DO INVESTORS USE CUSTOMER METRICS TO VALUE HIGH GROWTH SERVICE FIRMS?

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ABSTRACT

High growth service firms invest resources to acquire and retain customers, creating intangible assets. This paper tests whether investors use customer metrics to value these firms. Using a unique hand-collected data set, we show that investors discount the values of high growth service firms if their service costs per customer are high, perhaps because high service costs are associated with inefficient business operations. Conversely, investors boost the values of high growth service firms with high acquisition costs per customer, perhaps because higher acquisition costs are associated with customers who generate larger future cash flows. We also show that relatively high growth firms tend to disclose customer metrics more frequently, monthly rather than quarterly, helping to moderate the inherent uncertainty in their quarterly earnings. We find that customer metrics are incrementally informative to traditional financial performance measures, particularly when valuing high-growth service firms.

JEL: G12, G14, M41

KEYWORDS: Customers, Valuation, Intangibles

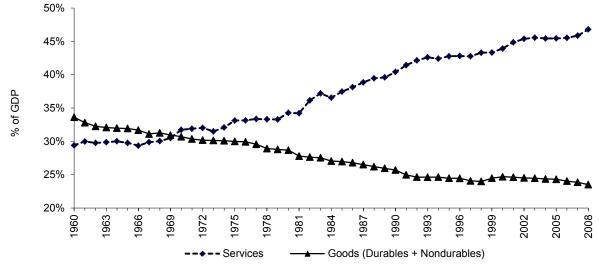
INTRODUCTION

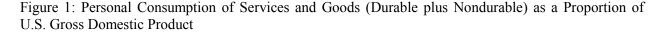
Investors struggle to correctly value many high-growth service firms because they often have negative cash-flows, no dividends or earnings, and little asset book value. Traditional valuation models that rely on these measures produce inaccurate or nonsensical prices. Damodaran (2001) suggests that one way around the problem is to forecast the traditional value measures and then discount. We argue that investors may instead value the firms by valuing their customers as intangible assets.

Non-traditional information disclosures are becoming more common, perhaps because the ratio of firms' intangible assets to physical assets has increased during the last 25 years. New technology-based service industries, like those built around the internet, are a larger part of our economy, and firms in those industries have proportionately more intangible assets. Indeed, the service sector of the U.S. economy has grown to far exceed the good producing sector. Figure 1 illustrates how personal consumption of services as a proportion of GDP started to grow around 1970, and accelerated in the 1980s and 1990s. Conversely, the relative consumption of physical goods (durables plus non-durables) has declined, particularly in the 1980s and 1990s.In line with this trend, the service sector's higher proportion of U.S. corporate investments has led to an increase in intangible assets. Figure 2 shows the impact on price to book ratios of U.S. companies at the 95th percentile of price-to-book during the same time period. Data for the S&P 500 are not available for the full period, but the index's price to book ratio also increased from 1.2 in 1978, to 3.1 in 2006, with a high of 4.9 in 2000. Hence, the dramatic increase in intangible assets is apparent even for large S&P 500 firms.

Note that the steady upward trend in market to book values starts in the late 1970s and early 1980s. This is about the same time that the U.S. service sector growth accelerated (see Figure 1). Although research on intangible asset values has grown, much of it focuses on R&D. But growth in corporate R&D probably does not explain the trend in intangible assets during the last 25 years because R&D spending as a proportion of sales was flat at about three percent from 1985 to 1999, while market to book values were

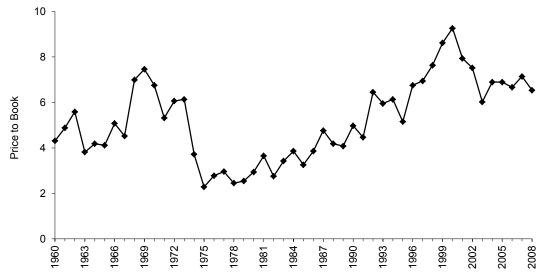
strongly rising (http://www.nsf.gov/statistics/iris/search_hist.cfm?indx=13). The rise in market to book values could be explained by the growth in other intangible assets.





Source: Bureau of Economic Analysis

Figure 2: The Ratio of Market Price to Book Value of Equity for U.S. Stocks at the 95th Percentile of Price to Book Value



Source: Kenneth French's website

We compile a unique data set collected from press releases and Securities and Exchange Commission (SEC) filings to study whether investors use customer metrics (new customers, customer service costs and customer acquisition costs) to value high-growth service firms. Wall Street analysts often track customer metrics to gauge the success and efficiency of a firm's competitive strategy. One indicator of the value of these disclosures is that the SEC has started to monitor them and penalize firms that misreport them. A growing number of firms report these numbers in their SEC filings. The SEC and the Department of Justice (DOJ) investigated AOL Time Warner's advertising arrangements and their methods used to

compute subscriber numbers reported in 2002 10Qs and press releases. In late 2004, Time Warner settled charges arising from these initial investigations, and other accounting and securities fraud charges, for over \$500 million. In June 2004, the SEC investigated how telecommunications and cable companies count their customers (Young and Grant 2004). Our customer metric results add to the relatively thin literature on non-traditional valuation.

We also study the inherent tension between customer service and customer acquisition spending. All else equal, investors prefer low costs, but sometimes higher current spending can be a good long-term investment because such spending creates intangible customer assets. For example, if service firms with relatively high growth opportunities spend more on customer acquisition, they may capture valuable customers before their competitors. In a low-growth market, this could be a poor strategy, particularly if a firm skimps on service expenditure to fund customer acquisition. In their recent literature review of the impact of marketing on firm value, Srinivasan and Hanssens (2009) note that executives are increasingly being held accountable for the financial impact of their marketing actions. They suggest that further research is needed to better understand the financial response to various marketing information and the valuation impact of different marketing intangibles.

The remainder of the paper is organized as follows. Section 2 contains a review of the relevant literature. In Section 3 we describe hypothesis development and the empirical models. Data collection and the sample are discussed in Section 4. In Section 5 we analyze the empirical results. Section 6 concludes the paper.

LITERATURE REVIEW

Researchers report significant relations between firm value and non-traditional disclosures. Demers and Lev (2001) and Trueman, Wong, and Zhang (2000) find that website traffic is positively related to the values of internet firms. Amir and Lev (1996) find that wireless communication firms' POPS (population size) and customer penetration (subscribers divided by POPS) better explain their stock prices than earnings, book values, and cash-flows. Indeed, Lev (2004) suggests that to improve investors' understanding of firm performance, managers need to supplement the accounting and financial information already available, with more detailed disclosure of their intangible assets.

