Do Customer Acquisition Cost, Call Usage and Customer Retention Matter in the Wireless Industry?

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Abstract

The paper studies the valuation role of financial and non-financial information by examining a rich set of proprietary performance measures for the wireless communication industry during the period 1997-2004. We utilize a structural approach which links marketing fundamentals of customer acquisition cost, customer retention and call usage to financial performance and valuation. We provide evidence suggesting that customer acquisition cost positively affects retention rates and that both customer acquisition cost and call usage are important indicators of profitability. In addition, customer acquisition cost and customer retention are shown to be positively associated with firm value. Notwithstanding these findings, although the wireless communication industry is characterized by rapid pace of technological and commercial change, fundamental accounting numbers are found to be value relevant on a stand alone basis.

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1. Introduction

Customer relationships are a key value driver of branding in many industries, especially in service sectors, such as retail, banking, healthcare and telecommunication, to name a few. Companies incur costs and invest time and effort to acquire customers and enhance customer satisfaction in order to retain them. Yet, these activities receive little reflection in financial statements. Furthermore, to the extent that any disclosure is provided, it is not typically done in a consistent fashion.

In a seminal study, Amir and Lev (1996) show that traditional financial measures, such as earnings and book value of equity, were value irrelevant in the wireless communication (mobile carrier) industry, suggesting the failure of the accounting model to capture value in science-based, high growth sectors. Combining certain non-financial indicators with accounting measures, however, resulted in a model in which the accounting variables became value relevant. The authors therefore concluded: "This finding demonstrates the *complementarity* between financial and non-financial information, as well as indicates that the traditional focus of accounting researchers on the former is overly restrictive and may lead to unwarranted conclusions."

Amir and Lev's (1996) paper inspired a stream of subsequent research into the role of non-financial information in a variety of industries, such as the airline, banking and internet. Broadly, these studies confirmed the usefulness of non-financial information in valuation. Yet, the literature has left a few intriguing questions unanswered. First, does the lack of value relevance of earnings and book value of equity hold in the more mature, but still fast growing, wireless industry? The possibility of finding evidence to the contrary, which may attenuate the claim that the accounting model fails in science-based, high-growth sectors, thus warrants re-examination of this industry. Second, although customer acquisition is a routine capital intensive activity for many corporations, the academic literature has largely been silent

with regard to the valuation implications of customer acquisition cost (*CAC*), probably due to a lack of lacking direct data. That is, little is known whether investing in it is a financially fruitful strategy.[1] The common wisdom among marketing professionals is that it costs far less to retain a customer than to acquire a new one (Coyles and Gokey, 2005). This raises the question whether *CAC* is negatively related to future costs and therefore positively associated with future operating profit, and if so, is this reflected in share prices? Exploring this issue could inform valuation models used by analysts in service-based industries, because forecasting financial statements relies on assessing future operating profits (Palepu, Healy and Bernard, 2004). In addition, it can provide direct information to managers on the potential financial benefits of investments in customer acquisition. Third, while it has been recognized in the marketing literature that customer retention (*CR*) is a crucial objective for customer relationship management (e.g. Bolton, 1998, and Gustafsson, Johnson, and Roos, 2005), both the accounting and marketing literatures provide little evidence on the determinants of *CR* and the link between *CR* and financial performance and valuation.

To address these interrelated questions, following Nagar and Rajan (2005), we employ a process-based approach to financial performance and value creation in which customer retention (the inverse of churn rate), usage, financial performance and valuation are linked as follows. First, customer retention is conjectured to be influenced by customer acquisition cost and average price per minute (*PPM*). Usage, measured as minutes of use per subscriber (*MOU*), is in turn determined by customer retention and prices. Finally, a firm's revenues, profitability, and market value are conjectured to be a function of *CR*, *MOU*, *PPM*, and *CAC* as well as earnings and book value of equity.

We collect a rich set of non-financial metrics from a proprietary industry data provider for publicly listed US and Canadian wireless firms for the period 1997-2004. The data indicate that the wireless industry has experienced significant change and growth during the sample period. Price per minute has

[1] Irrespective of practitioners' view of customer acquisition costs as an asset, for accounting purposes, they are regarded as advertising expenses, not as an asset. The authoritative standard on the treatment of advertising cost, AICPA's Statement of Position (SOP) 93-7, requires that such costs be expensed in the period in which they are incurred.

declined sharply, while usage has increased quite dramatically. This is due partly to greater product penetration, as evidenced by the evolution in subscriber numbers, and partly to technological advances. The magnitude of technological change is demonstrated by the significant shift from analogue to digital technology usage over the sample period. While 50% of subscribers used analogue technology in 1997, all but three percent used the more advanced digital technology by 2004.

The findings from our analyses show that current revenues and operating profit are positively associated with future revenues and future operating profit, respectively, up to six quarters ahead. This is in contrast to the popular view that in fast-changing industries accounting variables cannot be used on their own (i.e. without non-financial information) to assess future performance. The relationship between current and future financial performance persists when customer acquisition cost, customer retention and call usage are added as explanatory variables. The additional variables are largely insignificant in predicting future revenues but they increase the regression explanatory power for future operating profit. Specifically, *CAC* is positively associated with future operating profit in all six quarters. Based on the documented positive relation of *CAC* with future profits and the lack of association with future revenues, we conclude that greater investment in *CAC* likely increases future profitability because it reduces future costs. We also find that call usage is positively associated with future operating profits.

The value relevance of the accounting variables on a stand alone basis is also supported by market-based analysis. In contrast to Amir and Lev (1996), we find that operating profit and book value of equity are positively and significantly associated with market value. This also holds when a full valuation model incorporating non-accounting variables is examined. To the extent that the wireless industry has kept evolving, the difference in findings between the current sample period and the one originally reported by Amir and Lev (1996) is striking.[2]

[2] There exist some incomplete theories about the change in the valuation role and the predictive power of accounting variables along a firm's life cycle – from growth to maturity to decline (see, for example, Black, 1998)). In essence, these suggest that as growth opportunities vanish, accounting numbers would become more value relevant. However, we do not believe that the wireless industry in our sample period could be characterized as mature. We leave this issue to be explored in further research.

Using a structural approach we find that customer retention is positively related to customer acquisition cost. This suggests that greater investment in customer acquisition cost leads to a higher retention rate. To assess the path through which *CR* potentially influences other performance measures (e.g. usage, revenues or profits), we distinguish between its predicted and unpredicted elements. The predicted (unpredicted) component of *CR* is the fitted (residual) value from a regression of *CR* on its postulated determinants. Capturing a significant association between residual *CR* and a performance measure thus indicates an incremental effect of *CR* strategies employed by managers other than those modeled here (e.g. *CAC*). We do not find evidence supporting a positive relation between residual *CR* and either current usage or future operating profit. However, we do find evidence suggesting that residual *CR* is positively related to revenues five and six quarters ahead. We also find that *CR* is relevant for the explaining the share prices of loss-making firms. Thus, it can be argued that residual *CR* has a delayed effect on revenues and is a value indicator when earnings are less informative. Overall, the evidence highlights the importance of managing fundamentals such as *CAC* for obtaining high *CR* to achieve financial objectives, defined in terms of revenues and profitability. Other strategies to enhance *CR* may have only limited impact on revenues and profitability, as suggested by the lack of consistent association between residual *CR* and these financial measures.

Using a similar approach for *MOU*, we find that residual *MOU* exhibits a positive association with future operating profit for these time horizons. This indicates that there are methods used by wireless firms, in addition to investment in *CAC*, that may create a link between usage and future profitability. Nonetheless, the evidence is consistent with the postulated structure, whereby higher usage leads to greater profitability.

