Is Cash King? A Field Experiment on Mental Accounting in a Salesforce

Madhu Viswanathan
(madhu@email.arizona.edu)

Xiaolin Li
(lixx1012@umn.edu)

Om Narasimhan
(o.narasimhan@lse.ac.uk)

George John
(johnx001@umn.edu)

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¹Madhu Viswanathan is an Assistant Professor at the Eller College of Management, University of Arizona; Xiaolin Li is a doctoral student at the Carlson School of Management, University of Minnesota; Om Narasimhan is a Professor at the London School of Economics; George John is Professor of Marketing, Carlson School of Management, University of Minnesota.
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Abstract

The fungibility of money, along with its function as a medium of exchange, gives monetary transactions pride of place in neoclassical theories of economics. However, a growing number of laboratory studies and anecdotal field evidence (appealing to theories of mental accounting) have shown that consumers’ willingness to spend an additional unit of wealth depends upon the sources and categories of wealth, thus throwing serious doubt on the presumed fungibility of cash. This paper attempts to examine the notion of money fungibility in the context of salesperson effort. Given that firms desire to design the least cost pay basket to evoke a given level of effort, it is important to i) identify whether salespersons differ in their response to disparate forms of compensation, ii) quantify the impact of different sources of wealth, and iii) explore the underlying mechanisms at play. We seek to achieve the above objectives using a multi-method empirical approach. In particular, we use a field intervention, reduced form estimation to derive initial insights from the intervention, a structural model to uncover the differential response to cash versus non-cash compensation. We also implement a survey of our salespeople to pinpoint the precursors of separate budgets. We find converging evidence that salespeople maintain separate accounts for cash and non-cash bonuses, dispelling the neo-classical expectation that favors cash as king.
1 INTRODUCTION

Ever since the ancient Sumerians established laws governing monetary transactions, the fungibility of money has been a fundamental feature of civil society. More importantly, this interchangeability has led to money being the dominant mode of transaction in practically all forms of economic exchange. Indeed, even giving gifts is considered less efficient than giving cash in most circumstances (Waldfogel, 2009). However, a growing number of laboratory studies and some field evidence (appealing to notions of mental accounting) have shown that consumers’ willingness to spend an additional unit of wealth depends upon the sources and categories of wealth. Put differently, the fungibility of cash (see, for example, Thaler 2004 for an overview of findings in this area) is challenged by the separability of budgets.

This paper extends the idea of separate budgets to the domain of effort. We study how salesperson effort in response to rewards might depend on the cash versus non-cash nature of the reward. This is of considerable practical importance as non-monetary transactions\(^2\) have become a common feature of the compensation landscape. One recent study reports 78% of firms use tangible non-monetary compensation incentives, such as vacations or electronics products (Jeffrey and Shaffer 2007). This amounted to over $46 billion on non-monetary incentives in 2006 alone (Incentive Federation, 2007). The widespread prevalence and growth of non-monetary incentives is puzzling – standard economic theory predicts that employees should strictly prefer monetary to non-monetary transactions. With the flexibility offered by cash, salespeople, (who know their individual preferences better than the employer), should be able to match their choices better than the employer. Therefore, an employee’s effort responsiveness over the different forms of incentives within a given pay “basket” that might include cash, loyalty points, certificates, etc., should be the highest for cash. At best, s/he should be indifferent at the implied exchange rate value

\(^2\)We define non-monetary incentives as those incentives which are performance based, non-cash and non-trivial. According to our definition, a trip to Hawaii would be a non-monetary incentive while a plaque/trophy honoring the salesperson would not.
of the transaction. Thus, if 300 bonus points yields a salesperson a vacation to Hawaii available from a catalog of rewards, he should value this reward at its market cash value. Further, given non-zero transaction costs of administering non-monetary rewards, firms should also strictly favor monetary incentives\(^3\). The increasing use of non-monetary incentives suggests that this somewhat obvious prediction needs re-examination. However, while a large literature has looked at effort response to monetary incentive compensation, there has been comparatively little work contrasting monetary and non-monetary compensation. Do salespeople differ in their response to disparate forms of compensation; can we quantify the impact of different sources of compensation, and pinpoint the underlying mechanisms.

We seek to achieve the above objectives using a multi-method empirical approach that consists of a field intervention, reduced form analysis, a structural model, and a survey. The data for our study comes from an engagement with a large frozen food manufacturer in the U.S who worked with us to re-design its sales force compensation plans. The status quo plan for 590 salespeople consists of a commission on sales and bonuses for reaching three target quotas each month. The bonus incentive, which is the main focus of our research, amounted to around 10% of the total compensation. Achieving the first, second, or third quota levels yields a cash bonus of $75 and 20 “ovation\(^4\)” points, $150 and 40 points, or $225 and 60 ovation points respectively. Ovation points can then be exchanged for a variety of rewards ranging from movie rentals to vacation packages. Our strategy was to first conduct a field experiment to test the hypothesis that if the ovation points were simply valued at the market value of the products in the catalog, then the firm could induce the same effort (or perhaps higher effort given some level of transaction costs) by switching to an all-cash bonus regime.

We designed a field intervention to test the conjecture that if the Ovation points and

\(^3\)We recognize that in certain instances, firms might get some deep discounts for purchasing items in bulk which might make non-monetary incentives more appealing. Conversations with sales managers suggest that this is not the norm, and it is definitely not the case in our context.

\(^4\)“Ovation” is the name of the points plan and catalog at this firm
their cash equivalent were interchangeable, the firm could induce the same effort (or perhaps higher effort given some level of transaction costs) by switching to an all-cash bonus regime. Based on inputs from the firm’s chief sales executive, we changed the bonuses at the three target levels to $150, $300, and $450 respectively. These cash bonuses and the previous cash+points bonuses are equally costly for the firm.

We observe weekly sales, monthly targets and payouts for each salesperson in a 590 person sales force that sold a frozen foods product line to grocery stores. In addition, the firm provided us with monthly sales for the prior year. The analysis of our intervention yielded an estimate of 6.5% reduction in pre-post sales (after controlling for salesperson/route effects, month, and prior-year sales). Plainly, an equally costly all-cash contract yielded fewer sales. While this is supportive of separate budgets for cash and non-cash compensation elements, there is no direct evidence of their differential effort.

Do the salespeople respond as if their utility function consists of two separate components, and that these two components yield different amounts of utility? In order to better understand the posited effort mechanisms through which the intervention works, we build a structural model of salesperson effort. We specify a salesperson utility function that incorporates differential weights for the cash bonuses and non-cash ovation point bonuses. A dynamic single agent using the standard agent response framework is estimated for each salesperson using the Bajari, Benkard and Levin (2007) methodology employed in Misra and Nair (2011) and Chung et al. (2011). Our estimated utility function parameters show that a large fraction of salespeople weigh Ovation points higher than equally costly (to the firm) monetary bonuses. In other words, salespeople behave as if they maintain separate budget/accounts for cash versus non-cash bonuses, which confirm our conjecture regarding separate mental accounts.

