Investigating Dynamic Sales Quotas

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Abstract

This paper investigates sales quota dynamics at a *Fortune 500* firm. We offer theoretical justifications for observed quota updating processes and test three particular hypotheses related to the issue. First, current year quotas are computed as a weighted average of last year's sales and last year's quota (Bayesian Updating). Second, this year's sales quota increases more when last year's sales exceed last year's quota than this year's quota falls when last year's sales do not exceed last year's quota (Asymmetric ratcheting). And third, the quota setting process is influenced by market and salesperson heterogeneity. Our empirical results support the hypotheses of dynamic quota updating, asymmetric ratcheting, and of heterogeneity in the quota setting process

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1. Introduction

Quota setting is an integral part of the planning and control systems of most sales organizations. In fact, close to 90% of all sales organizations use quotas (Oyer 2000) and most tie compensation to the achievement of these quotas in some form or another (Joseph and Kalwani 1998). In most such organizations the "sales quota" acts as a communication and coordination device, assigns decision rights, and it is part of the firm's compensation and performance evaluation system. More importantly, quotas offer a firm the means by which to dynamically adjust the entire compensation and performance system within the organization at a rather minimal cost.

The dynamic adjustment of sales quotas, and issues relating to it, has been a continuing point of disagreement between the salesforce and management. The following excerpt sums up the typical concern voiced by salespeople…

> *…the message that sales quotas send is that if a salesperson makes the sales budget, their job is secure. The next logical step in the mind of a typical salesman is that if he or she exceeds this year's budget, next year's budget will be increased.*
>
> "Down with Sales Budgets" in Success, July 1995

While there is a plethora of anecdotal evidence that the practice of ratcheting sales quotas over time is widespread, there is virtually no academic research on the topic. Most of the extant sales and marketing literature treats quota setting as an allocation problem in a static setting (Mantrala, Sinha and Zoltners 1994; Darmon 1987). There is also a body of work that examines the impact that quotas have on behavior (Gaba and Kalra 1999; Chowdhury 1993; Ross 1991) but treats quotas as exogenously fixed. Most review papers (e.g. Coughlan 1993; Coughlan and Sen 1989) on salesforce compensation also highlight our lack of knowledge about how quotas are set and managed over time.

The quota setting process is complex and often involves the compilation and analysis of transaction level data pertaining to past performance and projections about future changes in the market. The quota setting process may be "Participative" wherein the salesperson being evaluated provides input into the process or it may be of the "Top-Down" variety, where the salesperson responsible for achieving the quota does not actively participate in the process. Benefits of the participative approach include communication of decentralized knowledge and enhanced salesforce motivation through goal acceptance by employees being evaluated. However, this process is time consuming and subject to gaming by the salespeople seeking to improve their performance vis-à-vis the quota benchmark. For example, sales people many be more inclined to communicate bad news (e.g., a customer is likely to go bankrupt) while withholding good news (e.g., expect to receive a large order from a new customer). In either case we would expect the firm to learn about market characteristics and the salesperson's productivity over time and reflect this learning in the management of quotas. This idea is in itself not new and was probably first proposed by Weitzman (1980) in a budgeting context. Recently the accounting literature has taken this issue up and has begun to explore issues such as asymmetric ratcheting (e.g. Leone and Rock 2002) of budgets.

This study builds on the basic ideas of Weitzman and empirically examines how management sets sales quotas for a large heterogeneous salesforce. Usually, senior management has information about past quotas, past sales, product market characteristics, and characteristics of the salespeople which they then use to construct quotas. In this paper we propose a framework in which management sets next year's quota as a weighted average of this year's sales and this year's quota. We show that this process is in line with existing theory. We empirically test this basic specification and a number of extensions using data from a large Fortune 500 firm. In particular this study raises and answers a number of questions: Do firms indeed ratchet quotas? Are they more likely to asymmetrically ratchet quotas upwards than downwards? Are quotas changed uniformly across salespeople? What factors play a role in the way quotas are updated?

This paper makes several contributions to the research literature on salesforce quotas. First, we study quota setting in a dynamic setting and offer a theoretical justification for the ratcheting of quotas. The literature has focused predominately on quota-related issues in a static framework and on the effects of quotas rather than its determinants. Second, we empirically implement our proposed framework which argues that quotas are weighted averages of past performance and past quotas. In addition we find that quotas increase more in response to favorable sales-quota gaps than they decrease for unfavorable gaps of the same magnitude. In this regard, we are also the first to formally test the notion of asymmetric ratcheting of sales quotas. Third, our paper tests sources of variation in quota setting across sales agents within the same firm. In a survey of 186 sales managers, Good and Stone (1991) found that while past performance is a factor in setting quotas, other factors such as characteristics of the product markets also influence the quota setting process. We find strong evidence for unobserved heterogeneity implying that firms tend to tailor quotas on the basis of a number of factors which may be unobservable to the researcher. However, we also find that by including market and salesperson characteristics in addition to unobserved heterogeneity within-firm variation in quota-setting can be better explained. For example, we find that the relative change in quota for a given salesperson is related to the degree of competition faced in the sales territory.

The rest of this paper is organized as follows: Section 2 develops the rational for asymmetric quota ratcheting based on the agency-theoretic sales force compensation literature. Section 3 describes our research site and the data. Section 4 presents the empirical findings and conclusions are offered in Section 5.

2.0 The Use of Quotas in Sales Force Compensation Plans

This section first describes why sales compensation schemes rely on quotas, why these quotas change over time and how quota setting might vary across salespeople. This discussion suggests several new ideas that are tested later in the paper.

2.1 The Dynamics of Sales Quotas

Basu, et al. (1985) applying Holmstrom's (1979) moral hazard model, assume that sales people generate expected sales by the following process:

$$E(S) = h + k\,e \qquad (1)$$

where $E(S)$ is expected sales, h, is the amount of sales in the territory if the agent exerts no effort, e, and k is the agent's productivity of effort. They find that the firm-value maximizing sales force compensation scheme is to pay each sales person a salary plus (usually a nonlinear) commission. The optimum Basu, et al. (1985) plan is the thin line in Figure 1 labeled "BLSS Plan." In order to induce optimum effort and still insure the sales person's participation, the sales compensation contract consists of a base salary plus a commission on sales that increases at an increasing rate.

