to suggest that the relative importance of chat reference in all reference services with regard to the research-related questions has changed in the recorded period or will change in the forecast period.

[Insert Figure 4 here]

6 Discussion

6.1 Interpreting the findings

The results obtained in the difference-in-differences estimation appear to be contradictory to the outcomes found in the time series analysis. However, the seemingly conflicting results essentially demonstrate a more complete picture of how patrons interact with a new reference service from its introduction to the eventual long-term routine usage.

In the initial stage of chat's implementation during its first academic year, a significant traffic migration from face-to-face reference to chat is confirmed and quantified by the difference-in-differences estimation. Based on our daily observations, besides its immediate accessibility to patrons (which is regarded as the primary contributing factor), the in-classroom promotions conducted by librarians, advertisements posted on the library website and patrons' curiosity toward a new reference tool may all contribute to the significant short-term impact captured in our analysis.

However, our time series analysis suggests that chat reference does not develop into a new major reference service in terms of usage volume over time. One possible explanation to this phenomenon is due to the limitation of online chat as a reference form. Jane and McMillan (2003) suggested that the lack of non-verbal cues such as eye contact or body language could be a major obstacle to providing reference via chat. Also, the transformation of patrons' searching habits is considered as another possible factor. The habit of self-service in information seeking process could lead to the decline in reference volume (Coffman and Arret, 2004), which is also reflected in our analysis and other reference volume assessment studies. In other words, it is likely that patrons tend to turn to librarians only with more complicated questions, which may either require extensive instructions or further searches by the librarians. However, with the time pressure during chat reference service, librarians may be inclined to either provide quick answers and direct links to the information sources without elaborating the entire process (Jane and McMillan, 2003), or resort to email to provide more in-depth reference help (Wikoff, 2008). The absence of step-by-step and personalized instructions may divert patrons with complicated questions back to the traditional face-to-face reference service.

As for the finding in the time series analysis regarding chat's relative importance, the most reasonable explanation may be that online chat has already been regarded as one of the regular reference services of the Scribner Library, and patrons have developed their habits of choosing reference tools according to their information needs over the time. As a result, the share of different reference services gradually reaches a relatively stable equilibrium. This is consistent with Chow and Croxton's (2014) study which suggested that patrons may choose virtual reference tools such as text message and online chat for their quickness of response and accessibility and traditional reference services for more complicated questions.

6.2 Accessibility vs. cost effectiveness

Seamless accessibility and cost effectiveness can be seen as two ends of the same rope. Every library is looking for a balance to better fit its institutional features. Extending service coverage under budget constraints is the reality that the Scribner Library and many other academic libraries are currently

facing. With ever growing expenditures, such as electronic resources, Geographic Information System (GIS) labs and other newly emerging digital tools, we are constantly exploring ways utilize the limited resources to best serve our patrons. This case study provides us some statistical evidence on whether we should keep that reference or save the budget for other library expenditures.

As the only library at Skidmore College, the Scribner Library handles all the reference service for patrons in the community. The ability to provide seamless reference service to its community members is regarded as one of library's priorities. As one of the top ranked baccalaureate institutions for the number of students studying abroad for at least one semester, online chat is understandably the most efficient reference tool in such situations. Therefore, despite its relatively low usage, online chat is still considered as one of the essential reference services that can facilitate access to our collections and extend the service coverage of our reference desk.

Usage rate represents part of the overall concern for chat, and total operating cost is another important component of the equation (Coffman and Arret, 2004). When libraries are evaluating the legitimacy of chat reference, besides the software cost, one also needs to take into consideration the staffing cost (Radford and Kern, 2006). At the Scribner Library, librarians provide chat reference service during their regular shifts. Given the relatively low volume from chat in most cases, one librarian is able to handle regular service at the reference desk and provide virtual reference help via chat window during the same shift, which saves the library extra costs on training and staffing for chat service. Thus, for certain library managers, if keeping chat reference is preferred, combining its staffing arrangement with regular reference service can be a possible solution. Alternatively, joining a chat reference service consortium to share the cost across institutions and libraries can be another possibility.

Overall, our decision to keep chat reference is in line with the strategic plan of the library and the college. Our findings from the moving average time series analysis also indicate that chat reference does not seem to "cannibalize" other reference services over a longer time frame. On the other hand, if keeping

⁹ "Skidmore Off-Campus Study & Exchanges," accessed April 15, 2016, https://www.skidmore.edu/ocse/about/message.php

the overall budget under control is of a higher priority in a library's strategic plan, then opting out of chat reference is certainly an option. Coffman and Arret (2004) also suggested that earlier virtual reference tools such as e-mail could be utilized as an alternative to chat, as long as the turn-around time of email responses can be greatly improved. The usability of email reference was also studied in Chow and Croxton (2014) by comparing five types of virtual reference tools. The fact that email shares a few characteristics with chat reference such as ease of use and reference with a trackable written record makes reference by email a potential low-cost alternative to chat.

7 Conclusion and Further Research

In this paper, two novel statistical methods (to the field of information and library science) are utilized to study the impact of chat reference in both the short term and long term. We find that while chat reference may negatively affect the volume of the traditional face-to-face reference in the short term, its long-term impact is limited. In addition, although chat reference usage seems to have suffered from the same declining trend as the traditional reference volume and does not help promote overall reference traffic, the results obtained in the long-term analysis also suggest that chat reference develops into a regular reference tool and shares a relatively stable volume with other reference services. In addition to being the first paper to assess the impact of chat reference on other reference services based on empirical data, this case study also contributes to research methodology in library science by outlining the implementation procedures of two statistical methods. For the librarians with basic statistical knowledge and proficiency in Microsoft Excel, the methodology in this study can be implemented in similar circumstances (e.g., assessing the usage volume among different reference services) and other settings with similar supporting data.

