Firm Website And Cost Of Equity

Hsin-Min Lu
Department of Information Management, National Taiwan University, Taipei, Taiwan, R.O.C., lu@im.ntu.edu.tw

Yu-Tai Chien
Department of Information Management, National Taiwan University, Taipei, Taiwan, R.O.C., kkcolaster@gmail.com

Follow this and additional works at: http://aisel.aisnet.org/pacis2012

Recommended Citation
http://aisel.aisnet.org/pacis2012/91

This material is brought to you by the Pacific Asia Conference on Information Systems (PACIS) at AIS Electronic Library (AISeL). It has been accepted for inclusion in PACIS 2012 Proceedings by an authorized administrator of AIS Electronic Library (AISeL). For more information, please contact elibrary@aisnet.org.
Abstract

Websites have become an essential component in firms’ IT portfolios. Many business processes require website functionalities to operate smoothly. This study aims at investigating how firm website affects cost of equity, an important factor in firm valuation. We conducted a cross-sectional regression using a unique dataset consisting of 3,312 firm websites operated by US public firms. Firm website measures, including size, number of in-links, and traffic, were collected from public sources. Empirical results indicate that higher website traffic is associated with lower cost of equity after controlling for firm-specific characteristics. Improving website traffic ranking from the bottom 10% to the top 10% leads to a 3% decrease in annual cost of equity. The results are both statistically and economically significant. Other firm website measures, such as size and the number of in-links, have no effect on cost of equity.
1. INTRODUCTION

Websites have become a common approach for firms to provide product information, support online transactions, offer customer support, and disseminate corporate information. Stakeholders such as customers, investors, and suppliers are all intended firm website users. While operating a website may have been rare in the late 20th century, it has become a common approach employed by the majority of public firms. Among all public firms in the US as of December, 2010, 82% of them run websites of various scales to support business activities.

Among the websites operated by US public firms, some are extremely large and contain hundreds of millions of webpages; others are often linked by other websites, enjoying a high online status; still others attract a large volume of traffic, indicating their popularity among Internet users. All these variables, to some extent, indicate the effectiveness of firm websites. As an important component in enterprise IT portfolios, firm websites should contribute to firm performance in order to justify their increasing investment. Firm-level studies on the relationship between the websites and firm performance, however, are still rare.

This study aims at investigating how firm website affects firm performance as measured by the cost of equity. Cost of equity plays a central role in firm valuation. In classical discounted cash flow analysis (Hackel & Livant 1992), firm value is determined by the present value of its future cash flow. Cost of equity decides the discount factor used in converting the future cash flow into its present value, assuming that equity investors are the source of financing. Other things being equal, lower cost of equity leads to higher firm value.

We posit that both IT resources and IT capacity may be observed through a firm’s website performance. Therefore the firm website performance measures adopted in this study, including size, number of in-links, and website traffic, can be used to explain the cross-sectional variation of the cost of equity, which eventually determines firm value. We conducted a large-sample empirical study to investigate the hypothesized relationships between firm website effectiveness and the cost of equity. Using 3,312 firm websites operated by US public firms, we find a strong relationship between web traffic and the cost of equity. Other things being equal, higher website traffic is associated with lower cost of equity. The size of the firm website and the number of in-links to the websites, on the other hand, provide no explanatory power to the cross-sectional variation of cost of equity.

This study provides large-sample empirical evidence on the relationship between firm website effectiveness and the cost of equity. We contribute to the IS literature by documenting that website traffic can impact firm valuation by reducing the cost of equity. Our findings are in line with the conventional wisdom to measure the website’s success by its traffic.

The remainder of this paper is organized as follows. The following section provides the background for our study and lays out the hypotheses. Empirical models and data are then presented, followed by our findings. We conclude with future research directions.

2. HYPOTHESES DEVELOPMENT

We start the discussion by summarizing how the cost of equity can be estimated using market data, followed by the factors that may affect the cost of equity as well as their connections to firm website effectiveness. Three hypotheses are then presented to guide our empirical study.

