Financial Markets Research in Marketing

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Not long ago, the use of financial market data was viewed as outside the area of marketing, and the interactions of marketing with the financial markets were little studied. Increasingly, marketers are better appreciating the benefits of understanding how financial market data can be used to assess the value implications of marketing constructs and studying the effects of marketing variables on the financial markets. We commend Srinivasan and Hanssens (2009; hereinafter, S&H) for taking on the daunting task of both outlining research approaches and summarizing some of the empirical findings to date. Marketing does not have a long track record of working with the financial markets theory and methods; work in this area is still evolving and, indeed, is in a state of flux. As such, the road map that S&H provide is of great value and can help shape future research in the area.

Although we have provided some of our own guidelines elsewhere (Jacobson and Mizik 2009a, b), we appreciate the opportunity to elaborate on some issues and to offer comments on the work of S&H. While we applaud S&H for highlighting a host of key considerations (e.g., the importance of working with unanticipated changes in a metric) and differ with them on some more nuanced points,[6] in this comment, we focus on three reoccurring issues in this research domain:

1. The use of vector autoregressive (VAR) modeling in identifying financial market anomalies,
2. The limitations to working with "levels models" in valuation analyses, and
3. Working with Tobin's q instead of the stock return metric.

Our objective is to reinforce some of the points S&H make and to open a dialogue on some other issues.

VAR MODELING FOR ANOMALIES IDENTIFICATION

Financial markets research in marketing has centered primarily on two key research issues:[7] (1) valuation (i.e., establishing value relevance of marketing metrics) and (2) identifying market anomalies (i.e., mispricing) related to marketing metrics. The first research area attempts to establish the long-term performance consequences (as summarized by changes in the firm's stock market valuation) of marketing actions and assets. Two methods—short-window event studies and longer-window stock return response models—are used in this research. In event studies, significant findings of abnormal returns following an event constitute evidence of the event's impact on firm performance. Findings of incremental (to accounting profitability) information content (i.e., value relevance) of a metric in response models suggest that the marketing construct has long-term effects that are not fully reflected in contemporaneous accounting performance. Under the assumption of efficient markets, because the market reacts immediately and forms unbiased expectation, these methods allow for the assessment of the value implications of marketing events and constructs.

Although the second research area tends to use some aspects of the efficient markets framework, it attempts to identify anomalies (i.e., delays in market reaction to new value-relevant information). Tests of market anomalies typically link future risk-adjusted stock returns of a firm to metrics in the investors' current information set. Some studies have argued and provided empirical evidence that the stock market may not fully and immediately appreciate consequences of strategic actions and assets. They show that a systematic long-term stock price adjustment might follow the initial reaction. A future-term price adjustment might stem from the market participants not being able to observe, not paying sufficient attention to, or not fully understanding performance implications of a firm action. In such cases, valuation models assessing contemporaneous market response would not capture the total long-term performance impact because an additional future-term effect might also exist. Nonstructural VAR models, such as the one S&H propose, are reduced form representations that can be used to examine delayed effects of marketing metrics on stock return and, as such, can assess potential marketplace mispricing.[8]

Although it has the potential to test for anomalies, given that marketing metrics are rarely available at very high frequency, nonstructural VAR modeling is limited in the context of assessing the value relevance of marketing metrics. Because investors impound value implications into the current price of the stock, most of the effect of marketing metrics is likely reflected in the contemporaneous association. Prior research has established that financial markets react to new information very quickly, sometimes within minutes. For example, the bulk of the market adjustment and settling following announcements (e.g., earnings and macroeconomic events) occurs within 5–15 minutes (Ederington and Lee 1993; Patell and Wolfson 1984). The absence of a lagged effect in VAR modeling does not mean that the financial markets do not value a particular metric. Rather, the effect of the metric on financial valuation may have already been incorporated previously into the price of the stock.

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[6]For example, we argue that the four-factor risk model is not a separate type of analysis assessing value relevance but rather simply a procedure for risk adjustment in analyses that examines abnormal stock return.

[7]Some recent research has also begun to investigate second-order effects (e.g., marketing's impact on volatility and risk), which is a methodologically and substantively distinct research area. Because of space constraints, we focus on the marketing–return relationship and leave discussion of our views on this developing research area for another occasion.

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[8]Other methods, with varying statistical properties, are typically used to assess mispricing. For example, the calendar-time portfolio approach is one of the more commonly used approaches in finance for testing for anomalies.

