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A Meta-analysis of Personal Selling Elasticities

Sönke Albers, Murali K. Mantrala, and Shrihari Sridhar

Personal selling can be a potent marketing instrument that plays a key role in the marketing mix of many industries. This study suggests that companies deploy direct salesforce resources for launching and establishing new products while shifting to other means of communications as products mature.

Report Summary

Personal selling (PS) is an important element in the marketing mix for many companies across various industries and sectors. There are currently an estimated 20 million full-time salespeople working for U.S. businesses, and personal selling is prevalent in noncommercial settings, such as U.S. military recruitment.

Despite the critical role and expenditures associated with this activity in numerous industries, there are few quantitative generalizations about personal selling's effects. To fill this gap, the authors analyzed estimates from 46 empirical studies published during the past four decades. The authors find the weighted mean of PS elasticities from these studies to be about .32, a number significantly larger than the mean estimates of advertising elasticity, which fall in the range of .1 to .2 in earlier analyses of advertising-sales effects.

The authors find that personal selling elasticity is higher when the products are in the early rather than late stages of their lifecycles and in European rather than U.S. markets. They also find that PS elasticity estimates from more recent studies are smaller than those from older studies. In addition, methodological features of past studies, such as the form of sales response function, the temporal data intervals used, and the omission of promotions or lagged effects, significantly bias elasticity estimates. After correcting for these methodology-induced biases, the weighted mean corrected PS elasticity is .352.

These results suggest that companies should deploy direct salesforce resources for launching and establishing new products while shifting to other means of communications as products mature. Similarly, personal selling efforts in European markets seem to be more effective than in the U.S., suggesting potential redeployment strategies for multinational firms.

The authors suggest that the efficient ratio of personal selling expenditures to total revenues is about 12.5%. Managers can use this ratio as a decision-making benchmark while setting PS expenditure levels. ■

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Introduction

There are currently an estimated 20 million full-time salespeople working for U.S. businesses (including about 15 million engaged in direct-to-consumer selling for companies such as Avon and Amway). In total, U.S. businesses are estimated to have spent about $800 billion on salesforces in 2006, almost three times the amount spent that year on advertising (Zoltners, Sinha, and Lorimer 2007). Personal selling is also prevalent in noncommercial settings, e.g., U.S. military recruitment efforts (Hanssens and Levien 1983). According to a Congressional Budget Office (CBO) study in 2006, the four arms of the U.S. military (Army, Marine Corps, Navy, and Air Force, including the respective National Guard and Reserve Forces) together employed nearly 21,450 recruiters in 2005, with the U.S. Army alone spending in excess of $100 million on experienced recruiters to meet its manpower goals in 2005 (Congress of the United States 2006).

Considering the critical role and expenditures associated with this activity in numerous industries, the lack of generalized quantitative estimates of personal selling's effects is remarkable.

The objective of this paper is to provide quantitative generalizations about the determinants of personal selling–sales (PS) elasticity and its magnitude via a formal meta-analysis of extant empirical studies encompassing a variety of market settings.

Marketing scholars have recognized the value of periodically conducting such meta-analyses of accumulated empirical studies of marketing instruments' effects on sales to draw out quantitative generalizations useful not only for assessing response parameter estimates made under different circumstances, but also for predicting parameter values that should occur under yet-unresearched circumstances (Farley, Lehmann, and Sawyer 1995). In particular, the elasticity of a firm's sales response to a marketing input, i.e., the percentage increase or decrease in sales for a 1% change in the level of the marketing variable, is an ideal measure for meta-analysis because it is dimensionless and easily interpretable. Quantitative generalizations about elasticities derived from meta-analysis are valuable for both building theory and guiding firms' marketing decisions (see, e.g., Hanssens, Parsons, and Schultz 2001, ch. 8; Farley, Lehmann, and Sawyer 1995). For example, they can provide a benchmark for average market responses under different conditions that can be used with an optimization procedure such as the Dorfman-Steiner (1954) equilibrium to assess the optimality of applied or proposed levels of a firm's marketing-mix variables in different market settings (Farley and Lehmann 1994).

Motivated by the above considerations, several notable meta-analysis papers have reported quantitative generalizations about the overall means of firm-level price and advertising–sales elasticities, and determinants of their variations across earlier studies (e.g., Andrews and Franke 1991; Assmus, Farley, and Lehmann 1984; Bijmolt, van Heerde, and Pieters 2005; Sethuraman and Tellis 1991; Tellis 1988). Until now, however, a similar meta-analysis of PS elasticities has not appeared in the marketing research literature. Indeed, quantitative empirical generalizations of any kind about the sales effects of personal selling (i.e., informative and persuasive personal communications by paid sales agents to prospective and current customers) are difficult to find in the literature.[1] For example, there is no paper focused on personal selling in *Marketing Science*'s highly acclaimed special issue on *Empirical Generalizations in Marketing* in 1995 (see, e.g., Bass and Wind 1995).[2]

An insufficient number of published studies at the time might explain why there was no meta-analysis research paper focused on PS elasticities in the mid-1980s. In general, data on personal selling efforts and effects have been difficult to obtain, limiting the number of salesforce-focused, market response studies relative to the volume of work on advertising and pricing. However, more data and studies have become available during the past two decades. Still, the only empirical generalizations with respect to PS elasticities are those provided by Hanssens, Parsons, and Schultz, who note that "personal selling elasticities have positive effects on sales, usually with decreasing returns to scale" (2001, ch. 8, p. 348). Further, Hanssens, Parsons, and Schultz (2001) state that "… personal communication or sales calling is *much more sales effective* than advertising" (emphasis ours); it appears they base this assertion on the observation that the modal value of PS elasticity found in military recruiting studies is about .5, as compared to the mean estimates of advertising elasticity falling in the range of .1 to .2 found in meta-analyses studies by Lambin (1976), Aaker and Carman (1982), Assmus, Farley, and Lehmann (1984), Sethuraman and Tellis (1991), and Lodish et al. (1995). However, Hanssens, Parsons, and Schultz's (2001, ch. 8) observations on PS elasticities are based on an informal review of five previous studies, of which four were drawn from defense recruiting in the 1980s, a setting that had typically revealed higher PS elasticities, averaging more than .4, e.g., Sohn (1996). Therefore, there is a need for a systematic research effort of larger scope to develop more robust or "good" empirical generalizations (Barwise 1995) with respect to the magnitude and determinants of PS elasticities. The work presented in this paper attempts to meet this need.

The database for our meta-analysis is comprised of observations from a large collection of empirical studies of personal selling's effects on sales outputs carried out during the past four decades by scholars in multiple disciplines (marketing, management, operations research, economics, health economics) and by industry- and government-based researchers. The individual studies originate from either the United States or Europe (Belgium, France, Germany, Italy, United Kingdom), and encompass a wide range of known research settings, models, data environments, and estimation methods. Specifically, our database includes 46 publications (studies)—with 5, 10, 11, and 20 papers from the 1970s, 1980s, 1990s, and the current decade respectively—providing a total of 3,193 PS elasticities (see Table 1).