Research on intangible asset valuation is limited by data availability. One exception is research and development (R&D) because firms must disclose R&D spending. Researchers have found a strong positive relation between intangible R&D assets and stock value, including Chan, Lakonishok, and Sougiannis (2001) and Eberhart, Maxwell, and Siddique (2004). Hall, Jaffe, and Trajtenberg (2005) and Hirschey, Richardson, and Scholz (2001) show that innovation output measures like patent counts and patent citations, are significantly related to firm market value. And a number of studies find that Food and Drug Administration (FDA) decisions affect firm value because they affect firms' intangible R&D assets. Ahmed, Gardella, and Nanda (2002) find that drug withdrawals, particularly FDA candidates in advanced stage clinical trials, lead to significant wealth losses for firms. Bosch and Lee (1994) find that FDA approval of a drug candidate translates to a significant positive abnormal return (+1.75%) for the firm, while FDA rejection causes a significant negative stock price reaction (-6.59%). Alefantis, Kulkarni, and Vora (2004) demonstrate that the announcement of FDA "fast track designation" for a drug candidate leads to a significant rise in stock price.

Our customer-based measures could be more closely related to firm market value than R&D output measures for several reasons. First, new customers are more homogenous than most R&D output measures; e.g., the value of patents varies widely. Second, customers are typically added in bunches, hence, variation in the value of any particular new customer has less impact on the average value of new

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customers. Finally, the time series relation between current and future new customers could be more stable than the relation between current and future patents.

Marketing researchers have for some time used customer metrics such as customer lifetime value (CLV), which is the value that a customer is expected to generate during the time he buys from the firm. For example, Day and Fahey (1988) note that the large variations in stock price-to-earnings and price-to-book ratios is caused by investors valuing stocks based upon something other than current earnings. Srivastava, Shervani, and Fahey (1999) argue that intangible marketing assets, like customers and brands, are traded like other assets and used to lower costs or raise entry barriers. Graham and Frankenberger (2000) show that changes in real advertising expenditures impact future earnings and market values. Rust, Lemon, and Zeithaml (2004) model the value of a marketing strategy as a function of CLV. Gupta, Lehmann, and Stuart (2004) demonstrate how valuing customers makes it feasible to value high-growth firms with negative earnings. Second, we provide evidence that investors use customer metrics to value firms, and the value effects differ depending upon disclosure frequency (monthly versus quarterly). Third, we examine whether differences in growth opportunities affect the relation between customer metrics and firm value. Szewczyk, Tsetsekos, and Zantout (1996) and Chen and Ho (1997) find that the market more favorably perceives capital expenditures by firms with high growth opportunities.

Our customer metrics data set is comparatively large. It includes 31 firms in 16 service industries covering 605 firm-quarter observations. Earlier studies of consumer metrics use considerably less data. For example, Gupta, Lehmann, and Stuart (2004) use five companies and rely on manager estimates as opposed to objective data. Amir and Lev (1996) study 14 firms from the cellular telephone industry. But the usable data available for our study is also limited by several factors. First, high growth is typically associated with new industries or breakthrough products (e.g. the internet). Except for a few winners, most firms do not sustain their growth for long. Second, the mortality rate for these firms is often high, so that many do not have enough data to be included in our study. Third, some firms have too little publicly available data because they were privately owned for a considerable period of time. Finally, some firms do not maintain a consistent method of computing their metrics, making only part of it useful.

Besides our unique data, our study contributes to the literature in other ways. First, we study whether customer metrics help explain firm value beyond traditional financial metrics. We use finance, accounting, and marketing literatures to guide our empirical models. Our results show more significant value effects for high growth firms, and that high growth firms benefit most from more frequent disclosure. Finally, we estimate the value effects (abnormal returns) of customer metrics using the actual event dates when firms announce their figures in press releases or SEC filings. Earlier studies of the effects of R&D figures, for example, use estimated event dates. Chan, Lakonishok, and Sougiannis (2001) assume that firms' annual R&D figures are announced to the market in April of each year, and Eberhart, Maxwell, and Siddique (2004) use a three month lag from firms' fiscal year ends as their event dates.

HYPOTHESIS DEVELOPMENT AND EMPIRICAL MODELS

Firms often report customer metrics quarterly, so it can be difficult to disentangle their effects on stock price from quarterly earnings announcements. To separate the effects, we use the value relevance and the earnings response coefficient (ERC) models. The models can provide complementary evidence because value relevance examines stock prices and ERC examines stock returns. Both can be adapted to examine whether specific information disclosures affect firm value, independent from the effects of earnings disclosures. For example, Kallapur and Kwan (2004) use the value relevance model to test the effects of information on brand assets, and Rajgopal, Venkatachalam, and Kotha (2003) use it to test for the effects of information on the value of virtual communities.

The ERC method could provide a better test of the significance of our customer variables because it models marginal changes (stock returns) as opposed to levels (stock price). We suspect that analysts who use customer metrics are more interested in how the data reflect firms' strategy changes. Nevertheless, Kothari and Zimmerman (1995) argue that neither methodology clearly dominates the other. Consequently, in line with Bodnar and Weintrop (1997) and Bodnar, Hwang, and Weintrop (2003), we test for the significance of customer metrics using both methods.

Value Relevance Model

We implement the value relevance model with the following regression of market value on book value, earnings, and other variables (X). In our case, X includes customer metrics.

MARKET VALUE = $\alpha + \beta_1$ *BOOK VALUE + β_2 *EARNINGS + β_3 *X + ε

A statistically significant coefficient on a variable in X indicates that it is associated with market value, after controlling for book value and earnings.

Hypothesis Development for the Value Relevance Method

Firms often spend large sums on advertising and marketing, primarily to acquire customers. Firms also invest in other operational activities to service existing customers. Our customer metrics include measures of customer acquisition and service costs. Advertising and marketing expense per new customer is our measure of customer acquisition cost. Service expense per customer is our measure of service cost. We hypothesize that:

H1: Per-customer acquisition costs and per-customer service costs are significantly related to market value.

Lower values of these metrics could indicate greater operational efficiency, and may have a positive impact on firm value. On the other hand, higher values of these metrics could indicate that a firm is building long-term investments in customer assets, spending heavily now to capture loyal customers for the long term. We hypothesize that the direction of the relation between customer metrics and market value depends on growth opportunities available to the firm.

