Factors Affecting Website Visit Duration: A Cross-Domain Analysis

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ABSTRACT

In this study we examine factors that impact on website visit duration, including user demographics, text and graphics content, type of site, presence of functionality features, advertising content and the number of previous visits. A random effects model is used to determine the impact of these factors on site duration and the number of pages viewed. The proposed model accounts for three distinct sources of heterogeneity arising from differences among individuals, websites and visit-occasions to the same website by the same person. Our model is fit using one month of user-centric panel data and encompasses the 50 most popular sites in a market. The results show that of the demographic variables, only user age and gender are significant, with older people and women visiting a site for longer. Entertainment and auction sites have significantly longer duration than all other site types, while sites with too much advertising have shorter durations.

INTRODUCTION

Having a large number of visitors is crucial for many websites, as a major part of their revenue derives from advertising (East 2003, p.85). An almost equally important performance measure, unique to websites, is user retention – sometimes referred to as ‘stickiness’ (Bhat et al 2002). It is defined as the time a user is on a website or a particular page within the site (Demers and Lev 2001) and is routinely reported by internet audience measurement agencies such as comScore/Media Metrix, Hitwise and Nielsen/Netratings. A related website measure is the depth of visit, measured by the number of pages viewed (Dreze and Zufryden 1997).

Website visit duration is important for several reasons. First, even though click through rates for banner ads have declined in the last five years, there is still value derived from mere exposure to the ads (Briggs and Hollis 1997; Flores 2002). Bucklin and Sismeiro (2003) and Danaher and Mullarkey (2003) find that exposure to web advertising is more likely for longer page durations, as happens analogously for longer exposure times to television ads (Rossiter et al. 2001). For example, Danaher and Mullarkey (2003) report that in going from 20 to 40 to 60 seconds in page exposure duration the unaided recall for a banner ad increases from 26 to 43 to 50 percent of visitors, respectively. Second, longer page duration also helps to maintain user interest in a site (Bucklin and Sismeiro 2003; Hanson 2000) and gives users more time to consider and complete purchase transactions (Bucklin and Sismeiro 2003). Moe and Fader (2004b) show that enhanced user interest helps generate repeat visits followed by greater long-term sales. Third, from a business investment point of view, Demers and Lev (2001) show that sites with longer visit duration also have higher monthly stock returns. While visit duration may not drive stock prices in a causal sense, some investors use website duration as an indicator of future earnings. This finding persisted even after the internet stock market crash in the spring of 2000 (Demers and Lev 2001).

Given the enduring and well-justified importance of website visit duration, the purpose of this study is to examine factors that affect visit duration and the number of pages viewed. These factors include demographic characteristics of visitors, the type of site, such as entertainment or news, and the site content, such as text, graphics and navigation features, as well as the number of previous visits. Ours is the first study to examine the characteristics of users and sites and how they impact on visit behavior. Moreover, rather than restricting ourselves to just one or two sites, we broaden the scope to the 50 major websites in a market.

We develop a random effects linear model for visit duration and depth that takes into account individual-level, product (i.e., website) and visit-occasion heterogeneity by generalizing a model developed by Ansari, Essegai and Kohli (2000) for movie ratings.

Our data come from a Nielsen/Netratings panel of over 3000 web-enabled people, all of whom provide personal demographic information. The Nielsen software measures the time panelists spend on a website and the number of pages viewed. Measures of website characteristics are obtained from a separate group of judges who assess each of the top 50 sites in terms of their text, graphics and advertising content as well as site features, such as the ability to customize pages, feedback provision, navigation aids and availability of chat rooms.

RELEVANT LITERATURE

Previous research into website browsing behavior is limited. To date, studies have investigated repeat visits (Chatterjee et al 2003; Moe and Fader 2004b) and purchase conversion rates (Moe and Fader 2004), while others have looked at the depth of search (Johnson et al 2000). Some interesting findings have emerged from these studies, such as web users engaging in only a limited amount of search across sites (Johnson et al 2000; Zauberaman 2003), despite the ease with which a wide search is possible on the internet. Moe and Fader (2004b) find that even though aggregate figures for customer loyalty (as measured by visits per visitor) show an increase over time for Amazon.com and CDNow.com, the

individual-level data reveal that someone making more frequent visits to these sites does so at a decreasing rate. This finding has an impact on downstream sales as Moe and Fader (2004b) subsequently show that more frequent shoppers have a higher probability of eventual purchase.

While the above studies look at internet browsing, banner ad exposure and purchasing behavior, only one prior study has direct relevance to ours, being that of Bucklin and Sismeiro (2003). They develop a model for analyzing internet clickstream data for visitors to an automotive website. Their study jointly takes into account a user's decision to select another page within a site or to exit the site and also models page duration, when another page is selected. Their page visit duration covariates are largely technical measures of the site. For example, their results show that longer page duration is associated with higher bytes transferred, greater cumulative pages viewed prior to the current page (i.e., visit depth), a reload request for a page, an error in a page transfer and longer server response time. Shorter page views are associated with having dynamic content (e.g., requiring a call to a site's database). While these measures are of technical interest to a webmaster, they are somewhat inaccessible to everyday web designers, web advertisers and e-commerce investors. For this reason we use website characteristics that are more user-friendly, such as graphics, text and advertising content. Our model of website duration differs from that of Bucklin and Sismeiro (2003) in several additional ways. As they have the browsing behavior for just one site collected by that site's server, there is no demographic information on their visitors. Indeed one of the frustrations for webmasters is that they often know very little about their visitors, with data being limited to just the browsing behavior for their own site. Potential demographic factors that affect website duration include gender, age, education and occupation (Dreze and Husherr 2003). By contrast our data come from a panel of web-enabled people monitored unobtrusively for a month, with demographic data collected at

recruitment. Moreover, we have the site duration and number of pages viewed for all sites visited that month, not just detailed clickstream data for a single site. This allows us to broaden our study to the top 50 websites in a market and develop a cross-website analysis, in contrast to previous studies that examine only one or two sites in detail.

THE MODEL

In this section we develop a class of models suitable for modeling website visit duration. As this class of models belongs to the broader class of generalized linear models, with a suitable change of dependent variable and link function, the same model structure can also be used for the number of pages viewed. To motivate our model we firstly discuss the data, as this illustrates the complexity and challenges of the modeling problem.