2.1. Estimating the Cost of Equity

Cost of equity is the expected return a firm pays to its equity holders to obtain their capital (Damodaran 2002). As such, cost of equity is a natural candidate to evaluate the risk of the firm and to discount future cash flow generated from the firm. Firms with lower cost of equity face lower financing cost and are more valuable.

Cost of equity is usually estimated with the help of asset pricing models. One of the commonly used asset pricing model is the Capital Asset Pricing Model (CAPM) (Sharpe 1964). According to the
CAPM, the expected return of a stock is determined by its exposure to market risk in the form of betas because investors are rewarded for holding non-diversifiable market risk. The betas in the CAPM can be estimated by regressing the excess stock return on excess market return.

Finance researchers have been attacking the CAPM model for its lack of empirical support (Fama & French 1992; Fama & French 1993). An alternative asset pricing model is the Fama-French three-factor model (Fama & French 1993). Empirical evidence shows that the traditional CAPM model cannot explain the systematic difference of expected return between high book-to-market ratio stocks and low book-to-market ratio stocks. Moreover, small caps usually have higher expected return compared to large caps even after controlling for the beta risk.

The Fama-French three-factor model includes two additional factors to address the shortcomings of the traditional CAPM. The first factor is SMB, which is the return difference between small-cap stocks and large-cap stocks. The second factor is HML, which is the return difference between stocks with high book-to-market ratio and stocks with low book-to-market ratio. Combined with the original market excess return, the three factors can better capture the risk factors left out in CAPM.

Specifically, for a firm i, the factor loadings in the Fama-French three-factor model can be estimated using the following model:

\[ r_{it} - r^f_t = \alpha_i + \beta_{i1}(Mkt_t - r^f_t) + \beta_{i2}\text{SMB}_t + \beta_{i3}\text{HML}_t + \epsilon_t \]  

(1)

where \( r_{it} \) is the return of stock i in month t; \( r^f_t \) is the risk free rate at month t; \( \text{Mkt}_t \) is the market return of month t; \( \text{SMB}_t \) is the return difference between small-cap stocks and large-cap stocks in month t; \( \text{HML}_t \) is the return difference between high book-to-market ratio stocks and low book-to-market ratio stocks in month t.

Different return intervals can be used to estimate the above model. Stock returns are available on an annual, a monthly, a weekly, or a daily basis. However, estimating the model using daily data may bias the coefficient because of nontrading. Returns in nontrading periods are zero. Including nontrading period returns may reduce the estimated coefficients. One way to address this issue is to use monthly returns instead of returns in shorter intervals. To ensure that the coefficients can be estimated with a reasonable accuracy, enough historical data need to be used. Many authors use five years of monthly data to estimate the model (see, e.g., (Kothari et al. 2009)). For the firm i, estimated coefficients multiplied by the average value of input factors (\( \text{Mkt}_t - r^f_t \), \( \text{SMB}_t \), \( \text{HML}_t \)) in the estimation period gives the cost of equity of the firm.

### 2.2. Cost of Equity Determinants

Previous studies on the cost of equity have documented its important determinants. First, the degree of information asymmetry between investors and firm management may affect the cost of equity (Easley & O’Hara 2004). Theoretical models show that uninformed investors, who only have access to public information, demand higher expected returns for stocks with a larger portion of private information. Empirical studies on firm disclosure level have also documented a negative relationship between firm disclosure level and the cost of equity. The empirical evidence is consistent with the theoretical model in the sense that higher disclosure level, such as more comprehensive discussions in annual reports filed with the Securities and Exchange Commission (SEC), transfers private information to the public domain and reduces the level of information asymmetry between investors and firm management.

Cost of equity may vary because of incomplete information. Some investors may know only a subset of stocks and thus only consider these stocks when making investment decisions. As a result, some stocks are recognized by more investors and enjoy a larger investor base. In equilibrium, stocks with a larger investor base tend to have lower cost of equity (Merton 1987).