Our meta-analysis is focused on *current-period* PS elasticities, reflecting the effect of current-period selling efforts on current-period unit sales, as the majority of studies in our database provide only these measures. Further, we concentrate on *firm- or brand-level* PS elasticities; no *industry-level* studies (see, e.g., Hanssens, Parson, and Schultz 2001, p. 350) are included in this meta-analysis. Some of the studies in our database involve personal selling to organizations or *institutions,* e.g., the selling of high-priced consumer goods to retailers (Beswick and Cravens 1977), the selling of building products to local contractors (Dalrymple and Strahle 1990), and the selling of airline tickets to travel agents (Fudge and Lodish 1977). Others involve personal selling to *individuals*, e.g., detailing of prescription drugs to physicians (Mizik and Jacobson 2004), or recruiting people to serve in various branches of the U.S. military such as the Navy (Carroll et al 1985) or the Army (Kearl, Horne, and Gilroy 1990). (Our database does not include any measurements of the effects of personal selling activity by sales assistants in retail store settings.)

Our research makes the following key contributions: First, we present the distribution of observed PS elasticities from a much larger and more comprehensive set of past studies than those covered in the previous literature. Second, similar to Bijmolt, van Heerde, and Pieters (2005), we identify and quantify the effects of significant drivers of interstudy differences in observed PS elasticities, falling in two classes: (a) *product-market (selling environment) characteristics*, e.g., product lifecycle stage, buyer type, geographic region, year of

Table 1
Studies Included in the Meta-analysis

#	Authors	Year	Publication Outlet	Volume (Issue), Pages	Estimates per Study	Average Elasticity
1	Albers	1996	*European Journal of Marketing*	30 (7), 68–82	1	.15
2	Albers Report 1	2001	Research Report	—	2	.48
3	Albers Report 2	1998	Research Report	—	1	.25
4	Albers Report 3	2004	Research Report	—	4	.19
5	Albers Report 4	2006	Research Report	—	24	.35
6	Albers Report 5	2006	Research Report	—	10	.15
7	Albers Report 6	2006	Research Report	—	4	.26
8	Albers Report 7	2005	Research Report	—	18	.04
9	Berndt et al.	2001	*American Economic Review*	85 (2), 100–5	1	.02
10	Berndt et al.	1994	Working Paper	—	4	.52
11	Berndt, Pindyck, and Azoulay	2000	NBER Working Paper #7772	—	28	.07
12	Berner and Daula	1993	Operations Research Center, Technical Report	—	1	.27
13	Beswick and Cravens	1977	*Journal of Marketing Research*	14 (2), 135–44	1	.22
14	Carroll, Rao, Lee, Shapiro, and Bayus	1985	*Marketing Science*	4 (4), 352–74	14	.30
15	Chintagunta and Desiraju	2005	*Marketing Science*	24 (1), 67–80	13	.79
16	Dalrymple and Strahle	1990	*Journal of Personal Selling and Sales Management*	10 (2), 59–68	3	.13
17	Dong, Manchanda, and Chintagunta	2006	Working Paper, University of Chicago	—	8	.11
18	Fischer and Albers	2007	Marketing Science Institute Working Paper	07–117	2831	.14
19	Fudge and Lodish	1977	*Interfaces*	8 (1, Part 2), 97–106	54	.25
20	Gatignon and Hanssens	1987	*Journal of Marketing Research*	24 (3), 247–57	2	1.10
21	Hagerty, Carman, and Russell	1988	*Journal of Marketing Research*	25 (1), 1–9	12	.36
22	Hanssens and Levien	1983	*Management Science*	29 (10), 1167–84	18	.21
23	Horsky and Nelson	1996	*Marketing Science*	15(4), 301–20	4	.51
24	Hruschka	1993	*Zeitschrift für Betriebswirtschaft*	63, 253–65	6	.43
25	Janakiraman, Dutta, and Stern	2005	Tanaka Business School Working Paper (DP05#42)	—	3	.13
26	Kearl, Horne, and Gilroy	1990	*Contemporary Policy Issues*	8(4), 68–78	2	.58
27	LaForge and Cravens	1981	*Journal of Personal Selling and Sales Management*	Fall/Winter, 10–16	2	.33
28	Lambert and Kniffin	1970	*Southern Journal of Business*	5 (1), 1–11	1	.78
29	Lodish et al.	1988	*Interfaces*	18 (1), 5–20	32	.49
30	Mahajan, Sharma, and Wind	1984	*Journal of Marketing Research*	21 (3), 268–77	7	.53

continued on next page

Table 1
Continued

#	Authors	Year	Publication Outlet	Volume (Issue), Pages	Estimates per Study	Average Elasticity
31	Manchanda and Chintagunta	2004	*Marketing Letters*	15 (2), 129–45	1	.17
32	Mantrala et al.	2007	*Journal of Marketing*	71 (2), 26–44	16	.35
33	Mizik and Jacobson	2004	*Management Science*	50 (12), 1704–15	3	.12
34	Montgomery and Silk	1972	*Management Science*	18 (10), B-485–501	6	.06
35	Morey and McCann	1980	*Management Science*	2 (2), 193–202	2	.34
36	Narayanan, Desiraju, and Chintagunta	2004	*Journal of Marketing*	68 (3), 90–105	6	.22
37	Narayanan, Manchanda, and Chintagunta	2005	*Journal of Marketing Research*	42 (3), 278–90	9	.24
38	Polich and Dertouzos	1986	Working Paper, RAND Corporation	—	1	.60
39	Ramaswamy et al.	1993	*Marketing Science*	12 (1), 103–24	6	.26
40	Rao and Turner	1984	*Journal of Personal Selling and Sales Management*	(2), 24–30	2	.35
41	Rosenthal et al.	2003	Working Paper, Henry J. Kaiser Family Foundation	—	3	.03
42	Shankar	1997	*Marketing Science*	16 (3), 271–93	3	.38
43	Skiera and Albers	2006	Working Paper, University of Kiel	—	6	.07
44	Smith, Gopalakrishna, and Smith	2001	*International Journal of Research in Marketing*	21, 61–76	6	.27
45	Turner	1971	*Journal of Marketing Research*	8 (2), 165–72	4	.75
46	Warner	1990	*Contemporary Policy Issues*	8 (4)	8	.37

data collection; and (b) *research methodology characteristics*, e.g., data aggregation interval and response model characteristics. Third, after adjusting for the predictable research methodology-induced biases found in our meta-analysis, we determine the mean estimate of PS elasticity over different selling environments to be about .352. We offer this as a benchmark *"market-based"* estimate of PS elasticity to guide investigations of personal selling–sales response relationships and assessments of the efficiency of personal selling expenditures in different market settings.