The findings reported here extend the literature by offering a number of interesting implications. First, from a valuation perspective, accounting variables seem to play an important role even in an environment where they are not expected to be meaningful by common wisdom. This insight should be useful to analysts, investors and other external users alike. It may also inform executives concerned with predicting future performance for internal purposes, such as budgeting. Second, many executive

compensation schemes employ a number of non-financial indicators based on the belief that accounting variables do not reflect changes in the business environment in a timely manner. Such schemes typically blend accounting and other variables to align managerial incentives with shareholders' interest. However, the choice of variables and the weights assigned to them likely varies across settings and circumstances (Bushman, Indjejikian and Smith, 1996 and Ittner, Larcker and Rajan, 1997). The analysis provided here may thus be helpful for the design of such schemes in the wireless industry. For example, the regression coefficients may be indicative of potential weights to be placed on accounting and non-financial performance measures. More specifically, the analysis shows that adding a number of non-financial measures may improve the explanatory power of a simple model based on accounting numbers only quite modestly, depending on the accounting performance measures used and the association period examined. In light of the findings of Said, HassabElnaby and Wier (2003) that over-investment in non-financial measures is associated with weaker future return-on-assets and current market-adjusted returns, this observation cautions against over-emphasizing non-financial measures in compensation schemes in fast-changing industries. Third, one important contribution of our study is that we analyze potential drivers of *CR* as well as the role of *CR* as a performance indicator. Specifically, the evidence suggests that customer retention is determined by factors such as customer acquisition cost and market share. However, once controlling for its determinants and current profitability, we find that *CR* has no predictive power for future profits.

The paper proceeds as follows: Section 2 provides the literature review. Section 3 presents the main model, whereas Section 4 discusses the data and the research design. Section 5 provides the results of the empirical analyses and Section 6 concludes.

2. Prior Literature

Following Amir and Lev (1996) the literature on the information content of non-financial performance indicators has been primarily concerned with exploring contexts where the role of financial statements is expected to be limited, such as the internet industry in its early stage. Trueman, Wong and Zhang (2000)

perform a joint test of financial and non-financial variables and show that measures of internet usage such as page views are indeed value drivers. Demers and Lev (2001) apply factor analysis to conclude that all web traffic factors are value relevant throughout the short period of their analysis (1999 and the first quarter of 2000). While these studies show a positive relation between non-financial measures and firm value, the burst of the internet bubble cast serious doubt as to the robustness of these relations in the long-term.[3]

Relatively few studies so far have attempted to investigate the valuation role of customer satisfaction measures and customer retention. To the best of our knowledge, none has directly examined the potential effect of customer acquisition cost on customer retention and subsequent financial performance in a large sample. Though the marketing literature distinguishes between satisfaction and retention (i.e. actual customer behavior), data on actual behavior are scarce. Thus, most marketing studies focus on the link between survey data of satisfaction and intentions, where the latter serves as a surrogate for behavior. Bolton (1998), however, points out that there are fundamental problems with this approach, especially with the predictive validity of intentions as expressed in surveys.

Ittner and Larcker (1998) provide some evidence that customer satisfaction measures are leading indicators of accounting performance and are positively associated with stock returns. However, their study employs a number of small different samples (some tests are based on one telecommunication firm and some on one bank) and an index of customer satisfaction based on survey data for very large firms. Their findings on the ability of customer satisfaction to predict future financial performance are mixed. Banker, Potter and Srinivasan (2000) examine customer satisfaction in the case of 18 managed properties of a single hotel chain. They define customer satisfaction by the likelihood of return, which is measured on the basis of customer answers on a feedback card. They also measure customer satisfaction by the number of complaints. Whereas the former measure exhibits an association with future financial performance, the

[3] Within more traditional industries, Liedtka (2002) shows that non-financial performance indicators are value relevant in the airline industry, and Nagar and Rajan (2001) examine the future sales implications of product quality measures for 11 plants of a manufacturing company. The release of industry-wide information is found to be value relevant by Chandtra et al (1999), who examine reports on aggregate new orders and shipments in the semi conductors industry, and by Hughes (2000) who is concerned with the impact of air pollution measures on the value of electric utility companies.

latter does not. Behn and Riley (1999) develop a proxy for customer satisfaction in the airline industry that is based on operating measures, such as on-time arrivals and lost bags. They find that this proxy, along with other non-financial performance indicators, is contemporaneously and significantly associated with operating income, revenues and operating expenses. However, their regression analysis does not control for traditional accounting measures, such as current and previous periods' income. Therefore, their study is silent on the incremental valuation role of customer satisfaction beyond that of traditional accounting measures. In addition, they do not explore the relation between customer satisfaction and long-term performance.

Bolton (1998) employs a customer satisfaction survey of a single US wireless company to find that higher survey satisfaction measures relate positively to longer relationship duration (i.e. they are negatively related to "churn", or, customer turnover). Nagar and Rajan (2005) build on the marketing literature (e.g. Bolton and Lemon, 1999) and propose a process-based approach to assess the impact of customer satisfaction in the banking industry. In their model, prices and service result from customer satisfaction: customer satisfaction leads to a greater use of banking services and profits increase in customer usage and customer satisfaction, after controlling for related costs. Using survey data for the US banking sector in 1994, they find that customer satisfaction is positively related to next period's earnings, after controlling for current period's earnings. As detailed in the following section, we modify Nagar and Rajan's (2005) model to incorporate a rich and unique dataset available for the wireless industry over a recent eight-year period. We extend Nagar and Rajan (2005) by investigating previously little-explored performance and valuation implications of customer retention and customer acquisition cost. Compared to the overall literature, we use a relatively long time period that spans both the bull market and the bear market after the 2000 crash and, and hence the findings are likely to be less susceptible to specific trends, fashions or bubbles in the stock market.

3. The Model

The process-based approach outlined below postulates some causal relationships between certain fundamental non-financial performance measures and financial indicators. The specific variable selection is guided by the nature of the proposed model, our reading of annual reports and analysts' reports as well as prior literature. Still, this model should be seen as exploratory in nature.

The first set of relations in the model posits that customer retention (*CR*) is a function of customer acquisition cost (*CAC*), unit price and market share of the operator. In the wireless industry free or reduced-cost handsets constitute a major component of *CAC*. It is quite plausible that the greater the handset "subsidy", the greater the customer's satisfaction is with the service, all else being equal. Bolton (1998) recommends establishing customer satisfaction at an early stage because it could lead to greater retention. Therefore, to the extent that customers' satisfaction is enhanced by greater customer acquisition cost, we would expect a positive relation between *CR* and *CAC*. We predict a negative relation between the unit price of the service (or price per minute, *PPM*) and *CR* because higher prices reduce the net benefits available to customers. Following Katz and Shapiro (1985), *CR* is conjectured to be positively related to an operator's market share, *MSHARE*. We hypothesize this link to result from positive network effects that are a key driver in industries such as wireless communication (Rajgopal, Venkatachalam and Kotha, 2003). Formally:

$$CR = f(CAC, PPM, MSHARE). \quad (1)$$

The second set of relations specifies that usage, as captured by customer average minutes of use (*MOU*), is a positive function of customer retention (*CR*) and market share (*MSHARE*), but a negative function of unit price (*PPM*). Actual customer satisfaction, as revealed by *CR*, is expected to be positively related to usage of the service (Bolton and Lemon, 1999). To the extent that calls within a network are less expensive than calls to other networks, customers are expected to make more calls when the number of subscribers to the network is larger. Formally:

$$MOU = f(CR, PPM, MSHARE). \quad (2)$$

Given the above relations, the model subsequently links measures of future financial performance with customer retention, usage, customer acquisition costs and market share:

$$FFINPERF = f(CR, MOU, CAC, PPM, MSHARE). \quad (3)$$

FFINPERF is a measure of future financial performance, such as sales or operating profit. Higher customer retention and greater usage should lead to better financial results.[4] We also expect a positive relation between *CAC*, *PPM* and *MSHARE,* and future revenues or profits. Equations (1) through (3) suggest that *CAC*, *PPM* and *MSHARE* also affect future financial performance through their effect on *CR* and *MOU*. We assess the contribution of these variables to future performance by first estimating the fitted (predicted) value of *CR* and *MOU* and their residual (unpredicted) values from the model specifications expressed in (1) and (2). We then include only the residuals of *CR* and *MOU* as explanatory variables in model (3) since their predicted values are a function of their determinants (*CAC*, *PPM* and *MSHARE*), which are also included as independent variables in the model.