As Coffman and Arret (2004) pointed out, we need to consider reference service as a whole and find out how to provide the best service based on careful thoughts and analyses. For libraries seeking to potentially replace the entire traditional reference service with virtual reference service, our findings can be enlightening. Although self-searching has nearly become second nature for many patrons in their

information seeking process, traditional reference guidance may still be needed when they encounter more complicated questions. Marketing or redesigning the chat interface (e.g., Mu et al., 2011) may boost its usage in the short term. Nevertheless, it requires a longer time frame and more sophisticated assessment to reach the conclusion of whether such change indeed meets the information needs of patrons in the long term. This case study provides an alternative perspective for assessing the effectiveness and legitimacy of a new reference service. The implication of our study is not limited to methodology and chat reference evaluation, it may also be generalized to new resources or services provided in academic libraries.

It is worth noting that this case study only provides a starting point for empirical analysis of reference usage data in academic libraries and introduces two statistical methods to library practitioners. The institutional features of the Scribner Library, e.g., the fact that it is the only library on campus with undergraduates as the majority of the user group and a high participation rate for study abroad programs, could possibly undermine the generalizability of our methodology. Therefore, future case studies assessing chat usage data at different institutions, e.g., a larger university with multiple libraries and both undergraduate and graduate enrollments, or a university with extensive online course offerings, can be performed in order to further generalize the applicability of this study.

References

- Ahmadi, M., Dileepan, P., Murgai, S.R. and Roth, W. (2008). An Exponential Smoothing Model for Predicting Traffic in the Library and at the Reference Desk. *Bottom Line: Managing Library Finances*, 21(2), pp.37-48.
- 2. Applegate, R. (2008). Whose Decline? Which Academic Libraries Are "Deserted" in Terms of Reference Transactions? *Reference & User Services Quarterly*, 48(2), pp.176-189.
- 3. Armann-Keown, V., Cooke, C.A. and Matheson, G. (2015). Digging Deeper into Virtual Reference Transcripts. *Reference Services Review*, 43(4), pp.656–672.
- Bravender, P., Lyon, C. and Molaro, A. (2011). Should Chat Reference be Staffed by Librarians? An
 Assessment of Chat Reference at an Academic Library Using LibStats. *Internet Reference Services Quarterly*, 16(3), pp.111–127.
- 5. Cabaniss, J. (2015). An Assessment of the University of Washington's Chat Reference Services. *Public Library Quarterly*, 34(1), pp.85–96.
- Neumark, D. and Wascher, W. (2000). Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania: Comment. *American Economic Review*, 90(5), pp.1362-1396.
- 7. Chow, A.S. and Croxton, R.A. (2012). Information-Seeking Behavior and Reference Medium Preferences. *Reference & User Services Ouarterly*, 51(3), pp.246-262.
- 8. Chow, A.S. (2014). A Usability Evaluation of Academic Virtual Reference Services. *College & Research Libraries*, 75(3), pp.309-361.
- 9. Coffman, S. and Arret, L. (2004). To Chat or Not to Chat. Searcher, 12(8), pp.49-56.
- Desai, C.M. (2003). Instant Messaging Reference: How Does It Compare? *The Electronic Library*, 21(1), pp.21-30.
- 11. Desai, C.M. and Graves, S.J. (2006). Instruction via Instant Messaging Reference: What's Happening? *The Electronic Library*, 24(2), pp.174-189.

- 12. Dubnjakovic, A. (2012). Electronic Resource Expenditure and the Decline in Reference Transaction Statistics in Academic Libraries. *Journal of Academic Librarianship*, 38(2), pp.94-100.
- 13. Enger, K.B. (2009). Using Citation Analysis to Develop Core Book Collections in Academic Libraries. Library & Information Science Research, 31(2), pp.107-112.
- 14. Jane, C. and McMillan, D. (2003). Online in Real-Time? Deciding Whether to Offer a Real-Time Virtual Reference Service. *The Electronic Library*, 21(3), pp.240-246.
- 15. Jeong, S.H. and Kim, S. (2010). Core Resources on Time Series Analysis for Academic Libraries: A Selected, Annotated Bibliography. *Proceedings of the Charleston Library Conference*.
- Lankes, R.D., Gross, M. and McClure, C.R. (2003). Cost, Statistics, Measures, and Standards for Digital Reference Services: A Preliminary View. *Library Trends*, 51(3), pp.401-413.
- 17. Lawrence, K., Klimberg, R. and Lawrence, S. (2009). Fundamentals of Forecasting Using Excel (1st ed.).

 New York, N.Y.: Industrial Press.
- 18. Logan, F.F. and Lewis, K. (2011). Quality Control: A Necessary Good for Improving Service. *Reference Librarian*, 52(3), pp.218–230.
- 19. Luo, L. (2008). Chat Reference Evaluation: A Framework of Perspectives and Measures. *Reference Services Review*, 36(1), pp.71-85.
- 20. Kwon, N. and Gregory, V.L. (2007). The Effects of Librarians' Behavioral Performance on User Satisfaction in Chat Reference Services. *Reference & User Services Quarterly*, 47(2), pp.137–148.
- Maloney, K. and Kemp, J.H. (2015). Changes in Reference Question Complexity Following the Implementation of a Proactive Chat System: Implications for Practice. *College & Research Libraries*, 76(7), pp.959–974.
- 22. Maness, J.M. (2008). A Linguistic Analysis of Chat Reference Conversations with 18–24 Year-Old College Students. *Journal of Academic Librarianship*, 34(1), pp.31–38.
- 23. Matteson, M.L., Salamon, J. and Brewster, L. (2011). A Systematic Review of Research on Live Chat Service. *Reference & User Services Quarterly*, 51(2), pp.172–90.