The remainder of this paper is organized as follows. In the next section, we present our meta-analysis methodology, the estimation results, and ensuing empirical generalizations with respect to the moderators of PS elasticity. Subsequently, we obtain the methodology bias-corrected distribution of PS elasticities in our database, the mean of which is .352. We then demonstrate how these results, combined with those of Bijmolt, van Heerde, and Pieters' (2005) price elasticity meta-analysis, can be used as inputs by managers in applying the Dorfman-Steiner (1954) theorem to assess the efficiency of reported ratios of personal selling spending to sales revenues. In particular, we comment on the implications for contemporary levels of personal selling efforts in the pharmaceutical industry and Army recruiting, two settings that figure prominently in our database. We conclude with a summary of our findings, general managerial implications, and directions for future research.

Methodology

Database compilation and scope

Table 1 lists the 46 papers (studies) included in our analysis. The steps for finding and compiling this collection of studies were as follows: First, we examined relevant publications that were cited in earlier reviews of the salesforce models research literature (e.g., Albers and Mantrala 2007; Hanssens, Parsons, and Schultz 2001, ch. 8; Manchanda and Honka 2005; Vandenbosch and Weinberg 1993). We also probed the references in those publications for additional studies reporting PS elasticities. Second, we used all available services for online bibliographic search (e.g., ABI/Inform, EBSCO, Google Scholar, Kluwer Online). Third, we searched the Web for relevant working papers. Finally, we asked researchers for the results of consulting engagements as well as copies of working papers in which they had estimated PS elasticities.

The final database of 46 studies includes only those that provide unambiguous estimates (either directly reported in the study or derived from estimated response model coefficients) of the elasticity of the ultimate output of interest (e.g., sales or market share, number of recruits) to personal selling effort. We excluded studies that use psychological criterion variables such as attitudes or purchase intentions. However, unlike Tellis (1988) and Bijmolt, van Heerde, and Pieters (2005), our database includes studies involving managerial judgment-based sales response estimation because of their prominent place in early salesforce decision modeling research (e.g., the CALLPLAN modeling approach used by Lodish [1971]) and intrinsic ability to provide individual-level elasticities rather than aggregate elasticities (see Albers and Mantrala 2007). As already noted, our database also includes working papers so as to avoid publication bias that would reduce interstudy variability in the meta-analysis (e.g., Rust, Lehmann, and Farley 1990).

Ultimately, the 46 studies yielded a total of 3,193 PS elasticity estimates. Notably, one single study (Fischer and Albers 2007) contributed 2,831 distinct brand-level PS elasticities, i.e., 89% of the total number of observations, while the remaining 45 contributed 362 (about the same total number of price-elasticity estimates utilized in Tellis's 1988 study and many more than the 128 and 55 advertising-elasticity estimates treated in the meta-analyses by Assmus, Farley, and Lehmann 1984 and Lodish et al. 1995). Noting that meta-analyses based on studies with widely differing numbers of measurements (observations) per study are common, Bijmolt and Pieters (2001) have shown that hierarchical linear model (HLM) estimation (e.g., Raudenbush and Bryk 1992) is the optimal procedure to account for the nested error structure, i.e., at the measurement level and the study level, that is present in such data. Their investigation, however, employed meta-analysis datasets that allowed for a maximum of 19% of the total observations to be contributed by one study. Therefore, to stay within this limit without sacrificing the information provided by the Fischer and Albers (2007) study, we employ a repeated HLM estimations approach in our meta-analysis, wherein each estimation run uses only a small, randomly drawn sample of the Fischer and Albers (2007) PS elasticity measurements combined with the remaining data from the 45 other studies. The details are provided in the section titled "Research methodology bias-corrected benchmark PS elasticity."

Independent variables included in the meta-analysis and coding

Table 2 presents the coding scheme for each of the selected independent variables, i.e., determinants of interstudy differences in PS elasticity estimates, examined in our meta-analysis, classified as either a *market characteristic* or *research methodology characteristic*. As indicated in Table 2, our selection of each of these independent variables was based on the use of a similar variable in one or more of the earlier published meta-analyses of price elasticity (Bijmolt, van Heerde, and Pieters 2005; Tellis 1988), advertising elasticity (Andrews and Franke 1991; Assmus, Farley, and Lehmann 1984) and determinants of a salesperson's performance (Churchill, Ford, and Walker 1985). However, due to the salesforce context of our research, our operationalizations (as indicated in Table 2) differ somewhat from those of the similar independent variables used in previous meta-analyses. Table 2 also indicates the *a priori* hypotheses with respect to the expected sign of the effect of each independent variable on the observed PS elasticities. The rationale for each hypothesized sign is discussed, along with the empirical results in the results section.

Two judges who were not members of the meta-analysis research team separately coded all the studies on the selected independent variables, using the coding scheme in Table 2. Agreement between the two judges was assessed to be greater than 90%. A third judge amicably resolved any remaining inconsistencies.

Estimation methodology

We model PS elasticity as a linear function of the selected independent variables (moderators), similar to Tellis (1988) and Bijmolt, van Heerde, and Pieters (2005). As already mentioned, our meta-analysis is based on multiple HLM estimation runs using samples of the Fischer and Albers (2007) observations along with the other studies' data in each run. More specifically, the steps in our procedure were as follows:

Step 0: We classified the 2,831 products for which elasticity estimates were obtained in the Fischer and Albers study into 12 broad, mutually exclusive and exhaustive therapeutic product categories.

Step 1: We then drew a stratified random sample of 7 observations from each of the 12 product categories, i.e., a total of 84 elasticity measurements from the Fischer and Albers study, and combined them with the 362 measurements from the remaining studies to obtain a total of 446 observations. Thus, the number of observations drawn from the Fischer and Albers study was about 19% of the observations for each run.

Step 2: The HLM model was estimated using a total of 446 observations. After each run, we recorded the estimated size, sign, and statistical significance of the impact of each moderator (*market and research methodology characteristics*) on PS elasticity.

Step 3: Steps 1 and 2 were repeated 2,000 times.

The computed means and standard deviations from Step 3 are reported in Table 3. It is evident from the low standard deviation of the estimates (e.g., .001 for the variable product lifecycle stage) that the estimates of each moderator were very similar in magnitude across 2,000 iterations. Also, the sign of each estimated effect was unchanged across all the 2,000 iterations. Last, we counted the times each moderator's effect on elasticity was found to be statistically significant (i.e., t-value ≧ 1.65, one-sided test). We then treated the mean estimate of each moderator's effect on PSE as significant if it was significant in 90% or more of the 2,000 iterations.

