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This article presents a meta-analysis of prior econometric estimates of personal selling elasticity—that is, the ratio of the percentage change in an objective, ratio-scaled measure of sales output (e.g., dollar or unit purchases) to the corresponding percentage change in an objective, ratio-scaled measure of personal selling input (e.g., dollar expenditures). The authors conduct a meta-analysis of 506 personal selling elasticity estimates drawn from analyses of 88 empirical data sets across 75 previous articles. They find a mean estimate of current-period personal selling elasticity of .34. They also find that elasticity estimates are higher for early life-cycle-stage offerings, higher from studies set in Europe than from those set in the United States, and smaller in more recent years. In addition, elasticity estimates are affected significantly by analysts' use of relative rather than absolute sales output measures, by cross-sectional rather than panel data, by omission of promotions, by lagged effects, by marketing interaction effects, and by the neglect of endogeneity in model estimation. The method bias–corrected mean personal selling elasticity is approximately .31. The authors discuss the implications of their results for sales managers and researchers.

Keywords: personal selling elasticity, meta-analysis, empirical marketing generalizations, sales management, hierarchical linear model

Personal Selling Elasticities: A Meta-Analysis

Every year, firms across various industries expend significant resources on their sales forces. In the United States alone, total spending on sales forces has been reported to be approximately $800 billion each year, close to three times the amount spent on advertising (Zoltners, Sinha, and Lorimer 2008). Motivated by these large expenditures, several econometric analyses aimed at assessing the effects of personal selling in a variety of contexts, including business-to-consumer and business-to-business marketing, pharmaceuticals promotion, and defense services recruitment, have been conducted over the past four decades (e.g., Beswick and Cravens 1977; Fischer and Albers 2010; Gatignon and Hanssens 1987). Thus far, however, there has been limited research to draw out generalized quantitative estimates of the effectiveness of the personal selling activity from this body of work. In contrast, several meta-analyses over the years have reported generalized estimates of the means of price and advertising–sales elasticities, as well as determinants of their variation across prior econometric studies (e.g., Andrews and Franke 1991; Assmus, Farley, and Lehmann 1984; Bijmolt, Van Heerde, and Pieters 2005; Sethuraman and Tellis 1991; Tellis 1988). The elasticity of response to a marketing input—that is, the ratio of the percentage change in output (e.g., dollar or unit sales) to the corresponding percentage change in the input (e.g., dollar expenditures on advertising)—is the favored measure in these meta-analyses because it is dimensionless and easily interpretable (Tellis 1988). The benefits of developing empirical generalizations about marketing elasticities for theory development and management have been discussed at length in the literature (see, e.g., Farley, Lehmann, and Sawyer 1995; Hanssens, Parsons, and Schultz 2001).

The extant research literature contains two narrowly focused and limited meta-analyses of personal selling elasticities. Sohn (1996) examines 16 elasticity measurements

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from four pre-1990 econometric studies of the effectiveness of military recruiting (long viewed as a form of personal selling; e.g., Hanssens and Levien 1983) and obtains a generalized estimate of Army recruiter elasticity of .48 (see also Hanssens, Parsons, and Schultz 2001). However, Sohn's findings are not based on a comprehensive review of all pre-1990 studies and, moreover, need to be updated using studies that have been conducted since 1990. More recently, using a meta-analysis of pharmaceutical promotions response models, Kremer and colleagues (2008) have reported generalizations with respect to the mean and determinants of estimates of pharmaceutical promotional elasticities, including personal selling (detailing) elasticities. However, their detailing-related findings are difficult to interpret because their meta-analytic model (1) pools elasticities of multiple promotion instruments (journal advertising, direct-to-consumer advertising, and detailing) and distinguishes between them through the use of dummy independent variables, which assumes homogeneous effects of covariates across the entire pharmaceutical marketing mix; (2) pools category-level and brand-level elasticities; and (3) pools short-term and long-term (e.g., stock) elasticities without accounting for heterogeneous carryover effects.

Thus, the marketing literature has yet to offer "good" empirical generalizations (Barwise 1995) about personal selling elasticity to assist sales force management and advance research. The current research aims to fill this gap through a comprehensive meta-analysis of 506 personal selling elasticity estimates derived from prior econometric studies. Specifically, we investigate how two classes of variables affect these elasticity estimates: (1) "market-setting characteristics" (e.g., geographic setting, product life-cycle stage) and (2) "research methodology characteristics" (e.g., data and response model characteristics). After adjusting for the significant methodology-induced biases found in our meta-analysis, we determine that the mean estimate of current-period elasticity is approximately .31 (while the mean carryover effect is .754). This value can be used as a benchmark to guide researchers and practitioners investigating personal selling effectiveness in various circumstances.

We organize the remainder of this article as follows: In the next section, we define the scope of our analysis and database, the variables that could affect the personal selling elasticities that we investigate, and hypotheses regarding the effects of a subset of these variables on these estimates. We then describe the model used to assess these effects and present the estimation results and the ensuing empirical generalizations. Although the bulk of the elasticity estimates are from pharmaceutical selling (56%) and military recruiting (26%) settings, we use adequate controls for differences between groups in obtaining the results. Subsequently, we obtain the method bias–corrected distribution of personal selling elasticities. We then discuss the implications of the results for sales force managers and researchers. After suggesting some avenues for further research, we conclude.

SCOPE OF STUDY

Personal Selling Elasticity Estimates Included in the Meta-Analysis

We restrict personal selling elasticity measurements included in the meta-analysis to those that fit the following six criteria.