Data Preview

Our data come from a panel of homes recruited and maintained by ACNielsen's Netratings service¹. The panel comprises over 3000 people and is based on a user-centric methodology, very much like that also used by ComScore Media Metrix (Coffey 2001). More details on the data are given later. Although Nielsen's user-centric method monitors a panelist's entire browsing behavior, several quality control checks and aggregations are applied prior to the data being provided to us. The key aggregation is that all URLs visited within the same domain are aggregated up to the domain name². The time period for our data is just the month of November 2000.

Our initial inspection of the data revealed several features that must be accounted for in a model of website duration. These include

¹ Note that only home-based browsing is monitored by the panel. Workplace web activity was not being monitored at the time we obtained these data.

² For instance, a person might visit aol.com, drill down several pages then leave to visit weather.com. The data provided to us has just the total time spent on the aol.com domain (not separate URLs within aol.com) and the total number of pages viewed.

- i) Different panelists do not visit the same repertoire of websites. For instance, in our data, the average number of different sites a person visits from the top 50 sites is just 4.3
- ii) Panelists do not use the web every day from their homes and there might be a lengthy time separation between web use
- iii) The same person may visit the same site more than once in a month
- iv) There is heterogeneity in visit duration among people, with some users tending to have consistently shorter or longer visits to all sites
- v) Sites that are similar in purpose often have similar duration times across different people. We see this, for example, with google.com, which usually has short one-page visits.

An additional modeling consideration that is not evident from the data is that websites may not look the same at each visit, due to dynamically created pages, or a different path being tracked by a visitor. This gives rise to product heterogeneity, something not often considered in the marketing literature, but recently identified by Ansari et al (2000) as an important issue when modeling a person's evaluation of a movie and by Ansari and Mela (2003) as germane to email marketing. Like movies and email, websites have a number of intangible features over and beyond observed attributes.

Since our measured variable is duration time, it is natural to initially consider a survival model, which has previously been applied in the marketing literature (e.g., Jain and Vilcassim 1991). Cox's (1972) proportional hazard model seems like a reasonable starting model as it incorporates covariates. However, to accommodate the anticipated individual-level heterogeneity noted in point (iv) above, Cox's model must be stratified by each person, which then precludes the estimation of demographic effects as they are constant within a person-based stratum (Allison 1995). This makes Cox's model unsuitable for our application.

An alternative method for handling individual-level heterogeneity is a random effects survival model known as the gamma frailty model (Hougaard 2001). While this model is suitable for person-level heterogeneity, it cannot be extended to incorporate product-level heterogeneity, a requirement identified above as potentially important in this application.

Rather than restricting ourselves to survival models, simply because the dependent variable is time, a much more flexible class of models becomes available if we instead model the log of duration. Since we are working with duration data that is right skewed it is natural to log transform the duration time (Mosteller and Tukey 1977). Indeed, a plot of $\log(\text{duration})$ for the 23,264 website visits in our database looks very much like a normal distribution. Using the log transform on duration enables us to employ a log-normal model (Allison 1995) that accommodates the heterogeneity, unequal personal website repertoires and multiple visits by the same person to the same website that characterize our data. A log-normal formulation for page duration was also used by Bucklin and Sismeiro (2003) in their model.

Notation

Let y_{ijk} be the log of the time that person i spends on website j for the k th visit. Since person i does not visit each website, we denote the index set of the sites they visit as W_i , with $W_i = \{j_1, j_2, \dots, j_{n_i}\}$. Each website $j \in W_i$, with n_i being the total number of different websites visited by person i , $i = 1, 2, \dots, n$. Since there are potentially multiple visits to website j by person i , k ranges from 1 to n_{ij} , where n_{ij} is the number of visits that person i makes to site j . Hence the total number of observations is $N = \sum_{i=1}^n \sum_{j=1}^{n_i} n_{ij}$.

Model Development

As mentioned above, and similar to the case of movies and music, websites cannot be completely described in terms of a few observable attributes. Visit duration at a website is shaped by a multitude of complex site attributes that impact its attractiveness, but

unfortunately these attributes are often difficult to observe and measure. A website's unobserved attributes contribute to its "feel and touch" and lead to differences in appeal across domains. In our modeling approach we therefore not only account for individual-level heterogeneity, but also account for website-level heterogeneity to allow for differences in website appeal and the downstream effect on website visit duration. In doing so, we build upon the methodology first proposed by Ansari, Essegai and Kohli (2000).

Our model has three components. In the first component, the dependent variable (log-duration) is modeled as a function of observed website attributes (denoted Z_j , being a $w \times 1$ vector of website j 's characteristics). These website attributes have different regression weights for each person (denoted β_i^Z) reflecting individual-level heterogeneity and result in a linear model, written as $\beta_i^Z Z_j$. The second component arises from considering the dependent variable to be a function of observed personal characteristics (denoted X_i , being a $d \times 1$ vector of person i 's demographic characteristics), which have different regression weights for each website (denoted β_j^X), reflecting site-level heterogeneity. The resultant linear model for this component is $\beta_j^X X_i$.

Unlike the Ansari et al (2000) case, where respondents rated each movie at most once, websites in our dataset are often visited multiple times by the same person. In fact about 47% of initial visits to one the top 50 websites in our data are followed by another visit to the same site later in the month, with an average of 2.2 return visits in a month. As a result, in our application, we need to capture not only the unobserved person and website heterogeneity, but also the observed and unobserved differences across multiple visit occasions to the same website by the same person.

Hence, a third component arises from considering the dependent variable to be a function of observed characteristics of a particular visit occasion to the same website by the

same person (denoted M_k , being a $m \times 1$ vector of the characteristics of the k -th observed visit, such as the day of the week or the number of previous visits to the site). To reflect occasion-level heterogeneity across multiple visits, we assign different regression weights for each person-website pair (denoted β_{ij}^M). The resultant linear model for this component³ is $\beta_{ij}^M M_k$. Hence, our model is a “triple heterogeneity” model: capturing person, product and visit-occasion heterogeneity, while the Ansari et al (2000) model is a double heterogeneity model that captures only person and product heterogeneity.