H2a: Per-customer acquisition costs and per-customer service costs are significantly negatively related to market value for relatively low-growth firms.

H2b: For relatively high-growth firms, the sign of the relations between market value and per-customer acquisition costs and per-customer service costs depends upon whether negative cost effects dominate positive long-term investment effects.

Why could the relations differ depending upon a firm's growth rate? High-growth firms are building their businesses, which typically require more up-front investment. For service firms, this investment is in customer acquisition. Investors may value heavy spending on rapid customer acquisition because it can allow the firms to attain economies of scale or first-mover advantages. Conversely, investors may not value customer acquisition as highly for low-growth firms with more steady-state businesses. Scale or first-mover benefits may be small compared to the benefits of cost efficiency and quality of service to current customers.

Empirical Model for the Value Relevance Method

The regression model to test for the value-relevance of our customer measures is:

$$MV_{jt} = \beta_0 + \beta_1 BV_{jt} + \beta_2 E_{jt} + \beta_3 SPC_{jt} + \beta_4 APC_{jt} + \beta_5 (GROWTH_{jt}*SPC_{jt}) + \beta_6 (GROWTH_{jt}*APC_{jt}) + e_{jt}$$
(1)

where,

MVi	= market value per share of equity,
BV_{it}	= book value per share of equity at the end of the financial period preceding the
5	announcement window,
$E_{it} =$	= earnings per share in the financial period preceding the announcement window,
SPC_{it}	= service expenditure per existing customer,
APC_{jt}	= acquisition expense per new customer,
CDOUTTL	

 $GROWTH_{jt}$ = measure of growth opportunities.

The dependent variable, MV, is the market value of equity one day after the announcement date. Book value of equity BV, measures the accounting value of assets less liabilities at the end of the fiscal period. In line with Rajgopal, Venkatachalam, and Kotha (2003) and Kallapur and Kwan (2004), we include earnings before extra-ordinary earnings, E, as an independent variable. The financial variables are calculated on a per-share basis following the approach adopted by Collins, Maydew, and Weiss (1997) and Francis and Schipper (1999).We test for the value relevance of customer metrics using two measures - service expenditure per existing customer, SPC, and acquisition expense per new customer, APC. These variables reflect the firm's operational efficiency in acquiring and retaining customers.

The direction of the relation between market value and our variables of interest, SPC and APC, could be influenced by growth opportunities. Consequently, our regressions include a GROWTH variable interacted with SPC and APC. Market-to-book ratio, a common measure of growth opportunities is a direct function of the dependent variable; therefore, we follow Goyal, Lehn, and Racic (2002) and use alternate proxies for growth opportunities. They test five commonly used proxies of growth opportunities - the ratio of market to book value of assets, the ratio of market to book value of equity, earnings-to-price ratio, the ratio of capital expenditure to book assets, and the ratio of R&D to book assets. Since the first three proxies are functions of the dependent variable, we test only the last two proxies, adapted for our study as appropriate. One proxy is the change in ratio of capital expenditure to book value of assets, and the other is the change in the ratio of R&D expenditure to book value of assets. From Hypothesis 2, the coefficient estimates (β_5 and β_6) on the GROWTH interaction variables could be positive, if investment effects dominate cost effects.Because we use panel data, our panel regressions include intercept dummies for each firm and each time period to capture firm-specific and time-specific effects.

Earnings Response Coefficient Model

Earnings response coefficients (ERCs) measure the sensitivity of stock returns to earnings surprises. We regress abnormal stock returns (ABRETURN) on unexpected earnings changes (UE), and other information variables of interest (X) as follows;

ABRETURN = $\alpha + \beta_1 * UE + \beta_2 * (X * UE) + \varepsilon$,

where α and β_1 are coefficients, β_2 is a vector of coefficients, and ε is an error term.

A traditional base ERC model would exclude X and simply estimate stock return response to unexpected earnings as ERC = β_1 . The common finding is $\beta_1 > 0$, that is, higher-than-expected earnings generate

positive abnormal returns. The larger the β_1 , the more sensitive a firm's stock return to its earnings surprises.

We add the customer metric variables in X to the model and estimate their coefficients in β_2 . For this discussion, assume that X contains one variable. If $\beta_2 > 0$ ($\beta_2 < 0$) and is statistically significant, then the variable makes a firm's return more (less) sensitive to unexpected earnings Of course, if $\beta_2 = 0$, then the information disclosure has no impact. The interpretation of the sign of β_2 is a bit counter-intuitive. $\beta_2 > 0$ essentially means that a firm's ERC is larger because of the information disclosure. The particular disclosure makes earnings a better signal of the firm's financial prospects. The average level of unexpected earnings could be smaller, but investors react proportionately more to a given level of the firm's financial prospects, and investors react proportionately less. For example, investors should react less to unexpected earnings announced by a firm with poor financial information systems because the earnings will contain more noise.

Hypothesis Development for the ERC Method

Firms invest in customer acquisition and customer service. Reichheld (1996) and Thomas (2001) find that the costs to acquire a customer are significantly greater than the cost of servicing them. But shifting funds from customer service to customer acquisition can produce dissatisfied customers who reduce purchases. Bolton (1998) and Richins (1983) suggest that dissatisfied customers also relate their unfavorable experiences to others, amplifying the direct negative effects that dissatisfied customers have on sales and firm value. Reichheld (1996) and Hughes (2006) find that customer retention critically affects the value of a customer to a firm, and hence, firm value.

Our sample includes firms from different industries and at different growth stages. Therefore, the absolute size of service and acquisition spending may be less informative to investors than their relative sizes. Reichheld (1996) and Thomas (2001) show that the relation between customer retention and customer acquisition is economically significant. Consequently, we use the ratio of service to acquisition spending to measure a firm's spending strategy. Our first ERC hypothesis is:

H3: Firms with larger ratios of service spending to acquisition spending have larger ERCs.

The intuition behind this hypothesis is that spending relatively more on customer service is likely to produce a stable customer base and easy-to-predict earnings. But when a firm reports an earnings surprise, investors are likely to see it as a relatively strong signal that something significant has changed. Therefore, stock returns will be more sensitive to earnings surprises.

Some of our firms report customer metrics monthly, although the majority reports them quarterly. Monthly updates should enable investors to better estimate quarterly earnings before they are announced. Therefore, monthly disclosures should also lead to larger market reactions to earnings surprises and larger ERCs. With similar reasoning, others suggest that higher quality earnings increase ERCs. For example, Balsam, Krishnan, and Yang (2003) and Teoh and Wong (1993) find higher ERCs for clients of industry specialist auditors and large (Big 6) auditors, respectively. Therefore, we hypothesize that:

H4: Firms that report monthly customer metrics have larger ERCs.