Multicollinearity can arise due to high correlations between the "within-study" (variables that change within studies only as well as the "across-study" (variables that change across and within studies) independent variables in HLM. Since there is no direct diagnostic for multicollinearity in HLM, we observed the variance inflation factors of the independent variables (VIF) (e.g., Mason and Perreault 1991) obtained through separate OLS estimations of the within-study and across-study independent variables. The VIF of each independent variable in each estimation was less than 10 (the highest being less than 5), suggesting acceptable multicollinearity. Together

Table 2
Variables Used in the Meta-analysis

#	Category*	Variable	Description	Precedence**	Coding Scheme	Expected Direction of Effect
1	MC	Year of data collection	Earliest year in the panel from which PS elasticities were estimated	AF, BHP	Mean centered variable	?
2	MC	Stage in product lifecycle	Captures whether the product was in the growth or mature stage of its product lifecycle	AF, BHP, T	1: New or growing markets, 0: Mature or declining markets	New > Old
3	MC	Geographic setting	Continent from which data were collected	AF, AFL, BHP, T	1: European countries 0: North America	Europe > North America
4	MC	Type of buyer	Captures whether the recipient of the sales call is an institutional or individual buyer, e.g., industrial products are sold to institutional buyers, whereas Navy recruiting efforts are targeted at individuals	CFHW	1: Nonorganizational buyers 0: Organizational buyers	Organizational buyer > Non-organizational buyer
5	RM	Estimation method	Captures whether the estimation method used was Ordinary Least Squares (OLS), Multi-stage and Generalized Least Squares (MLS), Maximum Likelihood (MLE), or Decision Calculus (DC)	AF, AFL, BHP, T	1: MLS , 0: OLS, 1: MLE, 0: OLS, 1: DC, 0:OLS	?
6	RM	Temporal aggregation	Captures the smallest data interval used	AF, AFL, BHP, T	1: Quarterly 0: Monthly 1: Yearly 0: Monthly	Quarterly < Monthly, Yearly < Monthly
7	RM	Functional form	Captures whether the response function is a constant elasticity (e.g., multiplicative) or a varying elasticity form (e.g., ADBUDG)	AF, AFL, BHP, T	1: Varying Elasticity (V) (NL), 0: Constant Elasticity (C)	?
8	RM	Sales output measure	Captures whether the sales output measure involves changes in both primary and selective demand (absolute measure) or only selective demand (share measures)	AF, AFL, BHP, T	1: Relative 0: Absolute	Relative < Absolute
9	RM	Heterogeneity in sales response	Captures whether heterogeneity in sales response is modeled	BHP	1: Accounted for 0: Not accounted for	?
10	RM	Lagged measures	Captures whether lagged effects of sales/ effort were included	BHP	1: Included 0: Omitted	Included < Omitted
11	RM	Omitted variables	Captures whether the variables of price (p), quality (q), advertising (a), and promotions (pr) were included or excluded	AF, FL, BHP, T	1: Included 0: Omitted	Included < Omitted for p, q, pr; Omitted < Included for Price

*MC: Market characteristics, RM: Research methodology. **AF: Andrews and Franke (1991), AFL: Assmus, Farley, and Lehmann (1984), CFHW: Churchill et al. (1985), BHP: Bijmolt, van Heerde, and Pieters (2005), T: Tellis (1988).

Table 3
Repeated HLM Estimation Results

Category of Covariates	Variable	Estimate	Std. Dev. of Estimate	% Times Significant ($p < .1$)
Constant	Intercept	**.6**	**.002**	**100**
Market Characteristics	Year of data collection (mean-centered)	**–.01**	**.00007**	**100**
	Product lifecycle stage			
	Late			
	Early	**.16**	**.0003**	**100**
	Country			
	Europe			
	United States	**–.23**	**.004**	**100**
	New Product * USA	**–.155**	**.01**	**90**
	Type of buyer			
	Institutional buyer	.08	.001	0
	Individual buyer			
Research Methods	**Estimation type**			
	OLS			
	MLS + GLS	–.001	.001	0
	MLE	.03	.0006	0
	DC	–.12	.004	0
	Temporal aggregation			
	Monthly			
	Quarterly	.13	.003	6
	Yearly	**–.15**	**.004**	**100**
	Functional form			
	Constant elasticity			
	Varying elasticity	**.17**	**.002**	**100**
	Sales output measure			
	Absolute			
	Relative	**–.21**	**.001**	**100**
	Heterogeneity in sales response			
	Not accounted for			
	Accounted for	–.09	.001	0
	Lagged sales effects			
	Omitted			
	Included	**–.16**	**.0009**	**100**

Table 3 continued on next page

with low correlations between the independent variables and high stability in the estimates, we ruled out multicollinearity as a threat.

Also, in addition to main effects, we checked for two-way interaction effects between all market characteristic variables. More specifically, as was done by Bijmolt, van Heerde, and Pieters (2005), we tested interaction effects one at a time to avoid multicollinearity problems. Using our repeated HLM procedure and treating each interaction effect as a covariate, we found one significant interaction effect among the market characteristic variables. Next, we report the results of our analysis.

Results

Frequency distribution of observed PS elasticities

Figure 1 (Panel A) displays the overall frequency distribution of the 3,193 observed PS elasticity estimates obtained from the 46 studies. As expected, we see that 98% of these elasticity estimates are positive. Next, we calculated the weighted mean of the elasticities to allow every study to contribute equally to the empirical generalization obtained. Specifically, if N represents the total number of studies (i.e., 46) and M_n represents the mean of all the PS elasticity estimates obtained in study n (where n ranges from 1 to N), then the weighted mean = $\sum_{n=1}^{N} \frac{M_n}{N}$. We found the "raw" weighted mean in our database (unadjusted for any methodology-induced biases) to be .320. Notably, this value from our meta-analyses is significantly lower than .5, the modal value of PS elasticity suggested by Hanssens, Parsons, and Schultz (2001, ch. 8, p. 348).

HLM model estimation results

The overall fit of our model to the data (mean R^2 across 2,000 iterations = .30) is satisfactory, since we are using our model for descriptive purposes, and also comparable to the model fits obtained in earlier meta-analyses (e.g., .16 in Bijmolt, van Heeerde, and Pieters 2005, and

Table 3
Continued

Category of Covariates	Variable	Estimate	Std. Dev. of Estimate	% Times Significant (p < .1)
Research Methods, *continued*	**Advertising variable**			
	Omitted			
	Included	–.05	.0001	0
	Promotions variable			
	Omitted			
	Included	**–.11**	**.0007**	**100**
	Price variable			
	Omitted			
	Included	.1	.005	0
	Quality variable			
	Omitted			
	Included	–.005	.005	0
Variance Explained	30%			

.29 in Tellis 1988). Eight of the 18 covariates (specifically, year of data collection term, two market characteristics, and five research methodology characteristics) were found to have significant effects on the estimated PS elasticity. We report and discuss the estimated effects of the various independent variables in the following paragraphs.

