The Relevance of Web Traffic for Stock Prices of Internet Firms

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Abstract

This study shows that web traffic is an important non-financial indicator of the market values of Business to Consumer (B2C) Internet firms. We add three important insights to the literature on the value-relevance of traffic. We show that traffic is a summary measure of the strategies that firms use to attract visitors to their websites. The value-relevance of traffic disappears once the exogenous determinants of traffic (e.g., setting up an alliance with America Online, creating affiliate referral programs, generating media visibility, incurring marketing expenditure and constraints imposed by cash availability) are accounted for in the value-relevance model. We also demonstrate that traffic contains no predictive information about future revenues once past revenues are accounted for. The value-relevance of traffic does not stem merely from its role as a predictor of future sales. Finally, we show that the stock market appears to use traffic as a measure of the web businesses' ability to create network effects. Network effects occur when the value of a website to a visitor may depend on how many others visit that site. Consistent with Metcalfe's law of network economics, we find that market values of web businesses increase non-linearly with traffic.

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1. Introduction

Many see the Internet as a revolutionary technology that will alter the way business, commerce, medicine, science, communications, the law, politics, and government are conducted (Gates, 2000; Christensen and Overdorf, 2000). Andrew Grove, the chairman of Intel Corporation, predicts that the Internet will become so pervasive that in the future every business will be an Internet business or no business at all (Grove, 1996).

Online retail sales are forecasted to reach $184 billion by 2004 as compared to $700 million in 1996 (Modahl, 2000). A precursor to generating such retail sales is attracting traffic to the firm's website. Web traffic is a non-financial measure actively followed by the investment community to value firms in the Business to Consumer (B2C) segment (*The Houston Chronicle*, November 22, 1999). One of the important reasons for traffic's popularity as a value-driver among the investment community is the continuing prevalence of somewhat anomalous relations between market values and key financial measures. An Internet venture like Amazon.com has achieved a higher valuation than the entire traditional book retailing and publishing industries combined, even though it has yet to turn a profit (Evans and Wurster, 1999). Despite a steep decline in the stock prices of web businesses this year (Demers and Lev, 2000), a large number of B2C firms continue to trade at high prices relative to their operating performance. As of July 31, 2000, Yahoo had a Price to Earnings (P/E) ratio of 386, eBay of 568, and Amazon.com traded at a multiple to revenue of 4.66 with a market capitalization 400 times its book value. Such apparently anomalous associations between market values and key accounting measures raise questions about the role of non-financial information such as website traffic in explaining the variation in the market values of B2C Internet firms.

Website traffic as a non-financial metric has three appealing characteristics. First, web traffic provides information about the extent of consumer interest in the web business and is central to revenue generation and growth of B2C Internet firms. Second, traffic numbers are readily obtainable from third-party survey firms such as PC Data Online, Nielsens and Media Metrix. Third, traffic is cross-sectionally comparable across several B2C business models such as portals (e.g., Yahoo), e-tailers (e.g., Amazon.com), content and community sites (e.g., iVillage) and sites providing financial services (e.g., E*trade).

We examine the value-relevance of web traffic using a sample of 92 firms covering portals, content and community sites, financial services sites and e-tailers over the five quarters beginning with the first quarter of 1999. We find that the number of unique monthly visitors to a site -- our measure of web traffic drawn from PC Data Online -- is positively associated with stock prices and adds significant incremental explanatory power (24 percentage points) to a regression of just financial statement information against Internet share prices.

After establishing that traffic is highly value relevant, we ask three research questions: (1) Is traffic value relevant in its own right, or is it merely a proxy for the strategies firms use to generate traffic? (2) Is traffic valued by the market because it predicts future sales? (3) Is traffic valued because it measures the potential customer relationships that network effects can create?

In our first set of empirical analyses, we model the factors and constraints affecting website traffic. In conducting such analysis, we are motivated by concerns about the problematic issue of endogeneity while interpreting the value-relevance of non-financial indicators (Ittner and Larcker, 2000). Ittner and Larcker (2000) observe that if all organizations in the sample are optimizing with regard to their choice of traffic, one would observe no association between traffic and organizational performance measures such as market value of equity, once the exogenous determinants of the choice of traffic are controlled for in the value-relevance model.

We posit that traffic levels are determined by several determinants such as an alliance with America Online (AOL), presence of an affiliate-marketing programs, the magnitude of marketing expenditure, the extent of media visibility attained by the firm, and the extent of cash available. Considering web traffic as an endogenous variable, we find that traffic is not value relevant in its own right, but is a proxy for the aforementioned strategies used by firms to generate traffic.

Our next objective is to explore why the stock market values traffic. One plausible explanation is that web traffic provides information about a firm's future sales. Consistent with Trueman et al. (2000b), we find that web traffic levels predict one- and two- quarter ahead sales. However, traffic *per se* does not explain future sales incremental to current sales of the firm. In other words, traffic has no incremental information about future revenues once the predictive information in past sales is controlled for. Moreover, both traffic and sales are incrementally value-relevant over each other. Hence, the market does not appear to value traffic merely because it predicts future sales.

Finally, we explore the possibility that web traffic is positively priced by the market because of potential future benefits from network effects generated by traffic. The value of a website to a visitor may depend on how many others visit that site. Once the number of visitors and hence the size of the virtual community created by the firm grows, more and more users find the firm's website attractive because of their ability to interact with other members of the community and their ability to share and contribute to member generated content. Moreover, accumulation of data about visitors' preferences makes it possible for vendors and advertisers to tailor products and services to visitors, thus making the site even more attractive to future visitors. This, in turn, increases the potential for future long-run profitability.

We investigate whether the stock market values traffic based on the number of potential relationships site visitors can create among themselves. Metcalfe's law of network economics predicts that if there are n people in the network, the value of the network is proportional to the number of other users, i.e., $n \times (n-1) = n^2 - n$ (Shapiro and Varian, 1999). If Metcalfe's law is descriptive of the data, we would expect the market values of web businesses to increase in the squared transformation of the number of unique visitors to the firm's website. Consistent with Metcalfe's law, we find that the market values of web businesses are positively associated with the squared transformation of the number of unique visitors to the firm's website. We also examine traffic-based acquisitions for the period September 1999 to June 2000 to provide corroborative evidence on network effects. Our results indicate that not only do target firms' traffic numbers account for 95 percent of the cross sectional variation in acquisition prices, but these acquisition prices are also a positive function of the squared transformation of the number of unique visitors acquired. Thus, evidence from the market for corporate control is also consistent with traffic's value-relevance stemming from its ability to measure potential relationships among site visitors.

Our study extends the growing body of literature on the valuation of Internet firms in two ways. First, concurrent work (e.g., Trueman et al., 2000) on the value-relevance of traffic and other non-financial measures such as customer satisfaction (Ittner and Larcker, 1998) or population coverage in the telecommunication industry (Amir and Lev, 1996) implicitly assume that managers are non-optimizers. These studies are silent about why value-maximizing managers would not increase non-financial measures, such as traffic, infinitely in an attempt to increase firm value (Lambert, 1998; Nagar, 2000). In contrast, we treat traffic as an endogenous choice variable that optimizing managers select based on other exogenous factors. We show that once the exogenous factors affecting traffic are controlled for, there is no relation between market values and traffic. This finding is consistent with the idea that managers set traffic levels optimally given the exogenous factors they face. Second, we contribute to the understanding of why traffic is value-relevant. In particular, we document evidence consistent with potential benefits from positive network externalities as one important explanation for the value-relevance of web traffic.

The remainder of the paper is organized as follows. Section 2 discusses the data and descriptive statistics. Section 3 explores the value-relevance of traffic. Section 4 examines alternative explanations for why web traffic is value-relevant, and section 5 presents some concluding remarks.

