



## Marketing Science

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To cite this article:

Jeffrey P. Dotson, Greg M. Allenby, (2010) Investigating the Strategic Influence of Customer and Employee Satisfaction on Firm Financial Performance. Marketing Science 29(5):895-908. <https://doi.org/10.1287/mksc.1100.0584>

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# Investigating the Strategic Influence of Customer and Employee Satisfaction on Firm Financial Performance

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The ability to demonstrate the impact of marketing action on firm financial performance is crucial for evaluating, justifying, and optimizing the expenditure of a firm's marketing resources. This presents itself as a formidable task when one considers both the variety and potential influence of marketing activity. We propose a hierarchical Bayesian model of simultaneous supply and demand that allows us to formally study the financial impact of a variety of marketing activities, including those that operate on different timescales. The supply-side model provides insight into how the firm allocates resources across its various subunits. We illustrate our approach in a services context by integrating data from three independent studies conducted by a large national bank. Our model allows customer and employee satisfaction to influence firm profitability by moderating the conditional relationship between the bank's operational inputs and its proclivity to produce revenue.

*Key words:* customer satisfaction; employee satisfaction; endogeneity; resource allocation

*History:* Received: July 1, 2008; accepted: April 13, 2010. Published online in *Articles in Advance* July 29, 2010.

## 1. Introduction

Marketing managers face increasing pressure to demonstrate the impact of their actions on firm financial performance. In practice, linking action to outcome poses a variety of methodological challenges. The influence of marketing intervention is often complex and can include multiple intervening, mediating, and moderating effects, whose results may be manifest on different timescales. Managers, for example, can directly influence sales through the use of short-term (i.e., tactical) activities like price and incentive promotions, or, rather, they can indirectly influence sales by modifying consumer attitudes toward the firm through the use of long-term (i.e., strategic) actions like advertising, service climate improvements, or increasing customer satisfaction. To capture the effects of tactical and strategic actions, models are needed that can integrate data from a variety of sources.

Response models calibrated using market data must also account for the presence of endogenously determined covariates. If managers set the inputs of a marketing response model,  $X$ , with an expectation of how they will influence the outcome,  $y$ , the inputs can no longer be treated as exogenous to the system of study. Endogeneity violates the assumptions of standard estimation approaches, which leads to misestimation of the true relationship between  $X$  and  $y$ . Resulting actions taken on the part of managers can

lead to a misallocation of firm resources. Endogeneity in response models can be effectively addressed by modeling the joint distribution of both  $X$  and  $y$ .

In this paper we propose a hierarchical Bayesian model that allows us to study the strategic influence of satisfaction on firm financial performance. We model unit-level revenue production as a function of managerially controllable inputs, and we allow latent levels of customer and employee satisfaction to exert an indirect influence on financial performance by altering the factor productivity of the firm's short-term actions. Structure is imposed upon the parameters of our model through the estimation of a system of simultaneous supply and demand. Our model explicitly deals with the potential for endogeneity in the input variables and produces managerially reasonable parameter estimates. By *reasonable*, we mean estimates that satisfy managerial expectations such as the algebraic sign of price elasticity or the presence of diminishing marginal returns. In the case of production functions, reasonable parameter values must guarantee the presence of diminishing returns to scale in the input variables, thus allowing for the existence of an optimal, interior solution to the resource allocation problem.

Our paper contributes to the literature in three ways. First, we advance the literature on strategically determined covariates by allowing for multiple, multiplicative inputs in a production function

framework with multiple budget constraints. This approach allows us to make inference about the allocation procedure of the firm (i.e., does the firm engage in centralized versus decentralized decision making). Specifically, we are able to assess how efficiently the firm coordinates the utilization of resources across its various subunits. Second, we extend the literature linking customer satisfaction to firm performance by conducting analysis at a more microlevel. Extant satisfaction-performance research has primarily focused on demonstrating the connection between aggregate measures of customer satisfaction and firm-level financial indicators (e.g., Tobin's  $Q$ , stock returns, etc.; Anderson et al. 1994, 2004). Third, we examine the influence of both customer and employee satisfaction in-line with recent research emphasizing the role of customer co-production, where the production process is influenced by both variables (Bendapudi and Leone 2003).

We apply our model to data provided by a national financial services firm where we integrate unit-level (i.e., banking branch) data from three independently conducted studies. We show that customer and employee satisfaction have both direct and indirect effects on branch-level revenue production. Our model allows us to assess the relative benefits of engaging in short-term versus long-term marketing activities. In addition, our results differ from a simple analysis that indicates that customer satisfaction has a negative impact on revenue production.

The remainder of this paper is organized as follows. Section 2 presents the general form of our model, the likelihood, and estimation strategy. In §3 we describe the data and setting used to empirically demonstrate our model. Alternative models are outlined in §4. Results are presented and discussed in §5. Final thoughts and areas for future research are offered in §6.

## 2. Model

The relationship between marketing activity and financial performance has received extensive attention in the marketing literature (Gupta and Zeithaml 2006, Rust et al. 2004). Existing models are often constructed using what are referred to as chain-links of effects. The service profit chain, for example, attempts to trace the influence of managerial action to firm performance through its influence on employee and customer satisfaction (Maxham et al. 2008, Kamakura et al. 2002, Heskett et al. 1994). Although these models are useful in the sense that they provide directional evidence that constructs like customer and employee satisfaction are, in fact, positively correlated with sales production, they do not impose the sort of structure on the response process required to optimize the firm's utilization of resources.

In this section we develop a hierarchical Bayesian model that integrates estimation of the effects of multiple marketing activities through simultaneous analysis of panel and cross-sectional data. Implicit in our approach is the notion that firms face two fundamental types of decisions: short-term (i.e., tactical) and long-term (i.e., strategic). By relating these decisions to a scalar outcome we are able to formally assess the trade-offs associated with engaging in tactical versus strategic marketing activities.

Our general modeling approach consists of the following two major components.

### 2.1. Demand Model

We begin by specifying a response model that relates short-term marketing activities to a unit-level financial outcome. We express revenue,  $y_{it}$ , realized by unit  $i$  in time  $t$  as a multiplicative function of  $k$  operational inputs,  $\{x_{kit}\}$ . Although we restrict our attention to a revenue generation process,  $y_{it}$  in Equation (1) could represent a variety of outcomes like unit sales or the number of new customers acquired:

$$y_{it} = \beta_{0i} \left( \prod_{k=1}^K x_{kit}^{\beta_{ki}} \right) e^{\varepsilon_{it}}. \quad (1)$$

Logarithmic demand models have been used extensively in both economic and marketing applications (Lilien et al. 1992). These models enable us to capture diminishing returns to scale in the inputs and allow us to interpret the  $\{\beta_{ki}\}$  as elasticities. We view the collection of  $\{\beta_{ki}\}$  in Equation (1) as a joint representation of the firm's technology (Varian 1992);  $\{\beta_{ki}\}$  fully characterize the expected relationship between operational or tactical inputs,  $\{x_{kit}\}$ , and a realized outcome,  $y_{it}$ . We refer to marketing actions that alter the conditional distribution of  $y_{it} | \{x_{kit}\}$  through the response coefficients  $\{\beta_{ki}\}$  as strategic (Mela et al. 1997).