- 24. McLaughlin, J.E. (2011). Reference Transaction Assessment. *Reference Services Review*, 39(4), pp.536-550.
- 25. Morais, Y. and Sampson, S. (2010). A Content Analysis of Chat Transcripts in the Georgetown Law Library. *Legal Reference Services Quarterly*, 29(3), pp.165–78.
- 26. Mu, X., Dimitroff, A., Jordan, J. and Burclaff, N. (2011). A Survey and Empirical Study of Virtual Reference Service in Academic Libraries. *Journal of Academic Librarianship*, 37(2), pp.120-129.
- 27. Murgai, S.R. (2006). Staffing Needs of the Reference Desk at the University of Tennessee at Chattanooga: A Statistical Approach. *Public Services Quarterly*, 2(2-3), pp.167-190.
- 28. Murgai, S.R. and Ahmadi, M. (2007). A Multiple Regression Model for Predicting Reference Desk Staffing Requirements. *Bottom Line: Managing Library Finances*, 20(2), pp.69-76.
- 29. Naylor, S., Stoffel, B. and van der Laan, S. (2008). Why Isn't Our Chat Reference Used More? Finding of Focus Group Discussions with Undergraduate Students. *Reference & User Services Quarterly*, 47(4), pp.342–354.
- 30. Nicol, E.C. and Crook, L. (2013). Now It's Necessary: Virtual Reference Services at Washington State University, Pullman. *Journal of Academic Librarianship*, 39(2), pp.161–168.
- 31. Radford, M.L. and Kern, M.K. (2006). A Multiple-Case Study Investigation of the Discontinuation of Nine Chat Reference Services. *Library & Information Science Research*, 28(4), pp.521-547.
- Radford, M.L. (2006). Encountering Virtual Users: A Qualitative Investigation of Interpersonal Communication in Chat Reference. *Journal of the American Society for Information Science & Technology*, 57(8), pp.1046-1059.
- 33. Rawson, J., Davis, M.A., Harding, J. and Miller, C. (2012). Virtual Reference at a Global University: An Analysis of Patron and Question Type. *Journal of Library & Information Services in Distance Learning*, 7(1–2), pp.93–97.
- 34. Ryan, S.M. (2008). Reference Transactions Analysis: The Cost-Effectiveness of Staffing a Traditional Academic Reference Desk. *The Journal of Academic Librarianship*, 34(5), pp.389-399.

- 35. Solorzano, R.M. (2013). Adding Value at the Desk: How Technology and User Expectations are Changing Reference Work. *Reference Librarian*, 54(2), pp.89-102.
- 36. Stevens, C.R. (2013). Reference Reviewed and Re-Envisioned: Revamping Librarian and Desk-Centric Services with LibStARs and LibAnswers. *Journal of Academic Librarianship*, 39(2), pp.202-214.
- 37. Tenopir, C. (2004). Chat's Positive Side. Library Journal, 129(20), pp.42.
- 38. Ward, D. (2004). Measuring the Completeness of Reference Transactions in Online Chats: Results of an Unobtrusive Study. *Reference & User Services Quarterly*, 44(1), pp.46-56.
- 39. Wikoff, N. (2008). Reference Transaction Handoffs: Factors Affecting the Transition from Chat to E-mail. *Reference & User Services Quarterly*, 47(3), pp.230–241.
- 40. Wooldridge, J. (2011). Econometric Analysis of Cross Section and Panel Data (1st ed.). Cambridge, Mass.: MIT.
- 41. Yang, S.Q. and Dalal, H.A. (2015). Delivering Virtual Reference Services on the Web: An Investigation into the Current Practice by Academic Libraries. *The Journal of Academic Librarianship*, 41(1), pp.68-86.
- 42. Zabel, D. (2005). Trends in Reference and Public Services Librarianship and the Role of RUSA Part One. References & User Services Quarterly, 45(1), pp.7-10.

Appendix 1.1: Simple moving average MA(4) analysis in Microsoft Excel: Setup¹⁰

- 1. Assign period numbers to all academic months t in the sampling period in A5:A32.
- 2. Create five fields of Semester in B5:B32, Month in C5:C32, and Chat (research) in D5:D32 and fill in the relevant information. The volume of chat (research) *Y_t* is obtained based on the pivot table view of the master reference transaction record.
- 3. Create fields for MA(4)_t in E5:E32, CMA(4)_t in F5:F32, $S_{t_I_t}$ in G5:G32, S_t in H5:H32, Deseasonalize Y_t/S_t in I5:I32, T_t in J5:J32 and Forecast Y'_t in K5:K32 to prepare for the calculation in Appendix 1.2 Table A2.

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¹⁰ Full spreadsheet template used in this study is available upon request.

Table A1: Data preparation

	Α	В	С	D	E	F	G	Н	I	J	K
1											
2											
3				Y _t		Baseline	Y_t /CMA(4)		Y_t/S_t		Y' _t
4	t	Semester	Month	Chat (research)	MA(4) _t	CMA(4)	$S_{t_{-}}I_{t}$	S _t	Deseasonalize	T_t	Forecast
5	1	Fall 2012	1	8							
6	2		2	36							
7	3		3	23							
8	4		4	28							
9	5	Spring 2013	1	19							
10	6		2	16							
11	7		3	28							
12	8		4	12							
13	9	Fall 2013	1	10							
14	10		2	25							
15	11		3	40							
16	12		4	25							
17	13	Spring 2014	1	9							
18	14		2	24							
19	15		3	25							
20	16		4	13							
21	17	Fall 2014	1	10							
22	18		2	24							
23	19		3	20							
24	20		4	17							
25	21	Spring 2015	1	14							
26	22		2	15							
27	23		3	14							
28	24		4	8							
29	25	Fall 2015	1	12							
30	26		2	13							
31	27		3	8							
32	28		4	3							

*N=4; CMA: centered moving average; $S_{t_{-}}I_{t_{-}}$: difference rate; $S_{t_{-}}$: seasonality component at time t; $I_{t_{-}}$: irregularity component at time t; $I_{t_{-}}$: trend component at time t.