The final relation that we examine is the firm's market value as a function of financial and non-financial indicators. Because we first want to assess the valuation role of accounting-based variables on a stand alone basis, we start with the traditional valuation model, which expresses firm value as a function of earnings and book value of equity (Ohlson, 1995). We modify it by replacing earnings with operating profit (*OP*) to maintain consistency with Equation (3). However, in robustness tests, we replace operating profit first with net income and then with earnings per share for the purpose of comparability with Ohlson (1995) and Amir and Lev (1996) respectively. We specify:

$$MV = f(OP, BVE), \quad (4)$$

[4] Prior literature has looked at the predictive ability of non-financial indicators under the view that it make take time for traditional financial performance to reflect what non-financial performance measures indicate in prior periods. Equation (3) is consistent with this view.

where *MV* represents market value. Subsequently, we estimate the full valuation model by augmenting Equation (4) with all the other variables used earlier, in particular *CR*, *CAC*, *MOU*, *PPM* and *MSHARE* as follows:

$$MV = f(OP, BVE, CR, MOU, CAC, PPM, MSHARE). \quad (5)$$

We predict that higher earnings, customer retention and usage should result in higher market value. As with the estimation of Equation (3), residual *CR* and *MOU* are used. Thus, the inclusion of *CAC* as an independent variable allows us to examine its overall valuation implications inclusive of those that obtain through its effect on *CR*. Similar reasoning applies to the other determinants of *CR* and *MOU* included in Equation (5).

4. Data, Measures, and Research Design

4.1 Sample

The sample is comprised of 26 US and Canadian publicly traded companies (see Appendix 1) for which accounting data are available in Compustat. The 26 firms included in the sample were identified from Bloomberg and Perfect Information. We require companies to be either purely mobile operators or telecommunication companies with more than 50% of their revenues generated from wireless operations. Non-financial data were obtained from the EMC World Cellular database. EMC is a commercial data provider for the global wireless industry which covers all the industry's key areas including subscriber statistics, subscriber forecasts, infrastructure suppliers, terminals, and ownership. Clients include operators, manufacturers and analysts. EMC collects data through primary contact with mobile operators (e.g. face-to-face contact, telephone, internet, press releases, etc) and augments it with data collected through the regulatory bodies in the countries of the companies. The data from EMC used in this study include: subscriber data, market share data, average revenue per user (*ARPU*), cost per customer acquisition (*CAC*), minutes of use (*MOU*), and the negative of churn rate which captures retention (*CR*). We construct the unit cost variable (*PPM*) as the ratio of *ARPU* to *MOU* and the ratio of digital to analogue technology subscribers (*TECH*).

The EMC key performance indicators (KPIs) are available on a monthly or quarterly basis for the period 1997–2004 (except for market share, which is available on an annual basis). The monthly variables (*MOU* and *CS*) are multiplied by a scale of 3 in order to achieve comparable magnitude to those with quarterly availability. Quarterly *MSHARE* is obtained by dividing the annual change in market share among the four quarters and cumulatively adding each quarterly change to the previous annual *MSHARE* level. The KPI data are not homogenously available for each company, causing the number of observations for each test to vary. Table 1 provides the definitions of EMC data items used in this study.

[Insert Table 1 about here]

4.2 Research Design

The model developed in Section 3 postulates that *CR* and *MOU* are functions of *CAC*, *PPM* and *MSHARE*. The estimation procedure described below also includes the following controls in order to correctly estimate the relations of interest: technological status of the service (*TECH*) and the portion of customers who pay for usage in advance or on a post-paid basis (*CONTR*). *TECH* is a firm-level index of the mix of analogue and digital cellular telephony technologies. It is included as a control since digital technology allows greater usage and more advanced applications, which may affect customer usage, satisfaction and retention. The rationale for the inclusion of *CONTR* is the following: In the post-paid arrangement a customer enters a contract that does not restrict usage and requires a subsequent payment on a periodic basis (e.g. monthly payment). Under the pre-paid contract usage of services is restricted to the amount pre-paid by the customer. Post-paid contracts typically involve a minimum periodic payment regardless of actual usage, but may entitle the customer to a certain number of free-of-charge minutes of use (bucket arrangements). Such contracts typically tie the user to a minimum period of service (e.g. a year). Pre-paid arrangements, on the other hand, expire automatically when the pre-paid amount is fully used up. Since the type of contractual relationship may restrict a customer's flexibility to change a wireless provider, the

dependent variables in (1) and (2) may be capturing contract type, which may in turn be correlated with the other independent variables. We therefore estimate Equations (1) and (2) as follows:

$$CR_{it} = \alpha_0 + \alpha_1 CAC_{it} + \alpha_2 PPM_{it} + \alpha_3 MSHARE_{it} + \alpha_4 CONTR_{it} + \alpha_5 TECH_{it} + \xi_{it} \quad (6)$$

$$MOU_{it} = \gamma_0 + \gamma_1 CR\_Res_{it} + \gamma_2 PPM_{it} + \gamma_3 MSHARE_{it} + \gamma_4 CONTR_{it} + \gamma_5 TECH_{it} + \psi_{it}. \quad (7)$$

The first explanatory variable in Equation (7) is *CR_Res*, which denotes the residual obtained from estimating Equation (6). This is done for two reasons. First, since *CR* and *MOU* are postulated to be functions of similar variables (*PPM*, *MSHARE*, *CONTR* and *TECH*), this approach enables an assessment of the full association between these variables and *MOU*. Second, *CR_Res* represents, by definition, the element in *CR* that is not influenced by the independent variables in Equation (6). As such, *CR_Res* captures possible influence of other, un-modeled, strategies potentially available to managers to enhance customer retention in order to affect usage. Finding *CR_Res* to be related to *MOU* can thus provide evidence on the effectiveness of such strategies beyond strategies related to customer acquisition costs, pricing, market share, technology and contractual arrangements.[5]

We would expect a positive sign for the coefficient of the percentage of customers using post-paid arrangements in Equation (6) because of the limitations placed on switching providers. On the other hand, post-paid customers are likely high-volume users (e.g. business accounts) which are more price-sensitive and thus more likely to switch a provider in the pursuit of a better deal. Therefore, we do not form a prediction for the sign of this variable in this regression. However, we expect its sign to be positive in Equation (7). We also predict a positive sign for *TECH* since a higher value of this metric represents greater use of digital technology, which enables a broader range of services.

Turning to the analysis of future financial performance, we use two financial measures: average revenue per user (*ARPU*) and operating profit. Since *ARPU* is essentially a measure of total revenue

[5] Note that we do not include *CAC* as an explanatory variable in Equation (7), because we are not aware of a theory supporting a causal relation between usage and *CAC*. Nonetheless, we also estimated Equation (7) including *CAC*. The coefficient was found to be statistically insignificant and no significant effect was detected on the other coefficients.

divided by the number of subscribers, we also scale operating profit by the number of subscribers to obtain operating profit per subscriber (*OPS*). We define future financial performance as *ARPU* and *OPS* for quarters *t+1* to *t+6*. We include current *ARPU* and *OPS* as explanatory variables in order to examine whether current accounting information can predict future performance. This also enables us to determine the *incremental* explanatory power of the non-financial variables over that of the current financial measures. We thus estimate two versions of Equation (3) as follows:

$$ARPU_{t+k} = \beta_1 + \beta_2 ARPU_t + \beta_3 CR\_Res_t + \beta_4 MOU\_Res_t + \beta_5 CAC_t + \beta_6 PPM_t + \beta_7 TECH + \beta_8 MSHARE + \beta_9 CONTR + \varepsilon_t \quad (8)$$

and

$$OPS_{t+k} = \delta_1 + \delta_2 OPS_t + \delta_3 CR\_Res_t + \delta_4 MOU\_Res_t + \delta_5 CAC_t + \delta_6 PPM_t + \delta_7 TECH + \delta_8 MSHARE + \delta_9 CONTR + \zeta_t, \quad (9)$$

where $k = \{1, 2, 3, 4, 5, 6\}$.[6] We again include of *CR_Res* and *MOU_Res* in these equations the same reasons discussed in the context of Equation (7).

