Investigating the Strategic Influence of Satisfaction on Firm Financial Performance

by

Jeffrey P. Dotson
Fisher College of Business
Ohio State University
dotson.83@osu.edu

Greg M. Allenby
Fisher College of Business
Ohio State University
allenby.1@osu.edu

June 2008
Investigating the Strategic Influence of Satisfaction on Firm Financial Performance

Abstract

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 that allows us to formally study the financial impact of a variety of marketing activities, including those that operate on different time scales. 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. We demonstrate the utility of our approach through a series of marketing policy counterfactuals.
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 time scales. 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. In order 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 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 firm’s technology. Structure is imposed upon the parameters of our model through the estimation of a model of simultaneous supply and demand. Our model explicitly deals with the potential for endogeneity in the input variables, and produces managerially reasonable parameter estimates.

We apply our model to data provided by a national financial services firm where we integrate 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. We explore this process through the use of a marketing policy counterfactual where we identify when and under what cost structure it would become profitable for the bank to focus its efforts on increasing the latent level of employee satisfaction as opposed to engaging in short-term sales incentive programs.

The remainder of this paper is organized as follows. Section 2 presents the general form of our model, the likelihood, and estimation strategy. In section 3 we describe the data and setting used to empirically demonstrate our model. Alternative models are outlined in section 4. Results are presented and discussed in section 5. Section 6 illustrates the practical value of our proposed model by considering a series of counterfactual scenarios. Final thoughts and areas for future research are offered in section 7.
2. Model

The relationship between marking 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 III et al., 2008; Kamakura et al., 2002; Heskett et al., 1994). While these models are useful in the sense that they provide directional evidence that constructs like customer and employee satisfaction are, in fact, 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 tradeoffs associated with engaging in tactical versus strategic marketing activities.

Our general modeling approach consists of two major components:

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, $\{x_{sit}\}$. 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.

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

(1)

The functional form of this model has been used extensively in both economic and marketing applications (Lilien et. al, 1992). It enables us to capture diminishing returns to scale in the inputs and allows 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.

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

$$\beta_{i} = \Gamma' \mu_{i}^{*} + \eta_{i}$$

(2)

where $\mu_{i}^{*}$ is a vector of $S+1$ variables that can include observable characteristics of the production process (e.g., product attributes, average advertising spend, etc.) or unobservable constructs like customer satisfaction or brand equity.

$$\mu_{i}^{*} = \left[ \begin{array}{c} 1 \\ \mu_{i1}^{*} \\ \vdots \\ \mu_{iS}^{*} \end{array} \right]$$

(3)

The former can be measured directly while the latter can be assessed through the use of survey data. Estimates of unobservable or latent constructs are related to observed data through equation (4):
\[ z_{ih}^i \sim N \left( \mu_i^i \sigma_i^i \right) \]  

(4)

where \( z_{ih}^i \) is a vector of responses for individual \( h \) in unit \( i \) and \( \mu_i^i \) is the estimate of interest included equation (3). This is done in anticipation of our empirical application where we include latent estimates of employee and customer satisfaction as covariates in equation (2). We allow for cross-unit heterogeneity by specifying distributions of random effects for both the location and covariance matrix of equation (4).

\[ \mu_i^i \sim N \left( \bar{\mu}_i^i, V_i^i \right) \]  

(5)

\[ \Sigma_i^i \sim IW \left( \bar{\Sigma}_i^i, \Omega_i^i \right) \]  

(6)

Collectively, equations (1-6) form the basis of a model of integrated decision making, where the influence of strategic action is manifest through the hyper-parameters of a hierarchical response model. We are informed about influence of tactical decisions on firm performance from within-unit variation across time (equation 1), while learning about the effects of strategic decisions occurs across units (equation 2). As illustrated in Section 6, this formal connection between tactical and strategic decisions allows us to compute the monetary benefit associated with altering as opposed operating within the firm’s extant technology.

**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 outcome, \( y \). The presence of endogenously determined covariates has been show 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., 2008; 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 \(\{x_{kit}\}\) in order 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 equation (7):

\[
\max_{\{x_{it}\}} \sum_i \sum_t \left( \beta_{0i} \left( \prod_{k=1}^{K} x_{kit}^{\beta_{ki}} \right) - \sum_{k=1}^{K} p_{kit} x_{kit} \right) \tag{7}
\]

subject to \(\sum_i \sum_t p_{kit} x_{kit} \leq m_k\)

where \(p_k\) is the cost and \(m_k\) denotes the budget constraint for input \(k\). This 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 \(\{x_{kit}\}\).

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

\[
L = \sum_i \sum_t \left( \beta_{0i} \left( \prod_{k=1}^{K} x_{kit}^{\beta_{ki}} \right) - \sum_k p_{kit} x_{kit} \right) - \sum_k \lambda_k \left( \sum_i \sum_t p_{kit} x_{kit} - m_k \right) \tag{8}
\]
This is accomplished by solving the first-order conditions presented in equation (9) for each branch, input, and time period.

\[
\frac{\partial L}{\partial x_{kit}} = 0, \quad \forall k, i, t
\]  

(9)

Equation (9) describes a system of first-order conditions that can be used to determine optimal values of \( \{x_{kit}\} \). 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 \( \beta_k > 0 \) for all \( k \), and \( \sum_{k=1}^{K} \beta_k \leq 1 \). If these conditions are met, equation (1) subsumes the properties of a Cobb-Douglas production function.

\[
\begin{align*}
\ln(x^*_{i}) &= \begin{bmatrix}
\ln(x^*_{i1}) \\
\vdots \\
\ln(x^*_{iK})
\end{bmatrix} = \begin{bmatrix}
(\beta_{i1} - 1) & \cdots & \beta_{Ki} \\
\vdots & \ddots & \vdots \\
\beta_{i1} & \cdots & (\beta_{Ki} - 1)
\end{bmatrix}^{-1} \times \\
&= \begin{bmatrix}
\ln(\lambda_1 + 1) - \ln(\beta_{i1}) - \ln(\lambda_{i1}) + \ln(p_{i1}) \\
\vdots \\
\ln(\lambda_K + 1) - \ln(\beta_{Ki}) - \ln(\beta_{K1}) + \ln(p_{K1})
\end{bmatrix}
\end{align*}
\]  

(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). Sub-optimal 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
\[ C_{kit}^* = C_{kit} e^{\hat{\zeta}_{kit}} = (p_{kit} x_{kit}) e^{\hat{\zeta}_{kit}}, \] where input cost error can arise from a variety of sources, including uncertainty about input prices, \( \{p_{kit}\} \), unanticipated fixed and variable expenses, etc.