We allow long-term strategic actions to influence the revenue generation process in Equation (1) by constructing a hierarchy on  $\{\beta_i\}$ :

$$\beta_i = \Gamma' \mu_i^* + \eta_i, \quad (2)$$

where  $\beta_i$  is a  $K + 1$  vector of response coefficients, and  $\mu_i^*$  is a vector of  $S + 1$  variables that can include observable characteristics of the production process (e.g., product attributes, average advertising expenses, etc.) or unobservable constructs like customer satisfaction or brand equity:

$$\mu_i^* = [1 | \mu_{1i} | \cdots | \mu_{Si}]'. \quad (3)$$

The former,  $\beta_i$ , can be measured directly, whereas the latter,  $\mu_i^*$ , can be assessed through the use of survey

data. Estimates of unobservable or latent constructs can be related to observed data through Equation (4):

$$z_{ih} \sim N \left( \mu_i = \begin{bmatrix} \mu_{1i} \\ \vdots \\ \mu_{Si} \end{bmatrix}, \Sigma_i \right), \quad (4)$$

where  $z_{ih}$  is a vector that contains survey responses to multiple questions for individual  $h$  in unit  $i$ ,  $S$  denotes the number of items in the survey instrument, and  $\mu_i$  is the estimated vector of interest included in Equation (3). Note that each element of the vector  $\mu_i$  corresponds to the estimated mean response of a particular question for unit  $i$  in the survey instrument, and  $\Sigma_i$  captures covariation across questions. This is done in anticipation of our empirical application where we connect cross-sectional employee and customer satisfaction data to a time series of operational measures through a set of shared parameters in Equation (2). We allow for cross-unit heterogeneity by specifying a distribution of random effects for both the location and covariance matrix of Equation (4):

$$\mu_i \sim N(\bar{\mu}, V_\mu), \quad (5)$$

$$\Sigma_i \sim IW(\bar{\nu}, \Omega). \quad (6)$$

We recognize that the use of multivariate normality in Equation (4) is a strong assumption, particularly in the case of survey data. However, it is important to note that  $\mu_i$  is the estimate we are most concerned with, as it feeds forward into the hierarchical distribution for  $\{\beta_i\}$ . By assuming normality in Equation (4), we are able to derive (in closed form) a full conditional distribution for  $\mu_i$  that is also normal. The assumption of normality for the latent mean of the satisfaction distribution  $\mu_i$  is justified through the use of the central limit theorem. The advantage of employing Equation (4) rather than simply imputing the calculated average value for each unit is that large values of  $\Sigma_i$  indicate unit-level survey response items with large variance whose effects are downweighted in inference about  $\Gamma$  in Equation (2).

Collectively, Equations (1)–(6) form the basis of a model of integrated decision making, where the influence of strategic action is manifest through the hyperparameters of a hierarchical response model. We are informed about influence of tactical decisions on firm performance from within-unit variation across time (Equation (1)), whereas learning about the effects of strategic decisions occurs across units (Equation (2)).

## 2.2. Supply Model

Response models calibrated using market data must account for the possibility that the operational inputs are endogenous to the system of study (Yang et al. 2003).

This occurs if managers set the inputs,  $X$ , with an expectation of how they will affect the response outcome,  $y$ . The presence of endogenously determined covariates has been shown to yield parameter estimates that are both biased and inconsistent (Villas-Boas and Winer 1999, Berry 1994). We address this issue by constructing a model that reflects our belief about the managerial decision process that gives rise to observed input variables  $X$ . Joint modeling of both the inputs  $X$  and output  $y$  of the response process has been shown to solve the issue of endogeneity, thus yielding consistent estimates of model parameters (Otter et al. 2009, Manchanda et al. 2004).

We implement this approach by specifying the supply-side model for  $X$  defined by Equation (7). In this model we assume that managers have at least an implicit knowledge of the response process defined by Equation (1) and set levels of marketing inputs  $\{x_{kit}\}$  to maximize firm profit over a finite time horizon,  $T$ , subject to a budget constraint. Managers identify optimal values of  $\{x_{kit}\}$  by solving the constrained optimization problem presented in Equation (7):

$$\begin{aligned} \max_{\{x_{kit}\}} \quad & \sum_i \sum_t \left( \beta_{0i} \left( \prod_{k=1}^K x_{kit}^{\beta_{ki}} \right) - \sum_{k=1}^K p_{kit} x_{kit} \right) \\ \text{subject to} \quad & \sum_i \sum_t p_{kit} x_{kit} \leq m_k, \end{aligned} \quad (7)$$

where  $p_k$  is the cost and  $m_k$  denotes the budget constraint for input  $k$ . The first term in Equation (7) corresponds to the revenue generation process defined by Equation (1), and the second term captures the total cost of inputs  $\{x_{kit}\}$ . Deriving a supply-side model from the constrained maximization problem presented in Equation (7) provides us with an efficient mechanism for studying the coordination of resources across both units of analysis and input variables. Ultimately, this will allow us to make inference about the structure of decision authority (i.e., centralized versus decentralized) within the firm.

The ideal solution to this allocation problem is obtained by first expressing the auxiliary function ( $\mathcal{L}$ ) presented in Equation (8) and then identifying the set of  $\{x_{kit}^*\}$  that jointly maximize this function:

$$\begin{aligned} \mathcal{L} = \sum_i \sum_t \left( \beta_{0i} \left( \prod_{k=1}^K x_{kit}^{\beta_{ki}} \right) - \sum_k p_{kit} x_{kit} \right) \\ - \sum_k \lambda_k \left( \sum_i \sum_t p_{kit} x_{kit} - m_k \right). \end{aligned} \quad (8)$$

This is accomplished by solving the first-order conditions presented in Equation (9) for each unit, input, and time period:

$$\frac{\partial \mathcal{L}}{\partial x_{kit}} = 0 \quad \forall k, i, t. \quad (9)$$

Equation (9) describes a system of first-order conditions that can be used to determine optimal values of  $\{x_{kit}\}$  (Zellner et al. 1966). By taking logs of this system of equations, we can solve for the profit-maximizing values of all input variables,  $\{x_{it}^*\}$ , via Equation (10). For a solution to exist, the response function defined in Equation (1) must be a legitimate economic production function. That is, it must exhibit diminishing returns to scale for positively valued inputs  $X$ . This is accomplished if  $\beta_{ki} > 0$  for all  $k$  and  $i$ , and  $\sum_{k=1}^K \beta_{ki} \leq 1$ . If these conditions are met, Equation (1) subsumes the properties of a Cobb–Douglas production function:

$$\begin{aligned} \ln(x_{it}^*) &= \begin{bmatrix} \ln(x_{1it}^*) \\ \vdots \\ \ln(x_{Kit}^*) \end{bmatrix} = \begin{bmatrix} (\beta_{1i} - 1) & \cdots & \beta_{Ki} \\ \vdots & \ddots & \vdots \\ \beta_{1i} & \cdots & (\beta_{Ki} - 1) \end{bmatrix}^{-1} \\ &\quad \times \begin{bmatrix} \ln(\lambda_1 + 1) - \ln(\beta_{0i}) - \ln(\beta_{1i}) + \ln(p_{1it}) \\ \vdots \\ \ln(\lambda_K + 1) - \ln(\beta_{0i}) - \ln(\beta_{Ki}) + \ln(p_{Kit}) \end{bmatrix}. \end{aligned} \quad (10)$$

We allow observed realizations  $\{x_{kit}\}$  to deviate from the optimal solution  $\{x_{kit}^*\}$  by introducing error  $\{\zeta_{kit}\}$  into the maximization problem defined in Equation (7). Suboptimal allocation of marketing resources occurs as a result of uncertainty regarding the cost for each input,  $\{C_{kit}\}$ . Management allocates  $\{x_{kit}\}$  across inputs, units, and time periods using  $C_{kit}^* = C_{kit} e^{\zeta_{kit}} = (p_{kit} x_{kit}) e^{\zeta_{kit}}$ , where input cost error can arise from a variety of sources, including uncertainty about input prices,  $\{p_{kit}\}$ , unanticipated fixed and variable expenses, etc.

