Evaluation of Salesforce Size and Productivity Through Efficient Frontier Benchmarking

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Abstract
The efficient operation of a salesforce is a critical element in the profitability of many firms. Three factors play key roles: the salesforce’s size, its allocation and its productivity. This gives rise to the following questions: can salesforce performance be improved by (1) hiring more salespeople, (2) allocating them more effectively to the various sales districts and/or (3) improving salesperson productivity through better calling patterns in terms of consumers and product line items?

The practice of most firms and the methodology used in most of the academic literature to address salesforce design and productivity questions is a “Bottom Up” approach. This approach starts with assessments by each salesperson of the sales and effort corresponding to each customer and prospect in their territory. These assessments are then aggregated to the territory, district and national levels. This paper takes an alternative “Top Down” approach. It is based on an estimated relationship between district level sales and salesforce size, effort and other variables. This more macro level decision tool can be used by management in parallel to, and as an objective check of, the more conventional and more subjective “Bottom Up” approach.

We develop an efficient frontier methodology which allows us to estimate how total district sales respond to salesforce size, district potential and competitive activity in the firm’s best performing districts. The methodology utilized is based on Data Envelopment Analysis (DEA) and yields a benchmark measure of each district’s efficient frontier sales (sales assuming the district’s salesforce allocates its effort as done in the best performing districts).

Based on the estimated response function we discuss the three potential sources of increased profitability: closing the inefficiency gap of each of the lower performing districts, optimally reallocating the current salesforce to the various districts, and changing the current size of the salesforce to its optimal level. The inefficiency gap issue is addressed through comparison of the parameter estimates for the best districts obtained through our methodology with those of an average district sales response function obtained using regression analysis. This comparison points to an important methodological finding. The use of multiple estimation results may lead to an improved understanding of the phenomenon being studied (in our case, the identification of the likely causes of district productivity inefficiencies). The latter two sources of increased profitability, salesforce reallocation and changes in the current salesforce size, are addressed analytically given the district level efficient frontier sales response function.

The proposed “Top Down” procedure using the efficient frontier methodology and the insights it provides are examined by evaluating the operations of two different salesforces, one selling manufacturing equipment and the other business equipment. In both cases, regression-based analysis would have resulted in a declaration that the status quo was close to optimal, while the frontier-based analysis pointed out that strong gains were possible in certain districts. In particular, for both firms, the greatest increases in profit are obtained through improved salesforce efficiency in the lower performing districts, not through salesforce size or district allocation adjustments. At the more micro-level, a comparison of the frontier and regression parameters made it possible to identify which specific changes in the daily operations of the salesforces would allow the realization of these potential productivity gains. In our two cases this could be obtained through more emphasis on pursuing prospective accounts.

(Salesforce; Benchmarking; Frontier Estimation)
1. Introduction
Many firms, such as producers of manufacturing and business equipment, are critically dependent on their salesforces to inform consumers about their products and to perform sales transactions. The results achieved by the salesforce are dependent upon its size, geographic breakup, and the allocation of individual salespeople’s time to specific types of consumers and to specific product line items. A methodology that can identify the facets of a firm’s salesforce operation that are ripe for improvement can be a key to increased profitability. For example, will hiring more salespeople improve profitability or is the current salesforce size optimal? Can the salesforce be better allocated to districts? Can the members of the salesforce improve their performance by changing their calling patterns? This paper develops and illustrates a methodology that is capable of providing insights into these questions.

Within an organization, technical salesforces are usually broken down into regions and then further into districts. Several salespeople operate within each district and often each salesperson has an exclusive territory in which to sell the product line of the firm through periodic calls on current and potential clients. While overall sales goals are determined by upper management, the detailed operations of a sales force are usually planned using a “Bottom Up” approach. With a district manager, each salesperson evaluates the likely sales to the customers and prospects in their territory. Sales goals and quotas are set, and when these are combined with those of the other salespeople in the district, a district sales forecast results. This forecast in turn can be aggregated with those of other districts to generate a national sales forecast. If the national forecast does not match the national sales goal, the individualized quotas can be adjusted. When the current salespeople are judged to be operating near their utmost capacity, salespeople may be added and territories realigned.

The existing literature on salesforce problems mirrors this “Bottom Up” approach. The basic unit of measurement is either the individual purchasing account or the individual salesperson’s territory, and the responses of these units to the number of sales calls are either estimated or subjectively determined. Knowledge of these response functions allows companies to plan the allocation of each salesperson’s time and to realign sales territories. Models representing the response of sales to the level of sales effort have been formulated and estimated by Lucas, Weinberg and Clowes (1975); Beswick and Cravens (1977); Lilien (1979); and Ryans and Weinberg (1979, 1987). The allocation of a salesperson’s time to customers and prospects across products has been examined by Montgomery, Silk and Zaragoza (1971); Lodish (1971, 1974, 1976, 1980); Fudge and Lodish (1977); and Lodish, Curtis, Ness and Simpson (1988). The design and operation of sales territories has been studied by Hess and Samuels (1971); Lodish (1975); Zoltners (1976); Zoltners and Sinha (1983); and Rangaswamy, Sinha and Zoltners (1990).

Within any individual salesperson’s territory, the allocation of a salesperson’s time to customers and prospects—and across the firm’s products—need not be controlled by these direct allocation methods. Indirect control of the salesperson’s efforts can be achieved through an appropriate compensation scheme. Assuming that each salesperson knows his or her territory better than anyone else in the firm, a compensation scheme which allows simultaneous maximization of the salesperson’s and firm’s objectives (i.e., income and profit) will lead the salesperson to allocate time such that it maximizes firm profit. The indirect control of salesforce efforts through compensation schemes has been studied by Farley (1964); Davis and Farley (1971); Srinivasan (1981); Basu, Lal, Srinivasan and Staelin (1985); Coughlin and Sinha (1989); Rao (1990); and Lal and Srinivasan (1993).