Combining the three components gives the full model,

$$(1) \quad y_{ijk} = \beta_j^X X_i + \beta_i^Z Z_j + \beta_{ij}^M M_k + \varepsilon_{ijk},$$

where ε_{ijk} is a random error being i.i.d. normal with mean zero and variance σ^2 , intended to capture any remaining unexplained variation.

In the spirit of the hierarchical Bayes method, the random effect regression coefficients in equation (1) can be decomposed into fixed and random parts as follows,

$$(2) \quad \begin{aligned} \beta_j^X &= \beta^X + \gamma_j, & \gamma_j &\sim N(0, \Phi), \\ \beta_i^Z &= \beta^Z + \lambda_i, & \lambda_i &\sim N(0, \Omega), \\ \beta_{ij}^M &= \beta^M + \mu_{ij}, & \mu_{ij} &\sim N(0, \Psi). \end{aligned}$$

Substituting equation (2) into equation (1) gives

$$(3) \quad y_{ijk} = \beta^X X_i + \beta^Z Z_j + \beta^M M_k + \lambda_i Z_j + \gamma_j X_i + \mu_{ij} M_k + \varepsilon_{ijk}$$

For the three random effect terms in equation (3) we can write

$$(4) \quad \begin{aligned} \lambda_i Z_j &\sim N(0, Z_j' \Phi Z_j), \\ \gamma_j X_i &\sim N(0, X_i' \Omega X_i), \\ \mu_{ij} M_k &\sim N(0, M_k' \Psi M_k). \end{aligned}$$

³ Strictly speaking, M_k should be written as $M_{(ij)k}$ to reflect that the k th visit is nested within the (ij) th person-website pair, but we use the M_k notation for simplicity.

By setting the first element of X_i , Z_j and M_k to be 1 to permit an intercept term and partitioning Φ , Ω and Ψ into

$$\Phi = \begin{bmatrix} \phi_1 & \phi_2' \\ \phi_2 & \Phi^* \end{bmatrix}, \quad \Omega = \begin{bmatrix} \omega_1 & \omega_2' \\ \omega_2 & \Omega^* \end{bmatrix} \quad \text{and} \quad \Psi = \begin{bmatrix} \psi_1 & \psi_2' \\ \psi_2 & \Psi^* \end{bmatrix},$$

the random effect linear combinations in equation (4) can be rewritten as

$$(5) \quad \begin{aligned} \lambda_i Z_j &\sim N(0, \phi_1 + 2\phi_2 Z_j^* + Z_j^* \Phi^* Z_j^*), \\ \gamma_j X_i &\sim N(0, \omega_1 + 2\omega_2 X_i^* + X_i^* \Omega^* X_i^*), \\ \mu_{ij} M_k &\sim N(0, \psi_1 + 2\psi_2 M_k^* + M_k^* \Psi^* M_k^*), \end{aligned}$$

where X_i^* , Z_j^* and M_k^* are, respectively, the demographic profile for person i , the vector of descriptors for website j and the vector of “visit occasion” descriptors for the k -th visit of person i to website j (each vector excluding the intercept term). Now denote the left hand side of the respective terms in equation (5) as $\tau_i = \lambda_i Z_j$, $\delta_j = \gamma_j X_i$ and $\eta_{ij} = \mu_{ij} M_k$. Hence, an alternative way to write equation (3) is⁴

$$(6) \quad y_{ijk} = \beta^X X_i + \beta^Z Z_j + \beta^M M_k + \tau_i + \delta_j + \eta_{ij} + \varepsilon_{ijk},$$

where $\tau_i \sim N(0, \sigma_\tau^2(Z_j))$, $\delta_j \sim N(0, \sigma_\delta^2(X_i))$ and $\eta_{ij} \sim N(0, \sigma_\eta^2(M_k))$, noting that the three variances are functions of Z_j , X_i and M_k , respectively. Notice that if the demographic, website and visit-occasion information is ignored in the variances of these random effects distributions (that is, only the first term in the variances of equation (5) is taken into account) then we simply have $\tau_i \sim N(0, \phi_1)$, $\delta_j \sim N(0, \omega_1)$ and $\eta_{ij} \sim N(0, \psi_1)$, which results in a standard mixed effects model with homoscedastic variances (Laird and Ware 1982).

Therefore, the difference between the Ansari et al (2000) model and a standard mixed effects model is their model has heteroscedastic random effects (which are functions of X_i and Z_j ,

⁴ Equation (6) can also be written with an explicit fixed effect intercept term as

$y_{ijk} = \alpha + \beta^{X^*} X_i^* + \beta^{Z^*} Z_j^* + \beta^{M^*} M_k^* + \tau_i + \delta_j + \eta_{ij} + \varepsilon_{ijk}$, where $\alpha = \beta_0^X + \beta_0^Z + \beta_0^M$.

and additionally M_k in our case), whereas the usual mixed effects model has homoscedastic random effects. Indeed a further generalization of the Ansari et al (2000) model is to have $\tau_i \sim N(0, \sigma_i^2)$, $\delta_j \sim N(0, \sigma_j^2)$ and $\eta_{ij} \sim N(0, \sigma_{ij}^2)$, where the variances are not constrained to be functions of observed variables. Later we shall empirically examine the fit of model (6) under these alternative variance specifications in the random effect terms.

Correlation Structure

Under the model in equation (6) we can derive the correlation in website duration within people and within websites. Knowing these correlations helps us gauge the way our model handles the anticipated person and website heterogeneity. Firstly, consider the correlation in duration for person i across two different websites j and j' , which is⁵,

$$(7) \quad \text{corr}(y_{ijk}, y_{ij'k}) = \frac{\sigma_\tau^2}{\sigma_\tau^2 + \sigma_\delta^2 + \sigma_\eta^2 + \sigma^2}, \quad j \neq j'.$$

This correlation results from individual-level heterogeneity and indicates the degree to which duration times are similar as a result of unobserved personal characteristics.