### 2.3. Likelihood and Estimation

We employ a full-information Bayesian approach to estimate our model, where the likelihood can be expressed as follows:

$$\begin{aligned} l(\text{data} \mid \text{else}) &= \prod_i \prod_t \pi(\ln(y_{it}) \mid \ln(\{x_{kit}\})) \pi(\ln(\{x_{kit}\})) \\ &= \prod_i \prod_t \pi(\hat{\varepsilon}_{it}) \pi(\{\hat{\zeta}_{kit}\}) \left| J_{it} \right|_{\hat{\zeta} \rightarrow \ln(x)}. \end{aligned} \quad (11)$$

The quantities  $\hat{\varepsilon}_{it}$  and  $\{\hat{\zeta}_{kit}\}$  are defined in Equations (12) and (13), respectively, and  $|J_{it}|_{\hat{\zeta} \rightarrow \ln(x)}$  is the Jacobian term that captures dependencies in the mapping of  $\hat{\zeta} \rightarrow \ln(x)$ . The Jacobian resulting from the change of variables from  $\hat{\varepsilon} \rightarrow \ln(y)$  is trivially equal to 1:

$$\hat{\varepsilon}_{it} = \ln(y_{it}) - \left( \ln(\beta_{0i}) + \sum_{k=1}^K \beta_{ki} \ln(x_{kit}) \right), \quad (12)$$

$$\begin{aligned} \begin{bmatrix} \hat{\zeta}_{1it} \\ \vdots \\ \hat{\zeta}_{Kit} \end{bmatrix} &= \begin{bmatrix} (\beta_{1i} - 1) & \cdots & \beta_{Ki} \\ \vdots & \ddots & \vdots \\ \beta_{1i} & \cdots & (\beta_{Ki} - 1) \end{bmatrix} \ln(\mathbf{x}_{it}) \\ &\quad - \begin{bmatrix} \ln(\lambda_1 + 1) - \ln(\beta_{0i}) - \ln(\beta_{1i}) + \ln(p_{1it}) \\ \vdots \\ \ln(\lambda_K + 1) - \ln(\beta_{0i}) - \ln(\beta_{Ki}) + \ln(p_{Kit}) \end{bmatrix}. \end{aligned} \quad (13)$$

Simultaneity present in the specification of Equation (13) results in the nontrivial Jacobian defined by Equation (14). Simultaneity in our model arises from the inclusion of a multiplicative demand model and corresponding supply-side model derived in Equation (10). The optimal value of each input,  $\{x_k\}$ , is a function of all other inputs,  $\{x_{-k}\}$ :

$$\left| J_{\hat{\zeta} \rightarrow x} \right| = \left| \sum_{k=1}^K \beta_k - 1 \right|. \quad (14)$$

It is important to note that Equation (13) can only be evaluated for values of  $\beta_{ki} > 0$ . Furthermore, the Jacobian in Equation (14) creates a ridge in the likelihood surface exactly equal to 0 when  $\sum_{k=1}^K \beta_{ki} = 1$ . As such, Equations (13) and (14) effectively bound the parameter space to include only reasonable values of  $\beta$ , or values of  $\beta$  that would give rise to a solution to Equation (10).

Bayesian estimation proceeds by recursively generating draws from the full conditional distributions of all model parameters (Rossi et al. 2005). The inclusion of the Jacobian term in Equation (11) prevents us from utilizing standard conjugate results to implement an efficient Gibbs sampler for model estimation. Instead, we rely on a hybrid sampler where a subset of the parameters are drawn using the Metropolis-Hastings algorithm (Chib and Greenberg 1995). Although this is simple to implement, the sampler substantially increases the computational burden of the routine. The estimation algorithm for our proposed model of simultaneous supply and demand is provided in the appendix. Extensive simulation studies were conducted to assess both the efficacy and mixing properties of all estimation routines.

### 3. Data

Empirically, we study the strategic effect of satisfaction on firm performance in the context of retail banking. Data are provided by a national financial

services firm and consist of three independently collected components: a time series of unit-level financial statements, a customer satisfaction study, and an employee satisfaction study, all collected during roughly the same time period.

### 3.1. Unit-Level Income Statements

The units of analysis in this study are retail banking branches. Income statements for approximately 13 months were made available for each of the firm's 898 retail locations. Each income statement contains detailed information about branch-level expenses and revenues. Expenses include monthly outlays for base salary, incentive compensation, training, etc. Revenue in retail banking can be classified into two main categories: production income and portfolio (or passive) income. Production income results from the accumulation of new business (e.g., new loans, new accounts, etc.). Passive income accrues as a result of existing loan and deposit balances. It is important to note that revenue generated as a result of changes to existing loan or deposit accounts (e.g., depositing more money to a savings account) is classified in our data set as passive, not production, income. Although categorized as passive, changes to deposit balances can be influenced through employee effort. As such, we use total revenue (i.e., the summation of both passive and production income) as the dependent variable in our model.

Both sources of income are computed using the "value method," which assigns a fixed monetary value to new and existing business activities and consumer relationships. For example, a bank may assign a value of \$2,000 for every \$100,000 originated in new mortgages. The value method is used in a manner consistent with the premise of cost-based accounting: to distribute aggregate revenue across the specific services provided by each branch. This facilitates a better understanding of the marginal contribution of various banking services to total profitability and should therefore allow management to more easily identify and reward activities of greatest importance.

We focus our attention on three key short-term input variables: full-time equivalents (FTE), base salary, and incentive compensation. The dependent variable of interest in this study is total branch-level revenue, i.e., production and passive income. These are, respectively, the inputs and output of the production function presented in Equation (1). FTE provides an aggregate measure of the number of full-time workers employed at a given branch. A part-time employee's contribution to this measure is defined as the percentage of hours they are employed, where the basis is a 40-hour work week. Base compensation measures the total monthly unconditional compensation for all employees at a given branch. This includes both salaries for exempt employees and

**Table 1** Descriptive Statistics for Branch-Level Income Statements

Financial variables	Mean	Minimum	Maximum
Weeks of data	12.5	6.0	13.0
Total income (\$000s)	88.5	1.4	465.6
FTE	9.1	1.0	34.0
Base salary expense (\$000s)	20.6	2.7	77.9
Incentive compensation (\$000s)	5.7	0.0	50.8

hourly wages for nonexempt employees. Incentive compensation consists of total monthly dollar expenditures in excess of base salary. As both base and incentive compensation are measured in dollars, their respective costs,  $p_{kit}$ , are equal to \$1. The cost for FTE is unobserved in our data set. As such, we include it as a control variable in the model. Summary statistics of these key variables are presented in Table 1.

Although FTE, base pay, and incentive compensation are not variables typically studied in marketing, we believe there are two reasons why they should be of interest to a marketing audience. First, the passage of the Gramm-Leach-Bliley Act in 1999 allowed retail banks to sell both savings and investment products at the same institution. As a result, it has become increasingly profitable for banks to adopt aggressive, sales-oriented cultures. As such, the managerially controllable variables included in our study fall within the domain of sales-force compensation, a topic that is of considerable interest to marketers (Misra et al. 2005). Second, the boundaries of classical marketing studies are becoming increasingly blurred as additional emphasis is placed on models of service and relationships. Conceptual frameworks like the service-profit chain and the cocreation of value stress the importance of both employees and customers in the determination of successful marketing programs (Heskett et al. 1994, Vargo and Lusch 2004).

### 3.2. Customer and Employee Satisfaction Studies

Employee and customer satisfaction studies were conducted once during the time period in question. Each consumer surveyed was asked to provide a holistic evaluation of the bank in addition to an assessment of specific service aspects of the branch they frequent most often. To avoid confusion, the branch in question is explicitly defined in the survey instrument. Employee responses are grouped according to their branch of employment.

Descriptive statistics for these data sets are presented in Table 2. Included in this table are the respective customer and employee questions used as variables in the analysis. An average of 37 customer responses were collected for each branch (minimum of 6, maximum of 87). In the survey, respondents were asked to rate their branch on a variety of service dimensions. Responses were recorded on a scale

**Table 2** Descriptive Statistics for Employee and Customer Satisfaction Studies

Variable	No. of branches	Mean	Std. dev.
Customer measures (1 to 10 scale; 1 = unacceptable, 10 = outstanding)			
Overall branch rating (proxy for customer satisfaction)	898	8.9	1.6
Rating of the courtesy and friendliness of branch tellers	898	9.1	1.4
Evaluation of time required to wait in line for service	898	7.9	2.2
Employee measures (1 to 10 scale; 1 = very dissatisfied, 10 = very satisfied)			
Overall job satisfaction	898	7.7	1.9
Decision-making authority required to do job effectively	898	8.1	1.8
Fair evaluation of job performance	898	7.7	2.0
Clear link between job performance and compensation	898	6.8	2.4
Satisfaction with rewards program (pay, bonus, 401(K), etc.)	898	6.9	2.1
Opportunities for personal growth and development	898	7.9	1.8

of 1 to 10, where 1 and 10 denote, respectively, “unacceptable” and “outstanding.” An average of seven employee responses were recorded per branch (minimum of 5, maximum of 19). These responses were also scaled from 1 to 10, where 1 and 10 indicate, respectively, “very dissatisfied” and “very satisfied.” To maintain consistency in the data and ease the interpretation of results, both customer and employee data were rescaled onto the 0–1 interval, where 1 represents the maximum possible positive response.