Raju and Srinivasan (1996) discuss the implementation problems associated with applying the BLSS model. First, one needs to specify a base salary and a different commission rate for each level of actual sales, S (or implement a complicated nonlinear plan.) Moreover, in large companies where multiple sales persons are deployed across the various territories, sales persons differ in terms of their productivity, k, size of sales territory, h, risk aversion, disutility of effort, and alternative employment opportunities. The BLSS plan requires that the commission structure and base salary of each sales person change as territory characteristics change or when sales people are relocated to new territories. Individual schemes might create incentives for agents to game the system regarding the agent's true productivity, k, or market size, h. Raju and Srinivasan (1996) argue that large firms with multiple territories will simplify the nonlinear BLSS plan to a piece-wise linear contract with a quota. Such an approximation is displayed in Figure 1 as the heavy line denoted "Quota-Based Plan." Under this approximation, the sales agent is paid a base salary α, and no commission on sales up to the quota, Q. Sales beyond the quota are paid a fixed commission rate, β. The sales agent faces a total compensation contract based on sales, $C(S)$,

$$C(S) = \begin{cases} \alpha & if \;\; S < Q \\ \alpha + \beta S & if \; S > Q \end{cases} \tag{2}$$

Using numerical simulations, Raju and Srinivasan (1996) compare the optimal nonlinear BLSS plan to the sub-optimal quota plan and document that the total sub-optimality is quite small, about 1%. What is striking is that they show that holding the salary and commission parameters fixed and by changing only the quota (*Q*) to adapt to changes in the structural parameters results in only a slightly larger distortion. Given that firms do not change commission rates very often (but do change quotas) this is an important finding.

In many companies (as in the firm for which we have data) two different commission rates, β_1 and β_2 are used, apparently to better approximate the curvature of the optimal compensation contract. Sales people in such firms face the following compensation contract:

$$C(S) = \begin{cases} \alpha + \beta_1 S & if \;\; S < Q \\ \alpha + \beta_1 Q + \beta_2 (S - Q) & if \; S > Q \end{cases} \tag{3}$$

where α is the sales person's base salary, *S* is actual sales, *Q* is their quota., β_1 is the commission rate on sales up to the point where *S* equals *Q*, and β_2 is the commission rate on sales in excess of *Q* $(\beta_2 > \beta_1 > 0)$. Presumably, the optimal quota *(Q*)* is the one that most closely approximates the optimal BLSS nonlinear compensation scheme in Figure 1. In most firms the commission rates, β_1 and β_2, are held constant across salespeople while α and *Q* are allowed to vary.

As mentioned earlier, Raju and Srinivasan show that using their piece-wise linear plan results in only small deviations from the optimal nonlinear plan. In replicating their approach with our two-rate plan we found very similar results. In the discussion that follows we assume that the firm holds the salary and the commission parameters fixed while varying quota to account for any exogenous changes in the environment or the agent's sales productivity. Under these assumptions we can then show that the optimal quota (Q^*) is a function of other parameters in the model. We write this as

$$Q^* = f\left(h, k, r, \sigma \ldots\right) \tag{4}$$

While this characterization is intuitive, the exact specification for the function is extremely complicated and cannot be obtained in closed form. Nevertheless we can remark on the movement of this optimal quota due to shifts in the exogenous parameters. Assuming (i) that the firm uses the piece-wise linear plan with two commission rates as the compensation plan to be implemented (equation (3)) and (ii) that salary and commission parameters are fixed and only the quota varies, we note the following.

Remark: *If there is an upward (downward) shift in the optimal compensation plan, then the quota will be decreased (increased). If there is no change in the optimal compensation plan, then the optimal quota remains unchanged.*

Figure 2 presents graphically the intuition behind this remark. Suppose the optimal nonlinear compensation plan is C_1. The plan "adbc" represents the piece-wise linear approximation. Suppose the optimum compensation plan shifts to C_2 (say because of a change in market size, i.e. in *h*.) Given that the base salary α and β_1 and β_2 are all fixed, the piece-wise linear approximation then becomes "ade" and the optimum quota shifts from Q_1^* to Q_2^*. In other words for every change in exogenous factors there is a new optimal plan and consequently a revised quota level that approximates this new plan.

This suggests that there are two possible reasons why a firm might adjust a sales person's quota over time. The first is the fact that although firms have estimates of the characteristics of the market, *h*, and agent, *k*, that information is by no means complete and precise. The firm likely learns about these parameters over time. In addition to this learning there is also the reality that these parameters are, in fact, dynamic and exhibit temporal shifts, especially the size of the market, *h*. Given the nonlinearity of the distribution of sales and the consequent complexity of the optimal compensation plan, tracing the locus of Q^* over time and agents is a non-trivial task.

In a theoretical piece Mantrala, Raman and Desiraju (1997) show (under particular assumptions about the compensation structure and firm profit function) that the optimal path of quotas can be set using a simple myopic updating rule. While the analytics are involved, it can be shown that their rule (equation 30 in their paper) is equivalent to a simple Bayesian updating rule.

The updating rule proposed by piece Mantrala, Raman and Desiraju (1997) is also consistent with the budget updating rule proposed by Weitzman (1980). In his model Weitzman (1980) assumes that the principal sets quotas solely as a function of last period's actual sales and quota.[1] We use Weitzman's model as a starting point for our specification of quota setting in the firm we study. Weitzman (1980) proposes the following quota-setting process

$$\Delta Q_t = a + b\left(S_{t-1} - Q_{t-1}\right) \tag{5}$$

In this model, the change in the quota this period, ΔQ_t, moves up and down by the same fraction, *b*, by which actual sales last period deviates from last period quota. The updating is symmetric because the change in quota that depends on the difference between last period's sales and last period's quota, *b*, is invariant as to whether last period's sales exceeds or falls short of last period's quota. The intercept, *a*, is the change in quota independent of performance. It is the amount the quota will change if the agent's sales exactly meet quota.