The “Bottom Up” approach requires very detailed information for its successful implementation. For example, for each customer and prospect an accurate function reflecting sales response to salesperson calling time is needed. Since these functions are usually estimated subjectively, their accuracy is far from perfect (e.g., Chakravarti, Mitchell and Staelin 1981) and aggregation compounds this problem. Therefore, it would seem worthwhile for top management to augment the “Bottom Up” planning of the salesforce operation with a “Top Down” evaluation when making decisions on such important matters as the size of the national salesforce. The “Top Down” approach is a more aggregated approach which allows top management an independent assessment (i.e., with little or no input from the salesforce) of the salesforce size, its geographic breakup...
and time allocation. In this approach, the basic unit of measurement is the sales district. District level sales response to the number of salespeople is estimated. Based on this function, the optimal number of salespeople in each district and thus the nation as a whole can be determined. The more detailed district level operational issues, such as the allocation of salespeople within the district to territories, customers, product lines, etc., can then be achieved using the “Bottom Up” methodology.

The benchmarking methodology developed in this paper estimates a function that reflects the “efficient frontier” sales response to salesforce size, effort and other variables. This efficient frontier sales function reflects the productivity of only the firm’s top performing districts. Using this response function, the profit maximizing number of salespeople may be found, each district’s efficient frontier sales can be calculated, inefficient districts can be identified and the extent of these inefficiencies can be revealed. Through comparison with regression-based estimates of the average sales response function, possible reasons for these inefficiencies can be uncovered.

The following study outlines and demonstrates this “Top Down” approach. The first section models district sales response to the number of salespeople, reviews the efficiency frontier methodology used to estimate this function and contrasts this procedure with regression analysis. The second section derives the optimal salesforce size in each district and nationally from the sales response analysis. In addition, the optimal reallocation of the national salesforce to districts when its size is constrained (at least in the short run) is derived. The third section examines the operations of two separate salesforces in very different industries and illustrates the efficient sales frontier estimation methodology and the optimization procedures. The fourth section provides a summary and suggests some further applications of the proposed benchmarking procedure.

2. Sales Response to the Number of Salespeople
Sales of a firm’s products, especially when industrial and commercial goods are involved, depend on the size and productivity of the firm’s salesforce. As advertising does for consumer goods, a salesforce for industrial or commercial goods informs customers and prospects of the existence and attributes of a firm’s products. In addition, for these goods the salesforce performs direct sales transactions.

Aggregate (national) sales response models are frequently used to measure the effectiveness of advertising. Estimation commonly is conducted through time series analysis. (For a review, see Hanssens, Parsons and Shultz 1990.) Unfortunately, the use of time series analysis to measure salesforce effectiveness is generally not feasible because not enough variation in the salesforce size occurs over time. Unlike advertising budgets which are handled by an outside advertising agency and are often drastically adjusted in response to business cycles and other events, salespeople are part of the firm’s organization and their employment is smoother over time. As a result, a cross-sectional rather than a time series analysis is more appropriate in salesforce applications. The natural unit of measurement for this cross-sectional analysis is the sales district. Typically, salesforces operating in the U.S. are divided into 25 or more separate sales districts, each usually having a different number of salespeople.

2.1 The District Sales Response Function
The firm’s sales in any district depend on the potential for its product line in that district and the selling effort exercised. A general formulation is

\[ \text{SALES}_i = (\text{POTEN}_i)(\text{SPEOP}_i)^\gamma, \]

where for district \( i \), \( \text{SALES}_i \) equals the firm’s sales, \( \text{POTEN}_i \) is its sales potential and \( \text{SPEOP}_i \) is the number of salespeople assigned to the district. The constant \( \gamma \) measures how sales are affected by the size of the salesforce. Since additional salespeople will have to call on less promising accounts, diminishing returns are associated with additional salespeople. This means that \( 0 < \gamma < 1 \).

District sales can originate from reorders by customers who purchased from the firm in the previous period or from purchases by prospects—consumers who either bought previously from competitors or are now in the market for the first time. A district’s sales potential for the firm, \( \text{POTEN}_i \), thus can be related to the size of the customer base sold to last period, \( \text{LCUST}_i \), the size of the prospect base, \( \text{PROSP}_i \), and the strength of the
competitive activity in that district. Consequently, the district potential can be formulated as

$$\text{POTEN}_d = e^{\alpha (\text{LCUST})^\beta_1 (\text{PROSP})^\beta_2 (\text{COMPT})^\beta_3}. \quad (2)$$

In general it is harder to convince a prospect to start buying from the firm than to get a past customer to order again. The relative magnitudes of $\beta_1$ and $\beta_2$ reflect the difficulty in selling to these segments. Since increased competitive activity is likely to reduce the potential sales left for the firm, the coefficient $\beta_3$ is expected to be negative.

Combining Equations (1) and (2) the resulting district sales response function is

$$\text{SALES}_d = e^{\alpha (\text{LCUST})^\beta_1 (\text{PROSP})^\beta_2 (\text{COMPT})^\beta_3 (\text{SPEOP})^\gamma}. \quad (3)$$

Employment of better salespeople—and improvements in their calling patterns and sales closing abilities through better training, management or a more appropriate compensation scheme—will result in increased salesforce effectiveness and greater district sales. This increased effectiveness would be reflected in equation (3) by either a larger $\gamma$ or larger values for $\alpha$, $\beta_1$ and $\beta_2$ (or some combination of these).

It is important to note that Equation (3) is a simplified model of district sales and, depending on the context, it may need adjustment for two reasons. First, the model specification as a multiplicative function is an approximation. The multiplicative function is frequently used since its log transformation is easy to estimate and unlike a linear function it assumes diminishing returns and thus is suitable for optimization. Nevertheless, other more complex functions, such as a Markovian model to deal formally with lagged sales and a specification to deal with lagged selling efforts, should be considered. Second, other marketing mix variables may need to be included in Equation (3) if they cause different sales levels across districts. Apart from salesforce size, pricing and advertising also impact sales. If the firm’s pricing and advertising policies do not vary across districts (for example, by the use of the same pricing policy in all districts and the use of national media for advertising) these variables need not be added. On the other hand, if district level advertising is conducted through, for example, direct mail or spot TV, its intensity in each district should be included.