Latent levels of aggregate customer and employee satisfaction are estimated using Equation (4) and are incorporated into the response model through Equations (2) and (3). As presented in Equation (4), responses to all survey questions are modeled as realizations from a heterogeneous multivariate normal distribution with a branch-specific mean and covariance matrix. A benefit of the assumption of multivariate normality is that it allows us to easily derive, for example, the conditional distribution of customer satisfaction given its determinants or drivers. This simplifies the process of tracing the influence of specific changes in the service climate (e.g., customer wait time) through the response process to revenue generation.

Retail banking provides an ideal setting to demonstrate the proposed model. As a result of the value method of accounting, branch managers are incentivized to maximize present period profitability (e.g., revenue less staffing costs) in accordance with Equation (7). In addition, relationships in retail banking tend to be sticky (i.e., there exist significant barriers to switching service providers). As such, short-term

competitive effects are not as important as they may be in other settings, thus justifying their exclusion from the model. Retail banking is also a relatively homogeneous industry. Product offerings tend to be very similar across firms and are virtually identical across units within a given firm. At the branch level, managers are primarily responsible for the effective utilization of their staff. As such, FTE, base salary, and incentive compensation are the only short-term (i.e., tactical) variables under the control of the branch manager.

It is important to note that in many service settings it is likely that changes in base compensation will also have an impact on employee satisfaction, thus exerting both a strategic and tactical influence on firm performance. In retail banking, however, base salary increases are often a function of tenure at the bank, and base salary reductions rarely (if ever) occur. In our data set, the variation we observe in base compensation is a reflection of the number and type of employees utilized in a given month (variability in part-time hours, temporary (e.g., peak-time) help, overtime of salaried employees, etc.) and not actual changes to the base compensation rate. Because these conditions are part of the negotiated terms of employment, we do not believe they will have an impact on employee satisfaction and thus allow base salary to exert a purely tactical influence on firm performance. It is important to note that structural changes to the terms of employment (e.g., increasing or decreasing the average wage rate across all employees) could have strategic consequences that would need to be incorporated into the model.

#### 4. Alternative Models

We explore the results of seven alternative models. Model descriptions and characteristics are provided in Table 3. The first model ( $M_1$ ) is a three-input demand model defined by Equation (15) without an informative supply-side model for  $\{x_{kit}\}$ :

$$y_{it} = \beta_{0i} x_{1it}^{\beta_{1i}} x_{2it}^{\beta_{2i}} x_{3it}^{\beta_{3i}} e^{e_{it}}, \quad (15)$$

where  $x_{1it}$ ,  $x_{2it}$ , and  $x_{3it}$  are, respectively, FTE, base salary in thousands of dollars, and incentive compensation in thousands of dollars.

To contrast  $M_1$  with models of simultaneous supply and demand we must also estimate an implied model for the input variables,  $X$ . Model  $M_1$  assumes that  $\{x_{kit}\}$  are exogenous to the system of study. Realizations of the input variables  $\{x_{it}\}$  are drawn from a multivariate normal distribution with a branch-specific mean and covariance matrix:

$$x_{it} \sim N(\bar{x}_i, \Sigma_{xi}). \quad (16)$$

**Table 3** Fit Statistics for Alternative Supply- and Demand-Side Models

Model	Description	Endogenous $X$	Constrained parameters	LMD $X$	LMD $Y$	LMD TTL
$M_1$	Unconstrained demand-side model for $y$ . Likelihood contribution of $X_{it} \sim N(\mu_i, \Sigma_i)$ .	—	—	14,709.88	1,645.71	16,355.59
$M_2$	Demand-side model with constrained parameter space for $\beta$ . Likelihood contribution of $X_{it} \sim N(\mu_i, \Sigma_i)$ .	—	X	14,709.88	1,219.62	15,929.50
$M_3$	Simultaneous supply and demand model where supply-side is modeled as a linear function of the $\beta$ s.	X	—	6,652.95	−732.18	5,920.78
$M_4$	Simultaneous supply and demand model with independent (unit-level) budget constraints over all inputs.	X	X	19,852.23	−2,943.99	16,908.24
$M_5$	Simultaneous supply and demand model with a single (unit-level) budget constraint over all inputs.	X	X	20,625.92	−2,889.55	17,736.38
$M_6$	Simultaneous supply and demand model with independent (bank-level) budget constraints over all inputs.	X	X	20,529.22	−4,650.15	15,879.07
$M_7$	Simultaneous supply and demand model with a single (bank-level) budget constraint over all inputs.	X	X	20,261.82	−5,247.83	15,013.99

Note. LMD, log-marginal density; TTL, total.

The second model considered ( $M_2$ ) extends the first through the a priori imposition of constraints over the parameter space. Response models provide utility to managers only to the extent that parameter estimates or functions of those estimates are deemed reasonable. In this context the requirement for reasonability is that  $\beta_k > 0$  for all  $k$ , and the  $\sum_{k=1}^3 \beta_k \leq 1$ . In  $M_2$  we impose these constraints upon the response process through the likelihood but do not allow the supply-side model to further inform estimation of  $\beta$ . This is accomplished by artificially inflating the variance of supply-side shock to be large. This is similar in spirit to Allenby et al. (1995) and Boatwright et al. (1999), who introduce parameter constraints through the prior. Unlike these papers, we do not have strong theoretical support to justify the imposition of constraints. As such, in  $M_2$  we effectively utilize the likelihood as a computational device to achieve reasonable results instead of a reflection of our true belief about the data-generating process.

The third model studied ( $M_3$ ) is a simultaneous supply and demand specification where  $X$  is set with knowledge of the response parameters  $\beta$ . This model, however, is not derived from the profit-maximizing behavior of managers. Instead, we model  $X$  as a linear function of  $\beta$ . This is consistent in spirit with the descriptive supply-side model introduced by Manchanda et al. (2004). Although this approach has the potential to accommodate endogeneity in the data, it does not ensure the existence of a globally optimal solution (e.g., parameters can still exhibit increasing and negative returns to scale) and ignores the interactive effect of the inputs. We operationalize this approach by extending the model in Equation (16) to include the hierarchical structure presented in Equation (17):

$$\bar{x}_i = \Delta' \beta_i + \xi_i. \quad (17)$$

Models  $M_4$  through  $M_7$  are the simultaneous supply and demand models derived from the first-order conditions of the maximization problem defined in Equation (7). They correspond to alternative assumptions regarding input budget constraints.

One advantage of using Bayesian estimation in this context is that it enables us to search over a wide variety of supply-side models to better understand the processes managers employ when making input-level decisions. We can compute Bayesian factors for these alternative models to determine which one best corresponds to the observed data (Rossi et al. 2005, Kass and Raftery 1995). This applies to both nested and nonnested model specifications.

We test a variety of supply-side models by making alternative assumptions about the collection of  $\{\lambda_k\}$ , the Lagrange multipliers or “shadow prices” of inputs  $\{x_k\}$ . These parameters correspond to the marginal change in the objective function (e.g., profitability) resulting from a relaxation of the budget constraint  $\{m_k\}$ :

$$\frac{\partial \mathcal{L}}{\partial m_k} = \lambda_k. \quad (18)$$

Although typically defined in terms of dollars, budget constraints can be specified in a variety of units. For example, in our application FTE is included as an input into the production function in order to control for the size of the branch. This allows us to assess the marginal increase in profitability associated with an increase in either base or incentive compensation, holding fixed the number of employees. The monetary cost of adding an additional unit of FTE is a function of both base and incentive compensation and is captured through the inclusion of those variables in the model. As such, we define  $m_1$  as a capacity constraint on the total number of FTE employable at any point in time. Budget constraints  $m_2$  and  $m_3$  are



defined as bounds on total dollar expenditures for base and incentive compensation.

Estimates of  $\{\lambda_k\}$  inform us about the degree to which allocation decisions are coordinated across the bank. Given the existence of a budget constraint, optimal bank-level behavior would be achieved when (provided all inputs are measured in the same units)

$$\frac{\partial \pi^*}{\partial x_{kit}} = \lambda \quad \forall k, i, t, \quad (19)$$

where  $\pi^*$  represents bank-level profitability over all time periods, as denoted by the top half of Equation (7). That is, the marginal increase in profitability resulting from an increase in  $\{x_{kit}\}$  is balanced across all inputs  $k$ , units  $i$ , and time periods  $t$ . If these conditions are met, we would conclude that marketing resources are optimally allocated across the organization.