**Likelihood and Estimation**

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

\[
\ell (\text{data} | \text{else}) = \prod_{i} \prod_{t} \pi (\ln(y_{it} | \ln(\{x_{kit}\})) \pi (\ln(\{x_{kit}\})) = \prod_{i} \prod_{t} \pi (\epsilon_{it}) \pi (\{\zeta_{kit}\}) \left| \sum_{\zeta_{kit}} \right| \tag{11}
\]

The quantities \( \epsilon_{it} \) and \( \{\zeta_{kit}\} \) are defined in equations (12) and (13) and \( \left| \sum_{\zeta_{kit}} \right| \) is the Jacobian term that captures dependencies in the mapping of \( \zeta \rightarrow \ln(x) \). The Jacobian resulting from the change of variables from \( \epsilon \rightarrow \ln(y) \) is trivially equal to 1.

\[
\epsilon_{it} = \ln(y_{it}) - \left( \ln(\beta_{0i}) + \sum_{k=1}^{K} \beta_{ki} \ln(x_{kit}) \right) \tag{12}
\]

\[
\begin{bmatrix}
\zeta_{1it} \\
\vdots \\
\zeta_{Kit}
\end{bmatrix} = 
\begin{bmatrix}
(\beta_{li} - 1) & \cdots & \beta_{Ki} \\
\vdots & \ddots & \vdots \\
\beta_{li} & \cdots & (\beta_{Ki} - 1)
\end{bmatrix}
\left( x_{it}^* \right) - 
\begin{bmatrix}
\ln(\lambda_i + 1) - \ln(\beta_{0i}) - \ln(\beta_{li}) + \ln(\mu_{it}) \\
\vdots \\
\ln(\lambda_K + 1) - \ln(\beta_{0i}) - \ln(\beta_{Ki}) + \ln(\mu_{Kit})
\end{bmatrix} \tag{13}
\]

Simultaneity present in the specification of equation (13) results in the non-trivial Jacobian defined by equation (14). Simultaneity in our model arises from the inclusion of the
supply side model derived from equation (10). The optimal value of a given input, \( \{ x_k \} \), is a function of all other inputs, \( \{ x_{-k} \} \).

\[
J_{e \rightarrow x} = \left| \sum_{k=1}^{K} \beta_k - 1 \right|
\]  

(14)

It is important to note that equation (13) can only be evaluated for values of \( \beta_{ik} > 0 \). Furthermore, the Jacobian in equation (14) creates a ridge in the likelihood surface exactly equal to 0 when \( \sum_{k=1}^{K} \beta_k = 1 \). As such, equations (13-14) 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, Allenby, and McCulloch 2005). The inclusion of the Jacobian term in equation (11) prevents us from utilizing standard conjugate results in order to implement an efficient Gibbs sampler for model estimation. Rather, 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, it does substantially increase 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 in order 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: an employee satisfaction study, a customer satisfaction study, and a time series of unit-level financial statements. All data sets were collected during roughly the same time period.

*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 firms' 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, deposit accounts, etc.). Passive income accrues as a result of existing loan and deposit balances.

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. That is, 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., passive and production 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 hourly wages for non-exempt employees. Incentive compensation consists of total monthly dollar expenditures in excess of base salary. Summary statistics of these key variables are presented in Table 1.

[Table 1]

**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. In order to avoid confusion, the branch in question is explicitly defined in the survey instrument. Employee responses are grouped according to their branch of employment.

[Table 2]

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 of 1 to 10, where 1 and 10 denote, respectively, “unacceptable” and “outstanding.” An average of 7 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.” In order 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 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 branch-specific mean and covariance matrix. As illustrated in Section 6, the assumption of multivariate normality will allow us to derive, for example, the conditional distribution of customer satisfaction given its determinants or drivers. This will allow us to trace the influence of specific changes in the service climate (e.g., customer wait time) through the response process to revenue generation.

4. Alternative Models

We explore the results of 7 alternative models. Model descriptions and characteristics are provided in Table 3. The first model (M₁) is a three input demand model defined by equation (15) without an informative supply side model for \( \{x_{kit}\} \):

\[
y_{it} = \beta_{0i} x_{1it}^{\beta_{i1}} x_{2it}^{\beta_{i2}} x_{3it}^{\beta_{i3}} \epsilon_{it} \quad (15)
\]
where \( x_{1t}, x_{2t}, \) and \( x_{3t} \) are respectively FTE, base salary in thousands of dollars, and incentive compensation in thousands of dollars.