1. *Elasticities obtained from settings in which the sales representative proactively visits potential buyers with the aim of gaining acceptance for his or her offering*. Any studies of agents' performance in settings in which customers themselves approach or call in for help from agents (e.g., retail sales assistants, customer service representatives) fall outside the ambit of this meta-analysis.
2. *Elasticities based on objective ratio-scaled measures of personal selling output and input*. Consistent with Rich and colleagues' (1999) definitions of objective versus subjective measures of salesperson performance, our meta-analysis includes only elasticities based on ratio-scaled objective measures of selling output (e.g., sales volume in units or dollars, number of orders, prescriptions, sign-ups) and similar measures of effort (i.e., the force, energy, or activity put into selling) (e.g., Brown and Peterson 1994). Examples of objective measures of input effort are "size" measures, such as the total number of salespeople or dollar expenditures on personal selling; "frequency" measures, such as the number of sales calls, customer visits, or details; and "time" measures, such as number of selling hours. (Thus, we exclude elasticities based on ordinal-scaled measures of intended effort, such as those used by VandeWalle and colleagues [1999], from the analysis.) As we already noted, pooling observations based on different objective measures of output and input is appropriate because elasticities are unit free. Subsequently, however, we investigate whether there are any systematic differences in elasticity estimates due to the type of objective output and input measures involved in the observations.
3. *Elasticities obtained through statistical/econometric analyses of actual personal selling input and output data*. Any empirical generalization must be based on repeated empirical evidence and not on empirically untested beliefs or expectations (see Barwise 1995; Bass 1995). Therefore, our database excludes elasticity measurements obtained from "decision calculus" or judgmental data-based assessments of sales response functions (employed, e.g., in the research of Albers [1996], Fudge and Lodish [1977], Lodish and colleagues [1988], and Rao and Turner [1984]).
4. *Elasticities derived from estimation of the relationship between the sales of an individual firm's (company- or selling unit–level) offering and personal selling effort on its behalf*. Because this research is aimed at helping individual companies' sales managers, we do not include analyses of relationships between demand at the industry level (or primary demand; see Hanssens, Parsons, and Schultz 2001) and total selling effort by the industry in this research unless a company-specific estimate of the personal selling elasticity can be drawn from them, such as in Fischer and Albers's (2010) study.
5. *Current-period elasticities*, *reflecting the effect of current-period selling efforts on current-period sales output*. Many of the papers in our database provide only current-period measures. Furthermore, pooling observations of short-term and long-term elasticites for meta-analysis, as in Kremer and colleagues (2008), is not meaningful when carryover effects (i.e., the effect of past-period efforts on current-period sales) are heterogeneous across study settings. Therefore, we use only estimates of current-period elasticity, either directly provided or derivable from author-reported lagged effects (see Table A1 in the Web Appendix at http://www.marketingpower.com/jmroct10).
6. *Elasticities that are unambiguously reported or derivable from the estimated coefficients and/or other relevant data reported in the paper*. This leads to the exclusion of some prior sales response studies, such as those of Parsons and Vanden Abeele (1981) and Brown (1990, p. 82).

Finally, we note that all objective data in the original studies can suffer from unreliability because of potentially faulty or bias-prone data collection procedures. However, our meta-analysis assumes that data reliability was checked in the original papers.

Database Scope

Our database spans the last four decades, includes personal selling elasticity measurements from the United States and Europe (Belgium, France, Germany, Italy, Netherlands, Portugal, and the United Kingdom), and encompasses a wide range of sales environments. The database (see Table A1 in the Web Appendix at http://www.marketingpower.com/jmroct10) includes relevant papers, authored by scholars in multiple disciplines (marketing, management, operations research, economics, and health economics) and by industry- and government-based researchers. We define a "paper" as a distinct document (e.g., a journal article, an unpublished dissertation, a working paper, a technical report) that offers some original analysis and findings. Thus, our database includes no duplications or redundant papers (see Wood 2008). Collectively, the papers in our database provide analyses of many distinct data sets, each containing information about output response to personal selling effort in some specific market setting. If and when a different estimation technique/model is applied to the same data set in either the same paper (e.g., Turner 1971) or different papers (e.g., Berndt et al. 1995; Berndt, Pindyck, and Azoulay 2003), we treat the resulting elasticity observations as multiple distinct measurements from one data set. Conversely, one paper may provide analyses of multiple distinct data sets, contributing one (or more) distinct personal selling elasticity estimate from each data set (e.g., Horsky and Nelson 1996). Applying these definitions, our database includes 75 research papers that use 88 distinct data sets, providing 506 personal selling elasticity measurements (see Table A1 in the Web Appendix at http://www. marketingpower.com/jmroct10).

METHODOLOGY

Database Compilation

We compiled our database from the following sources: (1) all relevant publications in previous sales force research review articles (e.g., Albers and Mantrala 2008; Hanssens, Parsons, and Schultz 2001; Manchanda and Honka 2005; Vandenbosch and Weinberg 1993; see also the references in these articles); (2) all available computerized publication search services (e.g., ABI/Inform from ProQuest, Business Source Premier from EBSCO, Kluwer Online); (3) all relevant working papers available on the Web (e.g., those on Social Science Research Network); (4) reports of relevant consulting engagements from prominent scholars; (5) archives of technical reports and/or working papers of the Marketing Science Institute, the Institute for the Study of Business Markets, and leading business schools; and (6) responses to a request for unpublished works posted on the marketing network ELMAR. Inclusion of unpublished works is important to avoid publication bias that would reduce measurement variability in the meta-analysis (e.g., Andrews and Franke 1991; Assmus, Farley, and Lehmann 1984; Rust, Lehmann, and Farley 1990; Tellis 1998). Finally, in the case of ambiguous elasticities, we contacted the original authors directly for clarifications.

The ultimate total of 506 personal selling elasticity estimates in our database is significantly larger than the 367 price elasticity estimates used in Tellis's (1988) study and the numbers of advertising elasticity estimates—128 and 55, respectively—treated in the meta-analyses by Assmus, Farley, and Lehmann (1984) and Lodish and colleagues (1995). Of these 506 elasticities, 284 (56%) are from pharmaceutical selling settings, 131 (26%) are from defense services settings, and 91 (18%) are from other settings (e.g., industrial goods, media selling).

Independent Variables Included in Meta-Analysis

Table 1 presents the coding scheme for each of the 28 independent variables in our meta-analytic model. The selection of these variables was guided by previous use in earlier meta-analyses of marketing (as indicated in the column labeled "Precedence") and additional suggestions from the anonymous expert reviewers of this research. These variables fall into three categories: (1) 11 variables for which we have hypotheses about their effects, (2) 3 variables whose omission from the sales response model may have biasing effects on elasticity, and (3) 14 other covariates that may also have statistically significant effects. The first three variables with hypotheses fall in the class of "market-setting characteristics," and the next four variables with hypotheses fall in the class of "research methodology characteristics."

