

Identifying Sales Performance Gaps with Internal Benchmarking

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Abstract

This research investigates how retailers can benefit from identifying the sales growth potential of in-store salespeople in every product category. The proposed novel approach helps retailers develop an equitable evaluation of their sales force, using both observable and unobservable factors that affect sales. By extending stochastic frontier regression to a multivariate case, the resulting factor-analytic frontier formulation leverages the correlation pattern of sales across product categories and salespeople over time. A unique data set, from a franchise chain with 481 salespeople, operating in 35 stores and selling 11 related product categories, identifies a gap between observed category profits and an estimated profit frontier for each salesperson and category. This novel model also can benchmark each salesperson against all others across product categories while accounting for observable and unobservable factors. This approach has practical value, in that retailers can identify both top-performing salespeople and underperformers, who then might be matched to establish a positive learning environment that aligns top performers with proven sales expertise in a product category with peers who struggle with that category.

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Retailers have increased the number of in-store salespeople and relied on them to improve performance (Franke and Park 2006). According to 2016 data from the U.S. Bureau of Labor Statistics, about 4.5 million people worked in retail sales, and growth of 7% is expected in the next 5 years. In several retail settings, the sales role has evolved, from simple responsibility for basic tasks such as locating products and checking product availability to performing more complex jobs, creating interpersonal connections, and offering information to help customers with their purchase decisions (Haas and Kenning 2014). As sales tasks become more complex, retailers have embraced learning programs that promise to share sales knowledge across the entire sales force. Mantrala et al. (2010) devised an agenda to identify relevant questions for sales managers, highlighting the need to create conditions in which salespeople share skills and abilities with peers. Furthermore, sales force efficiency is of particular interest to retailers, such that they seek to identify top performers among their sales staff and create opportunities for salespeople

to share sales-related best practices (Hyland and Beckett 2002). Yet retailers often fail to identify top performing salespeople who define best practices; they also fall short in creating sales learning programs that can disseminate best practices across the entire sales force (Bettencourt 2004).

At the root of the performance evaluation problem is the difficulty associated with measuring differences across salespeople, markets, and product categories, such that these distinctions often get overlooked in sales rankings (Kumar, Sunder, and Leone 2014). Managers create rankings to determine whether their salespeople are doing the *most* they can, but they forget to ask whether they are doing the *best* they can. One resolution might be to benchmark sales efforts against the competition (Horsky and Nelson 1996), but most managers cannot gather accurate information about competitors' efforts or account for the unique circumstances of their operations. The solution therefore is to implement internal benchmarking, which identifies performance standards and areas for potential growth by comparing the retailer's own salespeople against one another (Soni and Kodali 2010). There are documented advantages to applying internal benchmarking: It draws from available observable data, sets more realistic goals, allows for the transfer of best practices, and encourages organizational buy-in (Hyland and Beckett

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2002). However, the evaluation problem remains, because of model misspecification as performance-affecting factors are unobservable or unknown to analysts. When assessing sales performance, retailers often have limited information, especially with regard to the market factors that drive sales at each of their stores. For example, retailers may carry wide assortments of products at multiple locations that cater to customers living in diverse neighborhoods, each with different needs and preferences. Although managers keep close track of sales in each store for each category, they find it difficult to estimate how much more they might have sold if their salespeople's efforts were improved somehow (Arnold et al. 2009).

We propose a way to deal with such model misspecification in internal benchmarking by accounting for sales that are correlated across categories, because the unknown or unknowable environmental factors generally affect multiple product categories. That is, customers' requirements tend to be related across categories, such that total category spending on cosmetics, for example, in markets with larger populations of employed women should be higher for face, eye, and lip makeup. By leveraging such sales correlations among customer requirements across categories, we can extend multivariate cross-category stochastic frontier regression (SFR) to help retailers implement effective sales learning programs and tap into their potential for growth. To motivate the development of this model and provide empirical evidence, we focus on multi-store franchisees that sell a leading retail brand of cosmetic and health care products. From their sales force database, we gather 12-month sales performance data for 481 salespeople working in 35 retail stores in each of 11 product categories.

With this study, we offer two key contributions to sales force management in a retail context. First, we propose an internal benchmark approach that relies on a novel, multivariate, factor-analytic, SFR model that retailers can use to develop an equitable evaluation of their sales force by accounting for both observable and unobservable factors that affect sales. Moving beyond existing efforts to model sales productivity, our multivariate factor-analytic stochastic frontier model acknowledges that sales performance depends on unknown, unknowable, and unobservable success factors. We account for the sales, which are correlated across categories, and observable factors, including sales commissions, store potentials for product categories, and in-store promotions. The multivariate approach also extends univariate SFR approaches (Gauri, Pauler, and Trivedi 2009; Horsky and Nelson 1996; Kamakura, Lenartowicz, and Ratchford 1997), to a multi-category context. Moreover, our multivariate model relies on a factor-analytic frontier formulation to leverage all available information across categories and salespeople and thus incorporates the effects of unobservable factors on sales performance. The proposed model performs notably well in three robustness tests, including a test for one omitted key factor.

Second, we propose an internal benchmarking framework to draw on the knowledge embedded within the sales force to help salespeople in need of improvement. Research in sales management highlights the importance of embedded knowledge that resides in relationships among sales people and, in particular,

the norms and information flows that shape their interactions with customers (Bettencourt 2004). Previous sales management literature specifies the importance of informal relationships that emerge within the sales force as a way to share valuable information and drive sales performance (Verbeke, Dietz, and Verwaal 2011). Our study acknowledges the value of embedded knowledge and addresses the need for retailers to promote a learning environment for their salespeople (Chan, Li, and Pierce 2014). To leverage this embedded knowledge, we develop a gain index for each salesperson; we account for the maximum gain in monthly sales profits expected from the transfer of best practices of a growth advisor (i.e., top performer) to the learner salesperson (i.e., poor performer). According to the findings of our model and the suggested knowledge transfer program, franchisees could increase monthly sales by up to US\$40,000, simply by sharing the best practices of their top five salespeople, whom we refer to as growth advisors. We illustrate how retailers can identify top performers in each category and store network to promote the transfer of embedded knowledge across the retail chain and ultimately gain sales growth (Hyland and Beckett 2002).

In the next section, we discuss recent advances in literature on internal benchmarking and sales management. Thereafter, we present empirical evidence and describe our data and variables. We then detail the development of our multivariate factor-analytic extension of the stochastic frontier and our empirical application context. Finally, we discuss the results, outline some implications of our model for retail knowledge-sharing opportunities, and summarize our study's contributions and limitations.

Internal Benchmarking Across Product Categories and Salespeople

Previous research on benchmarking points to several alternative approaches for estimating productivity function. An alternative to a regression line that characterizes expected middle-of-the-road performance would be to find a frontier line that represents an upper boundary defined by top performers (Ratchford and Stoops 1988). Previous studies use data envelopment analysis (DEA) as an alternative frontier estimation of multiple inputs and outputs (Donthu and Yoo 1998); a hybrid approach to productivity estimation combines DEA and multivariate sliced inverse regression (MSIR) in two sequential stages (Sridhar, Mantrala, and Naik 2014). The major disadvantage of the DEA model is that it does not account for measurement errors (Gauri 2013); SFR is a well-established approach for defining the internal benchmarking frontier (Aigner, Lovell, and Schmidt 1977).

In a retail sales force context, a direct application of SFR can be carried out separately for each category, assuming that, conditional on the environmental factors in the analysis, the sales frontiers for the product categories are independent of one another. The major limitation of this approach is that differential performances observed in one product category across salespeople may be caused by any source of environmental heterogeneity across salespeople. Moreover, it is impossible to identify and measure all the environmental factors that shift the

sales frontier up or down in each category for each salesperson (Ratchford 2011), and the plethora of these factors may not even be known or knowable to managers. Consequently, independent category-by-category regressions are highly susceptible to model misspecification due to omitted variables. Even after controlling for the observed environmental factors, the unknown or unknowable environmental factors affect multiple categories, resulting in sales frontiers that are correlated across categories. Similarly, competitive activities likely correlate across categories. In a market with nearby pharmacies for example, the sales frontiers for a personal care retailer may be generally lower for skin care and hair products, because pharmacies are direct competitors in these categories.

Because previous internal benchmarking research has failed to leverage these likely correlations among customer requirements and competitive activities across categories, further development of a multivariate, cross-category extension of SFR clearly is necessary. This multivariate approach taps simultaneously into two sources of information readily available to any multicategory, multistore franchise: (1) sales of the focal category across the sales force overtime and (2) sales of other categories by the focal salesperson over time. In turn, retail managers can gauge the growth potential for each category and each salesperson by not only benchmarking against the top performing salespeople in the same category but also leveraging information from all the other seemingly unrelated categories, such that unobserved environmental factors can be accounted for when they affect more than one product category. For example, even if the analyst does not have, or has overlooked, data about nearby pharmacies, a multivariate approach accounts for this unobserved performance factor, as long as it affects both skin and hair products.

Selecting Sales Success Factors for Internal Benchmarking

Extant sales performance research provides some direction for understanding how retailers implement internal benchmarking and manage sales force productivity (Table 1). Previous studies have devoted attention to sales force productivity using survey and subjective data (Boles, Donthu, and Lohtia 1995), macro-level performance data (Horsky and Nelson 1996), firm records (Donthu and Yoo 1998), and secondary data (Assaf et al. 2012). Kumar, Sunder, and Leone (2014) note that it is imperative for managers to evaluate the sales force accurately, because of its great impact on customer satisfaction and long-term performance. When assessing productivity in complex contexts (e.g., multiple products and locations), developing an equitable expectation of sales performance becomes essential (Kamakura, Lenartowicz, and Ratchford 1997). Previous research has assessed the sales performance achieved through different price and format strategies in multiple store chains (Gauri 2013), merchandise planning of various regional stores (Grewal et al. 1999), and the performance of group-level retail stores (Gauri, Pauler, and Trivedi 2009). The purpose of the current study is to determine and compare efficiencies of salespeople across categories and stores, so we use a measure of

contribution margin per category as output to assess the performance of each salesperson.

Research has long attributed the success of retailers to various factors at the individual, store, and market levels. These factors might pertain to salesperson effort and incentive, management leadership, store square footage, inventory levels, market potential, or competition level (see Boles, Donthu, and Lohtia 1995). Research dealing with sales performance in the retail context draws heavily from cross-sectional survey data (Verbeke, Dietz, and Verwaal 2011). Despite the great importance of sales force evaluation, many retailers still strive to develop technology that can process key factors at such disaggregated levels (Franke and Park 2006). The lack of structured longitudinal data on individual salesperson-, store-, and market-level factors imposes a great challenge to sales performance research (Dant, Grünhagen, and Windsperger 2011). As Table 1 shows, our study is the first to include key observable factors (i.e., salesperson monetary incentive, store display at the category level, market and sales potential) drawn from firm records and syndicated market data. We selected the specific factors for this study on the basis of retail management input and previous literature (e.g., Boles, Donthu, and Lohtia 1995; Horsky and Nelson 1996; Kamakura, Lenartowicz, and Ratchford 1997), under the binding constraint that they are available to most retail franchise businesses.