To highlight that the coefficient *b* can be thought of as the relative weight placed on S_{t-1} and Q_{t-1}, Weitzman rewrites equation (5) as:

$$Q_t = a + bS_{t-1} + (1-b)Q_{t-1} \tag{6}$$

As *b* increases, the relative weight placed on S_{t-1} increases. In this equation b represents the weight that the firm places on current information (i.e. information

[1]Senior management likely considers other factors in setting quotas. As we show later, for example, characteristics of the agents and the product market also influence the quotas set by management.

contained in last period's sales) as compared to past information (i.e. information contained in last year's quota) while a represents an adjustment factor. If the firm had perfect knowledge of all parameters in equation (4) and had learned all there is to learn about agent and market characteristics then $b = 0$. In other words the updating process would have reached a steady state and there would be no more changes in the quota apart for accounting for exogenous market expansions or contractions (i.e. via a).

On the contrary, if the firm finds that the sales process is very noisy and it has no precise information about the model parameters then it would be forced to rely on the most current information. The realized sales amount in any period t, S_t, contains the most current information about model parameters. In such cases the firm would place all the weight on actual sales in setting the new quota and $b = 1$. Hence, b is bounded between zero and one.

The simple model in equation (6) accounts for the quota dynamics seen in most sales organizations. For example if sales exceed quota by a wide margin then the next period's quota gets pushed upwards. However, the contrary also holds true. It goes without saying that the parameters in the system evolve over time and vary across salespeople. Consequently, if the firm has amassed enough knowledge about its salespeople we would expect b to be small.

The preceding analysis argues why sales quotas are used and how they might be updated. The analysis does not explain why sales quotas would be ratchet asymmetrically over time, to which we now turn our attention.

2.3 Asymmetric Quota Ratcheting

A common complaint voiced by salespeople is that their employers update the quotas asymmetrically. In particular there is a common belief (albeit empirically unsubstantiated) that when salespeople beat quotas their quotas go up, however, when their sales fall short of targets the quotas are not reduced proportionately. Of course, the deduced rationale (forwarded by the salespeople) is profit mongering at the expense of salespeople. The model proposed in (6) does not allow for such possibilities and needs to be generalized. Before doing that however, we feel that this asymmetric updating of quotas is an important issue and warrants a more detailed discussion.

The asymmetric ratcheting phenomenon has also been noted in the updating of profits and budgets. For example, Holthausen, et al (1995, p. 61) describe a profit quota setting process at H.J. Heinz. At one time, H.J. Heinz used a top-down quota-setting process where profit quotas were set at 115% of prior-year actual or 115% of quota-year budget. In this case, the relative weights placed on S_{t-1} and Q_{t-1} depended on whether the manager exceeded or fell short of budget. As in the H.J. Heinz example, there is reason to believe that in general quotas are adjusted more when last period's sales exceed last period's quota, than when the quota exceeds sales. In what follows we present an economic argument which might explain why a firm might asymmetrically ratchet quota.

A possible rationale for asymmetric ratcheting stems from the classic moral hazard problem. The salesperson has complete control and discretion how effort is allocated which is unobservable and unenforceable to the firm. Based on the sales response function depicted in equation (1), if sales fall short of quotas then this shortfall could be due to controllable (e.g. because effort was low) or uncontrollable (e.g. some exogenous negative shock) factors. However, if the firm infers that the shortfall is attributable to controllable factors then by not reducing the next year's quota the firm is implicitly penalizing the salesperson for poor performance. By the same argument if sales exceed the prescribed quota the firm will raise the next period's quota operating under the belief that the positive sales-quota gap reflects an increased effort level on the part of the salesperson which should be sustained. Clearly this argument rests on the assumption that the firm can, to a degree, disentangle controllable and uncontrollable factors. We conjecture that a firm will use all available information to make such distinctions. For example, a salesperson that has been with the firm longer may have *less* asymmetric ratcheting simply because the firm has a good idea about the nature of exogenous variability associated with this individual and her territory and a better estimate of their efforts. Similarly we should expect markets that are more competitive to have lower asymmetric ratcheting in quotas since the uncontrollable uncertainty is higher.

In addition to the economic argument forwarded above there is also a mechanical explanation reason for quotas to ratchet asymmetrically.[2] A regional sales manager is often given a regional quota which is then disaggregated to individual salespeople. Each sales person's assigned set of customers is called his/her "territory." Each year, the manager of the region rebalances each sales person's list of customers based on changes in the composition of the sales force, changes in the size of individual customers in each sales person's territory, and general economic conditions in the region. If a salesperson's sales volume has expanded a lot because a few customers have expanded, some of this sales person's customers will be reassigned to other sales people whose sales have fallen because their customers have moved, merged, or gone out of business. Each sales person's quota is the sum of the individual, corporate determined expected sales of each customer assigned to the sales person by the regional manager. In this way, the regional sales manager tries to balance the workload across the entire sales force, whereby the sum of the individual sales persons' quotas equals the region's quota. But sales people do not want to give away "good" customers with whom they have established close contacts. Because of this process of rebalancing sales territories, sales that exceed quota tend to be permanent (not all of the excess sales get reassigned), and sales that fall short of the quota tend to be transitory (the shortfall is offset by newly assigned customers). While we cannot rule out the possibility of such rebalancing as a possible explanation for asymmetric ratcheting, we would like to add that since this process is observable and controllable the underlying cause for the induced asymmetry is consistent with our earlier economic argument.

The asymmetric ratcheting of quotas is graphically depicted in Figure 3. The horizontal axis reflects the difference between past sales and past quotas ($S_{t-1} - Q_{t-1}$) while the vertical axis reflects change in quotas ($\Delta Q_t = Q_t - Q_{t-1}$). If past sales exceed past quotas then as equation (7) suggests the change in quota will be equal to

[2] This argument was suggested to us by sales managers at the firm we later study in our empirical section.

$b_1\left(S_{t-1}-Q_{t-1}\right)$. This is reflected in the upward sloping line in the graph. As an example if sales exceeds quota by the amount SQ^+ the change in quota will be ΔQ^+. On the other hand if last year's sales falls short of quotas then the change in quota will be less than if the quota were exceed by an equivalent amount. For example if sales fell short by SQ^- (= $-SQ^+$) then the corresponding change in quota will only be ΔQ^-($<\Delta Q^+$). Finally, if last year's quotas is exactly met $\left(S_{t-1}-Q_{t-1}=1\right)$ then there might still be a change in quota as indicated by the parameter *a*.