The second correlation is that between duration times for the same website, but for two different people. Here, equation (6) gives

$$(8) \quad \text{corr}(y_{ijk}, y_{i'jk}) = \frac{\sigma_\delta^2}{\sigma_\tau^2 + \sigma_\delta^2 + \sigma_\eta^2 + \sigma^2}, \quad i \neq i'.$$

It is apparent that duration times for the same website may be correlated even for different people. Such a scenario is reasonable in our application, since website duration will often be

⁵ Note in equation (7) that we are using the homoscedastic form of the variance for τ_i , δ_j and η_{ij} . The correlation can easily be generalized to the situation where the variance of τ_i is different for each person and the variance of δ_j differs by website, but it is slightly more complicated.

determined by its function, features and layout, not all of which can be explicitly accounted for by observed variables.

The third correlation we consider is one that derives from the same person visiting the same website multiple times, namely, visit replication or repetition. This correlation is

$$(9) \quad \text{corr}(y_{ijk}, y_{ijk'}) = \frac{\sigma_\tau^2 + \sigma_\delta^2 + \sigma_\eta^2}{\sigma_\tau^2 + \sigma_\delta^2 + \sigma_\eta^2 + \sigma^2}, \quad k \neq k'.$$

It is reasonable to expect that duration times for visits to the same site by the same person are correlated, perhaps highly correlated. Notice that this third correlation is higher than either of the previous two, as would be expected, since, for example, two visits by the same person to aol.com are more likely to have similar duration than one visit to aol.com and another to amazon.com by that person.

Returning to our list of model requirements above, we see that the model proposed in equation (6) has all the necessary features for this application to website visit duration. These features include the ability to test for the impact of observed characteristics of web-users, websites and visit occasions. Moreover, the model captures heterogeneity across individuals and websites and allows for the possibility of multiple visits to a site by the same person. The downstream implied correlation structure from these sources of heterogeneity also seems reasonable. Lastly, there is no requirement in our model that each person visits the same subset of websites over the observation period.

Estimation Method

While equation (6) can be thought of as a mixed effects model, a number of data issues make its estimation by standard maximum likelihood rather challenging. Gelfand et al (1995) show that a typical requirement for estimability by maximum likelihood in mixed effect models is that $\sum_{j=1}^{n_i} n_{ij} > 1 + n_i$, i.e., there are more observations than parameters for each person. However, there are many instances in our dataset where a person visits one or two

websites only once a month. In such cases the Gelfand et al (1995) criterion is not met. One solution is to eliminate people with infrequent and light web activity, but this would skew the sample towards medium and heavy internet users.

Estimation of models with challenging data requirements has been made possible by recent developments in Bayesian estimation (Allenby and Rossi 1999; Gelfand and Smith 1990), principally Gibbs sampling, an iterative method for parameter estimation which pools information across respondents. This permits parameter estimation even in situations where data may be sparse at the individual level. We use the versatile WinBUGS software (Spiegelhalter et al 2003) to implement the Bayesian estimation. In our application we use 10,000 burn-in iterations and 20,000 estimation iterations, with three chains. Convergence of the parameter estimates is assessed via the Gelman and Rubin (1992) statistic.

Model for Pages Viewed

Earlier we stated that we want to model the number of pages viewed as well as the site duration. A histogram of the distribution of pages viewed immediately shows the Poisson distribution to be appropriate, as also found by Dreze and Zufryden (1997). However, the observed number of pages always starts at 1 rather than 0, since at least 1 page must be viewed by a website visitor. Thus we modify equation (6) so that the dependent variable is now the number of pages viewed less 1 and this dependent variable has a Poisson rather than a normal distribution. In the spirit of generalized linear models (McCullagh and Nelder 1989), we now apply the log link function to the right hand side of equation (6). Congdon (2003, p.93) shows that this can also be estimated by Gibbs sampling.

EMPIRICAL ANALYSIS

Data in Detail

As mentioned above, the data used to fit our models come from Nielsen's Netratings service in New Zealand, which has a user centric methodology. Nielsen's service is available in many countries, including the U.S. (www.netratings.com). Johnson et al (1999), Park and Fader (2004) and Moe and Fader (2004a; 2004b) also use user-centric data to fit their e-commerce models, but their data are supplied by comScore Media Metrix (www.comscore.com). Coffey (2001) details much of the Media Metrix user-centric web measurement methodology, which is broadly similar to Nielsen's.

The panel used in this study comprises 3284 people recruited in such a way as to represent people with internet access in New Zealand. Data were obtained for just the month of November 2000. During that month some 1852 panelists (56%) used the internet at least once⁶. The Nielsen/Netratings software (called 'Insight') is activated each time a panelist uses an internet browser at home. As homes may have multiple panelists, each person in the home 'logs on' when they open their browser by selecting their name from a list of household members aged 2 or more. Demographic information on age, gender, occupation and education are obtained at recruitment for each panelist, as well as the education and occupation of the main income earner in the home. Table 1 shows the demographic profile of the panel. Compared with the general population, this panel of internet users tends to be slightly younger and is better educated, with a corresponding skew towards students and professional employment. Such 'upscale' demographic skews have also been observed for internet users in the U.S. (Degeratu, Rangaswamy and Wu 2000) and the U.K (Emmanouilides and Hammond 2000).

The Nielsen software captures each URL and visit duration for that URL as the panelist proceeds through their internet session. However, as mentioned above, the data supplied to us are aggregated to the domain level, and report the total domain visit duration and the total

⁶ It is worth noting that in this market in November 2000 broadband penetration was less than 2%, with almost all panelists using a 14k, 28k or 56k phone modem for their internet connection. In a market with higher broadband penetration, duration times would tend to be lower due to faster downloading. This would differentially affect only sites with high graphics content.

number of pages visited⁷. In addition, if several internet browsing sessions occurred on the same day, data are aggregated across that day. Park and Fader (2004) and Moe and Fader (2004a; 2004b) also use data aggregated to a one-day level.

Over 23,000 different sites were visited in November, with two-thirds of those sites visited just once. Due to this low visit incidence for the majority of sites and because we later content analyze each site, we select just the top 50 websites⁸. Moreover, owing to the importance of advertising revenue for most websites, we consider only sites that carry advertising. This eliminated several banks and government websites, for example. Our final sample size based on visitors to at least one of these 50 sites is 1665 people, who had a total of 23,264 visits over the month. Table 2 gives an alphabetical listing of each website. Not surprisingly the top fifty sites are dominated by portals, Internet Service Providers (ISPs) and search engines. Other frequently visited sites are web hosting services, entertainment and software products.