Effects of market characteristics

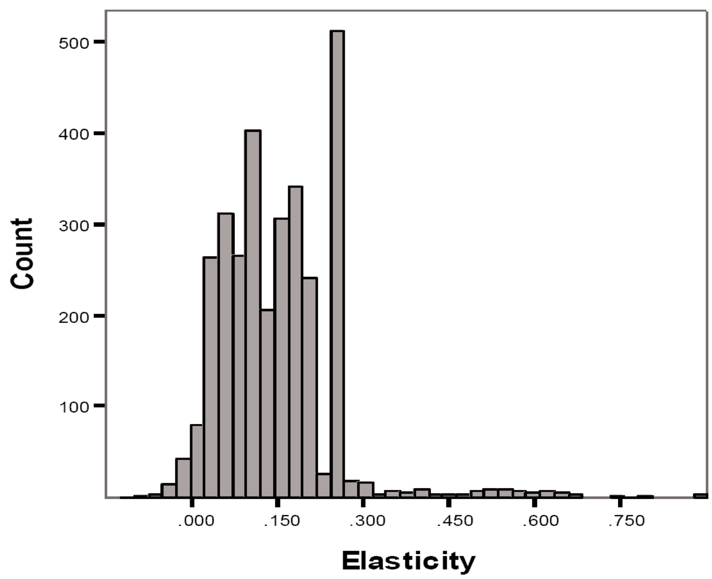
Year of Study. Our analysis indicates that PS elasticities appear to have decreased by about .01 each year in the time frame of study. In general, this observation is consistent with the lengthening of sales cycles in recent years, involving more relationship selling and partnering activities, and attributable to increasing product complexity, more demanding customers, and greater competition (e.g., Jones et al. 2005; Weitz and Bradford 1999). Simply put, more effort is being required to produce the same level of sales. Also, in recent years, which have been marked by increased military engagements, more effort is being required of military recruiters to enlist the same number of quality recruits each year. The Army National Guard, in fact, has missed its recruiting goal by at least 13% each year between 2003 and 2005 (Congress of the United States, 2006).

Product Lifecycle Stage (Early [introduction, growth] Stage versus Late [mature, decline] Stage). We expected the estimated PS elasticity to be higher in study settings involving products in the early rather than late stages of their lifecycles (see Table 2). Personal selling's key advantages relative to other marketing instruments, e.g., media advertising, direct marketing, etc., are that it permits two-way communication between buyer and seller that can address the former's questions and objections and offer demonstrations, etc. In the case of pharmaceutical marketing, physicians are more willing to meet with sales representatives when the reps have something new to show them. That is, sales calls for new drugs are more informative and persuasive, resulting in higher average PS elasticity values in the launch phase than those in the later stages of the lifecycle when details play a largely persuasive role (Narayanan, Manchanda, and Chintagunta 2005). More generally, there is much evidence for the influential role of personal selling in successful new product marketing (e.g., Cooper and Kleinschmidt 1988), especially *high search,* infrequently purchased products (e.g., Hagerty, Carman, and Russell 1988). The related adjustments in sales management practices such as new product-focused sales training and a shift from sales to activity quotas—e.g., number of demonstrations, rep-manager joint sales calls, etc.—at the time of new product launches also contribute to higher salesforce effectiveness in those situations (Wotruba and Rochford 1995; Zoltners, Sinha, and Lorimer 2006). As expected, we found a statistically significant main effect for the influence of product lifecycle on estimated PS elasticity. Specifically, PS elasticities for products in the early stages of their lifecycles are on average

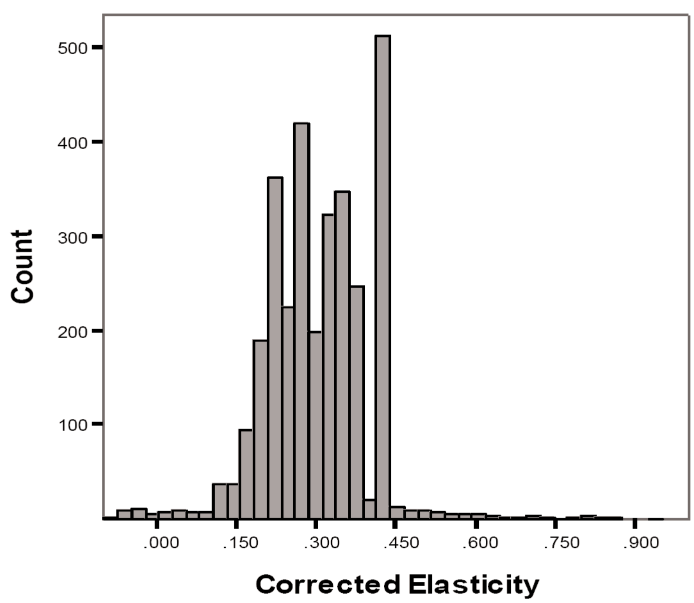
Figure 1

Histograms of Elasticities

Panel A. Histogram of Observed Raw Personal Selling Elasticities



Panel B. Histogram of Methodology Bias–corrected Personal Selling Elasticities



about .16 greater than those of products in later stages of their lifecycles.

Geographic Setting—United States versus Europe. There are two reasons for our expectation that the estimated PS elasticity would be lower in U.S. sales settings than in European sales settings. First, there is more saturated sales coverage (with lower marginal response to effort) in the U.S. pharmaceutical market, e.g., detailing expenditures in the United States have been reported to be three to four times larger than in Europe (Chintagunta and Desiraju 2005). Second, there are a number of cultural differences between the two settings. Prior work has shown that collectivistic cultures have a more favorable view of personal selling than individualistic cultures, due to their predispositions toward mutual learning, caring attitude, and respect (Fam and Merrilees 1998). The European countries are generally reputed to be more collectivistic than the United States (Schlegelmilch and Robertson 1995). Indeed, our meta-analysis finds PS elasticities in the United States to be .23 lower than those in Europe. This is similar to the finding in Farley and Lehmann (1994) and Assmus, Farley, and Lehmann (1984) with respect to advertising elasticity.

In addition, as indicated in Table 3, we find a negative and significant "New Product * USA" interaction effect over and above the main effects of product lifecycle stage and geographic setting. Specifically, U.S. products in the early stages of their lifecycles had a PS elasticity that was lower than that for European products by .155. As discussed earlier, personal selling plays an informative role in the introductory phase of the product lifecycle. Evidently, this effect of product lifecycle stage is reinforced in European contexts.

Type of Buyer—Institutional versus Individual. In their meta-analysis of the determinants of a salesperson's performance, Churchill et al. (1985) found that the relationship between a salesperson's performance outcomes and effort differs between settings involving institutional buyers and those involving individual customers. Previous research has shown the high importance of the salesforce in industrial marketing contexts (e.g., Jackson, Keith, and Burdick 1987; Moriarty and Spekman 1984; Parasuraman 1981). For example, Jackson, Keith, and Burdick (1987) note that industrial buyers in general consider salespeople to be the most important promotional element when making a purchase decision. Additionally, products are reordered quite frequently in an organizational setting, and many firms have well-established and straightforward repurchasing policies that do not involve as much work by the salesperson compared to the first purchase (Dwyer and Tanner 2002, p. 72). We hypothesized that this could generate a higher amount of sales for the same amount of effort and hence lead to a higher estimate of PS elasticity. However, while the sign of the effect of a change in setting from individual to institutional-buying is positive, we do not find that this effect is significant. One possible explanation is that there are more institutional-buying settings in our database involving new or modified rebuys, rather than routinized repurchases, leading to longer sales cycles (see, e.g., Anderson, Chu, and Weitz 1987). Industry reports identify that some business-to-business sales cycles to be about 10-18 months long due to the complex nature of the product requirements, company-mandated procedures, and multiple decision makers at many levels of management (Whetsel 2005).