A variety of deviations from optimal coordination are also possible. The following are alternative model specifications defined in terms of the budget constraint. As noted above, we include FTE as a control for branch size in our model and therefore only investigate optimality in the coordination of base salary and incentive compensation.

Model 4 ( $M_4$ ) presents a scenario where allocation decisions are made at the branch level, and separate budget constraints (and corresponding Lagrange multipliers) are defined for each unit  $i$  and each input  $k$ :

$$M_4: \quad \sum_t x_{kit} \leq m_{ki}. \quad (20)$$

Allocation decisions in model 5 ( $M_5$ ) are still made at the unit level but are coordinated across inputs. A single budget constraint is set for the sum of both base and incentive compensation. Model  $M_5$  corresponds to a scenario where the bank engages in decentralized decision making:

$$M_5: \quad \sum_t \sum_k x_{kit} \leq m_i. \quad (21)$$

Model 6 ( $M_6$ ) defines a scenario where allocation decisions are coordinated across units but not across inputs:

$$M_6: \quad \sum_t \sum_i x_{kit} \leq m_k. \quad (22)$$

Model 7 ( $M_7$ ) represents the optimal scenario described above, that is, allocative coordination across time, units, and inputs. Model  $M_7$  corresponds to the scenario where the bank engages in centralized decision making:

$$M_7: \quad \sum_k \sum_i \sum_t x_{kit} \leq m. \quad (23)$$

## 5. Results

Table 3 presents descriptions and fit statistics for models  $M_1$  through  $M_7$ . We compute Bayes factors for the respective models using the Newton–Raftery approximation to the log-marginal density (Newton and Raftery 1995). Fit statistics are provided for the marginal distributions of both  $y$  and  $X$  implied by the model under investigation, in addition to the joint distribution of the same.

In terms of the joint distribution of both  $X$  and  $y$ , we find that  $M_5$  outperforms all other models, including the statistical model,  $M_1$ . This suggests that resources are optimally balanced within but not across units, or that the bank engages in decentralized decision making. Within any given branch, the marginal increase in profitability resulting from a relaxation of the budget constraint is identical for both base salary and incentive compensation. Results for the marginal distribution of  $X$  indicate that the simultaneous supply and demand models allow us to better explain variation in the input variables relative to the model of exogeneity presented in Equation (16). For example, the log-marginal density for  $M_1$  is 14,709.88 as opposed to 20,625 for  $M_5$ . This result supports our premise that managers set  $X$  with an expectation of how it will influence  $y$  or that  $X$  is in fact endogenous.

A key object of interest in the Markov chain Monte Carlo (MCMC) output is the estimate of  $\Gamma$ , the coefficient matrix for the distribution of random effects for  $\beta$  defined in Equation (2);  $\Gamma$  informs us about the relationship between customer and employee satisfaction and the firm's technology (i.e.,  $\beta$ ). Posterior means for estimates of  $\Gamma$  for  $M_5$  are presented in Table 4. Parameter estimates with 95% of their mass above or below zero are presented in bold.

We observe that employee satisfaction is positively correlated with the multiplicative intercept  $\beta_0$ . This implies that branches whose employees are relatively more satisfied tend to exhibit a greater proclivity to produce revenue, all else equal. Although the posterior mean of the effect of customer satisfaction is positive, we are unable to conclude that it is statistically different from zero (i.e., the 95% credible interval contains zero). To frame this result, we estimated a reduced-form model with customer and employee satisfaction included as direct inputs into the production function. Interestingly, we found that customer

**Table 4** Impact of Satisfaction of Response Coefficients- $\Gamma$  Matrix

Posterior mean	Intercept	Customer satisfaction	Employee satisfaction
$\beta_0$ -Intercept	<b>2.24</b>	0.08	<b>0.20</b>
$\beta_1$ -FTE	<b>0.05</b>	-0.02	0.00
$\beta_2$ -Base salary	<b>0.78</b>	-0.02	<b>-0.06</b>
$\beta_3$ -Incentive pay	<b>0.10</b>	<b>-0.07</b>	<b>0.09</b>

satisfaction had a negative impact on revenue production, whereas the effect of employee satisfaction was positive. This suggests that models that ignore strategic effects (i.e., influence of satisfaction on factor productivity) will fail to capture the true impact of customer satisfaction.

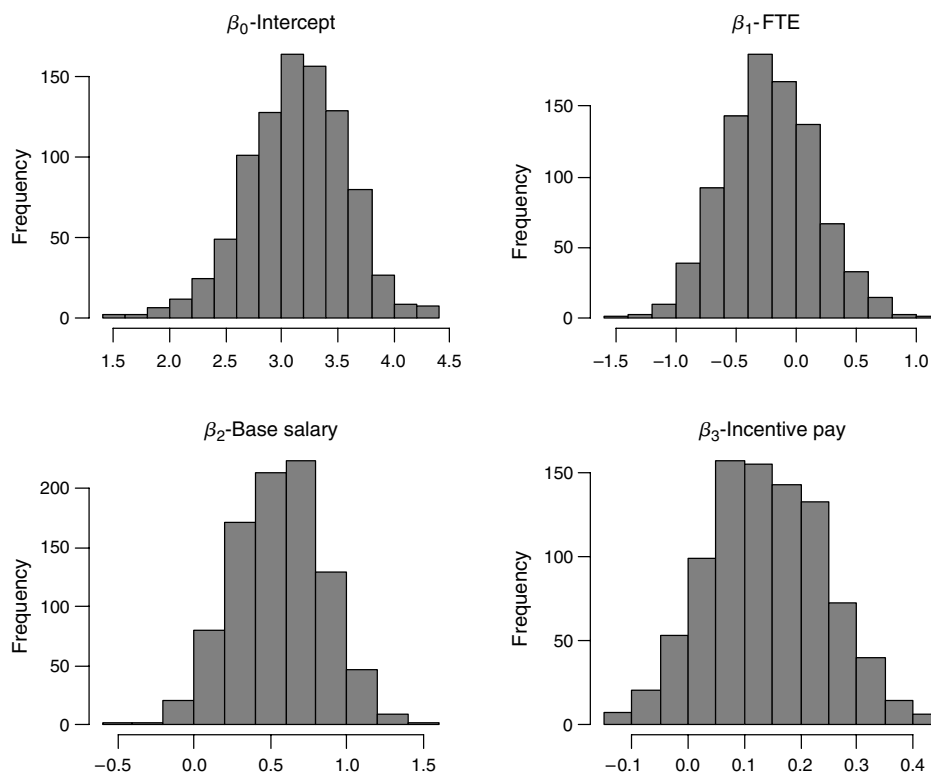
As a general note, we observe that employee satisfaction appears to have a stronger correlation with the productivity of the firm's technology than customer satisfaction. Specifically, employee satisfaction is significantly related to the multiplicative intercept and coefficients for base salary and incentive compensation, whereas customer satisfaction is only significantly related to the latter. This link from employee satisfaction to firm performance is interesting as it has received mixed support within the literature. Harter et al. (2002) and Edmans (2009) find evidence of a positive association between employee satisfaction and financial measures, whereas Keiningham et al. (2006), Wiley (1991), and Pritchard and Silvestro (2005) report either a null or negative relationship between the same.