Empirical Application Context

The data that we use to illustrate the proposed model for assessing a sales force come from franchisees operating 35 retail stores located in four non-contiguous regional markets in South America. The franchisor is a leading national brand of cosmetics and health care products (e.g., perfume, makeup, hair, skin care) that minimizes franchisee conflict in regional markets by granting full coverage of each regional market to one franchisee, through multiple stores. This franchise network represents an interesting setting to illustrate our model and study opportunities for internal benchmarking across the sales force for several reasons. First, in the stores, approaching customers and completing sales is an independent task conducted by a single salesperson. The salesperson's main job is to match customers' needs with the store's product portfolio by approaching customers and assisting them throughout the shopping visit. Customers may look around the shelves and try samples in the store, but one salesperson is responsible for completing the sales. The salesperson always has the opportunity to help in-store customers and ensure their satisfaction. Second, sales commission is the primary source of monetary incentive for driving selling effort; it varies by store location and product line. Third, salespeople do not compete directly and have equal opportunities to sell; there is no rank or hierarchy in the sales force, and store managers rotate salespeople to staff the store in peak hours throughout the week. Salespeople available to serve customers follow scheduled shifts, except when regular customers explicitly request a particular salesperson. Store managers and online training provide salespeople with the necessary product information to sell the product assortment, which is fully available in every store. Fourth, though store managers maintain close contact with their

Table 1
Representative research on sales performance and productivity estimation.

Reference	Data collection	Context	Data analysis	Productivity estimation	Sales performance	Key observed success factors			
						Monetary incentive	Product promotion	Market population	Sales potential per household
Assaf et al. (2012)	Secondary firm and market data	Supermarket chain internationalization	Stochastic frontier regression with dynamic assumption	Previous cost efficiencies affect the present value of cost efficiency	Overall annual sales	Yes	No	Yes	Yes
Boles, Donthu, and Lohtia (1995)	Survey	Salesforce in the advertising business	Data envelopment analysis	Classes of sales approach	Percentage of quota attained and subjective measures	Yes	No	No	Yes
Donthu and Yoo (1998)	Firm records	Stores of fast-food restaurants	Data envelopment analysis	Store efficiency frontier	Overall annual sales and satisfaction	No	Yes	No	No
Gauri (2013)	Secondary firm and market data	Grocery retailers	Stochastic frontier regression	Univariate approach	Overall weekly sales	No	Yes	Yes	No
Gauri, Pauler, and Trivedi (2009)	Secondary and market data	Grocery retailers	MLE of block groups	No	Retail sales performance	No	Yes	Yes	Yes
Grewal et al. (1999)	Firm records	Stores of automotive parts	Data envelopment analysis	Multiple product sales efficiency	Unit product sales	No	Yes	No	No
Horsky and Nelson (1996)	Firm records	Salesforce in chemical and business equipment	Data envelopment analysis	Sales district efficiency frontier	Overall monthly sales district	No	No	Yes	Yes
Kamakura, Lenartowicz, and Ratchford (1997)	Firm records	Branches of bank retail	Clusterwise estimation of multiple translog cost function	Efficiency of branches (data envelopment analysis)	Overall branch deposits and service fees	No	Yes	No	No
Kumar, Sunder, and Leone (2014)	Firm records	Salespeople in technology industry	Maximum likelihood of latent class models	No	Salesperson's future value	Yes	No	No	Yes
Sridhar, Mantrala, and Naik (2014)	Secondary firm and market data	Decision-making units in the newspaper industry	Data envelopment analysis and multivariate sliced inverse regression	Two-stage model to calibrate nonparametric efficiency	Overall unit sales	No	Yes	No	No
This study	Franchisee records and secondary market data	In-store salespeople in cosmetic and health care retail	Multivariate stochastic frontier regression (simulated-MLE)	Latent factors to account for correlated asymmetric error structure	Contribution margin per category (monthly)	Sales Commission per Category	Store display at the category level	Yes	Yes

local sales forces, the best practices of salespeople from other stores are out of reach, even though the franchisor is a multistore retailer, and top performing salespeople from one store potentially could share best practices with salespeople in other stores.

For this study, we had access to the following data for 11 product categories sold by 481 female salespeople during a period of 12 months:

$Profit_{ijt}$ = Log of contribution (before fixed costs) produced by salesperson i in product category j during month t .

$Comm_{ijt}$ = Log of sales commission (as percentage of sales) earned by salesperson i in product category j during month t .

$Display_{ijt}$ = Log of the area (in square meters) utilized to display product category j during month t in the store where salesperson i was employed.

D_{Aug_t} , D_{Dec_t} = Dummy variables for the months of August and December (the only two months with clear seasonal effects during the year across categories and salespeople).

$Hholds_i$ = Log of estimated population of households in the trade area served by the store where salesperson i operated.

$Potent_i$ = Log of the estimated market potential per household for cosmetics in the trade area served by the store where salesperson i operated.

We also obtained market variables (population of households and market potential per household) from a syndicated service, for the trade areas covered by each of the 35 stores, as well as the market potential for each postal code area covered by the store's trade area.

Model Development

Multivariate Factor-Analytic Extension of Stochastic Frontier

Following the fundamentals of SFR (Aigner, Lovell, and Schmidt 1977), we considered a sales force of I salespeople selling products in J categories over T months. In category j , for salesperson i and month t , there is an upper bound y_{ijt}^* , or sales frontier, that is shaped by the top-performing salespeople in category j , and can be defined as a function of K observed environmental factors (X_{kjt}) over time (Eq. (1)). In Appendix A, we provide a detailed, technical explanation of the univariate stochastic frontier regression used to estimate our multi-level data.

$$\ln(y_{ijt}) = \beta_{0j} + \sum_{k=1}^K \beta_{kj} \ln(X_{kjt}) + v_{ijt} - u_{ijt}. \quad (1)$$

The standard SFR, carried out category-by-category, faces a critical challenge in practice: Its results can be highly sensitive to the environmental factors included (or not) in the analysis. Many factors could shift the sales frontier but are not considered within X_{it} , because they are unknown or unobservable. One way to minimize this problem of unaccounted-for factors is to collect as much information about the market environment as possible. However, measures of environmental factors, available mostly from external sources, are bound to be inaccurate, and many of these environmental factors are simply unknown or unknowable.

With Eq. (1), we assume that all the unaccounted-for factors are reflected in the error component v_{ijt} , which we assume to be idiosyncratic to category j , salesperson i , and month t , as well as randomly distributed across the sales force, categories, and over time. However, such an assumption underutilizes the information available to a multicategory, multimarket vendor. Most customers make purchases from multiple product categories, and their requirements tend to be correlated across categories. For example, salespeople with strong sales of one type of makeup (skin, eyes, lips) also might earn high sales of other types, because of the type of customers they serve. Consequently, the sales frontiers of these categories should be correlated, as should the sales frontiers for fragrance-related categories (perfume, deodorant, soap). To tap into the potentially rich pattern of cross-category correlation in sales performance across salespeople, we propose the following multivariate factor-analytic extension to SFR:

$$\ln(y_{ijt}) = \beta_{0j} + \sum_{k=1}^K \beta_{kj} \ln(X_{kjt}) + \sum_{p=1}^P \gamma_{pj} Z_{pit} + v_{ijt} - u_{ijt}, \quad (2)$$

where Z_{it} denote a set of latent factors for salesperson i in month t , which we assume to be independently and identically distributed (i.i.d.) standard normal across salespeople and months; the number of these latent factors (P) and their impacts (γ_j) on the sales frontier of category j can be determined empirically. Because the values of Z_{it} are unobserved, we estimate them *jointly* with all the model parameters (β_j , γ_j , σ_{vj} , and σ_{uj}) from the observed data (y_{ijt} and X_{it}). Unlike Eq. (1), which we estimated separately by category, we had to estimate Eq. (2) simultaneously across all categories, because the latent factors captured the correlations across categories, due to the unobservable factors that affect sales potential. Appendix B contains details on the estimation, showing that a complex simulation-based maximum-likelihood estimation (MLE) algorithm is needed to uncover the latent space that captures the correlations across salespeople, product categories, and time periods. Because of the three-mode (i.e. salespeople, products, and months) nature of the data, and the complex two-part error structure of the proposed model, the standard singular-value decomposition in linear models (e.g., MSIR) is not applicable (see Appendix C for more details).

Uncovering the Principal Components of Unobserved Factors

Our multivariate factor-analytic extension of SFR (Eq. (2)) anticipates that, even after controlling for observed environmental factors X_{it} , there could be some correlation in the sales frontiers across categories, because unobserved environmental factors might affect the sales potentials of multiple categories across the sales force and over time. The latent factor scores for each salesperson in each month (Z_{it}) and their loadings on each category (γ_j) provide a parsimonious representation of such cross-category correlations, incorporating information about unobserved environmental factors to define the sales fron-

tiers. The sum of products between factor loadings and factor scores ($\sum_{p=1}^P \gamma_{pj} Z_{pit}$) will determine how much higher or lower the sales frontier for product category j and salesperson i should be adjusted, up or down, each month. Then the

factor loadings $\Lambda = \begin{Bmatrix} \gamma_{11} \cdots \gamma_{P1} \\ \vdots \\ \gamma_{1J} \cdots \gamma_{PJ} \end{Bmatrix}$ will capture the principal

components of the covariance in sales frontiers across the J product categories, because the implied covariance matrix can be

obtained directly, as $\Lambda \Lambda' + \begin{Bmatrix} \sigma_{v1}^2 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \sigma_{vJ}^2 \end{Bmatrix}$. If two cate-

gories have loadings of the same sign on the same dimensions of the latent factors, then salespeople with a high (low) sales frontier in one category also should have a high (low) frontier in the other.

More intuitively, in determining the sales frontier for each salesperson in each category, our proposed model simultaneously compares performances across not only salespeople but also categories. For the focal category, the sales frontier is shaped by the top performing salespeople within that category in each month, as a function of observed environmental factors. This frontier then can be adjusted further, upward or downward, depending on the focal salesperson's latent factor scores each month and the loadings on the focal category, resulting in a frontier for each salesperson that is more flexible than the single frontier defined by SFR, DEA, or SIR.

The factor loadings reflect how the sales frontier of the focal category correlates with those of the other categories, because of unobserved environmental factors that affect multiple categories. The latent factor scores capture the impact of those unobserved environmental factors and are defined so that they best explain the observed pattern of sales results across all categories of the focal salesperson in a particular month. Such cross-category information sharing for simultaneously defining multiple categories' sales frontiers is our key innovation; we subsequently illustrate how our integrated (across sales force and categories) benchmarking framework outperforms the traditional SFR (across the sales force only) approach in terms of fit, predictive fit, and robustness to unobserved performance factors.