Appendix 1.2: Simple moving average MA(4) analysis in Microsoft Excel: Computation procedures

1. Utilize Excel's built-in AVERAGE formula to calculate the values for MA(4)_t in E33:E57 and CMA(4)_t in F33:F56 for smoothed out chat (research) reference volumes at period t, i.e., without seasonality S_t and irregularities I_t . In other words, we compute

$$MA(4)_t = AVERAGE (Y_{t-2}, Y_{t-1}, Y_t, Y_{t+1})$$

$$CMA(4)_t = AVERAGE (MA(4)_t, MA(4)_{t+1})$$

- 2. Compute the difference rate $S_t I_t$ between chat (research) volume Y_t and CMA(4)_t by Y_t / CMA(4)_t at period t in G33:G56, e.g., difference rate of the 2013 Fall semester Month 1 = E39/F39.
- 3. Extract the seasonality component S_t from difference rate $S_t I_t$ by calculating the mean of difference rate $S_t I_t$ of the same academic month in every semester in A4:B8. For example:

$$S_t$$
 (Month 2) = AVERAGE (G36,G40,G44,G48,G52,G56)

- 4. Fill in the seasonality component values S_t for every academic month in H31:H62 accordingly from data in A4:B8 by using Excel's built-in VLOOKUP formula.
- 5. Calculate the deseasonalized chat (research) reference volume at period t by Y_t/S_t , in I31:I58, e.g., the deseasonalized chat (research) reference volume in the Spring 2013 semester Month 1 = D35/H35.
- 6. Run a simple linear regression using Excel's built-in data analysis tool Regression located in Data ribbon under Data Analysis with deseasonalized chat (research) reference volume in I31:I58 as Y variable (i.e., the dependent variable), and period t in A31:A58 as X variable (i.e., the independent variable). The summary report is presented in A10:I27. The coefficient values needed for forecasting (intercept value in B26 and the estimated time series coefficient β in B27) are highlighted as shown in Table A2.
- 7. Calculate the trend component T_t at period t using the following formula:

 T_t = intercept value + estimated time series coefficient (β) * time (t)

For example, the trend component of the Fall 2013 semester Month 1= \$B\$26 + \$B\$27 * A39.

8. Calculate the forecast volume *Y'*_t of chat (research) reference at period *t* during the sampling period in K31:K58 using the following formula:

 Y'_t = seasonality component (S_t) * trend component (T_t) .

9. Apply the same procedures and forecast the chat (research) reference volume in the next semester (the Spring 2016 semester) by following Step 7 and Step 8 as shown in A59:K62.

Table A2: Procedures to calculate MA(4) using Excel formula and data analysis tool