Research methodology, data, and model characteristics

Temporal Aggregation. Earlier work has shown that aggregation loses much of the temporal component of elasticity stemming from short-term variations in the marketing instrument, thereby leading to a lower estimated elasticity. For example, Assmus, Farley, and Lehmann (1984, p. 71) find that advertising elasticities estimated with yearly data are lower than those estimated with bimonthly or quarterly data. We sought to investigate whether temporal aggregation could similarly result in biased estimates of PS elasticities. We can expect temporal variations in both sales effort and sales similar to advertising (e.g., Gopalakrishna et al. 2007; Lal and Srinivasan 1993; Steenburgh 2004), due in part to the common use of nonlinear incentive mechanisms such as short-term (typically monthly or quarterly) sales quota-based lump-sum bonus plans in practice (e.g., Joseph and Kalwani 1998; Mantrala, Raman, and Desiraju 1997). This temporal variation will not be picked up in aggregated data; therefore we expected PS elasticities estimated from yearly and quarterly data to be lower than those estimated with monthly data.

Consistent with our expectation, we find PS elasticities estimated with yearly data to be .15 lower than those estimated with monthly data. However, contrary to our expectation, we find that PS elasticity estimated using monthly and quarterly data is not statistically different. Based on recent propositions established by Tellis and Franses (2006, pp. 221–2), our finding would suggest that the average unit exposure times of customers to personal selling in our database fall in this range.

Varying versus constant elasticity functional forms

We divided response functions into two broad categories, varying-elasticity form (e.g., *S*-shaped) and constant-elasticity (i.e., multiplicative or double-log) form. We expected elasticities estimated using varying-elasticity response functions to be higher than those from multiplicative functions, because, as the name states, constant-elasticity functions constrain short-term elasticity so it is the same over the range of the response function. As pointed out by Assmus, Farley, and Lehmann (1984), such models are likely to underestimate elasticities that are substantially smaller than 1 in magnitude (as is the case with observed PS elasticities) compared to models that allow for varying elasticity over the response function. As expected, we find that the use of a varying-elasticity functional form leads to an elasticity that is .17 more than the use of the more restrictive constant-elasticity form.

Relative versus Absolute Sales Criterion Measure. We hypothesized that estimated PS elasticities from models using relative sales (or market share) as the criterion measure should on average be smaller than those estimated from models using absolute sales as the criterion measure. This is because the latter is a measure of change in sales due to both primary (market size) and secondary (market share) changes resulting from a change in selling effort (see, e.g., Hagerty, Carman, and Russell 1988). In keeping with our rationale, we find that "relative" PS elasticities are .21 less than "absolute" PS elasticities.

Lagged Effects Included versus Lagged Effects Excluded. The accumulated PS literature shows that much of the sales level observed in one period may be due to carryover effects of efforts in previous periods. For example, Horsky and Nelson (1996) find a large carryover in the sales of chemical production equipment. Similarly, based on salesforce 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% the year after, and 52%–70% in the fourth year. Sinha and Zoltners attribute these high levels of carryover to physicians' prescriptions for chronic-care drugs and reluctance to switch if the drugs are effective. In the case of Army recruiting, recruiters are known to simply draw from an inventory of leads they have built up in earlier periods rather than make fresh calls, as a "demotivation stage" sets in toward the end of their contracts (Carroll, Lee, and Rao 1986). Therefore, the effectiveness of current-period recruiting efforts would be overstated if the number of lagged leads is omitted from the response model.

Thus, we hypothesized that the inclusion of lagged effects (sales or effort) should result in a smaller estimated (short-term) PS elasticity. Our results indicate that PS elasticities are smaller by .16 when lagged effects are included, compared to when they are omitted.

Promotions Included versus Promotions Not Included. We hypothesized that the inclusion of promotions (e.g., free samples, gifts, and temporary price reductions) in the sales response model would have a negative impact on PS elasticity estimates. This is because, if promotions are omitted in the settings where they are known to have a significant effect on sales, a disproportionately high weight might be attributed to the effectiveness of personal selling. Some of the studies where promotions have been omitted from our database include those involving pharmaceutical selling (Berndt, Pindyck, and Azoulay 2000), ad-space selling (Mantrala et al. 2007), and industrial product selling (Turner 1971). Among these, the omissions of promotions in response-model estimations involving pharmaceutical detailing and ad-space selling—where they are known to be effective and are frequently used—would contribute to upwardly biased PS elasticity estimates. Our estimation results show that the omission of promotions leads to a PS elasticity biased upward by .11.

Comments on nonsignificant research method characteristics

We hypothesized that the *omission* of a *relevant influencer* of sales will result in a PS elasticity *biased in the same direction* as that of the influence. Thus, since increases in advertising and quality could result in *increased* sales, omitting them should technically result in a PS elasticity biased *upward*. Similarly, if customers are very price sensitive in a setting, omitting price in the estimation should lead to a PS elasticity biased *downward*. However, although the effects of these three omitted variable dummies have the right sign, we find none of them are significant. The lack of evidence of biased PS elasticity estimates due to omissions of advertising, quality, or price variables by a number of individual studies in our database does not imply that these variables have no impact on sales, but simply that given our study's sample sizes or statistical power, we are unable to document an impact. It is also possible that the studies in our database that omitted advertising did so because it is not a significant marketing instrument used in those settings. For example, Jackson, Keith, and Burdick (1987) have reported that industrial buyers do not view trade advertising to be as important as personal selling in their purchase decisions, and a number of studies in our sample were set in markets involving such buyers, e.g., industrial products (Albers 1996), chemical production equipment (Horsky and Nelson 1996), and building products (Dalrymple and Strahle 1990). Similarly, the variables of product price and quality were typically omitted in study settings where they tended to stay fixed over long time horizons, e.g., prescription drug and military recruiting markets.

We also included two other variables in our analysis due to their precedence and relevance in other elasticity meta-analyses—*accounting for heterogeneity in sales response* and *choice of estimation method*. Our results show that it makes no difference to the PS elasticity estimate whether response models accounted for heterogeneity or not, although buyers are likely to be different in terms of their sensitivities to personal selling efforts for any number of reasons. This finding is in keeping with past theoretical work that shows that elasticities increasing or decreasing with heterogeneity depends on the distribution of heterogeneity (Hutchinson, Kamakura, and Lynch 2000) and is consistent with previous empirical research that has not found directionally consistent effects of ignoring heterogeneity on price elasticities, e.g., Chintagunta (2001); Ailawadi, Gedenk, and Neslin (1999); Bijmolt, van Heerde, and Pieters (2005). Similarly, we find that the choice of OLS (Ordinary Least Squares), MLS (Multi-Stage Least Squares), MLE (Maximum Likelihood Estimation), or DC (Decision Calculus) as an estimation method does not bias the PS estimate one way or the other. In theory, the choice of OLS as an estimation method when recursive or simultaneous systems are truly generating the data will lead to biased estimates compared to MLS (or MLE if the simultaneity is modeled). However, similar to Assmus, Farley, and Lehmann (1984) and Tellis (1988), we do not find bias in any particular direction.