Measuring Relative Sales Efficiency

Given the estimates of $\beta_j, \gamma_j, \sigma_{vj}, \sigma_{uj}$ and Z_i , we can compute a direct estimate of the composite residual: $\varepsilon_{ijt} \equiv v_{ijt} - u_{ijt} = \ln(y_{ijt}) - [\beta_{0j} + \sum_{k=1}^K \beta_{kj} \ln(X_{kjt}) + \sum_{p=1}^P \gamma_{pj} Z_{pit}]$. The conditional distribution of u_{ijt} given ε_{ijt} contains whatever information ε_{ijt} might provide about the salesperson's (log) relative sales efficiency ($-u_{ijt}$) (Kumbhakar and Lovell 2000). Jondrow et al. (1982) derive a formula for computing the expectation of u_{ijt} given ε_{ijt} :

$$E[u_{ijt} | \varepsilon_{ijt}] = \frac{\sigma_j \lambda_j}{1 + \lambda_j^2} \left[\frac{\phi(a_{ijt})}{1 - \Phi(a_{ijt})} - a_{ijt} \right], \quad (3)$$

where $\lambda_j \equiv \frac{\sigma_{uj}}{\sigma_{vj}}$, $\sigma_j^2 \equiv \sigma_{vj}^2 + \sigma_{uj}^2$, $a_{ijt} \equiv \frac{\lambda_j \varepsilon_{ijt}}{\sigma_j}$

where ϕ and Φ denote, respectively, the probability density function (PDF) and cumulative distribution function (CDF) of the standard normal distribution. From Eq. (3), the average log efficiency of a salesperson i in category j over a sampling period $t = 1, \dots, T$ is given by

$$\ln E_{ij} = \frac{-\sigma_j \lambda_j}{1 + \lambda_j^2} \left[\frac{\phi(\lambda_j (\sum_{t=1}^{12} y_{ijt}/12 - \sum_{t=1}^{12} y_{*ijt}/12) / \sigma_j)}{1 - \Phi(\lambda_j (\sum_{t=1}^{12} y_{ijt}/12 - \sum_{t=1}^{12} y_{*ijt}/12) / \sigma_j)} - \frac{\lambda_j (\sum_{t=1}^{12} y_{ijt}/12 - \sum_{t=1}^{12} y_{*ijt}/12)}{\sigma_j} \right] \quad (4)$$

Eqs. (3) and (4) produce measures of log efficiency in expectation, after accounting for both symmetric and asymmetric errors, thereby taking into account (symmetric) estimation and measurement errors, as well as the (asymmetric) unobservable heterogeneity in performance across salespeople.

In addition to the estimate of relative sales efficiency (E_{ij}), the estimate of $\lambda_j (\equiv \sigma_{uj}/\sigma_{vj})$ is also of particular interest, because it captures the relative sizes of the two residual components, v_{ijt} and u_{ijt} . When $\lambda_j \rightarrow 0$ (either $\sigma_{uj} \rightarrow 0$ or $\sigma_{vj} \rightarrow \infty$), the symmetric residual component (v_{ijt}) dominates the non-negative component (u_{ijt}) for determining $\varepsilon_{ijt} \equiv v_{ijt} - u_{ijt}$. If there is little variation in sales performances across the sales force for category j (i.e., all salespeople are equally efficient or inefficient with no one standing out), the estimate of λ_j will be small. A large estimate of λ_j instead would indicate substantial variation in sales performances across the sales force and thus the potential for growth for those relatively low-efficiency salespeople, to the extent that they can emulate the best practices of their high-efficiency counterparts.

Empirical Results

Table 2 presents the parameter estimates for our proposed model, including the intercept (β_{0j}), the effects ($\beta_{1j} \sim \beta_{6j}$) of the six observed exogenous factors¹ (*Comm_{ijt}*, *Display_{ijt}*, *D_Aug_t*,

¹ At a first glance, we worried that the shelf space allocated to each product category at the 35 stores might have been endogenously determined by the franchisees. However, the franchisor periodically determines the planogram across the entire franchise, with franchisees allowed some deviation from the centrally determined planogram, beyond obvious adjustments for store size. We chose to take the franchiser's planograms as given, for three reasons. First, we did not have any data on the deviations of each of the 35 stores from the centrally determined planogram other than the adjustments for store size. Second, it would be infeasible to find proper instruments to correct the planogram for endogeneity at the store and category levels. Third, our main interest is in assessing the per-

Table 2
Parameter estimates for the proposed model.

Category	Predictors							SFA Statistics		Loadings	
	Commission	Display	D_Aug	D_Dec	Households	Potential	Intercept	Sigma	Lambda	DIM1	DIM2
Hair	0.32	0.38	0.06	0.43	0.00	0.56	3.89	0.73	4.03	−0.64	0.46
Skin	0.28	0.55	0.27	1.08	0.00	0.52	4.49	0.81	7.35	−0.55	0.32
Makeup-Other	−0.16	0.70	−0.37	0.08	−0.06	0.65	0.85	0.78	1.38	−0.48	0.43
Makeup-Face	0.01	0.70	0.09	0.39	−0.09	1.72	−3.60	0.54	2.91	−0.70	0.46
Makeup-Lips	0.10	0.36	0.06	0.56	−0.01	0.98	0.46	0.46	3.66	−0.76	0.47
Makeup-Eyes	0.01	0.91	−0.11	0.53	−0.07	1.48	−2.46	0.50	2.23	−0.72	0.42
Perfume-Male	0.44	0.58	0.52	0.56	0.02	0.21	7.73	0.46	10.12	−0.87	0.08
Perfume-Fem	0.40	0.48	−0.09	0.83	0.04	0.39	5.99	0.40	4.99	−0.90	0.09
Soap	0.39	0.42	0.13	1.22	−0.02	1.04	0.87	0.48	2.24	−0.80	0.23
Deodorant	0.18	0.39	0.31	0.75	−0.03	0.26	6.07	0.62	11.73	−0.85	0.00
Other	0.11	0.54	0.10	0.58	−0.06	1.26	−0.81	0.47	3.02	−0.74	0.07
Loglikelihood=	−14,659.80										
BIC=	30,541.70										

Notes: Values in bold are statistically significant at the .01 level.

D_Dec_t , $Hholds_i$ and $Potent_i$), the residual distribution parameters ($\lambda_j \equiv \sigma_{uj}/\sigma_{vj}$ and $\sigma_j \equiv \sqrt{\sigma_{vj}^2 + \sigma_{uj}^2}$), and the latent factor loadings (γ_1 and γ_2), which are rotated and standardized for ease of interpretation. In determining the number of latent factors (i.e., P in Eq. (2)), we ran our model with up to three factors, and used the standard Bayesian Information Criterion (BIC) (Schwarz 1978) to choose the most adequate solution. The BIC values were 56,577, 33,389, 30,542 and 30,556 for 0, 1, 2, and 3 dimensions, respectively, to a two-factor solution best captures the pattern of unobserved heterogeneity in the data. Moreover, the substantial drop in BIC from 0 to 1 dimensions (from 56,577 to 33,389) revealed the considerable predictive power lost with the traditional independent SFR approach (i.e., our proposed model reverts to independent SFR for each category when the number of latent factors $p=0$).

As expected, the effect of *Potent* (market potential per household) on the *Profit* frontier for a salesperson was positive. Moreover, *Profit* was elastic on *Potent* for Makeup-Face, Makeup-Lips, Makeup-Eyes, Soap, and Other. Surprisingly, the effect of *Hholds* (population of households) was non-significant, except for one category in which it was negative. This negative effect may be due to collinearity with *Potent* (markets with high potential for cosmetics tend to be more densely populated in the areas covered by the stores in our study) and *Display* (shelf space allocated to each category, which indirectly captures store size). The percentage of commissions over sales (*Comm*) had a positive effect on the profit frontier for a salesperson, except for Makeup-Face and Makeup-Other. The shelf space allocated to a category (*Display*) had a positive effect on the salesperson's sales frontier for all categories, as expected, but the effect on profits was inelastic. December is clearly an important month in producing profits across all categories, while the frontier in August (when Father's Day is held in these markets)

is more profitable than normal for Perfume-Male and Deodorant.

Of particular interest is the estimate of λ_j ($\equiv \sigma_{uj}/\sigma_{vj}$), which indicates the relative size of variance in sales efficiencies across salespeople, as compared with variance in sales frontiers. For a particular category, a greater λ implies larger differences in sales efficiencies across salespeople. As λ approaches 0 though, we can infer that all salespeople are close to the sales frontier, with no one standing out. From Table 2, we see that all categories produced λ that were substantially larger than 0, so there is substantial variation in sales efficiency across the sales force for all categories (particularly Perfume-Male and Deodorant).

The factor loadings (γ_1 and γ_2) in our proposed model are intended to capture the latent factors that produce the cross-category correlation in sales frontiers. The sum of products between factor loadings and latent scores ($\sum_{p=1}^2 \gamma_{pj} Z_{pit}$) determines how much higher or lower the sales frontier for category j , salesperson i , and month t should be adjusted. As reported in Table 2, the factor loadings showed strong correlation among the 11 product categories, which is useful for defining the sales frontiers but not easy to interpret, given the number of factors and product categories. Nevertheless, it is possible to uncover some patterns, especially when viewing these results in a loading plot (Fig. 1). Overall, salespeople with higher than average sales in one category also tend to sell more than the average on other categories; these salespeople are positioned in the upper left quadrant of Fig. 1. However, sales in some categories tend to be more closely related to certain other categories. The categories represented by red solid vectors in Fig. 1 have sales frontiers that are more closely correlated than they are with the categories in the other group (blue vectors). These two groups also exhibit a clear distinction: The first group (red solid vectors) comprises of beauty-related products (makeup, haircare, skin care); the second group seems more related to fragrance or perfume. These results suggest there may be some overall efficiency in sales,

formance of the sales force, given the decisions already made by management and franchisor, rather than analyzing the effect of these managerial decisions.

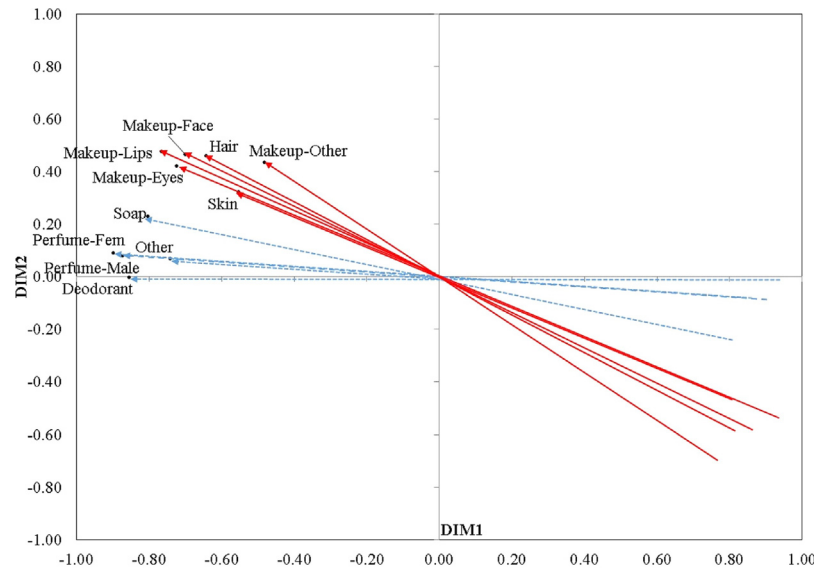


Fig. 1. Loading plot for the proposed model.

but some salespeople may be better than others in specific categories.

Instead of showing the scores Z_{it} for each salesperson and month, we present in Fig. 2 the average scores for the sales force employed by each of the 35 stores in our sample over the 12-month period. By comparing the loading plot in Fig. 1 with the average scores in Fig. 2, we determine that, all else being equal (i.e., exogenous factors), Stores 11, 5, 3, and 10 (light blue) have the largest profit frontiers across the 11 categories, though Store 11 exhibits the largest frontier for beauty products, and Store 5 leads for perfumes. After accounting for the observable factors, stores from the first (codes 1–11 in light blue) and second (codes 20–27 in dark blue) regional markets indicated larger profit frontiers than other markets (codes in the 30s in red and 40s in brown). These shifts in the average frontiers across stores illustrate how our proposed model accounts for unobserved factors affecting salesperson performance; salespeople operating within each of these stores would have their efficiency assessed relative to a frontier that is adjusted beyond the observed factors incorporated into the frontier, leading to a more equitable assessment that does not penalize or benefit salespeople for unobserved environmental factors affecting their performance.