Life-cycle stage of product (offering) (H_1). A key advantage of personal selling is that it permits two-way communication exchanges between buyer and seller that can address the buyer's questions and objections. This advantage tends to be more pronounced in the case of newer products or services and especially high-search, infrequently purchased new products (see, e.g., Hagerty, Carman, and Russell 1988). In this vein, Narayanan, Manchanda, and Chintagunta (2005) find that sales calls for new pharmaceuticals are more informative and persuasive, resulting in higher average personal selling elasticity values in the launch phase than those in the later stages of the life cycle. Therefore, we hypothesize the following:

> H_1: Personal selling elasticities are higher in market settings involving products in the early stages than products in the late stages of their life cycles.

Geographic setting: United States versus Europe (H_2). In general, European countries are reputed to be more collectivist than the United States (e.g., Hofstede 1983), which leads to a more favorable view of personal selling than in individualist cultures. In addition, in some industries (e.g., pharmaceuticals), Europe relies more heavily on information provided through sales forces than the United States, where direct-to-consumer advertising is allowed (Fischer and Albers 2010). There is also more saturated sales force coverage in the U.S. pharmaceutical market (e.g., Chintagunta and Desiraju 2005). Therefore, we hypothesize the following:

> H_2: Personal selling elasticities are lower in U.S. settings than in European settings.

Table 1
VARIABLES USED IN THE ANALYSIS

Number	*Type*[a]	*Variable*	*Description*	*Precedence*[b]	*Coding Scheme*	*Hypotheses*	*Significant Effect?*
1	MC	Stage in product life cycle	Captures whether the product was in the early or late (mature) stage of its product life cycle	AFL, BHP, and T	Base: Late (mature stage) Early stage: 1 (versus 0 for not)	Early > late (H_1)	Yes
2	MC	Geographic setting	Continent from which data were collected	AF, AFL, BHP, KBLW, and T	Base: European countries United States: 1 (versus 0 for not)	United States < Europe (H_2)	Yes
3	MC	Year of data collection	Mean year in the panel from which elasticities were estimated	AF, BHP, and KBLW	Mean-centered variable	Negative (H_3)	Yes
4	RM	Sales output measure	Captures whether the output is measured in absolute or relative (share) terms	AFL, BHP, KBLW, and T	Base: Absolute Relative: 1 (versus 0 for not)	Relative < absolute (H_4)	Yes
5–6	RM	Consideration of dynamics	Captures the modeling of dynamics (i.e., lagged effects)	AF, AFL, BHP, KBLW, and T	Dependent variable lagged: 1 (versus 0 for not lagged) Independent variable lagged: 1 (versus 0 for not lagged)	Dependent lagged versus otherwise (H_5) Independent lagged versus otherwise (H_6)	Yes (H_5–H_6)
7	RM	Interaction effects	Captures when interactions effects between personal selling and other marketing-mix elements (e.g., advertising) were included	This study	Included: 1 (versus 0 for not)	Included > omitted (H_7)	Yes
8	RM	Endogeneity in sales response	Captures whether endogeneity in sales response is modeled	BHP and KBLW	Accounted for: 1 (versus 0 for not)	Accounted for < not accounted for (H_8)	Yes
9–10	RM	Temporal aggregation	Captures the smallest data interval used	AF, AFL, BHP, and T	Base: Monthly data Quarterly: 1 (versus 0 for not) Yearly: 1 (versus 0 for not)	Quarterly < monthly (H_9), yearly < monthly (H_{10})	No
11	MS	Manuscript status	Captures whether the paper has appeared in an academic publication, is an institutional technical report, or is an unpublished working paper	BHP and KBLW	Unpublished working paper or technical report: 1 (versus 0 for not)	Unpublished < published (H_{11})	No
12–14	RM	Omitted variables	Captures whether the variables of price (p), advertising (a), and promotions (pr) were included or excluded	AF, FL, BHP, KBLW, and T	Included: 1 (versus 0 for not)	N.A.	Yes (promotions only)
15–17	RM	Functional form	Captures whether the response function is a multiplicative (log–log), semilog, additive, or some other	AFL, BHP, KBLW, and T	Base: "Other" Multiplicative: 1 (versus 0 for not) Additive: 1 (versus 0 for not) Semilog: 1 (versus 0 for not)	N.A.	No
18	RM	Heterogeneity in sales response	Captures whether heterogeneity in sales response is modeled	BHP	Accounted for: 1 (versus 0 for not)	N.A.	No
19–20	RM	Estimation method	Captures whether the estimation method used was ordinary least squares, multistage and generalized least squares, or maximum likelihood	AF, AFL, BHP, KBLW, and T	Base: Multistage least squares Ordinary least squares: 1 (versus 0 for not) Maximum likelihood: 1 (versus 0 for not)	N.A.	No
21	RM	Cross-sectional versus time series	Captures whether the data used were cross-sectional or time series	AFL	Base: Time series 1: Cross-sectional	N.A.	Yes

Table 1
CONTINUED

Number	Type[a]	Variable	Description	Precedence[b]	Coding Scheme	Hypotheses	Significant Effect?
22	MS	Marketing affiliation	Captures whether the source of the published article or the affiliation of the majority of the authors (if not published) is in the marketing discipline	KBLW	Marketing affiliation: 1 (versus 0 for not)	N.A.	No
23–24	RM	Sales environment	Captures whether the sales force is working in the pharmaceutical, military, or some other industry, such as industrial or media selling (a job in the military is viewed as a mature life-cycle-stage offering)	Idiosyncratic, but generally similar to AFL, BHP, KBLW, and T	Base: Other Military: 1 (versus 0 for not) Pharma: 1 (versus 0 for not)	N.A.	Yes
25–26	RM	Measure of aggregation of output	Captures at what level of aggregation the sales measure was collected	Idiosyncratic, but generally similar to AFL and KBLW	Base: District level Product/firm level: 1 (versus 0 for not) Customer level: 1 (versus 0 for not)	N.A.	No
27–28	RM	Sales effort measure	Captures whether sales effort is measured in size, frequency, or duration	This study	Base: Size measure Duration measure: 1 (versus 0 for not) Frequency measure: 1 (versus 0 for not)	N.A.	No

[a]MC = market-setting characteristics, RM = research methodology, and MS = manuscript status.
[b]AF = Andrews and Franke (1991), AFL = Assmus, Farley, and Lehmann (1984), CFW = Churchill and colleagues (1985), BHP = Bijmolt, Van Heerde, and Pieters (2005), KBLW = Kremer and colleagues (2008), and T = Tellis (1988).
Notes: N.A. = not applicable.