In the final step of our analysis we estimate the model specifications (4) and (5). Consistent with our focus on revenue and operating profit per subscriber we scale the firm's market value of equity three months after the fiscal quarter end by the quarter-end number of subscribers to obtain market value per subscriber (*MVS*).[7] Market value is expressed as a function of the financial and non-financial variables included above. We introduce an indicator variable, *NEG*, for loss-making firms and interact it with all the independent variables, given the prior evidence by Hayn (1995) that negative earnings are of lower persistence and thus of lower value relevance. Note that interacting the non-financial variables with *NEG* allows the regression to detect the incremental explanatory power of non-financials for loss making firms

[6] In order to address concerns that the EMC definition of revenues incorporated into the *ARPU* variable may differ from that reported by Compustat, we also estimate Equation (8) with *ARPU* defined as total revenue as reported in the financial statements divided by number of subscribers and the results are qualitatively similar to those obtained from using *ARPU*.

[7] The market value used is that at the end of the third month after the quarter end in order to ensure that financial reports have been released to investors. Since market value is a stock variable, we scale by the quarter-end number of subscribers. The same scale is used for operating profit and revenues for the purpose of consistency in definitions.

relative to profit-making firms. *NEG* is set equal to one, if operating profit before depreciation is negative, and zero otherwise. Therefore, the full model we estimate is:

$$\begin{aligned} MVS_t = {} & \varphi_1 + \varphi_2 NEG_t + \varphi_3 OPS_t + \varphi_4 BVS_t + \varphi_5 CR\_Res_t + \varphi_6 MOU\_Res_t + \varphi_7 CAC_t + \varphi_8 PPM_t \\ & + \varphi_9 TECH + \varphi_{10} MSHARE + \varphi_{11} CONTR + \varphi_{12} OPS_t * NEG_t + \varphi_{13} BVS_t * NEG_t \\ & + \varphi_{14} CR\_Res_t * NEG_t + \varphi_{15} MOU\_Res_t * NEG_t + \varphi_{16} CAC_t * NEG + \varphi_{17} PPM_t * NEG \\ & + \varphi_{18} TECH * NEG + \varphi_{19} MSHARE * NEG_t + \varphi_{20} CONTR * NEG_t + \upsilon_t, \end{aligned} \tag{10}$$

where *BVS* is book value per subscriber. We run all regressions with fixed year effects and clustering by firm in order to control for non-independence of same-firm observations over time.

4.3. Descriptive statistics

Table 2 presents the descriptive statistics for the sample. The number of quarterly observations for the different EMC variables varies from 316 to 596, as can be seen from Panel A. This panel shows that customer acquisition cost (*CAC*) ranges from $161 to $752 per customer with a mean (median) of $374 ($361). The wide range is likely explained by differences in packages offered to subscribers. This is evident from the change in *CAC* spending from 1997 to 2001 as revealed by Panel B. A wide variation is also present for *ARPU* and *PPM* (Panel A). The mean quarterly *ARPU* is $51 per customer, ranging from a minimum of $23 to a maximum of $86. Panel B reveals that the mean has been quite stable throughout the sample period. The average *PPM* is $0.15 with the maximum rate equal to 30 times the minimum rate. Panel B shows that there has been a steady decline in *PPM* over time. This trend is accompanied by a steady increase in quarterly *MOU* from a mean of 174 in 1997 to 791 minutes per user in 2004. With respect to customer retention, the mean churn rate is 2.5% per month, suggesting an annual average of 30% subscriber turnover. However, some firms are quite successful at keeping their customers satisfied, as the lowest monthly churn rate of 1.1% suggests. The high churn rates indicate that competition is quite intense. Furthermore, none of the sample firms has a large monopolistic power: the maximum value of *MSHARE* is 35% and the average is 6%. The use of post-paid contracts is quite pervasive, as is seen from the mean of 93% for *CONTR*. Panel B also reveals that over time wireless firms have introduced the concept of pre-paid contracts, though this is not very popular. The technology index, *TECH*, shows that most companies

in the sample period have fully switched to the digital standard. However, on average, 20% of all subscribers in the sample period use analogue technology. The industry is characterised by a significant technological change (Panel B). Whereas the mean *TECH* index is 50% in 1997, it has grown to 97% in 2004. Finally, the mean number of subscribers is just under 3 million, but subscriber numbers have experienced significant growth over time. Their distribution is right skewed with a maximum of over 21 million subscribers for AT&T wireless. Overall, the evolution in many of the EMC KPIs suggests that the wireless industry has experienced significant changes and growth during the sample period. This is reflected in rapid adoption of advanced technology, dramatic growth in subscriber numbers, sharp reduction in prices and increase in usage.

Panel C presents yearly descriptive statistics based on accounting variables. It indicates that sales, SG&A, and operating income have grown over time. There has also been significant growth in balance sheet items, such as total assets and liabilities. The increasing trend in these financial variables mirrors that observed in Panel B for the EMC variables.

[Insert Table 2 about here]

5. Findings

Table 3 presents the univariate contemporaneous correlations between the main variables used. A few relations are noteworthy. First, *CAC* and *CR* are positively related, consistent with higher spending on customer acquisition leading to higher retention rates. *MSHARE* and *CR* are also positively related, which is in line with the notion that greater market share results in greater satisfaction and hence higher retention. The negative relation between usage (*MOU*) and *CR* suggests that customers leaving a network tend to be high-volume users. This conjecture is also supported by the observation that *ARPU* is negatively correlated with *CR*. This is consistent with the negative relation between survey measures of customer likelihood of return and revenues documented by Banker et al. (2000) in the hotel industry. *OPS* is positively related to *CAC* and *CR*, indicating the possibility that more profitable firms spend more on *CAC* and retain a higher

fraction of the customer base. This relation does not comply with the findings in the banking industry (Ittner and Larcker, 1998, Nagar and Rajan, 2005) where no contemporaneous relation is found between customer satisfaction and earnings. However, it should be noted that customer satisfaction is not equivalent to customer retention.

[Insert Table 3 about here]

Table 4 reports the results from estimating Equation (6) and (7). The first column reports the determinants of customer retention, whereas the determinants of usage are reported in the second column. The coefficient on customer acquisition cost in the customer retention regression is positive and significant at the 1% level (*CAC* = 0.004, *t* = 2.68). Evaluated at the mean, a $3.74 (or, 1% of $374) increase in *CAC* is associated with 0.0015 = 3.74 x 0.004 increase in *CR* (or, 0.6% of 2.5). That 1% increase in *CAC* is associated with 0.6% improvement in retention rate indicates the importance of investment in customer acquisition cost for customer loyalty. Table 4 also indicates that market share is positively and significantly related to customer retention, as implied by positive network effects on customer satisfaction. Greater use of digital technology is associated with greater retention (*TECH* = 0.017, *t* = 2.15), but price per minute and contractual arrangements do not seem to be related to it.

[Insert Table 4 about here]

The results from the usage (*MOU*) regression indicate a statistically insignificant coefficient on *CR_Res*. As expected, higher unit price is negatively related to usage (*PPM* = - 7.762, *t* = -3.18) and a greater fraction of post-paid contracts is positively associated with usage (*CONTR* = 13.845, *t* = 5.32). Somewhat surprisingly, market share exhibits negative and statistically significant association with *MOU*. Technology is unrelated to usage.

To summarize the analysis at this stage, we find that customer acquisition cost and market share are positively related to customer retention, which is consistent with our predictions. Greater portion of post-paid contracts is positively associated with usage. Usage is unrelated to residual customer retention,

implying that strategies captured by the independent variables of the model fully incorporate mediating effects of customer retention on usage.