Relative Sales Efficiency Measure

The relevant and valuable results for a multicategory, multi-market retailer, such as the franchisees involved in this study, are measures of relative sales efficiency derived from the parameter estimates of our proposed model, $E_{ij} \equiv y_{ij}/y_{ij}^* = \exp(-u_{ij})$ for salesperson i and category j ; these sales efficiencies are the main focus of an internal benchmark study. Because a table listing the efficiency of 481 salespeople on 11 product categories would be overwhelming, in Table 3 we report the average efficiency of the sales force for each of the 35 stores (we present a more thorough benchmarking of the 481

salespeople subsequently). To simplify the interpretation, we highlight in red the top 10 performers in each of the 11 product categories, though there does not seem to be a clear pattern in the average sales efficiency across stores and product categories. The most prominent differences across salespeople and product categories have been captured by the shifts in stochastic frontiers in Figs. 1 and 2. Our model provides an equitable assessment of each salesperson, after accounting for observable and unobservable market differences that affect their sales potential, without favoring or penalizing salespeople in a particular store or product category for those differences.

Model Validation

Because our sales frontier and relative efficiency measures are derived from a novel model, their validity for identifying growth potentials and evaluating performances could be questioned. To address this concern, we conducted three validation tests.

Validation Test 1: Negatively Skewed Error

A key assumption of a stochastic frontier model such as ours is that the error term is a composite of two parts: $\varepsilon_{ij} \equiv v_{ij} - u_{ij}$, with v_{ij} (i.e., stochastic errors in the sales frontier) being symmetric and normally distributed, and u_{ij} (i.e., inefficiency in actual performance) being asymmetric and half-normally distributed across salespeople. An important implication of such an assumption is that the model's residuals are negatively skewed, as opposed to symmetric or positively skewed. Fortunately, this skew is empirically testable; Coelli (1995) offers a diagnostic statistic, $M3T = \frac{m_3}{\sqrt{6m_2^3/N}}$, where m_2 and m_3 are the second and third sample moments of standard regression residuals. According to the null hypothesis that the error term is symmetric, M3T is asymptotically distributed as a standard normal random variable. Thus, a negative and statistically significant M3T would reject

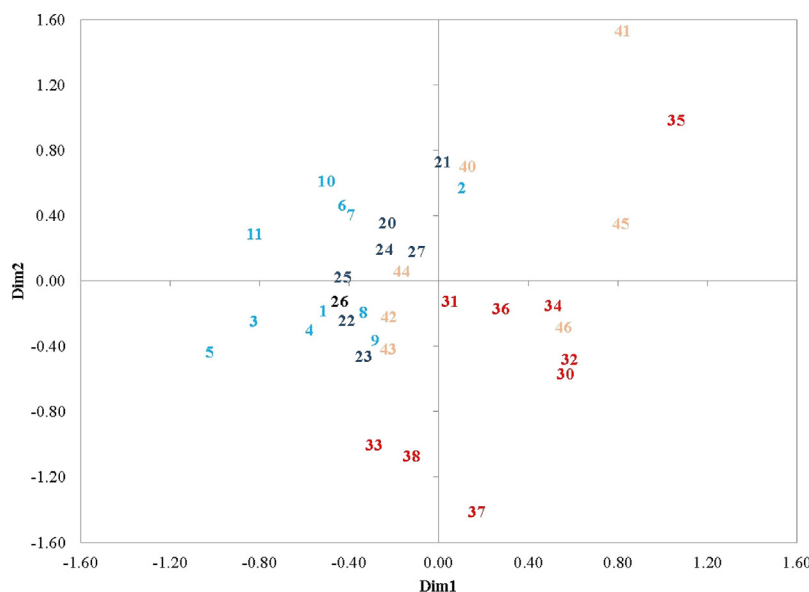


Fig. 2. Average factor scores for the salesforce in each store.

Table 3

Average efficiency of the sales force within each store and category. (For interpretation of the references to color in this table legend, the reader is referred to the web version of this article.)

Store	Hair	Skin	Makeup Other	Makeup Face	Makeup Lips	Makeup Eyes	Perfume Male	Perfume Female	Soap	Deodorant	Other
1	0.54	0.68	0.70	0.76	0.77	0.76	0.81	0.87	0.72	0.59	0.73
2	0.55	0.59	0.64	0.77	0.85	0.78	0.70	0.82	0.79	0.59	0.75
3	0.60	0.73	0.63	0.78	0.77	0.72	0.84	0.86	0.71	0.59	0.74
4	0.64	0.74	0.61	0.76	0.80	0.69	0.83	0.85	0.70	0.63	0.72
5	0.53	0.78	0.60	0.74	0.77	0.71	0.85	0.89	0.74	0.59	0.72
6	0.63	0.69	0.69	0.78	0.78	0.76	0.77	0.81	0.80	0.59	0.80
7	0.58	0.72	0.65	0.80	0.79	0.76	0.77	0.84	0.78	0.59	0.76
8	0.61	0.74	0.65	0.72	0.78	0.74	0.83	0.81	0.75	0.59	0.80
9	0.77	0.83	0.64	0.63	0.69	0.62	0.81	0.81	0.83	0.59	0.79
10	0.70	0.73	0.70	0.73	0.79	0.73	0.67	0.77	0.86	0.59	0.83
11	0.68	0.74	0.73	0.77	0.74	0.74	0.86	0.77	0.68	0.59	0.81
20	0.70	0.67	0.63	0.77	0.79	0.80	0.76	0.78	0.72	0.76	0.76
21	0.74	0.62	0.70	0.79	0.73	0.78	0.70	0.72	0.79	0.76	0.79
22	0.72	0.79	0.66	0.73	0.72	0.75	0.77	0.81	0.74	0.76	0.74
23	0.63	0.78	0.66	0.74	0.78	0.72	0.84	0.79	0.65	0.73	0.74
24	0.71	0.71	0.71	0.76	0.74	0.76	0.79	0.80	0.74	0.69	0.80
25	0.81	0.76	0.67	0.62	0.74	0.75	0.67	0.67	0.82	0.83	0.78
26	0.81	0.80	0.72	0.63	0.69	0.71	0.80	0.73	0.78	0.77	0.79
27	0.85	0.83	0.69	0.50	0.71	0.63	0.70	0.65	0.84	0.76	0.84
30	0.71	0.50	0.71	0.66	0.75	0.73	0.67	0.74	0.79	0.79	0.74
31	0.42	0.39	0.60	0.77	0.83	0.80	0.64	0.69	0.81	0.81	0.79
32	0.62	0.67	0.73	0.65	0.74	0.73	0.71	0.73	0.73	0.75	0.77
33	0.66	0.60	0.75	0.72	0.66	0.71	0.77	0.81	0.73	0.75	0.78
34	0.70	0.55	0.74	0.70	0.70	0.75	0.65	0.66	0.85	0.77	0.74
35	0.74	0.87	0.70	0.59	0.83	0.64	0.64	0.76	0.75	0.60	0.61
36	0.69	0.69	0.77	0.60	0.71	0.72	0.71	0.78	0.81	0.70	0.77
37	0.31	0.34	0.75	0.63	0.77	0.72	0.75	0.68	0.73	0.82	0.74
38	0.74	0.50	0.60	0.58	0.68	0.77	0.64	0.72	0.85	0.69	0.86
40	0.63	0.54	0.72	0.80	0.78	0.82	0.73	0.74	0.76	0.77	0.73
41	0.78	0.70	0.71	0.81	0.77	0.80	0.66	0.70	0.68	0.59	0.69
42	0.69	0.70	0.70	0.75	0.76	0.70	0.80	0.78	0.74	0.72	0.79
43	0.69	0.55	0.68	0.66	0.77	0.69	0.80	0.80	0.81	0.69	0.74
44	0.69	0.54	0.75	0.76	0.71	0.74	0.64	0.65	0.80	0.76	0.83
45	0.78	0.79	0.73	0.60	0.76	0.66	0.64	0.74	0.74	0.66	0.76
46	0.52	0.86	0.87	0.47	0.67	0.55	0.90	0.89	0.76	0.59	0.75

Notes: High efficiency scores in the category are highlighted in **bold red**.

the null hypothesis in favor of negatively skewed error distribution, or, the stochastic frontier formulation would be preferred over its standard regression counterpart.

We followed Coelli's procedure and calculated the diagnostic statistic M3T for all 11 product categories in our sample.

The results, reported in the last column of Table 4, show that all M3Ts were negative and statistically significant at the .01 level. Such clear-cut empirical evidence indicates that a stochastic frontier formulation, which implies negatively skewed errors, is more appropriate for our data, compared with its standard

Table 4
Summary statistics for the individual sales efficiencies over 12 months.

Category	Minimum	Maximum	Mean	Median	M3T
Hair Treatment	0.183	0.953	0.621	0.657	−8.0
Skin Treatment	0.338	0.984	0.646	0.703	−57.0
Makeup-Other	0.153	0.883	0.624	0.646	−35.6
Makeup-Face	0.193	0.943	0.696	0.740	−56.0
Makeup-Lips	0.311	0.955	0.732	0.769	−45.3
Makeup-Eyes	0.152	0.942	0.715	0.744	−35.4
Perfume-Male	0.637	0.982	0.756	0.764	−60.9
Perfume-Female	0.461	0.971	0.759	0.789	−7.0
Soap	0.167	0.976	0.727	0.751	−33.9
Deodorant	0.594	0.992	0.708	0.672	−29.8
Others	0.245	0.968	0.730	0.754	−35.9

Notes: Values in bold are statistically significant at the .01 level.

Table 5
Predictive validity test: root mean squared errors in the calibration and hold-out samples.

Category	Calibration MSE		Holdout MSE	
	Proposed	SFR	Proposed	SFR
Hair	0.72	1.41	0.73	1.77
Skin	0.80	1.34	3.05	3.92
Makeup Other	0.77	1.21	1.77	2.03
Makeup Face	0.56	1.35	2.24	3.12
Makeup Lips	0.49	1.41	1.30	1.27
Makeup Eyes	0.50	1.31	2.25	3.03
Perfume Male	0.44	1.44	1.26	1.69
Perfume Female	0.39	1.44	1.75	2.36
Soap	0.44	1.30	1.88	2.31
Deodorant	0.60	1.41	2.87	2.79
Other	0.46	1.22	3.34	3.99

regression counterpart, which implies symmetric errors. Moreover, at a conceptual level, using average sales from a linear regression model as the benchmark for performance assessment is an implicit acceptance of mediocrity rather than excellence.

Validation Test 2 — Predictive Validity Test

Unfortunately, it is not advisable to assess the predictive validity of the efficiency measures produced by (stochastic or non-stochastic) frontiers directly, because these measures come from an estimated model, so there is no “true” benchmark to assess validity. Nevertheless, we performed a predictive validity test to compare the validity of our estimated frontiers, relative to SFR, in terms of their deviation from observed sales across all salespeople and product categories. To perform this predictive validity test, we held out 20% of the observed sales randomly across salespeople, product categories, and months. We fit our proposed multivariate frontier and the traditional stochastic frontier to the 80% “observed” data, then used the estimated frontiers to determine how much the 20% “unobserved” (held-out) sales deviated from the estimated frontiers. Table 5 contains the predictive validity results of our proposed multivariate frontier model and the SFR, independently applied to each category. Because our proposed model benefits from information across all 11 product categories and accounts for unobserved hetero-

geneity across salespeople, our multivariate frontier fits better, that is, has a lower root mean square deviation (RMSE) from the observed sales than SFR in the calibration samples for all product categories. For the same reasons, our proposed frontiers tend to produce smaller deviations (lower RMSE) in the hold-out or unobserved sales, with two exceptions (Makeup-Lips and Deodorants), for which the differences in predictive fit are relatively minor. In the context of our application, our model is less likely to penalize (or benefit) certain salespeople because of unobserved factors affecting their sales performance and more likely to compare their performance in a more equitable fashion than SFR, because the estimated frontier tends to be closer to observed sales.