To test the possibility of asymmetric ratcheting in our company, we estimate a model that incorporates different slope parameters in equation (6) to arrive at:

$$\Delta Q_t = a + b_1\left(S_{t-1}-Q_{t-1}\right) + b_2 D * \left(S_{t-1}-Q_{t-1}\right) \qquad (7)$$

where *D* is a dummy variable that takes the value one if $S_{t-1}<Q_{t-1}$ and zero otherwise. This framework is similar to the one proposed be Leone and Rock (2001) who find that $b_1>0$ and $b_2 < 0$.

Equation (7) can be rewritten as:

$$\Delta Q_t = a + b\left(S_{t-1}-Q_{t-1}\right) \qquad (7')$$

where: $b = b_1 + b_2D$. Since from the updating argument, $0<b<1$ and from the asymmetric ratcheting analysis, $b_2<0$, then $b_1 >0$ because $b_1=b-b_2D$.

2.3 Heterogeneity in Quota Setting

In addition to the issue of asymmetric quota updating another complaint that salespeople have is the top-down manner in which quotas are set in sales organizations. In many cases (as in our research site) the quota setting process starts with the top management setting goals for the firm as a whole. These goals trickle down through the organization in the form of targets and finally reach salespeople in the form of quotas. In such systems, salespeople argue, individual salesperson and the size/potential of the territory are ignored and the quotas are therefore inefficient and unfair.

Most compensation design specialists, however, do not agree with this assertion. In their opinion even though regional and district level goals flow from the top down, individual quotas are set at a more micro level do take into account individual, territory and market differences. To test this possibility we modify the models presented earlier to allow for individual differences (heterogeneity) by specifying a random coefficients approach. Simply put, we specify and estimate an individual level regression for each salesperson. Details of this approach will be discussed in section 3.3.

To summarize, our discussion in this section highlights three issues pertaining to sales quotas which we aim to test using data from our research site.

a) Are current quotas a function of past quotas and sales?

b) Are quotas updated asymmetrically?

c) Does the quota updating process take into account salesperson and territory level heterogeneously?

3 Empirical Specification

3.1 The Base Models

The base models reflect the simplest models that test for the basic tenets of our proposed theory. These models[3] are described by:

$$\Delta Q_{it} = a + b\left(S_{it-1} - Q_{it-1}\right) + \varepsilon_{it} \qquad \text{(Model 1)}$$

$$\Delta Q_{it} = a + b\left(S_{it-1} - Q_{it-1}\right) + \varepsilon_{it} \text{ ; with } b = b_1 + b_2 D_{it} . \qquad \text{(Model 2)}$$

where:

ΔQ_{it} is the i^{th} salesperson's change in sales quota from *t-1* to *t*.

S_{it-1} is the i^{th} salesperson's actual sales in *t-1.*

Q_{it-1} is the i^{th} salesperson's quota in *t-1.*

D_{it} is one if $S_{it-1} < Q_{it-1}$ and 0 otherwise.

ε_{it} stochastic errors that are distributed $N\left(0, \sigma_t^2\right)$

[3] While we use the same notation for parameters in all models, the reader should note that these are different since they appear in different specifications. We have used the same notation to avoid clutter and confusion.

Model (1) is a benchmark model that estimates the average weight placed on current sales (*b*) and past quotas (*1-b*) in equation (5). As mentioned earlier, we expect that $0<b<1$. Model (2) tests whether quotas are updated asymmetrically. In particular, if year *t* quotas fall less when *t-1* sales fall short of the *t-1* quota than quotas increase when *t-1* sales exceed the *t-1* quota, then $b_2<0$.

3.2 Accounting for Heteroskedasticity

In all likelihood the extreme differences in the scale of various sales territories induces heteroskedasticity into our regression models. A possible correction for this problem is to scale the regression by a factor that removes the effect of heteroskedasticity. Unfortunately this approach presupposes that we know exactly the form taken by the heteroskedasticity component, which is unlikely. We therefore allow for a general multiplicative model of heteroskedasticity as follows:

$$\Delta Q_{it} = a + b\left(S_{it-1} - Q_{it-1}\right) + \varphi\left(Q_{it-1}\right)\varepsilon_{it} \qquad \text{(Model 3)}$$

$$\Delta Q_{it} = a + b\left(S_{it-1} - Q_{it-1}\right) + \varphi\left(Q_{it-1}\right)\varepsilon_{it}\text{; where } b = b_1 + b_2 D_{it}. \qquad \text{(Model 4)}$$

In particular we assume that the heteroskedasticity formulation is $\varphi\left(Q_{it-1}\right) = Q_{it-1}^{\eta}$, and hence the variance of the regression error is $\sigma_t Q_{it-1}^{\eta}$. This is a natural specification since the past quota contains all information available to the quota setter and is a good proxy for the scale of the salesperson's territory. A side benefit of this specification is that it nests alternative formulations of the quota adjustment process. If our results show that $\eta = 1$ then the model is equivalent to scaling all variables (and the intercept) by the quota and can therefore be interpreted as a regression where the variables are operationalized in percentage terms. On the other hand if $\eta = 0$ then we revert back to the case of no heteroskedasticity. Our primary purpose in specifying these models, however, is to ensure that heteroskedasticity is controlled for.

3.3 Incorporating Observed and Unobserved Heterogeneity

While the specifications in Models 1 – Model 4 test for the dynamics of quota setting, they do not allow for the parameters to vary across individual salespeople. There have been numerous studies (see e.g. Chintagunta, Jain and Vilcassim 1991; Gonul and Srinivasan 1993) that show that ignoring heterogeneity results in inefficient and biased estimates. In addition, investigating heterogeneity in quota setting is in itself of interest given our earlier discussion. We specify three extensions which incorporate heterogeneity. The first two of these are:

$$\Delta Q_{it} = a_i + b_i\left(S_{it-1} - Q_{it-1}\right) + h\left(Q_{it-1}\right)\varepsilon_{it}; \qquad \text{(Model 5)}$$

with $a_i \sim N\left(\mu_a, \sigma_a^2\right)$, $b_i \sim N\left(\mu_b, \sigma_b^2\right)$.

and

$$\Delta Q_{it} = a_i + b_i\left(S_{it-1} - Q_{it-1}\right) + h\left(Q_{it-1}\right)\varepsilon_{it} \qquad \text{(Model 6)}$$

with $a_i \sim N\left(\mu_a, \sigma_a^2\right)$, $b_i = b_{1i} + b_{2i}D_{it}$, $b_{1i} \sim N\left(\mu_{b_1}, \sigma_{b_1}^2\right)$ and $b_{2i} \sim N\left(\mu_{b_2}, \sigma_{b2}^2\right)$.