2. Data and Descriptive Statistics

2.1 Traffic data

We rely on web traffic data compiled by PC Data Online – an independent firm that measures Internet audiences. PC Data Online defines its Internet audience as individuals who access the World Wide Web or proprietary online areas such as America Online during the past 30 days using personal computers with Windows 95/98/NT as their operating system. PC data generates its data from a random panel of 100,000 participants who have installed the company's tracking software on their personal computers at home or at work. This software collects and stores a participant's web activities on his/her computer. Once the user has been online for 15 minutes, which may be split across one or more sessions, this data is encrypted and sent, in real time, via the Internet to PC Data Online.

Of the various metrics reported by PC Data Online, we focus on unique monthly visitors in our study.[1] PC Data Online defines unique visitors as the number of web-active individuals who visited a particular site(s) belonging to a web property (company) within a given time period. Each visitor is represented only once as a unique user. The data on unique monthly visitors for each month is usually posted within a week to fifteen days after the end of the month on PC Data Online's website. Traffic statistics compiled by PC Data Online are freely available to the public on PC Data's website.[2]

2.2 Sample and descriptive statistics

Our sample consists of a list of 92 publicly traded pure Internet firms (see Panel A of Table 1). We begin with a list of 120 firms from four categories of firms on the Internet Stock List at www.internet.com as of July 1, 2000: (i) Content and Community sites; (ii) E-tailers; (iii) Financial Services sites and, (iv) Portals. We focus on only the aforementioned categories because the business model for firms in these categories involves generating revenue by exploiting traffic attracted to their websites. The Internet Stock List compiled by Internet.com has been used to collect a sample of Internet firms in a number of previous studies (Trueman et al., 2000a, b; Hand, 2000a, b; Demers and Lev, 2000). To this list we add four firms (Excite, Geocities, Onsale, and Xoom.com) that have been acquired or merged before July 1, 2000. From the initial list of 124 firms, we exclude 18 firms for which traffic data was not available on PC Data Online for any quarter in our sample period. Fourteen more firms are dropped because we cannot find financial statements for any quarter during the sample period on the SEC's EDGAR database. Panel B of Table 1 presents a frequency distribution of firms sorted by industry type. As shown, e-tailers (38 of 92) and content and community sites (36 of 92) dominate the sample.

[1] We also consider the percentage of unique monthly visitors to total web population as an alternative measure and find similar results.

We hand-collect all financial data from 10-Qs and 10-Ks filed by firms available on the EDGAR database in SEC's website www.sec.gov. Information about unique monthly visitors for our sample firms comes from PC Data for the period February 1999 to March 2000. In particular, we use the quarterly average of unique monthly visitors (UNIVIS) for our empirical analyses. Thus, the quarterly average for the quarters ended March 31, 1999, June 30, 1999, September 30, 1999, December 31, 1999 and March 31, 2000 are lined with accounting data from 10-Qs for those quarters.[3,4]

Because PC Data issues a press release for a particular month's traffic within thirty days of the end of that month, we measure the market value of the firm's equity thirty days after the 10-Q quarter-end. Stock prices are obtained from www.finance.yahoo.com. Of the possible 460 firm quarters (92 firms over 5 quarters), we are left with 303 firm-quarters for our empirical analyses. This is because all firms in our sample were not publicly traded throughout the sample period. Also, note that the number of observations reported in the empirical analyses that follow may not equal 303. This is because statistical outliers, defined as firm-quarter observations with absolute values of R-student measures greater than 3, are deleted when estimating the regressions.

Panel C of Table 1 presents descriptive data on UNIVIS and a number of other independent variables used in the analyses. For descriptive reasons, we also provide data on the quarterly average of a firm's REACH, defined by PC Data Online as the percentage of unique

[2] The site has recently started restricting free access.
[3] Because PC data started reporting traffic numbers from February 1999, we assume that the average unique monthly visitors for the quarter ended March 1999 is the same as the average unique monthly visitors for February and March 1999.
[4] A small number of firms do not follow the calendar year for reporting purposes. For these firms we align the observations with the calendar quarters depending on the fiscal quarter ending dates. If the fiscal quarter ends within one month of a calendar quarter we include the observations in that calendar quarter. Observations for a firm with fiscal quarter ending in April or February will belong to the first calendar quarter. However, when calculating

monthly visitors to a firm's site scaled by the total web population. It is interesting to note that the mean firm attracts 7% of the Internet population in a quarter or 4.1 million unique visitors on average in a quarter. At least three-fourths of the observations in the sample report negative earnings because the third quartile cut-off of the earnings distribution is negative. For the median firm, quarterly losses ($10.68 million) actually exceed quarterly sales ($10 million). However, the median firm still has a market to book ratio of about 5. Next, we explore whether traffic explains some of the variation in market values, after controlling for financial information.

3. The value-relevance of traffic

3.1 Levels specification

In the absence of strong priors about how traffic should be incorporated into a model that relates market values to accounting and non-accounting information, we follow Amir and Lev (1996) and introduce UNIVIS, our proxy for traffic, as a linear additive value driver in regression (1) below:

$$MVE_{jt} = \beta_0 + \beta_1 BVE_{jt} + \beta_2 E_{jt} + \beta_3 Log(TA)_{jt} + \beta_4 UNIVIS_{jt} + \beta_{5i} IND_{jit} + \beta_{6k} QTR_{jkt} + \varepsilon_{jt} \qquad (1)$$

where MVE is market value of equity thirty days after the fiscal quarter end, E is earnings before extraordinary items, BVE is book value of common equity, Log(TA) is the natural logarithm of total assets, UNIVIS is average monthly unique visitors during the quarter, IND is an industry dummy that reflects the firm's membership in each of the four (i=1,2,..,4) industries studied (content and community sites, portals, e-tailers and financial services), QTR is a quarter dummy that identifies one of the five (k=1,2,..,5) quarters studied (i.e., 4 quarters in 1999 and the first quarter of 2000). Finally, j and t are firm and quarter subscripts respectively.

the average monthly unique visitors we use the average of visitors in the fiscal quarter and determine market value of equity using the stock price thirty days after the fiscal quarter end.

Because MVE is not scaled by a size deflator, we add the logarithm of total assets (Log (TA)) as an independent variable (Barth and Kallapur (1996)) and report White (1980) adjusted t-statistics to account for heteroscedasticity. Addition of Log(TA) as a scale control also helps us assess whether BVE is value-relevant in its own right as opposed to serving as a scale control. Industry dummies and quarter dummies are introduced to control for unaccounted omitted variables that may be correlated with industry membership or time.

Results of estimating equation (1) are presented in panel A of Table 2. We conduct the regression analyses in stages to document the incremental value-relevance of UNIVIS. In the first stage we consider only the financial variables, earnings and book value, along with the scale control, Log(TA). Consistent with Hand (2000) and Trueman et al. (2000), we find that the coefficient on earnings is negative and statistically significant (coefficient = -12.18, t-statistic = –1.91). The coefficient on book value is positive and statistically significant (coefficient = 4.49, t-statistic = 2.53). Earnings and book value, along with the scale control, explain 36.61% of the cross-sectional variation in market values of firms.

We then estimate a model that includes both financial variables and the traffic measure, UNIVIS. As shown in panel A of Table 2, the coefficient on UNIVIS is positive and significantly associated with stock prices (coefficient = 700.49, t-statistic = 4.54).[5] This suggests that market participants appear to attach a value of $700 per unique monthly visitor. We also find that UNIVIS provides significant incremental explanatory power (about 24%) for stock prices beyond that provided by financial measures. Notwithstanding the inclusion of UNIVIS, the signs and the significance of coefficients on book value and earnings remain unchanged. Thus, while traffic explains a significant portion of variation in stock prices, we cannot dismiss the relevance of financial information. We explore the robustness of the value-relevance result below.