Validation Test 3 — Robustness of the Stochastic Frontier to Omitted Factors

For any cross-sales force benchmarking exercise to be valid, the performances of the different salespeople need to be compared on an equal footing. To be equitable in evaluating each salesperson’s performance, managers therefore must control for a plethora of extraneous variables, many of which, unfortunately, are unknown or unknowable. Because of the inevitable existence of unobserved environmental factors, the real issue in practice is how to account for the impact of such factors *as much as possible*, even when they are not observable, and thereby minimize the “unfairness” of the resulting performance measures. That is, in choosing one benchmarking model over another, a key criterion should be the robustness of the model-based performance measure to omitted environmental factors.

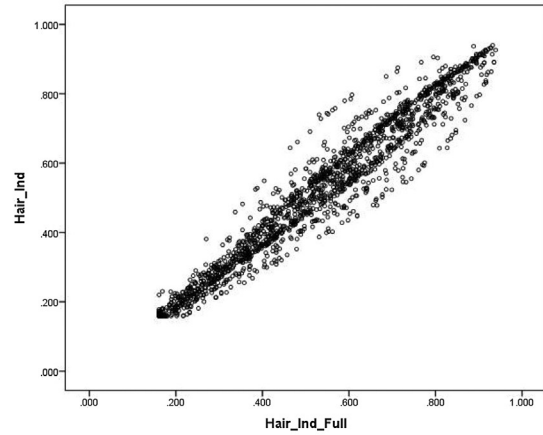
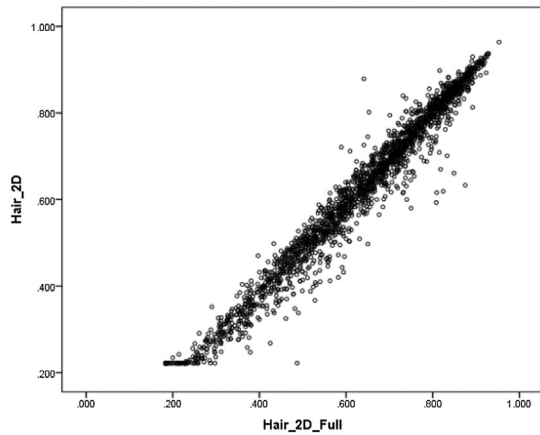
To compare the robustness of our proposed multivariate latent stochastic frontier model with the well-known SFR, we looked at how the sales efficiency of each salesperson in each product category and month changed when we excluded an important determinant of the frontier, that is, the potential for cosmetic purchases per household estimated for the trade area served by the salesperson ($Potent_i$). Sales efficiencies obtained with our proposed multivariate model should be less affected by the elimination of this important market factor than those obtained with SFR, because our proposed model benefits from the information contained in all categories when defining the frontier for each salesperson, product category, and month (i.e., our two latent factors account for unobserved environmental factors that cause the observed data to be correlated across salespeople and product categories over time). In contrast, SFR can only use information from the focal product category, because it treats each category independently.

In Fig. 3, we compare the sales efficiencies obtained with our proposed model and SFR when we include or exclude $Potent_i$ (market potential for cosmetics per household in the market served by salesperson i) for the most product categories. It shows how the assessment of the sales force in each product category would change if this single market factor were ignored by our proposed model and SFR. The right side of Fig. 3 shows that for some of the product categories (e.g., Skin Treatment, Makeup-Face, Makeup-Eyes, Soap), efficiency assessments of individual salespeople would change dramatically if market

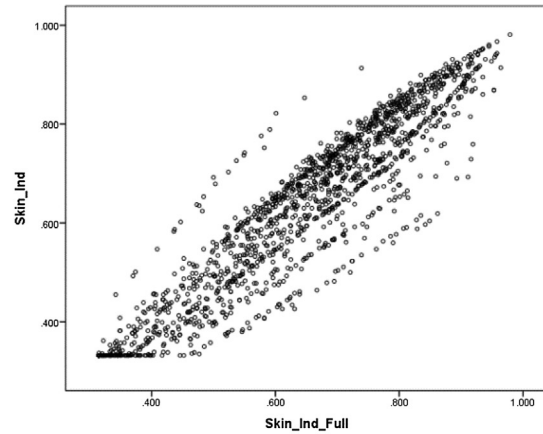
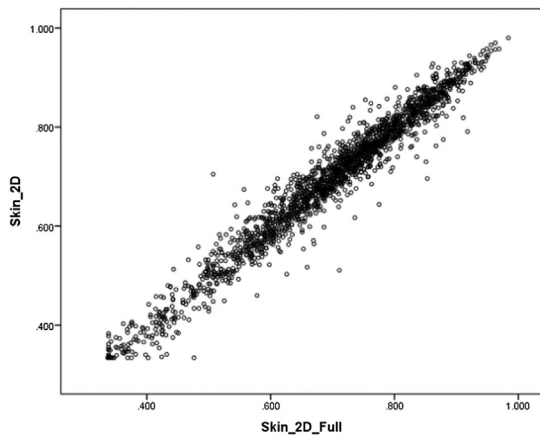
potential were ignored in an independent SFR regression. In contrast, the efficiency assessments attained with our proposed frontier (left side of Fig. 3) are much less sensitive to the inclusion/exclusion of market potential in the frontier specification.

For the other product categories, the differences are still evident but not as dramatic. These results demonstrate that our proposed multivariate latent stochastic frontier model is less sensitive to model misspecification than the extant SFR model, which is a

Panel A. Hair Treatment



Panel B. Skin Treatment



Panel C. Makeup - Face

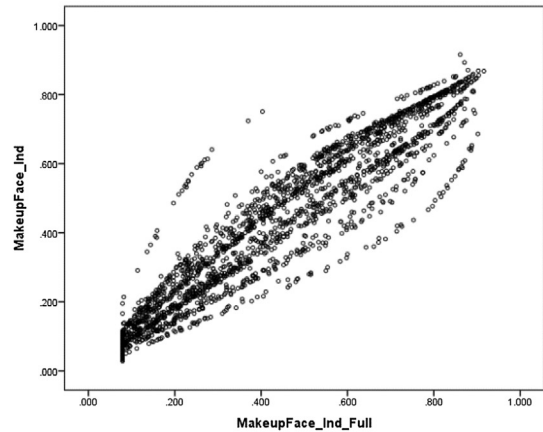
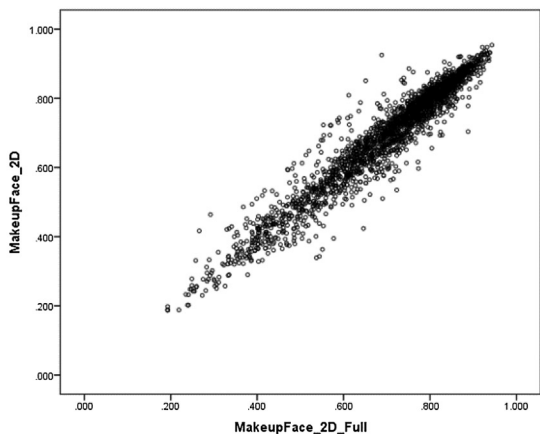
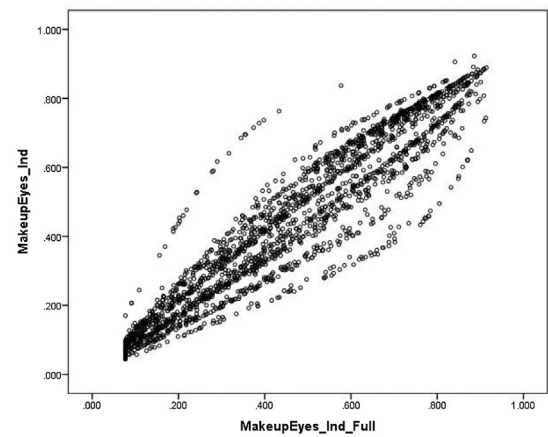
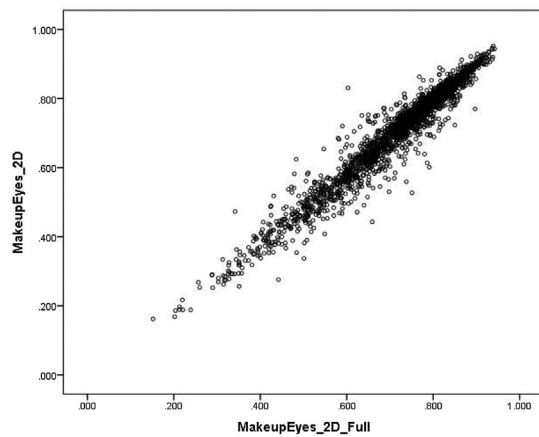
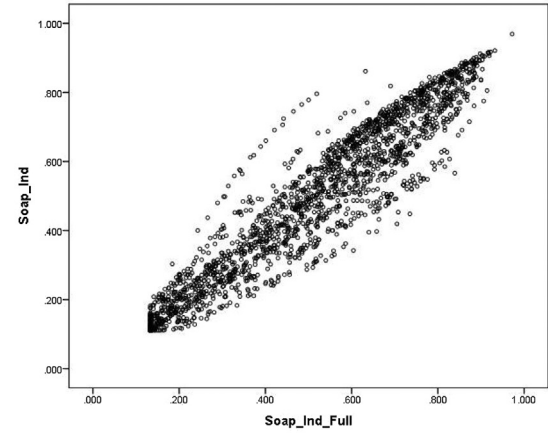
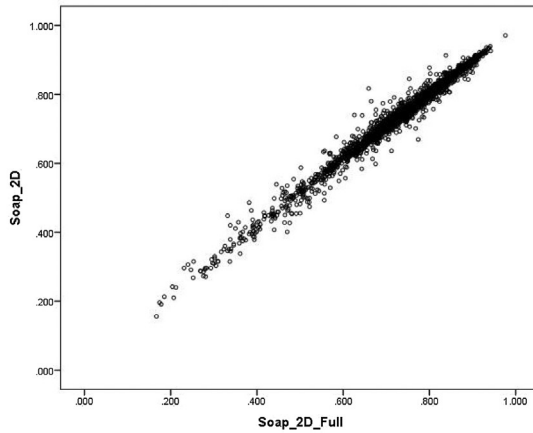


Fig. 3. Robustness to frontier misspecification.