In terms of the variables that do appear in Equation (3), an operational measure or measures for each must be identified. The size of the customer base is equal to the number of customers only if the quantity purchased by each customer is identical or the distribution of their order magnitudes is identical across districts. Consequently, lagged sales may prove a better measure. A similar issue arises with respect to the size of the prospect base. In addition, measurement of the number of prospects or their potential purchasing power is likely to be quite difficult. A combination of measures relating to overall market potential (customers plus prospects) may serve as a less difficult and less costly to obtain proxy for the size of the prospect base. A measure or measures for the company’s district salesforce size is another issue for concern. Utilizing its numerical size is strictly correct only if all salespeople are equally effective or the distribution of salespeople “quality” is the same in all districts. If not, other measures such as experience, tenure levels and subjective salesperson evaluations by the district manager may need to be added.

For competitive activity, this “quality” of salespeople issue is also relevant, although hard to ascertain.

Other cross-sectional complexities also may impact the model specification. Even if the number of customers and their individual purchase sizes are the same across districts, their geographic distribution within the territories of each district may vary. Salespeople in territories with less densely located customers (or prospects) will be less effective due to increased travel and corresponding corrections to the model may need to be made. Equation (3) allows no “spillovers” from one district to the next. This means that an effective salesforce in one district does not affect the sales in the adjacent districts nor do the customer bases “talk” across district lines. It also is assumed that the same product mix is demanded and offered in all districts. If there is reason to believe that “spillovers” occur or that certain brands are more popular in certain districts (or regions), appropriate model specifications may be necessary. Finally, if cross-sectional regression analysis is used to estimate the parameters of Equation (3), it is implicitly assumed that the parameters are identical for all districts. If salespeople are more effective in a particular district due to better district management or better calling patterns, time series analysis done separately for
each district would allow different parameter estimates for each district. Unfortunately, for the reasons mentioned earlier, this is usually impossible. However, in the following section an alternative procedure which may unveil the more effective district salesforces (and their parameter values) is presented.

Note that our modelling of the district sales response function, Equation (3), and its subsequent estimation are different in focus from the previous literature. Earlier models of sales response to salesforce effort, such as Beswick and Cravens (1977) and Ryan and Weinberg (1987), were aimed at predicting sales in an individual salesperson's sales territory. Nevertheless, the type of explanatory variables used in these studies also are utilized in our model. Moreover, the hypothesis that the parameters of Equation (3) may depend on the operation of the salesforce has been supported. Parsons and Vanden Abeele (1981) find the parameters measuring the effectiveness of selling effort to be dependent on the degree to which handouts and samples were distributed by salespeople in their sales calls.

2.2 Estimation Based on “Good Districts”
If all districts were designed with equal potential (i.e., POTEN, = $e^\delta$), but their sales varied due to differential salesforce sizes, we would expect the district level data and the concave average sales response function to look like those depicted in Figure 1. Actual district observations are shifted up or down relative to the average sales response function due to different salesforce productivities in the various districts. These inefficiencies or overefficiencies relative to the average performance may be modelled into the sales response function through a multiplication by $e^\mu$:

$$SALES_i = e^\delta(SPEOP_i)e^\mu_i.$$  \[4\]

Estimation of $\delta$ and $\gamma$ in the sales response function (4) may be carried out in a number of ways. One approach implied by Figure 1, is to run a simple linear regression (after a log transformation) where the $\mu_i$ correspond to the error terms. This estimation may be represented as:

$$\text{Min} \sum_{i=1}^{N} \mu_i^2$$  \[5\]

s.t. $\ln(SALES_i) = \delta + \gamma \ln(SPEOP_i) + \mu_i$

for every district $i$, $i = 1, 2, 3, \ldots, N$.

In essence, regression analysis obtains a measure of $\gamma$ which reflects the average response of district sales to district salesforce size. Consequently, it is a simple exercise to benchmark each district's performance relative to the expected average performance given its salesforce size.

A smart national salesforce manager, in evaluating a district's sales performance, may not want to benchmark it against an average performance. Rather, such a manager might like to compare district performance to a higher standard and push each district to achieve this higher benchmark. Thus, another possibility, depicted in Figure 2 as line II, is to estimate the response function
based on the districts whose performances are better than average (that is, those observations which lie above the average regression line I). The resulting estimated parameters \( \delta \) and \( \gamma \) pertaining to line II are expected to exceed those for line I.

This idea of benchmarking against the better performing districts can be taken further. For example, why not benchmark each district against the top performing quarter or eighth of the districts. Ideally why not pass the "benchmark" response line through the best performing district, as in line III of Figure 2, and encourage all other districts to obtain similar results. However, as one becomes more demanding, the number of observations remaining for the estimation task becomes small. In the case of line III in Figure 2, there is only one data point. Fortunately, there exists a class of estimation procedures ideally suited to estimate an envelope function such as line III. These procedures estimate an Efficient Frontier line passing through the most efficient sales district's data point while minimizing the line's distance from all of the other less efficient districts. A formulation of such a procedure is

\[
\min_{\delta, \gamma} \sum_{i=1}^{N} \mu_i \tag{6}
\]

s.t. \( \ln(\text{SALES}_i) = \delta + \gamma \ln(\text{SPEOP}_i) - \mu_i \)

for every district \( i \)

\( \mu_i \geq 0 \) for every district \( i \).

In the least squares estimation, the errors are on both sides of the estimated line and, therefore, receive both positive and negative values. In the efficient frontier estimation, only negative errors are possible since no district can outperform the efficient frontier. In addition, the efficient frontier estimation procedure strives to minimize the sum of these errors rather than the sum of their squares. If assumptions are made about the distribution of the error terms, \( \mu_i \), econometric techniques may be used to estimate problem (6). (Bauer (1990) provides a nice review.) Linear programming methods are used if no distributional assumptions are made. One such popular procedure is Data Envelopment Analysis (Seiford and Thrall 1990).

The statistical significance of the regression parameters can be measured using standard \( t \)-values. However, since the efficient frontier estimation utilizing linear programming does not make any distributional assumptions concerning the errors \( \mu_i \), standard \( t \)-tests are not applicable. Lack of such a test has been a bone of contention between econometricians and operations researchers regarding the value of this type of estimation procedure (see, e.g., Evans and Heckman 1988; Charnes, Cooper and Sueyoshi 1988). However, as shown by Horsky and Nelson (1995), in this instance a nonparametric bootstrap technique can be used to assess the distributions of these efficient frontier parameters and, thereby, provide a statistical test as to whether the parameters differ from zero. This technique uses repeated estimations on bootstrap samples of the data to generate the standard deviations of the parameters. Details of the bootstrap methodology as applied to the case discussed here are provided in Appendix A.