Amir and Lev (1996) find significant differences in value effects between telephone companies (low growth firms) and cellular companies (high growth firms). Therefore, the relation between firm value and customer metrics could differ when there is a significant difference in growth opportunities. We hypothesize that:

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H5: The relations proposed in H3 and H4 could differ between firms with high growth opportunities and firms with low growth opportunities.

The intuition behind this hypothesis is that investors could interpret the information conveyed by customer metrics differently depending upon a firm's growth opportunities. We have assumed that a specific value of a customer metric means the same thing across firms but this may not hold perfectly. For example, high growth may be associated with inherently uncertain earnings, and some firms may release monthly figures to help moderate the uncertainty. Therefore, our disclosure frequency indicator variable could pick up this uncertainty effect, so that the effect predicted in H4 may only appear for high-growth firms. Indeed, among our sample of firms, those that disclose monthly have significantly greater growth opportunities than those that disclose quarterly (average market to book value ratio of 6.29 compared to 3.25 for quarterly disclosers).

Empirical Model for the ERC Method

We isolate the impact of the public disclosure of customer metrics on stock returns from the impact of earnings surprises using the following regression model:

$$CAR_{jt} = \alpha_0 + \alpha_1 UE_{jt} + \alpha_2 (STA_{jt} * UE_{jt}) + \alpha_3 (FREQ_{jt} * UE_{jt}) + \alpha_4 (GROWTH_{jt} * STA_{jt} * UE_{jt}) + \alpha_5 (GROWTH_{jt} * FREQ_{jt} * UE_{jt}) + \alpha_6 (MTB_{jt} * UE_{jt}) + \alpha_7 (SIZE_{jt} * UE_{jt}) + e_{jt}$$

$$(2)$$

where, for firm j in time t,

CAR_{it} = earnings announcement cumulative abnormal returns,

UE_{it} = unexpected earnings (earnings surprise),

STA_{it} = ratio of service expenditure per customer to acquisition expense per new customer,

FREQ_{it} = indicator variable for frequency of disclosure,

 $GROWTH_{it}$ = indicator variable for growth opportunities,

 MTB_{it} = control variable for growth opportunities,

 $SIZE_{it} = control variable for firm size.$

The dependent variable CAR_{jt}, is the market model abnormal return in the event window around the firm's earnings announcement. For this short window, the start date is two days before the event and the end date is one day after the event (event window is [-2,1] with day 0 the announcement date). The market model parameters are estimated for the 255-day period ending at the start of the event window. We considered other methods to measure abnormal returns. Additional risk factors such as firm size, value or momentum (incorporated in the Carhart four-factor model) should have little effect on our short-term event study. Some studies calculate an alternate measure of abnormal returns using a matched pair sample. This approach to risk-equalized returns is not possible in our study, since non-disclosing firms would necessarily have to be from another industry with possibly very different risk characteristics (since firms that disclose customer metrics appear to follow industry norms where all firms in that industry disclose).Unexpected earnings UE, is measured as realized earnings per share minus consensus analyst forecasted earnings per share. Some studies have assumed a random walk earnings model, and hence reported earnings change to proxy for unexpected earnings. Others have used ARIMA models for data sets with long time series.

Hypothesis 3 implies that $\alpha_2 > 0$, that is, relatively more service expenditure increases ERCs. To test Hypothesis 3, we define STA as the ratio of service expenditure per customer to acquisition expense per new customer. This definition of STA is in line with papers in the literature that formulate the variable of interest as a ratio or as an indicator variable. This specification partly accounts for firm and time effects in regressions of cross-sectional times-series data. For example, Hughes (2000) tests the value relevance of nonfinancial measures of air pollution using a ratio EMIT (average percentage of SO₂ emitted per year relative to total emissions) and an indicator variable CLIM (annual average of the quarterly *Value Line* assessments of the regulatory environment). Park and Pincus (2001) test the response of equity markets to the mix of equity sources using the ratio of internal equity to external equity.

Hypothesis 4 implies that $\alpha_3 > 0$, that is, monthly disclosure increases ERCs. FREQ is an indicator variable equal to 1 if the firm releases figures monthly, and 0 if it releases them quarterly. We use the market-to-book ratio as a proxy for growth opportunities available to a firm. GROWTH is an indicator variable that takes the value 1 if market-to-book ratio is high (greater than 4), and 0 otherwise (as per Brigham and Ehrhardt (2005) p. 456: "The average company in the S&P 500 had a market/book ratio of about 4.23 in the summer of 2003"). The average for our sample is 4.09. The regression also includes GROWTH interacted with the focus variables STA and FREQ, and then UE, to measure the effect of growth on the relations between ERCs and STA and FREQ. Hypothesis 5 implies that α_4 and α_5 are statistically significant. The ERC relation could be affected by exogenous factors. Easton and Zmijewski (1989) and Collins and Kothari (1989) predict that ERC is negatively related to systematic risk, measured by the beta estimate obtained from the market model. We control for systematic risk by calculating a market-model adjusted CAR. Collins and Kothari (1989) find a positive relation between growth opportunities and ERC. MTB, the ratio of market value of equity to the book value of equity, is included as our proxy for growth opportunities. SIZE, measured by the logarithm of total assets, is included as an additional control. As with our earlier tests, all regressions include intercept dummies for each firm and each time period to capture firm-specific and time-specific fixed effects.

Data Collection and Sample

Customer Metrics: Data are collected for the period of January 1994 to December 2005. Firms are not required to disclose customer metrics, and they are not available in any public database. The data are scarce before 1994; however, investors have increasingly pressured fast-growing service firms to provide it. Many Wall Street firms, such as Salomon Smith Barney and Merrill Lynch, actively track this data and use it in analyst reports to their customers. In fact, Gupta, Lehmann and Stuart (2004) acknowledge receipt of detailed account information from Salomon Smith Barney.

Most customer metrics have to be manually collected, primarily from 10-K, 10-Q filings, and press releases. If a particular press release is not available on the corporate web-site, we attempt to obtain the missing data from other news resources such as Lexis-Nexis, PR Newswire, or through internet search engines Google and Yahoo. Some firms report the number of new customers acquired during a quarter. The variable for customers serviced (SC) is calculated as the difference between total customers at the end of the period and the number of new customers (NC). Our primary measure of NC is the figure reported by the firm; however, not every firm in our sample reports the number of new customers. Consequently, we use the quarterly net change in total customers as an alternate measure of NC.