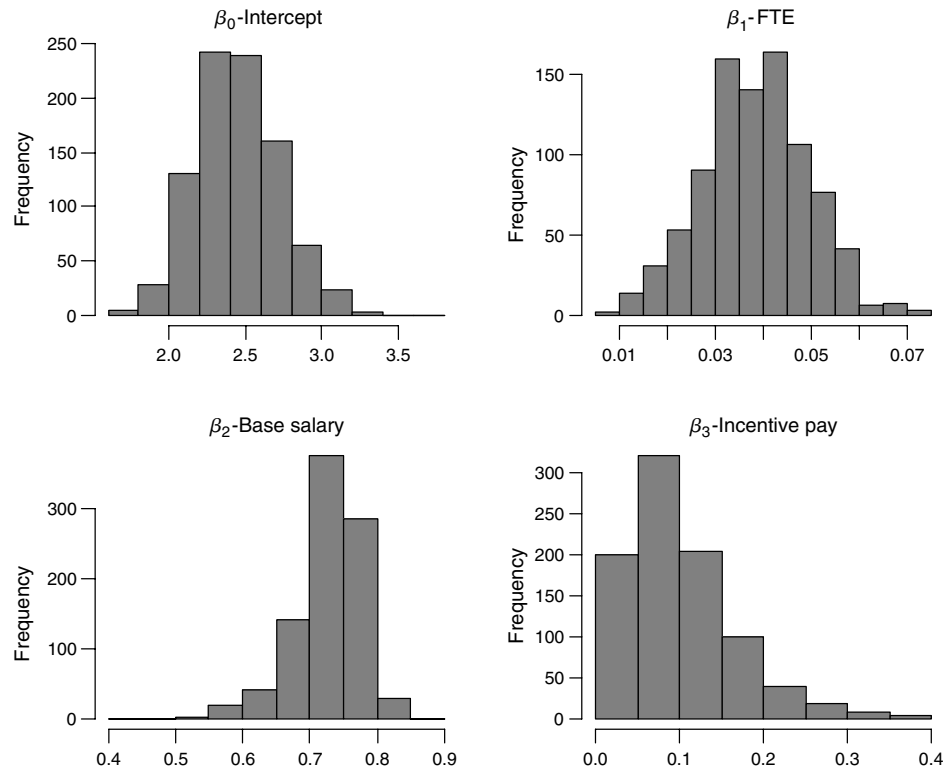
Our findings regarding the connection between customer satisfaction and firm performance may be related to the specific service context analyzed. Büschken (2005) discusses how the existence of switching costs in service organizations can attenuate the relationship between a customer's satisfaction or dissatisfaction and their relationship with the firm. In retail banking there exist significant monetary

(e.g., prepayment penalties on loans) and nonmonetary (e.g., hassle of changing accounts) costs associated with switching accounts to a competitor. As such, customers may elect to maintain their relationship with the bank in spite of feelings of dissatisfaction. If customer satisfaction is unrelated to consumer action, we would expect to observe the pattern of results presented in Table 4. It is certainly possible that customer satisfaction could play a more prominent role in improving the factor productivity of marketing action in other service contexts.

Employee satisfaction is negatively correlated with  $\beta_2$ , the response coefficient for base salary ( $\gamma_{3,3} = -0.06$ ), and positively correlated with  $\beta_3$ , the coefficient for incentive pay ( $\gamma_{4,3} = 0.09$ ). As the latent mean of employee satisfaction at a branch increases, the efficacy of base salary as a driver of revenue decreases while the efficacy of incentive compensation increases. Incentive compensation tends to be more effective as a driver of revenue at branches with employees who exhibit greater satisfaction, whereas the reverse is true for base compensation. This suggests that, all else equal, branches whose employees are relatively more satisfied would make better use of their resources by designing employee compensation contracts that place greater emphasis on incentive relative to base pay. Our results also indicate that customer satisfaction is inversely correlated with the response coefficient for incentive compensation,  $\beta_3$

Figure 1 Distribution of Posterior Means for Beta for  $M_1$ —Demand Side Only



**Figure 2** Distribution of Posterior Means for Beta for  $M_5$ —Simultaneous Supply and Demand

( $\gamma_{4,2} = -0.07$ ). Incentive compensation is less effective as a driver of revenue at branches whose customers are relatively more satisfied.

Figures 1 and 2 present a series of histograms of the mean of each branch's posterior distribution of  $\beta$ . Figure 1 is constructed using MCMC results from  $M_1$ , and Figure 2 uses results from  $M_5$ . We observe considerable heterogeneity across branches in the  $\beta$ s for both models. On average, the size of  $\beta$  appears to be larger for base salary than for either FTE or incentive pay. In the case of the  $M_1$ , we observe average  $\beta$ s for branches that are less than zero and greater than one. These results are counterintuitive and severely restrict  $M_1$ 's ability to provide guidance for future managerial decision making. A value of  $\beta < 0$  (i.e., negative returns to scale) implies an optimal expenditure of zero dollars, whereas  $\beta > 1$  (i.e., increasing returns to scale) implies full allocation of all available resources to that input.

As we do not observe corner solutions in our data, models that exhibit increasing or negative returns to scale fail the test of reasonability and are of little use to managers. We interpret the extreme coefficient estimates in  $M_1$  as a strong test against its plausibility because it rules out the possibility that the inputs were determined as part of some goal-directed process. This analysis can be viewed as a type of posterior predictive check, where the implied allocation of resources is the feature of the data with which we

are concerned (Gelman et al. 2004). Given the estimated parameters, the reduced-form model ( $M_1$ ) cannot account for the observed behavior of the firm.

The results of  $M_5$ , presented in Figure 2, are reasonable in the sense that all posterior mean estimates lie on the  $[0, 1]$  interval. Closer examination of these results demonstrates that our estimates of  $\beta$  adhere to the restriction that  $\sum_{k=1}^3 \beta_k \leq 1$ .

## 6. Conclusion

This paper presents a new approach to relating tactical and strategic marketing initiatives. Specifically, we model revenue production in retail banking as a function of employee compensation, and we allow customer and employee satisfaction to moderate the relationship between the same through a hierarchical Bayesian model. We handle potential endogeneity in the input variables by jointly estimating a demand-side model (i.e., model for  $y$ ) and supply-side model (i.e., model for  $X$ ). Our supply-side model is formally derived from a constrained optimization problem where managers are assumed to maximize profitability subject to a budget constraint. The resulting likelihood imposes a variety of constraints on the parameter spaces of  $\beta$ , thus yielding estimates consistent with the interior solutions observed in the data. The structure imposed upon our model allows us to utilize its results to guide managers in the allocation

of resources, a topic of general interest to marketing management.

Empirically, this work contributes to the literature on customer satisfaction. We find evidence of a relationship between customer and employee satisfaction and firm technology (i.e., factor productivity). That is, changes in satisfaction impact firm financial performance by altering the efficacy of the firm's tactical inputs through the response coefficients  $\{\beta_{ki}\}$ . Employee satisfaction is shown to be significantly related to a firm's baseline ability to generate revenue as well as the efficacy of its base and incentive compensation programs. However, customer satisfaction is shown to be inversely related to the effectiveness of incentive compensation. These findings are congruent with recent calls for work exploring alternative influences of customer satisfaction (Luo and Homburg 2007).

Although we believe our model is appropriate for the study of strategic satisfaction in the context of retail banking, there are a number of issues that should be considered before applying it to other settings. Our model does not control for the existence of competitive effects. If competition is important to the context under study, it should be reflected in the specification of both the demand- and supply-side models. Particular attention should be paid to determining if the effect of competition is tactical, strategic, or possibly both. Our model also assumes that both demand and supply are independent across branches. If cross-unit dependencies (e.g., proximity effects) do exist, they should be formally incorporated into the structure of the model. Finally, our model assumes that tactical actions (e.g., changes in base compensation) do not have a long-term impact on the strategic variables (e.g., employee satisfaction). As such, we cannot interpret the estimated relationship between satisfaction and firm technology as causal. Although interesting, the study of this issue would require repeated cross-sectional measures of satisfaction. Relaxation of these assumptions would all be interesting avenues for future research.

Our work raises a number of additional questions that are also worthy of future investigation. First, we define a strategic action to be any action that influences the technology of a firm. Technology in a regression-style response model includes both the location and scale of the conditional distribution of  $y|X$ . In this paper, however, we examine only the influence of satisfaction on the mean of the conditional relationship of sales and compensation (e.g., the effect of satisfaction on  $\beta$ ). It would also be interesting to explore the relationship between satisfaction and the variance  $\sigma^2$ . It is certainly possible that an inverse relationship could exist between the latent level of

customer and employee satisfaction and the variability of revenue generation at a branch.

A second issue that should be explored is related to recent work by Dotson et al. (2008). Both the customer and employee studies used in that paper provide sample information about the respective distributions of satisfaction. In this paper, we relate these distributions to financial performance through their latent mean. It would be interesting to see if other portions or percentiles of these distributions would yield different results than those observed in our current work. Furthermore, it would be useful to explore models that do not rely on the stringent assumption of normality in the distribution of consumer and employee responses.