The efficient frontier resulting from problem (6) forms an envelope around the districts representing the maximum sales possible given the number of salespeople. This frontier offers a well defined basis for benchmarking a district's sales effort. The relative extent to which a district's sales fall short of its maximum sales level (i.e., the size of \( e^w \)) offers a direct measure of salesforce productivity inefficiency in that district.

2.3 Benchmarking

So far, the discussion of sales response estimation procedures has been developed assuming a constant potential, \( e^w \), across districts. This is not realistic. A more flexible representation of district potential which allows it to vary across districts is depicted by Equation (2). The corresponding district sales response function (3) leads to the more general estimation function:

\[
\text{SALES}_i = e^{(\text{LCUST}_i)^{\alpha}(\text{PROSP}_i)^{\beta_3}} \times (\text{COMPT}_i)^{\beta_1}(\text{SPEOP}_i)^{\gamma} e^{\epsilon_i}. \tag{7}
\]

In the estimation of Equation (7) relative to the equations estimated in problems (5) and (6), \( \delta \) is replaced by \( \alpha + \beta_1 \ln(\text{LCUST}) + \beta_2 \ln(\text{PROSP}) + \beta_3 \ln(\text{COMPT}) \). Hence, the parameters \( \alpha, \beta_1, \beta_2 \) and \( \beta_3 \), rather than \( \delta \), are estimated.

Comparison of a district's actual sales with its benchmark sales offers a measure of the district's relative productivity. Many applications of Data Envelopment Analysis look at how output or costs depend on inputs,
and they focus on identifying inefficient decision making units and measuring the extent of their inefficiencies. Early marketing applications of this nature in the context of salesforce operation have been reported by Parsons (1990, 1991, 1994), Horsky and Nelson (1991) and Mahajan (1991).  

In addition, richer insights not discussed in the literature may be possible through comparison of the parameter values obtained using the various estimation procedures. Following the discussion concerning Figure 2, the sales response function (7) can be estimated using two different procedures. Regression analysis of all districts is denoted by REG and the efficient frontier procedure depicted in problem (6) when estimated using linear programming is denoted by EFF. One would expect the parameters of the sales response function (7) to change as the estimation method is changed from REG to EFF. For example $\beta_3$ may become closer to zero indicating relatively less effective competitive salespeople in the better performing districts. Alternatively, $\beta_1$ or $\beta_2$ may shift upwards indicating better utilization of the customer or prospect bases, respectively, in the better performing districts. This comparison of the parameter values may provide insights into the underlying causes of the inefficiencies.  

3. Salesforce Size, Allocation and Efficiency  
The manager of a national salesforce may consider several actions intended to increase the profit generated by the salesforce. Three such actions, which can be evaluated based on the sales response function estimation procedures outlined above, are  

(i) Improve the performance of "bad" districts by increasing the efficiency (productivity) of their salespeople to be in line with that in the best districts.  
(ii) Redeploy the current national salesforce based on an optimal allocation to districts.  
(iii) Increase (or decrease) the size of the salesforce to its optimal size with corresponding deployment to districts. The first two actions do not require a change in the size of the current salesforce. They are important because in the actual management of salesforces large shifts in size take time. Significant time and cost are involved in recruiting and training new salespeople as well as in assigning and introducing them to territories.  

3.1 Improved Efficiency  
Applying the EFF parameter results to Equation (3) allows the calculation of the expected maximum district sales assuming that the district does not change its salesforce size and that each salesperson improves his or her productivity to the level in the best districts. Based on this analysis, sales objectives for each district can be formulated and districts whose performances are especially poor can be singled out for additional attention by the national salesforce manager. It is also possible to assess the increases in sales and profit that would result if all non-efficient districts were to become efficient.  

A more difficult question is how the inefficient districts can become more efficient. An overall remedy is a change of district managers in the lower performing districts. More specific recommendations for improved salesforce productivity are revealed if the values of the estimated parameters in Equation (7) change as we move from REG to EFF. If the salesforce size parameter, $\gamma$, increases, it implies that incrementally additional salespeople are less effective in the lower performing districts. This might be remedied by, for example, hiring more qualified salespeople for these districts. A larger $\beta_1$ value in EFF implies that the top performing districts do a better job in generating sales from current customers (for example, obtaining more sales with a lesser time investment). This would suggest that inefficient districts improve their operation with respect to this segment. On the other hand, if $\beta_2$ increases, better handling of prospects is needed in the lower performing districts.
Note that since the combined parameters measure relative effectiveness, it is possible that the parameter \( \gamma \) may, in fact, decrease in EFF if \( \alpha, \beta_1 \), or \( \beta_2 \) increase. This may occur because larger values for the \( \alpha \) and \( \beta \) parameters imply that the efficient districts generate more sales from the clientele in their districts. Consequently, the sales opportunities available to an additional salesperson are more difficult.

### 3.2 Optimal Salesforce Size and Reallocation

As discussed above, the improved sales and profit due to improved productivity (efficiency) can be obtained without a change in the number of salespeople in the various districts. However, the sales response function allows us to assess the sales and profit impact of a change in the number of salespeople in any district. In fact, it is possible to identify each district’s optimal salesforce size. Alternatively, if the total national size is frozen at the current level, the impact on profit and sales of optimally reallocating the salesforce may be examined.

The profit derived from a district may be expressed as:

\[
\Pi_i = g(SALES_i) - c(SPEOP_i)
\]

\[
= g(POTEN_i)(SPEOP_i)^\gamma - c(SPEOP_i), \quad (8)
\]

where \( g \) is the gross margin and \( c \) is the fixed cost of a salesperson. If in different parts of the country the cost per salesperson varies, \( c \) can be replaced by \( c_i \). It follows that the optimal number of salespeople in district \( i \) is:

\[
SPEOP^*_i = \left[ \frac{g \gamma(POTEN_i)}{c} \right]^{1/1-\gamma}. \quad (9)
\]

Assuming that no part-time salespeople are employed, \( SPEOP^*_i \) must be rounded both up and down and the size with the higher profit should be chosen. The optimal national salesforce size is the sum of these district values:

\[
NSIZE^* = \sum_{i=1}^{N} SPEOP^*_i. \quad (10)
\]

It is evident from Equation (9) that districts with larger potentials, \( POTEN_i \), will be assigned more salespeople. It also follows from Equations (9) and (10) that—if the gross margin, \( g \), is increased or the cost per salesperson, \( c \), falls—the optimal district and national salesforce sizes will increase. Moreover, a similar outcome occurs if the salesforce becomes more efficient as mapped through an increase in either \( \gamma \) or the parameters governing the potential, \( \alpha, \beta_1, \) and \( \beta_2 \).