These analysis of the data from our field intervention constitute converging evidence of separate mental accounts that a salesperson keeps for cash and non-monetary incentives. With existence established, we now turn to an exploration of the possible reasons that give
rise to these two budgets. To this end, we conducted a survey of these very same sales-
people to pin down possible sources of the presence of separate budgets, viz., processing
mindsets, hedonic vs. utilitarian rewards, and intra-family budget partitions (we explain
each of these theories later, both in reviewing relevant prior literature, and in detailing our
survey methodology). We find support for processing mindsets and intra-family partitions
as drivers that evoke these cash and non-cash compensation budgets that in turn make it
desirable for firm to include non-monetary compensation.

Our study makes several contributions. We offer evidence that salespeople maintain
separate accounts for cash and non-cash bonuses. To the best of our knowledge, this is
the first evidence that effort response in the field tracks the separate budgets notion, thus
adding to the sparse field evidence on the existence and magnitude of separate budgets
influencing job effort. We probe the possible motivations behind a preference for non-
monetary rewards through a survey, and find interesting patterns behind this preference.
Our use of multiple approaches (field experiments coupled with structural estimation and
surveys) strengthen the robustness of our conclusions by providing convergent evidence.
Finally, our research is of immediate practical relevance to managers and firms in designing
sales force compensation plans.

Related Literature

There is a great deal of literature on incentive mechanisms in the context of salesforce man-
agement. The workhorse model for studying incentive compensation is the principal-agent
model, which has spawned a large modeling and empirical literature. Generally, these
studies confirm that monetary payments tied to outputs increase task effort (see Prender-
gast (1999) for a review of the work in economics, and Bergen et al. (1992) or Albers and
Mantrala (2008) for a more pragmatic managerial focus). Most of this work has dealt ex-
clusively with cash incentives, whether commissions or lump sum bonuses. There has been
a large literature, especially in psychology, that has looked at the role of extrinsic versus
intrinsic rewards, and the differing impact on various outcomes, such as goal attainment and creativity (see Banker et al. (1996) for an examination of a number of these effects). It is important to emphasize that our paper does not speak to the question of extrinsic versus intrinsic rewards. The two types of incentive compensation we consider are both extrinsic – one is quite clearly monetary (pure cash) while the other involves a mix of monetary and non-monetary compensation (reward points). Our focus, therefore, can more appropriately be said to be on the kind of extrinsic reward to offer (see Jeffrey and Shaffer (2007) for a similar point).

Perhaps the work closest to ours is that by Jeffrey (2002), who looks at various reasons why non-monetary rewards might be preferred to monetary ones. He draws on extant work in psychology to suggest that the ex-ante perceived value of the award may be enhanced by its evaluability (hedonic rewards might lead to an inflated valuation, because they lead to an affective reaction on the part of the recipient; see Loewenstein et al. 2001) and separability (theories of mental accounting that we have already referred to earlier; see Thaler 1999 and the literature referred to below). In addition, he suggests factors that may enhance the ex-post value of a non-monetary reward. These include justifiability (it is easier to justify to oneself a vacation that one earns through points than to justify spending the cash equivalent) and social reinforcement (the idea that it is easier to talk about the points one has earned, or the vacation one got as a reward, than to brag about the cash equivalent). While our emphasis is not on evaluating the relative merits of each of these explanations, it suggests a number of possible reasons why non-monetary rewards may be preferred (something we do find), and some of our survey questions to salespersons try uncovering evidence for a subset of the mechanisms above.

Finally, since our focus is on the possibility of mental accounting on the part of salespersons, the literature in that area is of considerable relevance. While many papers have shown indirect evidence of mental accounting on the part of diverse actors (e.g., Sahm et

\[ ^5 \text{While his focus is on a similar construct (the importance of non-monetary rewards), we differ comprehensively in approach, emphasis, and findings.} \]
al. 2010), there is practically no direct compelling econometric evidence. A recent working paper (Hastings and Shapiro 2011) attempts to address this gap, by looking at differences in the mix of gasoline consumed in response to price increases of various grades of gasoline. They find evidence that consumer price elasticities differ across the two situations, offering tentative evidence that consumers keep separate mental accounts. We build on their pioneering effort by conducting an actual field experiment that considers both monetary and non-monetary regimes, using this to derive tentative evidence for mental accounting, and then building a dynamic structural model to get at primitives that help us pin this explanation down more firmly.

2 Data Description

Our data contain details of incentive and compensation plans, weekly and monthly revenues, and corresponding monthly targets for 590 routes over 6 months beginning from June 2011. Additionally, we also possess 24 months of data on monthly revenues and category sales for each route\(^6\). Monthly targets and goals are set at the beginning of the year. The switch to a bonus scheme based on pure cash was made in October of 2011, which is the beginning of the fourth quarter of 2011. Overall, we observe three months of data for the bonus scheme based on ovations and three months of data for the scheme based on cash. (In what follows, we refer to these as the “ovation” regime and the “pure cash” regime, respectively.)

The company also provided us information on the tenure of each salesperson and the route he serviced. During our period of examination, there was almost no turnover\(^7\) or route reallocation. Thus in our data, each route is uniquely identified by a salesperson\(^8\).

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\(^6\) We do not have good compensation plan information prior to July 2011.

\(^7\) Around 20 routes saw a change in salespersons during entire observation length. These routes are not a part of our analysis.

\(^8\) That means we can’t separately identify a route effect from a salesperson effect. While we account for a salesperson/route fixed effect, we assume that any changes in sales occurred purely due to a change in effort expended by a salesperson. There is no ex-ante reason to believe that changes in compensation would
The absence of turnovers and route reallocations suggests the absence of learning effects that impact worker’s productivity, implying that the salesperson’s ability can reasonably assumed to be constant across our data period.

**Table 1** summarizes the information about the sales force. Note that there is a wide range in the sales potential of different routes. Typically, each route contains a couple of large stores. Plainly, store size affects the sales potential of a route, so we rely on the firm’s targets as well as to estimate our effort response at the individual salesperson level.

**Figure 1** graphs monthly sales from July 2011 to December 2011, which suggest a decrease in sales decreased in the post-switch period. There is also a time trend (constantly decreasing) evident in 2011 arising from poor category sales as shown in **Figure 2**. We account for the time trend by using category sales as a covariate. Further, we use the previous year’s sales as a control variable to account for seasonality in sales outcomes.

**Figure 3** plots the kernel density of monthly sales. From this figure, it is clear that the ovation distribution lies to the right of the pure-cash distribution, which suggests that average sales are higher in the former regime. (Kernel density plots based on weekly plots lead to very similar conclusions.)

