Journal of Business Research 118 (2020) 223–239

Contents lists available at ScienceDirect

Journal of Business Research

journal homepage: www.elsevier.com/locate/jbusres

Marketing intensity and firm performance: Contrasting the insights based on actual marketing expenditure and its SG&A proxy

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A R T I C L E I N F O

Keywords:
Marketing expenditure
Marketing intensity
Marketing spending
Firm performance
Profitability
SG&A
Tobin's q

A B S T R A C T

Voluminous research documents marketing's ability to produce results. However, there is limited *direct* evidence relating firm marketing expenditure to profitability, or marketing efficiency. The challenge arises from poor data availability on marketing decisions in firms and questionable surrogates commonly used in place of marketing expenditure. In response, we collect actual marketing expenditure data in a representative sample of firms and investigate the relationship between marketing intensity and common measures of current and future performance. We find the impact to be positive. We contrast these results with findings based on selling, general and administrative expense (SG&A), which is a popular marketing proxy. We show that using SG&A may lead to questionable inferences about the impact of marketing spending on accounting performance. We propose an alternate, less noisy, approximation to total marketing expenditure and investigate the focal relationship among our sampled firms which do not disclose their marketing costs.

1. Introduction

Just as a firm's management is held accountable to the shareholders for maximizing firm profitability, marketers are increasingly pressed to demonstrate to the senior management their profit contribution through both effective and efficient use of firm resources (Hanssens, Rust, & Srivastava, 2009; Kim & McAlister, 2011; Moorman, 2014). Supporting this imperative, marketing scholars have argued that greater financial accountability is essential for marketing's credibility as a business function, empowering marketers in the executive suite, and enabling better allocation of resources to strategic activities (Hanssens & Pauwels, 2016; Rust, Lemon, & Zeithaml, 2004). Accordingly, the Marketing Science Institute has designated efforts to link marketing investments to financial outcomes that are of primary interest to managers—profitability and firm value—among its top research priorities in recent years.

In response, there has been a dramatic increase in research at the interface of marketing and finance focused on the relationship between marketing initiatives and various stock-market-based measures, including short-term and long-term stock returns, stock price variation, and firm market value. The balance of the accumulating evidence suggests that marketing activity has a beneficial impact on these financial metrics. For example, numerous event studies show that investors react favorably to new product introductions (e.g., Sood & Tellis, 2009), sponsorship deals (Cornwell, Pruitt, & Clark, 2005), celebrity endorsements (Agrawal & Kamakura, 1999), improvements in customer satisfaction (Fornell, Mithas, Morgeson, & Krishnan, 2006), and distribution channel expansion (Homburg, Vollmayr, & Hahn, 2014). Complementary research finds that marketing initiatives benefit firm market value, in particular, the choice of corporate branding over mixed branding (Rao, Agarwal, & Dahlhoff, 2004); large-scale expansion into related service offerings by manufacturing firms (Fang, Palmatier, & Steenkamp 2008); and, sustained investment in customer satisfaction (Fornell, Mithas, Morgeson, & Hult, 2016); although, the impact of advertising is ambiguous, and may be contingent on context and expenditure levels (Kim & McAlister, 2011). Research also finds

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[1] The authors thank Joel H. Steckel for his helpful comments.

https://doi.org/10.1016/j.jbusres.2020.06.032
Received 17 October 2018; Received in revised form 14 June 2020; Accepted 16 June 2020

that a firm's advertising effort may benefit firms indirectly by lowering their systematic risk (Osinga, Leeflang, Srinivasan, & Wieringa, 2011) and idiosyncratic risk (Bharadwaj, Tuli, & Bonfrer, 2011).

Despite the widely held belief of marketing's beneficial role on average, the literature remains inconclusive about the impact of marketing activity on firm profitability.[2] Marketing expenditures represent a significant operating cost that, owing to competition, buyer resistance, and consumers' cognitive limitations, translates imperfectly into desired outcomes (e.g., Lodish et al., 1995). While some marketing initiatives have a direct impact on sales revenues, other marketing actions impact revenues and profits indirectly and over time, for example, via brand equity that, itself, requires sustained investment to build and maintain (Keller & Lehmann, 2006). Certain non-financial outcomes marketers view as important and invest in, such as customer loyalty and market share, may only have a weak or contingent relationship with profitability (Reinartz & Kumar, 2000; Szymanski, Bharadwaj, & Varadarajan, 1993). This opacity of marketing efficiency raises questions whether marketing costs may outweigh any financial benefits they produce (Buzzell & Gale, 1987).

Ideally, one would resolve the uncertainty by exploring, in a comprehensive framework, the short-term and long-term profit impacts of investing in specific marketing tools and personnel—marketing communications, salesforce, public relations, non-traditional media, other activities. Accounting for major marketing expenditures jointly is important, because firms tend to pursue programs which integrate marketing inputs for synergistic impact (e.g., Srinivasan & Hanssens, 2009). Yet, unfortunately, such fine-grained investigation is not possible in most contexts, since firms normally do not disclose their marketing expenditures in itemized form or in the aggregate; neither do they report matched campaign-level results.

The lack of detailed data on marketing inputs and associated outcomes has hindered scholarly efforts to assess the relationship between marketing expenditures and profitability (Hanssens, Rust, & Srivastava, 2009; Katsikeas, Morgan, Leonidou, & Hult, 2016). To get around these data limitations, scholars across business disciplines have increasingly used selling, general and administrative (SG&A) expense as a proxy measure for total sales and marketing expenditure in models of firm performance, including where marketing is employed as a control (e.g., Balsam, Fernando, & Tripathy, 2011; Dutta, Narasimhan, & Rajiv, 1999, 2005; Krishnan, Tadepalli, & Park, 2009; Li, Shang, & Slaughter, 2010; Luo, 2008). On the upside, the SG&A data item possesses desirable qualities that make it potentially a practical and useful marketing proxy—it subsumes total marketing expenditure and is reported by most public firms. On the downside, SG&A is the most aggregate of accounting categories, designated to capture virtually all non-production operating costs, including executive salaries, insurance, rent, information technology (IT) infrastructure, pension expense, bad debt expense, and depreciation (Needles, Powers, & Crosson, 2011; Standard & Poor's Compustat User's Guide, 2003, p. 269). This also makes SG&A a noisy and imperfect measure of a firm's total marketing effort. Despite the latter limitation, the use of SG&A as a marketing proxy in business research has spread without adequate empirical validation.

Only one published study investigates SG&A as a proxy for certain marketing expenses (Ptok, Jindal, & Reinartz, 2018). It separately evaluates SG&A as a surrogate for advertising, promotional expenses, and selling costs. The authors find that SG&A possesses content validity with respect to all three marketing measures, but lacks construct validity as a measure of advertising or promotional expenses. At the same time, that study concludes that SG&A represents a reasonable proxy for a firm's selling effort based on a moderately high 65% correlation with the number of salespeople variable used to assess the relationship. Whilst Ptok et al. (2018) generate valuable insights, they do not evaluate SG&A in its most *common* and *relevant* application as a proxy for *total* sales and marketing expenditure. Since SG&A subsumes advertising, promotional expenses, selling expenses and the cost of marketing personnel, it can conceivably represent an acceptable proxy for a firm's total marketing effort while not being a good proxy for specific marketing items that constitute the total. Our research addresses this critical gap.

Also noteworthy, our study differs from Ptok et al. (2018) with respect to sample generalizability and measurement characteristics. Ptok et al. (2018) evaluate 78 of the nation's largest advertisers and a separate sample of 86 companies with the largest sales forces, which, by definition, differ in marketing sophistication and expenditures from the "average" firm. Our broad-based sample more closely resembles samples typically used in scholarly research. Whereas Ptok et al. (2018) use a multi-step approach to impute estimates of advertising and promotional expenses for benchmarking purposes, our research uses marketing expenditure data as reported by firms. Taken together, these distinct characteristics of our research allow us to generate unique triangulating evidence on SG&A as a marketing proxy, including evaluating SG&A's performance if used as a selling expense proxy (as proposed by Ptok and colleagues).

In sum, our investigation makes three contributions to the literature. First, we use data on total sales and marketing expenditure in a representative sample of firms to generate *direct* evidence that marketing intensity has a positive impact on firm profitability. Our second contribution consists in comparing and contrasting this result with findings derived by using SG&A as a proxy measure for total marketing expenditure. To achieve comparability with the literature, we investigate the impacts both on accounting profit rates and stock market expectation of future earnings growth. This provides an important test of SG&A's performance as a marketing proxy in common models of firm performance. We show that, for some dependent variables, using SG&A may lead to different inferences about the impact of marketing activity on firm performance and discuss the likely reasons for the observed effect. Third, since most firms do not report their total marketing costs, and the SG&A-based proxy may be problematic in some contexts, we explore one way of constructing a less noisy estimate of total marketing expenditure that, with appropriate adaptation, may help generate improved estimates of marketing expenditure in other samples of interest. We use the alternative measure of marketing expenditure in our models of firm performance, while accounting for possible selectivity associated with firms' choice of marketing expenditure disclosure, to generate further confirmatory evidence concerning the positive impact of marketing intensity on current and future profitability among firms that do not disclose marketing costs (and for whom marketing's impact on firm performance is difficult to evaluate directly).

2. Marketing expenditure and firm profitability

The conceptual view of marketing holds that marketing activities drive accounting performance via a direct impact on current and future revenues. Marketing achieves this by uncovering under-served customer needs and market opportunities through research and sales prospecting; informing and developing the market through advertising, public relations, sales demonstrations, trials, and sampling; stimulating the market through sales promotions; and, getting orders through personal selling and direct marketing (e.g., Kotler & Keller, 2016). In addition, sustained investment in advertising, celebrity endorsements, sponsorships, and institutional marketing, as well as various customer maintenance and relationship-building programs, create valuable brand

[2] Although some authors have treated stock returns or market value as useful *holistic* proxies for accounting measures, the prevailing view is that firm performance is a multi-dimensional construct, with stock-market measures being distinct from accounting measures (e.g., Ambler & Roberts, 2008). Empirical evidence supports this treatment: stock returns show low correlation with accounting earnings (see Lev, 1989 for an overview), and many studies report low correlations between accounting profit ratios and firm valuation measures, including Tobin's q.

Table 1
Marketing expenditure descriptions and amounts (in $ million) from FY[a] 2012 10-K reports and Compustat.