In order to contrast \( M_1 \) with models of simultaneous supply and demand we must also estimate an implied model for the input variables, \( X \). \( M_1 \) assumes that \( \{ x_{kt} \} \) 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.

\[
x_{it} \sim N(\bar{x}_i, \Sigma_{ii})
\]  

(16)

The second model considered \( (M_2) \) extends the first through the \textit{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, Arora, Ginter (1995) and Boatwright, McCulloch, and Rossi (1999) who introduce parameter constraints through the prior. Unlike either of 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. Rather, we model \( X \) as a linear function of \( \beta \). This
is consistent in spirit with the descriptive supply side model introduced by Manchanda, Chintagunta, and Rossi (2004). We operationalize this by extending the model in equation (16) to include the hierarchal structure presented in equation (17).

\[ \bar{x}_i = \Delta' \beta_i + \xi_i \]  \hspace{1cm} (17)

Models \( M_4 \) to \( M_7 \) 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 in order to better understand the processes managers employee when making input-level decisions. We can compute Bayes factors for these alternatives in order to determine which model best corresponds to the observed data (Rossi et al., 2005; Kass and Raftery, 1995). This applies to both nested and non-nested model specifications.

Parameters of particular interest in our model are the set of \( \{ \lambda_k \} \), the Lagrange multipliers or “shadow prices” of inputs \( \{ x_k \} \). They correspond to the marginal increase in the objective function (e.g., profitability) resulting from a relaxation of the budget constraint, \( \{ m_k \} \):

\[ \frac{\partial L}{\partial m_k} = \lambda_k \]  \hspace{1cm} (18)

Although typically defined in terms of dollars, budget constraints can be specified in a variety of units. In our application, we do not know the monetary cost of adding an additional unit of FTE to a branch and therefore define the budget constraint \( m_1 \) as an upper bound on the total number of employees. Budget constraints \( m_2 \) and \( m_3 \) are 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):

\[
\frac{\partial L}{\partial x_{kit}} = \lambda; \forall k, i, t
\]  

That is, the marginal increase in profitability resulting from an increase in \( \{ x_{kit} \} \) are balanced across all inputs, \( k \), units, \( i \), and time periods, \( t \). In this case, 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 do not observe prices for additional units of FTE and therefore investigate only 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, \( k \).

\[
M_4: \sum_t x_{kit} \leq m_{ki}
\]  

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:

\[
M_5: \sum_t \sum_k x_{kit} \leq m_i
\]  

Model 6 \((M_6)\) defines a scenario where allocation decisions are coordinated across units, but not across inputs:
Model 7 ($M_7$) represents the optimal scenario described above. That is, allocative coordination across time, units, and inputs.

\[ M_7: \sum_k \sum_i \sum_t x_{kit} \leq m \]  \hspace{1cm} (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, $M_I$. This suggests that managers optimally balance inputs within, but not across units. Within a 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). This 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 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 0 are presented in bold face.

[Table 4]

In expectation, both customer and employee satisfaction are positively correlated with the multiplicative intercept, \( \beta_0 \). Increasing average customer and employee satisfaction for a branch will yield a direct increase in its proclivity to produce revenue, conditional upon fixed values of the input variables, \( X \).

As a general note, we observe that employee satisfaction appears to exert a greater influence on 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.

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 satisfaction at a branch increases the efficacy of base salary as a driver of revenue decreases while the efficacy of incentive compensation increases. 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, \( \beta_3 \) (\( \gamma_{4,2} = -0.07 \)).
As customers become increasingly satisfied, incentive compensation becomes a less effective driver of branch profitability.

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 $M_1$ while 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 0 and greater than 1. These results are counterintuitive and severely restrict $M_1$’s ability to provide guidance for future managerial decision making. A value of $\beta < 0$ implies an optimal expenditure of 0 dollars while $\beta > 1$ implies full allocation of all resources to that variable. These implied optimal values are inconsistent with current managerial action observed in our data.

[Figure 1]

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 $\sum_{k=1}^{3} \beta_k \leq 1$. As such, results from this model can be used to explore alternative allocation schemes and can provide useful managerial guidance. In the following section, we demonstrate how this can be accomplished using the results of our proposed model.

[Figure 2]
6. Optimal Resource Allocation

In this section of the paper, we examine a hypothetical business scenario in order to demonstrate how our proposed framework can inform managerial decision making. Retail banks utilize short-term promotions in order to feature an existing service or introduce a new product. Although these promotions are supported by traditional marketing activities, their success or failure hinges upon interpersonal sales efforts conducted at the branch. Sales incentive programs are used to motivate employees to take an active part in these promotions.

Consider the case where one division of the bank (100 branches) is preparing to engage in a month-long promotion of an existing consumer product. Regional managers have access to $100,000 of discretionary funds to be used to incentivize branch employees to actively participate in the promotion. Management’s task is to determine how to best allocate these funds across the region in order to maximize the financial success of the campaign. That is, to set levels of \( \{x_{i1}\} \) in order to achieve the greatest region-wide contribution margin.

We describe incremental revenue less incremental cost as contribution margin (CM) as opposed to profit. Promotional revenue realized in excess of cost contributes to offset region fixed (e.g., advertising, signage, etc.) and administrative expenses. We compare results of the following 7 allocation scenarios:

1. Uniform allocation across branches: under this first scenario each branch in the region is granted an additional $1,000 dollars to be used for incentive compensation.

Projections of the resulting contribution margin are made using the following equation:

\[
\sum_{i} \beta_{0i} x_{i1} + \beta_{1i} x_{i2} + \beta_{2i} x_{i3} - x_{i2} - x_{i3},
\]

where the baseline levels for inputs \( \{x_{i1}\} \), \( \{x_{i2}\} \), and \( \{x_{i3}\} \) are set to their corresponding averages observed in the data. We
account for parameter uncertainty in these projections by integrating over the posterior distribution of $\beta$. This allows us to assess both the expected increase and variance in resulting CM.

2. FTE proportional allocation: greater funds are given to branches with a larger number of employees. We project CM using the method described above.

3. Allocation proportional to the posterior mean of $\beta_{3i}$: greater resources are given to those branches whose employees are, on average, more sensitive to incentive compensation as a driver of revenue. This scenario follows Dorfman and Steiner’s (1954) optimal allocation rule for advertising expenditures.