The remainder of our empirical analysis consists of two components. First, we use the quasi-experimental setup to test whether salespersons are more productive with monetary or non-monetary bonuses. We examine the experimental data with a set of reduced form regressions. However, our reduced-form regressions, while instructive on the direction and magnitude of the impact of regime change, cannot speak to the possible drivers of this impact, since they does not yield effort estimates. In order to do so one needs a structural model of salesperson effort. Our second component, therefore, is a dynamic structural model of salesperson behavior to estimate the underlying unobserved effort and marginal cost of effort under different compensation schemes. We describe each of these pieces in turn.
2.1 Experimental Test

Our goal in this analysis is to investigate whether salespersons prefer cash to other non-monetary incentives. In general, given the fungibility of money and the non-zero costs associated with reselling goods purchased with ovation points, salespersons should prefer monetary rewards to non-monetary rewards. Under this hypothesis, they should expend more effort under a regime with cash incentives and should consequently have higher sales. We investigate the effect of the different bonus plans on sales with a model that is a standard specification for a fully within-subjects repeated measures design:

$$Sales_{it} = \alpha_i + \beta_1 Target_{it} + \beta_2 Regime_t + \beta_3 Sales_{i(t-12)} + \epsilon_{it}$$  (1)

where $Sales_{it}$ is the sales generated by salesperson $i$ in month $t$, and $\alpha_i$ are salesperson/route fixed effects that account for unobserved and permanent differences across salespersons and routes. The covariate vector $Target_{it}$ is the monthly quota, $Regime_t$ is an indicator variable for the type of compensation scheme, with 1 indicating the pure cash scheme, $Sales_{i(t-12)}$ is sales generated by salesperson $i$ in the corresponding month $t-12$ (the same month of the previous year) to control for seasonality effects, and $\epsilon_{it}$ are individual/route and time specific factors that are unobserved by the econometrician but affect sales. Table 2 reports results for this model. The coefficient on the regime dummy variable reveals a significant negative effect on sales ($\beta_2 = -6921.3$, $p = 0.000$). Evaluated at the mean, our estimate implies that an average sales person is 6.7% more productive under a compensation regime with ovation points than a compensation regime with pure-cash incentives. The above result is counter to the classical economics hypothesis that the impact of a shift to a pure cash incentive would have a positive effect on sales. In fact, the results seem to suggest that a salesperson on average prefers ovation points to cash. Does this preference extend to all salespersons? We examine heterogeneity across salespersons next.
Heterogeneous Effects across Ability Deciles

We use the following quantile regression to estimate the conditional distribution of log productivity at different quantiles:

\[ \text{Quant}_\theta(Sales_{it} \mid \cdot) = \beta_{1\theta} Target_{it} + \beta_{2\theta} Regime_{t} + \beta_{3\theta} Sales_{i(t-12)} + \epsilon_{it} \] (2)

where all variables are as previously defined. Table 3 reports the simultaneous estimates of eqn.2 at different quantiles indexed by \( \theta \). The results illustrate two important facts. One, they reinforce the previous finding that salespersons do indeed prefer ovation points over cash rewards (all the estimates of the Regime effect are negative and significant) and two, that the average effect of the intervention is substantially different across salespersons (the magnitude of the Regime effect is different across different quantiles; the differences are significant at the 95% confidence level). Sales in all quantiles dropped while switching from the ovations regime to the pure-cash regime. Salespersons in the 90\(^{th}\) quantile were affected the most by the change, with their average sales dropping by 6.7\%. Sales dropped at the 10\(^{th}\) quantile by 5.33\%, at the 25\(^{th}\) quantile by 4.91\%, at the 75\(^{th}\) quantile by 7.31\% and at the 90\(^{th}\) by 9.05\%. Further, the differences across quantiles were significantly different from zero. Figure 4 plots the kernel density of the intervention effect and clearly brings out heterogeneity across salespersons. Note that sales persons who have higher sales show a larger intervention effect.

Our experimental analyses show that sales decreased when compensation was changed from mixed to pure monetary incentives. This seems to suggest that ovations points and cash are treated differently by salespersons. Further, our results show considerable heterogeneity in salesperson response to the two schemes. Our results present some interesting follow up questions. How much do salespersons value ovation points over cash? Do they expend more effort when incentivized with ovation points? However, answering the questions is complicated because the underlying parameters of interest, salespersons’ effort and
marginal cost of effort are unobserved. To answer this question, we build a dynamic structural model of salesperson behavior. We then estimate the model using the Bajari, Benkard and Levin (2007) estimator.

3 Structural Model

We model the salesperson as a risk-averse agent making inter-temporal effort allocation tradeoffs to maximize his value function. As salesperson earn both monetary and non-monetary compensation, we assume that these two types of compensation are additive and separable. Before we proceed, we justify our choice of model. First, the selection of a risk-averse agent making inter-temporal tradeoffs is in line with a recent stream of literature that has shown that salesperson allocate effort inter-temporally in the presence of quota targets (Steenburgh 2008; Misra and Nair 2009; Chung et al. 2011; Copeland and Monnet 2003). The salesperson’s compensation for each period depends on the realized sales matched against a monthly target. Salespeople therefore reallocate their effort every period, depending on how far they are from achieving their monthly targets. For example, a salesperson who is very far from the target in week 3 will expend less effort than one who is close to the target. In turn, the salesperson’s current effort affects his position with respect to the target later. This inter-temporal shift in effort across weeks can be seen in Figure 5 that plots the weekly sales. It is important to note that the dynamics in the salesperson’s effort allocation combined with the non-linear incentive compensation scheme plays an important role in identifying the impact of effort on productivity. Our assumption of an additive and separable model is consistent with models of mental accounting (Thaler, 1985) who make similar assumptions.

In this section, we first describe the salesperson’s compensation plan and derive the utility function. We then discuss the state transitions and the optimal effort choice by the salesperson. Let \( I_t \) denote the weeks since the beginning of the sales period, and \( e_{it} \)
denote salesperson $i$’s effort in period $t$. The state variables for the salesperson are the total cumulative sales $Q_t$, the weeks since the beginning of the sales period $I_t$, the salesperson’s target $T_t$, and regime $R_t$. We use the vector $s_{it}$ to represent the vector of observable states.

**Compensation plan**

The compensation scheme offered by the firm consists of two components – a commission in cash (roughly 4% of sales) and a bonus that depends on target attainment. As explained earlier, there are two compensation regimes in our data, with the commission structure remaining unchanged across the two; in the first scheme, bonuses were paid using ovation points, while in the second scheme bonuses were purely cash. In the structural model, we take the contracts offered to the salesperson as exogenous and model them as a non-linear and period dependent scheme. The compensation scheme is period dependent in the sense that compensation for each period depends on achieving sales targets for that period. Furthermore, our compensation scheme is non-linear due to the fact that compensation may depend discontinuously on meeting targets. It is important to note that the firm does not observe effort expended by the salesperson. Incentives are therefore based on the observable outcome – sales.