Source:		10-k			Compustat	
Company	FY	Total Selling and Marketing Expense Description from 10-K Reports	Total Mktg	Adv	R&D	SG&A
Campbell Soup Co.	2012	No description provided	1020.0	506.0	125.0	1756.0
	2011		1007.0	492.0	129.0	1748.0
	2010		1058.0	515.0	123.0	1786.0
Church & Dwight Inc.	2012	Marketing expenses include costs for advertising (excluding the costs of cooperative advertising programs, which are reflected in net sales), costs for coupon insertion (mainly the cost of printing and distribution), consumer promotion costs (such as on-shelf advertisements and floor ads), public relations, package design expense and market research costs.	357.3	N/A	54.8	746.3
	2011		354.1	N/A	55.1	721.9
	2010		338.0	N/A	53.7	689.5
Ethan Allen Interiors Inc.	2012	Our marketing and advertising strategies are developed to drive traffic into our network of design centers and to EthanAllen.com. We create and coordinate print, digital and television campaigns nationally, as well as assist in international and local marketing and promotional efforts.	173.9	27.5	NA	340.7
	2011		161.6	26.2	NA	316.4
	2010		142.6	20.8	NA	293.4
Microsoft	2012	Sales and marketing expenses include payroll, employee benefits, stock-based compensation expense, and other headcount-related expenses associated with sales and marketing personnel, and the costs of advertising, promotions, trade shows, seminars, and other programs.	13,857	1600	9811	28,237
	2011		13,940	1900	9043	27,205
	2010		13,214	1600	8714	25,932
PMFG Inc.	2012	Sales and marketing expenses include payroll, employee benefits, stock-based compensation and other employee-related costs associated with sales and marketing personnel. Sales and marketing expenses also include travel and entertainment, advertising, promotions, trade shows, seminars and other programs and sales commissions paid to independent sales representatives. We market our products worldwide through independent sales representatives who sell on a commission basis. These independent representatives, substantially all of whom have technical backgrounds, work in conjunction with our application engineers. We also sell our products directly to customers through our internal sales force. Our promotional and marketing activities include direct sales contacts, participation in trade shows, an internet website, advertising in trade magazines and distribution of product brochures	12.2	0.2	0.6	36.3
	2011		11.9	0.2	0.5	35.1
	2010		11.2	0.1	0.5	34.1

[a] FY = Fiscal Year. 10-K reports normally show expenses over the preceding three years, with a single expense category description (if provided) applying to all the years.

and customer equity, which benefit firm fundamentals indirectly in various ways, and over time (e.g., Kumar, 2008; Morgan, 2012).

Within this framework, marketing investment has a range of divergent direct and indirect, impacts on components of the profit equation—a probabilistic positive impact on sales revenues, a deterministic negative impact on total marketing costs, and, potentially, a positive offsetting effect on certain marketing and operating costs (e.g., more efficient customer acquisition or lower product returns). Moreover, marketing investments may have a positive impact on earnings growth. Because of the complexity and opacity of these effects, the average net profit impact of marketing expenditure is not intuitively obvious. Extant empirical findings, which are quite limited, reflect this ambiguity.

In their widely-cited work, Buzzell and Gale (1987) use data generated by the Profit Impact of Market Strategy (PIMS) study in the 1960′s and 70′s to show a negative relationship between marketing intensity and return-on-investment (ROI) for business units of large industrial firms. They argue, accordingly, that marketing intensity represents a major cost driver that diminishes profitability in general. Although two subsequent studies using the same data have disputed those findings on methodological grounds, and demonstrated a positive relationship (Boulding, 1990; Jacobson, 1990), no additional evidence based on actual total marketing expenditure in cross-industry firm samples has emerged.

Extensive research using surrogate measures of marketing expenditure has not produced results that enable strong inferences about marketing's impact on firm profitability either. Variability in results involving advertising has been noted by many authors (e.g., Lodish et al., 1995; Kim & McAlister, 2011). Similarly, many published studies using SG&A report an insignificant or negative relationship between SG &A and accounting profits, but a mostly positive relationship with stock market expectations of future earnings growth reflected in Tobin's q. On the face of it, both proxies are problematic. Advertising represents a variable fraction of total marketing expenditure in different industries. SG&A subsumes various non-marketing costs. Unsurprisingly, inferences about marketing's impact proxied by advertising may diverge from those based on SG&A. For example, Morgan and Rego (2009) report results where advertising intensity has a positive impact on cash flows, but not Tobin's q, whereas marketing intensity based on SG&A produces the opposite set of results. On balance, the results variability involving marketing expenditure proxies may reflect true effects given the contingencies and sample characteristics of specific studies, although one must also consider possible instrument artifacts.

Accordingly, the current paper extends the literature by using marketing expenditure data from a diverse and representative sample of firms to explore the impact of marketing intensity on firm profitability, as well as expectation of future earnings growth. It extends measurement research by considering the implications of employing SG&A as a marketing proxy in conventional models of profit performance. We focus on SG&A, because it subsumes all sales and marketing costs, which makes it a more conceptually appropriate proxy for *total* sales and marketing expenditure than advertising, since the latter represents a portion of the total effort in many firms (FTC, 1977; Lilien, 1979). By the same logic, focus on SG&A is consistent with our research interest in a firm's total marketing intensity. Nevertheless, we discuss the limitations of advertising as a marketing proxy in Section 4.

3. Marketing expenditure reporting

3.1. Definition and reporting conventions

Although the U.S. Generally Accepted Accounting Principles require firms to disclose all material expenditures, the same guidelines, oddly, permit aggregation of marketing expenses with general and administrative (G&A) costs on financial statements. As a result, only some firms disclose their *total* marketing expenses as a single line item or itemized. We henceforth refer to these firms as 'reporting.' Most firms do not disclose their *total* marketing expenses in any format, but, instead, combine marketing with G&A costs and show the aggregate figure as a single SG&A expense. This effectively obscures a firm's total marketing expenditure, even if the firm breaks out advertising as a separate line item. We henceforth refer to these firms as 'non-reporting.' Our content analysis of a sample of firm financial statements, conducted to inform this investigation, shows that, consistent with the normative view of marketing activities (e.g., Kotler & Keller, 2016), firms commonly define marketing expenditures as the costs of activities and personnel associated with customer acquisition and retention, product sales, brand building, and institutional marketing. We provide examples of marketing expenditure definitions from 10-k reports in Table 1.

Reporting firms typically show their total sales and marketing expenditures as a single line-item on the consolidated income statement or in the footnotes. Thus, the measure is an aggregate amount capturing all sales and marketing activities by a corporate entity. As such, this measure (which we collect manually) is fully comparable with accounting data items available through common data sources, such as Compustat, with the same caveat that applies to those data items—this is a summary measure that captures, in a single number, a diverse range of related activities that may vary across firms.

3.2. Reasons for non-reporting

Given a relatively low frequency of marketing expenditure disclosure, it is critical to understand the reasons for (non)reporting to inform our empirical analyses. Unfortunately, the accounting literature provides limited guidance as to what influences firms' reporting conventions with respect to marketing expenses specifically. To identify the likely reasons for marketing expenditure (non)disclosure, we supplement general insights from the literature with a pilot study involving content analysis of a sample of firm financial statements for a 17-year period from 1996 to 2012. One of the key findings of this investigation is that marketing expenditure reporting is stable over time.[3] We next discuss the most plausible reasons for (non)reporting.

3.2.1. No marketing function

Some firms do not report marketing expenditure, because they do not engage in conventional marketing activities, or those activities constitute an immaterial portion of their operations. Most of those firms are in industries associated with the production or desk trading of natural resources and commodities, including commodity services, such as ocean freight transportation. This group also includes development-stage pharmaceutical firms, which tend to be pure R&D organizations. Our analysis of these firms shows that small pharmaceutical firms begin to develop own sales and marketing organization once they reach a certain scale, estimated to be in excess of $50 million in sustained annual sales.

3.2.2. Cost of reporting

Firms incur a range of economic costs associated with more detailed tracking, classification, auditing and reporting of expenditures (Berger & Hann, 2007). Although larger firms may mitigate these costs by implementing more sophisticated accounting systems, their greater operating scope and scale likely offset accounting efficiencies gained through technology. In contrast, smaller firms have lower marketing complexity, but they also have fewer resources to implement and support more extensive accounting. Regardless of available resources, the literature indicates that profit-maximizing firms will be reluctant to incur extra reporting costs.

[3] While several firms changed their reporting convention during our research window (e.g., stopped reporting), our main dataset has no firms that changed their marketing expense reporting approach multiple times.

3.2.3. Secrecy

Greater financial disclosure by firms may also impose various non-economic costs. In particular, observable variations in marketing spending may inform competitors about changes in a firm's strategies (Gigler, 1994; Healy & Palepu, 2001). Disclosure of sudden changes in marketing spending may also invite undesirable public scrutiny in some contexts. Hence, firms may find it beneficial to hide their marketing spending by aggregating it with G&A expenditures. Although considerations of secrecy likely apply to many firms, more dominant firms, and firms competing in oligopolistic markets may benefit relatively more from concealing specifics of their marketing expenditure.

3.2.4. Industry effects

Reporting practices involving marketing spending may also reflect industry conventions. Some industries, for example, those that produce controversial products or services, may prefer less transparency. For instance, since approximately 1992, pharmaceutical firms have tended not to disclose any elements of their marketing expenditure, in spite of being among the most marketing-intensive organizations. Other industries may have evolved with minimalist reporting of certain expenditures.

3.3. Marketing expense disclosure

Marketing expenditure disclosure by some firms may arise from legacy accounting practices. Due to inertia or switching costs, firms may continue with a particular accounting practice from their early days. The accounting literature also indicates that greater financial disclosure may provide tangible benefits for some firms. Most notably, more detailed reporting may draw financial analysts' attention, because greater information availability minimizes analysts' effort while increasing forecast accuracy. Analyst coverage of firms is believed to help reduce information asymmetries among investors and encourage investor interest (Bayer, Tuli, Skiera, 2017), which positively impacts stock liquidity (Healy & Palepu, 2001).

4. Limitations of advertising as a marketing proxy

A number of firms disclose their advertising spending, which has prompted some authors (e.g., Allen & Pantzalis, 1996; Hennart & Park, 1993) to use advertising as a proxy for total marketing expenditure. This specific application of advertising data is problematic on two levels. Advertising is reported by a fraction of firms (about 30% by our estimate), which restricts the size and composition of data samples used in empirical analyses. To the extent that the same (types of) firms are systematically included or excluded from the sampling frame based on advertising data availability, papers using advertising as a proxy for marketing may reflect the same unaccounted for bias in conclusions about marketing's impact (Kurt & Hulland, 2013).