4. Unconstrained optimal allocation (posterior mean): under this allocation scheme, $\{x_{3i}\}$ are set in order to solve the following mathematical programming problem:

$$\max_{\{x_{3i}\}} \sum_i \beta_{0i} x_{1i} + \beta_{1i} x_{2i} + \beta_{2i} x_{3i} + \beta_{3i} - x_{2i} - x_{3i}.$$  

Branch-specific point estimates equal to the posterior mean of the $\beta$’s are used to simplify the computations involved in obtaining a solution to this problem. As such, we are able to use standard, gradient-based optimization software. We do not impose any constraints on $\{x_{3i}\}$ and therefore admit the potential for corner solutions (i.e., $0$ allocations).

5. Unconstrained optimal allocation (full posterior distribution): in this scenario, we set $\{x_{3i}\}$ in order to maximize expected CM: 

$$\max_{\{x_{3i}\}} E_{\beta|\mathcal{D}} \left[ \sum_i \beta_{0i} x_{1i} + \beta_{1i} x_{2i} + \beta_{2i} x_{3i} + \beta_{3i} - x_{2i} - x_{3i} \right].$$

The expectation in this problem is taken with regard to the posterior distribution of $\{\beta_{3i}\}$. In implementation, this is accomplished through the use of a simulation-based optimizer. Although this results in an increase in computational time, it allows us to formally assess variability in CM projections resulting from parameter uncertainty.
6. Constrained optimal allocation (posterior mean): with one exception, this is identical to scenario 4. In this case bounds are placed on the space of possible allocation solutions, \( \{x_{3i}\} \). Specifically, we assert that all branches must receive at least $200 and no more than $2,000. Although sub-optimal relative to allocations 4 and 5, these constraints may constitute a more realistic representation of how managers would actually utilize our proposed model. That is, they would like to increase the efficacy of their promotional spend relative to scenarios 1-3, but are not willing to rely exclusively on the unconstrained “optimized” results of the model, or may wish to encourage some level of participation by all branches in the region.

7. Constrained optimal allocation (full posterior distribution): this is the constrained version of scenario 5, where the constraints are defined in scenario 6.

Means and standard deviations of expected incremental CM for all allocation schemes are presented in Table 5. We observe that expected CM is substantially improved for the model-based allocations (scenarios 3-7). Expected CM more than doubles as we move from the constant allocation scheme (scenario 1) to the unconstrained optimal allocation (scenario 5).

We also observe that the optimization-based allocations (scenarios 4-7) increase expected CM relative to the allocation based upon the size of the response coefficient, \( \beta_{3i} \) (scenario 3). For example, expected CM increases from $279K for scenario 3 to $471K for scenario 5. Although contrary to the Dorfman/Steiner (1954) result, this is consistent with our expectations given the functional form of our demand model. The optimal distribution of incremental funds will depend on both the size of \( \{\beta_{3i}\} \) as well as the extant allocation of \( \{x_{3i}\} \).

Our proposed model allows us to formally evaluate the costs and benefits associated with undertaking strategic as opposed to tactical actions. For example, under allocation scenario 5 we
observe expected incremental CM for the region equal to $471K. In Table 4 we also observe a positive association between employee satisfaction and the efficacy of incentive compensation as a driver of revenue, as manifest through $\beta_3$. It may be of managerial interest to know how much employee satisfaction would have to increase in order to generate a per-period rise in CM of $471K. This can be easily computed using the chain rule for differentiation:

$$\frac{\partial \Pi_i}{\partial \mu_i} = \frac{\partial \Pi_i}{\partial \beta_j} \frac{\partial \beta_j}{\partial \mu_i}$$

(24)

As presented in Table 6, a one-unit increase in employee satisfaction yields an expected, per-period increase of $358.9K in CM. As such, employee satisfaction would have to increase by 1.3 points (on a 10 point scale) in order to generate a CM increase of $471K.

We can extend this analysis further by recognizing that our model also contains information about the relationship between aggregate employee satisfactions and the specific job characteristics that drive the same. As presented in equation (4), we model employee responses to a battery of questions (including aggregate employee satisfaction) as realizations of a multivariate normal distribution with a branch-specific mean and covariance matrix. We can exploit the properties of the multivariate normal distribution in order to study the conditional distribution of aggregate satisfaction given its drivers. This is accomplished by partitioning the covariance matrix, $\Sigma^e$, as follows:

$$\Sigma^e = \begin{bmatrix} \Sigma_{11}^e & \Sigma_{12}^e \\ \Sigma_{21}^e & \Sigma_{22}^e \end{bmatrix}$$

(25)

where $\Sigma_{12}^e$ is a 1-by-5 matrix that reflects the covariance of aggregate employee satisfaction and its drivers and $\Sigma_{22}^e$ is a 5-by-5 matrix that contains the variance and covariance of the latter. We
can compute the matrix of coefficients for the regression of employee satisfaction on its drivers through the expression $\Sigma_{12}^e \Sigma_{22}^e ^{-1}$, as presented in Table 6.

The monetary impact of changes in employee satisfaction drivers can then be computed using an extension of the chain rule in equation (24). We observe that changes in employees’ satisfaction with opportunities for personal growth and development have the greatest impact on aggregate employee satisfaction and, by extension, incremental CM. A one point average increase in satisfaction with personal growth opportunities will yield a 0.314 increase in overall employee satisfaction and a corresponding increase in expected CM of $112.7K. Given estimated cost information for each of the drivers, this analysis allows us to assess specific actions that should be taken in order to most efficiently increase overall employee satisfaction.

Although our data set does not provide information about specific costs, we can utilize the results of our model to estimate an upper bound on the amount we would be willing to spend to improve the various employee satisfaction metrics. In the scenario described above, management is presented with two alternatives: the firm can operate within the confines of its existing technology and increase the productivity of sales promotions through the use of incremental employee compensation or, rather, the firm can invest in systemic improvements designed to increase aggregate employee satisfaction and, by extension, the efficacy the current incentive compensation allocation. Given these options, the firm would like to know the maximum amount they should be willing to spend to increase employee satisfaction by 1.3 points and forgo the use of short-term sales incentives.