Because empirical findings of mispricing run counter to efficient markets theory, they tend to be aggressively challenged. The view is that if the anomaly is truly present, investors will use it as a trading rule and, by doing so, will dissipate it. Fama (1998) claims that most empirical findings of mispricing do not stand up to close scrutiny and are not robust to sensitivity checks. It is our view that anomalies may exist, but it is incumbent on the researcher to undertake the needed sensitivity checks (e.g., alternative risk calculations, alternative return calculations) to better substantiate the validity of the finding.

Although studying market anomalies and mispricing is valuable, VAR-based analysis may have limited usefulness if the goal is to establish empirical regularities or generalizations. Market participants have an incentive to trade on and, thus, dissipate anomalies. As such, even those advocating a behavioral approach to financial markets (e.g., Shiller 2002) point out that anomalies may sometimes disappear or even switch signs over time. Empirical findings of mispricing have a history of being time or context specific (Schwert 2003).

Finally, we note that the notation S&H use in their Equation 4 is a bit confusing. In their discussion, they clearly state that their modeling is based on separate time-series VAR models for each firm. However, by using panel data notation in Equation 4 (i.e., by referring to firm i and period t in the same equation), it may give the unintended impression that the S&H discussion applies to panel data VARs as well. Indeed, it does not. Panel data VAR modeling typically requires a different estimation methodology than the one S&H detail (see, e.g., Holtz-Eakin, Newey, and Rosen 1988). Panel data VARs can help overcome the data requirements needed in strictly time-series VARs, but they also bring up several other issues requiring methods and considerations not addressed by S&H.

THE LIMITATIONS OF WORKING WITH LEVELS MODELS IN VALUATION ANALYSES

Several studies attempting to assess the financial market implications of marketing variables run "levels models," which link a highly autocorrelated financial performance metric (e.g., market value, Tobin's q, market-to-book ratio) to explanatory factors that are also autocorrelated (e.g., book value; earnings; intangible asset measures, such as customer satisfaction or a brand attribute). These regressions are used not just in the marketing literature but also across disciplines. For example, as Gow, Ormazabal, and Taylor (2009) note, market value models form the basis for an entire and ongoing research stream in accounting. Although an extensive literature stream has discussed the econometric limitations of these levels models, they continue to be estimated, published in journals, and their apparent implications given credence.

As S&H astutely note (p. 300), levels models "have limited value, from both a theoretical and a methodological perspective." Ordinary least squares (OLS) estimation assumes that the error terms are independent and identically distributed. When both the error term and the independent variable are positively autocorrelated, least squares estimates of the standard errors are biased and understate the true standard errors. The conventional t-statistic does not have a standard normal limiting distribution, which invalidates the use of t-distribution to test the hypothesis of statistical significance. In the presence of autocorrelated series, the number of occasions with |t| greater than 1.96 greatly exceeds 5%. The higher the autocorrelation in the series, the greater is the probability of observing a t-statistic above |1.96| (i.e., the greater is the extent to which OLS standard errors understate the true standard errors).

Although spurious regression is most widely discussed in a pure time-series context, it also comes into play in analyses of panel data. For example, Kao (1999) shows that though the spurious regression problem is unrelated to the number of cross-sectional observations, it increases with the number of time-series observations.[9] Petersen (2007) notes that as the number of periods of data used in the analysis doubles, OLS assumes a doubling in the amount of information. However, the amount of information increases by a factor less than two if the explanatory factors and the error exhibit autocorrelation. Consider the extreme case in which both the independent variable and the error term are perfectly autocorrelated. In this scenario, each additional period provides no additional information and has no effect on the true standard error of the estimate. However, the standard errors estimation from OLS assumes that each additional year provides N (the number of cross-sections in the panel) additional independent observations, and the estimated standard error shrinks accordingly, albeit incorrectly. As such, many of the statistically significant findings reported in the literature are nothing more than artifacts of the spurious regression phenomena.