In addition, firms that report their advertising spending typically do not specify how the advertising investments relate to their total sales and marketing costs. Research shows that advertising expenditure constitutes a different proportion of total marketing spending in different firms (Lilien, 1979). Lilien's findings are further substantiated by the Federal Trade Commission's (FTC, 1977) Annual Line of Business surveys. This government program, active between 1974 and 1977, surveyed 471 US corporations to collect accounting data disaggregated at the 4-digit SIC level. The data form separated media advertising spending from other selling and marketing expenses. These data show important differences across SIC industries. The report concludes (FTC, 1977, pp. 14-15) that "for all-manufacturing industry categories, the weighted average media-advertising-to-sales ratio is 1.2 percent; for total selling expenses to sales, the weighted average is 6.6 percent. This suggests that analyses using only media advertising expenses data necessarily ignore what is in fact the vast majority of selling activity."

While the ratio of advertising to total selling and marketing spending may be higher for consumer products manufacturers and service providers, it is far from one. For example, in our data, which we detail in subsequent sections, 106 firms report both advertising and total selling and marketing costs. Using firm-year observations, the ratio of advertising to total selling and marketing expenditure among firms that report both numbers is 19% for industrial firms, 46% for consumer firms, 20% for manufacturers, and 59% for service providers. The correlation between advertising and total marketing spending for firms that reported both is 62% in our full dataset. These statistics effectively support the conclusions of the FTC report. In Table 1, we show examples of advertising and marketing expenditure reporting by our sampled firms, including smaller firms and several household names from different industries.

5. Research design

We evaluate two profit rate models that, in a general form, specify firm profitability as a function of R&D intensity (i.e., value-creating investments), marketing intensity (i.e., value-capturing investments), common controls, and firm and year fixed effects. Model (1a) captures marketing's impact on current profit rate. This model includes profitability in the previous year as a predictor to incorporate possible dynamic effects. We lag all other independent variables and controls by one year to minimize endogeneity concerns.

$$\mathrm{PROFIT\_RATE}_{\mathrm{it}} = \gamma_{a0} + \gamma_{a1}\mathrm{PROFIT\_RATE}_{\mathrm{it}-1} + \gamma_{a2}\mathrm{R\&D\_INTENSITY}_{\mathrm{it}-1} + \gamma_{a3}\mathrm{MARKETING\_INTENSITY}_{\mathrm{it}-1} + \gamma_{a4}\mathrm{CONTROLS}_{\mathrm{it}-1} + \mathrm{ERROR}_{1\mathrm{ait}} \tag{1a}$$

Model (1b), which captures future profitability, evaluates the impact of marketing intensity on the mean future profit rate over the second and third year following marketing expenditure.

$$FUTURE\_MEAN\_PROFIT\_RATE_{it} = \gamma_{b0} + \gamma_{b1}R\&D\_INTENSITY_{it-1} + \gamma_{b2}MARKETING\_INTENSITY_{it-1} + \gamma_{b3}CONTROLS_{it-1} + ERROR_{1bit} \tag{1b}$$

Although our primary focus is on accounting profitability, we also evaluate a stock-market-based measure of expected future earnings growth (TOBIN'S_Q) as the dependent variable in our third model (1c). Tobin's q represents a summary measure of a firm's expected future profit evolution under the assumption of stock market efficiency. As such, it is a distinct, but conceptually relevant financial measure of profit performance commonly used in business research. Consistent with prior research, we use the same specification for this model as (1a) (e.g., Dutta, Narasimhan, & Rajiv, 1999, 2005; Morgan & Rego, 2009):

$$TOBIN'S\_Q_{it} = \gamma_{c0} + \gamma_{c1}PROFIT\_RATE_{it-1} + \gamma_{c2}R\&D\_INTENSITY_{it-1} + \gamma_{c3}MARKETING\_INTENSITY_{it-1} + \gamma_{c4}CONTROLS_{it-1} + ERROR_{1cit} \tag{1c}$$

In these models, we evaluate three different measures of marketing intensity. We first consider the impact of marketing intensity on firm profitability using actual sales and marketing expenditure data in a sample of firms that report those costs. We next compare and contrast the obtained results with those based on SG&A as a proxy measure for marketing expenditure. We then develop a model for predicting marketing expenditure using available information and show that the obtained estimates provide a meaningful improvement on SG&A as a marketing proxy. Afterwards, we present results using the alternative estimate of total marketing expenditure. Since only a fraction of public firms disclose their marketing expenditures, the latter exploration seeks to correct for a possible non-reporting (selection) bias using the Heckman model that we estimate jointly with the marketing expenditure prediction model and firm performance model.

5.1. Variables

Our primary dependent variable is return-on-assets (*ROA*). It is operationalized as earnings before interest and taxes (EBIT) divided by average total assets. We use EBIT in the ratio to net out the impact of capital structure and tax optimization decisions (e.g., Berger & Ofek, 1995). We additionally express future profitability using two distinct measures—mean ROA in the second and third year following marketing expenditure (*FROA*), and investor expectation of future earnings growth expressed in *Tobin's q*. The latter is conceptualized as the ratio of a firm's market valuation to the replacement value of its assets, so that higher values of Tobin's q indicate superior future profitability under the assumption of stock market efficiency. Since the replacement value of firm assets is usually unknown, we follow the popular procedure proposed by Chung and Pruitt (1994) to compute Tobin's q.

Next focusing on the independent variables, *R&D Intensity* is expressed as the ratio of R&D expenditures to total assets. In what we call the "Direct Model," *Marketing Intensity* is represented by the ratio of total sales and marketing expenditure to total assets (*MKTG*/Assets). In parallel, we evaluate the so-called "Proxy Model" that uses *SG&A/Assets* as a proxy for *Marketing Intensity*, consistent with the current use of SG&A in scholarly research. We operationalize SG&A expense as Compustat data item XSGA less Compustat data item XRD (R&D expenditure), since Compustat includes R&D expenditure in XSGA.

By definition, SG&A is the sum of total marketing expenditure and G&A. The Direct Model treats these effects separately as *MKTG/Assets* and *G&A/Assets*, which makes this model comparable to the Proxy Model. Note that marketing and G&A represent conceptually different expenditures with distinct anticipated impacts on profitability. In particular, marketing is viewed as a productive investment in profit generation (which we test in this research). G&A, which is also a decision variable, captures expenditure on important infrastructure, such as IT and personnel, but also includes overhead. As such, the latter is a cost item that, *a priori*, can have a net-negative impact on firm profitability.

The CONTROLS class of variables includes standard controls used to model firm performance, namely: market power, as reflected in *Market Share* at the four-digit SIC level; firm size, reflected in annual revenue (*Sales*); *Slack*, which is a measure of liquid resources, operationalized as the ratio of cash and equivalents to total assets; capital intensity (*Capital*), operationalized as the ratio of property, plant and equipment to the number of employees; revenue growth from the previous year (*Sales Growth)*; and, industry concentration, captured in Herfindahl-Hirschman Index (*HHI*) computed at the four-digit SIC level. The models also include calendar year fixed effects to control for differences in economic conditions over time, and firm fixed effects. We use logs of *Sales*, *Market Share*, *Sales Growth*, *Capital*, and *HHI* to correct for skewness.

5.2. Data and estimation

We started with a sample of 1300 firms, including all S&P 500 firms and 800 randomly selected firms active in 2009. We selected the non-S&P firms using a stratified sampling procedure. Our four broad strata capture the fundamental dimensions most commonly used to define businesses: manufacturing firms vs. services and industrial firms vs. consumer firms. We used the Fama-French industry-sector categories as the sampling frame (Fama & French, 1997).[4] We opted for Fama-French-defined industries over the better-known SIC classification, because one of our key analyses involves prediction of marketing expenditure using firm and industry data. The Fama-French classification achieves greater within-industry homogeneity of financial ratios, which is a particularly desirable quality for our purposes.

We next identified and excluded firms that do not engage in conventional marketing activities and which are, therefore, not the focus of our investigation. The exclusion was performed based on firm membership in specific four-digit SIC industries (identified in Table 2), such as SIC 4013, railroad infrastructure. We also excluded duplicate entries since some of our randomly sampled firms were S&P 500 firms. Our resultant baseline sample of unique firms that engage in conventional marketing activities included 1029 firms. We consulted each firm's income statement in the 10-k report for fiscal year 2009 (our baseline year) and, where available, obtained total marketing costs for 2007–2009 directly, since firms that disclose marketing costs normally do so on the income statement and include two past years of accounting data. For firms that do not disclose marketing costs on the income statement, we next conducted a keyword search using the terms "sales," "selling," "marketing," "advertising," "promotion," "sampling," and "detailing." We used research assistants to visually inspect the mentions and record references to specific expenditure amounts. We repeated the procedure for fiscal years 2006 and 2012 for all firms. Since marketing expenditure reporting conventions are stable over time, and financial statements present results using three-year sliding windows, the streamlined approach allowed us to gather data for all years from 2004 through 2012.

We next classified the firms as 'reporting' or 'non-reporting.' We categorized as 'reporting' only firms that directly disclose their total selling and marketing costs on the income statement or, in rare cases, break out all three major marketing expense sub-categories: (1) advertising, (2) selling, and (3) "other marketing" costs. The 'reporting' sample excludes firms that provide only partial disclosure. For example, Procter & Gamble only discloses advertising and SG&A, but not selling expenses or other marketing costs. Accordingly, it was classified as a 'non-reporting' firm.

We merged the marketing expenditure data collected directly from financial statements with accounting data obtained from Compustat. We winsorized all the variables at 0.5 percent in each tail to minimize the impact of outliers on our conclusions. To control for variation in results across our models which may be due to the inclusion or exclusion of specific firms, we excluded from our analysis firms with missing data in any of our models.[5] The resultant dataset consists of 5206 firm-year observations on 704 firms, including 1131 firm-year observations on 156 reporting firms and 4075 firm-year observations on 548 non-reporting firms. We show our sample composition by Fama-French and SIC industry composition in Table 2.

Our Eq. (1a) has a lagged dependent variable as a predictor. Under the standard assumption of serially uncorrelated errors and exogenous

[4] Fama and French (1997) proposed an algorithm that seeks to address problems inherent in the older SIC classification. Their approach aggregates SIC industries into 49 industry sectors (initially, 48 sectors) based on common operating characteristics so as to achieve greater within-industry homogeneity, with focus on financial ratios and risk. Since the categorization is based on SIC, it possesses similar characteristics and displays similar performance in capital markets research (Bhojraj, Lee, & Oler, 2003). This classification scheme has

(*footnote continued)*
achieved wide adoption in financial research. The code to generate Fama-French industries using popular statistical software is widely available online and through Wharton Research Data Services (WRDS).