Year of data collection (H_3). Sales cycles have noticeably lengthened in recent years as a result of greater relationship selling and partnering activities called for by increasing product complexity, more well-informed and demanding customers, and greater competition (Jones et al. 2005; Weitz and Bradford 1999). That is, more effort is required to produce the same level of sales. This also applies to military recruiting during the recent Iraq and Afghanistan wartime years (Congress of the United States, Congressional Budget Office Study 2006). Considering these trends, we hypothesize the following:

H_3: Within the span of our database, personal selling elasticities will decrease in magnitude as the year of data collection becomes more recent.

Relative versus absolute output measure (H_4). Elasticities based on absolute sales values capture changes in sales due to both primary (market expansion) and secondary (share expansion) changes resulting from varying selling effort (see, e.g., Hagerty, Carman, and Russell 1988). In contrast, share-based elasticities classify only a portion of the market expansion as primary demand (Steenburgh 2007). Accordingly, we hypothesize the following:

H_4: Personal selling elasticities from models using relative (share) output measures are smaller than those from models using absolute output measures.

Inclusion or not of lagged output effects (H_5) and lagged input effects (H_6). Personal selling effort has significant carryover effects across periods. For example, from sales force studies at 50 pharmaceutical companies, Sinha and Zoltners (2001) report that the aggregate sales carryover from selling effort in one year is 75%, 80% the next year, 62%–78% in the third year, and 52%–70% in the fourth year. Army recruiters also rely heavily on previously accumulated leads rather than make fresh calls toward the end of their contracts (Carroll, Lee, and Rao 1986). In such cases, the effectiveness of current-period recruiting efforts would be overstated if the lagged leads (lagged output effects) or past effort (lagged input effects) were omitted. Therefore, we hypothesize the following:

H_5 and H_6: Personal selling elasticities from response models that include lagged output (input) effects are smaller than those from response models that exclude these effects.

Inclusion or not of interactions of personal selling with other marketing communication variables (H_7). Interactions of personal selling and other marketing variables, such as advertising (e.g., Gatignon and Hanssens 1987; Gopalakrishna and Chatterjee 1992; Narayanan, Desiraju, and Chintagunta 2004), can affect sales. Because such interactions have positive effects, excluding them from a model could result in a deflated estimate of personal selling elasticity. This is because the marginal effect of personal selling on sales will be underestimated as it will not include the coefficient pertaining to the interaction term. Thus:

H_7: Personal selling elasticities from response models that include interactions between personal selling and other marketing communication variables are higher than those from response models that exclude such interaction effects.

Accounting for endogeneity of personal selling input (H_8). Endogeneity refers to a correlation between the input variable and the error term of the estimated response model, which arises, for example, if management allocates sales effort strategically or uses rules such as effort allocations proportional to past sales. Some researchers have accounted for endogeneity in model estimation—for example, through the use of instrumental variables (e.g., Chintagunta and Desiraju 2005), managerial decision rules (e.g., Hagerty, Carman, and Russell 1988), or simultaneous models (e.g., Murray and McDonald 1999)—though many have not. If an input such as personal selling is treated as exogenous when it is endogenous, both theoretical analyses and empirical evidence of its elasticity may be overestimated (e.g., Manchanda, Rossi, and Chintagunta 2004; Saridakis, Torres, and Tracey 2009). Therefore, we hypothesize the following:

H_8: Personal selling elasticities from models that account for endogeneity are lower than those from models that do not account for endogeneity.

Temporal aggregation of data (H_9 and H_{10}). Previous meta-analyses (e.g., Assmus, Farley, and Lehmann 1984; Bijmolt, Van Heerde, and Pieters 2005; Tellis 1988) have suggested that estimates of marketing instrument elasticities can vary as a result of differences in data measurement intervals. In the personal selling context, although some product sales cycles can be rather long (e.g., high-ticket business-to-business sales), many have shorter sales cycles (e.g., ad space sales, military recruiting, pharmaceutical product sales). In such settings, short-term temporal variations in both selling effort and resultant sales can occur (see Gopalakrishna et al. 2007; Steenburgh 2008) in part because of the prevalent use of nonlinear incentive mechanisms with monthly or quarterly incentive payouts (e.g., Zoltners, Sinha, and Lorimer 2006). Following Tellis (1988), we hypothesize that this temporal variation will not be picked up in quarterly (H_9) or annual (H_{10}) data as much as in monthly data. Thus:

H_9 and H_{10}: Personal selling elasticities estimated with quarterly (yearly) data are lower than those estimated with monthly data.

Manuscript status (i.e., published versus unpublished) (H_{11}). Publication bias (i.e., reduced interstudy variability and upwardly biased mean estimates) can arise when researchers do not submit or fail to publish papers with statistically insignificant or implausible findings (e.g., Rust, Lehmann, and Farley 1990). Accordingly, we hypothesize the following:

H_{11}: Personal selling elasticities derived from studies in unpublished papers are lower than those derived from studies in published papers.

Variables whose omission could bias personal selling elasticity estimates. If the response model specification in a particular study setting omits a relevant and plausible influencer of sales (e.g., price, advertising, promotions), the resultant personal selling elasticity estimate may be biased, though any predictions with respect to the direction of the bias may be unfounded (e.g., Clarke 2005). Therefore, although we do not put forth hypotheses, we investigate whether there are any systematic biases in personal selling elasticity observations due to omissions of price, advertising, or promotions from the original models.

Variables included as other covariates. We include here (1) relevant variables that have figured in previous meta-analyses, as indicated in Table 1, and (2) covariates specific to our meta-analysis. The latter include type of sales environment (or industry) setting (i.e., pharmaceutical sales, defense services, or "other" sales environments). The "other" category in our database comprises only business-to-business situations (e.g., consumer goods supplier sales to retailers, newspaper ad space sales to business advertisers, industrial goods supplier sales to other firms). Intuitively, we expect that the nature of the typical selling tasks varies across sales environment settings (e.g., product detailing [a form of "missionary" selling] in pharmaceutical markets, career counseling in military recruiting, relationship building in "other" settings). However, there can be variation in selling tasks even within each of these industry settings. For example, the pharmaceutical sales representative's task when promoting products to individual physicians is different from his or her task when pursuing formulary approvals from hospital buying centers (e.g., Roughead, Harvey, and Gilbert 1998). Similarly, business equipment selling can be different from selling chemical production equipment (Horsky and Nelson 1996). Therefore, we do not offer hypotheses about systematic effects of the sales environment setting on elasticity estimates, but we still investigate the issue.