3.2 Robustness checks

We conduct two sets of checks to assess robustness of the above results. First, we address econometric concerns such as correlation in error terms (sub-section 3.2.1) and the choice of functional form used to assess value-relevance (sub-section 3.2.2). Second, we examine the economic interpretation of the coefficient on UNIVIS after accounting for the effects of the stock market crash in B2C stocks in April 2000 (sub-section 3.2.3). We explain these checks in greater detail in the following paragraphs.

3.2.1 Serial and cross correlation in error terms

The results in panel A of Table 2 are based on a pooled cross-sectional OLS (ordinary least squares) model. Although we introduced industry and quarter dummies into the specification, the error terms in the model are likely to suffer from serial and cross-correlation. To address this issue we re-estimate regression (1) every quarter with industry dummies. In untabulated results, we find that UNIVIS is statistically significant in all the 5 quarters examined (mean coefficient = 470.13; mean t-statistic = 2.77). We also estimate equation (1) using the Generalized Least Squares (GLS) approach. Unlike OLS, the GLS model does not set the covariance among the error terms to zero. In untabulated results, we find that the coefficient on UNIVIS is strongly positive and statistically significant (coefficient = 600.21, $p < 0.01$). Thus, our value-relevance result is robust after controlling for serial or cross-correlation in errors.

3.2.2 Returns Analysis

[5] When Yahoo is excluded from the data set, the pricing multiple on a unique monthly visitor drops to $127 but it is statistically significant at $p<0.01$. We re-estimate all regressions reported in the paper after excluding Yahoo and find that the qualitative nature of the inferences remains unchanged.

To assess the robustness of the results reported in panel A of Table 2 to a returns specification, we estimate the following returns regression:

$$Ret_{jt} = \beta_0 + \beta_1 E_{jt} + \beta_2 \Delta E_{jt} + \beta_3 \Delta UNIVIS_{jt} + \beta_{4i} IND_{jit} + \beta_{5k} QTR_{jkt} + \nu_{jt} \qquad (2)$$

where Ret is the abnormal return measured as holding period return over a three-month period ending 30 days after fiscal quarter end adjusted for return on NASDAQ index, E is the earnings before extraordinary items, ΔE is the change in earnings before extraordinary items, ΔUNIVIS is the change in UNIVIS. All the independent variables are scaled by market value of equity determined 30 days after the previous fiscal quarter end. In equation (2) j and t are firm and quarter subscripts respectively, while IND and QTR are industry and quarter dummies respectively.

Following Easton and Harris (1991), earnings levels and earnings changes are introduced to control for accounting information. Panel B of Table 2 reports the results of estimating regression equation (2). While earnings levels are weakly significant, earnings changes are not statistically associated with abnormal returns. More important, we find that the coefficient on change in UNIVIS is positive and statistically significant (coefficient = 15.88, t-statistic = 1.91). Thus, the value-relevance of UNIVIS is robust to the changes specification.

3.2.3 Impact of the April 2000 stock market crash in B2C stocks

Demers and Lev (2000) examine the impact of April 2000 sell-off in B2C stocks on the pricing of various factors such as research and development expenditure, cash burn rate, strategic alliances and traffic. For descriptive reasons, we examine the effect of the April 2000 stock market crash on the implied pricing of web traffic for our sample firms. As noted, the market values corresponding to the accounting and traffic numbers are measured 30 days after the fiscal quarter end. Thus, for firms whose fiscal year ends on March 31, 2000 or later, market value of equity will incorporate the April sell-off. We interact each regressor in equation (1) with a dummy variable that is set to 1 if the observation corresponds to the first quarter of 2000 and zero otherwise. We find that the market appears to have marked down the price of web traffic by about $411 per unique monthly visitor. Nonetheless, the average weight placed by the market on a unique visitor after the market crash is still positive and statistically significant.

3.3 Traffic as a choice variable

The above analyses document that traffic exhibits systematic and robust value-relevance. However, an implicit assumption behind the valuation equation (1) is that traffic is not a choice variable for firms (Ittner and Larcker, 1998; Lambert, 1998; Nagar, 2000). The result that greater traffic implies greater market value begs the question as to why managers do not increase traffic even further to garner greater market values for their firms. Surely, there must be costs or constraints associated with increasing traffic. If such constraints and other exogenous determinants of traffic are controlled for in the value-relevance model, the traffic measure would cease to be value-relevant. That is, traffic may not be value-relevant in its own right. It might merely serve as a proxy for the underlying drivers of traffic. As Ittner and Larcker (2000) point out in their recent survey of managerial accounting research:

> "One particularly difficult endogeneity problem arises when the researcher wants to assess whether some managerial accounting choice [**traffic, in our case**] is associated with improved performance. As discussed in Demsetz and Lehn (1985), if all organizations in the sample are optimizing with regard to the accounting system choice [**traffic, in our case**], there should no be association between organizational performance and the observed (endogenous) choice, once the exogenous determinants of the choice are controlled in the structural model." (bold type added)

To address this endogeneity problem, we adopt a two-stage approach. In the first stage, we model traffic as a linear function of five exogenous, but not necessarily mutually exclusive, determinants: (i) an alliance with AOL (AOL), (ii) the presence of an affiliate program (AFF),

(iii) the extent of media visibility that the firm attracts (VIS), (iv) the extent of marketing expenditure incurred (M&A), and (v) the availability of cash balances (CASH).

$$\text{UNIVIS} = f\,(\text{AOL, AFF, VIS, M\&A, CASH}) \qquad (3)$$

where f is a linear function operator. The determinants of traffic are discussed in greater detail in section 3.3.1. In the second stage, we assess whether UNIVIS ceases to be value-relevant once the exogenous determinants of traffic are introduced into the value-relevance model. Hence, we test whether β_4 in equation (4) below is statistically indistinguishable from zero:

$$\begin{aligned} MVE_{jt} = {} & \beta_0 + \beta_1\,BVE_{jt} + \beta_2\,E_{jt} + \beta_3\,Log(TA)_{jt} + \beta_4\,UNIVIS_{jt} + \beta_5\,AOL_{jt} + \beta_6\,AFF_{jt} \\ & + \beta_7\,VIS_{jt} + \beta_8\,M\&A_{jt} + \beta_9\,CASH_{jt} + \beta_{10i}\,IND_{jit} + \beta_{11k}\,QTR_{jkt} + \varepsilon_{jt} \qquad (4) \end{aligned}$$

3.3.1 Modeling the Determinants of Traffic

In this section we discuss in detail the various determinants of web traffic.

Alliance with AOL (AOL): AOL, or America Online, is the world's largest Internet Service Provider (ISP). A significant amount of traffic is channeled to the Internet through its ISP service. AOL's user base not only includes the paying subscribers of AOL's ISP service (23.2 million as of June 30, 2000) but also users of AOL's other portals and services such as MapQuest.com, AOL Moviefone, Netcenter (more than 28 million registered users), ICQ.COM (with more than 20 million active registered users) and Digital City. One way for firms to promote themselves online is, therefore, to enter into an advertising alliance with AOL to maximize their website's exposure. Such alliances usually feature premier placement on AOL's welcome page or sponsorship of particular online areas or web pages for designated time periods. The alliances may also involve placing the firm's graphic links on the search results page in the AOL directory and the category pages in the AOL directory. Access to AOL's subscribers is so important to firms that they advertise the AOL keyword by which their sites can be found on AOL's network. As compensation for such advertisement, AOL receives cash payments and the opportunity for revenue sharing on sales made through its network. AOL may also take a portion of its compensation in the form of equity in the advertising firm. However, not all firms may choose to enter into an alliance with AOL because such an alliance is potentially expensive.