[5] The missing values for smaller firms (due to inconsistent reporting), some firms not reporting SG&A, and our use of lags and forward dependent measures account for most of the missingness in our data. Firms with missing R&D expenditure data were assigned a zero value for R&D and retained in the sample. This is consistent with common practice in strategy and financial research (e.g., Hirshleifer, Low, & Teoh, 2012; O'Brien, 2003) and theoretically justifiable. O'Brien (2003: 422) notes: "since 1975, firms have been required to expense and disclose virtually all R&D expenditures (White, Sondhi, & Fried, 1994: 397). Thus, missing values for R&D are likely the result of negligible expenditures. Furthermore, as Himmelberg, Hubbard, and Palia (1999) report, excluding firms from the analysis that do not report R&D expenditures biases the sample towards firms which make intensive investments in R&D."

Table 2
Composition of the full effective sample by industry sector and reporting status.

Fama-French Sector	Description	SIC Industries[a]	Non-reporting	Reporting
2	Food products	2000–2046, 2050–2063, 2070–2079, 2090–2092, 2095, 2098–2099	48	23
7	Entertainment	7800–7833, 7840–7841, 7900, 7910–7911, 7920–7933, 7940–7949, 7980, 7990–7999	50	11
9	Consumer goods	2047, 2391–2392, 2510–2519, 2590–2599, 2840–2844, 3160–3161, 3170–3172, 3190–3199, 3229–3231, 3260, 3262–3263, 3269, 3630–3639, 3750–3751, 3800, 3860–3861, 3870–3873, 3910–3911, 3914–3915, 3960–3962, 3991, 3995	38	14
11	Healthcare	8000–8099	57	9
13	Pharmaceutical products*	2833, 2834–2836*	61	8
14	Chemicals	2800–2829, 2850–2879, 2890–2899	75	11
21	Machinery	3510–3536, 3538, 3540–3569, 3580–3582, 3585–3586, 3589–3599	85	16
34	Business services	2750–2759, 3993, 7218, 7300, 7310–7342, 7349–7353, 7359–7369, 7374, 7376–7385, 7389–7394, 7396–7397, 7399, 7519, 8700, 8710–8713, 8720–8721, 8730–8734, 8740–8748, 8900–8911, 8920–8999, 4220–4229	84	15
36	Computer software	3570–3579, 3680–3689, 3695	7	20
41	Transportation	4000–4010, 4011*, 4013*, 4040–4049, 4100, 4120–4121, 4130–4131, 4140–4142, 4150–4151, 4170–4173, 4190–4200, 4210–4219, 4230–4231, 4240–4249, 4400*, 4412*, 4480–4600, 4610*, 4611–4700, 4710–4712, 4720–4749, 4780, 4782–4785, 4789	20	12
44	Restaurants, hotels, motels	5800–5829, 5890–5899, 7000, 7010–7019, 7040–7049, 7213	10	8
45	Banking	6000, 6010–6036, 6040–6062, 6080–6082, 6090–6100, 6110–6113, 6120–6179, 6190–6199	13	9
Total Unique Firms			548	156

[a] Firms in SIC industries denoted with an asterisk and development-stage pharmaceutical firms normally do not engage in conventional marketing activities.

explanatory variables, it is still subject to the well-known 'dynamic bias' (Nickell, 1981) – which is a type of endogeneity whereby the lagged dependent variable can be correlated with the error term. To address this problem, we use a system GMM approach for estimation (Blundell & Bond, 1998; Feng, Morgan, & Rego, 2015). The procedure re-arranges the original equation to form differences and stacks the level equation and the differenced equation together. The further lagged dependent variable in its differenced form and level form are used as instrumental variables to correct for the endogeneity (as detailed in Roodman, 2009).[6] The models pass the AR(II) test to confirm serially uncorrelated error terms, and the overidentification tests for instrumental variable validity. We use a fixed effect estimator to estimate models of *FROA* and *Tobin's q*.

6. Results

6.1. Descriptive statistics

Table 3 shows descriptive statistics in the effective sample and subsamples of reporting and non-reporting firms, whereas Table 4 shows the correlations. As the first step towards assessing possible bias in the data, we compare the means and proportions of our variables between the subsamples of reporting and non-reporting firms. The last column in Table 3 shows the statistics produced by our tests. Overall, we find mixed evidence that the subsets of reporting and non-reporting firms are different on key characteristics. The reporting and non-reporting firms have similar sales and SG&A. ROA and FROA are also similar at 7% on average, although the average Tobin's q is slightly higher. While there are differences in asset size, these differences are driven entirely by a handful of reporting companies—most notably, Bank of America, Citibank and JP Morgan Chase have assets in excess of $1 trillion in the years under study.[7] Likewise, the considerable differences in capital intensity are driven by several extreme outliers among non-reporting firms, most notably, Aircastle Ltd., which leases aircraft, and the luxury resorts operator Host Hotels & Resorts in the hospitality industry.

The reporting firms in our sample have lower organizational complexity as evidenced by such firms operating in 0.49 fewer industry segments on average. Additionally, the reporting firms have significantly higher slack resources. Research suggests that the amount of slack resources is related to observable firm characteristics, most notably size and growth (e.g., Sharfman, Wolf, Chase, & Tansik, 1988), which we seek to control for in our models.

6.2. Results based on observed marketing expenditure

Table 5 shows side-by-side results for the Direct Model and Proxy Model for our three dependent variables. [8]The Direct Model is estimated in the subset of reporting firms. For comparison purposes, the Proxy Model is separately estimated in the subset of reporting firms and the full sample. The regressions include firm fixed effects and year dummies that are not shown.

First, we observe that the obtained coefficients are of the expected sign and consistent with those reported in prior research, including a negative coefficient on R&D in ROA regressions (e.g., see Hirshleifer, Low, & Teoh, 2012). This gives a measure of face validity to the models. For the dynamic model, we also check the second-order autoregressive test to confirm the model errors are not serially correlated, and the first stage F-statistic to confirm the relevance of the instrumental variables. Next, our results for R&D are noteworthy, since R&D is a major discretionary expense that is similar to marketing and SG&A in important ways. Our regressions show a negative relationship between R&D intensity and ROA and FROA, but a positive relationship with Tobin's q. Such divergence in results between the two dependent measures is consistent with prior research (Hirshleifer, Low, & Teoh, 2012), and supports the argument that the accounting and stock market measures

[6] To our knowledge, there is no theoretical guidance as to how many lags to include as instrumental variables in the system GMM estimation. Under the assumption of serially uncorrelated disturbance term, the lags of the dependent variable and exogeneous variables are valid instrumental variables. The results shown in Table 4 have passed the tests of overidentification and serially uncorrelated errors, and by using the second to the seventh lags. Some other lag choices that pass the two aforementioned tests yield qualitatively similar results.

[7] Researchers sometimes omit banks from their samples, because banks' treatment of customer deposits as assets is different from the conventional

(footnote continued)
treatment of assets in other industries. Since banks are among the most active marketing organizations, we retain them in our sample. We consider results without banking companies in our sensitivity analyses. Our results are robust.

[8] To ensure comparability with prior studies that provide a direct benchmark for our results (e.g., Mizik & Jacobson, 2007; Morgan & Rego, 2009), we use non-clustered standard errors. Our sensitivity analyses using bootstrapped clustered standard errors produce qualitatively similar results.

Table 3
Descriptive statistics and tests of differences of means and proportions between firms with different reporting status.

			Full Effective Sample	Reporting Firms		Non-reporting Firms			
Variable[a,b]	N[c]	Mean	Std. Dev.	Mean (μ1)	Std. Dev.	Mean (μ2)	Std. Dev.	Diff. μ1-μ2	t-statistic[d]
ROA	5160	0.07	0.20	0.07	0.20	0.07	0.20	0	−0.83
FROA	5028	0.08	0.19	0.07	0.19	0.08	0.19	−0.01	−1.46
Tobin's q	5197	2.08	2.50	2.26	1.87	2.02	2.65	0.24	3.48***
Assets	5206	15,174	82,684	33072.6	151,944	10206.5	47087.9	22866.2	4.99***
Sales	5206	4956.62	12,441	4597.4	13835.8	5056.3	12025.4	−459.0	−1.01
SG&A	5206	982.44	2766	1040.9	3023.2	966.2	2690.5	74.64	0.75
MKTG	1131			339.4	906.4				
G&A	1131			807.1	3574.2				
R&D	5206	216.40	936.76	168.0	820.6	241.1	1056.7	−73.12	−2.48*
Segments	5206	2.61	2.04	2.24	1.89	2.71	2.07	−0.46	−7.16***
Slack	5206	0.16	0.17	0.23	0.20	0.15	0.16	0.08	12.47***
Capital	5206	102.22	216.82	66.69	83.81	112.1	240.1	−45.39	10.06***
Mkt Share	5206	0.12	0.20	0.08	0.16	0.13	0.21	−0.05	−8.41***
Sls Growth	5206	0.12	0.34	0.14	0.32	0.11	0.34	0.03	2.79**
HHI	5206	0.27	0.19	0.25	0.24	0.27	0.20	−0.02	−3.02**
Analysts	5206	8.99	8.43	10.61	10.03	8.53	8.29	2.08	6.50***
		Proportion		Proportion (p1)		Proportion (p2)		Diff. p1-p2	Chi-sq.
All Firms	659	100.00		23.37		76.63			
Goods	393	59.64		56.49		60.59		−4.10	0.82
Consumer	336	50.99		60.39		48.12		12.27	7.11**
S&P 500	153	23.22		25.97		22.38		3.59	0.86

[a] MKTG = total marketing expenditure.
[b] Assets, Sales, SG&A, MKTG, and R&D are expressed in $ millions.
[c] N = firm-year observations.
[d] Superscript *, **, and *** denote statistical significance at $p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively.

capture different aspects of firm performance which may be affected differently by the same set of activities (Venkatraman & Ramanujam, 1986).

Focusing on our key variables, we find that the coefficient on *MKTG/Assets* in the Direct Model is statistically significant and positive for all our dependent variables (all p's < 0.05). This result provides important direct evidence that a firm's marketing intensity has a net positive impact on profitability and expected future earnings growth on average, holding all else constant. In contrast, the coefficient on *G&A* in the Direct Model is significantly negative in the profit rate regressions (all p's < 0.001), indicating that increased G&A costs reduce accounting profitability. That G&A intensity is significantly positively associated with Tobin's q suggests that G&A captures important investments that may benefit earnings growth long-term. They may include IT infrastructure, support personnel, and facilities costs. On a related note, this result has implications for the likely behavior of SG&A in models of Tobin's q.