In the next stage of the analysis we first assess the relation between future *ARPU* and current *ARPU*, controlling for fixed year effects and non-independence of same-firm observations. If accounting information does not have predictive power on its own, the coefficient on current *ARPU* would not be statistically significant. Panel A of Table 5 presents the results from this analysis. It shows that the coefficient on current *ARPU* varies between 0.95 and 0.99 and is significant in all estimation horizons. The *R*-squared obtained for all quarters is high though it declines as the association horizon is extended. This suggests strong persistence of revenues per subscriber up to six quarters ahead.[8] Since *ARPU* is essentially a scaled financial variable (revenues divided by number of subscribers), this finding is inconsistent with the argument that financial information in this industry is not useful on a stand-alone basis.

[Insert Table 5 about here]

Adding *CR_Res*, *MOU_Res* and *CAC* to the regression allows us to evaluate their incremental explanatory power over that of the current *ARPU*. The results from this analysis are reported in Panel B of Table 5. They indicate that only current *ARPU* is consistently positive and significant in all quarters. The other variables are largely insignificant. However, *CR_Res* is positive and significant in the last two horizons. This suggests that *ARPU* tends to improve when past customer retention increases owing to factors not captured by the *CR* determinants in Equation (6). However, any such effect shows up with a considerable delay. This stands in contrast to some prior literature where only short lags have been documented (e.g. Ittner and Larcker , 1998, and Banker et al, 2000 in the context of customer satisfaction) and indicates the possibility that the responsiveness of financial performance to customer retention need not take place in the short-term. Having a larger fraction of post-paid subscribers is also positively associated with future *ARPU* for the first three quarters. This is somewhat expected given that post-paid contracts do not typically bind for very long periods.

[8] The removal of the fixed effects reduces *R*-sq. only by an average of 1-2 %.

Table 6 presents the results from the estimation of Equation (9). Panel A reports the results from the basic model in which future *OPS* is regressed on current *OPS* and year fixed effects with observations clustered by firm. The coefficient on current *OPS* is positive and highly significant but decreases as the association horizon is extended. The *R*-squared also falls from 0.93 to 0.5 from the first to the sixth quarter. This evidence suggests that current *OPS* can be used to assess future *OPS*, though the strength of the association seems to decline over time.

[Insert Table 6 about here]

Panel B reports the results for the full model. In addition to current *OPS,* a number of other variables exhibit incremental explanatory power for future *OPS*. Specifically, *CAC* is positively and significantly associated with *OPS* in all six quarters. Since it is not associated with *ARPU*, this evidence is consistent with the idea that customer retention obtained through investment in *CAC* saves future costs. Indeed, when we calculate the correlation between current *CAC* and future selling general and administrative expenses (after excluding *CAC*) we find a negative and significant relationship for all six windows (not tabulated). This may be explained by a substitution effect between *CAC* and customer retention costs: increasing initial investment in a new customer reduces future costs needed to retain that customer.[9] In addition to *CAC*, the coefficients on *CONTR* and *PPM* are also positive and significant for six and five quarters ahead, respectively. However, in an environment of decreasing prices (see Panel B of Table 2) the positive association between future *OPS* and *PPM* indicates that operating profits suffer as competition drives prices down. The lack of coefficient significance for *CR_res* implies that customer retention does not affect future operating performance once its determinants *CAC, PPM, MSHARE*, and *CONTR* are controlled for. The statistically significant coefficient on *MOU_Res* in all association windows, except the first, is consistent with wireless firms employing strategies incremental to those captured here that have a positive influence on future profitability. The coefficients on *MOU_Res*, *PPM*

[9] Customer retention costs are not reported by EMC. We are therefore unable to explore the link between *CAC* and customer retention costs.

and *CONTR* tend to increase over the association horizon, in contrast to the coefficient on current *OPS*. A possible implication of this finding is that an effective compensation scheme whose focus is future *OPS* should place increasingly greater weight on these non-financial variables relative to current *OPS* when management's target period is extended into the future. The *R*-squared of this regression model gradually decreases from 0.87 for the one-quarter-ahead window to 0.70 for the six-quarter-ahead window. Note that the decline in *R*-squared in Panel A is even steeper. This implies that non-financial variables are increasingly more predictive of future profitability relative to current *OPS*.[10]

Table 7 presents the results from the analysis of market value per subscriber. As discussed earlier, we augment the basic valuation model to allow for differing coefficients for profitable and loss-making firms (Hayn, 1995). The left column of Table 7 reveals that *OPS* has a positive and statistically significant association with market value for profitable firms (coefficient = 12.313, t = 3.46). *OPS* is also statistically significant for loss firms, as is indicated by the negative coefficient on *OPS***NEG*. *BVS* is value relevant for loss-making firms at the 1% level (*BVS***NEG* = 1.8883, t = 3.41). As for profitable firms, the coefficient is positive and marginally significant. These observations suggest that market participants expect losses to be reversed. Overall, the evidence from the basic model is consistent with earnings and book value being value relevant in the wireless industry on a stand-alone basis.

[Insert Table 7 about here]

In the full model (Equation 10), reported in the right column of Table 7, *OPS* and *BVS* retain their signs and level of significance for all firms. Of the non-financial variables, *CR_Res* and *CAC* exhibit incremental explanatory power, but only for loss-making firms. Specifically, the coefficient on *CR_Res*NEG* is positive and significant at the 5% level whereas the coefficient on *CAC* is positive and significant at the 10% level. This suggests that market participants employ *CAC* and *CR* information to

[10] To the extent that R-squared is a measure of informativeness, this suggests that current *OPS* becomes noisier with respect to future *OPS* as the association horizon is extended. Ittner et al. (1997) find that the use of non-financial performance measures in bonus contracts is an increasing function of the noise in financial performance measures. The evidence provided in Table 6 thus supports the practice documented by Ittner et al. (1997).

supplement accounting information for loss-making firms. Based on this we infer that market participants do not regard *CAC* as an expense, but rather as a value indicator, since its coefficient is not negative. Note also that the coefficient on *CR_Res* is positive and marginally significant (coefficient = 74.038, t = 1.61). This is in line with the notion that the market rewards firms for which customer retention is higher, though the effect is more pronounced for loss-making firms. The value irrelevance of the other independent variables reinforces the previous findings on the usefulness of the accounting variables.

Collectively, the results from Table 7 stand in contrast to Amir and Lev's findings (Table 4, Panel A) that earnings and book value of equity alone are not value-relevant, on the basis of which they concluded that accounting metrics fail to capture value in high-growth and fast-changing industries. One potential explanation for the difference in findings may be attributable to the different regression specification employed here. In particular, whereas Amir and Lev (1996) use *EPS* and book value per share, we use operating profit scaled by the number of subscribers. To obtain direct comparability with their specification, we also estimate Equation (10) with *EPS* and book value per share. This model (untabulated) yields qualitatively similar results to those reported in Table 7. Specifically, the coefficients on book value per share and *EPS* for profitable firms are positive and statistically significant. This result holds when all other independent variables, inclusive of the interaction effects, are added to the basic model. In the full model, the coefficient on *CAC*NEG* is positive and statistically significant, similar to that in Table 7. However, *CR_Res*NEG* is statistically insignificant.

6. Summary and Conclusions

We extend the literature on the valuation role of financial and non-financial information by examining the wireless industry during the period 1997-2004. We utilize a structural approach which links customer acquisition cost, customer retention and call usage to financial performance and valuation. Although the wireless industry maintains a rapid pace of technological and commercial changes, fundamental accounting numbers are found to be value relevant. We provide evidence, using a unique dataset, that customer acquisition cost is likely an important factor in a firm's strategy to create value. Specifically, it is shown

that customer acquisition cost is positively associated with customer retention, future profits and market values. Importantly, customer acquisition cost predicts future operating profits, but not future revenues, which suggests that successful investment in customer acquisition cost is capable of saving future expenses and hence improve profitability.