A	В	С	D	Е	F	G			J	K
Month	S.									
	· · · ·	\$33:\$C\$	58,A5,\$G\$33:\$G\$5	.8)						
2			58,A6,\$G\$33:\$G\$5							
3			58,A7,\$G\$33:\$G\$5							
4			58,A8,\$G\$33:\$G\$5							
SUMMARY OUTPUT										
Regression S										
Regression S										
Multiple R	0.5695865									
R Square	0.32442878 0.29844527									
Adjusted R Square Standard Error	6.22410245									
Observations	28									
Observations	20									
ANOVA										
	df	SS	MS	F	Significance F					
Regression	1	483.7	483.6988468	12.48594987	0.001557494					
Residual	26	1007	38.73945128							
Total	27	1491								
	- 47									
	Coefficients		t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%		
Intercept	25.0226578	2.417	10.35297527	1.02452E-10	20.05453913					
β	-0.51453895	0.146	-3.533546359	0.001557494	-0.813855791	-0.21522	-0.813855791	-0.2152221		
			ν.		Dlin-	V (CNAA(A)		V /5		٠.
	Comoston	Month	(hat (research)	NAN(A)	Baseline	Y _t /CMA(4)	£	Y _t /S _t	-	For
t	Semester Fall 2012	Month 1	Chat (research)	MA(4) _t	CMA(4).	S _{t_} I _t	S _t =VLOOKUP(C31,\$A\$5:\$B\$8,2,FALSE)	Deseasonalize =D31/H31	T _t =\$B\$26+\$B\$27*A31	Fore
2		2	36						=\$B\$26+\$B\$27*A32	
3		3		-AVERACE(D31,D34)	=AVERAGE(E33:E34)	_E22/E22	=VLOOKUP(C32,\$A\$5:\$B\$8,2,FALSE)		=\$B\$26+\$B\$27*A33	
4		4			=AVERAGE(E34:E35)				=\$B\$26+\$B\$27*A34	
		1			=AVERAGE(E35:E36)		=VLOOKUP(C34,\$A\$5:\$B\$8,2,FALSE)		=\$B\$26+\$B\$27*A35	
	Spring 2013						=VLOOKUP(C35,\$A\$5:\$B\$8,2,FALSE)			
6 7		2		=AVERAGE(D34:D37)	=AVERAGE(E36:E37)		=VLOOKUP(C36,\$A\$5:\$B\$8,2,FALSE)	=D36/H36	=\$B\$26+\$B\$27*A36	_
				=AVERAGE(D35:D38)	=AVERAGE(E37:E38)		=VLOOKUP(C37,\$A\$5:\$B\$8,2,FALSE)		=\$B\$26+\$B\$27*A37	
		4 1		=AVERAGE(D36:D39)	=AVERAGE(E38:E39)		=VLOOKUP(C38,\$A\$5:\$B\$8,2,FALSE)		=\$B\$26+\$B\$27*A38	
	Fall 2013	2		=AVERAGE(D37:D40)	=AVERAGE(E39:E40)				=\$B\$26+\$B\$27*A39	
10					=AVERAGE(E40:E41)		=VLOOKUP(C40,\$A\$5:\$B\$8,2,FALSE)		=\$B\$26+\$B\$27*A40	
11		3 4		=AVERAGE(D39:D42)	=AVERAGE(E41:E42)			=D41/H41	=\$B\$26+\$B\$27*A41	
12				=AVERAGE(D40:D43)	=AVERAGE(E42:E43)		=VLOOKUP(C42,\$A\$5:\$B\$8,2,FALSE)		=\$B\$26+\$B\$27*A42	
	Spring 2014	1		=AVERAGE(D41:D44)	=AVERAGE(E43:E44)				=\$B\$26+\$B\$27*A43	
14		2		=AVERAGE(D42:D45)		=E44/F44		=D44/H44	=\$B\$26+\$B\$27*A44	
15 16		3 4		=AVERAGE(D43:D46)	=AVERAGE(E45:E46) =AVERAGE(E46:E47)		=VLOOKUP(C45,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C46,\$A\$5:\$B\$8,2,FALSE)		=\$B\$26+\$B\$27*A45 =\$B\$26+\$B\$27*A46	
	7 Fall 2014	1		=AVERAGE(D44:D47)	=AVERAGE(E47:E48)	=E46/F46 =E47/F47		=D46/H46 =D47/H47	=\$B\$26+\$B\$27*A46 =\$B\$26+\$B\$27*A47	
	1 all 2014				, ,	=E47/F47 =E48/F48	=VLOOKUP(C48,\$A\$5:\$B\$8,2,FALSE)		=\$B\$26+\$B\$27*A47	_
		2	24	-AVERAGE(D46-D40)			- v LOOKOF (C40,3M33.3D30,Z,FAL3E)	-D-10/1140		
18		2		=AVERAGE(D46:D49)	. ,			=D49/H49		=HA0
18 19		3	20	=AVERAGE(D47:D50)	=AVERAGE(E49:E50)	=E49/F49	=VLOOKUP(C49,\$A\$5:\$B\$8,2,FALSE)		=\$B\$26+\$B\$27*A49	_
18 19 20)	3 4	20 17	=AVERAGE(D47:D50) =AVERAGE(D48:D51)	=AVERAGE(E49:E50) =AVERAGE(E50:E51)	=E49/F49 =E50/F50	=VLOOKUP(C49,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C50,\$A\$5:\$B\$8,2,FALSE)	=D50/H50	=\$B\$26+\$B\$27*A50	=H50
18 19 20 21) Spring 2015	3 4 1	20 17 14	=AVERAGE(D47:D50) =AVERAGE(D48:D51) =AVERAGE(D49:D52)	=AVERAGE(E49:E50) =AVERAGE(E50:E51) =AVERAGE(E51:E52)	=E49/F49 =E50/F50 =E51/F51	=VLOOKUP(C49,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C50,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C51,\$A\$5:\$B\$8,2,FALSE)	=D50/H50 =D51/H51	=\$B\$26+\$B\$27*A50 =\$B\$26+\$B\$27*A51	=H50 =H51
18 19 20 21 22) 	3 4 1 2	20 17 14 15	=AVERAGE(D47:D50) =AVERAGE(D48:D51) =AVERAGE(D49:D52) =AVERAGE(D50:D53)	=AVERAGE(E49:E50) =AVERAGE(E50:E51) =AVERAGE(E51:E52) =AVERAGE(E52:E53)	=E49/F49 =E50/F50 =E51/F51 =E52/F52	=VLOOKUP(C49,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C50,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C51,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C52,\$A\$5:\$B\$8,2,FALSE)	=D50/H50 =D51/H51 =D52/H52	=\$B\$26+\$B\$27*A50 =\$B\$26+\$B\$27*A51 =\$B\$26+\$B\$27*A52	=H50 =H51 =H52
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18 19 20 21 22 23 24	Spring 2015	3 4 1 2 3 4	20 17 14 15 14 8	=AVERAGE(D47:D50) =AVERAGE(D48:D51) =AVERAGE(D49:D52) =AVERAGE(D50:D53) =AVERAGE(D51:D54) =AVERAGE(D52:D55)	=AVERAGE(E49:E50) =AVERAGE(E50:E51) =AVERAGE(E51:E52) =AVERAGE(E52:E53) =AVERAGE(E53:E54) =AVERAGE(E54:E55)	=E49/F49 =E50/F50 =E51/F51 =E52/F52 =E53/F53 =E54/F54	=VLOOKUP(C49,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C50,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C51,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C52,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C53,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C54,\$A\$5:\$B\$8,2,FALSE)	=D50/H50 =D51/H51 =D52/H52 =D53/H53 =D54/H54	=\$B\$26+\$B\$27*A50 =\$B\$26+\$B\$27*A51 =\$B\$26+\$B\$27*A52 =\$B\$26+\$B\$27*A53 =\$B\$26+\$B\$27*A54	=H50 =H51 =H52 =H53 =H54
18 19 20 21 22 23 24 25	Spring 2015	3 4 1 2 3 4	20 17 14 15 14 8	=AVERAGE(D47:D50) =AVERAGE(D48:D51) =AVERAGE(D49:D52) =AVERAGE(D50:D53) =AVERAGE(D51:D54) =AVERAGE(D52:D55) =AVERAGE(D53:D56)	=AVERAGE(E49:E50) =AVERAGE(E50:E51) =AVERAGE(E51:E52) =AVERAGE(E52:E53) =AVERAGE(E53:E54) =AVERAGE(E54:E55) =AVERAGE(E55:E56)	=E49/F49 =E50/F50 =E51/F51 =E52/F52 =E53/F53 =E54/F54 =E55/F55	=VLOOKUP(C49,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C50,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C51,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C52,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C53,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C54,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C55,\$A\$5:\$B\$8,2,FALSE)	=D50/H50 =D51/H51 =D52/H52 =D53/H53 =D54/H54 =D55/H55	=\$B\$26+\$B\$27*A50 =\$B\$26+\$B\$27*A51 =\$B\$26+\$B\$27*A52 =\$B\$26+\$B\$27*A53 =\$B\$26+\$B\$27*A54 =\$B\$26+\$B\$27*A54	=H50 =H51 =H52 =H53 =H54 =H55