Comparing these results with those based on the Proxy Model estimated in the full sample and the subset of reporting firms, we observe an insignificant or negative coefficient on the marketing intensity variable proxied by *SG&A/Assets* in the *profit rate* regressions. This pattern is consistent with prior research that models SG&A's impact on profit performance (e.g., Feng, Morgan, & Rego, 2015). Substantively, this result indicates a zero or negative return on marketing investment when SG&A is used as a proxy measure for total marketing expenditure in models of firm profitability. This is because the estimated coefficient on *SG&A/Assets* is forced to pick up two opposite effects that we separate in the Direct Model (while controlling for all other variables' effects): the true positive return on marketing expenditure and G&A's effect that is a major accounting cost. Of note, the coefficient on SG&A is significantly positive in the regressions of Tobin's q, as could be expected based on the observed convergent impacts of marketing and G&A on Tobin's q in the Direct Model.

Nevertheless, our findings present a separate challenge for our investigation, since they require that we identify a less noisy measure of total marketing expenditure to properly evaluate our profit rate models in the subset of non-reporting firms. We detail this effort and our regression results based on the alternative measure in the following sections.

7. Alternate measure of total marketing expenditure

7.1. Marketing expenditure prediction model specification

Our approach to marketing expenditure prediction is based on the premise that there is likely a structural relationship between marketing activity reflected in marketing mix spending and variables that capture key aspects of the firm, its operating activity, and its business environment.[9] For example, larger firms will have, on average, larger sales and marketing functions, engage in more extensive marketing activities and spend correspondingly more on marketing. The approach incorporates SG&A as a key predictor, because it is a widely available data item that subsumes all marketing costs. However, we seek to correct for SG&A's noisiness by including additional predictors that are likely correlated with marketing activity.

In this step, our primary purpose is statistical prediction, while keeping in mind that such prediction model should capture important economic factors that may impact marketing expenditures. This simplifies our task considerably by allowing us to disregard formidable econometric challenges, such as endogeneity. Our secondary purpose is to demonstrate one practical approach to constructing alternate estimates of firm marketing expenditure that are less noisy than SG&A. We hope (the spirit of) our approach can be used, with appropriate modifications, to develop models of marketing expenditure for other samples of interest. Therefore, we seek to identify a parsimonious set of variables that has maximum explanatory power in predicting marketing costs while being conceptually relevant, publicly available and easy to use. With this goal in mind, we use OLS regression to evaluate the following model:

[9] We assume that expenditures may change over time (e.g., increase as the firm grows), although, *on average*, the structural relationships between key variables are likely to be relatively stable within a limited time window like the one we evaluate. Extant empirical evidence supports this—firms tend to adjust their financial ratios (e.g., SG&A/Assets) to industry means (e.g., Frecka & Lee, 1983; Lev, 1989).

Table 4
Correlations in the full effective sample.[a,b]

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1	Reporting																						
2	ROA	−0.01																					
3	FROA	−0.02	0.80																				
4	Tobin's q	0.04	0.08	−0.05																			
5	Assets	0.11	−0.01	−0.02	−0.04																		
6	Sales	−0.02	0.08	0.07	−0.03	0.62																	
7	SG&A	0.01	0.09	0.06	−0.02	0.62	0.90																
8	MKTG	.	0.11	0.11	0.05	0.28	0.62	0.53															
9	G&A	.	−0.02	−0.02	−0.10	0.96	0.95	0.96	0.28														
10	R&D	−0.03	0.09	0.09	0.03	0.13	0.57	0.69	0.88	0.08													
11	Segments	−0.09	0.07	0.06	0.07	−0.01	0.20	0.14	0.33	−0.06	0.18												
12	Slack	0.19	−0.05	−0.05	0.20	−0.03	−0.08	−0.04	0.10	−0.06	0.05	−0.10											
13	Capital	−0.09	0.00	0.00	0.00	−0.01	0.02	−0.01	0.07	0.00	0.03	−0.01	−0.09										
14	Mkt Share	−0.10	0.11	0.10	0.10	0.01	0.26	0.16	0.22	0.03	0.06	0.18	−0.16	−0.01									
15	Sls Growth	0.04	0.04	0.00	0.00	−0.01	−0.02	−0.03	−0.01	−0.04	−0.02	−0.03	0.08	−0.02	−0.05								
16	Acquisitions	0.03	0.07	0.06	0.01	0.13	0.18	0.19	0.27	0.13	0.18	0.09	−0.04	0.02	0.04	0.05							
17	Divestitures	−0.09	−0.02	−0.03	−0.08	0.02	0.03	0.02	0.01	0.01	−0.01	0.17	−0.10	−0.02	0.06	−0.11	0.03						
18	Goods	−0.06	−0.02	−0.02	0.01	−0.13	−0.02	0.00	0.02	−0.20	0.14	0.16	0.02	0.00	0.06	−0.02	−0.07	−0.06					
19	Consumer	0.11	0.06	0.05	0.02	0.04	0.07	0.13	0.08	−0.01	0.12	−0.17	0.00	−0.04	−0.01	0.00	0.02	−0.01	−0.16				
20	S&P 500	0.06	0.15	0.14	0.04	0.27	0.44	0.40	0.42	0.32	0.23	0.10	−0.04	−0.03	0.22	−0.05	0.22	0.05	−0.05	0.11			
21	HHI	−0.04	−0.01	−0.02	−0.01	−0.14	−0.06	−0.12	−0.13	−0.19	−0.13	0.06	−0.09	−0.09	0.55	−0.02	−0.06	−0.01	0.10	−0.08	−0.15		
22	Recession	0.01	−0.06	−0.02	−0.07	−0.01	−0.01	−0.01	−0.02	−0.02	−0.01	0.03	−0.01	0.01	−0.01	−0.13	−0.06	0.00	0.00	0.00	−0.01	0.01	
23	Analysts	0.10	0.22	0.20	0.05	0.25	0.42	0.38	0.51	0.30	0.25	0.08	0.02	0.04	0.19	0.01	0.27	0.00	−0.10	0.10	0.68	−0.20	−0.06

[a] For all variables, except MKTG and G&A, the correlations greater than $\rho = 0.03$, 0.04, and 0.05 are significant at $p < 0.05$, 0.01, and 0.001, respectively; for MKTG and G&A, the correlations greater than $\rho = 0.06$, 0.07, and 0.08 are significant at $p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively.
[b] There are 1131 reporting firms. The number of observations for the other variable are shown in Table 1 in the column labeled "N".

Table 5
Regressions of firm profit performance on actual and proxy measures of total marketing expenditure (MKTG = actual marketing expenditure, G&A = general and administrative expense SG&A = selling, general and administrative expense).

DV Model[a,b] Key IVs Sample	ROA Direct MKTG Reporting	ROA Proxy SG&A Reporting	ROA Proxy SG&A All Firms	FROA Direct MKTG Reporting	FROA Proxy SG&A Reporting	FROA Proxy SG&A All Firms	Tobin's q Direct MKTG Reporting	Tobin's q Proxy SG&A Reporting	Tobin's q Proxy SG&A All Firms
Constant	0.070	−0.160*	−0.300***	−0.064	−0.144	0.113***	−3.825***	−4.192***	−5.107***
	[0.100]	[0.085]	[0.024]	[0.087]	[0.086]	[0.041]	[1.105]	[1.082]	[0.810]
ROA$_{t-1}$	0.314***	0.505***	0.563***				0.700*	0.778*	1.192***
	[0.065]	[0.072]	[0.038]				[0.429]	[0.410]	[0.299]
R&D/Assets	−1.082***	−1.016***	−1.092***	−0.988***	−0.972***	−0.475***	1.475	1.208	2.429**
	[0.256]	[0.266]	[0.148]	[0.136]	[0.132]	[0.058]	[1.774]	[1.692]	[1.179]
MKTG/Assets	0.321**			0.113**			1.666**		
	[0.157]			[0.055]			[0.714]		
G&A/Assets	−0.576***			−0.153***			3.301***		
	[0.095]			[0.040]			[0.583]		
SG&A/Assets		−0.156*	0.018		−0.016	−0.055***		2.651***	2.377***
		[0.090]	[0.033]		[0.026]	[0.014]		[0.364]	[0.294]
Log Sales	0.006	0.009**	0.018***	0.025*	0.033**	0.013**	−0.831***	−0.853***	−0.677***
	[0.004]	[0.004]	[0.001]	[0.010]	[0.010]	[0.005]	[0.136]	[0.135]	[0.092]
Log Capital	−0.025***	−0.015	0	0.021**	0.018**	−0.002	−0.164	−0.149	−0.135
	[0.008]	[0.009]	[0.003]	[0.009]	[0.009]	[0.005]	[0.117]	[0.116]	[0.089]
Log Sales Growth	−0.071***	−0.074***	−0.051*****	0.031**	0.038**	0.013**	0.805***	0.811***	0.720***
	[0.018]	[0.018]	[0.008]	[0.015]	[0.015]	[0.006]	[0.187]	[0.185]	[0.118]
Log Market Share	0.010	0.004	−0.006***	−0.028**	−0.027**	−0.011*	−0.017	−0.034	0.047
	[0.007]	[0.007]	[0.002]	[0.010]	[0.011]	[0.005]	[0.131]	[0.131]	[0.100]
Log HHI	0.025***	0.030***	0.014	0.008	0	0.007	−0.073	−0.011	−0.006
	[0.007]	[0.007]	[0.003]	[0.015]	[0.015]	[0.007]	[0.195]	[0.192]	[0.141]
R-squared	2728 (16)[c]	2466 (15)[c]	13,597 (15)[c]	0.832	0.829	0.842	0.637	0.641	0.686
Hansen test (p =)	0.416	0.193	0.607						
AR(II) test (z =)	−0.816	0.061	0.206						
Firms	156	156	704	155	155	697	156	156	704
Observations	971	971	4470	1090	1090	5028	1128	1128	5193

[a] The ROA models are estimated with a system GMM estimator. We use a firm Fixed Effect Estimator to estimate FROA and Tobin's q. All models are significant at $p < 0.001$. The models also include year fixed effects that are not shown.
[b] Standard errors are in brackets; superscript *, **, and *** denotes significance at $p < 0.1$, $p < 0.05$, and $p < 0.01$, respectively.
[c] Since the literature does not define R-squared for dynamic panel data models, we show the Wald test statistic for our dynamic ROA models. Degrees of freedom are shown in parentheses. These models are significant at $p < 0.001$.

$$\mathrm{MKTG}_{it} = \beta_0 + \beta_1 \mathrm{FIRM}_{it} + \beta_2 \mathrm{EVENTS}_{it} + \beta_3 \mathrm{INDUSTRY}_i + \beta_4 \mathrm{ECONOMY}_t + \mathrm{ERROR}_{2it} \quad (2)$$

In the above equation, MKTG represents firm *i*'s total marketing and selling expenses in year *t*. The right-hand-side terms represent classes of variables, as discussed below. We include in the prediction model the variables suggested by the accounting and marketing literatures, subject to the variables being available through common data sources, such as Compustat.