Finally, the supply-side models developed in this paper were based upon an evaluation of presumed optimal behavior, conditional upon the structure of our proposed model. Supply-side models are needed that more accurately reflect the processes whereby managers actually make decisions. This could include situations where managers must simultaneously maximize multiple, potentially conflicting outputs (i.e., multiple-output production functions). Rather than searching over the space of possible supply-side models defined by the researcher, it would be useful to elicit managerial input during model construction. This could be efficiently accomplished through closer collaboration between researchers and managers. We leave these issues to future research.

#### Appendix. Estimation Algorithm for $M_5$

Bayesian estimation for the simultaneous supply and demand model proceeds by recursively generating draws from the full conditional distributions of all model parameters. The nonstandard nature of our model prevents us from relying exclusively on conjugate results. As such, we implement a hybrid sampler and draw a subset of the model parameters using the Metropolis-Hastings algorithm. We divide the MCMC sampler into six distinct blocks and alternate parameter draws within and across units. We define the following quantities to simplify exposition of the algorithm.

As defined in Equation (11), the full likelihood for the model can be re-expressed according to (24):

$$l(\text{data} | \text{else}) = \prod_i \prod_t \pi(\hat{\epsilon}_{it}) \pi(\hat{\xi}_{1it}, \hat{\xi}_{2it}, \hat{\xi}_{3it}) \left| \frac{J_{it}}{\hat{\xi} \rightarrow \ln(x)} \right|, \quad (24)$$

where  $\pi(\cdot)$  denotes the multivariate normal density function, and the quantities  $\hat{\epsilon}_{it}$  and  $\hat{\xi}_{kit}$  can be computed according to (25) and (26), respectively. The Jacobian term is defined in Equation (27).

$$\hat{\epsilon}_{it} = \ln(y_{it}) - (\ln(\beta_{0i}) + \beta_{1i} \ln(x_{1it}) + \beta_{2i} \ln(x_{2it}) + \beta_{3i} \ln(x_{3it})), \quad (25)$$

$$\begin{bmatrix} \hat{\xi}_{1it} \\ \hat{\xi}_{2it} \\ \hat{\xi}_{3it} \end{bmatrix} = \begin{bmatrix} (\beta_{1i}-1) & \beta_{2i} & \beta_{3i} \\ \beta_{1i} & (\beta_{2i}-1) & \beta_{3i} \\ \beta_{1i} & \beta_{2i} & (\beta_{3i}-1) \end{bmatrix} \begin{bmatrix} \ln(x_{1it}) \\ \ln(x_{2it}) \\ \ln(x_{3it}) \end{bmatrix} \quad (26)$$

$$- \begin{bmatrix} \ln(\lambda_1) - \ln(\beta_{0i}) - \ln(\beta_{1i}) \\ \ln(\lambda_2 + 1) - \ln(\beta_{0i}) - \ln(\beta_{2i}) \\ \ln(\lambda_3 + 1) - \ln(\beta_{0i}) - \ln(\beta_{3i}) \end{bmatrix},$$

$$\left| \frac{J_i}{\hat{\xi} \rightarrow \ln(x)} \right| = \det \begin{bmatrix} \frac{\partial \hat{\xi}_{1it}}{\partial \ln(x_{1it})} & \frac{\partial \hat{\xi}_{1it}}{\partial \ln(x_{2it})} & \frac{\partial \hat{\xi}_{1it}}{\partial \ln(x_{3it})} \\ \frac{\partial \hat{\xi}_{2it}}{\partial \ln(x_{1it})} & \frac{\partial \hat{\xi}_{2it}}{\partial \ln(x_{2it})} & \frac{\partial \hat{\xi}_{2it}}{\partial \ln(x_{3it})} \\ \frac{\partial \hat{\xi}_{3it}}{\partial \ln(x_{1it})} & \frac{\partial \hat{\xi}_{3it}}{\partial \ln(x_{2it})} & \frac{\partial \hat{\xi}_{3it}}{\partial \ln(x_{3it})} \end{bmatrix}$$

$$= |\beta_{1i} + \beta_{2i} + \beta_{3i} - 1|. \quad (27)$$

The error terms for the supply and demand equations are assumed to be distributed as follows:

$$\hat{\varepsilon}_{it} \sim N(0, \sigma_i^2), \quad (28)$$

$$\begin{bmatrix} \hat{\xi}_{1it} \\ \hat{\xi}_{2it} \\ \hat{\xi}_{3it} \end{bmatrix} \sim N(0, \Sigma_{xi}). \quad (29)$$

Conditional on initial values, the sampler proceeds as follows (repeating until convergence has been achieved):

*Block 1: Within Units.* Iterate through each unit (i.e., branch) in the data set drawing:

*Step 1.*  $[\{\beta_{ki}\} | \text{else}] \propto [\{y_{it}\} | \{x_{kit}\}, \{\beta_{ki}\}, \sigma_i^2][\{x_{kit}\} | \{\beta_{ki}\}, \{\lambda_{ki}\}, \Sigma_{xi}][\{\beta_{ki}\} | \Gamma, \mu_i^*, \Sigma_\beta]$ .

Draw  $\beta_i$  using a Metropolis-Hastings (M-H) step, where the contribution for the first two factors of the likelihood for unit  $i$  is equal to

$$\prod_t \pi(\hat{\varepsilon}_{it}) \pi(\hat{\xi}_{1it}, \hat{\xi}_{2it}, \hat{\xi}_{3it}) \left| \frac{J_{it}}{\hat{\xi} \rightarrow \ln(x)} \right|,$$

where the Jacobian is defined in Equation (27), and the hierarchical prior for beta is specified as

$$\beta_i \sim N(\Gamma' \mu_i^*, \Sigma_\beta).$$

Acceptance probabilities are computed using the standard M-H algorithm (see Rossi et al. 2005, p. 88). The step size of the proposal density was tuned so that the acceptance rate of draws was close to 30%. It is important to note that the likelihood for the model can only be evaluated for  $\{\beta_{ki}\}$  that correspond to the first condition outlined in §2. That is,  $\beta_{ki} > 0$  for all  $k$  and  $i$  (the likelihood is undefined otherwise). As such, starting values for  $\{\beta_{ki}\}$  must be selected that correspond to this condition as well as the second condition for economic production functions,  $\sum_{k=1}^K \beta_{ki} \leq 1$ . It may be useful to reinforce these constraints in the MCMC by proposing only values of  $\beta_{ki} > 0$ . We find that if the routine is properly initialized the draws of  $\{\beta_{ki}\}$  will be constrained

(through the likelihood) to the region defined by the second condition.

*Step 2.*  $\{\lambda_i\} | \text{else}] \propto [\{x_{kit}\} | \{\beta_{ki}\}, \{\lambda_i\}, \Sigma_{xi}][\{\lambda_i\} | \bar{\lambda}, \Sigma_\lambda]$ .  $\{\lambda_i\}$  are also drawn by first employing the following change of variables:  $\lambda_i^* = \ln(\lambda_i + 1)$ . The transformed variables,  $\{\lambda_i^*\}$ , are drawn using a M-H step where the likelihood contribution is equal to

$$\prod_t \pi(\hat{\xi}_{1it}, \hat{\xi}_{2it}, \hat{\xi}_{3it}) \left| \frac{J_{it}}{\hat{\xi} \rightarrow \ln(x)} \right|$$

with a corresponding hierarchical prior specified for  $\{\lambda_i^*\}$ :

$$\{\lambda_i^*\} \sim N(\bar{\lambda}, \Sigma_\lambda).$$

*Step 3.*  $[\sigma_i^2, \Sigma_{xi} | \text{else}]$ .

Conditional on a realizations of  $\beta_i$  and  $\{\lambda_{ki}\}$ ,  $\sigma_i^2$  is drawn from an inverse chi-square distribution, and  $\Sigma_{xi}$  is a standard draw from an Inverted Wishart distribution (see Rossi et al. 2005, Chapter 2).

*Block 2: Across Units.*

*Step 4.*  $[\Gamma, \Sigma_\beta | \text{else}]$ .