It is important to recognize that customer and employee satisfaction are constructs that evolve slowly across time. Satisfaction improvements will yield benefits not only in the period in which they are enacted, but throughout a finite future time horizon. The bank should view
actions taken to improve satisfaction as capital investments (i.e., an investment in technology) and evaluate them accordingly.

We know that, in expectation, increasing employee satisfaction by 1.3 points will yield an increase in region CM equal to a monthly outlay of $100K in short-term incentive compensation. Suppose the bank applies a $\delta = 12\%$ discount rate to capital investments of this type and believes that the proposed process changes will be sufficient to maintain the desired increase in employee satisfaction without further investment for a 3 year period. Given the discount rate and time horizon, we can compute the net present value of future CM realizations via equation (26):

$$\sum_{t=1}^{36} (1-\delta)^{t/12} CM_t$$

where $CM_t$ is contribution margin realized in month $t$, in this case equal to $471K$. Application of this formula results in a net present value of future CM of approximately $14$ million.

We can also use this formula to compute the net present value of the future cash outlays associated with promotional expenditures (i.e., $100K$ per month), thus providing a present value equivalent of total promotional cost. This value, equal to approximately $2.97$ million, is the maximum dollar amount that the firm should be willing to spend to engage in the employee satisfaction improvements described above. If the cost of improving average employee satisfaction by 1.3 points exceeds $2.97$ million, the bank would be better off to continue to rely on short-term sales incentive promotions.

7. 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 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 on 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 future allocation of resources.

Empirically, this work contributes to the literature on customer satisfaction. We find evidence that the influence of customer satisfaction is manifest through firm technology. That is, changes in customer satisfaction impact firm financial performance by altering the efficacy of the firm’s tactical inputs through the response coefficients, $\beta_{ki}$. In expectation, customer satisfaction is positively related to a firm’s baseline ability to generate revenue. However, increases in customer satisfaction also decrease the effectiveness of operational inputs like base salary and incentive compensation. These findings are congruent with recent calls for work exploring alternative influences of customer satisfaction (Luo and Homburg, 2007).

Our work raises a number of interesting questions that are 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, Retzer, and Allenby (2008). Both the customer and employee studies used in this 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. Rather than searching over a 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.
References


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 non-standard 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 in order to simplify exposition of the algorithm.

As defined in equation (11), the full likelihood for the model can be expressed according to (A1):

$$\ell(\text{data} \mid \text{else}) = \prod_i \prod_t \pi(e_{it}) \pi(\xi_{1it}, \xi_{2it}, \xi_{3it}) \left| J_{\xi \rightarrow x_{it}} \right|$$

where $\pi(\cdot)$ denotes the multivariate normal density function and the quantities $e_{it}$ and $\xi_{kit}$ can be computed according to (A2) and (A3). The Jacobian term is defined in (A4).

$$e_{it} = \ln(y_{it}) - \ln(\beta_0) + \beta_i \ln(x_{1it}) + \beta_2 \ln(x_{2it}) + \beta_3 \ln(x_{3it})$$

$$\begin{bmatrix} \xi_{1it} \\ \xi_{2it} \\ \xi_{3it} \end{bmatrix} = \begin{bmatrix} \beta_i - 1 \\ \beta_i \\ \beta_i \end{bmatrix} \begin{bmatrix} \beta_i \\ \beta_i - 1 \\ \beta_i \end{bmatrix} \begin{bmatrix} \ln(x_{1it}) \\ \ln(x_{2it}) \\ \ln(x_{3it}) \end{bmatrix} = \begin{bmatrix} \ln(\lambda_i) - \ln(\beta_0) - \ln(\beta_i) \\ \ln(\lambda_i) - \ln(\beta_0) - \ln(\beta_i) \\ \ln(\lambda_i) - \ln(\beta_0) - \ln(\beta_i) \end{bmatrix}$$

$$\left| J_{\xi \rightarrow x_{it}} \right| = |\beta_i + \beta_2i + \beta_3i - 1|$$

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

$$e_{it} \sim N\left(0, \sigma_i^2\right)$$

$$\begin{bmatrix} \xi_{1it} \\ \xi_{2it} \end{bmatrix} \sim N\left(0, \Sigma_{\xi_{it}}\right)$$
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 dataset drawing:

1. $\left[\{\beta_{ki}\} \mid \text{else}\right] \propto \left[\{x_{ki}\} \mid \{\beta_{ki}\}, \sigma^2_{si}\right] \left[\{x_{kit}\} \mid \{\beta_{ki}\}, \{\lambda_{ki}\}, \Sigma_{si}\right] \left[\{\beta_{ki}\} \mid \Gamma, \mu^*, \Sigma_{\beta}\right]

   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:

   $$\prod_i \pi(e_{it}) \pi(\zeta_{1it}, \zeta_{2it}, \zeta_{3it}) \left| J_{it} \right|$$

   where the Jacobian is defined in equation (A4) and the hierarchical prior for beta is specified as:

   $$\beta_i \sim N(\Gamma \mu^*, \Sigma_{\beta})$$

   Acceptance probabilities are computed using the standard algorithm (see Rossi, Allenby, and McCulloch 2005 – page 88)

2. $\left[\{\lambda_{ki}\} \mid \text{else}\right] \propto \left[\{x_{ki}\} \mid \{\beta_{ki}\}, \{\lambda_{ki}\}, \Sigma_{si}\right] \left[\{\lambda_{ki}\} \mid \lambda, \Sigma_{\lambda}\right]