Estimation risk is another factor that may influence the cost of equity (Barry & Brown 1985). Investors need to estimate the parameters in a pricing model to support their decision making process. Some firms have relatively little historical information compared to others. Theoretical models (Barry & Brown 1985) show that parameter uncertainty impacts the systematic risk of a stock under market equilibrium. Firms with little historical information have larger systematic risk and thus higher cost of
equity. Along this line, a later study (Lambert et al. 2007) shows that firm disclosure regarding a firm’s future cash flow can reduce the estimated variance of expected return and decrease the assessed covariance between a firm’s cash flow and the market’s cash flows. Higher level of disclosure thus reduces the cost of equity.

### 2.3. From Firm Websites to Cost of Equity

The development of Internet technology has made it easier for firms to run websites. Reliable web server software is available at very low or no cost. The price of computer hardware and a high-speed Internet connection continues to drop. The knowledge and skill to operate a website are also widely available.

While operating and maintaining a website with “basic” functionalities has become a straightforward task, integrating firm websites into existing business activities and creating value for various stakeholders are not trivial. Designing, implementing, and managing a successful website requires sufficient IT investment and mature IT capacities to organize undifferentiated factors into resources that are valuable, rare, hard to imitate, and difficult to substitute (Liang et al. 2010; Melville et al. 2004).

Firm management decides on the composition of its website functionalities to best serve the intended user. The degree to which a firm website impacts firm performance depends on a firm’s IT capability to deliver an effective website and adjust the website to changing user requirements. As such, it is reasonable to expect firms in different industries may choose to implement different functionalities because of divergent user requirements (Lee et al. 2010). Moreover, firms in the same industry may choose to deviate from a popular website design to better serve their users.

Website functionalities, as a result, are evolving characteristics that cannot be used alone to measure website effectiveness. One alternative is to measure the usability of firm websites (Agarwal & Venkatesh 2002), assuming usability leads to use and delivers intended value. Our study did not measure usability. Instead, we measure website usage directly. Persistent website traffic, to some degree, indicates the effectiveness of firm websites.

The second measure adopted in this study is the number of in-links to a firm website (Liu 2006). An in-link to a firm website is a webpage containing uniform resource locators (URLs) to that website. The number of in-links is an important factor that determines the online status of a firm website. In-links to a website can be considered as an outside recognition of the target website. Firm websites receiving more in-links are often considered to have higher online status (Pant & Srinivasan 2009). Popular webpage ranking algorithms such as PageRank (Brin & Page 1998) also use in-link information to decide on the order to display webpages in response to a query. We argue that receiving in-links from webpages outside of a firm website is a signal indicating that the firm website indeed provides value to its users. Firm websites with higher numbers of in-links are more effective compared to those with lower numbers of in-links.

We also measure the size of a website in this study. Larger websites require higher IT investment and more advanced skills to manage and operate. The size of websites, as a result, can be considered as a proxy for the IT resources dedicated to firm websites. Larger websites often provide richer content that, if organized well, is more likely to satisfy their users. Moreover, larger websites may provide a better platform for personalization technologies that can further enhance website usability.

From an investor’s perspective, having access to richer information on a firm website reduces the search cost. Larger amounts of relevant information can thus be incorporated into the decision making process. As suggested by the theoretical models for the cost of equity, larger amounts of relevant information can reduce the estimation risk and lower the cost of equity. We hypothesize that there is a negative relationship between the size of firm websites and the cost of equity:

**Hypothesis 1:** Larger firm websites are associated with lower cost of equity.
The number of in-links to a firm website can be considered as a measure of online reputation. More in-links suggests a higher level of recognition from webpages outside of a firm website. We argue that firm websites with more in-links are associated with larger investor bases, which leads to lower cost of equity. The intuition behind our argument is that firm websites with more in-links can be found more easily by investors who have no prior knowledge about the firm.