The FIRM category includes the most salient firm characteristics and operating variables. Namely, a firm's total *Assets* is a common measure of firm size and resource base. There is a direct relationship between a firm's size and resources and the size of its marketing organization (e.g., Homburg et al., 1999). We include a firm's revenue (*Sales*), which is a key measure of a firm's operating activity that is contemporaneously correlated with sales and marketing activity (e.g., Needles, Powers, & Crosson, 2011). Higher revenue is associated with greater marketing spending and a more intensive sales effort (which is reflected in higher selling expenses, such as salary and commissions). The model includes *SG&A* as a key predictor that subsumes total marketing expenditure. We include the number of business *Segments* in which a firm operates to reflect a firm's organizational complexity, which increases with diversification and affects resource allocations in firms (e.g., Ramanujam & Varadarajan, 1989). *Slack* is included, because firms are known to treat marketing expenditure as a discretionary item that varies as a function of available resources (e.g., Chapman & Steenburgh, 2011; Mizik & Jacobson, 2007). We next include in the FIRM category three variables that capture the most salient line-of-business differences among firms, because firms of different types may have different marketing expenditure patterns (Zajac, Kraatz, & Bresser, 2000). We include *Capital* intensity (discussed previously), as firms in process-oriented industries tend to score highly on this measure, whereas services tend to be more human-capital-intensive on average. The indicator variables *Goods* and *Consumer* capture whether firm *i* predominantly produces goods (including software) or services, and whether it predominantly serves consumer or organizational markets. We classify firms based on each firm's six-digit NAICS industry classification provided in Compustat. In cases where the NAICS classification is missing or unclear, we use self-descriptions firms provide in Item 1 "Business" of their 10-k reports. We additionally include annual sales growth (*Sales Growth*), since increased growth is frequently supported by increased marketing spending (e.g., Bell, Keeney, & Little, 1975). The variable *Market Share* is included because market share is gained and maintained through marketing investments (e.g., Bell, Keeney, & Little, 1975). This variable is operationalized as the ratio of firm *i*'s revenue to total industry sales at the four-digit SIC level.

The EVENTS category reflects two common special events—acquisitions and divestitures—that may increase or decrease the size of a firm's marketing organization, sales force, and spending. The *Acquisitions* variable provides a count of instances, (obtained from SDC Platinum) where firm *i* acquired assets in the current year. The *Divestitures* variable takes on the value of 1 if the firm reported proceeds from divestiture in its 10-k report. Using categorical or count variables rather than transaction amounts minimizes instances of missing data, since acquisition and divestiture amounts are not available for many merger and acquisition transactions.

We include INDUSTRY variables on the grounds that industry characteristics influence business practices and expenditure patterns among firms (e.g., Zajac, Kraatz, & Bresser, 2000). Specifically, we enter in the prediction model the Herfindahl-Hirschman Index, *HHI*, and industry fixed effects based on the Fama-French industry sector classification. The ECONOMY category includes one indicator variable, *Recession*. General economic conditions, such as expansions or recessions, are known to affect demand for goods and services. Although we include sales and sales growth in the model directly, fluctuations in revenues that are driven by business cycles may have a distinct impact on marketing spending (Srinivasan, Lilien, & Sridhar, 2011).[10] We identified the recessionary years—2008 and 2009 (predominantly)—based on the National Bureau of Economic Research definitions.

To minimize the impact of skewed distributions and outliers, and also to reduce the incidence of out-of-bound fitted values (since unlogged values are non-negative), we use logs of all continuous variables.

7.2. Results

In order to select a parsimonious model for practical purposes, we estimate three versions of the prediction model (shown in Table 6).[11] Model 1 includes only industry dummies. Model 2 is the full model. Model 3 is the most parsimonious model that achieves performance equivalent to the full model on all performance measures. We select Model 3 using backward stepwise regression. All three models include industry fixed effects that are not shown to facilitate the presentation. We use two benchmarks to assess the models' performance: (1) the mean absolute percentage error (MAPE) of the estimated model, and (2) the correlation between *MKTG* and $\widehat{MKTG}$. The last four rows of the table compare these metrics with the same statistics based on SG&A.

The regressions are significant at the 0.001 level. The R^2 values of approximately 0.91 indicate that our predictors explain a large proportion of variance in the dependent variable. An examination of the focal MAPEs and underlying differences between the predicted and actual marketing expenditure amounts reveals that our approach underpredicts marketing costs on average. Nevertheless, the resultant MAPEs are two-to-three times smaller than the MAPEs based on SG&A. The obtained correlations between the actual and predicted values are approximately 43 percentage points, or 81%, higher than the 53% correlation between actual marketing spending and SG&A observed in the full sample. Therefore, the proposed approach generates marketing cost predictions that are considerably more precise on average than SG&A.

The statistically significant coefficients on *Assets*, *SG&A*, *Slack*, *Consumer*, *Divestitures*, *S&P 500* and *HHI* are all of the expected sign. This lends face validity to the prediction model. A closer examination of the regression results shows that three of the variables: *SG&A*, *Segments*, and *Slack*, together with the industry sector fixed effects, provide all of the explanatory power. The positive coefficient on *SG&A* indicates that higher SG&A costs are associated with higher marketing expenditures. The significantly positive coefficient on *Slack* suggests that, holding all else constant, firms with greater liquid resources spend more on marketing. This result is consistent with prior research (e.g., Chapman & Steenburgh, 2011). Interestingly, the coefficient on *Segments* is significantly negative. Being a measure of diversification, the 'Segments' variable is positively related both to firm size and organizational complexity (Ramanujam & Varadarajan, 1989). When 'Segments' is included in a model of marketing expenditure together with SG&A, the latter picks up the effect of firm size on marketing expenditure, as it is more strongly correlated with size, whereas 'Segments' captures the impact of organizational complexity, holding the other variables constant. The observed relationship is weakly negative, suggesting that more complex organizations tend to spend less on marketing. This is consistent with prior research that finds increased competition for resources and multiple priorities in more complex organizations, which affects discretionary expenditures (Berger & Ofek, 1995). For example, diversification is shown to have a negative impact on R&D intensity (Baysinger & Hoskisson, 1989).

Table 6
OLS regression results for total marketing expenditure (DV = Log MKTG).

Model[a,b,c]	(1)	(2)	(3)
Variables	Industry Effects	Full	Reduced
Constant	5.222***	−3.764***	−3.403***
	[0.173]	[0.222]	[0.160]
Log Assets		0.084**	
		[0.040]	
Log Sales		−0.060	
		[0.059]	
Log SG&A		1.099***	1.104***
		[0.048]	[0.017]
Segments		−0.048***	−0.042***
		[0.012]	[0.012]
Log Slack		0.153***	0.152***
		[0.021]	[0.022]
Log Capital		−0.010	
		[0.027]	
Goods		0.161***	
		[0.061]	
Consumer		0.117**	
		[0.050]	
Log Sales Growth		0.165	
		[0.112]	
Log Market Share		−0.054**	
		[0.024]	
S&P 500		0.212***	
		[0.073]	
Acquisitions		−0.017	
		[0.044]	
Divestitures		−0.256***	
		[0.072]	
Log HHI		0.141***	
		[0.041]	
Recession		0.025	
		[0.046]	
Firms	156	156	156
Observations	1,131	1,131	1,131
R-squared	0.414***	0.918***	0.914***
Adj-R-squared	0.409	0.916	0.913
MAPE ($\widehat{MKTG}$)	148.09	33.26	32.63
MAPE (SG&A)	92.46	92.46	92.46
ρ(MKTG, $\widehat{MKTG}$)	0.43	0.98	0.97
ρ(MKTG, SG&A)	0.53	0.53	0.53

[a] The regressions include 11 industry-sector fixed effects that are not shown.
[b] Standard errors are in brackets.
[c] Superscript *, **, and *** denotes significance at $p < 0.1$, $p < 0.05$, and $p < 0.01$, respectively.

7.3. Validation

We conduct three validation tests. First, we conduct a rolling window analysis over five-year windows in which we use the first three years of data to fit the prediction model and the next two years (i.e., a holdout sample) to validate it (e.g., Pauwels & Hanssens, 2007). We show these results in Table 7. For example, Model 1 uses the data for 2004–2006 for estimation, and the data for 2007–2008 for validation. The estimation results show both parameter stability and performance stability over time. The R^2 values are stable in the range of 89%–92%. Moreover, we obtain consistent improvement in each holdout sample in the MAPEs and correlations of actual and estimated marketing expenditures relative to SG&A. The holdout MAPE means and medians are two to four times smaller for $\widehat{MKTG}$ than for SG&A. (The medians are not shown in the table. They are 7.4% on average for $\widehat{MKTG}$ compared

[10] Our robustness checks with an alternate specification that uses year dummies produced equivalent results.
[11] The models for which we report results in Tables 6 and 7 are not panel data models. Since their purpose is marketing expenditure prediction, these models do not include firm fixed effects. Using clustered standard errors in those models does not affect our results.

Table 7
Results of rolling window regressions for years 2004–2012.

Model[a,b,c]	(1)	(2)	(3)	(4)	(5)
Estimation Years	2004–2006	2005–2007	2006–2008	2007–2009	2008–2010
Constant	−3.558***	−3.482***	−3.425***	−3.448***	−3.533***
	[0.268]	[0.250]	[0.227]	[0.213]	[0.227]
Segments	−0.063**	−0.062***	−0.048***	−0.041**	−0.035*
	[0.026]	[0.021]	[0.018]	[0.017]	[0.018]
Log SG&A	1.110***	1.111***	1.102***	1.097***	1.103***
	[0.029]	[0.026]	[0.023]	[0.021]	[0.022]
Log Slack	0.116***	0.123***	0.104***	0.109***	0.109***
	[0.037]	[0.037]	[0.034]	[0.033]	[0.036]
FF49_2	2.677***	2.658***	2.541***	2.536***	2.547***
	[0.220]	[0.210]	[0.192]	[0.180]	[0.188]
FF49_7	2.261***	2.441***	2.366***	2.424***	2.482***
	[0.245]	[0.230]	[0.209]	[0.195]	[0.208]
FF49_9	2.839***	2.698***	2.586***	2.625***	2.671***
	[0.221]	[0.212]	[0.195]	[0.185]	[0.193]
FF49_11	1.596***	1.663***	1.577***	1.665***	1.791***
	[0.267]	[0.253]	[0.230]	[0.214]	[0.224]
FF49_13	2.924***	2.782***	2.666***	2.702***	2.727***
	[0.265]	[0.246]	[0.221]	[0.207]	[0.216]
FF49_14	2.752***	2.395***	2.308***	2.211***	2.252***
	[0.269]	[0.247]	[0.222]	[0.207]	[0.222]
FF49_21	2.723***	2.664***	2.576***	2.592***	2.612***
	[0.226]	[0.216]	[0.198]	[0.188]	[0.199]
FF49_34	2.277***	2.291***	2.303***	2.367***	2.310***
	[0.230]	[0.216]	[0.197]	[0.187]	[0.199]
FF49_36	2.687***	2.608***	2.540***	2.590***	2.620***
	[0.195]	[0.188]	[0.174]	[0.165]	[0.172]
FF49_41	1.693***	1.646***	1.746***	1.873***	1.917***
	[0.213]	[0.202]	[0.187]	[0.178]	[0.187]
FF49_44	1.597***	1.515***	1.434***	1.419***	1.395***
	[0.219]	[0.213]	[0.199]	[0.190]	[0.197]
Obs. used in estimation	386	418	446	465	446
R-squared	0.891	0.899	0.914	0.924	0.918
Validation Years	2007–2008	2008–2009	2009–2010	2010–2011	2011–2012
MAPE ($\widehat{\text{MKTG}}$)	42.73	47.51	37.15	30.33	24.31
MAPE (SG&A)	105.28	132.21	110.10	78.51	62.97
Holdout ρ(MKTG, $\widehat{\text{MKTG}}$)	0.97***	0.97***	0.98***	0.97***	0.97***
Holdout ρ(MKTG, SG&A)	0.60***	0.53***	0.49***	0.51***	0.51***
Obs. used in validation	306	312	290	254	232