   $\{\lambda_{ki}\}$ are also draw using the M-H algorithm where the likelihood contribution of the first factor is equal to:

   $$\prod_i \pi(\zeta_{1it}, \zeta_{2it}, \zeta_{3it}) \left| J_{it} \right|$$

   with a corresponding hierarchical prior specified for $\{\lambda_{ki}\}$:

   $$\{\lambda_{ki}\} \sim N(\lambda, \Sigma_{\lambda})$$

3. $\left[\sigma^2_i \mid \text{else}\right]$  
   
   Conditional on a draw of $\beta_i$, $\sigma^2_i$ is a standard draw from an inverse chi-square distribution (see Rossi, Allenby and McCulloch 2005 – page 25)
Block 2: Across Units

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:

$$\Sigma_\beta \sim IW(\nu_0 + N, V_0 + S_\beta)$$
$$\Gamma \sim N\left(\tilde{\Gamma}, \Sigma_\beta \otimes \left(\mu'' \mu^* + A_\beta\right)^{-1}\right)$$

where:

$$\tilde{\Gamma} = \text{vec}(\tilde{M}_\beta), \tilde{M}_\beta = \left(\mu'' \mu^* + A_\beta\right)^{-1} \left(\mu'' \mu^* \tilde{M}_\beta + A_\beta \tilde{M}\right)$$
$$S_\beta = \left(\beta - \mu^* \tilde{M}_\beta\right)^T \left(\beta - \mu^* \tilde{M}_\beta\right) + \left(\tilde{M}_\beta - \tilde{M}\right)^T A_\beta \left(\tilde{M}_\beta - \tilde{M}\right)$$

and $\hat{M} = \left(\mu'' \mu^*\right)^{-1} \left(\mu'' \beta\right)$

All priors were specified using standard, non-informative values.

5. $[\Lambda, \Sigma_\lambda | \text{else}]$

Conditional on realizations of $\{\lambda_{ki}\}$, $\Lambda$, $\Sigma_\lambda$ can be estimated using a multivariate regression of $\{\lambda_{ki}\}$ 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

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

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

7. $[\mu_{ki}^c | \text{else}] \propto [\mu_{ki}^c | \bar{z}_{ki}, \mu_{ki}^c, \Sigma_i^c, \Sigma_\beta][\beta_\iota | \mu_{ki}^c, \Gamma, \Sigma_\beta]$
Inference for the latent level of aggregate customer satisfaction, $\mu_{ci}$, proceeds by first recognizing that the distribution of $\mu_{ci}$ is proportional to the product of three multivariate normal distributions: A, B, and C. We derive the posterior distribution for $\mu_{ci}$ by re-expressing A, B, and C in terms of the univariate normal for $\mu_{ci}$ and combining quadratic forms as described in Box and Tiao (1973):

$$\mu_{ci}^c \sim N\left(\mu_{ci}, \Sigma_{\mu_{ci}}\right)$$

where:

$$\mu_{ci}^c = \left(\Sigma_A^{-1} + \Sigma_B^{-1} + \Sigma_C^{-1}\right)^{-1}\left(\Sigma_A^{-1} \mu_A + \Sigma_B^{-1} \mu_B + \Sigma_C^{-1} \mu_C\right)$$

$$\Sigma_{\mu_{ci}} = \left(\Sigma_A^{-1} + \Sigma_B^{-1} + \Sigma_C^{-1}\right)^{-1}$$

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

Factor A (contribution from the prior):

$$\mu_A = 0$$

$$\Sigma_A = 100$$

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

$$\mu_B = \mu_{ci}^c + \Sigma_{i2}^c \left(\Sigma_{22}^{-1} \left(\alpha - \mu_{ci}^c\right)\right)$$

$$\Sigma_B = \Sigma_{11}^c - \Sigma_{i2}^c \Sigma_{22}^{-1} \Sigma_{21}^c$$

where:

$$z_{ih}^c \sim N\left(\mu^c, \Sigma_i^c\right)$$

$$\Sigma_i^c = \begin{bmatrix} \Sigma_{i1}^c & \Sigma_{i2}^c \\ \Sigma_{21}^c & \Sigma_{22}^c \end{bmatrix}$$

Factor C (contribution from the model for the demand response coefficients, $\beta$):
\[ \beta_i = \Gamma' \mu^*_i + \eta_i \]

Begin by partitioning as follows:

\[
\Gamma' = \begin{bmatrix}
\Gamma_{11} & \Gamma_{12} \\
\Gamma_{21} & \Gamma_{22}
\end{bmatrix}
\]

Compute:

\[
\beta_i - \Gamma_1 \begin{bmatrix} 1 \\ \mu_i^c \end{bmatrix} = \Gamma_2 \mu_i^c
\]

\[
\mu_c = \left(\Gamma_2' \Gamma_2\right)^{-1} \Gamma_2' \left(\beta_i - \Gamma_1 \begin{bmatrix} 1 \\ \mu_i^c \end{bmatrix}\right)
\]

\[
\Sigma_c = \left(\Gamma_2' \Gamma_2\right)^{-1} \left(\Gamma_2' \Sigma_\beta \Gamma_2 \right) \left(\Gamma_2' \Gamma_2\right)^{-1}
\]

**Block 4: Across Units**

8. \[ \overline{\mu}^c, V_\mu^c \mid \text{else} \]

Conditional on realizations of \( \mu_i^c \), estimation of \( \overline{\mu}^c \) and \( V_\mu^c \) proceeds through the use of a multivariate regression as defined in step 4.

9. \[ \Omega^c \mid \text{else} \]

We follow Jen, Chou, and Allenby (2007) when drawing parameters for the distribution of random effects specified for \( \Sigma_i^c \).