We faced some challenges in the data collection process because there is no public database that provides these customer metrics or even the names of companies that disclose this information. Furthermore, some provide the data only sporadically; e.g., only if they experienced a significant increase in customer base. Some firms, such as Amazon, provide customer-level data but not in the format required in our model. Many firms, particularly those in the telecommunication industry such as AT&T and Verizon, sometimes

change their computation methods. Because we require consistency of the reported data, firms that do not follow a particular reporting method for an extended period of time are omitted from our sample.

The final sample consists of 31 firms that report the number of customers between fiscal year-ending periods between January 1995 and December 2005. Some firms do not report the number of customers, but they report other metrics that are close proxies. Table 1 lists the specific metric reported by each firm in the final sample. Based on NAICS 2007 industry codes obtained from the COMPUSTAT database, the firms come from 16 service industries including software, broadcasting, telecommunications, internet, brokerage, insurance, rental, programming, consulting, educational, and medical services.

Firm name	Industry*	Metric for number of customers	Time Period	Disclosure frequency	Size (\$M)	M/B	P/E
AMERIGROUP	524114	Membership	2000-2005	Quarterly	759.7	2.61	15.46
Ameritrade	523120	Open client accounts	1998-2005	Monthly	8291.1	6.24	103.47
Career Education	611210	Student population	1999-2005	Quarterly	770.6	4.56	29.14
Centene	524114	Medicaid membership	2002-2005	Quarterly	373.6	3.43	17.44
Charles Schwab	523120	Active client accounts	1995-2005	Monthly	29933.4	7.18	54.74
Coventry Health Care	621491	Health plan membership	2000-2005	Quarterly	2138.3	2.98	15.96
DeVry	611310	All enrollments	1994-2005	Monthly	487.0	7.61	36.07
DIRECTV	515210	U.S. subscribers	2004-2005	Quarterly	15488.7	2.75	61.39
E*Trade	523110	Active accounts	1998-2005	Monthly	20367.6	2.79	49.62
eBay	517919	Confirmed registered users	1998-2005	Quarterly	3856.0	20.83	355.59
EchoStar		6					
Communication	517510	Subscribers	1998-2005	Quarterly	5490.5	-9.67	124.59
eCollege	541511	Distance student enrollments	2000-2005	Quarterly	67.0	4.89	205.50
eLoyalty	541611	Customers	1999-2005	Quarterly	99.3	1.94	NA
Health Net	524114	Health plan membership	2001-2005	Quarterly	3572.3	2.68	32.61
Humana	621491	Medical membership	1999-2005	Quarterly	4933.6	1.61	17.19
Insight Communications	515210	Revenue generating units	2000-2005	Quarterly	3657.4	1.22	NA
Interwoven	511210	Customers	2000-2005	Quarterly	382.8	3.33	423.50
iPass	561990	Forbes Global 2000 customers	2003-2005	Quarterly	225.5	2.66	24.84
Molina Healthcare	524114	Medical membership	2003-2005	Quarterly	499.6	3.05	23.30
National Discount Broker	523120	Customer accounts	1999-2000	Monthly	377.3	2.41	19.63
Netflix	532230	Subscribers	2000-2005	Monthly	208.7	7.17	467.33
SIRIUS Satellite Radio	515112	Subscribers	2002-2005	Monthly	1703.0	5.79	NA
Strayer Education	611310	Student enrollments	1998-2005	Quarterly	144.5	11.45	31.54
TD Waterhouse	523120	Active accounts	1999-2001	Monthly	10148.8	2.58	37.79
UnitedHealth	524114	HealthCare&Unipri membership	1997-2005	Quarterly	15073.9	4.52	20.09
Webstreet	523120	Active accounts	2000-2001	Monthly	79.60	2.19	NA
WellChoice	524114	Medical membership	2003-2005	Quarterly	3257.2	2.27	17.16
WellPoint	524114	Medical membership	1997-2004	Quarterly	21658.5	1.99	14.94
WellPoint	524114	Medical membership	2002-2005	Quarterly	7868.8	3.23	16.15
Western Wireless	517210	Global subscribers	1996-2005	Quarterly	1982.1	-6.36	78.08
XM Satellite Radio	515112	Subscribers	2000-2005	Monthly	1623.0	14.36	NA

Table 1: Sample Description

List of the 31 firms in our sample with descriptive data and the reported metric used to measure the number of customers. Industry classification is based on NAICS 2007 industry codes obtained from the COMPUSTAT database. Sample covers fiscal year-ending periods between January 1995 and December 2005. For each firm, we report sample period, disclosure frequency, firm size (measured as average total assets), average market-to-book ratio M/B, and the average price-earnings ratio P/E.

The firms range in size from eCollege with \$67 million average book value of assets to Charles Schwab with \$29933 million average asset value, with a median firm size of \$1982 million. The median market-to-book (M/B) ratio of sample firms is 2.98, and ranges from -9.67 for EchoStar to 20.83 for eBay. In fact, only two of our 31 firms have positive M/B ratios less than the median U.S. firm's ratio of 1.77 (the ratio of market price to book value of equity for U.S. stocks is the average obtained from the 50th

percentile of price to book values from 1995 to 2005 using data from Kenneth French's website.). EchoStar and Western Wireless have negative M/B ratios, reflecting write-offs leading to negative book values. Firms have price-earnings (P/E) ratios ranging between 14.94 for WellPoint to 467.33 for Netflix, with a median P/E ratio of 30.34 (Since negative price-earnings multiples are not meaningful, we do not report P/E ratios for 5 firms in our sample.). Table 1 also lists the disclosure frequency for each firm (monthly or quarterly).

Financial Metrics

The financial accounting data for January 1994 through December 2005, such as revenues, customer acquisition expenditure, and service expenditures, are obtained from the firm's press releases and SEC filings. The stock market data, such as daily stock returns, are obtained from the Center for Research in Security Prices (CRSP) database. Data to calculate the other financial accounting variables such as book value, earnings, size, and the various growth proxies are obtained from the COMPUSTAT database.