Let $W_{it} = W_{it}(s_{it}, e_{it}, e_{it}^i; \phi)$ be the dollar compensation earned by the salesperson. Compensation $W_{it}$ consists of three components, a base wage consisting of commission $C_{it}$ on sales, a lump-sum bonus $BL_{it}$ for achieving the monthly target, and an incentive bonus $BI_{it}$ for sales beyond the target.

$$W_{it} = C_{it} + BL_{it} + BI_{it} \quad t = 1, 2, \ldots, T \quad (3)$$

Commission is given by $C_{it} = \alpha_{it} y_{it}(s_{it}, e_{it}, e_{it}^i; \phi)$, where $y_{it}$ is agent $i$’s sales in period $t$ and $\alpha$ is the commission rate on sales. The lump sum bonus $BL_{it} = I\{Q_t > Q_t\}BL_{it}$, where $I\{\cdot\}$ is an indicator variable that is equal to 1 when cumulative sales $Q_t$ is greater than that
period’s target. Finally, the incentive bonus $BI_{it}$ is given as:

$$BI_{it} = I(\sum_{t=1}^{T} y_{it} > Q_i)(\gamma_{nm}BI_{ovation} + \gamma_{cash}BI_{cash}) + I_{cash}BI_{cash} \tag{4}$$

where $\gamma_{nm}$ and $\gamma_{cash}$ capture a salesperson’s sensitivity to bonuses in ovations and cash respectively. Since both the base wage and the bonuses are in dollar denominations, we normalize $\gamma_{cash}$ to 1.

**Salesperson’s Per Period Utility**

At the beginning of each period $t$, the salesperson decides the effort he needs to expend. His utility depends upon the compensation earned, which in turn is a function of the incentive scheme and the realized sales. The salesperson incurs a cost in providing the effort necessary to achieve sales, and this is captured by a quadratic cost of effort function $c(e) = c_i e_{it}^2$. Denoting salesperson $i$’s risk aversion as $r_i$, his per-period utility as a function of compensation, $W_{it}$ is given by:

$$u_{it} = E(W_{it}) - r_i \text{Var}(W_{it}) - c_i e_{it}^2 \tag{5}$$

The expectation and variance in compensation is taken with respect to the demand shocks $\varepsilon_{it}$. The above representation is similar to those used in Chung et al. (2011) and Misra and Nair (2011) and is the certainty equivalent form of an exponential CARA utility function with normal errors.

**State Transitions**

There are four states variables that affect the salesperson’s effort decision, and consequently that period’s sales. The first state variable, cumulative sales, $Y_{it}$ is incremented by the realized sales each week, except at the beginning of each month where it is reset to zero.
The transition for cumulative sales is:

\[
Y_{it} = \begin{cases} 
0 & t = 1 \\
Y + y_{it-1} & t = 2, \ldots, T 
\end{cases}
\]  

(6)

where \(y_{it-1}\) is salesperson \(i\)'s sales in period \(t - 1\). The next three state variables, the target and the number of weeks since the beginning of the time period, and the regime dummy variable are deterministic. The target, \(Target_{it}\) changes every month but is announced at the beginning of each fiscal year. The salesperson knows exactly how much sales is needed to achieve the target every month. The target levels combined with cumulative sales affects the effort that needs to be expended. The transition of the fourth state variable, weeks since the beginning of the time period, is:

\[
I_t = T - t + 1; \quad t = 1, 2, \ldots, T
\]

(7)

**Agent Actions**

Given the state transitions, the agent’s problem is to choose effort to maximize the discounted present value of utility. Let \(\beta\) be the discount factor. For any \(0 \leq I_t \leq T\), his optimal effort policy is described by a value function that satisfies the following Bellman equation:

\[
V(Y_{it}, e_{it}, I_t; \phi) = \max u(Y_{it}, e_{it}, I_t; \phi) + \beta \int_{\varepsilon} V(Y_{it} = Y(Y_{it}, y_{it}, e_{it}, I_t; \phi)) f(\varepsilon) d\varepsilon
\]

(8)

Where \(\phi\) contains all the parameters related to the agent’s preferences; the disutility parameter \(c_i\) and the conversion factor \(\gamma_i\). The optimal effort at time \(t\) maximizes this state dependent value function, i.e., \(e = \arg\max V(\cdot)\).
4 Estimation

We follow the two-step estimation strategy outlined in Bajari et al. (2007). Two-step estimators, introduced by Hotz and Miller and then extended by Bajari et al. (2007) and Agerreagabiria and Mira (2007) are a popular way of estimating dynamic models because they reduce the computational burden significantly. In the first step, transition policies (conditional choice probabilities) are estimated flexibly as a function of the states; in practice one uses reduced form regressions to correlate actions to states. In the salesperson context, this amounts to recovering the policy function governing effort choice as a function of states. However, this is complicated because the action of interest, namely effort, is unobservable. In line with prior work (Chung et al. 2010; Misra and Nair 2011), we therefore assume that effort is a deterministic function of the states. In the second step we use the policy functions estimated in the first stage, calculate the value function and impose optimality to recover the individual cost of effort and the marginal rate of substitution between monetary and non-monetary incentives for all salespersons.

It is important to incorporate unobserved heterogeneity when estimating dynamic models to distinguish between state dependence and spurious dependance (Heckman 1991). We use a recent method developed by Arcidiacano and Miller (2011) to accommodate unobserved heterogeneity in a fashion similar to a latent class approach. From an estimation point of view, our approach is closest to the method followed in Chung et al. 2011. We now discuss the details of our two-step estimation procedure.

4.1 Step 1: Effort Response Function

In this step, we need to estimate a mapping between the observable states and actions of the sales person. However, in the salesforce context, the action, effort is not observable. This therefore requires us to make some assumptions on the relationships between the observable states, effort and the observable outcome sales. In particular, we assume that
sales is monotonically increasing in effort and the effort response is completely specified by the observed state variables. We define the effort response and sales response functions that we estimated below.

**Effort Response:** It is recommended that the first stage estimation be as flexible and non-parametric as possible. Accordingly, we use a second degree Chebyshev polynomial function to approximate the effort response function. The orthogonality property of the Chebyshev function enables it to approximate arbitrarily well any continuous function. In practice, our effort response function $e_{it}(s_{it}) = \lambda s_{it}$ is estimated using a second order Chebyshev polynomial of the state variables defined earlier. Briefly, the state variables are cumulatives sales $Y_{it}$, the target, $Target_{it}$, the number of weeks since the start of the time period, and regime dummy.

**Sales Response:** Given the effort response function, we model the production function $(y_{it})$ for salesperson $i$ at week $t$ as consisting of two parts: (1) control variables $(z_{it})$, including monthly sales in the previous year to control seasonality, total category sales in the same week, and (2) sales induced due to effort $(e_{it})$.

$$y_{it} = \mu' z_{it} + e_{it}(s_{it}) + \epsilon_{it} \tag{9}$$

where $\epsilon_{it}$ are unobserved productivity shocks and assumed to be distributed i.i.d across salespersons and time.