Formally, assume that all investors possess no knowledge about firms and gather information about investment targets through web browsing. An investor lands on a random page and then follows the links to collect information or jumps to another random page. The probability that a page will be visited is the page ranking score in the PageRank algorithm (Brin & Page 1998). This score is usually higher for pages with more in-links.

If we assume that investors know about a firm only through the random browsing behavior described above, then a firm will have a larger investor base if its website receives a higher number of in-links. Under the assumption of incomplete information (Merton 1987), firms with a larger investor base are associated with lower cost of equity. This leads us to our second hypothesis:

Hypothesis 2: Firm websites with more in-links are associated with lower cost of equity.

The traffic on firm websites is associated with the cost of equity through the reduction of information asymmetry. Website users become familiar with a firm’s business processes, products, and services through the use of its website. While a firm’s financial information is not always available on its website, experiencing the service delivered through the website provides first-hand information for potential investors to assess the firm’s performance and future development. Higher website traffic indicates the effectiveness of a firm website in disseminating firm-specific information and thus reduces the degree of information asymmetry between investors and firm management. Theoretical models on the cost of equity suggest that reduced level of information asymmetry leads to lower cost of capital (Easley & O’Hara 2004):

Hypothesis 3: Higher website traffic is associated with lower cost of equity.

3. **EMPIRICAL MODEL**

We study the relationship between firm websites and the cost of equity by regressing the cost of equity on firm website effectiveness measures. Three firm website effectiveness measures are included in our empirical model: size of a firm website (WebSize), rank of a firm’s website traffic (WebTrafficRank; a smaller rank indicates a higher level of traffic), and number of in-links to a firm website (WebInLInK). Firm characteristics such as size and book-to-market ratio are also included to control the systematic variation of the dependent variable. We first discuss the dependent variable, followed by independent variables and control variables. The regression model and the dataset used in our empirical study are then presented.

3.1. **Dependent Variable: Cost of Equity**

We follow the procedure commonly used in the finance literature to estimate the cost of equity. Cost of equity of a firm was estimated using the Fama-French three-factor model (Fama & French 1993). We used monthly return instead of weekly or daily return data to minimize the potential problems caused by illiquid stocks. Specifically, for each firm traded in NYSE, AMEX, or NASDAQ, we estimated Equation (1) and computed cost of equity.

We obtained the factor data (rf, Mktf, SMBf, and HMLf) from Dr. Kenneth French’s website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html). Monthly returns of individual stock were obtained from the Center for Research in Security Prices (CRSP). For each firm, five years of monthly data (ending December, 2010) were used to estimate model coefficients. The average
value of each factor in 2010 was then used to compute the cost of equity of individual stock. Stocks with less than three years of historical data were dropped.

### 3.2. Independent Variables

This study considers three independent variables: size of a firm website, the traffic rank of a firm website, and the number of in-links to a firm website. A prerequisite for data collection is a comprehensive list of firm websites operated by public firms. We constructed this list by querying Yahoo! Finance using all tickers of public firms. Firm website URLs were then extracted and recorded in a database.

The size of a firm website was retrieved by querying Google and obtaining the count of URLs under the website. For example, the firm website of the S1 Corporation is http://www.s1.com. The size of S1 Corporation’s website was estimated by searching Google for “site:s1.com” and recording the returned result count. Similarly, the number of in-links to a firm website was also obtained through Google query. Using the previous example, the number of in-links to s1.com was estimated by issuing “link:s1.com” to Google.

We estimate the traffic to a firm website using data obtained from alexa.com. For a given website, alexa.com reports the rank of its traffic. The rank is based on the three-month traffic average observed by alexa.com. All three independent variables were collected during the last week of December, 2010.

### 3.3. Control Variables

Some firm characteristics are known to be associated with the cost of equity. One example is the size of a firm (Barry & Brown 1984). Book-to-market ratio is also considered as a factor that can explain the systematic variation of cost of equity (Fama & French 1992). We also include the number of analysts following a particular firm as suggested by previous studies on the cost of equity (Kothari 2001).