In the short run, if the national salesforce is not allowed to change its size, \( NSIZE \), but a redeployment of its members is acceptable to management, a constrained profit maximization problem results. In this case, the national profit maximization problem becomes

\[
\text{Max } \sum_{i=1}^{N} \Pi_i \\
= \sum_{i=1}^{N} [g(POTEN_i)(SPEOP_i)^\gamma - c(SPEOP_i)] \\
\text{s.t. } \sum_{i=1}^{N} SPEOP_i = NSIZE.
\]

The corresponding optimal district salesforce sizes are

\[
SPEOP^{**}_i = NSIZE \frac{(POTEN_i)^{1/(1-\gamma)}}{\sum_{i=1}^{N} (POTEN_i)^{1/(1-\gamma)}}. \quad (12)
\]

Thus, the existing salesforce is redeployed such that each district receives an allocation which is dependent on its relative potential. If the national salesforce size is allowed to grow but is constrained to be below the optimal national size, \( NSIZE^* \), the allocation to districts will also follow Equation (12). As with the nonconstrained profit maximization, the actual district salesforce sizes obtained through Equation (12)
must be rounded either up or down to the more profitable integer value while maintaining the total national size. Alternatively, one can use an incremental, integer-value-based algorithm to find the constrained profit maximizing integer value for district salesforce sizes.

4. A Study of Two Salesforces
The "Top Down" salesforce evaluation methodology forwarded in this paper was used to examine the operations of two different salesforces. District level sales response functions were estimated. Next, the empirical results were used to investigate how additional profit could be made for each firm through (1) improving the efficiency of the existing salesforce in less efficient districts, (2) improving the operation of the existing salesforce by better allocation to districts, and (3) increasing or decreasing the size of the salesforce.

Firm A is a business equipment manufacturer while Firm B is a chemical production equipment manufacturer. Each firm is one of the largest manufacturers in its respective product class. Firm A employed 230 salespeople in 26 districts while Firm B employed 129 salespeople in 27 districts. In both firms, the pricing and advertising policies were identical across their sales districts. For each district, the following yearly data were collected: sales, the number of a company’s own and competitive salespeople (and some related salesforce "size" variables), and measures of the customer and prospect bases. Cost per salesperson and gross margin also were obtained for each firm.

The number of a company’s own salespeople was collected from monthly logs and and working months aggregated to form non-integer values for the salesforce size. For Firm A, a 1 to 10 rating of each salesperson’s "quality" as assessed by his or her district manager and eye-to-eye contact hours also were available. Adjusting for the "quality" of each salesperson allows a relaxation of the assumption, implicit in our development of the sales response function, that every salesperson has equal intrinsic selling ability. The eye-to-eye contact hours do not include time spent on nonselling activities such as travel and as such may prove to be a better measure of salesforce selling effort than the number of salespeople.

The number of competitive salespeople was collected through a survey of each firm’s salespeople and district managers. Some subjective assessments were required as some of the smaller competitors employed dealers instead of sales representatives in certain districts and their "people" equivalent had to be approximated. Moreover, management at Firm B felt that some of the smaller competitors were paying more attention to the Los Angeles and New York City areas (for example, by employing sales representatives rather than dealers), and as a result, the effectiveness of the competitive sales operations in the two districts was larger than in the other districts. Consequently, for Firm B two variables were used to represent competitive activity. One variable being the number of competitive salespeople and the other variable being a dummy variable equal to one for these two particular districts and zero otherwise. It follows that the parameter associated with this dummy variable is expected to be negative.

The customer base for each district was measured either by the number of customers in the previous year or lagged sales. The latter is preferable since it takes into account the purchasing power of the customers. Unfortunately, this was available only for Firm B. As stated previously, the size and geographic dispersion of the various customers (and prospects) if not distributed equally across districts may impact the productivity of district salesforces. However, both firms used a centralized national accounts sales group to deal with especially large customers, such as the U.S. government. With respect to the geographic dispersion of the customer and prospect bases, for Firm B a rough measure in the form of each district’s area in square miles was included. For Firm A, the eye-to-eye contact hours measure deals with this issue.

Data concerning the prospect base were not directly available so various measures of overall market potential, such as the population size or the number of refineries in a district, were used as proxies. For each firm, about twenty different proxy variables...
Table 1  Firm A: Sales Response Function Parameter Estimates

<table>
<thead>
<tr>
<th>Parameter</th>
<th>REG</th>
<th>EFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>α</td>
<td>3.472*</td>
<td>2.072</td>
</tr>
<tr>
<td>β₁</td>
<td>0.440**</td>
<td>0.334*</td>
</tr>
<tr>
<td>β₂</td>
<td>0.153</td>
<td>0.389**</td>
</tr>
<tr>
<td>β₃</td>
<td>-0.069</td>
<td>-0.136*</td>
</tr>
<tr>
<td>γ Number of Salespeople</td>
<td>0.432**</td>
<td>0.382**</td>
</tr>
<tr>
<td>R² (Adjusted R²)</td>
<td>0.93 (0.92)</td>
<td>-</td>
</tr>
<tr>
<td>N</td>
<td>26</td>
<td>26</td>
</tr>
</tbody>
</table>

* Statistically significant at 10% level.
** Statistically significant at 5% level.

were collected. Some were chosen based on the types of businesses and industries that did business with Firms A and B. Other proxy variables were general economic and demographic indices. These proxies were obtained from U.S. County Census reports as well as commercial data sources. The data generally were available at the county level and had to be aggregated to correspond to the county composition of each firm’s sales districts.