Conditional on realizations of  $\beta, \mu^*$  inference for  $\Gamma$  and  $\Sigma_\beta$  proceeds through use of a standard multivariate regression:

$$\Sigma_\beta \sim \text{IW}(\nu_0 + N, V_0 + S_\beta),$$

$$\text{vec}(\Gamma) \sim N(\tilde{\Gamma}, \Sigma_\beta \otimes (\mu^{*'} \mu^* + A_\beta)^{-1}),$$

where

$$\tilde{\Gamma} = \text{vec}(\tilde{M}_\beta), \tilde{M}_\beta = (\mu^{*'} \mu^* + A_\beta)^{-1} (\mu^{*'} \mu^* \hat{M}_\beta + A_\beta \bar{M}),$$

$$S_\beta = (\beta - \mu^* \tilde{M}_\beta)' (\beta - \mu^* \tilde{M}_\beta) + (\tilde{M}_\beta - \bar{M})' A_\beta (\tilde{M}_\beta - \bar{M}),$$

$$\text{and } \hat{M}_\beta = (\mu^{*'} \mu^*)^{-1} (\mu^{*'} \beta).$$

Standard, weakly informative priors were used for this update:

$$\bar{M} = \begin{matrix} 0 \\ 0 \\ 0 \\ 0 \end{matrix} \text{ is a } 3 \times 4 \text{ matrix of 0s,}$$

$$A_\beta = 0.01 \times I_3, \text{ where } I_3 \text{ is a } 3 \times 3 \text{ identity matrix,}$$

$$\nu_0 = 7,$$

$$V_0 = \nu_0 \times I_4.$$

*Step 5.*  $[\bar{\lambda}, \Sigma_\lambda | \text{else}]$ .

Conditional on realizations of  $\{\lambda_i\}$ ,  $\bar{\lambda}, \Sigma_\lambda$  can be estimated using a multivariate regression of  $\{\lambda_i\}$  on the unit vector with length equal to the number of branches under study,  $\iota_N$ . Full conditional distributions for the mean and covariance matrix follow those outlined in Step 4.

*Block 3: Within Units.*

*Step 6.*  $[\mu_i^c, \Sigma_i^c | \text{else}]$ .

$\mu_i^c$  and  $\Sigma_i^c$  can also be drawn through the use of a multivariate regression of observed customer satisfaction survey responses on the unit vector,  $\iota_N$ .

*Step 7.*  $[\mu_{1i}^c | \text{else}] \propto [\mu_i^c | \bar{\mu}^c, V_\mu^c][z_{ih}^c | \mu_i^c, \Sigma_i^c][\beta_i | \mu_i^*, \Gamma, \Sigma_\beta]$ .

Inference for the latent level of aggregate customer satisfaction,  $\mu_{1i}^c$ , proceeds by first recognizing that distribution

of  $\mu_{1i}^c$  is proportional to the product of three multivariate normal densities: A, B, and C. We derive the posterior distribution for  $\mu_{1i}^c$  by re-expressing A, B, and C in terms of the univariate normal for  $\mu_{1i}^c$  and combining quadratic forms as described in Box and Tiao (1973):

$$\mu_{1i}^c \sim N(\bar{\mu}_{1i}^c, \Sigma_{\mu_{1i}^c}^c),$$

where

$$\begin{aligned}\bar{\mu}_{1i}^c &= (\Sigma_A^{-1} + \Sigma_B^{-1} + \Sigma_C^{-1})^{-1}(\Sigma_A^{-1}\mu_A + \Sigma_B^{-1}\mu_B + \Sigma_C^{-1}\mu_C), \\ \Sigma_{\mu_{1i}^c}^c &= (\Sigma_A^{-1} + \Sigma_B^{-1} + \Sigma_C^{-1})^{-1},\end{aligned}$$

and the contribution for each factor A, B, and C can be computed as follows.

Factor A (Contribution from the prior):

$$\begin{aligned}\mu_A &= 0, \\ \Sigma_A &= 100.\end{aligned}$$

Factor B (Contribution from the model for observed customer satisfaction responses):

$$\begin{aligned}\mu_B &= \mu_{1i}^c + \Sigma_{12}^c \Sigma_{22}^{c-1} (a - \mu_{-1i}^c), \\ \Sigma_B &= \Sigma_{11}^c - \Sigma_{12}^c \Sigma_{22}^{c-1} \Sigma_{21}^c,\end{aligned}$$

where

$$\begin{aligned}z_{ih}^c &\sim N\left(\mu_i^c = \begin{bmatrix} \mu_{1i}^c \\ \vdots \\ \mu_{hi}^c \end{bmatrix}, \Sigma_i^c\right), \\ \Sigma_i^c &= \begin{bmatrix} \Sigma_{11}^c & \Sigma_{12}^c \\ \Sigma_{21}^c & \Sigma_{22}^c \end{bmatrix}.\end{aligned}$$

Factor C (Contribution from the model for the demand response coefficients  $\beta$ ):

$$\beta_i = \Gamma' \mu_i^* + \eta_i.$$

Begin by partitioning as follows:

$$\Gamma_{k \times 3}' = \begin{bmatrix} \Gamma_1' & \Gamma_2' \\ \Gamma_{k \times 2}' & \Gamma_{k \times 1}' \end{bmatrix}.$$

Compute

$$\begin{aligned}\beta_i - \Gamma_1' \begin{bmatrix} 1 \\ \mu_{1i}^c \end{bmatrix} &= \Gamma_2' \mu_{1i}^c, \\ \mu_C &= (\Gamma_2' \Gamma_2)^{-1} \Gamma_2' \left( \beta_i - \Gamma_1' \begin{bmatrix} 1 \\ \mu_{1i}^c \end{bmatrix} \right), \\ \Sigma_C &= (\Gamma_2' \Gamma_2)^{-1} (\Gamma_2' \Sigma_{\beta} \Gamma_2) (\Gamma_2' \Gamma_2)^{-1'}.\end{aligned}$$

Block 4: Across Units.

Step 8.  $[\bar{\mu}^c, V_\mu^c | \text{else}]$ .

Conditional on realizations of  $\mu_{1i}^c$ , estimation of  $\bar{\mu}^c$  and  $V_\mu^c$  proceeds through the use of a multivariate regression as defined in Step 4.

Step 9.  $[\Omega^c | \text{else}]$ .

We follow Jen et al. (2007) when drawing parameters for the distribution of random effects specified for  $\Sigma_i^c$ .

The conditional posterior for  $\Omega^c$  is  $IW(\nu_0^c + N\bar{\nu}^c, (\Omega_0^{c-1} + \sum_{i=1}^N \Sigma_i^{c-1}))$ .

Step 10.  $[\bar{\nu}^c | \text{else}]$ .

The posterior distribution for  $\bar{\nu}^c$  does not have a closed-form expression and must therefore be drawn using a M-H step, where the likelihood contribution for  $\bar{\nu}^c$  is equal to

$$\begin{aligned}\prod_{i=1}^N \left( 2^{\bar{\nu}^c} \pi^{\frac{1}{2}} \Gamma\left(\frac{\bar{\nu}^c}{2}\right) \Gamma\left(\frac{\bar{\nu}^c - 1}{2}\right) \right)^{-1} \frac{|\Omega^c|^{-1} |\bar{\nu}^c|^{2}}{|\Sigma_i^c|^{(\bar{\nu}^c + 3)/2}} \\ \cdot \exp\left\{-\frac{1}{2} \text{Tr}((\Sigma_i^c)^{-1} (\Omega^c)^{-1})\right\}.\end{aligned}$$

Steps 11–15 are the employee analogs of customer Steps 6–10 (the superscript  $e$  denotes employee). Parameter estimation follows directly.

Block 5: Within Units.

Step 11.  $[\mu_i^e, \Sigma_i^e | \text{else}]$ .

Step 12.  $[\mu_{1i}^e | \text{else}] \propto [\mu_i^e | \bar{\mu}^e, V_\mu^e][z_{ih}^e | \mu_i^e, \Sigma_i^e][\beta_i | \mu_i^*, \Gamma, \Sigma_\beta]$ .

Block 6: Across Units.

Step 13.  $[\bar{\mu}^e, V_\mu^e | \text{else}]$ .

Step 14.  $[\bar{\nu}^e | \text{else}]$ .

Step 15.  $[\Omega^e | \text{else}]$ .

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