### 3.4. Cross-Sectional Regression Model

We study the relationship between firm website effectiveness and cost of capital using the following empirical model:

\[
\text{ce}_i = \beta_0 + \beta_1 \log \text{WebSize}_i + \beta_2 \log \text{WebTrafficRank}_i + \beta_3 \log \text{WebInLink}_i + \sum_{g=1}^{K} \alpha_g X_{g,i} + \epsilon_i \tag{2}
\]

where \(\text{ce}_i\) is the cost of equity of firm \(i\). Three firm website effectiveness measures are included in our empirical model: firm website size (\(\text{WebSize}\)), traffic rank (\(\text{WebTrafficRank}\)), and number of in-links (\(\text{WebInLink}\)). Control variables include firm size (\(X_1\)), book-to-market ratio (\(X_2\)), and number of analysts following the firm (\(X_3\)). We have also included industry dummy variables (\(X_4 \text{ to } X_{11}\)) to control for the variation across industries. To adjust for the potential effect of heteroscedasticity, we adopted the White heteroscedasticity consistent estimator for the covariance matrix.

Hypothesis 1 posits that larger websites are associated with lower cost of equity. As such, \(\beta_1\) should be negative. The relationship between website traffic and the cost of equity (Hypothesis 3) can be investigated by testing the estimated value of \(\beta_2\). Firm websites with larger traffic have higher (smaller) rank. As a result, a positive \(\beta_2\) supports Hypothesis 3. Hypothesis 2 can be tested with the estimated value of \(\beta_3\), which should be negative if Hypothesis 2 is true.

### 3.5. Sample Selection

In December, 2010, 6,436 stocks were being trading on NYSE, AMEX, and NYADAQ. We collected a list of tickers used by public firms from major stock exchange websites in the US. These tickers were then used to query Yahoo! Finance and collect the company website listed on the profile pages. We learned through this process that website URLs of public firms can be obtained from multiple sources. For example, both NYSE and NYADAQ provide the data. Other finance portals such as Google Finance also list firm websites. After comparing the data from these sources, we concluded
that Yahoo! Finance provides the most comprehensive and accurate firm website URLs. We thus compile our dataset using firm website URLs from Yahoo! Finance only.

As discussed above, the cost of equity was estimated using monthly return. We use annualized (multiplied by 12) cost of equity in this study. Firm size and book-to-market ratio were computed by merging return data with accounting data following the procedure in Fama and French (1993). The number of analysts following a firm was collected from Yahoo! Finance.

Using the 6,436 tickers collected from the stock exchange websites, we identified 5,500 firm websites. After merging with historical return and accounting data and removing missing values, we arrived at a sample of 3,312 firms. Table 1 lists the composition of our sample according to industry sectors. Our sample covers all major industry sectors and has a similar composition with population. The summary statistics of key variables are listed in Table 2.

<table>
<thead>
<tr>
<th>Industry</th>
<th># of Firms</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Services</td>
<td>649</td>
<td>19.6%</td>
</tr>
<tr>
<td>Financial</td>
<td>642</td>
<td>19.4%</td>
</tr>
<tr>
<td>Technology</td>
<td>628</td>
<td>19.0%</td>
</tr>
<tr>
<td>Healthcare</td>
<td>411</td>
<td>12.4%</td>
</tr>
<tr>
<td>Consumer Goods</td>
<td>311</td>
<td>9.4%</td>
</tr>
<tr>
<td>Industrial Goods</td>
<td>269</td>
<td>8.1%</td>
</tr>
<tr>
<td>Basic Materials</td>
<td>269</td>
<td>8.1%</td>
</tr>
<tr>
<td>Utilities</td>
<td>98</td>
<td>3.0%</td>
</tr>
<tr>
<td>Other</td>
<td>27</td>
<td>0.8%</td>
</tr>
<tr>
<td>Conglomerates</td>
<td>8</td>
<td>0.2%</td>
</tr>
</tbody>
</table>