4.1 Sales Response Estimation

A priori it was not clear which market potential variables best represent the prospective customer base. Since a high degree of collinearity was found between many of these proxies, their number was first reduced by examining their correlation matrix and choosing a relatively independent subset. This resulted in about five proxy variables for each firm. Then for each firm, the sales response function was estimated using REG and EFF with the remaining proxy variables as well as with the other explanatory variables. Based on goodness of fit, statistical significance and the intuitive appeal of the parameters, certain proxy variables were chosen to remain in the analysis. In principle, significance in either or both of the estimation techniques led to the inclusion of a proxy variable. The sales response functions chosen for both firms are

FIRM A:

\[
\text{SALES} = e^{\alpha}(\text{LCUST})^{\beta_1}(\text{POPUL})^{\beta_2} \\
\times (\text{COMPT})^{\beta_3} (\text{SPEOP})^{\gamma}
\]  

(13)

FIRM B:

\[
\text{SALES} = e^{\alpha}(\text{LAGSL})^{\beta_1}(\text{FOODM})^{\beta_2}(\text{REFIN})^{\beta_3} \\
\times (\text{COMPT})^{\beta_4} (\mu^{\beta_5}D_{\text{LA/NY}})(\text{SPEOP})^{\gamma}
\]  

(14)

LCUST = Number of customers in the previous period
LAGSL = Lagged sales
POPUL = Population size
FOODM = Number of food manufacturing plants
REFIN = Number of refineries
COMPT = Number of competitive salespeople
D_{LA/NY} = Dummy variable for Los Angeles and New York City
SPEOP = Number of own salespeople.

The estimated parameter values of the sales response functions (13) and (14) using REG and EFF are reported in Tables 1 and 2. The REG results represent an average sales response. The EFF results reflect only how sales in the top (efficient) districts respond to salesforce size and

Table 2  Firm B: Sales Response Function Parameter Estimates

<table>
<thead>
<tr>
<th>Parameter</th>
<th>REG</th>
<th>EFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>α</td>
<td>9.322**</td>
<td>7.576**</td>
</tr>
<tr>
<td>β₁ Lagged Sales</td>
<td>0.398**</td>
<td>0.400**</td>
</tr>
<tr>
<td>β₂₁ Number of Food Manufact. Plants</td>
<td>-0.085</td>
<td>0.106*</td>
</tr>
<tr>
<td>β₂ Number of Refineries</td>
<td>0.036**</td>
<td>0.050**</td>
</tr>
<tr>
<td>β₃ Number of Competitive Salespeople</td>
<td>0.054</td>
<td>0.032</td>
</tr>
<tr>
<td>β₄ NYC or LA</td>
<td>-0.212</td>
<td>-0.284**</td>
</tr>
<tr>
<td>γ Number of Salespeople</td>
<td>0.658**</td>
<td>0.573**</td>
</tr>
<tr>
<td>R² (Adjusted R²)</td>
<td>0.87 (0.83)</td>
<td>-</td>
</tr>
<tr>
<td>N</td>
<td>27</td>
<td>27</td>
</tr>
</tbody>
</table>

* Statistically significant at 10% level.
** Statistically significant at 5% level.
the other variables. The statistical significances of the EFF parameters are measured using the bootstrap method referred to earlier.

Sales response for Firm A also was estimated using the effective number of salespeople based on the district managers' ratings of their salespeople and eye-to-eye contact hours rather than the number of salespeople. These alternative measures of salesforce size yielded statistically inferior results and, therefore, were not pursued further. For similar reasons, for Firm B, the district square mileage variable used to measure the density of the customer (and prospect) base was dropped.

4.2 Parameter Values and Benchmarking
Actual sales as well as predicted district sales based on the REG and EFF parameter estimates for Firms A and B are provided in Figures 3 and 4. As expected the sales predictions are higher when EFF parameter estimates are used than when REG estimates are used. Comparison of actual district sales and EFF-based predicted sales provides a measure of district salesforce performance. The ratio of these two values provides an intuitive efficiency rating of how close each district's performance is to the frontier. These ratios are provided in Figures 5 and 6. The rather random distribution of these efficiency ratios over district sales levels shows that (a) there is no apparent bias in the frontier estimation procedure regarding the sales level and (b) that "big" or "small" districts are not inherently more efficient.

The sales response function parameter estimates provided in Tables 1 and 2 generally conform with expectations and provide further insights relating to salesforce management and performance. Comparisons across the two estimation techniques show that a company's own salesforce size is a consistently significant factor. However, it has a slightly lower impact on district sales in the premier districts. Since the more efficient districts do not necessarily have larger salesforces, this cannot be due to scale effects. It seems that, indeed, the addition of salespeople in the more efficient districts is marginally less productive. This may be due to the finding discussed below that these salesforces already generate more sales from the clientele in their districts. Consequently, additional sales are more difficult. As expected, the competitive salesforce size has a detrimental, but small, effect on the sales of Firm A. While this parameter is positive for Firm B it is small and is not statistically significant. This "incorrect" sign may result because competitors have assigned more salespeople to the more lucrative districts. In addition, the $D_{18}/NY$ parameter $β_{32}$ for Firm B is negative. As expected the effectiveness of competitive sales efforts in the Los Angeles and New York City districts is found to be greater than in other districts.

The parameters for past sales activity (LCUST or LAGSL) and for potential clients (proxied by total market potential variables POPUL or FOODM and REFIN) reveal a key insight. For Firm A, relative to the average response function estimated using REG, the best producing districts reflected by the EFF parameters show a much larger sales impact of POPUL while the impact of LCUST is smaller. For Firm B, the efficient frontier sales response function also shows an increased impact of REFIN and FOODM, while the lagged sales parameter is essentially unchanged. This observation is further reinforced when the significance of the parameters is taken into account. Not all the prospect base proxy variables, such as POPUL for Firm A, are significant in REG but all are significant in EFF. What is thus evident for both firms is that in the best producing districts sales are more strongly tied to the potential customer base.

The increased sizes of the potential customer parameters under the EFF formulation imply that in the efficient districts either more attention or better focused attention is paid to prospects. Conversely, the reduced size of the existing customer base parameter for Firm A implies that less attention is directed at these accounts in total. In all likelihood the less promising customers (in terms of sales versus effort required) are given less attention or dropped in the more efficient districts. For Firm B, the same level of response is witnessed for current accounts across efficient and inefficient districts although as pointed out above more attention is paid to promising prospects in the better performing districts.