18 19 20 21 22 23 24 25 26	Spring 2015	3 4 1 2 3 4 1	20 17 14 15 14 8 12	=AVERAGE(D47:D50) =AVERAGE(D48:D51) =AVERAGE(D49:D52) =AVERAGE(D50:D53) =AVERAGE(D51:D54) =AVERAGE(D52:D55) =AVERAGE(D53:D56) =AVERAGE(D54:D57)	=AVERAGE(E49:E50) =AVERAGE(E50:E51) =AVERAGE(E51:E52) =AVERAGE(E52:E53) =AVERAGE(E53:E54) =AVERAGE(E54:E55)	=E49/F49 =E50/F50 =E51/F51 =E52/F52 =E53/F53 =E54/F54 =E55/F55	=VLOOKUP(C49,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C50,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C51,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C52,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C53,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C54,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C55,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C56,\$A\$5:\$B\$8,2,FALSE)	=D50/H50 =D51/H51 =D52/H52 =D53/H53 =D54/H54 =D55/H55 =D56/H56	=\$B\$26+\$B\$27*A50 =\$B\$26+\$B\$27*A51 =\$B\$26+\$B\$27*A52 =\$B\$26+\$B\$27*A53 =\$B\$26+\$B\$27*A54 =\$B\$26+\$B\$27*A55 =\$B\$26+\$B\$27*A56	=H50 =H51 =H52 =H53 =H54 =H55 =H56
18 19 20 21 22 23 24 25 26	Spring 2015	3 4 1 2 3 4 1 2	20 17 14 15 14 8 12 13	=AVERAGE(D47:D50) =AVERAGE(D48:D51) =AVERAGE(D49:D52) =AVERAGE(D50:D53) =AVERAGE(D51:D54) =AVERAGE(D52:D55) =AVERAGE(D53:D56)	=AVERAGE(E49:E50) =AVERAGE(E50:E51) =AVERAGE(E51:E52) =AVERAGE(E52:E53) =AVERAGE(E53:E54) =AVERAGE(E54:E55) =AVERAGE(E55:E56)	=E49/F49 =E50/F50 =E51/F51 =E52/F52 =E53/F53 =E54/F54 =E55/F55	=VLOOKUP(C49,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C50,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C51,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C53,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C53,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C54,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C55,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C55,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C55,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C55,\$A\$5:\$B\$8,2,FALSE)	=D50/H50 =D51/H51 =D52/H52 =D53/H53 =D54/H54 =D55/H55 =D56/H56 =D57/H57	=\$B\$26+\$B\$27*A50 =\$B\$26+\$B\$27*A51 =\$B\$26+\$B\$27*A52 =\$B\$26+\$B\$27*A53 =\$B\$26+\$B\$27*A54 =\$B\$26+\$B\$27*A54 =\$B\$26+\$B\$27*A55 =\$B\$26+\$B\$27*A56 =\$B\$26+\$B\$27*A57	=H50 =H51 =H52 =H53 =H54 =H55 =H56
18 19 20 21 22 23 24 25 26 27	Spring 2015	3 4 1 2 3 4 1 2 2 3	20 17 14 15 14 8 12	=AVERAGE(D47:D50) =AVERAGE(D48:D51) =AVERAGE(D49:D52) =AVERAGE(D50:D53) =AVERAGE(D51:D54) =AVERAGE(D52:D55) =AVERAGE(D53:D56) =AVERAGE(D54:D57)	=AVERAGE(E49:E50) =AVERAGE(E50:E51) =AVERAGE(E51:E52) =AVERAGE(E52:E53) =AVERAGE(E53:E54) =AVERAGE(E54:E55) =AVERAGE(E55:E56)	=E49/F49 =E50/F50 =E51/F51 =E52/F52 =E53/F53 =E54/F54 =E55/F55	=VLOOKUP(C49,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C50,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C51,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C53,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C53,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C54,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C55,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C55,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C55,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C55,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C58,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C58,\$A\$5:\$B\$8,2,FALSE)	=D50/H50 =D51/H51 =D52/H52 =D53/H53 =D54/H54 =D55/H55 =D56/H56	=\$B\$26+\$B\$27*A50 =\$B\$26+\$B\$27*A51 =\$B\$26+\$B\$27*A52 =\$B\$26+\$B\$27*A52 =\$B\$26+\$B\$27*A53 =\$B\$26+\$B\$27*A55 =\$B\$26+\$B\$27*A56 =\$B\$26+\$B\$27*A56 =\$B\$26+\$B\$27*A56 =\$B\$26+\$B\$27*A57 =\$B\$26+\$B\$27*A57	=H50 =H51 =H52 =H53 =H54 =H55 =H56 =H57 =H58
18 19 20 21 1 22 23 24 25 26 27 28	Spring 2015 Fall 2015 Spring 2016	3 4 1 2 3 4 1 1 2 2 3 4 1 1	20 17 14 15 14 8 12 13	=AVERAGE(D47:D50) =AVERAGE(D48:D51) =AVERAGE(D49:D52) =AVERAGE(D50:D53) =AVERAGE(D51:D54) =AVERAGE(D52:D55) =AVERAGE(D53:D56) =AVERAGE(D54:D57)	=AVERAGE(E49:E50) =AVERAGE(E50:E51) =AVERAGE(E51:E52) =AVERAGE(E52:E53) =AVERAGE(E53:E54) =AVERAGE(E54:E55) =AVERAGE(E55:E56)	=E49/F49 =E50/F50 =E51/F51 =E52/F52 =E53/F53 =E54/F54 =E55/F55	=VLOOKUP(C49,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C50,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C51,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C52,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C53,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C54,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C55,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C55,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C55,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C55,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C58,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C59,\$A\$5:\$B\$8,2,FALSE)	=D50/H50 =D51/H51 =D52/H52 =D53/H53 =D54/H54 =D55/H55 =D56/H56 =D57/H57	=\$B\$26+\$B\$27*A50 =\$B\$26+\$B\$27*A51 =\$B\$26+\$B\$27*A52 =\$B\$26+\$B\$27*A53 =\$B\$26+\$B\$27*A54 =\$B\$26+\$B\$27*A55 =\$B\$26+\$B\$27*A55 =\$B\$26+\$B\$27*A57 =\$B\$26+\$B\$27*A57 =\$B\$26+\$B\$27*A58	=H50 =H51 =H52 =H53 =H54 =H55 =H56 =H57 =H58
18 19 20 21 22 23 24 25 26 27 28	Spring 2015 Fall 2015 Spring 2016	3 4 1 2 3 4 1 2 2 3	20 17 14 15 14 8 12 13	=AVERAGE(D47:D50) =AVERAGE(D48:D51) =AVERAGE(D49:D52) =AVERAGE(D50:D53) =AVERAGE(D51:D54) =AVERAGE(D52:D55) =AVERAGE(D53:D56) =AVERAGE(D54:D57)	=AVERAGE(E49:E50) =AVERAGE(E50:E51) =AVERAGE(E51:E52) =AVERAGE(E52:E53) =AVERAGE(E53:E54) =AVERAGE(E54:E55) =AVERAGE(E55:E56)	=E49/F49 =E50/F50 =E51/F51 =E52/F52 =E53/F53 =E54/F54 =E55/F55	=VLOOKUP(C49,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C50,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C51,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C53,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C53,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C54,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C55,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C55,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C55,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C55,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C58,\$A\$5:\$B\$8,2,FALSE) =VLOOKUP(C58,\$A\$5:\$B\$8,2,FALSE)	=D50/H50 =D51/H51 =D52/H52 =D53/H53 =D54/H54 =D55/H55 =D56/H56 =D57/H57	=\$B\$26+\$B\$27*A50 =\$B\$26+\$B\$27*A51 =\$B\$26+\$B\$27*A52 =\$B\$26+\$B\$27*A52 =\$B\$26+\$B\$27*A53 =\$B\$26+\$B\$27*A55 =\$B\$26+\$B\$27*A56 =\$B\$26+\$B\$27*A56 =\$B\$26+\$B\$27*A56 =\$B\$26+\$B\$27*A57 =\$B\$26+\$B\$27*A57	=H50 =H51 =H52 =H53 =H54 =H55 =H56 =H57 =H58 =H59