To identify firms that had a co-marketing alliance with AOL, we scan the press releases made by both AOL and our sample firms since 1997. If an Internet firm has an advertising alliance with AOL, we coded a variable AOL as one for every quarter during which the alliance is active. Otherwise, we set the variable AOL to zero.

Affiliate Programs (AFF): An affiliate program is a referral service from other websites on the Internet to the firm's website. When traffic is channeled from an associate web site to a firm's web site, the associate site earns referral fees for sales generated at the firm's site (Kotha 1998). Setting up affiliate programs is an efficient way to expand a firm's presence on the web and create a community of retailers working for the firm. Commenting on Amazon.com's affiliate program, the *Economist* (1997, p.10) points out

> Amazon.com knows that it will probably never be the best site for rock climbing information or quantum physics discussions, but that the sites specializing in such subjects would be great places to buy books. A link to Amazon is easy, and potentially lucrative, way for such specialist sites to do that at one remove: a click on the link takes a viewer to Amazon's relevant page.

Thus, setting up an affiliate program leverages the capabilities of the Internet without incurring any additional overhead, unlike physical stores that require a large outlay of financial capital. The goal of the affiliate program is to gain greater name and brand recognition on the Internet where over 1.6 million stores currently operate (Hoffman and Novak, 2000). In such a noisy and fragmented environment, capturing the consumer's attention is critical to attracting traffic. Furthermore, given that analysts estimate that less than 2% or 3% of the people who see an advertisement on the web actually click through to see more, promoting the firm's presence via affiliate programs greatly increases the probability of drawing traffic (Kotha 1998).

Information about a firm's affiliate programs is collected by scanning the firm's press releases. If a firm announced an affiliate program, we code the variable AFF as 1 for every quarter after the program initiation date. Otherwise, the variable AFF was set to zero.

Media visibility (VIS): The amount of attention the media dedicates to an Internet firm may be critical to generating customer traffic to the firm's website. In the off-line world, consumer traffic depends on geographical location. However, web consumers move easily and instantaneously across the Internet, guided primarily by their awareness of firms' websites, not geographical proximity. Hence, increasing awareness through greater media exposure improves the probability of attracting new visitors to a firm's website. The greater the number of articles written about a firm, the more information online visitors have to draw on in forming impressions about a firm. Because media exposure is generally beyond the direct control of the firm, the information provided by the media also tends to have higher source credibility than a firm's own marketing efforts (Wartick, 1992). Thus, the amount of media exposure is likely to increase the extent of consumer interest in a firm's site.

We measure media visibility (VIS) as the total number of articles published about the Internet firm in the "Major Newspapers" database of the *Lexis/Nexis* electronic database for quarterly periods for each firm. We select this database because it includes daily newspapers that reflect the focus of the current media and general public attention.

Marketing expenditures (M&A): Marketing and advertising expenditures could generate traffic to a firm's website by creating awareness of and acceptance for its products or services.

Marketing expenditure also enables a firm to differentiate itself from its competition (Porter, 1980). We use quarterly marketing and advertising expenditures reported in firms' 10-Qs as the measure (M&A) in our empirical analysis. Because firms do not fully disclose marketing expenditures on specific strategies such as raising media visibility or entering into an AOL alliance, we expect to see correlation between M&A and other determinants of traffic creation.

Cash constraints (CASH): The above discussion suggests that firms can increase traffic by adopting several strategies. However, financial constraints may prevent firms from devoting infinite resources just to chase web traffic. We proxy for such financial constraints by the cash holdings (CASH), measured as short term investments and cash equivalents, at the end of the quarter reported in the firm's 10-Q. The greater the CASH, the larger the traffic levels that the firm can achieve. Alternatively, the level of cash availability might constrain firms from attaining traffic levels higher than the one actually achieved by the firm.

Using the above hypothesized determinants we model UNIVIS as follows:

$$\begin{aligned} UNIVIS_{jt} = {} & \delta_0 + \delta_1 \, AOL_{jt} + \delta_2 \, AFF_{jt} + \delta_3 \, VIS_{jt} + \delta_4 \, M\&A_{jt} + \delta_5 \, CASH_{jt} \\ & + \delta_6 \, Log(TA)_{jt} + \delta_{7i} \, IND_{jit} + \delta_{8k} \, QTR_{jkt} + \eta_{jt} \end{aligned} \tag{5}$$

As before, Log(TA) is added to serve as a scale control, and we control for heteroskedasticity using White's (1980) correction. The industry and quarter dummies are introduced to account for uncontrolled omitted variables that vary with industry membership and time.

Panel C of Table 1 provides descriptive statistics about the exogenous factors that determine traffic. There is significant dispersion in the extent of media visibility that firms are able to muster. The average firm in the sample is mentioned in the major newspapers 42.21 times in a quarter, whereas the inter-quartile gap ranges from 2 to 25 mentions per quarter. The average firm spends \$15.54 million a quarter on marketing and advertising – a substantial sum when compared to negative earnings of \$19.48 million for the average firm. The average firm has \$147.57 million in cash relative to \$445.22 million in total assets. The relatively high cash levels probably reflect proceeds from initial public offerings awaiting deployment into operating or investing activities. We also note (not tabled) that 24% of the firm quarters have AOL alliances while 39% have affiliate programs.

For descriptive purposes, we report the Pearson and Spearman correlations between UNIVIS and the hypothesized exogenous determinants of UNIVIS. Panel A of Table 3 shows that UNIVIS is significantly correlated (under both Spearman and Pearson correlations) with all the hypothesized determinants of traffic, with the exception of the affiliate programs variable. For the affiliate programs variable (AFF) only the Spearman correlation is significantly positive.

The multivariate regressions reported in panel B show that AFF and VIS are positive, as hypothesized, and statistically significant at conventional levels. In particular, the effect of media visibility on UNIVIS is significantly positive (coefficient 0.04, t-statistic = 8.87). The coefficients on AOL and CASH are not statistically significant in the multivariate model. One interpretation of this result is that the strategies used to create traffic are not mutually exclusive. Consistent with this interpretation, the correlation between select determinants of traffic is quite high. For example, the Pearson correlation between M&A and AOL is 0.32 while the Pearson correlation between M&A and CASH is 0.54. Contrary to expectations, the coefficient on M&A is negative and significant (coefficient = -0.03, t-statistic = –3.37). However, the univariate correlation between M&A and UNIVIS reported in panel A of Table 3 is positive and significant, as expected. The adjusted R-square of the multivariate model is 78%, suggesting that the hypothesized exogenous determinants explain a substantial portion of the cross-sectional variation in UNIVIS. To confirm further that endogeneity of traffic is a potential problem in making inferences about the value-relevance of traffic, we conduct the Hausman test and find that the Hausman t-statistic is 19.43 and significant at $p< 0.01$.