Table 2 also gives the median site duration (measured in seconds) and the median number of pages viewed. There is much variation in visit duration and depth across the sites. For example, the portal gohip.com has a median duration time of only 43 seconds, while the median duration time for games/entertainment sites like Imperialconflict.com, neopets.com and swirve.com all exceed 1000 seconds (about 16 minutes). Likewise for the number of pages viewed, where search engines like altavista.com and google.com average between 1 and 2 pages viewed, whereas many of the entertainment sites average over 10 pages viewed.

Content Analysis of the Top 50 Websites

In addition to characteristics of internet users, we also study website features to see if they have any impact on visit duration. Understanding the effect of website design and

⁷ Our data also have the number of hits, which is distinct from the number of pages viewed.

⁸These 50 sites had the highest total count of the number of pages viewed over the month.

content on a user's visit duration might help webmasters tailor their sites to retain visitors for longer, with the resulting downstream benefits mentioned above.

Some potential website design features that have been examined previously in the context of visit duration include the text and graphics content and background complexity (Dreze and Zufryden 1997), advertising content (Dreze and Zufryden 1997; Hofacker and Murphy 2000) and functionality, for example, content customization, search functions and discussion boards (Bezjian-Avery et al 1998; Ghosh and Dou 1998). All of these features are easy for a web user to assess and are similarly easy for a webmaster to manipulate. For instance, if a web user notes that there is a lot of advertising on a site's home page, resulting in unappealing ad clutter (Kent 1993) that lowers visit duration, then the webmaster can attempt to reduce the clutter without markedly sacrificing advertising revenue.

The assessment of each of the top 50 websites was made by three judges, who were instructed to visit each domain and examine the site for five minutes by clicking across pages. During this surfing period, judges rated the site's textual, graphics and background complexity, advertising content as well as the functionality items. This made the content analysis more detailed than merely using the homepage (as done by Ha and James 1998), but not so time consuming as to make the evaluation too arduous.

The coding instructions and coding forms are based on the work of Grenfell (1998). The instructions specified how the analyses were to be conducted, as well as defining all of the technical terms used in the coding sheet. Text and graphics content, as well as background complexity, are measured on a five point scale, where 1 denotes 'simple' and 5 denotes 'complex'. Advertising content is coded so that codes 1 through 5 denote 1, 2-3, 4-5, 6-7 and 8 or more ads, respectively, on a typical page⁹. Functionality is measured via 19 items based largely on the measures used by Grenfell (1998) and Ghose and Dou (1998)

⁹ Obviously there are differing numbers of ads per page, so judges later reported that they used the home page as an initial indication of ad quantity, then modified their assessment (if necessary) after the 5 minute browsing period.

including features such as online help, search functions, site maps, user registration, email contact availability, chat rooms and message boards. Table 3 gives the complete list. Each of these items is coded on a two point scale (yes=1/no=0). An overall functionality score between 0 and 1 is obtained for each website by averaging the 19 items.

Inter-judge reliability is assessed by using Rust and Cooil's (1994) Proportional Reduction in Loss (PRL) index, which is a generalization of Cronbach's alpha that takes into account the number of judges and the number of scale categories for each item. Rust and Cooil (1994) recommend that PRL values should be higher than 0.7 for adequate inter-judge reliability. The PRL values obtained in our study were generally very high, being .79 for text content, .65 for graphics content, .75 for background complexity, .91 for advertising content, while the average PRL across the 19 functionality items was .89. Therefore, we can reasonably conclude that the assessment of the content of the top fifty sites is reliable.

The middle columns of Table 2 display the ratings for each of the sites on the text, graphics, background and advertising attributes, as well as the average functionality score, while Table 3 shows the percentage of sites that were rated as a 4 or 5 (i.e., high) on these attributes. We see that over 40% of the sites are judged to have high text content, while very few have high background complexity and advertising content. The overall average functionality score is 49%.

Model Variables

Our model for website duration in equation (6) contains three broad groups of variables: demographic characteristics of users; website characteristics; and variables related to visit occasions. We now give more details on the actual variables used in our empirical application of the model in equation (6).

Demographic Descriptors. Table 1 gives the four demographic variables that are measured on each panelist. In the model, gender is binary coded with a 1 for males and 2 for females. We

use the exact panelist age (ranging from 2 to 83 years) rather than code age into categories.

Table 1 lists three education categories, which we code as two dummy variables, with the baseline being ‘grammar school or some high school’ (low education), medium education is those with ‘high school or some college’ and the second dummy variable is those with a college degree (high education). The occupation categories listed in Table 1 are similarly dummy variable coded, with ‘retired/unemployed’ as the baseline.

Website Descriptors. The observed website characteristics are listed in Table 3. Site type is dummy variable coded, with portals being the baseline. The site attribute scores for text, graphics, background complexity and advertising content given in Table 2 are used directly in the model. As some of the 19 functionality items are either highly correlated among themselves (e.g., items 2-4 and 17-19) or correlated with particular site types, we use just the average functionality score for each website, as reported in Table 2.

Visit Occasion Descriptors. These variables pertain to the conditions under which a particular visit takes place. The first variable is called ‘Weekend Visit’ and indicates whether a particular visit occurs on a weekday or weekend, being coded as a 1 if the observed visit occurs on a Saturday or a Sunday. Following Bucklin and Sismeiro (2003), the second variable measures the cumulative number of previous visits to a given website by a given person¹⁰. We operationalize this by creating a variable called ‘CVisit’, which is the cumulative number of previous visits to a particular site by a panelist prior to the occurrence of the present visit, but only from November 1, 2000 which is the beginning of our observation window. For example, if a person visits google.com on 2, 7, 11 and 20 November, then CVisit has a value of 0 on 2 November, but increments to 1, 2 then 3,

¹⁰ Since our data are restricted to just the month of November, we have no way of knowing when a panelist first visits a particular website, i.e., the data are left censored. It is, therefore, very hard to claim that such a variable captures any potential learning or fatigue effects due to multiple visits by the same person to the same website.

respectively, on 7, 11 and 20 November¹¹. Average values of CVisit, for just the final visit in November to a site by a person, are given for each website in the last column of Table 2. It can be seen that entertainment and games sites, for example, generally have more multiple visits within a month.