An approach to dealing with spurious regression problems is to compute standard errors that explicitly account for the autocorrelation in the residual. For example, both Petersen (2007) and Gow, Ormazabal, and Taylor (2009) advance the use of cluster-robust standard errors estimation (Arellano 1987; White 1984). Cluster-robust standard errors are obtained by relaxing the assumption of error independence and allowing for correlation within a "cluster" (e.g., observations coming for the same firm but in different years). Rather than assuming it is zero as in least squares analysis, cluster-robust standard errors are based on estimates of the residuals covariance within a cluster. The use of robust standard errors does not change the coefficient estimates, but it affects the standard errors and, thus, the t-statistic. Although the degree to which cluster-robust standard errors differ from OLS standard errors depends on the autocorrelation of the series and the number of time-series observations, in our experience with the approach using the market value series, autocorrelated marketing metrics, and ten years of annual data, it gave rise to cluster-robust standard errors approximately two to three times the size of the OLS standard errors (and, as such, t-statistics are half to one-third the size of the OLS t-statistics).

A limitation of using levels models with cluster-robust standard errors is that the analysis is based on the assumption that the firm-specific effects inducing autocorrelation in the residuals are uncorrelated with the explanatory factors. This assumption may well be violated. To the extent

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[9]Care needs to be exercised in distinguishing among cross-sectional, panel data, and time-series studies. The distinction is important because, for example, panel data studies that do not account for autocorrelation involve a different set of issues and biases than cross-sectional studies.

that firm-specific effects are correlated with the explanatory factors, the estimated coefficients will be biased and inconsistent. This suggests, for example, the need to take first differences to remove time-invariant firm-specific effects or to address the stationarity issue that S&H raise.

However, a concern with taking differences is that the effects of measurement error may be exacerbated (Griliches and Hausman 1986). That is, the "signal-to-noise" ratio tends to be lower for differenced data than for levels data. (Depending on the nature of the measurement error, measurement error might actually be reduced by taking first differences.) Thus, the researcher is faced with the unenviable task of choosing between omitted variable bias and measurement error bias. When the analysis is focused on assessing the information content of a specific metric, the measurement error concern becomes less of an issue. The research question in such studies is whether the metric is reflective of value-relevant information (i.e., whether shocks to the metric contain a signal sufficiently associated with financial market outcomes). When the analysis is focused on the information content of a construct (as reflected by a measure), greater ambiguity exists and the choice comes down to a levels model with cluster-robust standard errors versus a first-differences specification. In any event, levels models that ignore autocorrelated errors (a commonly used approach) are clearly an unacceptable option.

Although the econometric issues we discuss are well established, it is less clear-cut how the results from studies running levels models subject to spurious regression concerns should be treated. Because the estimated values may seem plausible, they are often given credence and are used to support a given theory. Although S&H claim that these levels models "have limited value," they make use of the results from such studies to support their propositions. A problem with this approach is that propositions are assumed to be supported by valid statistical analyses, when they are not. Future research has a tendency not to question the studies that serve as the foundation for the proposition but rather assumes that the empirical work underlying the proposition has been adequately vetted. As a result, future research may not be building on a foundation as solid as might be presumed.

Indeed, there is a tendency for some studies to get misinterpreted over time to agree with a particular viewpoint. For example, counter to common interpretation and S&H's discussion (p. 306), Ittner and Larcker (1998) do not find that "changes in customer satisfaction are associated with increases in abnormal returns." Ittner and Larcker report that market value is associated with the level of customer satisfaction in cross-sectional analysis. However, they do not test, nor do they report, whether changes in market value are associated with changes in satisfaction. In a footnote, Ittner and Larcker report that they ran an event study linking abnormal return to the change in satisfaction, but they did not find statistically significant results.[10] Yet it is

common to interpret Ittner and Larcker's findings as if they ran analyses based on changes, when indeed they did not.

As such, we differ with S&H on how to use results from levels models that do not account for autocorrelation (i.e., we place less credence on the findings). Our recommendation is more consistent with that advocated by Granger and Newbold (1974, p. 117), who state that if an equation is found to have strongly autocorrelated residuals "the only conclusion that can be reached is that the equation is misspecified." Levels models that do not account for the autocorrelated properties of the series should not form the basis for a research study, manuscripts relying on these studies should not be accepted for publication, and the findings from these studies should not be given credence.

WHY USE TOBIN'S Q INSTEAD OF STOCK RETURN?

Srinivasan and Hanssens recommend Tobin's q as preferable to the market-to-book ratio for empirical modeling of firm valuation. However, they do not articulate why Tobin's q or the market-to-book ratio should be used instead of stock return for analyses that assess business performance. Although certain contexts (e.g., some forecasting situations) may warrant the use of a measure other than stock return (Mizik and Jacobson 2009), we suggest that for most applications—particularly those attempting to establish a causal link—it is more expedient and advantageous to use stock return as the financial performance metric. Because in most contexts it has superior properties, research not using stock return should explain why it makes use of an alternative financial market performance metric.