Research methodology bias–corrected benchmark PS elasticity

Following the lead of Tellis (1988, p. 337), we propose that rather than the raw weighted mean of .32 noted earlier, a more appropriate generalized estimate to take from this meta-analysis for future research purposes (e.g., use as priors in Bayesian estimation procedures) and practical applications is the weighted mean obtained after correcting each individual PS estimate for the statistically significant biases introduced by researchers' methodology choices. Specifically, according to our results reported in Table 3, a study that omitted the promotion variable in the response model would report a PS elasticity that is biased upward by .11. Similarly, studies that use data aggregated at a yearly level would report selling elasticities that are lower by a factor of .15 than those that utilize data aggregated at the monthly level. Next, the PS elasticity estimates from studies that used constant-elasticity functional forms would be biased downward by a factor of .17 compared to PS elasticity estimates from studies using varying elasticity functional forms. Finally, PS elasticity estimates from studies that omitted lagged effects would be biased upward by a factor of .16 compared to those derived from models that included lagged effects. Therefore, taking the appropriate reference sales response model as one that includes promotion and lagged effects, allows for varying PS elasticity, and uses monthly rather than yearly data intervals (considering that the unit exposure time in personal selling is closer to a month than a year), we proceed to "correct" each of the 3,193 measurements in our database for their deviations, if any, from this reference model. Such corrections for methodology-introduced biases yield the distribution of personal selling elasticities shown in Figure 1 (Panel B).
The remaining variation in the studies' bias–corrected elasticities is now attributable to only

differences in the study settings' market characteristics.

The weighted mean of the methodology bias–corrected elasticities in our database is .352 (see Figure 1, Panel B). As we show in the next section, combined with earlier price elasticity meta-analysis results, this market-based benchmark value of PS elasticity can serve as a useful input in evaluating the efficiency of personal selling expenditures to sales ratios in settings where more detailed sales-effort response data are not available.

Managerial Assessment of Personal Selling's Efficiency

According to the Dorfman-Steiner (1954) theorem, the profit-maximizing level of personal selling spending (assuming that other marketing efforts such as advertising are held constant) is the level at which the marginal revenue product of personal selling spending is equal to the price elasticity (assuming the unit selling price is set optimally relative to unit production cost). This condition implies $(PS_S/R) = -(PS_E/P_E)$ where PS_S denotes personal selling spending; PS_E is the personal selling elasticity; R denotes revenues; and P_E represents the price elasticity. The use of this ratio to create good salesforce-related decisions has been previously demonstrated by Albers (2000).

Assessing average personal selling spending to sales ratios by firms in different industries

In employing the mean estimate of price elasticity of –2.81 (applicable to 1999) delivered by Bijmolt, van Heerde, and Pieters (2005, Table 3) and our bias-corrected estimate of .352 for PS elasticity, the Dorfman-Steiner (1954) theorem condition indicates that the efficient ratio of personal selling expenditures to total revenues is about 12.5% (assuming prices are set optimally). This ratio can be used as a decision-making benchmark by managers to assess whether their personal selling expenditures are near optimal levels. For example, Table 4 indicates that many industries in 1998–1999 were apparently under-spending on personal selling based on their reported (PS_S/R) ratios in the first column of Table 4. Compared to the efficient benchmark of 12.5%, the index values shown in Table 4 suggest that on average, firms in the majority of industries listed, 15 of the 23, were under-spending on personal selling in 1998–1999. Given more detailed data, this analysis can of course be refined for a firm in any industry by further adjusting the market-based estimate of PS elasticity for the estimated effects of its own market characteristics as revealed by our meta-analysis. Therefore, our meta-analysis results can be used as a "*starting point for optimization*" (Farley and Lehmann 1994).

Focus on the pharmaceutical industry

Within the industries listed in Table 4, of particular interest is the pharmaceutical industry characterized by a PS_S/R ratio of 5.6% in 1998–1999 compared to the efficient benchmark of 12.5%. This could be one reason that many firms in this industry found it feasible to launch into a "detailing arms race" about that time (Elling et al. 2002). By 2006, the pharmaceutical industry appears to have overcorrected, resulting in intensive coverage of physicians that caused them to resist meeting with medical sales reps (e.g., Berenson 2006). Indeed, if we apply our meta-analysis finding of a yearly rate of reduction in PS elasticity of .01, then the PS_E values at the end of 2006 would be about .272. Similarly, Bijmolt, van Heerde, and Pieters (2005, p. 151) found an autonomous time trend suggesting that price elasticities increase .04 in magnitude each year, implying that the contemporary benchmark value for P_E is about –3.13. This implies that the efficient PS_S/R ratio in 2007 should be about 8.7% (continuing with the assumption that prices are set optimally). However, recent research by Novartis, cited by the Eularis consulting company (www.Eularis.com), indicates that actual PS_S/R ratios in the pharmaceutical

Table 4

Industry Assessment of Overspending in Personal Selling

Industry*	Actual (PS_S/R)% **	Optimal (PS_S/R) % with $PS_E = .352$; $P_E = -2.81$	Index = $(PS_S/R)/(PS_E/P_E)$	Optimality***
Business services	10.5	12.5	.78	Under
Chemicals	3.4	12.5	.25	Under
Communications	9.9	12.5	.73	Under
Construction	7.1	12.5	.53	Under
Educational services	12.7	12.5	.94	NearOpt
Electronics	12.6	12.5	.93	NearOpt
Electronics comps	4.9	12.5	.36	Under
Fabricated metals	7.2	12.5	.53	Under
Food products	2.7	12.5	.20	Under
Health services	13.4	12.5	.99	NearOpt
Hotels	1.9	12.5	.14	Under
Instruments	14.8	12.5	1.10	Over
Machinery	11.3	12.5	.84	NearOpt
Manufacturing	6.6	12.5	.49	Under
Office equipment	2.4	12.5	.18	Under
Paper and allied products	8.2	12.5	.61	Under
Pharmaceuticals	5.6	12.5	.42	Under
Printing and publishing	22.2	12.5	1.65	Over
Real estate	2.8	12.5	.21	Under
Retail	15.3	12.5	1.13	Over
Rubber and plastics	3.6	12.5	.27	Under
Transportation equipment	6.2	12.5	.46	Under
Wholesale consumer goods	11.2	12.5	.83	NearOpt
Overall Mean	8.19			

*Source: Zoltners, Sinha, and Lorimer (2004, Table 1.2).
**PS_S: Personal selling costs, PS_E: Personal selling elasticity, P_E: Price elasticity, R: Sales revenue.
***Over: Overspending, Under: Underspending, NearOpt: Nearly optimal.

industry are currently closer to 10%. A downsizing correction is clearly in order. Interestingly, Pfizer announced a 20% reduction in its U.S. salesforce (approximately 2,400 reps) in November 2006 that was followed closely by pullbacks in sales efforts by Bristol-Myers Squibb, Abbott Labs, and Johnson & Johnson (Berenson 2006; Hensley 2007; McGuire 2007).