Model (5) allows for unobserved heterogeneity in the Weitzman specification. The two random effects incorporated are in the intercept and the ratchet parameter (b). Correspondingly, Model (6) allows for unobserved heterogeneity in the asymmetric ratcheting model. There are three random effects here pertaining to the intercept, the symmetric and asymmetric ratcheting parameters.

The final model we estimate analyzes the effect of observed territory and salesperson characteristics on the key ratcheting parameters. This allows us to better understand what types of salespeople or markets would exhibit asymmetric ratcheting. Particularly, we specify,

$$\Delta Q_{it} = a_i + b_i\left(S_{it-1} - Q_{it-1}\right) + h\left(Q_{it-1}\right)\varepsilon_{it} \qquad \text{(Model 7)}$$

with $b_i = b_{i1} + b_{2i}D_{it}$, $a_i \sim N\left(\mu_a, \sigma_a^2\right)$,

$$b_{1i} \sim N\left(\mu_{b_1} + Z_i'\delta_{b_1}, \sigma_{b_1}^2\right),\; b_{2i} \sim N\left(\mu_{b_2} + Z_i'\delta_{b_2}, \sigma_{b_2}^2\right)$$

Where Z_{it} is a vector of territory and individual characteristics which will be specified later.

The formulations presented in this section are extremely flexible as they allow all parameters to vary across individuals based on both observed and unobserved factors. In all of these models (i.e. models 5 through 7) the presence of statistically significant variances ($\sigma_a^2, \sigma_{b_1}^2, \sigma_{b_2}^2$) would suggest that the ratcheting of quotas is done on an individual basis. In addition statistically significant δ's would suggest that the quota updating process is influenced by observed characteristics.

As mentioned earlier, models 1 through 4 are straightforward to estimate via maximum likelihood and we do not belabor the details here. For models 5 through 7 we use a simulated maximum likelihood approach. In particular we use quasi-Monte-Carlo methods to integrate out the random coefficients and maximize the simulated likelihood. We then use standard empirical Bayes' methods[4] to "estimate" individual level parameters for each salesperson. These individual Bayes' estimates are useful as they allow us to uncover the underlying distribution of parameters across salespeople.

This completes our discussion pertaining to the econometric specification of our models. We expect that model (7), because of its inherent richness in data and formulation will dominate all other models.

4 Research Setting and Data

This section describes in more detail our research setting, the data provided, and summary statistics before the next section provides the empirical tests.

4.1 Research Setting

For our analysis we focus on the quota setting process of one particular firm (denoted by the letter 'A'). Firm 'A' with annual sales revenue in excess of $15 billion is the market leader in a particular type of machinery, services, and supplies sold to other businesses. It designs, sells, and services it products and has a dedicated sales force. The firm has been in business over 75 years and in 1998, the time period of our study, employed over 80,000 people. Although the firm operates in various product and service

[4] This involves sampling from the estimated densities of the random parameters and then taking a likelihood weighted average for each individual. See Brownstone and Train (1999) for an example. More details on the estimation method and the estimation of individual effects are available from the authors.

markets we restrict our focus to one particular division that employs about 4000 sales people in their United States operations. We further restrict ourselves to a smaller sub-group that are all considered to be on the same level within the sales hierarchy. In other words they are all sales 'reps'. Sales people are also deleted from the sample if they changed territories between 1996 and 1998. This narrows down our effective size to about 1762 individual salespeople. This particular division is the flagship of the company and accounts for a substantial portion of all revenues generated. Moreover, firm A is widely regarded as having a world-class direct-sales force.

Sales people specialize by selling broad product categories. Hence, sales people sell particular portfolios of products and services to a pre-assigned set of customers (territory). As discussed above, each regional sales manager determines the sales person's territory and portfolio of products at the beginning of the year. Each sales person's annual contract designates among other things the following:

- a portfolio of products that the salesperson is responsible to sell (not all salespeople sell all the products, some sales people specialize in selling a certain product class)
- a corresponding base commission rate for each product
- a quota for each individual salesperson
- an incremental commission rate for sales over quota
- a fixed salary

4.3 Variables

Firm A provided us the following data on each sales person for three calendar years (namely 1996 through 1998)

Sales, S_{t-1}. The annual sales for each sales person in year (t-1).

Quotas, Q_{t-1} and Q_t. Each sales person has an annual sales quota for each year. If the sales person's sales fall short of the quota, the sales person's commission on sales is β_1 and for sales in excess of the quota, the commission rate is $\beta_1 + \beta_2$.

Tenure, TEN. A sales person's tenure is measured as the number of months the sales person has been employed at Firm A. We use the logarithm of this number in our analysis.

Competition, COMP. To measure each sales person's competitive environment, three senior marketing managers located in corporate headquarters categorized each product class. These three individuals are together responsible for all compensation design specifications. Each member was asked to independently rate all product classes on a 1-7 scale where "7" represents a product class in a very competitive market. The average of the three managers' 1-7 scores is assigned to that product class and all sales people assigned to sell that product class receive the same competition score.

Market Size, MSIZE. Market size, like competition, is measured by the same three senior marketing managers. Again, a seven-point scale is used where "7" denotes, "there is a large market for products sold in this product class." The average of the three responses is used as the "market size" for each product class and all sales people assigned to sell that product class is assigned the same market size.

To assess the reliability of the ratings for competition and market size obtained from the three senior managers we calculated reliability coefficients (Cronbach's α). In particular competition was 0.81 and market size was 0.95. We conclude that there is a high degree of agreement among the three managers.

Volatility, VOL. The coefficient of variation of monthly sales is calculated as the standard deviation of 1996 monthly sales divided by the mean monthly sales in 1996.