*N=4; CMA: centered moving average; S_t _ I_t : difference rate; S_t : seasonality component at time t; I_t : irregularity component at time t; I_t : trend component at time t.

Appendix 1.3: Simple moving average MA(4) analysis in Microsoft Excel: Results and visualization

- 1. Results calculated through the procedures outlined in Table A2 are now shown in Table A3.
- 2. Visualize the Forecast Y'_t with chat (research) volume Y_t and CMA(4)_t by invoking Excel chart (type: Line with Markers), with Y_t in D31:D58, CMA(4)_t in F33:F56 and Y'_t in K31:K62 as Legend Entries (Series), and Semester in B31:B62 and Month in C31:C62 as Horizontal (Category) Axis Labels (as shown in Figure 3).

Table A3: Estimation results and visualization

	Α	В	С	D	E	F	G	Н	I	J	K
1											
29				Y _t		Baseline	Y _t /CMA(4)		Y _t /S _t		Y' t
30	t	Semester	Month	Chat (research)	MA(4) _t	CMA(4) _t	$S_t I_t$	S ,	Deseasonalize	T,	Forecast
31	1	Fall 2012	1	8				0.72	11.15	24.51	17.59
32	2		2	36				1.15	31.26	23.99	27.63
33	3		3	23	23.75	25.13	0.92	1.29	17.86	23.48	30.24
34	4		4	28	26.5	24.00	1.17	0.87	32.21	22.96	19.96
35	5	Spring 2013	1	19	21.5	22.13	0.86	0.72	26.48	22.45	16.11
36	6		2	16	22.75	20.75	0.77	1.15	13.89	21.94	25.26
37	7		3	28	18.75	17.63	1.59	1.29	21.74	21.42	27.59
38	8		4	12	16.5	17.63	0.68	0.87	13.80	20.91	18.18
39	9	Fall 2013	1	10	18.75	20.25	0.49	0.72	13.93	20.39	14.63
40	10		2	25	21.75	23.38	1.07	1.15	21.71	19.88	22.89
41	11		3	40	25	24.88	1.61	1.29	31.06	19.36	24.93
42	12		4	25	24.75	24.63	1.02	0.87	28.76	18.85	16.39
43	13	Spring 2014	1	9	24.5	22.63	0.40	0.72	12.54	18.33	13.16
44	14		2	24	20.75	19.25	1.25	1.15	20.84	17.82	20.52
45	15		3	25	17.75	17.88	1.40	1.29	19.41	17.30	22.28
46	16		4	13	18	18.00	0.72	0.87	14.95	16.79	14.60
47	17	Fall 2014	1	10	18	17.38	0.58	0.72	13.93	16.28	11.68
48	18		2	24	16.75	17.25	1.39	1.15	20.84	15.76	18.15
49	19		3	20	17.75	18.25	1.10	1.29	15.53	15.25	19.63
50	20		4	17	18.75	17.63	0.96	0.87	19.55	14.73	12.81
51	21	Spring 2015	1	14	16.5	15.75	0.89	0.72	19.51	14.22	10.20
52	22		2	15	15	13.88	1.08	1.15	13.02	13.70	15.78
53	23		3	14	12.75	12.50	1.12	1.29	10.87	13.19	16.98
54	24		4	8	12.25	12.00	0.67	0.87	9.20	12.67	11.02
55	25	Fall 2015	1	12	11.75	11.00	1.09	0.72	16.72	12.16	8.73
56	26		2	13	10.25	9.63	1.35	1.15	11.29	11.64	13.41
57	27		3	8	9			1.29	6.21	11.13	14.33
58	28		4	3				0.87	3.45	10.62	9.23
59	29	Spring 2016	1					0.72		10.10	7.25
60	30		2					1.15		9.59	11.04
61	31		3					1.29		9.07	11.68
62	32		4					0.87		8.56	7.44

^{*}N=4; CMA: centered moving average; $S_{t_{-}}I_{t_{-}}$: difference rate; $S_{t_{-}}$: seasonality component at time t; $I_{t_{-}}$: irregularity component at time t; $I_{t_{-}}$: trend component at time t.