3.3.2 Value-relevance of traffic after controlling for the determinants of web traffic

Next, we assess whether the value-relevance of traffic disappears when the exogenous determinants of traffic are introduced in the value-relevance model. In particular, if UNIVIS is merely a proxy for the exogenous determinants that create traffic, we would expect β_4, the coefficient on UNIVIS in regression equation (4), to be statistically indistinguishable from zero. Table 4 reports the results of estimating equation (4). As expected, β_4 is not statistically significant (coefficient = -7.40, t-statistic = -0.17). Of the exogenous determinants of traffic, media visibility (coefficient = 35.43, t-statistic = 9.84) and cash balances (coefficient = 2.20, t-statistic = 2.37) are strongly associated with market value. In sum, the value-irrelevance of traffic in the presence of the exogenous determinants of traffic suggests that traffic is a summary measure of the strategies used by a firm to generate traffic.[6]

4. Economic motivations for the value-relevance of web traffic

4.1 Web traffic as a leading indicator of future revenues

In this section we examine the economic reasons that web traffic is value-relevant. Firms attract traffic to their websites primarily to convert web surfers to customers. Even if surfers do not purchase goods and services during one visit, the firm can build relationships with the website visitors that can be converted to future sales. A good example of such relationship building is “the Eyes” program offered by Amazon.com (Kotha, 1998). The program is a personal notification service in which customers can register their interests in a particular topic

[6] This inference is insensitive to two robustness checks. First, we consider the possibility that higher market values attract more traffic. This induces simultaneity in the market value specification. Therefore, we estimate equations (5) and (1) simultaneously after including the market value of equity as an additional variable in equation (1). Second, we estimate (4) and (5) using a Generalized Least Squares (GLS) specification.

or author on the website. Once customers register, they are notified by e-mail each time a book by their favorite author, topic, or interest is published (Kotha, 1998). Such notifications are likely to result in future sales for Amazon.com.

The above discussion suggests that traffic should be associated with future revenues of the firm. To assess whether this relation holds in the data, we conduct the following regression:

$$SALES_{jt+n} = \gamma_0 + \gamma_1 UNIVIS_{jt} + \gamma_2 \, Log(TA)_{jt} + \gamma_{3i} \, IND_{jit} + \gamma_{4k} \, QTR_{jkt} + \varphi_{jt} \qquad (6)$$

where n=1, 2 and SALES = sales revenues. All other variables are as defined previously.

The dependent variables are one-quarter and two-quarter ahead sales.[7] As before, Log(TA) serves as a scale control and industry and quarter dummies are introduced to account for industry or time related correlation in the error terms. The results of estimating (6) are presented in panel A of Table 5.

It is interesting to note that UNIVIS is strongly related to SALES for up to two quarters ahead. After controlling for size, one additional visitor when compared to the cross-sectional mean appears to be associated with \$2.78 in sales one quarter ahead and \$2.91 in sales two quarters ahead. The adjusted R-squares are 42.71% for the two-quarter ahead model and 43.04% for the one-quarter ahead model. These results are consistent with Trueman et al.'s (2000b) findings that traffic explains cross-sectional variation in future sales. However, note that Trueman et al. (2000b) do not control for time-series trends in revenue. To control explicitly for such time-series correlation in sales we introduce past sales into equation (6) (see equation (7) below).[8] That is, we examine whether traffic is incrementally informative in predicting future sales once we control for past sales.

[7] We are unable to examine the effect of traffic on longer time periods because we run out of observations to conduct a meaningful statistical analysis.

[8] A more appropriate control variable would be the sales of the same quarter one year ago so that seasonal trends are controlled for. However, we do not have enough time series observations to control for seasonality in sales.

$$SALES_{jt+n} = \gamma_0 + \gamma_1 UNIVIS_{jt} + \gamma_2 Log(TA)_{jt} + \gamma_{3i} IND_{jit} + \gamma_{4k} QTR_{jkt} + \gamma_5 SALES_{jt} + \varphi_{jt} \quad (7)$$

where n=1,2.

Results of estimating equation (7) are presented in panel B of Table 5. Results indicate that traffic is not incrementally informative about future sales one or two quarters ahead, once past sales are controlled for in the model. The explanatory power (R^2) of model (7) is significantly higher than that of model (6), ranging between 94% and 95%. Thus, past sales completely swamps the information content of web traffic for future sales.

The dominance of past sales over web traffic in predicting future sales has potentially interesting implications for the value-relevance of sales and traffic. If web traffic is value-relevant because it merely captures information in future sales, then web traffic's value-relevance should disappear once current sales is controlled for in the model. To assess the value-relevance of traffic in the presence of sales in the model, we estimate equation (8):

$$\begin{aligned} MVE_{jt} = {} & \beta_0 + \beta_1 BVE_{jt} + \beta_2 E_{jt} + \beta_3 Log(TA)_{jt} + \beta_4 UNIVIS_{jt} + \beta_5 SALES_{jt} \\ & + \beta_{6i} IND_{jit} + \beta_{7k} QTR_{jkt} + \varepsilon_{jt} \end{aligned} \quad (8)$$

Results of the above regression reported in Table 6 show that both SALES and UNIVIS are both positive and statistically significant. This indicates that traffic contains value relevant information above and beyond sales revenues, a result that is open to at least three alternative interpretations. First, it is plausible that traffic captures valuable information about sales beyond two quarters. Because we do not have access to a long time series of future sales observations, we cannot fully rule out this explanation. Second, market participants may value web traffic for strategic uses of information that a firm obtains from traffic to its websites, to develop sustainable competitive advantages. A web firm can learn valuable insights about customer behavior by tracking web visitors' click stream patterns. Tracking visitor behavior on a firm's website can provide important knowledge about the nature and needs of visitors even if such visitors fail to buy goods and services. For example, Amazon.com continually analyzes search lists to identify products that visitors cannot find in its online stores (*Economist Intelligence Unit*, 2000, p.35). Such data on failed searches enable Amazon to learn about visitors' preferences and decide accordingly which new product lines to enter. Thus, traffic may provide information about firms' growth options. An attendant benefit to accumulating data on failed searches is that such data helps e-tailing firms and their supply chain partners to maintain optimal inventory both in terms of product mix and quantity stocked. A firm's ability to access and harness knowledge about customer behavior is likely to increase with the extent of traffic. This is because the statistical reliability of data about consumer preferences is likely to increase with the extent of visitor traffic to the website. Yet another explanation for the value-relevance of traffic, over and above sales revenues, is that the market views the firm's traffic as a measure of the network effects that users can generate. We explore this third explanation in greater detail below.

4.2. Does traffic capture network effects?

Network effects arise when the value of connecting to a network depends on the number of other people already connected to it (Shapiro and Varian, 1999; p.174). Once the number of visitors, and the size of the virtual community created by the firm grows, more and more users find the firm's website attractive because of their ability to interact with other members of the community and their ability to share and contribute to member generated content (e.g., book reviews generated by readers at Amazon.com). For instance, the ability to interact with more community members can be very valuable to an auction site like Ebay. Ebay's auction site is more popular than any other auction site (including free auction sites such as Yahoo Auctions) because of the huge virtual community that Ebay has created. A marginal buyer or seller has strong incentives to transact on Ebay because this increases the probability of finding members who would take the other side of the trade.

A bigger member base creates opportunities for advertisers and vendors to market a range of products and services to those members. Accumulating data about member profiles and transaction profiles makes it possible to attract even more vendors and advertisers to tailor the products and services to the members, thus making it attractive for members to join the firm's virtual community (Hagel and Armstrong, 1997; Kotha, 1998). This increases the potential for revenue streams from advertisements and subscription-based revenues for content and community companies and portals. For E-tailers and financial services firms, the size of the virtual community increases the potential for selling goods and services to a wider audience with the added advantage of customers selling to one another via product reviews. Thus, chasing traffic in the earlier time periods may be value maximizing down the road because the leaders with larger traffic (or user base) can dominate their product space as positive feedback effects take hold (Shapiro and Varian, 1999; Hagel and Armstrong, 1997).