Although Tobin's q is theoretically appealing, its use has limitations in empirical work. When a researcher takes into account its dynamic properties, analysis using Tobin's q has characteristics similar to analysis based on stock return, albeit with constraints that may not be warranted. Furthermore, measurement error issues associated with calculating asset replacement value (the denominator in q) add a set of problems that researchers using stock return do not face. It is also the case that the properties of stock return have been more systematically studied and stock return is available at a higher periodicity. Although the use of stock return has its limitations (e.g., investor expectations may not be correct), Tobin's q has these same issues. As such, we do not believe that there is any benefit to using Tobin's q as compared with stock return.

Consider a Tobin's q model of the following form:

$$(1) \qquad \log Q_{it} = \alpha_i + \beta X_{it} + \varepsilon_{it},$$

where q is the ratio of the market value of an asset to its replacement cost and X is a vector of variables of interest. As S&H, among others, note, Tobin's q may have a unit root, which requires taking first differences of the data, or first-differencing may be necessary to control for the presence of a fixed effect α_i. The differencing yields the following:

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[10]Another part of their analysis involves assessing the link of abnormal return to the level of customer satisfaction (not the change in satisfaction). Although Ittner and Larcker (1998) report statistically significant effects, it is questionable whether this finding would have external validity (e.g.,

appear in future periods) given the tenuous nature of this specification implying that investors expect all firms to have the same level of satisfaction.

$$(2) \qquad \Delta \log Q_{it} = \beta \Delta X_{it} + \eta_{it}.$$

To simplify the analysis, consider Equation 2 for a firm without debt. Then, Equation 3 can be rewritten as

$$(3) \quad \log(MktValue_{it}/Assets_{it}) - \log(MktValue_{it-1}/Assets_{it-1})$$

$$= \log(MktValue_{it}/MktValue_{it-1}) - \log(Assets_{it}/Assets_{it-1})$$

$$= \beta \Delta X_{it} + \eta_{it},$$

where $Assets_{it}$ is the replacement value of firm i's assets at time t. Equation 3 can be reexpressed as

$$(4) \qquad StkR_{it} - AssetGrowth_{it} = \beta \Delta X_{it} + \eta_{it}$$

or, equivalently, as

$$(5) \qquad StkR_{it} = AssetGrowth_{it} + \beta \Delta X_{it} + \eta_{it}.$$

Unconstrained analysis of Equation 5 can be undertaken by estimating the following:

$$(6) \qquad StkR_{it} = \phi AssetGrowth_{it} + \beta \Delta X_{it} + \eta_{it}.$$

As such, Tobin's q–based modeling, given its dynamic properties, can be viewed as a stock return model but with the effect of asset growth constrained to 1.00. To the extent that the constraint is valid, the Tobin's q specification will be more efficient than the stock return model. To the extent that the constraint is not valid, the Tobin's q model will be misspecified because of an unwarranted restriction. We are not aware of research investigating this issue, but we have reservations about the validity of the constraint.[11]

Q theory of investment (Mussa 1977; Tobin 1969) postulates that the equilibrium market value of an asset set composing a firm is equal to the replacement value of these assets. As such, asset growth may well have a unit correspondence with growth in market value (i.e., stock return). However, this need not be the case. Furthermore, in practice, empirical analysis does not measure replacement cost, because it is unobservable. Instead, it is typically proxied by the book value of physical assets. This neglects (1) the difference between book value and replacement value and (2) the role of intangible assets. As such, deviations of Tobin's q from unity may reveal little about the extent to which market value differs from replacement value (which theoretically would stem from, for example, management quality or monopoly power); rather, it may indicate the degree to which asset replacement value is mismeasured.

Furthermore, the dynamic properties of empirical measures of Tobin's q may not reflect the properties on the underlying theoretical construct. For example, the persistence of Tobin's q may not be reflecting the persistence of "monopoly profits" but rather the persistence of measurement error. Measures of Tobin's q may have properties more similar to the market-to-book ratio than to the theoretical construct Tobin envisioned. It is difficult to explain

the vastly different dynamic properties prior research has assigned to Tobin's q metrics. Some have modeled it as having a unit root, others have modeled it as an autocorrelated series, and yet others have modeled it as a white noise series. These unresolved ambiguities again point to the advantages of working with stock return, in which statistical properties are well established and modeling practices and findings tend to be much more uniform.