Tables and Figures

Table 1: Sample reference transaction record

Timestamp	Question	Type of Reference	Type of Question	Time	Gender	Further Action
1/20/15 11:25	The printer is jammed	In person	Technology	0-10 mins	Female	Referred to IT Help Desk
1/20/15 13:56	paper clips	In person	Supplies	0-10 mins	Male	
	Looking for a specific course reserve					
1/20/15 20:19	article not available through the course	In person	Research	10-20 mins	Female	
	reserves site.					
2/17/15 11:50	Is the BI room available?	Phone	Policy	0-10 mins	Female	

Table 2: Sample chat reference transaction

id	Guest ID	protocol	queue	profile	started	accepted	ended	wait	duratio n	operat or	ip	referrer
2361619	2486668	web	skidref		12/18/12 15:41	12/18/12 15:42	12/18/12 15:46	59 (s)	283 (s)	lhofma	64.30.	http://web.ebscohost.com.luc
	0381355									nn	81.52	y2.skidmore.edu:2048/ehost/
	8632494											detail?sid=55e8b488-9be7-
	19290@li											4f39-83ec-
	braryh3lp											dee2b25773ab%40sessionmgr
	.com											111&vid=6&bk=1&hid=119&b
												data=JnNpdGU9ZWhvc3QtbGl

Table 3: Sample processed reference data in Excel spreadsheet format

Date	Type of Reference	Type of Question
9/20/12	fact to face	Research
9/20/12	IM	Research
9/20/12	phone	Directional
9/20/12	fact to face	Technology
9/20/12	fact to face	Directional

Table 4: Summary statistics of reference transactions (Fall 2011 – Fall 2015)

	Research Qty	Percentage	Non-research Qty	Percentage
Face-to-face	2629	76.96%	3895	90.67%
Email	90	2.63%	73	1.70%
Phone	157	4.60%	83	1.93%
Roving	27	0.79%	12	0.28%
Chat *	513	15.02%	233	5.42%
Total	3416	100.00%	4296	100.00%

^{*} Data on chat transaction starts in the Fall 2012 semester.

Table 5: Computation framework for the difference-in-differences estimator

_	Before 2011 Fall / 2012 Spring	After 2012 Fall / 2013 Spring	Differences
Treatment Group Face-to-face (research)	$\tilde{Y}_{TG,tl}{=}T_{TG,tl}/n_l$	$\mathbf{\bar{Y}}_{TG,t2}\!\!=\!\!T_{TG,t2}/n_2$	$\Delta \bar{Y}_{TG}\!\!=\!\!\bar{Y}_{TG,t2}\!\!-\!\!\bar{Y}_{TG,t1}$
Control Group Supplies	$\tilde{Y}_{CG,tl}{=}T_{CG,tl}/n_l$	$\bar{Y}_{CG,t2}\!\!=\!\!T_{CG,t2}\!/n_2$	$\Delta \tilde{Y}_{CG} \hspace{-0.1cm}=\hspace{-0.1cm} \tilde{Y}_{CG,t2} \hspace{-0.1cm}- \hspace{-0.1cm} \tilde{Y}_{CG,t1}$
Differences			$\beta_{diff\text{-}in\text{-}diffs}\!\!=\!\!\Delta\tilde{Y}_{TG}\!\!-\!\!\Delta\tilde{Y}_{CG}$

 $^{*\}bar{Y}$ = mean; n = reference days; T= number of transactions

Table 6: Computation results of the difference-in-differences estimator

	Before 2011 Fall / 2012 Spring	After 2012 Fall / 2013 Spring	Differences
Treatment Group	4.36	3.34	-1.02***
Face-to-face (research)	(3.07)	(2.68)	(0.31)
Control Group	1.68	1.92	0.24
Supplies	(1.59)	(1.83)	(0.18)
D100			-1.26***
Differences			(0.36)

Note: Standard deviation results are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Estimation results of the moving average time series analysis (Fall 2012 – Fall 2015)

	Time Series Coefficient	Intercept	P-value	Decline-Rate (%)
Chat (research)	-0.515	25.022	0.0016	-2.06%
Face-to-face (research)	-1.425	87.366	0.0026	-1.63%
Chat (research)/ All reference (research)	-0.0012	0.2117	0.4161	-0.57%

Figure 1: Difference-in-differences estimate of the treatment effect

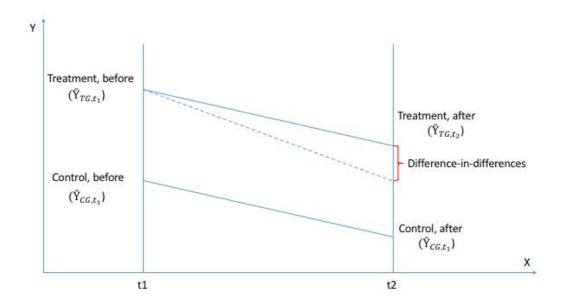


Figure 2: Volume trend for face-to-face (research) questions

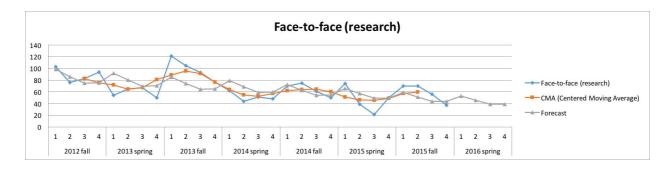


Figure 3: Volume trend for chat (research) questions

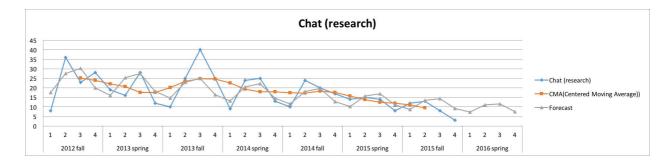


Figure 4: Volume trend for the overall share of chat (research) questions