Network effects can be empirically detected by evaluating whether the value of the network increases non-linearly with the number of users in the network. Part of the motivation behind this empirical test is Metcalfe's law, named after Bob Metcalfe, the inventor of the Ethernet. According to Metcalfe's law, if there are n people in the network, the value of the network is proportional to the number of other users, i.e., $n \times (n\text{-}1) = n^2\text{-}n$ (Shapiro and Varian, 1999, p.184).[9]

[9] The intuition behind Metcalfe's law in his own words is as follows: "When you connect computers together, the cost of doing so is n, but the value is n^2, because each of the machines that you hook up gets to talk to all of the other machines on the network. When you graph that, you see that over time your costs go down while the value of the network goes up." (Red Herring Magazine, Nov 1994)

To assess whether traffic is valued by the market as a barometer of the firm's ability to generate network effects, we introduce the squared transformation of UNIVIS variable ($UNIVIS^2$) in the value-relevance model (equation 1). If network effects drive the pricing of traffic by the stock market, we would expect the coefficient on $UNIVIS^2$, to be positive and statistically significant in the following regression model:

$$MVE_{jt} = \beta_0 + \beta_1 BVE_{jt} + \beta_2 E_{jt} + \beta_3 Log(TA)_{jt} + \beta_4 UNIVIS_{jt} + \beta_5\, UNIVIS^2_{jt} + \beta_{6i}\, IND_{jit} + \beta_{7k}\, QTR_{jkt} + \varepsilon_{jt} \qquad (9)$$

Results reported in Table 7 show that β_4 is negative but statistically insignificant (coefficient = -100.30, t-statistic = -0.77). More important, β_5, the coefficient on $UNIVIS^2$ is positive and strongly significant (coefficient = 30.24, t-statistic = 11.23). Thus, this result is consistent with market participants valuing traffic because of potential network effects generated by the firm.

Acquisitions

Consistent with the notion of acquiring traffic in an attempt to generate network effects, some acquirers pay significant sums for acquiring website traffic even if the target has no revenues. As a case in point, in October 1999, Excite@home, an Internet portal, agreed to acquire Bluemountainarts.com, an electronic greeting card website, for $780 million in cash and stock. Although Bluemountainarts.com had virtually no revenues and profits, acquisition of Blue Mountain Arts instantly added 9.2 million more monthly visitors to Excite's network and increased Excite's reach of the Internet population from 24% to 34% (Excite.com press release, October 25, 1999).

To provide corroborative evidence on whether traffic measures a firm's ability to create network effects, we examine the association between traffic and an alternative value indicator, i.e., acquisition prices in web mergers and acquisitions. We obtain a sample of 89 acquisitions of

Internet companies for the period January 1999 to June 2000 for which traffic information was also available. Because many of the acquired firms are privately held we are unable to obtain financial data for them. We conduct two sets of regressions to ascertain the relation between acquisition prices and the number of visitors acquired. In the first regression, unique visitors measured as of the month prior to the acquisition is related to traffic as a linear explanatory variable. In the second regression, a squared transformation of unique visitors is also introduced as a regressor. If the market for corporate control also views traffic as a measure of network effects, we would expect the acquisition prices to increase non-linearly with the number of unique visitors acquired.

Descriptive statistics and the regression results are provided in Table 8. We find that acquiring firms pay a mean (median) price of \$494.15 (\$104.13) per unique monthly visitor. Panel B shows that target firms' traffic numbers account for virtually all the cross-sectional variation (more than 95%) in acquisition prices, consistent with the hypothesis that the market for corporate control values future growth potential from network effects. The strong explanatory power of the regression suggests that firm-level financial information (such as book value or earnings) that is not available to us may not capture value relevant information not accounted for by traffic. Furthermore, the acquisition prices increase non-linearly with traffic as evidenced by the positive and statistically significant coefficient on the squared transformation of the number of visitors acquired (coefficient = 3.16, t-statistic=3.13). Thus, evidence from acquisitions is also consistent with the conjecture that traffic captures potential benefits from network effects.

5. Concluding remarks

In this study we explore the role of a key non-financial measure, web traffic, in explaining the cross-sectional variation of B2C Internet firms. We find that unique monthly visitors to a firm's website explain a substantial portion of the cross-sectional variation in equity values of Internet firms. This result obtains after controlling for traditional financial measures such as earnings and equity book values. However, the value-relevance of traffic disappears once we control for the strategies used by firms to increase traffic. Hence, we interpret web traffic as a summary measure of the extent of the firm's involvement in various strategies designed to improve traffic to its website. This result also suggests that firms are in equilibrium when managers set the traffic levels of their firms in response to the exogenous determinants the face.

We find that traffic has no incremental predictive power for future sales after controlling for past sales. This suggests that traffic may be value-relevant for reasons other than providing information about future sales. We conjecture that the capital market participants value potential network effects and potential customer relationships that traffic brings even though such traffic does not necessarily result in current sales.

Consistent with Metcalfe's law that the value of the network increases with the square of the number of users in the network, we find that market value of our sample firms is a positive function of the squared number of unique monthly visitors. Furthermore, the acquisition prices paid by acquirers also increases at an increasing rate with the number of unique visitors acquired. Our tests are, of course, constrained by the availability of only 5 quarters of time series observations. More direct tests of the network effects hypothesis can be conducted when enough time-series observations of Internet firm financial performance become available.

Explaining the cross-sectional variation in the market valuations of Internet firms represents an interesting and continuing challenge. Researchers (e.g., Trueman et al., 2000a,b; Hand, 2000b; Demers and Lev, 2000 and Rajgopal, Venkatachalam and Kotha, 2000) have, thus far, restricted the search of non-financial value drivers to B2C firms because clear quantifiable measures of consumer interest such as traffic or online customer experiences are available for such firms. Exploring the non-financial measures that would explain stock prices of Internet firms in other sectors such as infrastructure services or B2B (Business to Business) commerce is a potentially intriguing but challenging avenue for future research.

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Table 1

Descriptive Statistics

Panel A: Sample of firms

	Name		Name		Name		Name
1	About Com Inc	25	E-Stamp Corp	49	Infoseek	73	Priceline Com Inc
2	Alloy Online	26	Earthweb Inc	50	Infospace Inc	74	Quepasa Com Inc
3	Amazon Com Inc	27	Ebay Inc	51	Insweb Corp	75	Quokka Sports Inc
4	Ameritrade Holding	28	Edgar Online Inc	52	Internet.Com Corp	76	Smarterkids Com Inc
5	Artistdirect Inc	29	Egghead Com	53	Iturf Inc	77	Snowball Com Inc
6	Ashford Com Inc	30	Emusic.Com Inc	54	Ivillage Inc	78	Sportsline Com Inc
7	Ask Jeeves Inc	31	Etoys Inc	55	Knot Inc	79	Starmedia Network
8	Audible Inc	32	Excite	56	Launch Media Inc	80	Student Advantage(Ipo)
9	Audiohighway.Com	33	Expedia Inc	57	Looksmart Ltd	81	Switchboard Inc
10	Barnesandnoble Com Inc	34	Fashionmall Com Inc	58	Lycos Inc	82	Talk City Inc
11	Beyond Com Corp	35	Fatbrain Com Inc	59	Mapquest	83	Theglobe Com Inc
12	Bigstar Entmt Inc	36	FTD Com Inc	60	Marketwatch.Com	84	Thestreet.Com Inc
13	Bluefly Inc	37	Garden Com Inc	61	Mortgage Com Inc	85	Ticketmaster Online Ctys
14	Buy Com Inc	38	Geocities	62	MP3 Com Inc	86	Ubid
15	Careerbuilder Inc	39	GO2NET Inc	63	Musicmaker Com Inc	87	Value America Inc
16	Cdnow / N2k Inc	40	GoTo Com Inc	64	NBC Internet Inc	88	Vitaminshoppe Com Inc
17	Cmgi Inc	41	Healthcentral Com	65	Netbank	89	Witcapital
18	CNET Networks Inc	42	Healthgate Data Corp	66	Netradio Corp	90	Women Com Networks
19	Crosswalk Com Inc	43	Homegrocer Com Inc	67	Nextcard Inc	91	Xoom.Com
20	Cyberian Outpost Inc	44	Homestore Com Inc	68	Onsale	92	Yahoo Inc
21	Drkoop Com Inc	45	Hoovers Inc	69	Peapod Inc		
22	Drugstore Com Inc	46	Ilife Com Inc	70	Pets Com Inc		
23	E Trade Group Inc	47	Improvenet Inc	71	Planetrx Com Inc		
24	E-Loan Inc	48	Infonautics Corp	72	Preview Travel		