We incorporate unobserved heterogeneity in a latent class form by allowing for discrete segments. Let sales person $i$ belong to segment $k$, $k \in \{1, \ldots, K\}$ with probability $q_{ik}$. Let the population probability of belonging to segment $k$ be $\pi_k$. Let $\mathcal{L}(Y_{it}|z_{it}, s_{it}, k, \Theta_k)$ be the likelihood of salesperson $i$’s sales being $y_{it}$ at time $t$ conditional on the observables $z_{it}$ and $s_{it}$, unobservable segment $k$ and segment parameters $\Theta_k = \{\mu_k, \lambda_k, \sigma_k\}$. Then, the likelihood of observing sales over the time period $t = 1, \ldots, T$ for segment $k$ is given by:
where \( L_{ikt} = \mathcal{L}(Y_{it}|z_{it}, s_{it}, k, \Theta_k) \). Based on the assumption that the demand shocks are normally distributed, the individual likelihoods are given by the expression

\[
L_{ikt} = \frac{1}{\sigma_k \sqrt{2\pi}} e^{-\frac{1}{2} \frac{e_i^2}{\sigma_k^2}}
\]

We obtain the overall likelihood of individual \( i \) by summing over all the unobservable segments,

\[
L(Y_i|z_i, s_i; \Theta, \pi) = \sum_{k=1}^{K} \pi_k L_k(Y_i|z_i, s_i; \Theta_k, q_i)
\]

The log-likelihood for \( N \) individuals is therefore given by,

\[
\sum_{i=1}^{N} \log L(Y_i|z_i, s_i; \Theta, \pi) = \sum_{i=1}^{N} \log \left( \sum_{i=1}^{N} \pi_k \prod_{t=1}^{T} L_{ikt} \right)
\]

We maximize equation 11 using the EM algorithm approach specified in Arcidicano and Miller (2011). The algorithm iterates between the Expectation and Maximization steps. In the expectation step, the conditional probabilities of being in each state, along with the parameter estimates are updated. Once updated, the maximization step proceeds as if the unobserved states are known and uses the conditional choice probabilities as weights.

Let \( q_{ik} \) the probability that individual \( i \) belongs to segment \( k \) be given by

\[
\Pr(k|y_i, z_i, s_i; \Theta, \pi) = q_{ik}(y_i, z_i, s_i; \Theta, \pi) = \frac{L_k(Y_i|z_i, s_i; \Theta_k, q_i)}{L(Y_i|z_i, s_i; \Theta, \pi)}
\]

We start with an initial value of \( \Theta^0 \) and \( \pi^0 \) using the parameters from our regression analysis as the starting values. After obtaining \( \{\Theta^m, \pi^m\} \) in the \( m^{th} \) step, the iteration process for the \( m+1 \) step is as follows

1. Compute \( q_{ik}^{m+1} \) using the values \( \{\Theta^m, \pi^m\} \) obtained in the \( m^{th} \) step in equation 12.
2. Obtain $\Theta^{m+1}$ by maximizing equation 11 evaluated at $q_{ik}^{m+1}$.

3. Update $\pi^{m+1}$ by taking the average over the sample such that

$$\pi^{m+1}_k = \frac{1}{N} \sum_{i=1}^{N} q_{ik}^{m+1}$$

Continue iterating steps 1-3 till convergence.

The above estimation provides us segment level parameter estimates of the coefficients on the control variables ($\mu$), the Chebyshev polynomials on state variables ($\lambda$) and the distribution of revenue shocks ($\sigma$).

### 4.2 Step 2: Value Function

In this step, we use the estimates from the first step, the sales and effort response function and impose optimality to recover the dynamic parameters governing effort choice in each period. Briefly, the estimation procedure is as follows. First, the value function is constructed using forward simulations. The sequence of steps in the forward simulations is as follows:

a) Calculate the effort response function using the initial states and estimates from the first stage, b) Draw a demand shock from the distribution of demand shocks $f(\varepsilon)$, c) compute the sales response function, update the states and calculate the per-period utility, d) Repeat the steps a)-c) with the updated state values for all time periods, and e) Obtain the value function by averaging the sum of the discounted flow utility over multiple simulated values of $\varepsilon$. Once the value function is calculated, the next step is to impose optimality to recover the dynamic parameters. The optimality assumption implies that any alternate strategies obtained by perturbing the strategies observed in the data must not be optimal and consequently the value function obtained from such alternate strategies must be lower than the value function obtained from optimal strategies. Given a set of alternative policies, the BBL estimator finds parameters such that deviations from optimal policies are minimized.

As in Bajari, Benkard and Levin (2007), we utilize the fact that the parameters enter the value function linearly. Equation 5 can be rewritten in matrix form as the product of a
row vector and column vector.

\[ u_{it} = \left[ E(W_{it}^m) E(W_{it}^{nm}) Var(W_{it}) - e_{it}^2 \right] \cdot [1 \gamma r c]' \]  

(13)

We compare the importance of non-monetary compensation with respect to monetary compensation. We therefore normalize the coefficient on \( E(W_{it}^m) \), the compensation from wages to 1. Likewise, the risk aversion coefficient is assumed to be 0.02 based on previous literature. Let

\[ W_i(s_{it}, e(s_{it}, \epsilon)) \equiv E_e(\cdot) \sum_{t=0}^{T} \beta^t [E(W_{it}^m) E(W_{it}^{nm}) Var(W_{it}) - e_{it}^2] \]

Then the value function is

\[ V_i(s_{it}, e(s_{it}, \epsilon)) = W_i(s_{it}, e(s_{it}, \epsilon)) \cdot [1 \gamma r c]' \]  

(14)

Imposing the optimality condition over all alternate policies, we get

\[ W_i(s_{it}^*, e^*(s_{it}, \epsilon)) \cdot [1 \gamma r c]' \geq W_i(s_{it}, e(s_{it}, \epsilon)) \cdot [1 \gamma r c]' \]

where \( s_{it}^*, e^*(s_{it}, \epsilon) \) are optimal policy responses observed in the data.

We rewrite the above equation as the following,

\[ g(e; \theta) = [W_i(s_{it}^*, e^*(s_{it}, \epsilon)) - W_i(s_{it}, e(s_{it}, \epsilon))] \cdot [1 \gamma r c]' \]

We created \( n_s = 200 \) alternative policies by adding an error drawn from a standard normal to generate alternate effort responses. The simulation based minimum-distance estimator searches for parameters such that deviations from the optimal policy is minimized. The linearity of the estimator is particularly useful here as we do not have to recompute the value function for each set of parameter values. The objective function that is minimized is given by:
\[
\min_\theta Q_n(\theta) = \frac{1}{n_s} \sum_{j=1}^{n_s} 1(g(e_j; \theta) > 0)g(e_j; \theta)^2
\]

We compute the second stage estimation separately for each segment.

**Note on Identification**

We seek to estimate i) the salesperson’s effort response function, ii) the salesperson’s cost of effort coefficient, and iii) the weight on ovation points (given that we normalize the weight on cash to 1, this represents the salespersons’ subjective conversion rate for ovation points). Our key identification assumptions are a) effort is a deterministic function of the state variables only, and b) the effort response function is not salesperson specific.