RESULTS

Model Comparison

Several alternative models were discussed above, which we now compare. The first is a model with fixed effects only (equation (6) without the τ_i , δ_j and η_{ij} terms), which is equivalent to an OLS regression model. The second model is Ansari et al's (2000) random effects model where the random effects are, in turn, linear functions of demographic and website covariates¹². The remaining two models are based on equation (6), one where the random effects are homoscedastic and the other where they are heteroscedastic.

We compare models via their log-likelihood and Bayes information criterion, which takes into account the number of estimated parameters. When using Gibbs sampling for Bayesian estimation (as we do), Spiegelhalter et al (2003) recommend their DIC criterion, which is similar to BIC, and also does not require alternative models to be nested within each other. The model with the lowest BIC and DIC values is deemed to be the best.

As an additional model comparison, we also split our data into calibration and validation data sets. In our case we use the first 1000 people (corresponding to 13544 site visits) for calibration, leaving 665 people (with 9720 visits) in the validation dataset. We compare across the four models for both datasets using three criteria: relative absolute deviation (RAD), being the average of the absolute value of the difference between the estimated and actual log duration divided by the estimated log duration; the mean absolute

¹¹ Since CVisit ranges from 0 to 30, and is heavily skewed to the right, we follow Bucklin and Sismeiro (2003) by taking a log transformation and using $\log(1+CVisit)$ in the model.

¹² Note that Ansari et al's (2000) model does not have the $\beta_{ij}^M M_k$ term in equation (1).

deviation (MAD), being the absolute value of the difference between the estimated and actual log duration; and the root mean squared error (RMSE), being the square root of the averaged squared differences between the estimated and actual log duration.

Table 4 shows that the highest log-likelihood occurs for the mixed effects model with heteroscedastic random effects¹³. However, this model also has the most parameters. When the number of parameters is taken into account the BIC and DIC criteria both show that the mixed effects model with homoscedastic random effects is the best model. Notice that both mixed effects models are an improvement over Ansari et al's (2000) model, showing the benefit of including fixed and random effects for visit occasions to the same site by the same person.

The RAD, MAD and RMSE criteria for the calibration show that the mixed effects model with homoscedastic random effects performs as well as the model with heteroscedastic random effects and is better than the other two models. For the validation data all the models do worse than for the calibration data, but perform similarly. Hence, on balance, the mixed effects model with homoscedastic random effects performs as well or better than the alternative models. This demonstrates that a relatively simple random effects model that incorporates personal and product heterogeneity can perform just as well as a more complex ones in this class of models. Therefore, from now on we report results for just this model.

Parameter Estimates for the Visit Duration Model

Table 5 gives the parameter estimates for the mixed effects model with homoscedastic random effects. This time we use the entire sample of 1665 people. Only two demographic variables are statistically significant, gender and age. The positive estimated coefficients for these two variables shows that in general women visit websites for longer and that visit

¹³ Due to convergence problems we had to constrain the number of variance parameters for η_{ij} to be 1, i.e., just σ_η^2 , rather than the 7189 variance parameters permissible under full heterogeneity. Similarly for τ_i . The number of variance parameters for δ_j is the required 50, however.

duration increases with age. Education and occupation do not have a significant impact on the length of a site visit. This finding on the age of web users is supported by a previous study by Dreze and Hussherr (2003) where eye fixation times on web pages are longer for older people. However, they did not find a significant gender effect.

Not surprisingly, entertainment sites have significantly longer visit durations than portals (the baseline site type) at the .1% level of significance. Additionally, at the 5% level of significance, auction sites also have longer visit durations than portals.

Of the website characteristics, graphics content is significant at the 10% level and advertising content is statistically significant at the 5% level. The longer duration for sites with high graphics content is likely due to the combined effect of many entertainment sites having high graphics content and the longer download times for graphics via a phone modem. The negative coefficient for advertising shows that higher levels of advertising on the site is associated with shorter site visits. Dreze and Hussherr (2003) find that many web users actively avoid banner ads (even though they may be peripherally exposed to the ad). Moreover, Schlosser et al (1999) find that web ads are disliked more than ads in conventional media. This is consistent with our finding, where sites with too much advertising may be driving away visitors¹⁴.

The estimates of the variance components in equation (6) are also given in Table 5. The largest component corresponds to the visit occasion effects by the same person to the same website, followed by website effects and then individual-specific effects. The estimated correlations obtained via equations (7) through (9) are, respectively, 0.02, 0.04 and 0.32. This indicates reasonable correlation in visit duration times for the same person to the same website, but near zero correlation within individuals and within websites. The large estimated

¹⁴ We examined possible interaction effects between demographics, website type and ad content. Unfortunately, some of these interactions are inestimable due to no variation in advertising levels across a website type. Also, the age*ad content interaction is highly collinear with the separate effects of age and ad content, which masks the significance of these main effects.

value of σ^2 relative to the other variance components is indicative of the high variability in duration times even when explanatory factors and heterogeneity are accounted for. Having said this, the value of $\hat{\sigma}^2$ goes from 1.6 up to 2.4 when the three random effect terms are omitted from the model, showing that the addition of random effects makes a big improvement in model fit.

Parameter Estimates for the Visit Depth Model

Table 5 also gives the parameter estimates for the model of the number of pages viewed. As explained above, our model for pages visited is easily adapted from equation (6) as a generalized linear model with a Poisson-distributed dependent variable and a log link function. This model is also fit using WinBUGS.

Table 5 shows that none of the demographic variables are statistically significant. Furthermore, only entertainment sites have significantly more pages viewed than all other website types. Of the site attributes, graphics, advertising content and functionality are significant at the 5% level. As with visit duration, the significance of graphics content may not be so much owing to the graphics themselves, but more because of the high graphics content of most entertainment sites. The negative coefficient for advertising is consistent with the website duration model and demonstrates that too much advertising is an impediment to further depth of a site visit, probably for the same reason it might be an impediment to a longer visit.