The remaining covariates in the model are the level of aggregation of sales output measure and type of sales effort measure used. The definitions of all these dummy variables are in Table 1.

Data Coding

Two judges who were not members of the meta-analysis research team separately coded all the observations in the database on the selected independent variables, using the coding scheme shown in Table 1. Agreement between the two judges was greater than 90%. A third judge amicably resolved any remaining inconsistencies.

Estimation Model and Procedure

We model personal selling elasticity as a linear function of the selected independent variables (determinants) as in Tellis (1988) and Bijmolt, Van Heerde, and Pieters (2005). There are two levels of variation in the database; the 506 personal selling elasticity measurements come from 88 different data sets, and the number of elasticity measurements per data set varies (see Table A1 in the Web Appendix at http://www.marketingpower.com/jmroct10). Measurements within a data set share values on several determinants, though they may differ on other determinants. Because determinants at the measurement level (lower level) and data set level (higher level) contribute to variation in personal selling elasticity, but some measurements are not independent within a study, there is a nested error structure for which we must account.

In the context of meta-analyses, Bijmolt and Pieters (2001) show that hierarchical linear model estimation (e.g., Raudenbush and Bryk 1992) rather than ordinary least squares is the optimal procedure to account for the nested error structure. Therefore, we use hierarchical linear model estimation. Because the estimation procedure is standard, we refer readers to Bijmolt and Pieters (2001, p. 159) and Raudenbush and Bryk (1992, p. 440) for the details. We use the PROC MIXED procedure in the software SAS to estimate the model. Table 2 displays the results.

Robustness Checks

We performed several checks to ensure the robustness of the results. First, because there is no direct diagnostic for multicollinearity in hierarchical linear modeling, we checked the condition index that has a value of 8.07, which indicates low multicollinearity.

Second, because a large number of extant personal selling response models fall in the military and pharmaceutical sales environments, we examined the data to determine whether pooling of elasticities from pharmaceutical, military, and other sales environments is justified, especially because the respective distributions (see Figure 1, Panels A–D) are different. Specifically, if an expanded model (from the one in Table 2) with interaction terms of dummy variables for military and pharmaceuticals (relative to "other") with all the other independent variables shows no significant interactions, pooling is justified.[1] Because extreme multicollinearity would preclude running the hierarchical linear model with 25 main effects and all possible interactions simultaneously, we tested the effect of each of the new interaction terms in the meta-analytic model one at a time (similar to Bijmolt, Van Heerde, and Pieters 2005). We found no significant interaction term, which establishes that pooling is justified.

Third, because the author Sönke Albers contributed several data sets to the total of 88, we created an author-specific dummy variable to determine whether observations from the Albers's studies were significantly different from those of other studies included in the meta-analysis. We found that they were not and therefore do not include this dummy variable in the final results. Fourth, we tested for various plausible interaction effects among all the independent variables. We found and retained only one positive and significant effect of an interaction—that between the yearly temporal aggregation determinant and the product life-cycle variable. Fifth, we tested for the effects of several other possible covariates appearing in previous meta-analyses or suggested by an anonymous reviewer: number of observations in the data set, whether competitive marketing efforts were explicitly modeled, interactions between temporal aggregation and the inclusion of lagged effects, and whether inputs and outputs were measured in monetary (versus physical) units. We did not find any of these effects to be significant and thus excluded them from the final model.

RESULTS

Frequency Distribution of Observed Personal Selling Elasticities

Figure 1, Panel A, displays the overall frequency distribution of the 506 current-period personal selling elasticity estimates in the database. As we expected, 99% of these estimates are positive. The "raw" mean in the database (unadjusted for any methodology-induced biases) was .34.

[1]We thank the associate editor for this suggestion.

Table 2
ESTIMATION RESULTS

Variable	*Estimate*	*SE*	p-*Value*	*Lower Bound*	*Upper Bound*	*Predicted Elasticity*
Intercept	***.883***	***.171***	***<.0001***	***.602***	***1.164***	
Variables with Hypotheses						
Stage in Product Life Cycle						
Late						.271
Early	***.264***	***.040***	***<.0001***	***.198***	***.330***	.535
Geographic Setting						
Europe						**.428**
United States	***–.110***	***.061***	***.072***	***–.211***	***–.010***	**.318**
Trend						
Year of data collection (mean centered)	***–.005***	***.003***	***.091***	***–.009***	***–.0001***	1982: .351 1992: .304 2002: .26
Sales Output Measure						
Absolute						**.416**
Relative	***–.241***	***.094***	***.013***	***–.396***	***–.086***	**.175**
Consideration of Dynamics						
No lagged effects						**.396**
Independent variable lagged	***–.220***	***.071***	***.002***	***–.337***	***–.102***	**.177**
Dependent variable lagged	***–.115***	***.06***	***.055***	***–.214***	***–.017***	**.281**
Interaction Effects						
Omitted						**.326**
Included	***.184***	***.075***	***.015***	***.061***	***.307***	**.510**
Endogeneity in Sales Response						
Not accounted for						**.373**
Accounted for	***–.091***	***.054***	***.094***	***–.181***	***–.002***	**.282**
Temporal Aggregation						
Monthly						
Quarterly	–.075	.064	.242			
Yearly	–.022	.087	.797			
Yearly × early stage in product life cycle	***–.274***	***.127***	***.032***	***–.482***	***–.065***	*Not Yearly* / *Yearly*
Early						.544 / .248
Late						.280 / .258
Manuscript Status						
Published						
Not published	.025	.054	.635			
Variables Whose Omission May Bias Elasticities						
Promotions Variable						
Omitted						**.382**
Included	***–.124***	***.054***	***.021***	***–.212***	***–.036***	**.258**
Advertising Variable						
Omitted						
Included	–.032	.059	.589			
Price Variable						
Omitted						
Included	.066	.077	.398			
Other Covariates						
Sales Environment						
Other						**.502**
Military	.015	.122	.896			.517
Pharmaceuticals	***–.228***	***.107***	***.036***	***–.404***	***–.052***	**.274**
Cross-Sectional Versus Time Series						
Time-series data						**.365**
Cross-sectional data	***–.185***	***.079***	***.019***	***–.314***	***–.055***	**.181**
Functional Form						
Other						
Multiplicative	–.144	.111	.195			
Additive	–.109	.128	.398			
Semilog	–.197	.123	.114			
Estimation Type						
Augmented least squares						
Maximum likelihood	–.038	.072	.592			
Ordinary least squares	–.02	.058	.734			
Heterogeneity in Sales Response						
Not accounted for						
Accounted for	.008	.068	.906			