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6 Due to confidentiality issues the data reported have been rescaled. District sales figures and the cost per salesperson are multiplied by the same constant. This rescaling affects only the size of the intercept term $α$. The optimal salesforce size results are not affected nor are the relative changes in sales and profits due to the various managerial actions. The rescaling does affect the absolute magnitudes of the sales and profit figures reported.

7 This inference could have been cross-validated had the eye-to-eye contact hours for Firm A been separately specified for existing customers and prospects. Unfortunately, they were not.
become efficient, all districts would realize efficient frontier sales and corresponding profits.

Tables 3 and 4 provide the actual sales, profits and salesforce allocations for each firm as well as those that would be achieved if all districts became efficient, if the existing salesforce were reallocated across districts to maximize profit, and if an optimal salesforce size and allocation were implemented. The latter values are calculated using both the REG and EFF parameter estimates. It is interesting to see that for Firm A the optimal REG-based salesforce size is marginally smaller than the current one while the EFF-based size is slightly larger. Note that the optimal salesforce size as specified in Equation (9) is dependent on the values of $\gamma$ and POTEN. Despite $\gamma$ being slightly larger under REG, the optimal salesforce size is larger under EFF due to its larger potentials. For Firm B, both estimation procedures end up recommending huge, roughly four-fold increases in salesforce size. Contrary to Firm A, the REG-based salesforce size is larger than the one implied by EFF. In this case, the difference in the size of the $\gamma$ parameters is large enough to overcome the larger potentials estimated using EFF.
Tables 3 and 4 also detail the change in profit which would result from the three managerial alternatives outlined earlier based on the EFF parameters. For Firm A, profits can be increased by 29.2% if all current salespeople become efficient. Reallocating the salesforce across districts would only improve profits by another 0.4%. A further move to the optimal salesforce size would result in a negligible profit increase. Firm B, in addition to increasing productivity in its inefficient districts, may also need to increase its salesforce size. Its profits can be increased by 40.8% if its salespeople act more efficiently. An additional 2.7% profit increase could be obtained by reallocating these salespeople and a further 34.6% added by increasing their number. However, the increase in size is immense. Is this justified? Figures 7 and 8 trace the potential national profit that results when the national salesforce is optimally allocated based on the REG and the EFF parameters for various national salesforce sizes. For Firm B, starting at about 300 salespeople, the profit function becomes rather flat raising a question about the value of adding hundreds of salespeople for a minimal expected increase in profits. Even assuming that recruitment and training costs are negligible (neither is taken into account in our
analysis), the risky nature of the small expected additional cash flow relative to the certain additional fixed costs may be enough to tame the implied hiring flurry.\textsuperscript{8}

This risk issue is further enhanced by the extrapolation of Firm B's district salesforce sizes to levels far exceeding those currently witnessed. In Tables 3 and 4, we see that the current district salesforces vary in size from 4 to 30.38 for Firm A and from 2 to 9.08 for Firm B. When changing the salesforces to their optimal size, the district salesforce sizes for Firm A range from 5 to 26, actually less than the current range. For Firm B, the range is from 3 to 37 with 19 of the districts having a salesforce size greater than 9, the maximum size currently. This extrapolation issue raises a concern over whether the estimated coefficient of salesforce size, $\gamma$, might be improper for use in this higher size range. In Tables 1 and 2, we see that the EFF value of $\gamma$ is 0.382 for Firm A and 0.573 for Firm B. Given that Firm A generally has larger district salesforces this might imply that, had there been districts with larger salesforces for Firm B, its value of $\gamma$ would be smaller. Correspondingly, a smaller optimal salesforce size would result. The practical implication is that while the national salesforce of Firm B should be increased in size, its growth should be gradual. This will allow the value of $\gamma$ to be updated to reflect sales response to a higher range of district salesforce sizes before a more drastic growth in the number of salespeople is implemented. Quicker learning about the value of $\gamma$ at larger salesforce sizes can be achieved through experimentation, if doing so is acceptable to management.

4.4 Conclusions
The bottom line observation on the operation of each of the two salesforces is that their national size and district allocation were determined reasonably well by man-

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\textsuperscript{8}This flatness of the profit function over a wide range of salesforce size is an empirical regularity (Zolters and Sinha 1996).
agement. For both of these firms, the most promising way to improve profitability is not the shifting of salespeople among districts or the hiring of more salespeople. Rather, it is through improved salesforce productivity. In particular, more emphasis on prospects seems to be a key tool for achieving this improved productivity. In poorly performing districts, individualized “Bottom Up” plans with a stronger focus on prospects should be implemented. Moreover, a nationwide compensation scheme which better rewards salespeople for sales to new accounts might merit consideration. It thus appears that for these two firms how they spend their marketing budget is at least as important as how much they spend. A similar conclusion is reported in an advertising study by Eastlack and Rao (1986) and a numerical analysis by Mantrala, Sinha and Zolters (1992).

4.5 Implementation
Some elaboration is warranted about the use of the estimation results for actual managerial action with implications for the future. The parameter values estimated and the optimal policies implied are valuable in evaluating the current operation of the salesforce. Recommendations concerning future salesforce size and allocation are only correct if no changes occur in the future concerning either the values of these parameters or the values of the variables affecting district potentials. If any of these values change, a new optimal national salesforce size and district allocation will emerge. With respect to the parameters, this implies that ideally the estimation should be redone each year and even then some subjective changes to the parameters may be needed. For example, if a new product is about to be introduced, shifts in the parameters could be anticipated. In terms of the levels of the variables affecting district potentials, forecasted values for the PROSP and COMPT measures should be used as should current year values for LCUST measures.