Table 1 (continued)

Panel B: Sample firms by industry type

Type	Industry	No. of firms
1.	Content providers	36
2.	E-tailers	38
3.	Financial Services	8
4.	Portals	10
	Total	92

Panel C: Descriptive statistics

(N=303)

Variable	**Mean**	**Std.dev.**	**Median**	**1st quartile**	**3rd quartile**
UNIVIS (million)	4.10	6.82	1.65	0.50	4.72
REACH	0.07	0.12	0.03	0.01	0.08
E ($ million)	-19.48	67.04	-10.68	-21.93	-5.37
BVE ($ million)	206.14	343.84	93.90	40.84	225.16
TA ($ million)	445.22	1188.32	133.53	58.54	352.57
SALES ($ million)	34.54	75.10	10.00	3.95	30.12
MVE ($ million)	2906.56	8440.27	455.81	159.75	1715.26
MVBV	16.92	62.46	4.70	2.42	10.24
VIS	42.21	110.26	10.00	2.00	25.00
M&A	15.54	22.75	8.79	4.30	18.19
CASH	147.57	260.89	67.55	30.22	143.04

Notes:
Variables are defined as follows: UNIVIS = the average monthly unique visitors during a quarter, REACH = the average proportion of unique visitors to total web population during a quarter, E = income before extraordinary items, BVE = book value of equity, TA = total assets, SALES = sales revenues, MVE = market value of equity, MVBV = market to book ratio, VIS = media visibility measured as the number of articles in leading newspapers and magazines, M&A = marketing and advertisement expenditures, CASH = cash and cash equivalents.

Table 2

Summary statistics for the regression of market values and returns on financial measures and web traffic

Panel A: Levels specification

$$MVE_{jt} = \beta_0 + \beta_1 BVE_{jt} + \beta_2 E_{jt} + \beta_3 Log(TA)_{jt} + \beta_4 UNIVIS_{jt} + \beta_{5i} IND_{jit} + \beta_{6k} QTR_{jkt} + \varepsilon_{jt} \qquad (1)$$

Variable	Pred. Sign	(N=296) Coeff. Estimate	t-stat	(N=295) Coeff. Estimate	t-stat
Intercept	?	-6463.46	-3.97*	849.19	0.53
BVE	+	4.49	2.53*	5.71	4.76*
E	+	-12.18	-1.91**	-10.28	-2.72*
Log(TA)	+	1012.92	3.16*	-347.04	-1.08
UNIVIS	+			700.49	4.54*
Adj. R^2		36.61%		61.03%	

Panel B: Changes specification

$$Ret_{jt} = \beta_0 + \beta_1 E_{jt} + \beta_2 \Delta E_{jt} + \beta_3 \Delta UNIVIS_{jt} + \beta_{4i} IND_{jit} + \beta_{5k} QTR_{jkt} + \nu_{jt} \qquad (2)$$

Variable	Pred. Sign	(N=207) Coeff. Estimate	t-stat
Intercept	?	-0.55	-6.26*
E	+	0.86	1.30***
ΔE	+	-0.19	-0.28
ΔUNIVIS	+	15.88	1.91**
Adj. R^2		35.56%	

Notes:
1. ***,**,* represents significance at 10%, 5%, and 1% respectively. t-statistics are one-tailed where the sign is predicted, two-tailed otherwise. Reported t-statistics are adjusted for White's (1980) correction for heteroskedasticity.
2. Coefficients on quarter dummies and industry dummies have not been reported for expositional convenience.
3. Regression results are presented after deleting outlier observations represented by the absolute value of R-student statistic greater than the three.
4. Ret = abnormal stock return determined by subtracting return on NASDAQ index from the holding period return over the quarter, ΔE = change in income before extraordinary items, ΔUNIVIS = change in average monthly unique visitors during a quarter. Independent variables in equation (2) (except the industry and quarter dummies) are scaled by the market value of equity at the beginning of the return formation period. See the notes to Table 1 for other variable definitions.

Table 3

Correlation statistics and regression results of determinants of web traffic

Panel A: Pearson and Spearman correlation matrix

Variables	UNIVIS	AOL	AFF	VIS	M&A	CASH	Log(TA)
UNIVIS	1.00	0.18*	0.25*	0.51*	0.52*	0.53*	0.57*
AOL	0.10**	1.00	0.07	0.23*	0.23*	0.16*	0.23*
AFF	-0.00	0.07	1.00	0.12**	0.06	0.02	0.05
VIS	0.71*	0.20*	-0.00	1.00	0.58*	0.52*	0.62*
M&A	0.38*	0.32*	0.02	0.59*	1.00	0.54*	0.65*
CASH	0.45*	0.14**	-0.01	0.58*	0.54*	1.00	0.88*
Log(TA)	0.48*	0.24*	-0.00	0.46*	0.65*	0.64*	1.00

Panel B: Determinants of traffic

$$UNIVIS_{jt} = \delta_0 + \delta_1\, AOL_{jt} + \delta_2\, AFF_{jt} + \delta_3\, VIS_{jt} + \delta_4\, M\&A_{jt} + \delta_5\, CASH_{jt} + \delta_6\, Log(TA)_{jt} + \delta_{7i}\, IND_{jit} + \delta_{8k}\, QTR_{jkt} + \eta_{jt} \quad (5)$$

Variable	Pred. Sign	Coeff. Estimate	t-stat (N=291)
Intercept	?	-4.75	-4.22*
AOL	+	-0.35	-0.98
AFF	+	0.74	2.54*
VIS	+	0.04	8.87*
M&A	+	-0.03	-3.37*
CASH	+	0.00	0.32
Log(TA)	+	0.97	5.32*
Adj. R^2		78.11%	

Notes:
1. In Panel A, Pearson correlation statistics are presented below the diagonal and Spearman correlation statistics are presented above the diagonal.
2. ***,**,* represents significance at 10%, 5%, and 1% respectively. t-statistics are one-tailed where the sign is predicted, two-tailed otherwise. Reported t-statistics are adjusted for White's (1980) correction for heteroskedasticity.
3. Coefficients on quarter dummies (QTR) and industry dummies (IND) have not been reported for expositional convenience.
4. Regression results are presented after deleting outlier observations represented by the absolute value of R-student statistic greater than the three.
5. See notes to Table 1 for variable definitions.