Finally, some researchers in marketing have incorrectly attached alternative interpretations to results obtained from stock return (Equation 6) and Tobin's q (Equation 1) models, declaring the coefficients derived from stock return models "short-term" effects and the results obtained from Tobin's q models "long-term" effects. This interpretation is misguided for two reasons. First, as we show, a simple transformation reexpresses Tobin's q in terms of stock return. Because the interpretation of the structural economic relationships does not change with simple equation manipulations, the interpretation of the coefficient β in Equations 1 and 6 also does not change. As such, the estimates and their interpretation should be identical. The reason for obtaining different estimates from Equations 1 and 6 lies not with the alternative financial market–based measure but rather from researchers' failure to model the dynamic properties of the Tobin's q series, which leads to biases in Equation 1 estimates. Second, all effects identified in stock return models are long-term or permanent effects. Because stock return is the first difference of market value and the underlying metric of market value is a unit root process, the effects are permanent (i.e., long-term) (see Dekimpe and Hanssens 1995, 1999).

SUMMARY AND CONCLUSIONS

We encourage further research to take into account the dynamic properties of financial measures and not to rely on results from previous analyses making use of levels models that ignore the effects of autocorrelation on the statistical properties of the results. We suggest that it would be more expedient for analyses to be based on stock return rather than Tobin's q, which is subject to several unresolved issues associated with, for example, measurement error. Future analyses need to be clear whether they are assessing value relevance or financial market mispricing. Mispricing research, whether using unrestricted VAR models or other methods (e.g., calendar-time portfolios), is less likely to uncover empirical regularities because of the role of financial market participants in dissipating trading opportunities.

We commend S&H for reviewing and providing guidance for a research stream that does not have a firm foundation in marketing but will undoubtedly be a more important part of marketing research in the future. Some of our differences with points that S&H raise are not criticisms of their work per se, but rather are our reflections on the ongoing dialogue required for marketing to advance in using financial market data. We look forward to this dialogue.

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[11]We are also not aware of research investigating another implicit constraint—the extent to which the components in the Tobin's q ratio respond similarly to marketing stimuli. That is, does the market value of equity have the same properties as debt?

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Marketing Issues in Corporate Finance

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Srinivasan and Hanssens (2009) describe a rich set of interactions between marketing and the study of asset valuation in finance. Ideas from marketing research can be applied to other areas of finance as well, such as the analysis of corporate financial policy. Marketing themes have increasingly been developed in recent work on the sale of financial securities, mergers and acquisitions, and capital structure.

THE MARKETING OF FINANCIAL SECURITIES

In the simplest model of corporate finance, firms choose which financial claim to issue and immediately sell it for its fair market value. However, it has long been recognized that there is a marketing component to the sale of securities by firms. An influential article by Ross (1989) argues that marketing plays an important role in providing information about new financial claims. In Ross's model, an investment bank serves in part as a marketing network, and the role of the marketer is to explain the nature of the claim being sold to investors.

In any theoretical setting that departs from homogeneous investor rationality (e.g., those of behavioral finance), investors may have a variety of views on the attractiveness of different securities. In choosing which claims to sell, the firm is essentially designing a product for a market of consumers with a range of preferences. In behavioral models, therefore, the marketing and framing of financial claims is a crucial component of security design (Shefrin and Statman 1993). Studying the beliefs of investors is a form of market research for a firm that is planning to sell a security (Garmaise 2001).

The need for marketing is likely to be greatest in initial public offerings (IPOs), in which a firm seeks public equity investment for the first time. In practice, in the United States, an IPO is preceded by a significant marketing effort, including a road show of presentations to both institutional and retail investors and a book-building process, in which the investment bank that is leading the offering solicits bids for shares and records them in an order book. Notably, the book-building process is increasingly popular in other countries, often displacing other sales mechanisms, such as auctions, soon after their introduction (Sherman 2005).

From a marketing perspective, the central role of book building in the IPO issuance process raises several questions. First, why has the book-building mechanism emerged as the most successful method of distribution, despite some evidence that other mechanisms may yield higher prices? Degeorge, Derrien, and Womack (2007) argue that book building may serve an advertising function. Do marketing findings for other products help explain the relative advan-

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