Given these two assumptions, effort is identified by the inter-temporal variation between weekly sales and the states. More specifically, the nonlinear compensation plan causes salespersons to reallocate their effort based on their distance to the target. This dynamic behavior is enough to identify the cost of effort parameter. The individual subjective conversion rate on ovation points is identified by the salesperson’s observed target attainment behavior and paid ovation points across time in the mixed regime. Note that this parameter is not identified for salespeople who never attain targets in either of the two regimes. In our data, 214 salespersons never attained targets. To check if this group of salespersons differed from the target-achieving group in their response to non-monetary incentives, we compared productivity differences for the two groups across the two regimes and found no significant differences. For ease of exposition, we explain our results only for the group of salesperson who attained targets at least once.

**5 Results**

We present the results in the sequence in which we discussed the estimation procedure earlier.
Step 1:

Table 4 reports estimates from Step 1 with 3 segments. Last year sales and category sales were both significant. Last year sales controlled for seasonality in sales trends while category sales captured any external trends impacting the entire category. The Chebyshev polynomial ($\lambda$) estimates were all significant. Because the Chebyshev polynomial function is difficult to interpret, we examined their impact of effort. We found that the effort responses across segments 2 and 3 was very similar while that of segment 1 was very different. This is not surprising given the estimates (the estimates for segments 2 and segments 3 are similar while estimates for segment 1 are distinctly different). In general, we find the expected pattern on the effort response across segments. The salesperson’s initial effort is low when he is still far away from the target. When he is approaching the target, the effort is accelerated. After he hits the target, the effort is lower again. This pattern does reinforce the need to model the dynamics of the salesperson effort decision accurately. More importantly, our forward simulations show a pretty good map with the observed sales data. At the monthly level, the correlation of predicted sales with observed sales was 0.88.

Step 2:

Recall that the desired output for this stage is a segment specific subjective conversion rate ($\gamma_k$) and cost of effort coefficient ($c_k$). Table 5 contains the results from the second stage estimation across the three segments. We find considerable heterogeneity in the conversion rate across segments. Segment 1 has a conversion rate close to 0 while segments 2 and 3 have conversion rates around 10.50 and 11.50 respectively. Given the conversion rate of 3.75 used by the company internally (but not disclosed to the salespeople), this suggests that an Ovation point is on average worth 2.8 and 3.06 times its cash cost to the firm. Our estimated cost of effort coefficients shows heterogeneity, with an average of 0.11. Finally, note that we fixed risk aversion at 0.02 and the discount rate at 0.9, which is similar to findings from prior literature. For robustness we tried risk aversion rates from 0.002 to 0.3
and discount rates from 0.9 to 0.98, and found our results largely unchanged.

5.1 Discussion

We have marshaled multiple pieces of evidence to show that a compensation structure that provides incentives only in cash is viewed substantially differently from one that provides non-monetary incentives (also). We started with an intervention that switched salespeople from a mixed regime with non-monetary incentives to a pure cash regime that was equivalent in cost terms. This should not have had any effect; instead, there was a significant fall in sales, after controlling for a host of background factors. This certainly suggests that salespersons seemed to derive different bits of utility from cash vs. non-monetary incentives, i.e., that they put these in two different buckets. We explored this further with a structural model that estimated the efforts put in by salespersons, and found that on average, there was a fall in effort in moving to the pure cash regime. This is entirely consistent with the reduced form evidence just presented. Further, an estimation of the rate at which salespeople convert dollars to ovation points suggests that ovation points seem to be giving them utility over and above what an “objective” rate would suggest. While the exact conversion rate that should be used as a benchmark is a matter of debate, it is incontrovertible that salespeople seem to weight each of these two methods of compensation differently.

The above, coupled with the fact that there is a fair deal of heterogeneity in the rate at which salespeople convert ovation points to dollars suggests a need to probe further into how salespeople perceive these two modes of compensation. To that end, we conducted a survey that tried to find tentative evidence for a number of possible explanations.

6 Unpacking the Drivers of Separate Budgets

There are a number of psychological reasons why non-monetary incentives may work better than monetary incentives. In this section, we seek evidence linking these constructs to the
utility from non-monetary rewards.

Construal level Theory: Considerable research in both marketing and psychology has identified the implications of Construal Level theory (CLT) on the way individuals represent and evaluate objects and events (Dhar and Kim 2007; Fiedler 2007; Kardes et al. 2006; Trope and Liberman 2000; 2003). According to this theory, stimuli that are psychologically near are mentally represented in a concrete (low level of abstraction) fashion, while stimuli that are psychologically distant are represented in a more abstract fashion. Abstract representations lead to people appreciating higher level constructs (like appreciating the forest) while concrete thinking is associated with local information processing (appreciating the trees). Abstract thinking also lead to people focusing on the desirability (and hence positive aspects) of an item while concrete thinking can increase the negative aspects of an action. In the context of money, construal level could lead to positive or negative associations. For example, salespeople who construe money at a concrete level are likely to have specific and negative associations with it (e.g., monthly expenditures) while those who construe it at the abstract level are likely to have positive associations about the happy things money can buy. Salespersons who chronically construe money concretely may thus prefer ovations because they don’t have negative associations with it, while salespersons who chronically construe it abstractly might be indifferent between ovations and money.

Hedonic vs. Utilitarian Benefits: According to Holbrook (1999), the value a consumer derives from a good or experience is a combination of utilitarian and hedonic benefits. “Utilitarian” refers to the functional, instrumental, and practical benefits of consumption offerings, while “hedonic” refers to their aesthetic, experiential, and enjoyment-related aspects (Batra and Ahtola 1990; Dhar and Wertenbroch 2000; Strahilevitz and Myers 1998). In our context, the rewards from the Ovation catalog may be considered to be more hedonic, e.g., a vacation trip to Hawaii, or tickets to watch a movie or theater. The fact that these rewards are more hedonic suggests, in turn, that they are likely to be processed in a more affective manner, thus making it likely that their “value” is enhanced over and above the
Intra-family Budgets: Families are multi-person entities that must agree to consumption choices over the entire family budget. Intra-family bargaining focuses on the interdependencies among family decisions that affect outcomes like labor supply (Mansear and Brown 1980, Chiappori 1988). Essentially, labor supply is the result of an optimal time allocation within the household optimizing over the production of all family members. Factors such as wage rates affect bargaining power within the household and consequently affect labor supply in the market. However, “personal” versus “family” budget categorizations also come into play.

Cash rewards are more likely to be considered part of the joint income of the household and bargained away without providing additional utility to the individual. On the other hand, non-monetary rewards are less fungible and transferable, giving the salesperson greater control over their allocation. In concrete terms, an extra $500 in cash is much more likely to go into the household expenditure kitty directly, than ovation points that can potentially buy an iPad worth $500. In other words, non-monetary rewards are less likely to be bargained away in any negotiating process, thus enhancing the salesperson’s individual utility.

6.1 Questionnaire Development

Our measures are grounded in existing theoretical literature reviewed above. To test the hypothesis on intra-family bargaining, we developed two measures. Our first measure captured the amount of money spent on non-discretionary or essential items, such as rent/mortgage and groceries. The second measure captured the total number of family members in the household. We used these two measures instead of directly asking the total income earned by a particular household because the firm was wary that questions related to income might be viewed unfavorably by the sales force. We administered our survey on a sample of 10 sales executives to verify wording, response formats and clarity of instructions, and made
appropriate changes based on their feedback. Appendix A outlines the final survey that was administered.