Table 1. Industry Breakdown

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost of Equity</td>
<td>0.097</td>
<td>0.200</td>
<td>-0.839</td>
<td>2.437</td>
</tr>
<tr>
<td>Log(WebSize)</td>
<td>6.228</td>
<td>2.315</td>
<td>0.000</td>
<td>19.240</td>
</tr>
<tr>
<td>Log(WebInlink)</td>
<td>4.303</td>
<td>1.506</td>
<td>0.000</td>
<td>9.909</td>
</tr>
<tr>
<td>Log(WebTrafficRank)</td>
<td>13.482</td>
<td>2.174</td>
<td>0.000</td>
<td>17.116</td>
</tr>
<tr>
<td>Log(Size)</td>
<td>12.698</td>
<td>2.034</td>
<td>6.760</td>
<td>19.648</td>
</tr>
<tr>
<td>Log(BM)</td>
<td>-0.160</td>
<td>0.990</td>
<td>-5.885</td>
<td>5.442</td>
</tr>
<tr>
<td>Log(# of Analy+1)</td>
<td>1.646</td>
<td>1.089</td>
<td>0.000</td>
<td>3.970</td>
</tr>
</tbody>
</table>

Table 2. Descriptive Statistics

The firm website measures show large variation. Both WebSize and WebInlink are right-skewed. A lot of firm websites are small while a small fraction of them are quite large. Logarithm transformation gives a more bell-shaped-like distribution. Figure 1 (b) plots the histogram of Log(WebSize). The distribution is still right-skewed with an inflated number of small websites on the left. An interesting question is whether the distribution follows the power law, as some studies on web structures suggested (Border et al. 2000). Plotting the distribution of WebSize on a log-log scale (not shown) reveals that our data are clearly not generated from distributions following the power law. One explanation is that our sample is constructed from websites operated by public firms. These websites, in general, are larger compared to a randomly selected website, which may be run by individuals with scarce IT resources.
The histogram of Log(Weblink) (Figure 1 (a)) reveals a similar pattern. A small number of websites enjoy a large number of in-links. The median of Weblink is only 70 while the maximum value is 20,100. Figure 1 (c) shows the scatter plot of the three firm website measures (log(Websize), log(Weblink), and log(WebTrafficRank)). It is clear from the scatter plot that Websize and Weblink are positively correlated (middle-left grid). Larger websites usually receive more in-links compared to smaller ones. The linear relationship, however, is far from perfect. Other firm characteristics such as complementary IT resources may play an important role in generating in-links.

Websize is negatively correlated with WebTrafficRank (upper-left grid of Figure 1 (c)). Larger websites usually attract higher traffic and thus rank higher. Not surprisingly, the relationship between Weblink and WebTrafficRank is negative. More in-links to a website is associated with higher rank in web traffic.