The marketing and accounting literatures provide only scant evidence on the determinants of customer retention and its eventual role in driving financial performance. The current study considers therefore the relation between customer retention and future performance and shows that customer retention is determined by factors such as customer acquisition cost, market share and technology. Once controlling for these variables, there is evidence of delayed association between retention and future revenues but not future profits. This suggests that implementing other strategies for enhancing retention may not lead to greater financial performance. Nonetheless, we find some evidence that customer retention enhances market values.

More generally, the current study provides fresh evidence on the relative importance of accounting versus non-financial information in a fast changing environment. Overall, accounting variables seem highly useful in predicting future financial performance, even in the absence of any additional non-financial information. Yet, as the association horizon is extended we document a decrease in the predictive ability of current profit and an increase in the explanatory power of certain non-financial variables for future profitability. From a normative perspective, this may be useful for the design of compensation contracts that involve a mix of accounting and non-accounting performance measures, where the weight of these measures is dependent on the target period.

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Table 1: Definitions of EMC Variables

Variable	Definition	Time Period Reported	Frequency of Reporting by EMC
***CAC* (customer acquisition cost)**	Cost in USD per customer acquisition. Includes handset subsidies, marketing, advertising and administration costs, dealer commissions and bonuses, SIM card cost, credit check costs, share of fixed costs (offices, employees, etc)	Quarterly	Quarterly
***CR* (customer retention)**	(Churn, or percentage of customers leaving the network in relation to the subscriber base) x -1	Monthly	Quarterly
CONTR	Ratio of subscribers on postpaid contract to total number of subscribers per company	Monthly	Monthly**
MSHARE	Number of subscribers per company divided by total number of subscribers in a given country. Market share in segmented markets is number of subscribers per company divided by total number of subscribers in the region	Annual	Annual*
ARPU	Average revenue per user in $US. Includes monthly service charges (subscription fee, call charges, voice + data, messaging, value added services, outbound roaming, interconnect, inbound roaming, connection fees)	Monthly	Quarterly
***MOU* (minutes of use)**	Minutes of use per subscriber. Usage counted towards *MOU* includes voice calls (international, domestic, outbound roaming, voicemail) internet or data calls	Monthly	Quarterly
***TECH* (Technology status)**	A weighted average index of analogue (value = 0) and digital (value = 1) technology, weighted by number of analogue and digital technology subscribers.	Monthly	Monthly**
***NSUB* (number of subscribers)**	Total number of subscribers. Includes subscribers on contracts (postpaid) and subscribers using prepaid services.	Monthly	Monthly

* Market share is reported at the end of each year. For the purpose of obtaining quarterly market share data, the change in market share has been obtained using a linear interpolation.

** This variable is not directly reported by EMC. It is computed on the basis of total number of subscribers and technology type reported by EMC at the indicated frequency.

Table 2: Descriptive Statistics of Consolidated EMC and Accounting Variables, 1997-2004

Panel A: Mean, Median, Min and Max Values of EMC and Accounting Variables

EMC variables	No of companies	No of company quarters	Mean value	Median value	Min value	Max value
CAC (USD)	25	416	374	361	161	752
CR (%)	26	459	-2.5	-2.4	-5.6	-1.1
CONTR (%)	26	596	93	100	27	100
MSHARE (%)	26	592	6	1	0	35
ARPU (USD)	26	511	51	52	23	86
MOU	21	317	426	389	103	1,600
PPM (USD)	21	316	0.15	0.13	0.02	0.60
TECH	26	596	0.80	1	0	1
NSUB (thousands)	26	596	2,946	900	490	21,792
Accounting variables						
Sales	26	605	457	115	0	5,406
SG&A	23	453	172	51	0.5	1,489
Op. income before depr.	26	600	97	8	-596	1,291
PPE	26	575	1,933	626	85	16,374
Total assets	26	575	4,964	1,508	105	47,876
Liabilities	26	575	3,255	1,286	0.1	22,646
Net income	26	608	-48	-25	-2,041	1,471
EPS	26	591	-1.3	-0.4	-73	9

All figures in millions of U.S. dollars, except EPS (dollars)

Definitions of Accounting Variables:

Sales	Total revenues (Compustat quarterly data # 2)
SG&A	SG&A expenses (data # 1)
Operating income	Operating income before depreciation (data # 21)
PPE	Property plant and equipment (data #42)
Total assets	Total assets (data #44)
Net income	Net income (data #54)
EPS	Earnings per share (data #19)
Total assets (TA)	Total assets (data # 44) minus Intangible assets (data #234 + data #235)

Table 2 (Continued): Descriptive Statistics of Consolidated EMC and Accounting Variables, 1997-2004

Panel B: Mean and Median Values of Consolidated EMC Variables by Year

		1997	1998	1999	2000	2001	2002	2003	2004
***CAC*:**	Mean	508	468	389	373	350	355	358	355
	Median	550	424	359	350	342	362	382	351
	No of obs.	10	32	48	73	82	74	64	33
CR:	Mean	-2.33	-2.02	-2.15	-2.59	-2.70	-2.79	-2.52	-2.57
	Median	-2.16	-1.80	-2.00	-2.38	-2.50	-2.50	-2.50	-2.70
	No of obs.	10	34	54	80	82	79	72	48
CONTR:	Mean	100	98	91	89	91	92	92	92
	Median	100	100	99	97	98	100	100	100
	No of obs.	54	63	77	94	85	79	73	71
MSHARE:	Mean	5	6	6	5	6	7	6	6
	Median	1	2	1	1	1	2	1	1
	No of obs.	49	63	77	94	84	80	73	71
ARPU:	Mean	54	48	49	52	51	52	52	52
(*USD*)	Median	54	48	47	54	52	53	55	55
	No of obs.	16	56	66	88	84	77	72	52
MOU:	Mean	174	190	284	332	384	451	552	791
	Median	123	198	229	340	389	455	551	760
	No of obs.	9	19	34	54	65	55	49	32
PPM:	Mean	0.37	0.22	0.18	0.17	0.15	0.12	0.10	0.07
(*USD*)	Median	0.41	0.18	0.17	0.17	0.14	0.12	0.10	0.08
	No of obs.	9	19	34	54	65	54	49	32
TECH:	Mean	0.50	0.60	0.71	0.78	0.84	0.91	0.95	0.97
	Median	0.20	1	1	1	1	1	1	1
	No of obs.	54	63	77	94	85	79	73	71
NSUB:	Mean	954	1,225	1,511	2,090	3,119	4,030	4,820	5,338
(000)	Median	122	322	459	661	1,042	1,236	1,432	1,567
	No of obs.	54	63	77	94	85	79	73	71

Panel C: Mean and Median Values of Accounting Variables by Year

		1997	1998	1999	2000	2001	2002	2003	2004
Sales:	Mean	127	162	241	280	424	602	736	860
	Median	30	24	42	63	94	145	157	207
	No of obs.	48	54	77	95	91	80	73	70
SG&A:	Mean	40	63	98	101	175	219	248	261
	Median	39	45	44	46	46	56	72	67
	No of obs.	28	34	49	63	69	64	64	65
Op.	Mean	29	12	23	55	120	199	263	284
Income:	Median	-1	-6	-6	-6	11	40	61	65
	No of obs.	53	92	96	91	80	73	70	16
PPE:	Mean	859	1,145	1,403	1,891	2,503	2,911	3,068	3,156
	Median	585	619	561	532	755	856	819	772
	No of obs.	51	69	79	88	80	73	70	17
Total	Mean	1,620	1,970	2,667	3,322	5,559	7,052	7,202	7,440
Assets:	Median	898	1,326	1,173	1,125	1,501	2,013	1,914	1,882
	No of obs.	48	51	69	79	88	80	73	70
Liabilities:	Mean	1,336	1,911	2,514	3,294	4,303	4,896	5,032	5,050
	Median	768	936	1,170	1,251	1,592	1,597	1,899	2,048
	No of obs.	51	69	79	88	80	73	70	17
Net	Mean	-48	-56	-70	-43	-91	-83	24	32
Income:	Median	-28	-22	-32	-27	-38	-34	-8	-10
	No of obs.	57	92	96	91	80	73	70	17
EPS:	Mean	-0.57	-2.13	-3.91	-0.54	-0.76	-1.44	-0.24	-0.35
	Median	-0.25	-0.67	-1.04	-0.46	-0.49	-0.35	-0.10	-0.09
	No of obs.	53	82	92	91	77	72	70	17