The operations of salesforces A and B were actually examined as parts of two separate consulting projects.
some time ago. At that time the “Top Down” approach discussed in this paper was conducted on the basis of the REG estimation only. For Firm A, it was concluded that its current salesforce size and allocation was nearly optimal. The national sales manager did, however, view the analysis as informative and requested that it be re-done the following year using the current year’s data to assess whether a newly implemented compensation scheme was effective. This estimation revealed that indeed the salespeople parameter, \( \gamma \), increased in size. The implication being a small increase in salesforce size was warranted. Consequently, the size of the force was increased with the new cohort being allocated to districts based on the constrained allocation formulation (12). For Firm B, it was concluded that the size of the salesforce should be gradually increased. Formulation (12) again was utilized for this purpose. In both firms, the national sales managers expressed great interest in the identity of the under-performing and over-performing districts. After identifying the “good” and “bad” districts (based on the REG analysis) a rather speculative discussion followed as to the likely causes of the productivity differences. Several years later the benchmarking analysis described in this paper was pursued by the authors and the results presented to the managers of Firm A. These managers found our conclusions as to the likely causes of salesforce inefficiency to be particularly insightful and plausible. In addition, they pointed out that several firms have recently broken their salesforce into two groups—one for maintaining existing accounts (“farming”) and the other for pursuing new accounts (“hunting”)—in recognition of the fact that some salespeople are better at turning prospects into customers than others.

In the first stage of the “Top Down” procedure, linear programming is used to estimate a district-level, efficient frontier sales response function reflecting the relationship of sales to salesforce size and to other variables that exists only in the top performing districts. This allows the firm to benchmark each district’s sales against a sales estimate based on performance that is in line with that of the best performing districts. Moreover, comparison of the average regression and efficient frontier estimation procedures points to an important methodological finding. The use of multiple estimation results may lead to an improved understanding of the phenomenon being studied (in our case, the identification of the likely causes of district productivity inefficiencies). The estimation stage of the “Top Down” procedure is followed by a second stage in which the optimal reallocation of the current salesforce and the optimal salesforce size are determined and the profitability gains associated with these actions and with improving efficiency are evaluated.

The proposed “Top Down” procedure was illustrated for two salesforces. In both cases, the regression-based analysis would have resulted in a declaration that the status quo was close to optimal, while the frontier-based analysis pointed out that strong gains were possible in certain districts. Given both methods of analysis, a comparison of their parameters made it possible to identify which specific changes in the daily operation of the salesforce would allow the realization of these potential productivity gains.

The benchmarking methodology proposed in this study can be useful in other contexts as well. In particular, in smaller salesforces, individual salesperson performance and territory level response functions may be evaluated. Moreover, the methodology can be applied to nonsalesforce related situations in which other marketing efforts, such as advertising, are expended with different degrees of success.

5. Summary and Other Applications

In this study, a procedure for evaluating the size, allocation and productivity of a salesforce was suggested and illustrated. This “Top Down” procedure can be used by management in parallel to, and as an objective check of, the more conventional and more subjective “Bottom Up” approach to salesforce effort allocation. Even though this procedure can be viewed as a macro-level decision tool, it can also generate interesting micro-level managerial insights.

Appendix A: A Bootstrap Based Significance Test

The idea is to approximate the standard deviations of the efficient frontier parameters using a computational approach. Given an estimate of a parameter’s standard deviation, a simple \( t \) or normal distribution based statistical significance test follows. A common technique used in such situations is bootstrapping (Efron and Gong 1983, Efron and Tibshirani 1993). This procedure generates information concerning the parameters’ standard deviations through repeated estimations...
using bootstrap samples of the N available observations. First, the coefficients of the efficient frontier sales response function, $h = (\hat{\delta}, \hat{\gamma})$, and corresponding error terms, $e_i$, are estimated following the bootstrap samples. Then B different bootstrap samples are generated by "bootstrapping the residuals." Each bootstrap sample is generated as follows. To the estimated frontier sales level for each district an error term is appended. This error term $e_i(b)$ is selected randomly with replacement from the $e_i$ generated by (6). This results in a bootstrap sample of district sales levels, $Sales_i(b) = e_i(e)e_i^{(b)}$. These bootstrap sample sales levels are then related to the independent variables via problem (6), the result being a bootstrap replicate of the sales response coefficients, $\hat{h}(b)$. Note that each bootstrap sample involves different Sales(b) and, hence, results in different parameter estimates. The standard deviation of these bootstrap replicates for a particular parameter $\hat{h}$ is an estimate of standard deviation of $\hat{h}$:

$$s^{B_est} = \sqrt{\frac{1}{B-1} \sum_{b=1}^{B} \left( \hat{h}(b) - \frac{1}{B} \sum_{b=1}^{B} \hat{h}(b) \right)^2}.$$  

(A.1)

Typically, 50 to 200 replications are required to generate an accurate estimate of a parameter's standard deviation. In this paper we set B = 1,000. Consequently, a test statistic for the hypothesis that $\hat{h}$ equals zero is

$$BE = \frac{\hat{h} - 0}{s^{B_est}}.$$  

(A.2)

This statistic converges weakly to the standard normal distribution. Horsky and Nelson (1995) demonstrate the ability of this test to identify significant parameters in the context of linear programming-based estimation of an efficiency frontier.

Note that the bootstrap test statistic described above is the most basic. More advanced and computationally intensive methods that generate more accurate bootstrap confidence intervals are aimed at accounting for things like bias and skewness in the distribution of the bootstrap replicates (see Efron and Tibshirani 1993). We tried the most commonly used procedure of this type, the percentile interval method, and, in our context, found its performance to be similar to that of (A.2). In other applications, more sophisticated methods than (A.2) may be needed.

The procedure proposed in Horsky and Nelson (1995) was reviewed and certified by the Marketing Science reviewers of this manuscript.

References


PUBLISHED PAPERS


WORKING PAPERS


“Attribute Importance Weights and Retail Placement”, with Debbie Desrochers.

“Product Line Considerations in New Product Development”, with Dan Horsky.

WORKING PAPERS continued

“Bot Commerce: Implications of Markets Utilizing Search Engines”, with Rajiv Dewan.

“Competitive Multiaattribute Demand, Cost and Repositioning”, with Jeongwen Chiang and Dan Horsky.
“Determinants of Information System Replacement”.

“Price and the Multiattribute Model”.

CURRENT RESEARCH

“Information Processing Affects on Reservation Price Measurement”.

“Shelf Space Arrangement and Attribute Level Perceptions”.

PRESENTATIONS


PRESENTATIONS continued


PRESENTATIONS continued


The Updating of Attribute Weights as Preferences Turn into Choice,” with Dan Horsky, National ORSA/TIMS Meeting in New York, October 1989


"Testing the Significance of Attribute Weights Estimated from Ordinal Preference Data", with Dan Horsky, National ORSA/TIMS Meeting in Denver, October 1988


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