The first two columns of Table 3 list the largest websites operated by US public firms. It is not surprising to see that the largest firm websites are run by virtual firms. Yahoo! Inc. manages 227 million webpages, followed by eBay Inc. and Google Inc. Almost all firms in the top 15 list are in IT-related business (software, Internet portals, data service, computer hardware, communication, etc.). The only exception is Lowe’s Companies, which is a home improvement retailer.
<table>
<thead>
<tr>
<th>Firm</th>
<th>Web Size</th>
<th>Firm</th>
<th>Web Inlink</th>
<th>Firm</th>
<th>Web Traffic Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yahoo! Inc.</td>
<td>227,000,000</td>
<td>Adobe Systems Incorp.</td>
<td>20,100</td>
<td>Google Inc.</td>
<td>1</td>
</tr>
<tr>
<td>eBay Inc.</td>
<td>126,000,000</td>
<td>Microsoft Corp.</td>
<td>13,500</td>
<td>Yahoo! Inc.</td>
<td>4</td>
</tr>
<tr>
<td>Google Inc.</td>
<td>124,000,000</td>
<td>Google Inc.</td>
<td>11,500</td>
<td>Amazon.com, Inc.</td>
<td>15</td>
</tr>
<tr>
<td>Amazon.com, Inc.</td>
<td>74,500,000</td>
<td>Constant Contact, Inc.</td>
<td>9,670</td>
<td>eBay Inc.</td>
<td>21</td>
</tr>
<tr>
<td>EDGAR Online, Inc.</td>
<td>65,900,000</td>
<td>Apple Inc.</td>
<td>7,040</td>
<td>Microsoft Corp.</td>
<td>23</td>
</tr>
<tr>
<td>Microsoft Corp.</td>
<td>35,200,000</td>
<td>Cisco Systems, Inc.</td>
<td>6,660</td>
<td>Apple Inc.</td>
<td>41</td>
</tr>
<tr>
<td>Answers Corp.</td>
<td>25,800,000</td>
<td>International Business</td>
<td>6,120</td>
<td>Adobe Systems Incorp.</td>
<td>59</td>
</tr>
<tr>
<td>Hewlett-Packard Comp.</td>
<td>14,500,000</td>
<td>Intel Corp.</td>
<td>6,120</td>
<td>Netflix, Inc.</td>
<td>114</td>
</tr>
<tr>
<td>Blackboard Inc.</td>
<td>13,900,000</td>
<td>Yahoo! Inc.</td>
<td>5,840</td>
<td>Answers Corp.</td>
<td>138</td>
</tr>
<tr>
<td>Apple Inc.</td>
<td>12,800,000</td>
<td>Oracle Corp.</td>
<td>5,580</td>
<td>Bank of America Corp.</td>
<td>153</td>
</tr>
<tr>
<td>Adobe Systems Incorp.</td>
<td>11,700,000</td>
<td>Hewlett-Packard Comp.</td>
<td>5,380</td>
<td>Dell Inc.</td>
<td>199</td>
</tr>
<tr>
<td>International Business</td>
<td>9,370,000</td>
<td>General Electric Corp.</td>
<td>3,720</td>
<td>Hewlett-Packard Comp.</td>
<td>208</td>
</tr>
<tr>
<td>Machines Corp.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Oracle Corp.</td>
<td>8,210,000</td>
<td>VMware, Inc.</td>
<td>3,490</td>
<td>Best Buy Co., Inc.</td>
<td>245</td>
</tr>
<tr>
<td>Lowe’s Companies, Inc.</td>
<td>8,070,000</td>
<td>Red Hat, Inc.</td>
<td>3,440</td>
<td>United Parcel Service, Inc.</td>
<td>260</td>
</tr>
<tr>
<td>Cisco Systems, Inc.</td>
<td>6,030,000</td>
<td>Delta Air Lines Inc.</td>
<td>3,290</td>
<td>Salesforce.com Inc</td>
<td>270</td>
</tr>
</tbody>
</table>

Table 3. Lists of Top Websites According to Size, Number of In-links, and Traffic Rank

The middle two columns of Table 3 list the firm websites receiving the most in-links. Adobe Systems receives the largest amount of in-links, 20,100, in our dataset. This amount of in-links is 50% higher than the second place website. The high in-links to Adobe Systems may be a result of their successful free PDF reader and other related products. Similar to the list of largest firm websites, the majority of firms are in IT-related business. One exception is Delta Air Lines, which is in the transportation industry.

The last two columns of Table 3 list the top websites with the highest traffic. Google Inc. enjoys the highest traffic among all public firms, followed by Yahoo! Inc. and Amazon.com. Note that we do not consider websites operated by public firms but not listed on the Yahoo! Finance profile pages. As a result, the traffic rank of Microsoft Corp. did not include other websites run by the same company.