Table 4

Regression results of estimating the market value equation after accounting for factors that determine web traffic

$$MVE_{jt} = \beta_0 + \beta_1 BVE_{jt} + \beta_2 E_{jt} + \beta_3 Log(TA)_{jt} + \beta_4 UNIVIS_{jt} + \beta_5 AOL_{jt} + \beta_6 AFF_{jt} + \beta_7 VIS_{jt} + \beta_8 \; M\&A_{jt} + \beta_9 CASH_{jt} + \beta_{10i} IND_{jit} + \beta_{11k} QTR_{jkt} + \varepsilon_{jt} \quad (4)$$

			(N=291)
Variable	**Pred. Sign**	**Coeff. Estimate**	**t-stat**
Intercept	?	-164.48	-4.87*
BVE	+	2.56	3.37*
E	+	-2.77	-1.47***
UNIVIS	?	-7.40	-0.17
AOL	+	244.31	0.75
AFF	+	-189.94	-0.96
VIS	+	35.43	9.84*
M&A	+	-4.22	-0.49
CASH	+	2.20	2.37*
Log(TA)	+	5.49	0.00
Adj. R^2		81.81%	

Notes:
1. ***,**,* represents significance at 10%, 5%, and 1% respectively. t-statistics are one-tailed where the sign is predicted, two-tailed otherwise. Reported t-statistics are adjusted for White's (1980) correction for heteroskedasticity.
2. Coefficients on quarter dummies (QTR) and industry dummies (IND) have not been reported for expositional convenience.
3 Regression results are presented after deleting outlier observations represented by the absolute value of R-student statistic greater than the three.
4. See notes to Table 1 for variable definitions.

Table 5

Regression results examining the relation between web traffic and future revenues

Panel A: Regression of one-quarter and two-quarter ahead sales on traffic

$$SALES_{jt+n} = \gamma_0 + \gamma_1 UNIVIS_{jt} + \gamma_2 Log(TA)_{jt} + \gamma_{3i} IND_{jit} + \gamma_{4k} QTR_{jkt} + \varphi_{jt} \quad (6)$$

Variable	Pred. Sign	Dependent Variable: $SALES_{jt+1}$ (N=207) Coeff. Estimate	t-stat	$SALES_{jt+2}$ (N=128) Coeff. Estimate	t-stat
Intercept	?	-63.77	-2.88*	-77.34	-2.42**
UNIVIS	+	2.78	3.81*	2.91	2.77*
Log(TA)	+	18.59	4.14*	22.07	3.90*
Adj. R^2		43.04%		42.71%	

Panel B: Regression of one-quarter and two-quarter ahead sales on traffic after controlling for current sales information

$$SALES_{jt+n} = \gamma_0 + \gamma_1 UNIVIS_{jt} + \gamma_2 Log(TA)_{jt} + \gamma_{3i} IND_{jit} + \gamma_{4k} QTR_{jkt} + \gamma_5 SALES_{jt} + \varphi_{jt} \quad (7)$$

Variable	Pred. Sign	Dependent Variable: $SALES_{jt+1}$ (N=205) Coeff. Estimate	t-stat	$SALES_{jt+2}$ (N=127) Coeff. Estimate	t-stat
Intercept	?	-8.37	-1.15	-4.56	-0.37
UNIVIS	+	0.15	0.70	-0.28	0.81
Log(TA)	+	3.27	3.20*	2.00	1.34***
SALES	+	1.07	40.50*	1.60	36.95*
Adj. R^2		94.03%		94.91%	

Notes
1. ***,**,* represents significance at 10%, 5%, and 1% respectively. t-statistics are one-tailed where the sign is predicted, two-tailed otherwise. Reported t-statistics are adjusted for White's (1980) correction for heteroskedasticity.
2. Coefficients on quarter dummies (QTR) and industry dummies (IND) have not been reported for expositional convenience.
3. Regression results are presented after deleting outlier observations represented by the absolute value of R-student statistic greater than the three.
4. See notes to Table 1 for variable definitions.

Table 6

Regression results examining the relation between web traffic and market value of equity after controlling for sales

$$MVE_{jt} = \beta_0 + \beta_1 BVE_{jt} + \beta_2 E_{jt} + \beta_3 Log(TA)_{jt} + \beta_4 UNIVIS_{jt} + \beta_5 SALES_{jt} + \beta_{6i}\, IND_{jit} + \beta_{7k}\, QTR_{jkt} + \varepsilon_{jt} \quad (8)$$

		(N= 296)	
Variable	**Pred. Sign**	**Coeff. Estimate**	**t-stat**
Intercept	?	888.14	0.56
BVE	+	4.95	4.08*
E	+	-0.94	-0.28
Log(TA)	+	-559.59	-1.72***
UNIVIS	+	599.39	3.89*
SALES	+	25.79	4.07*
Adj. R^2		65.30%	

Notes:
1. ***,**,* represents significance at 10%, 5%, and 1% respectively. t-statistics are one-tailed where the sign is predicted, two-tailed otherwise. Reported t-statistics are adjusted for White's (1980) correction for heteroskedasticity.
2. Coefficients on quarter dummies (QTR) and industry dummies (IND) have not been reported for expositional convenience.
3. Regression results are presented after deleting outlier observations represented by the absolute value of R-student statistic greater than the three.
4. See notes to Table 1 for variable definitions.

Table 7

Summary statistics for the regression of market values on financial measures, web traffic measure (unique visitors) and the squared term of unique visitors

$$MVE_{jt} = \beta_0 + \beta_1 BVE_{jt} + \beta_2 E_{jt} + \beta_3 Log(TA)_{jt} + \beta_4 UNIVIS_{jt} + \beta_5\, UNIVIS^2_{jt} + \beta_{6i}\, IND_{jit} + \beta_{7k}\, QTR_{jkt} + \varepsilon_{jt} \qquad (9)$$

		(N= 295)	
Variable	**Pred. Sign**	**Coeff. Estimate**	**t-stat**
Intercept	?	-1863.85	-1.33
BVE	+	4.99	4.75*
E	+	-8.90	-2.17**
Log(TA)	+	294.11	1.52***
UNIVIS	?	-100.30	-0.77
$UNIVIS^2$	+	30.24	11.23*
Adj. R^2		81.61%	

Notes:
1. ***,**,* represents significance at 10%, 5%, and 1% respectively. t-statistics are one-tailed where the sign is predicted, two-tailed otherwise. Reported t-statistics are adjusted for White's (1980) correction for heteroskedasticity.
2. Coefficients on quarter dummies (QTR) and industry dummies (IND) have not been reported for expositional convenience.
3. Regression results are presented after deleting outlier observations represented by the absolute value of R-student statistic greater than the three.
4. $UNIVIS^2$ refers to UNIVIS squared. See notes to Table 1 for other variable definitions.

Table 8

Results relating acquisition prices and web traffic

Panel A: Descriptive statistics

(N=89)

Variable	Mean	Std.dev.	Median	1st quartile	3rd quartile
ACQPR ($ million)	365.75	1384.55	38.70	11.00	166.00
$UNIVIS_{acq}$ (millions)	1.88	4.92	0.39	0.17	1.11
Price per unique monthly visitor	494.15	2183.78	104.13	38.12	236.84

Panel B: Coefficient estimates from regressing acquisition prices on unique visitors

(N= 86)

Variable	Pred. Sign	Coeff. Estimate	t-stat	Coeff. Estimate	t-stat
Intercept	?	-47.69	-0.50	-42.52	-0.56
$UNIVIS_{acq}$	?	260.91	20.79*	151.84	3.74*
$UNIVIS_{acq}^2$	+			3.16	3.13*
Adj. R^2		94.66%		96.58%	

Notes
1. ***,**,* represents significance at 10%, 5%, and 1% respectively. t-statistics are one-tailed where the sign is predicted, two-tailed otherwise. Reported t-statistics are adjusted for White's (1980) correction.
2. Regression results are presented after deleting outlier observations represented by the absolute value of R-student statistic greater than the three.
3. Variables are defined as follows: ACQPR = acquisition price, $UNIVIS_{acq}$ = the monthly unique visitors of the acquired firm measured as of the month prior to the acquisition, $UNIVIS_{acq}^2$ = $UNIVIS_{acq}$ squared.