Panel D. Makeup – Eyes



Panel E. Soap



Panel F. Deodorant

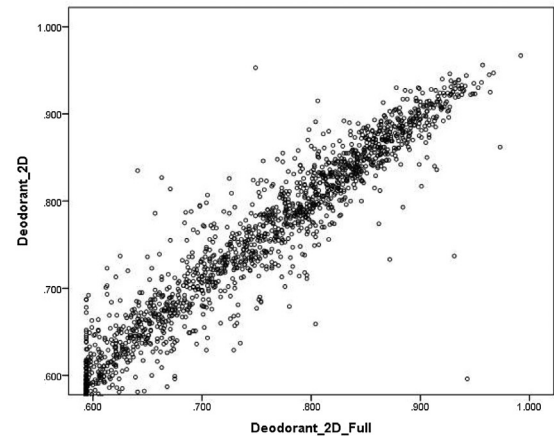
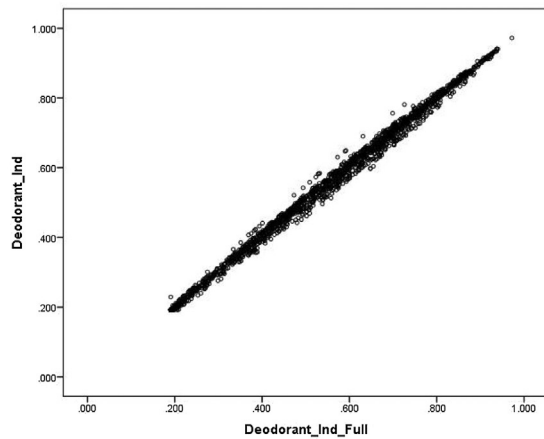


Fig. 3. (Continued)

valuable feature for internal benchmarking and assessing sales force performance, because it leads to more equitable efficiency assessments. The proposed model accounts for both observable

and unobservable market factors, leading to a more equitable assessment.

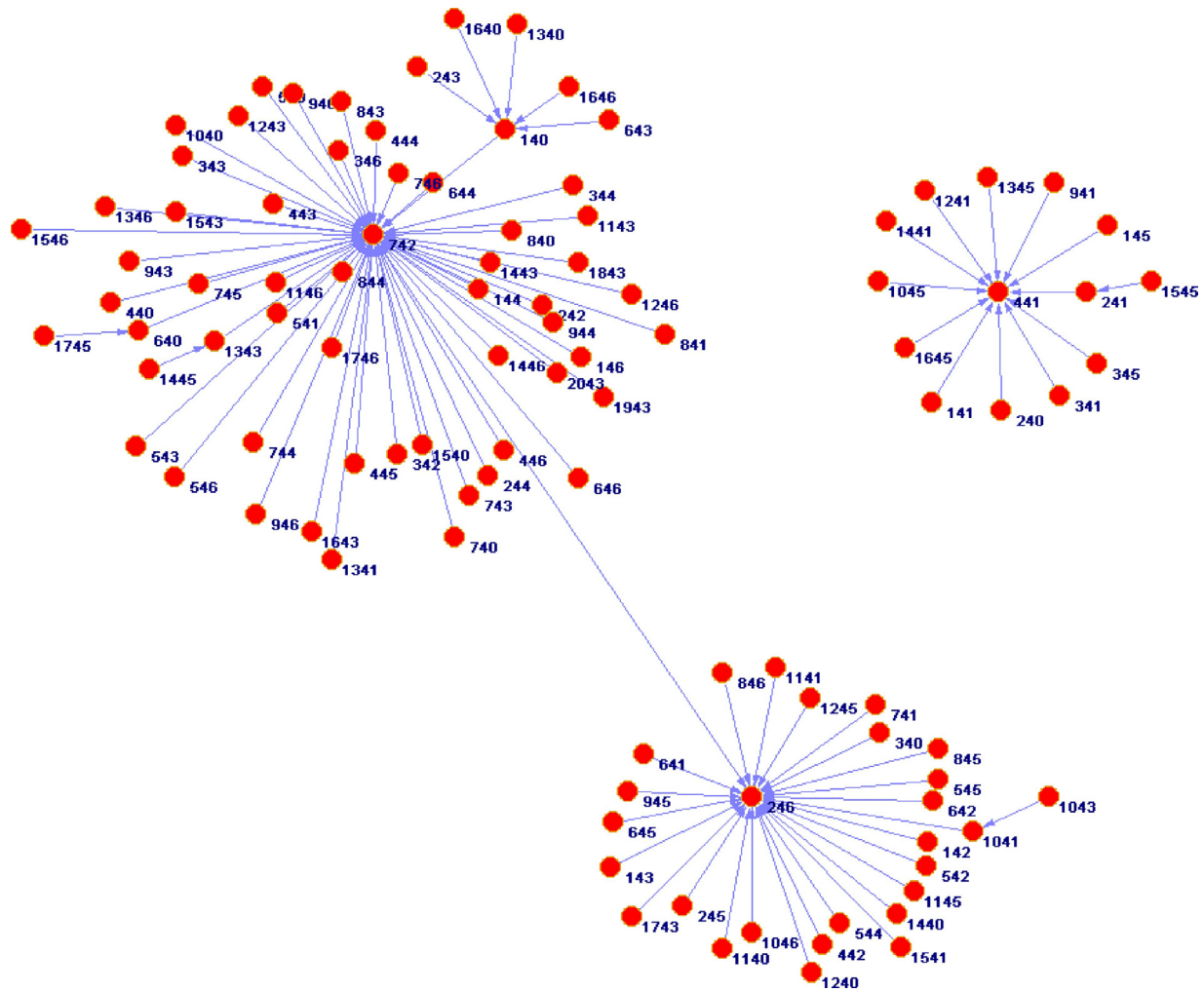


Fig. 4. Embedded knowledge transfer network for market 4.

Discussion and Implications

Our study contributes to the literature on internal benchmarking by proposing and establishing the robustness of a novel, multivariate, factor-analytic stochastic frontier regression, accounting for both observable and unobservable factors that affect sales efficiencies. It also contributes to sales management literature by drawing from the results of our proposed model and fostering knowledge sharing embedded in the sales force. Given an equitable estimation of salesperson efficiency, retailers can accurately identify and select those who represent best practices and those who can learn from them. Previous research has shown the importance of knowledge sharing within the sales force in the retail context, because it fosters leadership behavior (Bettencourt 2004), adaptive selling (Franke and Park 2006), improved service performance (Leong, Randall, and Cote 1994), and improved retail sales performance (Noble, Sinha, and Kumar 2002). Knowledge sharing in the sales realm requires extra motivational effort to create a positive environment in which salespeople become more willing to give and get (Steward et al. 2010). This positive environment builds in learning programs that nurture internal conversations, debates,

exploratory discussions, and teaching moments (Dweck 2012). The propensity of salespeople to engage in learning programs increases when they focus on any bit of best practice with proven impact on performance (Chan, Li, and Pierce 2014). To encourage full engagement, retailers should select salespeople to play the role of growth advisors (i.e., experts on the topic) and learners (i.e., underperforming salespeople) (Gino and Staats 2016). In such learning programs, salespeople can present their repertoires of skills, know-how, and outstanding practices that affect and are affected by their influence groups (Madhavan and Grover 1998). By assigning top performers to play the role of growth advisors and share their knowledge, retailers can disseminate the crucial know-how that resides only in the minds of a few key individuals across their sales force (Hyland and Beckett 2002).

To illustrate the contribution of our study to salesperson knowledge sharing, we show how retailers could use the estimated efficiencies to design learning programs across their sales force. We group *growth advisors* (i.e., top performers) and *learners* (i.e., underperformers) by a dyadic measure ($Gain_{ij}$) that accounts for the maximum gain in monthly sales profits expected

from the transfer of best practices from the *growth advisor* i to the *learner* i' :

$$Gain_{ii'} = \frac{\sum_{t=1}^{12} \sum_{j=1}^{11} \max \left\{ (E_{ijt} - E_{i'jt}) y_{i'jt}^*, 0 \right\}}{12}, \quad (5)$$

where,

E_{ijt} = efficiency of salesperson i in category j and month t , obtained from Eqs. (3) and (4), and

$y_{i'jt}^*$ = sales frontier for salesperson i' , category j in month t , estimated from Eq. (2).

The measures of $Gain_{ii'}$ indicate how much profit margin the franchisee and underperforming salesperson i' could gain from the transfer of best practices within each dyad. We recommend that the adjacency matrix formed by these measures across the sales force be analyzed as a network, to match growth advisors and learners as part of a particular session of a learning program. This step would be critical to nurturing a positive learning environment, because it aligns top performers with tested and proven expertise in the sale of a given product category with peers who struggle to sell the category (Dweck 2012).

Fig. 4 illustrates the network obtained for connected salespeople who can help or be helped in Market 4. Each node represents a salesperson (identified by the store code in the last two digits and the person's within-store code in the digits on the left); the arrows point from the learner toward the growth advisor. Fig. 4 represents the network as an unweighted directed graph, and therefore, the length of the links between nodes is defined arbitrarily to simplify the representation (a direct graph weighted by $Gain$ yields a very dense graph, impossible to interpret visually). Because all stores are located within the same market, it would be feasible for salespeople to meet at mutually convenient locations and time periods. The structure of this network shows two independent groups: a small group, centered on Salesperson 441, and a larger and more complex group formed by two connected sub-groups centered on Salespersons 742 and 246. This second group offers some interesting insights. First, with regard to the group centered on Salesperson 742, we see that Salesperson 1745 may learn from Salesperson 640 who, in turn, can learn from Salesperson 742. This type of indirect link happens because we computed our $Gain$ metric across 11 product categories. In other words, Salesperson 640 may teach his or her best practices in some categories but also learn from Salesperson 742 in other categories. The same explanation applies in the finding that Salesperson 742 is the center of learning for a large number of peers but can also learn from Salesperson 246. Rather than having all salespeople in the room for a best practice workshop, the retailer might focus on a few highly motivated salespeople. This process matches learners with top performers across markets and categories. For this reason, it is important not to interpret it as a typical social network, as previous sales researchers have done (Gonzalez, Claro, and Palmatier 2014). The network defined by $Gain$ reflects only first-order relationships and therefore should not be extrapolated to higher-order indirect effects. For example, degree centrality (weighted or unweighted) is a useful network measure to describe each salesperson, but eigenvector-centrality is not applicable (Bolander et al. 2015).

Fig. 5 depicts the entire network, across the sales force in all four markets, to illustrate the interesting structure of groups for particular sessions of the learning programs to share embedded knowledge. Low performers benefit from top performers' practices converted to knowledge and couched in the language of particular product categories and markets. A more complex structure with many more groups will arise when management chooses to define learning groups at the product category level, at which the links between growth advisors and learners are based on the relative efficiencies of a specific product category.

Previous research on learning suggests there should be concrete evidence of the real gains for the sales force and for managing efficiencies in the retail chain (Melton and Hartline 2013). Although we cannot show actual improvements (because the knowledge transfer program was not implemented during our research period), in Fig. 6 we show the weighted (by $Gain$) inbound and outbound degree centrality for all salespeople who should participate in the learning program, according to the maximum profit gains to be expected if learners reach the same level of sales efficiency as their designated growth advisor. Panel A in Fig. 6 shows the inbound degree centrality, measuring (in local currency) how much each salesperson can benefit others through the learning program. Salesperson 424, for example, could help his or her peers generate over \$10,000 in local currency by transferring his or her best practices to them. The best practices of Salesperson 733 could help generate close to \$10,000 of profits in local currency. In this cross-category analysis, we see only 33 growth advisors (of 481) who are sharing their best practices; moreover, the value of their help is highly concentrated in the top six advisors. Again, the number of advisors might be larger if the learning network were implemented on the basis of the efficiencies of one category at a time. Panel B, in Fig. 6, shows the outbound centrality, measuring the maximum gain expected by each salesperson from the learning program, with 475 learner salespeople benefiting from it. Notably, the number of growth advisors (33) and learners adds up to more than the actual size of the sales force, because some salespeople play both roles across product categories. As with the inbound centralities, the gains expected from the learners are highly skewed, with large disparity, suggesting that salespeople benefit from the learning program to varying degrees.