The reason for the negative coefficient for functionality is less obvious. However, it is noteworthy from Table 2 that 6 of the 8 sites with functionality scores greater than 0.65 include four portals, a news site and a search engine, each with a median number of pages viewed of one or two. Hence, the issue may not be so much that having lots of functionality features is a deterrent to deeper search, but that the type of site with lots of features does not typically induce deep visits.

We have a significant positive coefficient at the 10% level for the Weekend Visit variable. This demonstrates that more pages are viewed on weekends compared with weekdays, an intuitively reasonable finding, as residential web users have more time available in the weekend. Lastly, note that cumulative number of previous visits has no significant influence on duration or pages viewed. While Bucklin and Sismeiro (2003) and Johnson et al (2003) found learning effects across repeat website visits, as we mentioned before, due to the left-censoring of our observational data, it is difficult to use the CVisit variable to make inferences about potential learning effects across multiple website visits.

CONCLUSION

The purpose of this research is to examine factors that might impact on website visit duration and depth. This is of interest to both advertisers and webmasters. Advertisers are keen to know the demographic profile of the audience for their chosen media and some broad comparisons of website types, while webmasters want to know how to redesign their website to attract visitors for longer. Regarding demographics, only gender and age of a visitor have any impact on visit duration, with women and older users staying for longer. As Danaher and Mullarkey (2003) show that longer visits result in higher banner advertising recall, the implication is that web advertising in general is more suited to women rather than men and older rather than younger people. This might come as a surprise to web advertisers, who generally target younger males due to their high internet use (Gershberg 2004). Education and occupation have no affect on visit duration or the number of pages viewed.

Of the website types, entertainment sites have significantly longer visit duration and more pages viewed than other websites. Auction sites have significantly longer duration (but not pages viewed) than other websites (except entertainment sites of course). Of the website attributes, too much advertising results in significantly shorter visit duration and fewer pages viewed. User intolerance of website advertising has also been found by Dreze and Hussherr

(2003) and Schlosser et al (1999). As many websites are supported primarily by advertising (East 2003), this presents a challenge to webmasters. That is, how to attract advertising revenue without simultaneously driving away visitors.

Sites with higher graphics content also have longer visit duration and more pages viewed. However, the likely reason for this is that entertainment sites tend to have higher levels of graphics and we have already seen that entertainment sites have significantly greater visit duration and depth.

We also demonstrate some insights into how to simultaneously model individual-level and product-specific heterogeneity. Previous models by Ansari et al (2000) and Ansari and Mela (2003) for movies and email, respectively, have used linear combinations of random and fixed effects. We show that these models are members of a larger class of random effects models with heteroscedastic variances. However, our empirical findings illustrate that this additional complexity might be unnecessary and a simpler homoscedastic random effects model may suffice. Nonetheless, the importance of incorporating heterogeneity for products as well people is corroborated.

Finally, we also highlight the importance of capturing visit-occasion heterogeneity. This third source of heterogeneity arises whenever customers have multiple interactions with the product. In such situations, we demonstrate how a triple-heterogeneity model can be developed to simultaneously incorporate person-specific and product-specific heterogeneity, as well as heterogeneity that is specific to person-product combinations.

One area for future work is the use of individual-specific parameter estimates to help customize a site for a particular person, with an aim to maximize visit duration. This is analogous to Ansari and Mela (2003) who customize email content to maximize click through rates.

Table 1: Demographic Profile of Panelists

Gender		Panel Percent	Population Percent
Gender	Male	54	49
	Female	46	51
Age	2-19	25	24
	20-29	12	14
	30-39	20	17
	40-49	19	16
	50-59	17	12
	60+	7	17
Education	Grammar school or some high school only	34	54
	High school graduate or some college	46	34
	Bachelor or postgraduate degree	21	12
Occupation	Blue collar	7	20
	Administration/sales	10	10
	Homemaker	6	9
	Student	21	20
	Self-employed	12	8
	Professional	32	16
	Retired/unemployed/other	12	17

*Sample base is the 1665 people that accessed at least one of the top 50 sites in November 2000

Table 2: List of the Top Fifty Websites with Average Visit Duration and Site Attributes