Realized earnings and forecasted earnings, measured by median analyst forecast of EPS immediately before the announcement date, are obtained from the First Call and I/B/E/S databases. Realized earnings, as reported in First Call and I/B/E/S, are un-restated earnings; thus represent the actual reported figure on the announcement date. For a variety of reasons (e.g., incorrect reporting or non-reporting of estimate changes) analyst estimates in the First Call or I/B/E/S databases may be inaccurate. Hence, we used median value of consensus estimates to calculate unexpected earnings. These are used to compute unexpected earnings, UE. Realized earnings were obtained from First Call, and augmented with data from I/B/E/S if necessary. The median analyst consensus estimates are listed in First Call Summary Statistics. If the statistic was not listed in this form, we calculated the necessary statistics from analyst's individual estimates in First Call or I/B/E/S. In line with Gupta, Lehmann, and Stuart (2004), we use selling and marketing expenses reported by the firm to proxy for customer acquisition expenditure. This is not a precise measure, since some portion of this expense may go towards customer service. Nevertheless, several studies have found that the proportion of marketing-related expenditure directed toward customer acquisition is significantly higher than that directed toward customer retention (Reichheld 1996). Thomas (2001) estimates that it takes twelve times more marketing spending to acquire a customer than it does to retain them (initial acquisition cost per customer to be \$26.94 versus annual retention cost per customer of \$2.15). Firms do not report any directly identifiable measure of customer service expenditure. One could argue that the service industry firms that make up our sample invest primarily in acquiring customers and in serving them. Consequently, our measure of customer service expenditure is calculated as the difference between total operating expenditure and marketing expenditure. Our measure of customer service and customer acquisition is a break-up of the "organization capital" studied by Lev and Radhakrishnan (2005). They find that this measure is relevant to measuring firm value, but financial analysts may not fully incorporate it in valuations since it does not appear on financial statements.

EMPIRICAL RESULTS

Value Relevance Model

The final merged database of our hand-collected data, CRSP data, and COMPUSTAT data has 170 observations when using our first measure of new customers, NC. These are cases where the company discloses the number of new customers. The alternative measure, quarterly net change in total customers, provides 517 observations because it can be calculated for all firms. Table 2 reports summary statistics for the variables in our empirical model. As expected, the market values of firms in our sample greatly exceed their book values. Also, the median values of both our GROWTH variables are positive, indicating that firms in our sample increase investments in capital expenditures and R&D relative to their book values. Since few firms disclose quarterly R&D numbers, the alternate measure of our GROWTH

variable has fewer observations. Though the median service cost per customer (SPC) is \$287, it ranges from \$9 per customer to \$3.6 million per customer. Similarly, when using change in total customers to measure new customers, acquisition costs per customer (APC) varies between -\$2.0 and \$5.4 million per customer, with a median \$727 spent per customer. When using the quarterly net change in total customers, may get negative APC figures if the number of total customers declines. For the smaller sample of firms that report new customers, the range for APC is \$30 to \$2 million with a median of \$272.

Table 3 reports regression tests of the value relevance model in equation (1) for each measure of NC separately. The growth variable (GROWTH) is defined as the change in ratio of capital expenditure to book value of assets. As expected, we find a positive relation between market value (MV) and book value (BV). The relations are significant at the 1 percent level for both measures of NC. Also, as expected, we do not find a significant relation with earnings E.

We find only weak evidence supporting hypotheses 1 and 2. First, SPC and APC are significantly related to market value, but only for high growth firms when we use our more inclusive measure of new customers. For high-growth firms, investors mark down stocks with high service costs and mark up stocks with high acquisition costs. This could mean that investors believe that high service costs indicate operating inefficiencies, while the negative effects of high acquisition costs are swamped by the positive long-term investment benefits of customer acquisition. At least for our sample, spending more to acquire customers pays off.

Variables	Observations	Median	Mean	Standard Deviation	Minimum	Maximum
MV	605	28.420	36.352	30.955	0.6400	241.250
BV	605	6.855	8.410	10.153	-59.994	65.579
Е	605	0.1200	0.1487	0.4570	-1.760	1.970
SPC (\$1000)	598	0.2867	94.632	400.44	0.0090	3625.8
APC (\$1000) - NEW CUSTOMERS	183	0.2720	86.481	296.70	0.0304	2037.8
APC (\$1000) - TOTAL CUSTOMERS	584	0.7273	1210.06	5179.10	-2049.6	54100.0
GROWTH - CAPEX	580	0.0029	0.0002	0.0349	-0.3110	0.1245
GROWTH - R&D	124	0.0001	-0.0002	0.0055	-0.0351	0.0298

Table 2: Summary Statistics of the Various Variables Used in Value Relevance Regression Model

The model is: $MV_{jt} = \beta_0 + \beta_1 BV_{jt} + \beta_2 E_{jt} + \beta_3 SPC_{jt} + \beta_4 APC_{jt} + \beta_5 (GROWTH_{jt}*SPC_{jt}) + \beta_6 (GROWTH_{jt}*APC_{jt}) + e_{jt}$ The variables are defined as market price per common share MV, book value per share of common equity BV, earnings per share E, service cost per (total) customer SPC, and acquisition cost per new customer APC. New customers used to calculate APC is measured in two ways, (1) number of new customers reported by some firms, and (2) quarterly change in total customers reported by all firms in our sample. GROWTH indicates growth opportunities available to the firm measured in two ways, (1) the change in the ratio of capital expenditure to book value of assets. The sample includes panel data for 31 firms covering quarterly financial periods between January 1995 and December 2005.

We also tested the model using the alternate measure of GROWTH (the change in ratio of R&D to book value of assets). Unfortunately, few firms in the COMPUSTAT database report quarterly R&D, which significantly reduces our sample sizes. Results using the smaller samples are similar to those presented in Table 3. We also tested the value relevance model using gross, rather than per share MV, BV and E. The results were essentially the same. Compared to a levels model like the value relevance model, a change model like the ERC model could provide stronger tests of the relations because it relies on incremental changes measured during a short event window. The abnormal return used as the independent variable should isolate the effects of the variables of interest more precisely.