The conditional posterior for \( \Omega^c \) is \( IW\left(v_0^c + N \overline{\nu}_c, \left(\Omega_0^{c-1} + \sum_{i=1}^{N} \Sigma_i^{c-1}\right)\right)\)

10. \[ \overline{\nu}^c \mid \text{else} \]

The posterior distribution for \( \overline{\nu}^c \) does not have a closed form expression and must therefore be drawn using a M-H step, where the likelihood contribution for \( \overline{\nu}^c \) is equal to:
\[
\prod_{i=1}^{N} \left( 2^\nu \pi^{-\frac{1}{2}} \Gamma \left( \frac{\nu}{2} \right) \Gamma \left( \frac{\nu - 1}{2} \right) \right)^{-1} \left| \Omega^\nu \right|^{-\frac{\nu}{2}} \exp \left\{ -\frac{1}{2} \text{tr} \left( \left( \Sigma_i^\nu \right)^{-1} \left( \Omega^\nu \right)^{-1} \right) \right\}
\]

Steps 11 through 15 are the employee analogs of customer steps 6-10. Parameter estimation follows directly.

**Block 5: Within Units**

11. \(\left[ \mu_i^\nu, \Sigma_i^\nu | else \right]\)

12. \(\left[ \mu_i^\nu | else \right] \propto \left[ \mu_i^\nu | \Pi^\nu, V^\nu \right] \left[ z_{ih}^\nu | \mu_i^\nu, \Sigma_i^\nu \right] \left[ \beta_i \right. | \mu_i^\nu, \Gamma, \Sigma_\beta \]

**Block 6: Across Units**

13. \(\left[ \Pi^\nu, V^\nu | else \right]\)

14. \(\left[ \Sigma^\nu | else \right]\)

15. \(\left[ \Omega^\nu | else \right]\)
Figure 1
Distribution of Posterior Means for Beta for $M_I$ - Demand Side Only
Figure 2
Distribution of Posterior Means for Beta for $M_3$ – Simultaneous Supply and Demand
Table 1  
Descriptive Statistics for Branch Level Income Statements

<table>
<thead>
<tr>
<th>Financial Variables</th>
<th>Mean</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weeks of Data</td>
<td>12.5</td>
<td>6</td>
<td>13</td>
</tr>
<tr>
<td>Total Income (000's)</td>
<td>$88.5</td>
<td>$1.4</td>
<td>$465.6</td>
</tr>
<tr>
<td>FTE</td>
<td>9.1</td>
<td>1.0</td>
<td>34.0</td>
</tr>
<tr>
<td>Base Salary Expense (000's)</td>
<td>$20.6</td>
<td>$2.7</td>
<td>$77.9</td>
</tr>
<tr>
<td>Incentive Compensation (000's)</td>
<td>$5.7</td>
<td>$0.0</td>
<td>$50.8</td>
</tr>
</tbody>
</table>
Table 2
Descriptive Statistics for Employee and Customer Satisfaction Studies

<table>
<thead>
<tr>
<th>Variable</th>
<th>n</th>
<th>Mean</th>
<th>Std Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Customer Measures (1 to 10 Scale; 1 = Unacceptable, 10 = Outstanding)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Overall branch rating (proxy for customer satisfaction)</td>
<td>898</td>
<td>8.9</td>
<td>1.6</td>
</tr>
<tr>
<td>Rating of the courtesy and friendliness of branch tellers</td>
<td>898</td>
<td>9.1</td>
<td>1.4</td>
</tr>
<tr>
<td>Evaluation of time required to wait in line for service</td>
<td>898</td>
<td>7.9</td>
<td>2.2</td>
</tr>
<tr>
<td><strong>Employee Measures (1 to 10 Scale; 1 = Very Dissatisfied, 5 = Very Satisfied)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Overall job satisfaction</td>
<td>898</td>
<td>7.7</td>
<td>1.9</td>
</tr>
<tr>
<td>Decision making authority required to do job effectively</td>
<td>898</td>
<td>8.1</td>
<td>1.8</td>
</tr>
<tr>
<td>Fair evaluation of job performance</td>
<td>898</td>
<td>7.7</td>
<td>2.0</td>
</tr>
<tr>
<td>Clear link between job performance and compensation</td>
<td>898</td>
<td>6.8</td>
<td>2.4</td>
</tr>
<tr>
<td>Satisfaction with rewards program (pay, bonus, 401k, etc.)</td>
<td>898</td>
<td>6.9</td>
<td>2.1</td>
</tr>
<tr>
<td>Opportunities for personal growth and development</td>
<td>898</td>
<td>7.9</td>
<td>1.8</td>
</tr>
</tbody>
</table>
Table 3
Fit Statistics for Alternative Supply and Demand Side Models

<table>
<thead>
<tr>
<th>Model</th>
<th>Description</th>
<th>Endogenous X</th>
<th>Constrained Parameters</th>
<th>LMD X</th>
<th>LMD Y</th>
<th>LMD TTL</th>
</tr>
</thead>
<tbody>
<tr>
<td>$M_1$</td>
<td>Unconstrained demand-side model for $y$. Likelihood contribution of $X_i \sim N(\mu, \Sigma)$</td>
<td>--</td>
<td>--</td>
<td>14,709.88</td>
<td>1,645.71</td>
<td>16,355.59</td>
</tr>
<tr>
<td>$M_2$</td>
<td>Demand-side model with constrained parameter space for $\beta$. Likelihood contribution of $X_i \sim N(\mu, \Sigma)$</td>
<td>--</td>
<td>$\times$</td>
<td>14,709.88</td>
<td>1,219.62</td>
<td>15,929.50</td>
</tr>
<tr>
<td>$M_3$</td>
<td>Simultaneous supply and demand model where supply-side is modeled as a linear function of the $\beta$’s (MCR).</td>
<td>$\times$</td>
<td>--</td>
<td>6,652.95</td>
<td>-732.18</td>
<td>5,920.78</td>
</tr>
<tr>
<td>$M_4$</td>
<td>Simultaneous supply and demand model with independent (unit-level) budget constraints over all inputs.</td>
<td>$\times$</td>
<td>$\times$</td>
<td>19,852.23</td>
<td>-2,943.99</td>
<td>16,908.24</td>
</tr>
<tr>
<td>$M_5$</td>
<td>Simultaneous supply and demand model with a single (unit-level) budget constraint over all inputs.</td>
<td>$\times$</td>
<td>$\times$</td>
<td>20,625.92</td>
<td>-2,889.55</td>
<td>17,736.38</td>
</tr>
<tr>
<td>$M_6$</td>
<td>Simultaneous supply and demand model with independent (bank-level) budget constraints over all inputs.</td>
<td>$\times$</td>
<td>$\times$</td>
<td>20,529.22</td>
<td>-4,650.15</td>
<td>15,879.07</td>
</tr>
<tr>
<td>$M_7$</td>
<td>Simultaneous supply and demand model with a single (bank-level) budget constraint over all inputs.</td>
<td>$\times$</td>
<td>$\times$</td>
<td>20,261.82</td>
<td>-5,247.83</td>
<td>15,013.99</td>
</tr>
</tbody>
</table>
Table 4  
Impact of Satisfaction of Response Coefficients - $\Gamma$ Matrix