Limitations and Further Research

In this study, we have addressed the critical retail challenge of sharing in-store salespeople's embedded knowledge by implementing a cross-category, cross-salespeople internal benchmarking based on a multivariate factor-analytic stochastic frontier regression. Our illustration shows promising gains for a learning program based on growth advisors and learners who are identified and matched, according to our proposed internal benchmarking approach. Nevertheless, it is important to keep in mind that our proposed framework produces a relative performance assessment, in relation to the best attained by others, after accounting for observable and unobservable factors. Being "efficient" in a product category, in our model, does not necessarily mean that a salesperson has attained his or her maximum sales

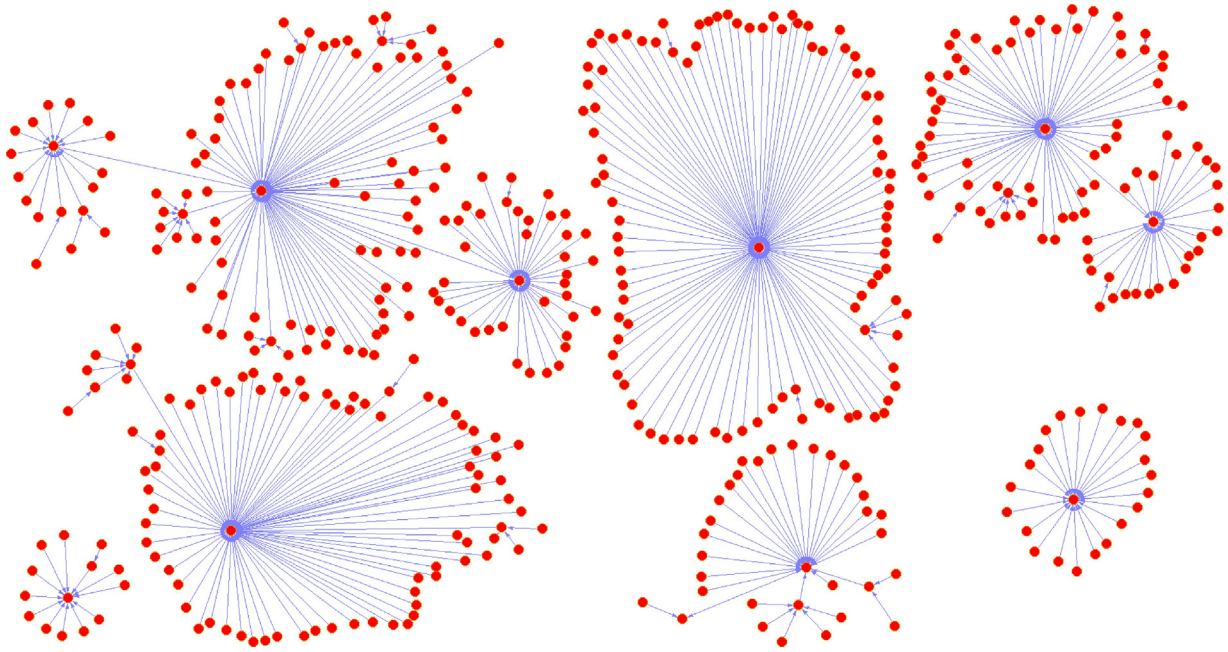


Fig. 5. Embedded knowledge transfer network across all markets.

potential in the focal category. It implies that his or her sales performance in that category is on par with the best in the sales force for the focal category, after taking into account observed environmental factors and sales in all other categories. Therefore, the growth potentials identified by our model are only as ambitious as a goal of replicating the results of the internal best performers.

Following common practice in stochastic frontier literature, we assumed a log-log link between inputs and outputs. One way to extend our proposed model would be to ignore the asymmetric errors in Eq. (2) and apply a SIR to multilevel data to obtain piecewise-linear link functions, which could be approximated by the closest parametric forms in a subsequent multivariate stochastic frontier model. Despite the potential biases caused by ignoring the asymmetric errors in the first stage and the need for a multilevel extension of multivariate SIR, additional research could endeavor to achieve this potential extension.²

We relied on available franchisee and market data from a cosmetics retailer to develop our model; we thus studied franchisees who were not able to collect reliable metrics for competition, because cosmetic products appear in many retail formats (pharmacies, drugstores, department stores, general merchandise stores, grocery stores) and in online and direct marketing channels. In future applications of our model, managers in other industries with access to multilevel data could account for other available and reliable observable variables.

Furthermore, our proposed internal benchmarking framework, like other performance measurement tools (Kumar, Sunder, and Leone 2014), is intended to evaluate the relative performance of different product categories and different salespeople after controlling for all available observed environmental

factors. If we could control for all extraneous variables, the performance gap identified by our framework, by definition, would be attributable to the salesperson. In practice—because it is impossible to identify and measure properly all extraneous variables—it is not possible to explain unequivocally the differences in performance across salespeople. It is valuable, therefore, to motivate salespeople to transfer embedded knowledge.

Although our benchmarking framework cannot prove that all gaps identified can be filled by specific behaviors or characteristics of salespeople, it does serve to focus managers' attention on the small number of salespeople and categories that offer the greatest growth opportunities to the sales force. It is also important to note that our benchmarking framework is not intended to be normative or prescriptive; it does not suggest the exact course that managers should take to overcome salesperson inefficiency and motivate low performers to replicate top performers' results. Our framework should be viewed as the first diagnostic step in a systematic and equitable benchmarking study aimed at sharing embedded knowledge in the sales realm. The next step is an approach known as *process benchmarking*, through which best practices can be systematically examined, codified, and widely transferred internally (O'Dell and Grayson 1998). It shows the extent to which identified performance gaps can be filled, and which course of managerial action should be addressed, by comparing the practices of top performers with those of bottom performers and identifying areas of distinction. In line with the call for careful examination of in-store salespeople (Haas and Kenning 2014), the main practical implication of our internal benchmarking framework is that it helps managers focus on a few “prime suspects,” which is helpful when they face multiple categories and hundreds of salespeople, all operating under different environmental conditions.

² We acknowledge an anonymous reviewer for proposing such an extension.

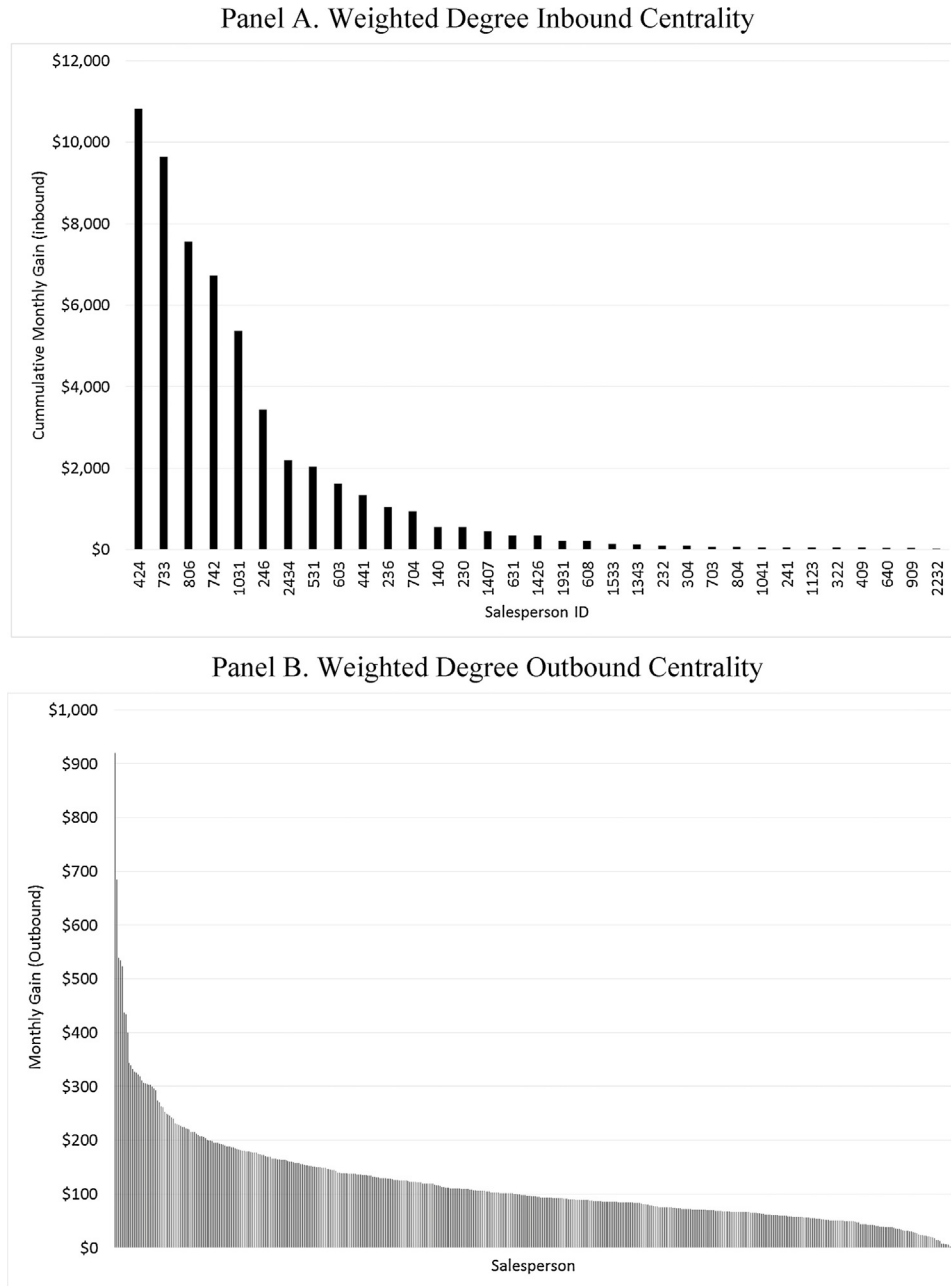


Fig. 6. Expected profit gains of learning programs.

Appendix A.

(A.1) Univariate Stochastic Frontier Regression

The SFR accounts for category j , salesperson i , month t , and an upper bound y_{ijt}^* , or the sales frontier. The frontier is shaped by the top performing salespeople in category j , and can be defined as a function of environmental factors. In practice, because the retailer never has full information about the market environment and cannot identify the top sales performers with certainty, y_{ijt}^* is not directly observable and must be inferred, conditional on the requirement that y_{ijt}^* must be no smaller than y_{ijt} , the actual annual sales in category j for salesperson i in month t . The retailer

intends to use the inferred y_{ijt}^* as a performance benchmark in gauging its growth potential (i.e., $\Delta_{ijt} \equiv y_{ijt}^* - y_{ijt}$) and sales efficiency (i.e., $E_{ijt} \equiv y_{ijt}/y_{ijt}^*$).