	Estimates Us	Estimates Using Alternative Measures Of New Customers				
Independent Variables	New Customers As Rep	New Customers As Reported By Firms				
BV	2.509 (5.34)	***	1.395 (8.94)	***		
E	-2.893 (-0.67)		-1.568 (-0.53)			
SPC #	3.420 (0.20)		0.001 (0.16)			
APC *	-0.001 (-0.61)		0.001 (0.33)			
GROWTH*SPC [#]	-3.513 (-0.21)		-1.682 (-2.30)	**		
GROWTH*APC #	0.766 (0.21)		1.630 (1.76)	*		
Intercept	69.139 (5.21)	***	40.236 (2.72)	***		
Adjusted r-squared Observations	0.631 170		0.372			

 Table 3: Regression Results of the Value Relevance Model

The model is: $MV_{jt} = \beta_0 + \beta_1 BV_{jt} + \beta_2 E_{jt} + \beta_3 SPC_{jt} + \beta_4 APC_{jt} + \beta_3 (GROWTH_{jt}*SPC_{jt}) + \beta_6 (GROWTH_{jt}*APC_{jt}) + e_{jt}$. The dependent variable is the market price per common share MV. The independent variables are book value per share of common equity BV, earnings per share E, service cost per (total) customer SPC, and acquisition cost per new customer APC. New customers used to calculate APC is calculated in two ways, (1) number of new customers reported by some firms, and (2) quarterly change in total customers reported by all firms in our sample. Results using the former calculation are reported in the first column, and the latter calculation in the second column. The control variable GROWTH indicates growth opportunities available to the firm, measured as the change in ratio of capital expenditure to book value of assets. Student t-statistics are reported in parentheses. Sample includes panel data for 31 firms covering quarterly financial periods between January 1995 and December 2005. Both regressions include dummy variables for each firm and each year (not reported in table to save space). *, **, *** indicate significance at the 10%, 5% and 1% level respectively. [#]Divide estimate by 10,000.

Earnings Response Coefficient Model

Table 4 lists descriptive statistics for the variables used in tests of the ERC model. Because percent changes are used, there is one less observation for each firm in the database. Firms that report customer metrics monthly make up 28.4 percent of the observations in our sample. Most firms in the sample have positive earnings surprises (UE) with a median (mean) surprise of 1 cent per share (1.8 cents per share). As expected, this surprise is impounded in stock prices with a median (mean) positive cumulative abnormal return of 0.44 percent (0.404 percent) around the announcement date.

The ratio of service to acquisition costs, STA, for the smaller sample of firms that report new customers, has a median value of 0.345 (mean of 0.476), confirming that firms spend considerably less servicing existing customers than acquiring new ones. Using our alternate measure of new customers (the quarterly net change in total customers), the median value is 0.127 (mean of 0.216). High-growth opportunities firms' observations comprise 33.4 percent of the sample.

Table 5 reports regression results for the ERC model using the smaller sample of firms that report new customers. The sample contains 163 firm-quarter observations. For robustness, we report results for two specifications; one with GROWTH defined as a continuous variable and the other with GROWTH defined as an indicator variable. As expected, UE and cumulative abnormal returns (CARs) are positively related. The relation is significant (p-value < 0.01) using the GROWTH indicator variable. And as predicted in Hypotheses 3, firms with larger STAs have larger ERCs. But inconsistent with Hypothesis 4, we find firms that disclose more frequently have smaller ERCs. But the negative estimates on FREQ are statistically weak (p-value < 0.10 using the continuous GROWTH variable and insignificant otherwise).

Variables	Observations	Median	Mean	Standard deviation	Minimum	Maximum
CAR	584	0.0046	0.0040	0.1125	-0.6579	0.7315
UE	605	0.0100	0.0180	0.1451	-0.7200	1.950
STA - New Customers	183	0.3448	0.4757	0.3861	0.0443	2.241
STA - Total Customers	584	0.1274	0.2165	0.6525	-3.266	5.027
FREQ	584	0.0000	0.2842	0.4514	0.0000	1.000
GROWTH - Continuous	605	2.941	4.089	13.469	-94.632	181.07
GROWTH - Discrete	605	0.0000	0.3338	0.4719	0.0000	1.000
Size	605	21.898	21.537	1.769	16.932	24.663

Table 4: Summary Statistics of the Variables Used in the Earnings Response Coefficient (ERC) Model

The model is: $car_{jt} = a_0 + a_1ue_{jt} + a_2(sta_{jt}*ue_{jt}) + a_3(freq_{jt}*ue_{jt}) + a_4(growth_{jt}*sta_{jt}*ue_{jt}) + a_5(growth_{jt}*freq_{jt}*ue_{jt}) + a_6(mtb_{jt}*ue_{jt}) + a_7(size_{jt}*ue_{jt}) + a_{jt}$ e_{jt} The variables are the cumulative abnormal return CAR over daily event window [-2,1], unexplained earnings (or earnings surprise) UE, the ratio of service cost per total customers to acquisition cost per new customer STA, and the frequency of disclosure of customer metrics by the firm FREQ. New customers used to calculate STA is measured in two ways, (1) number of new customers reported by some firms, and (2) quarterly change in total customers as reported by all firms in our sample. FREQ is an indicator variable that takes the value 1 if the firm discloses these metrics on a monthly basis, and 0 otherwise. GROWTH indicates growth opportunities available to the firm measured as the market-to-book ratio (for the continuous form). An alternate discrete measure of GROWTH takes the value 1 if market-to-book ratio (growth opportunities) is high (greater than 4), and 0 otherwise. In line with earlier studies, the market-to-book ratio MTB, and the natural logarithm of assets SIZE are included as control variables. The sample includes panel data for 31 firms covering quarterly financial periods between January 1995 and December 2005.

Table 5: Regressions Results of the Earnings Response Coefficient (ERC) Model Using New Customers Measured as the Number of New Customers Reported by Some Firms

	Estimates Using Alternative Measures Of Growth			
Independent Variables	Continuous Growth	Discrete Growth		
UE	7.225 (1.60)	12.073 *** (2.75)		
STA*UE	4.506 ** (2.27)	2.446 * (1.90)		
FREQ*UE	-1.458 * (-1.72)	-0.399 (-0.65)		
GROWTH*STA*UE	-0.683 ** (-2.42)	-3.499 ** (-2.03)		
GROWTH* FREQ*UE	0.435 (2.29) **	2.323 ** (2.02) **		
MTB*UE	0.229 *** (2.77)	0.049 ** (2.23)		
SIZE*UE	-0.365 * (-1.89)	-0.548 *** (-2.83)		
Intercept	0.041 (0.35)	0.156 (1.33)		
Adjusted R-Squared	0.188	0.171		
Observations	163	163		

The model is : $car_{ji} = a_0 + a_1ue_{ji} + a_2(sta_{ji}*ue_{ji}) + a_3(freq_{ji}*ue_{ji}) + a_4(growth_{ji}*sta_{ji}*ue_{ji}) + a_5(growth_{ji}*freq_{ji}*ue_{ji}) + a_5(steq_{ji}*ue_{ji}) + a_5(ste_{ji}*ue_{ji}) + a_5(ste_{ji}*ue_{ji$

As predicted in Hypothesis 5, these relations differ between high growth and low growth firms using either GROWTH variable. Indeed, the signs of the relations may differ between high and low growth

firms. The positive relation between STA and ERCs is weaker and perhaps negative for high growth firms. And the negative relation between FREQ and ERCs is weaker and perhaps positive for high growth firms. One can interpret these results as follows. Relatively high service spending makes low growth firms earnings more predictable, but this may not hold for high growth firms. And firms that disclose more frequently could have inherently less predictable earnings (whether they are high growth or not), but more frequent disclosure by high growth firms significantly moderates their earnings uncertainty. Indeed, Fraser, Tarbert, and Tee (2009) find that that stock return response to financial news is lower on average for industries with relatively high intangible assets. Our sample is composed of relatively high growth companies that typically have greater intangible assets; hence, we could be picking up the same negative effect. Furthermore, it makes sense that the firms with the least predictable earnings would respond by issuing customer metrics monthly instead of quarterly.