Making up the shortfall in Army recruiting

Since the abolishment of the mandatory draft, U.S. military recruiting has depended heavily on personal selling efforts of recruiters to meet its targets (e.g., Hanssens and Levien 1983; Warner et al. 2003). However, recent Congressional Budget Office reports indicate that the Army has been falling short of its recruiting goals. For example, in the year 2005, the active Army, Army National Guard, and the Army Reserve missed their targets by

Table 5
Estimated Recruiters' Strength and Expenditure*

Defense Category	Target	Attained	Shortage (%)	Current Number of Recruiters	Personal Selling Elasticity (PSE)	Recruiter Increase Desired (%)	Current Spending (millions of dollars)	Spending Increase Desired (millions of dollars)
Active Army	80,000	73,373	8.3	5,953	.32	26.1	258.1	67.2
Army National Guard	63,002	50,219	20.3	4,955	.32	63.8	45.9	29.3
Army Reserve	28,485	23,859	16.24	1,399	.32	51.1	42.9	21.7

*Source: Congressional Budget Office Study (2006).

6,627 (8.28%), 12,783 (20.29%), and 4,626 (16.24%), respectively. The recent shortfalls have been attributed to a healthier civilian economy, a rise in college attendance, the decline in veteran influencers, and unfavorable attitudes toward military service (U.S. Congress 2006; Warner et al. 2003). Thus, the questions for the Army at the end of 2005 were: How many more recruiters are needed to make up the shortfall? How much additional expenditure will this involve? (The estimated recruiter strength at the end of 2005 is shown in Table 5.) We can provide some guidance with the help of our meta-analysis results.

Specifically, the desired percentage increase in the number of recruiters is equal to the desired percentage increase in recruits divided by the PS elasticity. From our database of studies, we find that the weighted mean of the bias-corrected PS elasticities for the military setting was .43 in 1998. Based on the yearly rate of reduction of .01, the recruiting elasticity would drop to .318 in 2005. With this PS elasticity value, the appropriate increases in the number of recruiters for the active Army, National Guard, and Army Reserve in the year 2006 would have been 26.1%, 63.8%, and 51.1%, constituting spending increases of $67.2 million, $29.3 million, and $21.7 million, respectively. To reduce their shortfall in recruits, the active Army and the Army Reserve did in fact increase their recruiter strengths in 2006 but by only 10% and 29%, respectively, compared to the desired increases of 26% and 51.1%. Apparently, the active Army and the Army Reserve acted on the assumption that the PS elasticity was much higher than .318, if budgets were not constrained.

Conclusions

In this paper, we offer empirical generalizations with respect to the mean PS elasticity and its determinants from a meta-analysis of previous studies for the first time in the marketing literature. Our meta-analysis, which is based on 3,193 estimates of PS elasticities obtained from 46 studies, yields a raw (unadjusted for methodology biases) weighted mean PS elasticity of .32. While this is smaller than the value of .5 suggested by earlier informal reports, it is still larger than the mean advertising elasticity of .15 from previous meta-analyses of studies of advertising effects (Hanssens, Parsons, and Schultz 2001). Further, PS elasticity estimates are significantly affected by several market and research methodology characteristics. We determine that the *bias-corrected*, weighted-mean of the PS elasticity is .352 while the weighted but *uncorrected* PS mean elasticity is .32. We then show that our meta-analysis findings can be utilized together with the existing generalizations on price elasticity in assessing the efficiency of personal selling spending to sales ratios commonly tracked by sales managers.

Although our meta-analysis shows that the PS elasticity estimates reported by more recent studies are lower than those appearing in older studies, the mean PS elasticity is still significantly higher than that of advertising elasticity. Thus, personal selling remains a relatively potent marketing instrument that plays a key role in the marketing mix of many industries. Indeed, according to the Dorfman-Steiner (1954) theorem for profit-maximizing firms that rely on both advertising and personal selling efforts to drive sales, the efficient ratio of their personal selling to advertising expenditures should be equal to the ratio of their elasticities. Thus, based on the meta-analysis estimates of .352 for PS elasticity and .18 for advertising elasticity (this is a simple average of the mean estimates from multiple advertising meta-analyses reported by Hanssens, Parsons, and Schultz 2001, pp. 328–9), personal selling spending should be about two times advertising spending for a firm that employs both. This guideline, of course, can and should be refined to account for specific market settings and idiosyncratic firm practices. Even so, there is little doubt regarding the need to allocate a greater proportion of the marketing budget to personal selling compared to advertising, given the large gap between the mean elasticities of these marketing instruments revealed by meta-analyses.

Considering, however, the expense associated with personal selling and its variable elasticity across market settings indicated by our meta-analysis, sales managers have to become more adept in finding ways to maintain and enhance salesforce productivity. One obvious option is to redeploy their salesforce efforts to more elastic settings—where personal selling makes a difference. It is well known that improved allocations of selling efforts across product portfolios and geographic areas can often deliver higher profits at lower than current investment levels (see, e.g., Mantrala, Sinha, and Zoltners 1992). More specifically, our meta-analysis results indicate that responsiveness to selling effort is high in new product introductions while PS elasticity is lower in sales of older products. This suggests that companies should deploy direct salesforce resources for launching and establishing new products while shifting to other means of communications as products mature, e.g., e-detailing (electronic detailing) in the case of older, well-known pharmaceuticals. Similarly, shifting more personal selling resources from the U.S. to European markets seems desirable for multinational firms.

Our meta-analysis also shows that estimates of PS elasticity can be inflated by the omission of lagged effects and promotion variables and underestimated with the use of constant elasticity models. Researchers, therefore, should aim to incorporate these findings in building future salesforce response models. Further, considering the typical times between successive calls on customers in field settings, monthly or quarterly data intervals are more appropriate to use than annual data that tend to result in PS elasticities that are biased downward.

In conclusion, the relatively high mean elasticity for personal selling revealed by this meta-analysis of previous studies highlights the continuing importance of research in marketing focused on improving salesforce productivity. We hope the findings in this paper serve as a catalyst for such work.

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Notes

1. Zoltners, Sinha, and their colleagues at the consulting firm ZS Associates, Inc. (ZS) offer some valuable generalizations on salesforce effects such as carryover effects, drawn from numerous consulting studies—e.g., Sinha and Zoltners (2001); Zoltners, Sinha, and Lorimer (2006). However, details of the settings and models employed in the individual studies and their meta-analysis are not available because they are proprietary.

2. The extant literature contains several meta-analyses related to behavioral aspects of salesperson performance (Churchill et al. 1985), job satisfaction (Brown and Peterson 1993, 1994), and customer orientation (Franke and Park 2006).

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