Table 3: Spearman\Pearson Correlation Matrix

Variables	*ARPU*	*OPS*	*CAC*	*CR*	*CONTR*	*MSHARE*	*MOU*	*PPM*	*TECH*
ARPU		**0.25**	**0.42**	**-0.15**	**0.56**	**-0.38**	**0.46**	**-0.10**	**0.36**
OPS	**0.22**		**0.69**	**0.21**	**0.32**	0.01	-0.05	**0.30**	**-0.43**
CAC	**0.34**	**0.67**		**0.23**	**0.46**	**-0.27**	-0.05	**0.32**	**-0.27**
CR	**-0.11**	**0.25**	**0.26**		**0.17**	**0.19**	**-0.43**	**0.40**	**-0.40**
CONTR	**0.54**	**0.21**	**0.53**	0.05		**-0.37**	**0.27**	**0.14**	-0.06
MSHARE	**-0.44**	0.08	**-0.30**	**0.18**	**-0.54**		**-0.25**	-0.06	**-0.33**
MOU	**0.60**	0.05	**0.09**	**-0.44**	**0.35**	**-0.25**		**-0.73**	**0.59**
PPM	-0.11	**0.14**	**0.20**	**0.46**	-0.01	0.01	**-0.82**		**-0.76**
TECH	**0.47**	**-0.32**	0.05	**-0.42**	**0.35**	**-0.43**	**0.67**	**-0.52**	

Coefficients of 10% significance or less appear in bold. Pearson (Spearman) correlations are shown above (below) the diagonal.

Table 4: Determinants of Customer Satisfaction (*CR*) and Usage (*MOU*)

	CR	*MOU*
CAC	0.004***	
	(2.68)	
CR_Res		-6.889
		(-0.37)
PPM	-0.001	-7.762***
	(-0.35)	(-3.18)
MSHARE	0.084**	-17.927*
	(2.12)	(-2.02)
CONTR	0.022	13.845***
	(1.18)	(5.32)
TECH	0.017**	-3.221
	(2.15)	(-0.86)
Constant	-13.133***	1,767.407**
	(-5.62)	(2.55)
N of obs.	350	350
R-squared	0.30	0.73

Notes:

Model estimated :

$$CR_{it} = \alpha_0 + \alpha_1 CAC_{it} + \alpha_2 PPM_{it} + \alpha_3 MSHARE_{it} + \alpha_4 CONTR_{it} + \alpha_5 TECH_{it} + \xi_{it} \quad (6)$$

$$MOU_{it} = \gamma_0 + \gamma_1 CR\_Res_{it} + \gamma_2 PPM_{it} + \gamma_3 MSHARE_{it} + \gamma_4 CONTR_{it} + \gamma_5 TECH_{it} + \psi_{it} \quad (7)$$

where *CR_res* is the residual from the regression with *CR* as dependent variable. For variable definitions, see Table 1.

Regressions are estimated with year fixed effects and clustering by firm. Observations are winsorised at the top and bottom 1% of the distribution and observations with studentised residuals greater than two are excluded from the analysis. *, **, *** represent significance levels of 10%, 5% and 1%, respectively.

Table 5: Analysis of Future Average Revenue per User (ARPU)

Panel A: The association between future *ARPU* and current *ARPU*

	$ARPU_{t+1}$	$ARPU_{t+2}$	$ARPU_{t+3}$	$ARPU_{t+4}$	$ARPU_{t+5}$	$ARPU_{t+6}$
ARPU	0.99***	0.96***	0.97***	0.97***	0.97***	0.95***
	(121.16)	(39.21)	(38.51)	(35.28)	(27.63)	(19.64)
Constant	1.91*	5.18***	4.89***	-1.05	1.73	4.59
	(2.08)	(2.92)	(4.24)	(0.70)	(0.86)	(1.29)
N of obs.	331	308	285	267	244	224
R-squared	0.97	0.94	0.94	0.93	0.92	0.89

Panel B: The association between future *ARPU* and current *ARPU* and non-financials

	$ARPU_{t+1}$	$ARPU_{t+2}$	$ARPU_{t+3}$	$ARPU_{t+4}$	$ARPU_{t+5}$	$ARPU_{t+6}$
ARPU	0.972***	0.924***	0.916***	0.924***	0.904***	0.872***
	(63.1)	(23.7)	(20.6)	(20.8)	(18.1)	(13.0)
CR_Res	0.041	0.213	0.108	0.174	0.333*	0.394*
	(0.66)	(1.66)	(0.84)	(1.27)	(1.95)	(1.82)
MOU_Res	-0.000	-0.000	-0.001	0.000	0.001	0.001
	(-1.57)	(-0.48)	(-0.76)	(0.39)	(0.70)	(0.69)
CAC	0.000	0.001	0.000	0.001	0.002	0.002
	(0.15)	(0.45)	(0.080)	(0.22)	(0.52)	(0.51)
PPM	0.002	-0.001	-0.004	-0.003	-0.001	0.001
	(0.67)	(-0.13)	(-0.52)	(-0.41)	(-0.16)	(0.12)
TECH	0.008	0.014	0.017	0.014	0.017	0.028
	(0.93)	(0.78)	(0.77)	(0.61)	(0.67)	(0.86)
MSHARE	0.004	-0.010	-0.028	-0.036	-0.053	-0.032
	(0.19)	(-0.41)	(-0.94)	(-0.85)	(-1.14)	(-0.63)
CONTR	0.024**	0.038*	0.047*	0.034	0.044	0.057
	(2.42)	(2.02)	(1.75)	(1.09)	(1.07)	(0.96)
Constant	-0.620	1.747	1.791	-0.468	-0.729	0.072
	(-0.56)	(0.76)	(0.63)	(-0.14)	(-0.15)	(0.011)
R-squared	331	308	285	267	244	224
N of obs.	0.97	0.94	0.94	0.94	0.92	0.90

Notes:

Model estimated:

$$ARPU_{t+k} = \beta_0 + \beta_1 ARPU_{it} + \beta_2 CR\_Res_{it} + \beta_3 MOU\_Res_{it} + \beta_4 CAC_{it} + \beta_5 PPM_{it} + \beta_6 TECH_{it} + \beta_7 MSHARE_{it} + \beta_8 CONTR_{it} + \xi_{it}$$

where *MOU_res* is the residual from the estimation of Equation (7):

$$MOU_{it} = \gamma_0 + \gamma_1 CR\_Res_{it} + \gamma_2 PPM_{it} + \gamma_3 MSHARE_{it} + \gamma_4 CONTR_{it} + \gamma_5 TECH_{it} + \psi_{it}$$

and *CR_res* is the residual from the estimation of Equation (6):

$$CR_{it} = \alpha_0 + \alpha_1 CAC_{it} + \alpha_2 PPM_{it} + \alpha_3 MSHARE_{it} + \alpha_4 CONTR_{it} + \alpha_5 TECH_{it} + \xi_{it}$$

For variable definitions, see Table 1.

Regressions are estimated with year fixed effects and clustering by firm. Observations are winsorised at the top and bottom 1% of the distribution and observations with studentised residuals greater than two are excluded from the analysis. *, **, *** represent significance levels of 10%, 5% and 1%, respectively.