A well-known approach to infer the sales frontier (y_{ijt}^* 's) is to apply SFR to one product category at a time, regressing the actual sales (y_{ijt} 's) against a set of observed salespeople and market-specific environmental factors (X_{it} 's) over time (Greene 2002). The same set of environmental factors can be applied to all categories (thus only the i subscript in X_{it}), with each environmental factor's actual impact on a particular category's sales frontier determined empirically. In essence, such an approach involves benchmarking salespeople against one another within each focal category, irrespective of other product categories. After account-

ing for differences in the observed environmental factors, the top performing salespeople in the focal category help define a sales frontier for the category. In a standard SFR, the sales frontier of category j for salesperson i and month t is given by:

$$y_{ijt}^* = f(X_{it}, \beta_j) \cdot \exp(v_{ijt}), \quad (\text{A.1})$$

where $f(\cdot)$ is a function with its form to be specified and parameters (β_j) to be determined; and $\exp(v_{ijt})$ reflects the shift of the frontier due to all the environmental factors that are influential but are unknown or unknowable to the retailer. Furthermore, v_{ijt} is assumed to be idiosyncratic to salesperson i , category j , and month t and is purely random from the analyst's perspective.

Sales efficiency E_{ijt} (defined as the ratio between y_{ijt} and y_{ijt}^*) can also be written as an exponential $E_{ijt} \equiv y_{ijt}/y_{ijt}^* = \exp(-u_{ijt})$, where $u_{ijt} > 0$, because by definition $y_{ijt} \leq y_{ijt}^*$ and $E_{ijt} \leq 1$. u_{ijt} can be interpreted as a measure of the percentage by which salesperson i 's sales in category j fail to reach the frontier in month t , the level achieved by the best performing counterparts. Along with Eq. (A.1), observed sales by salesperson i and category j can be written as:

$$y_{ijt} = y_{ijt}^* \cdot E_{ijt} = f(X_{it}, \beta_j) \cdot \exp(v_{ijt}) \cdot \exp(-u_{ijt}). \quad (\text{A.2})$$

Assuming that $f(X_{it}, \beta_j)$ takes a log-linear form, Eq. (A.2) can be re-written as:

$$\ln(y_{ijt}) = \beta_{0j} + \sum_{k=1}^K \beta_{kj} \ln(X_{kjt}) + v_{ijt} - u_{ijt}, \quad (\text{A.3})$$

where K denotes the number of observed environmental factors. To consider Eq. (A.3) in our kind of multi-level data, we make two additional assumptions: (1) v_{ijt} is distributed i.i.d. normal across salespeople and months with standard deviation σ_{vj} , such that $v_{ijt} \sim N(0, \sigma_{vj})$; and (2) u_{ijt} is distributed i.i.d. half-normal across salespeople and months with standard deviation σ_{uj} , such that $u_{ijt} \sim |N(0, \sigma_{uj})|$. Because it is non-negative, the second error component ($u_{ijt} \geq 0$) in $u_{ijt} \sim |N(0, \sigma_{uj})|$ on Eq. (A.3) ensures that the fitted regression line is shaped by data points near the top, rather than the center, as in standard regression. Therefore, we can estimate β_j , σ_{vj} , and σ_{uj} from the observed sales data (y_{ijt} 's) and environmental factors (X_{it} 's), which in turn allows us to infer the frontier as $y_{ijt}^* = \exp(\beta_{0j} + \sum_{k=1}^K \beta_{kj} \ln(X_{kjt}) + v_{ijt})$.

Appendix B.

(B.1) Estimation of the Multivariate Factor-Analytic Extension of Stochastic Frontier Model

As $\sigma_j^2 \equiv \sigma_{vj}^2 + \sigma_{uj}^2$, and $\lambda_j \equiv \frac{\sigma_{uj}}{\sigma_{vj}}$, let ϕ and Φ denote, respectively, the PDF and CDF of the standard normal distribution. The likelihood contribution of category j in salesperson i (conditional on ε_{ijt}) can be written as (Kumbhakar and Lovell 2000):

$$L_{ijt}(\varepsilon_{ijt}) = 2\sigma_j^{-1} \phi(\varepsilon_{ijt}\sigma_j^{-1}) \Phi(-\lambda_j \varepsilon_{ijt}\sigma_j^{-1}), \quad (\text{B.1})$$

where $\varepsilon_{ijt} \equiv v_{ijt} - u_{ijt} = \ln(y_{ijt}) - [\beta_{0j} + \sum_{k=1}^K \beta_{kj} \ln(X_{kjt}) + \sum_{p=1}^P \gamma_{pj} Z_{pit}]$. Because Z_{it} ,

the latent factor scores, are unobserved they must be integrated out, leading to the (unconditional) likelihood:

$$L = \prod_i \int \left\{ \prod_j 2\sigma_j^{-1} \phi(\varepsilon_{ijt}|Z_{it}) \sigma_j^{-1} \right\} \Phi(-\lambda_j(\varepsilon_{ijt}|Z_{it}) \sigma_j^{-1}) \phi(Z_{it}) dZ_{it}. \quad (\text{B.2})$$

We estimate our stochastic frontier factor model via simulated maximum likelihood (SML), replacing the P-dimensional integration over Z_i in Eq. (B.2) with a summation over 300 P-dimensional Halton draws to simulate the latent factor scores (with a different set of draws for each salesperson):

$$L \approx \prod_i \left\{ \frac{1}{K} \sum_{k=1}^K \prod_j \left[2\sigma_j^{-1} \phi(\varepsilon_{ijt}|Z_{it}) \sigma_j^{-1} \right] \Phi(-\lambda_j(\varepsilon_{ijt}|Z_{it}) \sigma_j^{-1}) \right\}. \quad (\text{B.3})$$

A gradient search on Eq. (B.3) leads to estimates of the parameters for the stochastic frontier (γ_j and β_j), along with the parameters for the residual distributions (λ_j and σ_j). Conditional on these model parameters, the latent factor scores for salesperson i (Z_{it}) can be obtained as a weighted average of a set of random draws (Z_r) from the standard normal distribution, $N(0, I_P)$, where $r \in [1, \dots, R]$, and P is the dimensionality of the factor scores:

$$Z_{it} = \frac{\sum_{r=1}^R Z_r \prod_j \left[\phi(\varepsilon_{ijt}|Z_r) \sigma_j^{-1} \right] \Phi(-\lambda_j(\varepsilon_{ijt}|Z_r) \sigma_j^{-1})}{\sum_{r=1}^R \prod_j \left[\phi(\varepsilon_{ijt}|Z_r) \sigma_j^{-1} \right] \Phi(-\lambda_j(\varepsilon_{ijt}|Z_r) \sigma_j^{-1})}. \quad (\text{B.4})$$

Given the estimates of factor loadings ($\hat{\gamma}_j$) and regression coefficients ($\hat{\beta}_j$) for category j , along with salesperson i 's factor scores ($\hat{Z}_{it}$) and observed environmental factors (X_{it}), the expected (log) sales potential for product category j of salesperson i is $\hat{\beta}_{0j} + \sum_{k=1}^K \hat{\beta}_{kj} \ln(X_{kjt}) + \sum_{p=1}^P \hat{\gamma}_{pj} \hat{Z}_{pit}$. This estimate represents the best performing (log) sales per customer the retailer could expect for category j of salesperson i and month t , given the observed environmental factors and its sales in all the other categories of salesperson i and month t . Note that the factor structure defined by the factor loadings and scores accounts for correlation in sales potentials across product categories, so our proposed model can parsimoniously yet adequately leverage sales data from all the other categories to determine how much more the retailer could have sold in the focal category, as benchmarked against internal top performers. This factor structure also allows for unobserved heterogeneity in sales potential across salespeople, because each salesperson has a set of unique factor scores along the latent dimensions, which results in salesperson-level adjustments in the sales frontier.

Given $\hat{\lambda}_j$ and $\hat{\sigma}_j$, and the residual estimate $\hat{\varepsilon}_{ijt} = \ln(y_{ijt}) - \hat{\beta}_{0j} - \sum_{k=1}^K \hat{\beta}_{kj} \ln(X_{kjt}) - \sum_{p=1}^P \hat{\gamma}_{pj} \hat{Z}_{pit}$, Eqs. (B.3) and (B.4) produce category and salesperson-specific measures of relative

sales efficiency. These measures benchmark the retailer's performance in one product category and salesperson against a frontier estimated across all salespeople, taking into account not only the observed environmental factors but also observed sales per customer in all the other product categories.

Appendix C.

Comparing and Contrasting the Proposed Framework and Two-Stage DEA and MSIR approach

We identify multiple benefits of our multivariate approach to assess salespeople's performance when comparing it against the two-stage DEA and MSIR proposed by [Sridhar, Mantrala, and Naik \(2014\)](#). First, their efficiency scores for each salesperson would be obtained by DEA in the first stage, thereby incurring problems of measurement error estimation ([Gauri 2013](#)), as presented in [Table C1](#). In contrast, our proposed model relies on dual errors, a symmetric error accounting for measurement and random errors, and an asymmetric error accounting for the variation in log-efficiencies across salespeople. Second, the first-stage DEA produces a single cross-category efficiency measure for each sub-DMU (in our case, the salesperson), thereby ignoring the possibility that a salesperson might be at the frontier in one product category but need improvement in others. In contrast, though we account for the interdependencies among product categories across salespeople and time periods, we obtain a multivariate frontier that allows us to measure efficiency for each salesperson in each product category. Third, we consider valuable information contained in the relationship among the multiple outputs (product categories) only in the second-stage analysis of DMUs (in our case the stores) via MSIR, which does not affect the efficiency measurements of the sub-DMUs (salesperson). In contrast, this relationship among the multiple product categories is directly incorporated into our frontier analysis and resulting measures of efficiency for each salesperson and product category.

Fourth, SIR (and its multivariate extension), is a minimum-variance estimator that minimizes squared errors or covariances among predictors within and across slices. Therefore, the multivariate functions estimated by MSIR are not frontiers, because they are designed to pass through the middle of the error "cloud." Interpreting deviations from the MSIR function as (in)efficiency leads to a "drive to mediocrity," a common criticism of statistical approaches based on the minimization of symmetric random errors ([Kumbhakar and Lovell 2000](#)). Fifth, though MSIR accounts for the covariances among predictors and dependent variables across multiple outputs and DMUs, resulting in linear functions that best explain each output as functions of the predictors, it still defines a single linear function for each output. In other words, all DMUs are evaluated in relation to the same linear function for each output, albeit at different locations (defined by the inputs) of the function. In contrast, our multivariate factor-analytic stochastic frontier regression takes advantage of the three-mode (salespeople by categories by months) nature of the data, resulting in a more flexible, equitable frontier that is adapted to each salesperson and category.

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Table C1
Modeling benchmarking and key benefits.

Modeling techniques	Error structure	Estimation approach	Managerial implication	Previous research
DEA	Account for normal random symmetric error (stochastic DEA)	Univariate non-parametric frontier	Ranking and diagnosis	Donthu and Yoo (1998) and Grewal et al. (1999)
SFR	Account for normal random symmetric and half-normal asymmetric error	Univariate stochastic frontier estimation	Ranking and diagnosis	Gauri (2013) and Assaf et al. (2012)
Two-stage (DEA + Regression)	Account for normal random symmetric error	Multivariate sliced inverse regression with a single semi-parametric frontier and symmetric errors	Ranking and diagnosis	Sridhar, Mantrala, and Naik (2014)
Multivariate Factor-Analytic Stochastic Frontier	Account for multivariate, correlated normal symmetric and half-normal asymmetric error	Simulation-based estimation of latent factors robust to unobservable factors affecting performance	Equitable assessment of top performers and those in need of improvement (effective learning programs)	Our frontier model

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