4.3.1 Summary Statistics

Table 1 presents summary statistics for our variables. The final data set contains 1,762 salespeople. Mean sales in 1996 (1997) were about $3.87 ($4.44) million, which exceeded the mean 1996 quota of about $3.38 ($3.84) million. The mean quota rose to about $4.49 million in 1998. There is considerable variation and skewness in actual sales and quotas. Individual sales persons' 1996 sales range from about $11,300 to over $79 million. The typical sales person might have 100 small accounts, each with average sales of $38,000, whereas another sales person might be assigned to just one very large customer with sales of $50 million.

The mean change in quota in 1997 (1998) was about $0.452 ($0.757) million and the mean difference between 1996 (1997) sales and 1996 (1997) quota was $0.487 ($0.608) million. About 37% of the salespeople failed to meet the 1996 quota (D=1) and 38% in 1997.

The average sales person has been employed in Firm A for about 171 months, with a range of 19 months to over 38 years. The average product class is fairly competitive (5.2 out of 7) and fairly large (5.98 out of 7). No product class was ranked as being uncompetitive or small as the range of these two variables is 3 – 7. Finally, the volatility variable, *VOL*, (the coefficient of variation of monthly sales) has a mean of 5.95.

5 Estimation Results and Discussion

5.1 Basic Tests of Quota Ratcheting

Table (2) presents the results of our basic analysis for models (1) through (6). Model (1) estimates the simple Weitzman model without asymmetric ratcheting and without the added complications of heteroskedasticity correction and heterogeneity, while Model (3) and Model (5) add the heteroskedasticity correction and heterogeneity to the framework. As we mentioned earlier the slope coefficient on $S_{t-1} - Q_{t-1}$ in all these models is expected to be between 0 and 1. Note that we did not place any restrictions on the parameter space. In all three specifications, i.e. the naïve, heteroskedasticity corrected and heterogeneous versions of the Weitzman model, the slopes are between 0 and 1 and are highly statistically significant. In Model 1, if sales exceed (fall short) quota by $1, the next year's quota increases (decreases) by $0.2461. This change reduces to $0.1526 in the heteroskedastic and heterogeneous specifications (i.e. Model 3 and 5). Under the Bayesian updating interpretation the firm places a large amount of weight (approx. 75%-85%) on the past quota to set current quotas, implying that the firm has accumulated a large amount of information about the salesforce and the market and is using that to set targets.

The importance of controlling for heteroskedasticity is seen in the Akaike Information Criteria (AIC). In Model 1 the AIC is 7681 and falls to 3782 in the heteroskedastic version i.e. in model (3). The coefficient η reflects the degree of heteroskedasticity. Recall that if $\eta=0$ then there would be no evidence of heteroskedasticity. On the other hand if $\eta=1$ we could have scaled the model by past quotas. Our analysis reveals that η is statistically significant and is approximately 0.69. There is a significant improvement in fit (as seen in the AIC) due to this correction.

Surprisingly, the addition of heterogeneity to the heteroskedastic Weitzman model does not add much. Most parameters remain at their original levels. This is even more surprising in light of our later findings of strong heterogeneity when we move to the asymmetric ratcheting case.

The results obtained in these models underline the dynamic nature of quota ratcheting. In particular they highlight the fact that the firm acts as a Bayesian updater when setting quotas and that in the data we observe the weight placed on new information (i.e. on sales) is relatively small.

5.2 Results on Asymmetric Ratcheting

Even numbered models (i.e. model 2, 4 and 6) allow for asymmetric ratcheting by including a multiplicative dummy variable, $D^*(S_{t-1}\text{-}Q_{t-1})$. If quotas are increased *more* when sales exceed quotas in the last year are reduced when sales fall short of quotas, then the coefficient on the interactive dummy variable, $D^*(S_{t-1}\text{-}Q_{t-1})$, should be negative. In addition, the coefficient on ($S_{t-1}\text{-}Q_{t-1}$), i.e b, should remain between 0 and 1.

The estimates from Table (2) provide some evidence for asymmetric ratcheting. Model (4) reveals the sign of b_2 is negative and is marginally significant and that quotas only fall by \$0.0772 (0.1724 – 0.0952) when sales fall short of quota by \$1. On the other hand when sales exceed quotas by \$1, quotas rise by \$0.1724. Thus in absolute terms there seems to be evidence supporting asymmetry in the quota ratcheting process.

The heterogeneous specification in Model (6) provides additional insight into the nature of asymmetric ratcheting. While the mean effect of b2 ($\mu_{b_2} = -0.0993$) in model (6) continues to be close to the level in model 4, the results suggest that there is a very strong variance around that mean. The standard deviation for the asymmetric ratcheting effect is large and significant ($\sigma_{b_2} = 0.2206$). This implies that while for a few salespeople there may not be asymmetric ratcheting for the large majority this phenomenon is a stark reality. Individual level empirical Bayes' estimates of b2 reveal that almost 95% of all salespeople have negative parameters. To some extent this also explains why in the absence of heterogeneity the estimated effects were weak. The kernel density of these individual posterior effects (b_{2i}) is depicted in Figure 4. The vertical line depicts the posterior mean (-0.0974), and the posterior variance was calculated to be about 0.0019.

We also note that the estimate of the symmetric quota ratcheting parameter b1 ($\mu_{b_1} = 0.1851$) remains between 0 and 1 and is highly statistically significant. In addition the variance for this effect is also large and significant ($\sigma_{b_1} = 0.1058$). This finding, coupled with the finding that the heterogeneous Weitzman specification does not reveal significant heterogeneity, seems to suggest that these individual effects get washed away upon aggregation. In other words, ignoring asymmetry in the specification "hides" the fact that the quota setting process is indeed heterogeneous.

Figure 5 depicts graphically the density of the individual total ratcheting parameters as computed via the empirical Bayes' approach. This effect is the sum of the symmetric and asymmetric components. The first obvious finding is the bimodality of the density. This bimodality could only be generated if there were two groups of salespeople whose quotas were updated in significantly different ways. In our specification the only such underlying difference is the asymmetry effect. This is further evidence that the ratcheting of quotas is asymmetric at Firm A.