4. **EMPIRICAL FINDINGS**

We conducted the cross-sectional regression (Equation (2)) and corrected the potential heteroscedasticity problem using White’s covariance estimate (White 1980). The adjusted R-square is 0.129 and the null hypothesis that the model does not have explanatory power to the data is rejected at a 99% confidence level. The hypothesis that all industry dummies are zero is rejected, indicating that the cost of equity is different across industry sectors.

Table 4 lists the regression results. The estimated coefficient of Log(WebTrafficRank) is significantly positive (0.0058; t-value=2.13; p-value=0.03). The positive coefficient of Log(WebTrafficRank) indicates that websites with smaller rank (i.e., higher traffic) are associated with lower cost of equity. Hypothesis 3 is supported.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
<th>t-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.069</td>
<td>1.03</td>
</tr>
<tr>
<td>Log(WebTrafficRank)</td>
<td>0.0058**</td>
<td>2.13</td>
</tr>
<tr>
<td>Log(WebSize)</td>
<td>0.0019</td>
<td>0.84</td>
</tr>
<tr>
<td>Log(WebInlink)</td>
<td>-0.0023</td>
<td>-0.61</td>
</tr>
<tr>
<td>Log(Size)</td>
<td>-0.0077**</td>
<td>-2.30</td>
</tr>
<tr>
<td>Log(BM)</td>
<td>-0.021***</td>
<td>-4.10</td>
</tr>
<tr>
<td>Log(# of Analy + 1)</td>
<td>0.040***</td>
<td>7.15</td>
</tr>
</tbody>
</table>

Table 4. Regression Results

To see the potential effect of website traffic on the cost of equity, consider firms with Log(WebTrafficRank) at the 10th and 90th percentiles. The difference in Log(WebTrafficRank) is 5.2 (15.8-10.6). Using the estimated coefficient in Table 4, the difference in Log(WebTrafficRank) can be converted to a 3% difference in the cost of equity (5.2 × 0.0058 = 0.03 = 3%). That is, improving the rank in web traffic from the bottom 10% to the top 10% can reduce the cost of equity by 3% annually, which is economically significant.

The estimated coefficients of Log(WebSize) and Log(WebInlink) are not significantly different from zero. As a result, we do not have empirical evidence supporting Hypotheses 1 and 2. Note that the three website measures are correlated. However, only Log(WebTrafficRank) is significant if we consider all three variables simultaneously. One explanation is that website traffic is a better measure for website effectiveness compared to the size and in-link measure.

The three control variables, firm size, book-to-market ratio, and number of analysts following, all have estimated coefficients that are significantly different from zero. The coefficient of Log(Size) is negative, indicating that larger firms usually have lower cost of equity. The logarithm of book-to-market ratio is associated with a negative coefficient, indicating that firms with higher book-to-market ratio are associated with lower cost of equity. The number of analysts following a firm is positively associated with the cost of equity.

5. CONCLUSION

This study investigates the relationship between firm website effectiveness and the cost of equity. We adopted the cost of equity as a firm performance measure because of the central role played by the cost of equity in firm valuation. We collected three variables to measure the effectiveness of firm websites: the firm website’s size, number of in-links, and traffic rank. Using 3,312 firm websites operated by US public firms, we identified a statistical and economically significant relationship between firm website traffic and the cost of equity. Higher traffic leads to lower cost of equity after controlling for firm size, book-to-market ratio, and the number of analysts following the firm. Improving firm website traffic from the bottom 10% to the top 10% is associated with a 3% decrease in annual cost of equity. Other firm website variables such as firm website size and the number of in-links are not significant in our cross-sectional regression. Our study confirmed the conventional wisdom to focus on website traffic when operating a website.

We are working on refining the website effectiveness measures to include additional websites not listed on the Yahoo! Finance. In addition to these measures adopted in this study, we are also interested in creating structural measures that represent the closeness between firm websites. The structural measures may provide additional information that cannot be captured by variables used in traditional firm valuation models.
Acknowledgements

This work was supported in part by the Taiwan National Science Council under the grant NSC 99-2410-H-002-261, and 100-2410-H-002-025-MY3.

References