6.2 Survey Administration

We administered the survey to all the 590 salespeople currently employed by the firm. The salesperson was informed that the survey was a part of a University research project examining salesperson behavior and was administered online. In addition, they were also assured that their individual responses would not be shared with the firm. We mailed the survey link to each salesperson, giving them a month to respond. After a couple of reminder emails, we received 263 completed questionnaires. Of these, 22 were eliminated due to excessive missing data, leaving a final sample of 241. To assess non-response bias, we compared respondents to non-respondents along a host of dimensions (sales, income, age, etc.) and found no statistically significant difference between the two groups.

6.3 Results

We examine responses to the survey using the following three equations that capture the theories mentioned above.

\[
y_{it} = \mu' z_{it} + \alpha_{Regime_{i}} + \beta_{Regime} \ast Abstract_{i} + \epsilon_{it} \tag{15}
\]

\[
y_{it} = \mu' z_{it} + \alpha_{Regime_{i}} + \beta_{Regime} \ast Hedonic_{i} + \epsilon_{it} \tag{16}
\]

\[
y_{it} = \mu' z_{it} + \alpha_{Regime_{i}} + \beta_{Regime} \ast NonDiscIncome_{i} + \beta_{Regime} \ast HHsize_{i} + \epsilon_{it} \tag{17}
\]

where \(y_{it}\) is the sales for salesperson \(i\) in week \(t\), \(z_{it}\) are control variables such as category
sales and seasonality, Regime is a dummy variable which is equal to 1 if the incentive package is pure cash, \( \text{Abstract}_i \) and \( \text{Hedonic}_i \) are scales that measure the extent to which salespersons view bonuses as respectively abstract and hedonic, and \( \text{NonDiscIncome}_i \) and \( \text{HHsize}_i \) measure the socio-economic characteristics of each salesperson. To tie back to our earlier discussion of the theories involved, Abstract captures the processing mindset of construal level theory, Hedonic mirrors the distinction between hedonic and utilitarian, and \( \text{NonDiscIncome}_i \) and \( \text{HHsize}_i \) tie back to intra-family bargaining.

The results of our survey show that salespersons differ considerably on processing mindset as it relates to Construal Theory (mean \( \text{Abstract} = 4.36 \), sdev=1.83 on a 7-point Likert scale), on viewing the gifts as hedonic vs. utilitarian (mean \( \text{Hedonic} = 4.54 \), sdev=1.96), and on the extent of non-discretionary expenditure as a percentage of their total income (mean \( \text{NonDiscIncome} = 65\% \), sd=24\%).

The results from our analysis (Tables 6 and 7) highlight several interesting facts and offer tentative support to two of the three theories we had suggested as possible explanations. First, our results show that a salesperson’s construal of money as abstract or concrete does influence his productivity. In particular, we find that the productivity of salespersons who view an item as more concrete goes up in the ovation regime. This is in line with our reasoning which suggests that concrete construal level thinking leads to a decreased valuation of money and an increased valuation of an ambiguous reward type. Second, we find no evidence that a salesperson’s perception of rewards as hedonic or functional affects his productivity. While we expected non-monetary rewards to be more hedonic in nature, we found that the rewards site offers multiple functional items like toolkits and kitchen gadgets, making it very hard to disentangle the functional from the hedonic aspects for non-monetary rewards in general. Finally, our results find mixed support for the intra-family bargaining theory. We find that non-discretionary income has an impact on salesperson productivity across regimes. The coefficients on the interaction term is negative and significant, suggesting that households that spend most of their income on essential purchases
like utilities and groceries tend to value ovation points more than cash. The coefficient on the interaction term on household size was not significant. As suggested by theory, cash rewards are much more likely to be bargained away when joint spending is high.

7 Conclusion

The objective of this paper was to examine the role played by non-monetary incentives in compensation schemes for salespersons. While increasingly popular in industry, such incentives have received little attention from academics. Our approach consisted of a field intervention that varied the components of the compensation package offered to a set of salespersons, with one package consisting of non-monetary incentives coupled with cash, and the other consisting solely of cash. The results of this intervention suggested that sales fell 6.7%, after controlling for a variety of background factors. While suggestive of the fact that salespeople viewed these two compensation elements differently, we sought to generate further evidence that salespeople effort responses non-monetary incentives differently from cash. To this end, we built a structural model that explicitly allowed for the possibility that cash and non-monetary incentives could provide different bits of utility to a salesperson. In addition, the structural model let us derive estimates of the effort that the salesperson put in, in response to each incentive scheme. Results from this model confirmed what the earlier analysis hinted at; salespeople indeed viewed cash and non-monetary rewards as distinct entities, and the effort they put in reflected this fact.

Armed with fairly strong evidence about the presence of separate budgets, we then conducted a survey to assess whether psychological constructs implicated in laboratory work correlate with the preference for non-monetary rewards over their cash equivalent. Here we found that both the presence of thinking per construal level theory (i.e., perceiving the reward as abstract versus concrete), and the possible presence of intra-family bargaining, enhanced the evaluation of non-monetary benefits. Our results have immediate implica-
tions for theory and practice. On the theory side, our paper is among the first to provide direct econometric evidence for the presence of multiple elements in the utility function. In practical terms, this suggests the need to pay careful attention to the inclusion of non-monetary rewards in devising an incentive package for a sales force. Two things stand out. First, it seems clear that adding non-monetary rewards provides bang for buck to the firm. Second, that this return can be enhanced by taking actions that make it more likely that the reward is processed affectively, i.e., by making the reward more hedonic than utilitarian. This increases the likelihood that the reward’s value is enhanced in the salesperson’s assessment.

While we view the multiple pieces of converging evidence as providing fairly strong support for the presence of mental accounting in the salesforce, there are many additional avenues to explore on this topic. First, our focus has been on tangible non-monetary incentives. It is not clear how these relate to completely non-monetary rewards such as plaques or certificates. Are these sets of rewards best used in conjunction, and what is the effort response if they are used thus? Second, we have not explicitly solved for the “optimal” plan that the firm can offer to salespeople (for a first step in this direction, see Jiang and Palmatier 2009). This is an important and computationally laborious task that we leave for future research.
References


Table 1: **Description of Contracts**

<table>
<thead>
<tr>
<th>Period</th>
<th>Contract Components</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>July 2011-September 2011</td>
<td>Commission</td>
<td>4% of monthly dollar sales</td>
</tr>
<tr>
<td></td>
<td>Lump-sum Bonus</td>
<td>$300</td>
</tr>
<tr>
<td></td>
<td>Bonus beyond monthly target</td>
<td>$75+20 points for exceeding target;</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$150+40 points for exceeding 108% of target;</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$225+60 points for exceeding 115% of target;</td>
</tr>
<tr>
<td>October 2011-December 2011</td>
<td>Commission</td>
<td>4% of monthly dollar sales</td>
</tr>
<tr>
<td></td>
<td>Lump-sum Bonus</td>
<td>$300</td>
</tr>
<tr>
<td></td>
<td>Bonus beyond monthly target</td>
<td>$150 for exceeding target; $300 for exceeding 108% of target;</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$450 for exceeding 115% of target;</td>
</tr>
</tbody>
</table>