Table 2

CONTINUED

Variable	*Estimate*	*SE*	p-*Value*	*Lower Bound*	*Upper Bound*	*Predicted Elasticity*
Marketing Affiliation						
Yes	–.061	.072	.398			
No						
Measure of Aggregation of Output						
Sales entity level						
Entire product/firm level	–.069	.087	.428			
Customer level	.079	.091	.386			
Sales Effort Measure						
Size measure						
Frequency measure	.089	.077	.248			
Duration measure	.022	.086	.798			
R^2 = .314						

Notes: All statistically significant results are set to bold and italics. In the last column, we provide the predicted elasticity for all significant coefficients only.

This value from our meta-analyses is significantly lower than .5, which is Hanssens, Parsons, and Schultz's (2001) recommended modal value of personal selling elasticity. The means of the pharmaceutical sales, military recruiting, and other personal selling elasticities are .245, .514, and .387, respectively (Figure 1, Panels B–D). Notably, the raw overall mean of .34 is close to the average value of .335 of 87 personal selling elasticity measurements from prior subjective (decision calculus) model-based analyses (see Albers 1996; Fudge and Lodish 1977; Lodish et al. 1988) that we excluded from the meta-analysis.

Carryover Effects

Of the 506 current-period elasticities in the database, 207 were derived from models that provided estimates of carryover effects. The mean estimate of these carryover effects is .76 (consistent with Sinha and Zoltners's [2001] observations), with a standard deviation of .25.

Hierarchical Linear Model Estimation Results

We report the model estimates in Table 2. As highlighted here and in the last column of Table 1, we found 12 statistically significant effects, including one post hoc interaction effect. The overall fit of the model to the data (R^2 = .314) is satisfactory, considering that we are using the model for descriptive purposes, and it is also higher than the model fits obtained in previous meta-analyses (e.g., .16 in Bijmolt, Van Heerde, and Pieters [2005] and .29 in Tellis [1988]). In addition, we report the upper bound and the lower bound (90% confidence interval) of the effects and, similar to Bijmolt, Van Heerde, and Pieters (2005), the predicted personal selling elasticity at each discrete level (e.g., new product, old product) of each of the 12 variables with significant effects, keeping all other independent variables in the model at their sample mean values. Next, we summarize and discuss these results.

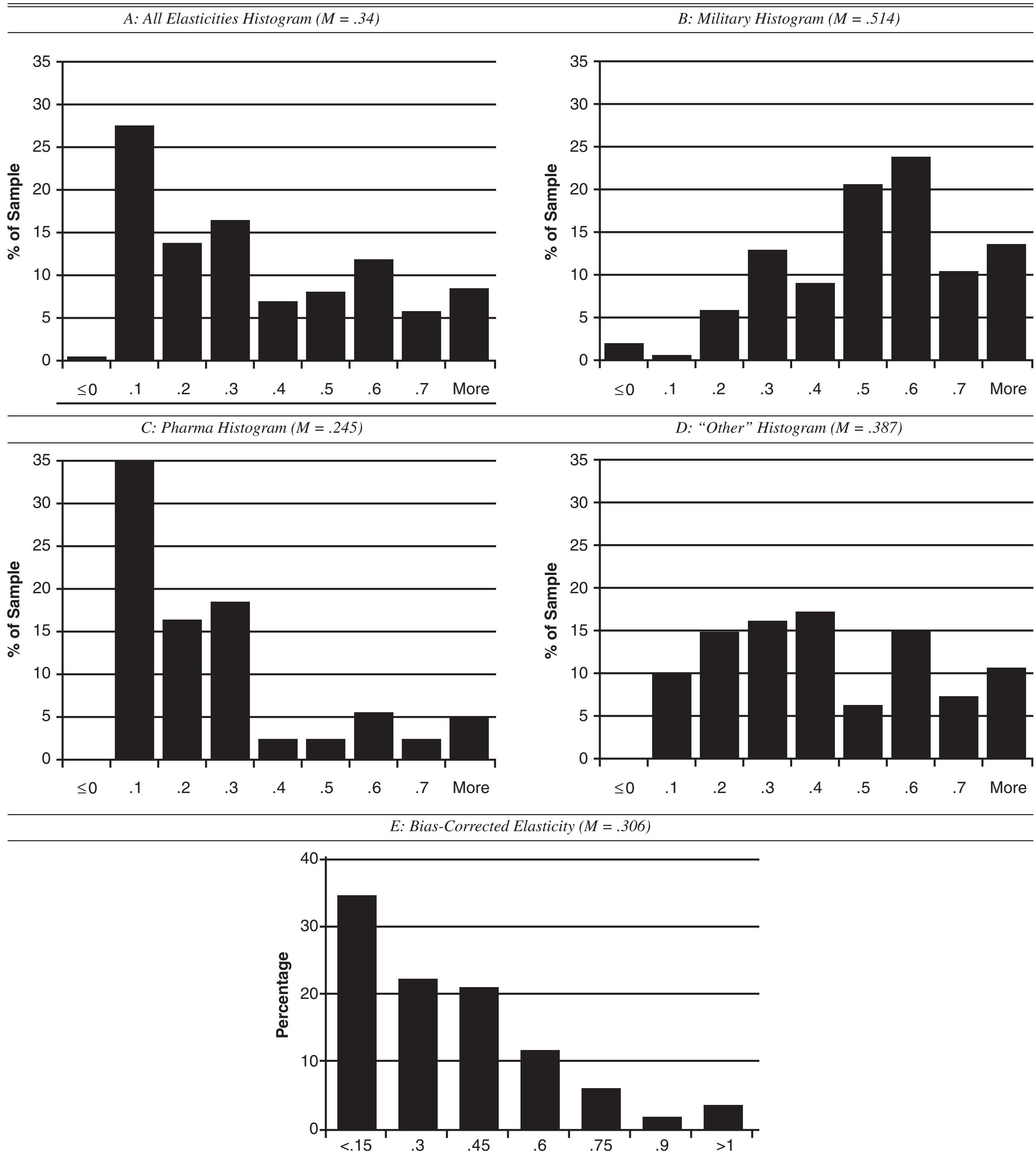
Summary of Significant Effects Found in Meta-Analysis