Table 6: Analysis of Future Operating Profit per User (OPS)

Panel A: The association between future *OPS* and current *OPS*

	OPS_{t+1}	OPS_{t+2}	OPS_{t+3}	OPS_{t+4}	OPS_{t+5}	OPS_{t+6}
OPS	0.757***	0.652***	0.579***	0.551***	0.496***	0.438***
	(13.9)	(12.1)	(8.25)	(7.82)	(6.96)	(5.78)
Constant	29.700***	44.111***	47.687***	37.718***	51.983***	53.398***
	(5.30)	(5.92)	(5.64)	(4.08)	(3.43)	(4.54)
N of obs	287	268	251	232	214	198
R-squared	0.83	0.72	0.67	0.67	0.62	0.54

Panel B: The association between future *OPS* and current *OPS* and non-financials

	OPS_{t+1}	OPS_{t+2}	OPS_{t+3}	OPS_{t+4}	OPS_{t+5}	OPS_{t+6}
OPS	0.655***	0.525***	0.463***	0.475***	0.397***	0.323***
	(9.61)	(6.07)	(5.07)	(5.41)	(4.14)	(3.29)
CR_Res	-0.345	-0.488	-0.529	-0.829	-1.262	-2.054
	(-0.43)	(-0.48)	(-0.44)	(-0.68)	(-1.09)	(-1.62)
MOU_Res	0.007	0.011*	0.015**	0.024**	0.029***	0.035**
	(1.53)	(1.88)	(2.13)	(2.86)	(2.94)	(2.53)
CAC	0.059**	0.095***	0.089***	0.066**	0.074**	0.079**
	(2.85)	(3.40)	(2.94)	(2.21)	(2.47)	(2.39)
PPM	0.088**	0.121**	0.116*	0.092	0.145*	0.193*
	(2.57)	(2.28)	(2.01)	(1.34)	(2.00)	(1.97)
TECH	0.009	0.102	0.139	0.190	0.274*	0.382**
	(0.086)	(0.94)	(1.06)	(1.41)	(1.89)	(2.52)
MSHARE	0.321*	0.376*	0.394	0.170	0.352	0.592
	(1.83)	(1.81)	(1.39)	(0.50)	(0.96)	(1.33)
CONTR	0.283***	0.251**	0.386**	0.425**	0.450**	0.587***
	(3.18)	(2.44)	(2.24)	(2.73)	(2.58)	(3.90)
Constant	-20.158	-24.404	-25.913	-41.883	-71.057*	-102.970**
	(-1.04)	(-1.14)	(-0.99)	(-1.47)	(-1.95)	(-2.44)
N of obs	287	268	251	232	214	198
R-squared	0.86	0.79	0.75	0.76	0.73	0.70

Notes:

Model estimated:

$OPS_{t+k} = \delta_0 + \delta_1 OPS_{it} + \delta_2 CR\_res_{it} + \delta_3 MOU\_res_{it} + \delta_4 CAC_{it} + \delta_5 PPM_{it} + \delta_6 TECH_{it} + \delta_7 MSHARE_{it} + \delta_8 CONTR_{it} + \varsigma_{it}$

where *MOU_res* and *CR_res* are defined as in Table 5.

OPS is defined as operating income before depreciation expense and customer acquisition expense scaled by the number of subscribers. Customer acquisition expense is calculated as CAC*New subscribers for the period, where New subscribers = (N of Subscribers in the end of period t – N of Subscribers in the end of period t-1 + Churn*(N of Subscribers in the end of period t + N of Subscribers in the end of period t-1)/2. For other variable definitions, see Table 1.

Regressions are estimated with year fixed effects and clustering by firm. Observations are winsorised at top and bottom 1% of the distribution and observations with studentised residuals greater than two are excluded from the analysis. *, **, *** represent significance level of 10%, 5% and 1%, respectively.

Table 7: Analysis of Market Value per Subscriber

	MVS	*MVS*
OPS	12.313***	11.726**
	(3.46)	(2.16)
BVS	0.340	0.167
	(1.68)	(0.76)
CR_Res		74.038
		(1.61)
MOU_Res		0.314
		(0.79)
CAC		0.345
		(0.25)
PPM		5.705
		(1.00)
TECH		11.605
		(1.09)
MSHARE		0.693
		(0.047)
CONTR		-9.470
		(-1.21)
*OPS*NEG*	-34.056***	-30.667***
	(-4.54)	(-3.63)
*BVS*NEG*	1.883***	1.841***
	(3.41)	(4.14)
*CR_Res*NEG*		323.445**
		(2.28)
*MOU_Res*NEG*		0.655
		(0.90)
*CAC*NEG*		9.058*
		(1.75)
*PPM*NEG*		6.267
		(0.62)
*TECH*NEG*		20.676
		(0.71)
*MSHARE*NEG*		-96.328
		(-0.75)
*CONTR*NEG*		12.854
		(0.50)
NEG	2,777.879***	-4,795.593
	(4.69)	(-0.86)
Constant	-97.070	-860.518
	(-0.27)	(-0.58)
N of Obs.	294	294
R-squared	0.67	0.73

Model estimated:

$$MVS_t = \varphi_1 + \varphi_2 NEG_t + \varphi_3 OPS_t + \varphi_4 BVS_t + \varphi_5 CR\_Res_t + \varphi_6 MOU\_Res_t + \varphi_7 CAC_t + \varphi_8 PPM_t + \varphi_9 TECH + \varphi_{10} MSHARE + \varphi_{11} CONTR + \varphi_{12} OPS_t * NEG_t + \varphi_{13} BVS_t * NEG_t + \varphi_{14} CR\_Res_t * NEG_t + \varphi_{15} MOU\_Res_t * NEG_t + \varphi_{16} CAC_t * NEG + \varphi_{17} PPM_t * NEG + \varphi_{18} TECH * NEG + \varphi_{19} MSHARE * NEG_t + \varphi_{20} CONTR * NEG_t + \upsilon_t,$$

where: *NEG* = 1, if operating income before depreciation < 0, NEG = 0 otherwise. For other variable definitions, see Table 1. Regressions are estimated with year fixed effects and clustering by firm. Observations are winsorised at top and bottom 1% of the distribution and observations with studentised residuals greater than two are excluded from the analysis. *, **, *** represent significance level of 10%, 5% and 1%, respectively.

Appendix 1
List of companies with available financial data, 1997-2004
Minimum, mean and maximum market capitalisation for the period with available financial data

Company Name	Country	No of quarters	Market Cap (mil of USD)		
			Min	Mean	Max
1. BCE Mobile Communications	Canada	23	1,743	2,110	2,393
2. Clearnet Communications	Canada	12	427	1,161	2,591
3. Microcell Telecommunications	Canada	32	10	737	2,885
4. Rogers Wireless	Canada	32	715	1,923	3,827
5. Aerial Communications Inc	USA	13	265	1,093	5,796
6. Airgate P*CR*	USA	20	6	394	1,305
7. Alamosa	USA	22	21	711	2,316
8. Alltel	USA	20	12,482	16,562	19,941
9. AT&T Wireless	USA	31	6,264	18,374	41,367
10. Dobson Communications	USA	32	28	901	2,149
11. Leap Wireless	USA	23	2	405	1,680
12. Nextel Communications	USA	29	2,812	17,634	56,187
13. Nextel Partners	USA	22	667	3,219	7,902
14. NTELOS	USA	13	1	226	516
15. Omnipoint Corporation	USA	12	393	1,152	3,004
16. Powertel	USA	17	269	1,169	2,999
17. Rural Cellular Communications	USA	32	10	248	903
18. Sprint P*CR*	USA	32	1,999	21,078	62,769
19. Telecorp	USA	9	1,691	3,167	4,546
20. T-Mobile USA (previously Voicestream)	USA	32	2,718	17,993	26,420
21. Tritel	USA	4	1,533	3,050	4,095
22. Triton P*CR* Holdings Inc	USA	26	142	1,446	3,699
23. Ubiquitel	USA	19	20	301	655
24. US Cellular Corporation	USA	32	2,034	3,807	8,854
25. US Unwired	USA	25	39	431	1,027
26. Western Wireless	USA	32	213	1,991	5,180