To conclude, the results in Table 2 are consistent with our earlier predictions. First, in adjusting the quotas, past sales and quotas receive positive weights between 0 and 1. This result provides strong evidence that firms are dynamic optimizers in the quota setting process. Second, we also find some evidence that less weight is placed on past sales in computing current quotas when past sales fall short of past quotas. In other words there is some evidence that firms ratchet quotas asymmetrically. Third, there is significant heterogeneity which suggests that Firm 'A' tailors the quota ratcheting process to individual salespeople or markets.

5.3 Identifying Sources of Asymmetry

While the results in Table (2) broadly answer the three key questions raised in this paper they do not explain why such heterogeneity exists in the quota setting process. Model (7) estimates the effects of both observed market and salesperson characteristics and unobserved heterogeneity on the ratcheting parameters in a simultaneous framework. The results obtained from the estimation procedure are presented in Table 3.

The explanatory variables impact two key parameters in the framework, namely the symmetric ratcheting parameter (b_1) and the asymmetry parameter (b_2). A quick look at the impact of these variables have on b_1 suggests that the explanatory variables do little to explain the heterogeneity in the symmetric ratcheting parameter (i.e. in b_{1i}). The only variable that matters here is volatility in monthly which has a positive and significant coefficient. In the rest of this discussion we will focus on the asymmetry parameter and the effect that the explanatory variable have on it. These are reflected in table 3 under the (b_2-Variable) effects. Our results reveal that Competition, Volatility and Tenure are the key determinants of asymmetry in ratcheting.

The effect of competition on the asymmetry parameter is positive (0.1209) and is statistically significant. This implies that salespeople selling in more competitive environs tend to have a lower degree of asymmetric ratcheting. To see this note that the overall sign of b_2 (i.e. $\mu_{b_2} + Z_i'\delta_{b_2}$) is usually negative hence competition makes it *less* negative. This finding is intuitive in that competition adds a level of uncertainty which is beyond the control of the salesperson and hence the firm chooses to ratchet more symmetrically by changing quotas symmetrically in response to increases or decreases competition.

The effect of Tenure is also positive and significant. In other words a salesperson that with a longer tenure tends to get ratcheted *less* asymmetrically. One plausible explanation for this goes back to our earlier discussion that ties together asymmetry and the changes in the composition of a salesperson's territory. Since an experienced salesperson has a fairly stable and established territory we should expect fewer changes in the composition of this territory. In addition since the firm has learnt enough about this salesperson any fluctuations in sales would in all possibility be ascribed to exogenous forces. Given these two effects one would conjecture that the firm would react symmetrically to increases and decreases in sales for an experienced salesperson. Consequently we would tend to see lower levels of asymmetry.

Perhaps the most interesting finding is the one pertaining to Volatility. Recall that volatility is measured by the within year variation in sales for a given salesperson. Our findings suggest that salespeople exhibiting higher volatility will have *more* asymmetric ratcheting of their quotas, which seems counterintuitive. However, if one assumes that within year sales volatility is controllable by the salesperson then what we are observing is the firm in effect saying that any shortfalls relative to quota that arise due to the mismanagement of effort over the year will be penalized. Indeed, in the firm we are studying, interviews with managers and salespeople suggest that a large part of the variation in intra-year sales arise because of variations in effort allocations over the year. Now, this is not to say that our volatility measure does not have a purely uncontrollable noise component. It probably does, and it is possible that a given salesperson may suffer because of unverifiable exogenous shocks. We feel that it is in such situations that salespeople tend to complain about the asymmetry in the ratcheting process.

To summarize, if a relatively experienced salesperson operates in a market with low competition and not much variance in sales, given that the firm has knowledge about the expected return, there is little reason for the firm not to react symmetrically in the face of sales-quota discrepancies. On the other hand if there are forces that are deemed controllable by the salesperson causing sales to fall short of quotas the firm tends to react by penalizing the salesperson via an asymmetric response in quota setting.

The sum of these effects leads us to conclude that our economic argument pertaining to asymmetric quota setting is valid. The firm ratchets quotas asymmetrically when there is a high level of *controllable uncertainty* and a low level of *uncontrollable uncertainty*.

5 Summary and Conclusion

Most sales compensation plans include quotas that must be met before any incentive compensation is paid. Often researchers take these targets as exogenous when examining the incentive effects of compensation plans with targets. However, to the extent the future targets depend on past performance, this ratcheting likely affects the incentives of agents (Weitzman, 1980). This study examines how sales quotas for sales people are determined and provides additional evidence that these quotas are a function of past sales and quotas. Based on the agency-theoretic sales force compensation literature that argues that sales quotas and fixed sales commissions are accurate approximations of the optimum nonlinear sales person compensation contract, we show that quotas are updated dynamically and ratchet asymmetrically. In particular, quotas increase more when sales exceed quotas than when sales fall short of quotas by the same amount. Moreover, we find that quotas are adjusted based on individual sales person's characteristics such as their tenure with the firm and also characteristics of the product markets such as the nature of competition and volatility of sales. By underlining the differences between controllable and uncontrollable factors the paper also sheds light on why and when a firm might adopt an asymmetric ratcheting policy.

Our results are an important first step to better understanding the dynamics of quota systems in sales organizations and should provide an impetus for future work in this area. A possible direction would be to generalize and extend the work of Mantrala, Raman and Desiraju (1997) by developing theoretical models that examine the nature and causes of asymmetric ratcheting within a dynamic agency framework. On the empirical side future work could replicate our findings are other research sites and examine other determinants of the quota setting process. Finally, there is nothing in this paper and our approach that limits it's applicability to the sales context. Given that targets are a commonly used mechanism in most organizations it might be fruitful to implement our models in other contexts (e.g. marketing budgets, expense accounts, profit centers etc.)

While we feel our results are strong we would like to acknowledge several caveats that limit the generalizability of our results. Our data is from one U.S. corporation, albeit one that is considered to have a "world class" direct sales force. Also, we only have a few years of data and a limited number of explanatory variables. Furthermore, our understanding of the quota setting process in this data is based on conversations with a few senior managers and sales people. Undoubtedly, there are other factors that likely drive the quota setting process of which we are unaware and/or do not have the necessary data. Future research on this topic could address these issues.