[a] Standard errors are in brackets.
[b] Superscript *, **, and *** denotes significance at $p < 0.1$, 0.05, $p < 0.01$, respectively.
[c] FF49_ represent fixed effects for our focal industry sectors referenced in Table 1.

with 25.1% on average for SG&A.)

Our second validation procedure is 10-fold cross-validation that involves validating in holdout samples results obtained on calibration data sets (e.g., Breiman & Spector, 1992). This exercise helps us to check for possible overfits. We randomly divide our data into 10 approximately equal sets 500 times. This procedure is done at the firm level (i.e., by the gvkey firm identifier). In each cross-validation run, we use 9 'training' data sets to generate model coefficients. The coefficients are used to obtain fitted values of marketing spending in the hold-out set and compare them with the actual marketing spending in that dataset. Then, the results of the cross-validation runs are averaged for comparison and reporting purposes. This validation procedure produced parameters that are similar to those in the original model, with similar correlations (0.93) and equivalent improvement in MAPEs to those reported in Table 6.

Our third validation involves evaluating how the predicted and actual values of marketing relate to SG&A costs. We find that *MKTG* constitutes 45% of SG&A on average, and $\widehat{MKTG}$—39%. A comparison of the two distributions confirms that our approach under-predicts marketing costs. Next, we evaluate the proportion of $\widehat{MKTG}$ values that fall outside the natural range for marketing spending that is bound by 0 and SG&A. Since our dependent variable is in log form, the predicted values are naturally bound by 0 when unlogged. On the opposite end of the range, 10 fitted values, or 0.2% of the sample, exceed the SG&A bound. This is a very low number and does not seem to affect the underlying distribution of the dependent variable. In deriving the final solution, we recommend that researchers adopting this approach set $\widehat{MKTG}$ values that exceed SG&A to equal SG&A (net of R&D).

On balance, our validation results show that the parameter estimates in our prediction model are remarkably stable, and our approach is able to generate considerably more precise estimates of total marketing expenditure for the non-reporting firms in our effective sample.

8. Performance model with the alternate measure of marketing expenditure

8.1. Modeling possible sample selection bias

We develop our performance model in the full sample within the Heckman framework, which allows us to assess sample selection bias in conjunction with a firm's choice of marketing expense reporting. Our approach jointly models the probability of marketing expenditure disclosure, the amount of that expenditure, and its impact on firm ROA, as detailed in the next section. The Heckman model has well-known limitations arising from its linear functional form, and the fact that the selection mechanism is modeled with the normality assumption of the errors. We use a two-step estimation of the Heckman model because this imposes less structure on the data—it does not require a joint normality assumption of the errors across the equations. (We also evaluate an alternative commonly used distributional assumption in estimating the selection equation—the type I extreme value distribution. The alternative model's estimated coefficients are robust.) On balance, though the Heckman model is an imperfect approach to exploring sample selection bias in the data, this method is one way to check whether selectivity is a concern under well-accepted assumptions.

The selection model is informed by our exploration of marketing expenditure disclosure discussed in Section 3. Accordingly, this model includes the variables that reflect firm characteristics or conditions that may be associated with a firm's choice of the reporting convention, namely: Assets, Sales, SG&A, Segments, Capital, Slack, Goods, Consumer, Sales Growth, Market Share, S&P 500, HHI, Recession, and industry fixed effects. Additionally, the model includes a count variable that captures the number of analysts following a firm, *Analysts*, to satisfy Heckman exclusion restriction. Greater (desired) analyst coverage motivates firms to be more forthcoming with information (e.g., Hong, Lim, & Stein, 2000; Lang & Lundholm, 1996). However, it is unlikely that analyst coverage, in contrast to analyst forecasts or investor expectations, directly impacts a firm's decision of how much to spend on marketing.[12]

We obtain data on analyst coverage from the I/B/E/S database.

8.2. Estimation

To assess the firm performance impact of marketing intensity using the proposed alternative measure of marketing expenditure, we estimate a joint model of three equations by adding the following selection equation to equations (1) and (2):

$$\begin{aligned}\text{Reporting}_{it} &= 1[\alpha_0 + \alpha_1 \text{FIRM}_{it} + \alpha_2 \text{EVENTS}_{it} + \alpha_3 \text{INDUSTRY}_i + \alpha_4 \text{ECONOMY}_t + \alpha_5 \\ &\quad \text{ANALYSTS}_{it} + \text{ERROR}_{3it} > 0]\end{aligned} \tag{3}$$

Eqs. (3) and (2) are the selection and prediction equations, respectively, and form our Heckman model. The prediction model uses information on marketing spending by the reporting firms. In the performance model of Eq. (1), marketing expenditures by non-reporting firms are estimated using the coefficients from Eq. (2). To reflect the fact that marketing intensity in Eq. (1) is an estimated quantity from Eq. (2), we use a bootstrap procedure to account for the errors that may be associated with such estimates and to produce valid standard errors for the estimated coefficients (Wooldridge, 2010, pp. 441-442). Specifically, we re-sample with replacement and re-estimate the model 500 times. In each round, we first estimate Eq. (3) with a probit model and construct the inverse Mills ratio for each observation (Wooldridge, 2010, pp. 802-808). Afterwards, we use OLS to estimate Eq. (2) on the reporting firms, adding the inverse Mills ratios as an additional regressor. We next use the estimated coefficients from Eq. (2) to predict the marketing expenditures[13] and then calculate marketing intensity, $\widehat{MKTG}/Assets$, and overhead intensity, $\widehat{G\&A}/Assets$, for the non-reporting firms. (We derive the $\widehat{G\&A}$estimate by subtracting $\widehat{MKTG}$ from SG&A. In the final step, we use these predictions, the actual observed spending (where available), and inverse Mills ratios (as an additional regressor), to obtain the coefficients in Eqs. (1a), (1b), and (1c) with the appropriate estimation method for each of the dependent variables. Upon completion of the 500 repeated samples and estimations, we form the bootstrap standard errors and coefficients.

8.3. Results

Table 8 shows results for the joint Heckman and performance models. The selection model has the required significant positive coefficient on the exclusion variable (*Analysts*), but the inverse Mills ratio (IMR) coefficient is not statistically significant. Therefore, we fail to find evidence of sample selection bias within the Heckman framework. Focusing next on the performance models, we observe significantly positive coefficients on marketing intensity based on our alternate measure (all p's < 0.05), in line with the results reported in Table 5. This strengthens the evidence that marketing intensity is positively associated with current and future profitability, in contrast with the questionable results based on the SG&A proxy. Additionally, this result demonstrates that the proposed approach to estimating firm marketing expenditure can enable better inferences about marketing's impact when used in models of firm performance.

9. Discussion and conclusions

Research exploring the impact of marketing activity on various performance outcomes has yielded extensive evidence of marketing's effectiveness, or ability to produce results. By contrast, studies to elucidate how marketing intensity impacts firm profitability by explicitly relating marketing inputs to outputs expressed in dollar terms have failed to generate strong or direct empirical support for marketing's efficiency. Scholarly efforts to provide the answers have been hampered by limited data availability on firm marketing expenditures and associated profit outcomes. This has prompted extensive adoption of marketing expenditure surrogates in business research, in particular firm advertising expenditure and SG&A. The resultant findings have painted a mixed picture of marketing's impact—mostly positive for Tobin's q, but usually not significant or negative for accounting profits. We have argued in this research that, although some of the observed variability in past results likely reflects sample idiosyncracies and contingencies addressed in those studies, some findings may also be driven by instrument artifacts, which calls for a separate empirical assessment of the common proxies.

In response, we implement an extensive data collection effort in a carefully constructed sample of firms to identify companies that disclose their total sales and marketing expenditure. An important feature of the resultant data is that it covers all marketing costs, including marketing personnel costs, which are normally not captured in available measures of marketing activity, such as advertising. We use these data to examine the impact of marketing intensity on the reporting firms' current and future accounting profit rates. To achieve greater comparability with extant research, we also evaluate marketing's impact on a conceptually related measure of expected future earnings growth reflected in Tobin's q. Our study and results have several important implications for business research and marketing practice.

9.1. Research implications

Our study shows that marketing intensity is significantly positively associated with contemporaneous and future accounting profits, as well as expected future earnings growth. Our results for accounting profits are consistent with the findings by Boulding (1990) and Jacobson (1990) who examined marketing ROI at the business unit level using PIMS data. Unlike those studies, we focus on actual total marketing expenditure in a multi-industry sample of firms. Our findings provide important *direct* evidence that investment in marketing activities and personnel enhances firm profitability in a range of industries. This

[12] Since institutional outreach to analysts is typically done by senior executives or investor relations departments (Mola, Rau, & Khorana, 2013), it does not draw on a firm's marketing resources. More substantively, there is a clear distinction between analyst coverage *per se* (i.e., how many analysts follow a firm) and analysts' earnings forecasts. Our review of the literature and conversations with financial executives do not reveal a link between analyst coverage and resource allocation by firms. In contrast, consensus forecasts set investor expectations for firm performance and, as such, affect firm (investment) behavior.

[13] We set 10 marketing expenditure estimates that exceeded SG&A to equal SG&A. Our robustness check using unadjusted values shows that the adjustment has no impact on our results.

Table 8
Results of a joint model using the alternate measure of marketing expenditure.