Site Name	Site Type	Text content	Graphics content	Back-ground complex	Advert. content	Function-ality score	Median Visit Duration	Median Pages viewed	Av. CVisit
about.com	Portal	4	1	1	2	0.42	110	3	.5
altavista.com	Search	3	1	2	1	0.68	106	1	1.3
amazon.com	Retail	4	3	2	1	0.53	156	3	.3
aol.com	Portal	3	3	1	3	0.53	84	2	.4
ask.com	Search	1	1	1	1	0.47	87	2	.4
bluemountain.com	Greetings	4	4	3	1	0.53	288	5	.6
bolt.com	Entertainment	4	3	4	3	0.58	318	10	2.9
bonzi.com	Portal	4	1	1	1	0.32	53	1	.4
Cartoonnetwork.com	Entertainment	1	4	1	2	0.37	280	7	.7
clear.net.nz	ISP	3	3	2	2	0.53	101	2	1.8
cnet.com	Service	3	3	2	2	0.42	114	2	.7
cnn.com	News	4	4	2	2	0.68	164	2	2.4
ebay.com	Auction	2	1	1	1	0.79	224	3	2.3
egreetings.com	Greetings	2	3	3	2	0.42	440	4	.6
excite.com	Portal	4	2	3	2	0.74	91	2	1.8
ezboard.com	Messaging	2	4	3	1	0.42	1188	8	2.2
flybuys.co.nz	Service	2	3	2	1	0.32	307	6	.4
foxkids.com	Games	1	4	1	2	0.26	570	8	.4
go.com	Portal	4	2	2	2	0.37	118	2	.7
gohip.com	Portal	3	2	1	2	0.32	43	2	1.9
google.com	Search	1	1	1	1	0.53	98	2	2.1
homestead.com	Hosting	1	3	2	1	0.42	110	4	.6
hotbar.com	Software	1	3	2	1	0.26	107	7	5.5
icq.com	Messaging	4	3	3	1	0.74	51	1	1.6
ihug.co.nz	ISP	3	3	3	4	0.47	66	1	2.5
Imperialconflict.com	Games	2	2	3	1	0.53	1473	22	10.0
lycos.com	Portal	3	2	2	1	0.84	74	1	.9
microsoft.com	Software	3	2	2	1	0.47	60	2	1.1
msn.com	Portal	4	3	2	1	0.68	176	3	3.7
mtnsms.com	Messaging	1	2	2	1	0.26	275	4	2.5
nbc.com	Portal	4	2	2	3	0.47	71	2	.7
neopets.com	Entertainment	3	3	3	1	0.42	1185	16	2.8
netscape.com	Portal	4	3	2	3	0.79	82	1	2.5
nzcity.co.nz	Portal	4	3	2	3	0.53	65	2	3.7
nzherald.co.nz	News	4	3	3	2	0.47	241	2	2.3
nzoom.com	Portal	4	4	3	2	0.47	101	2	1.7
paradise.net.nz	ISP	1	3	3	1	0.32	66	2	3.1
passport.com	Portal	2	1	1	1	0.37	66	2	4.4
shockwave.com	Entertainment	2	3	1	3	0.37	174	3	.5
stuff.co.nz	News	4	3	2	2	0.32	151	3	2.4
swirve.com	Entertainment	4	3	2	1	0.47	5089	22	6.5
trademe.co.nz	Auction	3	2	2	1	0.63	222	7	2.4
tripod.com	Hosting	4	2	2	1	0.53	76	2	.5
webshots.com	Software	3	3	2	1	0.47	90	3	1.2
xtra.co.nz	Portal	4	2	2	1	0.42	69	1	2.3
xtramail.co.nz	Service	2	3	2	1	0.37	171	3	2.5
yahoo.com	Portal	4	2	1	1	0.58	163	4	3.0
zdnet.com	Service	4	2	3	2	0.63	145	3	1.5
zfree.co.nz	ISP	3	4	2	2	0.37	127	2	3.6
zone.com	Games	3	4	4	4	0.53	259	3	5.9

Table 3: Profile of Sites and Description of the Functionality Items – Top 50 Websites

		Percent
Site Type	Auction	4
	Entertainment	20
	ISP	8
	News	6
	Portal	30
	Service	26
	Software	6
Site Features	High text content	42
	High graphics content	16
	High background complexity	4
	High advertising content	4
Functionality Item	Description	Percent with item
1	A button or function that allows a user to change the site's language?	24
2	A button or function that allows a user to change the site's graphic or text content mix?	12
3	A button or function that allows a user to change the site's page layout?	16
4	A button or function that allows a user to customize the site's content?	32
5	Are there any email contact addresses on the site?	74
6	Can users view product/service information on the site?	98
7	Is there any form of online help available?	84
8	Does the site have a basic search function?	80
9	Does the site have a detailed site map available?	30
10	Does the site have links related to other relevant parts of the site present?	94
11	Can you download site paraphernalia (e.g. wallpaper) on this website?	36
12	Does this site have user registration as an option?	84
13	Does the site encourage feedback via online survey forms?	30
14	Does the site encourage feedback via email?	76
15	Does the site have online problem diagnostics tools?	2
16	Does the site have a clear section that features recent updates?	58
17	Does the site have any chatrooms available?	32
18	Does the site have topic-specific discussion forums?	34
19	Does the site have message boards available?	32
Average functionality score (on a 0 to 1 scale)		48.8%

Table 4: Model comparison

Measure	Model			
	Fixed Effects only*	AEK**	Mixed Effects – homoscedastic effects	Mixed Effects – heteroscedastic effects
Log-likelihood	-25026†	-22549	-21532	-21528
Parameters	25	46	28	77
BIC	-25145	-22768	-21665	-21894
DIC	50101	47374	46754	46778
<i>Calibration Data</i> (13544 obs.)				
RAD,%	26.2	22.3	20.7	20.7
MAD	1.21	1.00	0.92	0.92
RMSE	1.54	1.28	1.18	1.18
<i>Validation Data</i> (9720 obs.)				
RAD,%	27.0	27.3	27.5	27.6
MAD	1.24	1.23	1.23	1.24
RMSE	1.57	1.55	1.55	1.56

* Equivalent to OLS regression model

**AEK is the original Ansari et al (2000) model

†Log-likelihood for the null model with an intercept only is -25624

Table 5: Parameter Estimates for Duration and Pages Viewed Models

	Duration Model		Pages Viewed Model	
	Mixed Effects with homoscedastic effects		Poisson GLM with homoscedastic effects	
	Estimate	t-stat	Estimate	t-stat
Intercept	4.31	14.8	.02	0.2
Gender (female)	.07	2.2	.03	1.6
Age	.01	4.7	.00	0.3
Moderate education	-.04	-1.1	-.02	-0.4
High education	-.01	-.2	.04	0.8
Little education*	-	-	-	-
Blue collar	-.08	-1.0	-.01	-0.2
Administration/sales	-.10	-1.4	.04	0.5
Homemaker	-.07	-.8	-.06	-0.7
Student	.02	.3	.09	1.3
Self-employed	-.04	-.6	-.06	-0.9
Professional	-.06	-1.0	.03	0.5
Retired/unemployed*	-	-	-	-
Software	-.23	-.9	.41	1.2
Auction	.68	2.3	.66	1.6
Entertainment	1.20	5.9	1.25	4.6
Services	.21	1.3	.17	0.7
ISP	-.19	-.9	-.35	-1.1
News	.33	1.5	.01	0.0
Portal*	-	-	-	-
Text content	-.05	-.7	-.02	-0.2
Graphics content	.12	1.7	.22	2.3
Background complexity	.06	.7	.01	0.1
Advertising content	-.16	-2.3	-.24	-2.3
Functionality	-.37	-.9	-.65	-2.3
Weekend Visit	.00	.1	.03	2.4
Log(1+CVisit)	.02	1.4	-.01	-1.5
σ_{τ}^2	.05		.23	
σ_{δ}^2	.09		.51	
σ_{η}^2	.62		1.07	
σ^2	1.59		-	

*Baseline dummy variables

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