<table>
<thead>
<tr>
<th>Posterior Mean</th>
<th>Intercept</th>
<th>Customer Satisfaction</th>
<th>Employee Satisfaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_0$ - Intercept</td>
<td>2.24</td>
<td>0.08</td>
<td>0.20</td>
</tr>
<tr>
<td>$\beta_1$ - FTE</td>
<td>0.05</td>
<td>-0.02</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_2$ - Base Salary</td>
<td>0.78</td>
<td>-0.02</td>
<td>-0.06</td>
</tr>
<tr>
<td>$\beta_3$ – Incentive Pay</td>
<td>0.10</td>
<td>-0.07</td>
<td>0.09</td>
</tr>
<tr>
<td>Scenario</td>
<td>Incremental Contribution Margin*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>-------------------------------------------------------------------------</td>
<td>----------------------------------</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>mean</td>
<td>std dev</td>
<td></td>
</tr>
<tr>
<td>1. Uniform Allocation ($1,000 to each branch)</td>
<td>$220</td>
<td>$6</td>
<td></td>
</tr>
<tr>
<td>2. FTE Proportional Allocation</td>
<td>$228</td>
<td>$6</td>
<td></td>
</tr>
<tr>
<td>3. Allocation Proportional to size of $\beta_{3i}$ (posterior mean)</td>
<td>$279</td>
<td>$6</td>
<td></td>
</tr>
<tr>
<td>4. Unconstrained Optimal Allocation (posterior mean)</td>
<td>$465</td>
<td>--</td>
<td></td>
</tr>
<tr>
<td>5. Unconstrained Optimal Allocation (full posterior)</td>
<td>$471</td>
<td>$26</td>
<td></td>
</tr>
<tr>
<td>6. Constrained Optimal Allocation $200 Min, $2000 Max (posterior mean)</td>
<td>$401</td>
<td>--</td>
<td></td>
</tr>
<tr>
<td>7. Constrained Optimal Allocation $200 Min, $2000 Max (full posterior)</td>
<td>$406</td>
<td>$15</td>
<td></td>
</tr>
</tbody>
</table>

* thousands of dollars
### Table 6
Expected Financial Impact of Changes in Employee Satisfaction and Employee Satisfaction Drivers

<table>
<thead>
<tr>
<th>Employee Satisfaction Drivers</th>
<th>Expected impact of employee satisfaction on region CM*</th>
<th>Average impact of job characteristics on employee satisfaction</th>
<th>Expected impact of job characteristics on region CM*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Personal growth and development</td>
<td>$\frac{\partial \Pi}{\partial \mu_i}$ 0.314</td>
<td>$\frac{\partial \mu_i}{\partial \mu_{j,t}}$</td>
<td>$\frac{\partial \Pi}{\partial \mu_{j,t}} \cdot \frac{\partial \mu_i}{\partial \mu_{j,t}}$</td>
</tr>
<tr>
<td>Satisfaction with rewards</td>
<td>$\frac{\partial \Pi}{\partial \mu_i}$ 0.204</td>
<td>$\frac{\partial \mu_i}{\partial \mu_{j,t}}$</td>
<td>$\frac{\partial \Pi}{\partial \mu_{j,t}} \cdot \frac{\partial \mu_i}{\partial \mu_{j,t}}$</td>
</tr>
<tr>
<td>Fair evaluation of job performance</td>
<td>$\frac{\partial \Pi}{\partial \mu_i}$ 0.197</td>
<td>$\frac{\partial \mu_i}{\partial \mu_{j,t}}$</td>
<td>$\frac{\partial \Pi}{\partial \mu_{j,t}} \cdot \frac{\partial \mu_i}{\partial \mu_{j,t}}$</td>
</tr>
<tr>
<td>Pay-performance link</td>
<td>$\frac{\partial \Pi}{\partial \mu_i}$ 0.158</td>
<td>$\frac{\partial \mu_i}{\partial \mu_{j,t}}$</td>
<td>$\frac{\partial \Pi}{\partial \mu_{j,t}} \cdot \frac{\partial \mu_i}{\partial \mu_{j,t}}$</td>
</tr>
<tr>
<td>Decision making authority</td>
<td>$\frac{\partial \Pi}{\partial \mu_i}$ 0.137</td>
<td>$\frac{\partial \mu_i}{\partial \mu_{j,t}}$</td>
<td>$\frac{\partial \Pi}{\partial \mu_{j,t}} \cdot \frac{\partial \mu_i}{\partial \mu_{j,t}}$</td>
</tr>
</tbody>
</table>

* thousands of dollars