Hypothesized effects. We find support for the hypotheses regarding the effects of three market-setting characteristics (H_1–H_3) and five research methodology characteristics (H_4–H_8). Specifically, in accordance with H_1 and H_2, we find that personal selling elasticities for products in the early stage of their life cycles are higher than those of products in later stages of their life cycles by .264, and personal selling elasticities in the United States are lower than those in Europe by .110—similar to the findings of Farley and Lehmann (1994) and Assmus, Farley, and Lehmann (1984) with respect to advertising–sales elasticity. In addition, in accordance with H_3, personal selling elasticities appear to have decreased by approximately .005 each year in the time frame of the analysis. Next, in accordance with H_4–H_8, we find that elasticities estimated using relative (share) measures of output are lower than elasticities estimated using absolute output measures by .241; elasticities when lagged independent (dependent) variables are accounted for in response model estimation are lower than when they are omitted by .220 (.115); elasticities are higher by .184 when interaction effects between personal selling and other marketing variables (e.g., advertising, promotions) are included in the response model; and elasticities from models that account for endogeneity are less than those from models that do not by .091.

Other significant effects. Considering other selected variables without hypotheses, as shown in Table 2, we find that if yearly data were used to estimate personal selling elasticities of products in the early stage of the life cycle, these estimates would be lower by .274 than those obtained from the three other situations (i.e., late stage–yearly, late stage–monthly, early stage–monthly). This could be because short-term sales and effort variations that are more likely in early-stage product selling situations would not be picked up in annual data–based response model estimations.

With regard to omitted variables' effects, we find that the omission of promotion from response models has a significant effect. Specifically, personal selling elasticities are inflated by approximately .124 when promotion is not included. Regarding the covariates included in the meta-analytic model, we find that pharmaceutical selling (detailing) elasticities are significantly lower by .228 than the ones from "other" (business-to-business) settings. This result is consistent with observations in the extant literature that while industrial buyers tend to view industrial salespeople positively and as the most important source of information in their purchase decisions (e.g., Jackson, Keith, and Burdick 1987; Moriarty and Spekman 1984; Stafford and Stafford 2003), the targets customers for pharmaceutical marketers (i.e., physicians) tend to be wary of detailing and

Figure 1
HISTOGRAM OF RAW AND CORRECTED RESULTS



Notes: Panels A–D represent raw elasticity.

view it as a less important source of pharmaceutical product information than, for example, journal advertising and physician meetings and events (e.g., Manchanda and Honka 2005).

Finally, personal selling elasticities from cross-sectional data are lower by .185 than those from panel data, which have both time-series and cross-sectional components. In contrast, Assmus, Farley, and Lehmann (1984, p. 71) find support for their argument that time-series data–based advertising elasticities would be smaller than those estimated from cross-sectional data because time-series models often cannot distinguish between lagged advertising effects and positive serial correlations in disturbances while cross-sectional analyses are not subject to this problem. However, this argument presumes that all panel data–based studies account for lagged effects. In our database, the majority of earlier panel data–based analyses ignore lagged effects, thus inflating their elasticity estimates. This inflation is apparently large enough for their mean to exceed that from purely cross-sectional data–based models in our database.

Summary of Nonsignificant Effects

As Table 2 shows, 17 variables in the analysis, including 3 with hypotheses, were not found to have significant effects. Specifically, the hypotheses about the main effects of using either quarterly or annual data instead of monthly data (H_9 and H_{10}) were not supported. In addition, we found no support for H_{11} regarding the impact of manuscript status. Still, the test ensured that we controlled for any possible systematic differences due to unpublished studies, in keeping with Cook and colleagues' (1993) view that rigorous meta-analyses should include results of both published and unpublished works.

With regard to the omitted variables' effects, the omission of advertising or price from the response model does not bias the obtained personal selling elasticity estimate one way or the other. However, this does not mean that these variables have no impact on sales output; rather, within the context of our study's sample sizes and statistical power, we are unable to document an impact. It is possible that the analyses in our database that omitted these instruments did so because they tend to stay fixed over long time horizons in those settings. It is also possible that both positive and negative correlations between personal selling effort and advertising and between personal selling and price exist in different study settings in our database.

With regard to the remaining covariates, we do not find any significant difference between personal selling elasticities from military recruiting and "other" selling situations. This could be because personal selling activity plays a role in organizations' personnel recruiting efforts that is comparable in influence and importance to its role in industrial buying. Specifically, the personnel psychology literature shows that recruiting representatives' behaviors (e.g., informativeness, personableness, competence, aggressiveness) are critical and influential in high-involvement career choice decisions by targeted prospects (e.g., Harris and Fink 1987; Maurer, Howe, and Lee 1992; Rynes, Heneman, and Schwab 1980).

We also do not find any significant effect of functional form (shape) on personal selling elasticity. The four functional forms used in sales response models in the data set are the multiplicative (log–log), semilogarithmic, additive (i.e., a linear response to personal selling), and "other" (e.g., logit, quadratic, square root functional forms). As Tellis (1988) notes, which functional form is appropriate in any setting is an empirical issue. Different functional forms can yield different sales elasticities over the same range of input. Likewise, personal selling elasticities estimated through the use of ordinary least squares, multistage least squares, or maximum likelihood estimation are not statistically different from one another, a result consistent with the findings of Assmus, Farley, and Lehmann (1984) and Bijmolt, Van Heerde, and Pieters (2005). In addition, similar to the findings of prior empirical studies by Chintagunta (2001) and Bijmolt, Van Heerde, and Pieters (2005), our results show that elasticity estimates are not biased in any particular direction when response models do not account for heterogeneity, though buyers are likely to be different in their sensitivities to personal selling efforts for any number of reasons.