Table 2: **Impact of Intervention on Sales**

Dependant Variable: Monthly Sales in Dollars

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient (Std. Error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regime</td>
<td>-6921.29 (427.78)</td>
</tr>
<tr>
<td>Target</td>
<td>0.28 (0.01)</td>
</tr>
<tr>
<td>Previous Sales</td>
<td>0.31 (0.01)</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>Yes</td>
</tr>
<tr>
<td>Category Effect</td>
<td>Yes</td>
</tr>
</tbody>
</table>

$R^2 = 71.56\%$

All variables are significant at the 0.01 level.
Table 3: **Quantile Regression**

Dependant Variable: Monthly Sales in Dollars

<table>
<thead>
<tr>
<th>Quantiles</th>
<th>Variables</th>
<th>Coefficient (Std. Error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>q10</td>
<td>Regime</td>
<td>-5433.91 (705.51)</td>
</tr>
<tr>
<td></td>
<td>Target</td>
<td>0.38 (0.14)</td>
</tr>
<tr>
<td></td>
<td>Previous Sales</td>
<td>0.30 (0.15)</td>
</tr>
<tr>
<td>q25</td>
<td>Regime</td>
<td>-5008.44 (495.46)</td>
</tr>
<tr>
<td></td>
<td>Target</td>
<td>0.41 (0.00)</td>
</tr>
<tr>
<td></td>
<td>Previous Sales</td>
<td>0.33 (0.00)</td>
</tr>
<tr>
<td>q50</td>
<td>Regime</td>
<td>-5964.16 (449.39)</td>
</tr>
<tr>
<td></td>
<td>Target</td>
<td>0.43 (0.01)</td>
</tr>
<tr>
<td></td>
<td>Previous Sales</td>
<td>0.37 (0.01)</td>
</tr>
<tr>
<td>q75</td>
<td>Regime</td>
<td>-7461.51 (496.79)</td>
</tr>
<tr>
<td></td>
<td>Target</td>
<td>0.42 (0.01)</td>
</tr>
<tr>
<td></td>
<td>Previous Sales</td>
<td>0.43 (0.01)</td>
</tr>
<tr>
<td>q90</td>
<td>Regime</td>
<td>-9235.96 (779.16)</td>
</tr>
<tr>
<td></td>
<td>Target</td>
<td>0.48 (0.03)</td>
</tr>
<tr>
<td></td>
<td>Previous Sales</td>
<td>0.45 (0.03)</td>
</tr>
</tbody>
</table>

All variables are significant at the 0.01 level. Regression also included control variables like route fixed effects and category growth indicators which are not reported.

Table 4: **Parameter Estimates - Sales Response**

<table>
<thead>
<tr>
<th>Variables</th>
<th>Seg1</th>
<th>Seg2</th>
<th>Seg3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-26.32</td>
<td>-40.27</td>
<td>-40.48</td>
</tr>
<tr>
<td>Previous Sales</td>
<td>0.09</td>
<td>0.10</td>
<td>0.10</td>
</tr>
<tr>
<td>Total Category Sales</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>(\lambda)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cumulative Sales</td>
<td>0.07</td>
<td>0.20</td>
<td>0.20</td>
</tr>
<tr>
<td>Target</td>
<td>0.22</td>
<td>0.23</td>
<td>0.24</td>
</tr>
<tr>
<td>Timing</td>
<td>6.84</td>
<td>8.95</td>
<td>8.88</td>
</tr>
<tr>
<td>Regime</td>
<td>-1.92</td>
<td>-1.93</td>
<td>-1.90</td>
</tr>
<tr>
<td>CumulativeSales(^2)</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Target(^2)</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Timing(^2)</td>
<td>-1.25</td>
<td>-1.42</td>
<td>-1.40</td>
</tr>
<tr>
<td>CumulativeSale*Target</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>CumulativeSale*Timing</td>
<td>-0.04</td>
<td>-0.06</td>
<td>-0.06</td>
</tr>
<tr>
<td>Timing*Target</td>
<td>-0.01</td>
<td>-0.01</td>
<td>-0.01</td>
</tr>
</tbody>
</table>
Table 5: **Dynamic Parameter Estimates**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Seg1</th>
<th>Seg2</th>
<th>Seg3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conversion Rate ($\gamma$)</td>
<td>0.004</td>
<td>10.50</td>
<td>11.50</td>
<td></td>
</tr>
<tr>
<td>Cost of effort ($c$)</td>
<td>0.10</td>
<td>0.12</td>
<td>0.11</td>
<td></td>
</tr>
</tbody>
</table>

Table 6: **Correlation between Sales and Processing Mindset**

Dependant Variable: Weekly Sales in Dollars

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficient (Std. Error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regime</td>
<td>-1661.20*** (180.05)</td>
</tr>
<tr>
<td>Previous Sales</td>
<td>0.13*** (0.02)</td>
</tr>
<tr>
<td>Total Category Sales</td>
<td>0.00*** (0.00)</td>
</tr>
<tr>
<td>Regime*Abstract(Interaction of Regime and Specific thinking on Money)</td>
<td>-150.24** (69.54)</td>
</tr>
<tr>
<td>Constant</td>
<td>-5084.71** (1596.12)</td>
</tr>
</tbody>
</table>

$R^2 = 0.32$

*** = $p < 0.01$; ** = $p < 0.05$

Table 7: **Correlation between Sales and Non-discretionary Expenditure**

Dependant Variable: Weekly Sales in Dollars

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficient (Std. Error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regime</td>
<td>-757.50*** (353.83)</td>
</tr>
<tr>
<td>Previous Sales</td>
<td>0.13*** (0.00)</td>
</tr>
<tr>
<td>Total Category Sales</td>
<td>0.00*** (0.00)</td>
</tr>
<tr>
<td>Regime*NonDiscExp (Interaction of Regime and Non-discretionary expenditure)</td>
<td>-407.79** (134.69)</td>
</tr>
<tr>
<td>Regime*HHSize (Interaction of Regime and Household size)</td>
<td>214.85 (170.61)</td>
</tr>
<tr>
<td>Constant</td>
<td>-6000.92** (1347.80)</td>
</tr>
</tbody>
</table>

$R^2 = 0.32$

*** = $p < 0.01$; ** = $p < 0.05$
Figure 1: Monthly $ Sales

Monthly Average Dollar Sales

Pre-Intervention

Post-Intervention

Figure 2: Category Monthly $ Sales

Category Monthly Dollar Sales in 2011

Pre-Intervention

Post-Intervention
Figure 3: Kernel Density of Monthly Productivity

Figure 4: Kernel Density of Intervention Effect
Figure 5: **Effort as a function of Distance to Target**

*Effort plotted in Figure 5 is estimated from step 1 effort response function*