Model[a,b,c,d]\ DV:	Reporting		MKTG		ROA		FROA		Tobin's q	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Constant	0.920	[0.741]	−3.364***	[0.439]	−0.278***	[0.084]	−0.105	[0.100]	4.073***	0.856
Analysts	0.021**	[0.010]								
Log Assets	0.078	[0.114]								
Log Sales	−0.384***	[0.120]			0.002	[0.004]	−0.004	[0.009]	−0.561***	[0.126]
Log SG&A	0.207**	[0.089]	1.112***	[0.045]						
Segments	−0.030	[0.032]	−0.039	[0.030]						
Log Slack	0.132**	[0.055]	0.131**	[0.060]						
Log Capital	−0.031	[0.065]			0.019	[0.014]	0.004	[0.013]	−0.231**	[0.102]
Goods	0.035	[0.298]								
Consumer	0.484**	[0.239]								
Log Sales Growth	0.267***	[0.101]			−0.044***	[0.019]	0.001	[0.008]	0.443***	[0.117]
Log Market Share	−0.016	[0.082]			−0.001	[0.004]	−0.012	[0.008]	0.032	[0.075]
S&P500	−0.548**	[0.236]								
Acquisitions	0.014	[0.058]								
Divestitures	−0.152	[0.119]								
Log HHI	0.007	[0.112]			0.018***	[0.005]	−0.001	[0.009]	−0.006	[0.114]
Recession	0.126***	[0.031]								
IMR[b]			−0.170	[0.220]	0.013	[0.011]	0.020	[0.017]	−0.008	[0.224]
ROA_{t-1}					0.553***	[0.099]			0.803*	[0.447]
R&D/Assets	0.553	[0.947]			−0.066	[0.316]	−0.123	[0.132]	1.965	[1.620]
MKTG/Assets					0.425**	[0.197]	0.203**	[0.096]	1.629*	[0.948]
G&A/Assets					−0.439***	[0.162]	−0.026	[0.055]	0.814	[0.500]
Model Fit [d]	−2208		0.915		13,922 (16)		0.873		0.786	
Observations	5206		1131		4470		5028		5193	

[a] The ROA model is estimated with a system GMM estimator. FROA and Tobin's q models are estimated with firm fixed effects estimator. The ROA, FROA and Tobin's q models also include year fixed effects that are not shown. All the models are significant at $p < 0.001$.
[b] IMR = inverse Mills ratio.
[c] Superscript *, **, and *** denotes significance at $p < 0.1$, $p < 0.05$, and $p < 0.01$, respectively. The S.E.'s are bootstrap standard errors.
[d] We show Log Likelihood for the Reporting model, model Wald chi2 statistic (d.f.) for the ROA model, and R-squared for all other model.

addresses an important empirical gap in the literature that has largely relied on conceptual frameworks to profess marketing's profit contribution, and lends support for the normative view of marketing as a driver of accounting performance, in spite of being an important operating cost.

Our parallel investigation of the marketing intensity-profitability relationship using SG&A offers the first empirical assessment of this popular proxy for total marketing expenditure. The measure has seen increased use in business research, in spite of known limitations and lack of empirical validation. Using SG&A in our profit rate models produces discrepant results in pooled data and the subset of reporting firms (for which the focal relationship is observed to be positive). The results based on SG&A imply that marketing intensity has an insignificant or negative impact on accounting profits. The erroneous inference arises because the coefficient on SG&A is forced to pick up two divergent effects on ROA (as illustrated by our Direct Model)—the weaker positive effect of marketing activity (that generates sales) and the strongly negative effect of G&A expenditures (i.e., overhead costs).

However, we find a positive association between G&A and Tobin's q, implying that, while the overhead component of SG&A has a cost-like effect on profits, it has a more complex benign effect on a firm's expected earnings growth captured in Tobin's q, possibly because some components of overhead costs may contribute to the infrastructure supporting future growth, as elucidated by recent research in finance (Eisfeldt & Papanikolaou, 2013). Unsurprisingly, the combined effect on Tobin's q of marketing and G&A, captured in SG&A, is also strongly positive, consistent with prior research that uses SG&A in models of Tobin's q. Hence, SG&A enables correct inferences about marketing's impact in our regressions of Tobin's q.

Overall, our combined results are consistent with the view that accounting ratios and financial metrics reflect different dimensions of firm performance, possibly also different time horizons. We find that G&A and marketing expenditures may have a harmonious effect on some performance measures and a divergent effect—on others. Therefore, the use of SG&A as a proxy for total marketing expenditure may not be equally suitable for all dependent variables. A specific implication of our findings, considering the pattern of past results, is that SG&A may perform reasonably well in models of Tobin's q and, possibly, other forward-looking stock-based measures. As a caveat, SG&A may overstate marketing's impact on Tobin's q, since it also captures the positive impact of G&A. Therefore, SG&A may be more useful as a control for marketing expenditure rather than a key predictor.

Our analysis casts doubt on the suitability of using SG&A as a surrogate measure of marketing expenditure in models of firm profitability, however, since G&A acts as an important negative cost that offsets the positive impact of marketing expenditure. Building on this finding, our third contribution consists in proposing an approach to generating less noisy estimates of total marketing expenditure that can be employed, with appropriate adaptation, in future research requiring a measure of total marketing expenditure. The approach uses only publicly available data, and is supported by voluminous research in marketing and accounting which points to a likely structural relationship between marketing activity and key characteristics of the firm and its operating environment. Our demonstration shows that the alternate measure of marketing expenditure outperforms SG&A in models of profit performance. It performs as well as SG&A in models of Tobin's q. Since the proposed measure enables a less noisy, more conservative estimate of marketing expenditure, it may be preferable to SG&A in models of Tobin's q in some research contexts.

9.1.1. *Prediction model implementation*

Combining actual total marketing expenditure data, where available, with predicted spending for non-reporting firms may allow researchers to create larger samples with lower overall error in the marketing spending variable. While manual data collection on marketing expenditure, like implemented in this research, is quite effortful, recent developments in automated financial data extraction, such as directEdgar (directedgar.com), can streamline the process to a considerable extent. Since three-year sliding window prediction models yield stable coefficient estimates (as shown in Table 7), researchers may be able to use three years of data as a benchmark. Alternatively, some researchers may find it convenient to use our model *as is* to predict total selling and marketing expenditure for a sample drawn from our focal Fama-French industries, including the reporting firms. To aid scholars in implementing our approach for further validation or adaptation, we summarize the steps as follows.

a. Construct *SG&A* as Compustat item XSGA minus Compustat item XRD (R&D), with missing values for XRD replaced by 0;

b. Construct *Slack* as the ratio of Cash and Equivalents to Total Assets;

c. Obtain the number of business *Segments* from Compustat business information file (which is offered separately from Compustat North America);

d. Estimate total marketing expenditure $\widehat{\text{MKTG}}$ = Exp (–3.403 + 1.104*(ln *SG&A*) – 0.042*Segments + 0.152*(ln *Slack*) + 2.568*FF49_2 + 2.516*FF49_7 + 2.777*FF49_9 + 1.751* FF49_11 + 2.824* FF49_13 + 2.449* FF49_14 + 2.691* FF49_21 + 2.347* FF49_34 + 2.670* FF49_36 + 2.010* FF49_41 + 1.494* FF49_44), where the FF49_ represent the Fama-French industry-sectors detailed in Table 2, and FF49_45 is the baseline category that was dropped for estimation. (We recommend that model not be used *as is*, without establishing that the coefficients are robust in the sample of interest);

e. Constrain the resultant measure within its natural bounds by setting $\widehat{\text{MKTG}}$ values that exceed SG&A to equal SG&A.

Future research may use this algorithm as a reference. They may also choose to start with our full prediction model, observe the coefficient stability, model explanatory power as in our Table 7, and then reduce to a parsimonious model for prediction.

9.2. Managerial implications

Our results have several actionable implications for managers and marketing practitioners. Marketers have often struggled to demonstrate to their superiors a net-positive profit impact of their resource allocations (Hanssens & Pauwels, 2016; Stewart, 2009). Lack of clarity on the matter has prompted some consultants to argue that marketing intensity may harm firm profitability and advise restraint in marketing spending (e.g., Carlson, 2016). We believe our results can help correct such misperceptions, promote a more constructive view of marketing's holistic impact on business performance among the business public, and serve to improve marketers' reputation and standing vis-à-vis other functional areas in the firm.

Our approach to estimating firm marketing expenditures may also have practical applications in the industry. Data collection and analytics companies, such as IMS Health, could adapt our approach, in conjunction with their proprietary data, to verify or fine-tune certain aspects of their data collection algorithm. The approach can also be used to estimate the costs of more opaque marketing expenditures that data aggregators and analytics firms may not capture through their customary channels. Finally, firms and financial analysts may use our approach to help benchmark (elements of) firm marketing expenditures in certain industry contexts.

9.3. Limitations and future research

We explore the relationship between marketing activity and firm profit performance at a course-grained level of total selling and marketing intensity. We believe our approach provides an important complementary perspective to studies focused on specific marketing activities. In particular, using the aggregate expenditure metric circumvents some of the challenges arising when one is unable to isolate the separate effects of distinct marketing activities, which are usually intertwined. The aggregate variable also captures marketing overhead costs, including personnel, which are not always allocated to specific activities and, therefore, the costs of those marketing activities may be understated for firms with significant in-house capabilities. Hence, using total marketing expenditure allows us to assess the average profit impact of a firm's total marketing effort across all activities and touchpoints. Nevertheless, our aggregate marketing expenditure measure limits our ability to generate strategy recommendations.

We believe our framework for producing alternate estimates of total marketing expenditure warrants further assessment and development in future research. While using SG&A to predict marketing expenditures is not ideal, the approach is logically justifiable. It uses an observable quantity to predict something unobservable, which makes SG&A a legitimate predictor in this case. We also acknowledge that our prediction model and the associated claims only apply to our dataset. In our data, we were able to generate marketing expenditure estimates that may reflect some bias, but, as a trade-off, produce a much lower mean absolute percentage error and a higher correlation with actual expenditure amounts. Extending the approach to other industries would require model development and validation on data from those industries. Likewise, our analysis demonstrates coefficient stability over the focal time-frame, which covers the most recent years that would be particularly relevant for current research. Caution should be exercised when using the derived coefficients much further in the past or future. In particular, it may be useful to assess how the coefficient on 'Segments' has evolved in recent years, since our rolling window regression hints at declining significance and magnitude of this variable from approximately 2007. Fortunately, our approach can be easily replicated to develop a prediction model over other samples and time frames of interest. Finally, while have made every effort to construct a valid sample, we believe the strength of the statistical evidence we present has been impacted by our sample size.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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