Finally, we do not find any significant differences in estimates of personal selling elasticities based on different output aggregation measures or types of input measures (see Table 2). This affirms that it is meaningful to seek generalizations with respect to dimensionless elasticities, despite variations in the constituent output and input measures.

Focus on Pharmaceutical Detailing Elasticities: Differences from Kremer and Colleagues (2008)

In their meta-analysis of pharmaceutical promotions elasticities, Kremer and colleagues (2008) report a mean detailing elasticity of .326, compared with our raw mean of .245 for the pharmaceutical industry. However, these numbers are not comparable. Our number of .245 refers to the mean current period, company-level detailing elasticity, but it is difficult to determine what Kremer and colleagues' number of .326 refers to because they pool short-term and long-term (with heterogeneous carryovers), as well as brand-level and industry-level (primary demand), elasticites. In addition, in their calculations, Kremer and colleagues do not take into account whether interaction terms between detailing and other variables were included in the original models, so some of their elasticity derivations of elasticities are downward biased. They also treat several nonsignificant elasticities as exactly zero (while we treat them as missing values), and they "double-count" other elasticities in their database. Finally, only 22 of the 36 detailing-related papers in Kremer and colleagues' database meet all six of the aforementioned criteria for inclusion in our meta-analysis. In addition, 16 of the 38 pharmaceutical sales response papers in our database are not included in Kremer and colleagues' analysis.

Research Method Bias–Corrected Benchmark Elasticity

Following Tellis's (1988, p. 337) lead, we propose that rather than the raw mean of .34, a more appropriate and practically useful generalized estimate to draw from this meta-analysis is the mean obtained after correcting each individual personal selling estimate for the statistically significant biases that result from researchers' methodology choices. Specifically, we propose that the appropriate reference response model for assessing personal selling elasticity is one that includes promotion effects, either a lagged independent variable (sales input) or a lagged dependent variable (sales output); accounts for endogeneity of personal selling; includes interaction effects between personal selling and marketing-mix elements; and uses monthly rather than yearly data intervals for new product settings, considering that the unit exposure time (i.e., time between successive calls on customers in field settings; see Tellis and Franses 2006) in personal selling is closer to a month than a quarter. After "correcting" each of the 506 measurements in our database for their deviations, if any, from this reference model using the results in Table 2, we obtain the corrected elasticity distribution shown in Figure 1, Panel E, whose mean is .31 and whose variation is now due only to differences in market-setting characteristics. As we discuss in the next section, this market-based benchmark value of personal selling elasticity can serve as a useful input for marketing and sales managers and for sales researchers.

IMPLICATIONS FOR MANAGERS AND RESEARCHERS

Targeting Product Markets for Personal Selling Efforts

The finding that responsiveness to selling effort is higher in early than late stages of product life cycles suggests that managers should focus their sales force efforts on launching and establishing new products and then perhaps shift to other means of communications as products mature (e.g., e-detailing in the case of older, well-known pharmaceuticals). Similarly, the results suggest that if gross margins and current sales are equal across both territories, deployment of more selling efforts in European than in U.S. markets would be desirable (e.g., Skiera and Albers 1998).

Checking Plausibility of Findings

Marketing-mix analysts often refer to the generalized result from an earlier meta-analysis to check the plausibility of their own findings. For example, Chintagunta and Desiraju (2005, p. 76) use the magnitude of advertising elasticity (a mean value of .21 based on Farley and Lehmann [1994]) to support their estimate of personal selling elasticity, apparently because a "good" empirical generalization (e.g., Barwise 1995) with respect to personal selling elasticity was not available at the time of their study. The method bias–corrected personal selling elasticity mean of .31 derived in this study can now serve as a more appropriate benchmark for such validation checks.

Starting Values in Estimation Routines

Because data environments have become richer and more disaggregate in nature, the estimation of econometric models that exploit these features has become increasingly time consuming; for example, Narayanan, Desiraju, and Chintagunta (2004) report that their model parameter estimation could take several hours. To reduce such long model estimation times, our meta-analysis estimate of personal selling elasticity can serve as a reasonable starting value or a good "prior" in Bayesian estimation.

Improving Study Design

To obtain less biased results in future sales force response studies, analysts are well advised to include lagged effects, to include interactions with other marketing variables, and to account for endogeneity of personal selling. However, when the researcher/analyst does not have all the required data, our meta-analysis findings can help adjust the obtained estimate of personal selling elasticity for the "predictable method-induced biases" (Tellis 1988).

Further Research

The findings and insights herein are restricted by the quantity and quality of the personal selling response models in our database. They could be enhanced and improved with further research on personal selling response in more diverse market settings, along with more detailed descriptions of the selling task. For the sake of having a maximum impact (e.g., Farley, Lehmann, and Mann 1998), we hope that future studies (1) are from European, South American, or Asian settings; (2) use different levels of temporal aggregation; (3) include the critical omitted variables; and (4) account for endogeneity in sales response. To assist in future personal selling sales response model research design, in the Web Appendix (Table A2; see http://www.marketingpower.com/jmroct10), we provide the correlations among our research design variables within and between the two levels (data set and measurement) in our database.

CONCLUSIONS

Farley, Lehmann, and Sawyer (1995, p. G37) note that "the prime benefit of meta-analysis in marketing has been that, with judicious use, it has delivered generalized quantitative estimates of such important measures as price and advertising elasticities." However, despite its prominence in many companies' marketing budgets, until now, the literature has not offered any good empirical generalizations with respect to personal selling elasticity. This article helps fill this gap in the empirical marketing generalizations literature. Specifically, we find that current-period personal selling elasticities tend to be

- Larger (1) in the early (versus late) stage of the offering's life cycle and (2) when interaction effects between personal selling and other marketing communication elements are included, and
- Smaller (1) in the United States (versus Europe), (2) as the year of data collection becomes more recent, (3) in pharmaceutical sales settings than in other (e.g., business-to-business, media selling) sales settings, (4) when relative (versus absolute) sales output measures are used, (5) when lagged effects of output or effort are included, (6) when promotions are included, (7) when cross-sectional rather than panel data are used, (8) when endogeneity of personal selling is accounted for, and (9) when yearly data are used for early-stage products.

The finding of a method bias–corrected mean personal selling elasticity value of approximately .31 indicates that personal selling remains a relatively potent instrument in the marketing mix of many industries. This underscores the continuing importance of research in marketing focused on improving sales force productivity.

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