Finally, the signs of the estimates on the control variables MTB (positive and significant) and SIZE (negative and significant) are in line with results from previous studies. Table 6 reports test results for the ERC model using the change in total customers as an alternate measure of NC. The sample is much larger (504 observations). Overall, the results from the larger sample are statistically weaker, perhaps because the change in total customers is a noisy proxy for the true number of new customers. The change in total customers new customers with customers lost due to attrition. Nevertheless, relations between CAR and UE, MTB, and SIZE are maintained. But STA and FREQ no longer have a statistically significant impact on ERCs, except for high growth firms.

Estimates Using Alternative Measures of Growth				
Independent Variables	Continuous Growth	Discrete Growth		
UE	2.830 ** (2.41)	2.441 ** (2.11)		
STA*UE	-0.270 (-1.64)	-0.248 (-1.52)		
FREQ*UE	0.206 (1.30)	0.144 (0.94)		
GROWTH*STA*UE	-0.055 (-2.19) **	-1.151 ** (-2.17)		
GROWTH* FREQ*UE	0.024 (1.08)	0.820 ** (2.09)		
MTB*UE	0.009 **	0.001 (0.68)		
SIZE*UE	-0.119 ** (-2.28)	-0.099 * (-1.95)		
Intercept	-0.011 (-0.10)	-0.010 (-0.09)		
Adjusted R-Squared	0.091	0.089		
Observations	504	504		

Table 6: Regressions Results of the Earnings Response Coefficient (ERC) Model Using New Customers Measured as the Quarterly Change in Total Customers

The model is: $car_{jt} = \alpha_0 + \alpha_t ue_{jt} + \alpha_2(sta_{jt}^*ue_{jt}) + \alpha_3(freq_{jt}^*ue_{jt}) + \alpha_4(growth_{jt}^*sta_{jt}^*ue_{jt}) + \alpha_5(growth_{jt}^*freq_{jt}^*ue_{jt}) + \alpha_5(mtb_{jt}^*ue_{jt}) + \alpha_5(mtb_{jt}^*ue_{jt}) + \alpha_5(ste_{jt}^*ue_{jt}) + \alpha_5(ste_{jt}^*ue_{jt}) + \alpha_5(ste_{jt}^*ue_{jt}) + \alpha_5(mtb_{jt}^*ue_{jt}) + \alpha_5(ste_{jt}^*ue_{jt}) + \alpha_5(ste_{jt}^*ue_{jt}$

Robustness Tests

We ran additional tests to examine the robustness of our results. Overall, we found the results to be quite robust. First, we re-ran all of the regressions and included industry dummies along with the time and firm-specific dummies. We found a significant change in the intercepts but nothing else. Second, we ran the regressions after excluding observations with negative earnings. Results were little changed. Finally, we tested whether customer metrics drive analyst earnings estimates. We found no significant relations between changes in our metrics and changes in mean analyst earnings estimates. This is a bit surprising because we know that some analysts discuss customer metrics in their investment reports to clients. Nevertheless, Tables 3, 5, and 6 show that customer metrics help explain firm value, even in the presence of traditional financial metrics such as earnings, book value, and earning surprises. Indeed, customer metrics are incrementally informative, particularly for high growth firms.

CONCLUSIONS

We test for the information content of customer metrics, as compared to earnings, book value and analyst estimates. We test whether investors use customer metrics to value high growth service firms. Customer metrics are now more frequently reported by firms and tracked by Wall Street analysts. Specifically, we test for the effects of customer metrics on firms' market values and stock price changes using the value relevance and earnings response models.

We use data on customer metrics for 31 firms from 1994-2005 obtained primarily through manual collection from 10-K and 10-Q filings, and press releases. Our hypotheses are tested using the value relevance and the earnings response coefficient (ERC) models. Since the value relevance model examines stock prices and the ERC model examines stock returns, their findings may complement each other.Results using the value relevance model are relatively limited, perhaps because the model relies on variables measured in levels as opposed to changes (see Holthausen and Watts (2001) and Kothari and Shanken (2003) for comprehensive critiques of the value-relevance models). Nevertheless, we find some evidence that investors boost the stock prices of high growth firms that spend more on customer acquisition, and discount the stock prices of high growth firms that spend more on customer service.

A change model like the earnings response model may better identify the marginal relations between firm value and customer metrics because our sample includes many high growth firms where change is the norm. Indeed, the earnings response model results largely support our hypotheses. A firm's ratio of customer service to acquisition spending and their disclosure frequency both significantly affect their earnings response coefficients (ERCs), showing that each affects firm value.

We also find that value effects can differ between high growth and low growth firms. The effects are in the expected direction, except for the effect of disclosure frequency, which is weakly negatively related to ERC. One would expect greater disclosure to reduce earnings uncertainty, making investors more sensitive to any earnings surprise. One possible explanation of these results is that firms with inherently uncertain earnings are more likely to disclose frequently, so that our frequency indicator variable picks up this unobservable uncertainty. This explanation is consistent with the fact that frequent disclosers are the higher growth firms, on average. Furthermore, we find that the negative effect can actually be reversed for high growth firms, that is, frequent disclosure improves high growth firms' earnings predictability, even if their earnings are naturally more uncertain than those of other firms.

Our results show that customer metrics are relevant in firm valuation, and when applied alongside traditional financial performance measures, better explain firm value, particularly for high-growth service firms. Further research is needed to identify efficient proxies for the number of new customers. While many firms report some measure of total customers, few firms report that for the number of new

customers. Another proxy would validate our theoretical model for a larger sample of firms, and more accurately measure the value of intangible customer assets.

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