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Figure 1

Basu et al (1985) BLSS and Quota-Based Sales Person Compensation Plan

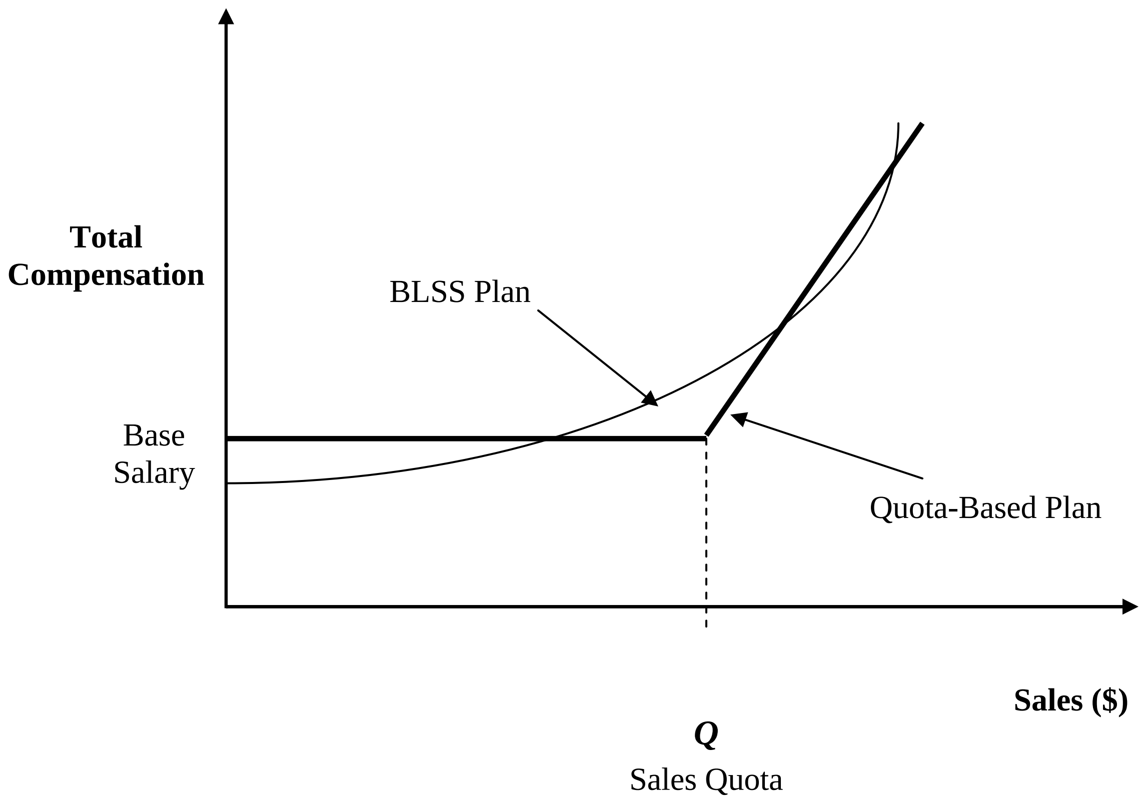

Figure 2

Basu et al (1985) BLSS and Quota-Based Sales Person Compensation Plan

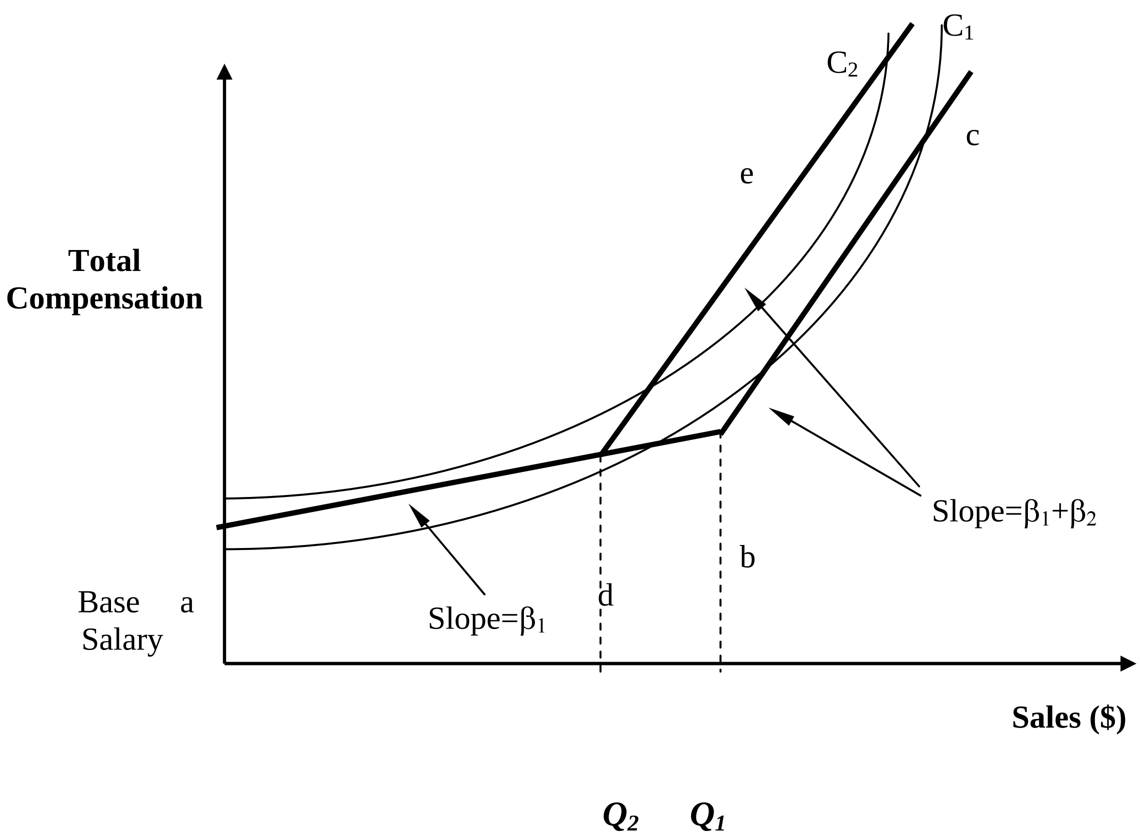

Figure 3
Leone and Rock type Asymmetric Ratcheting

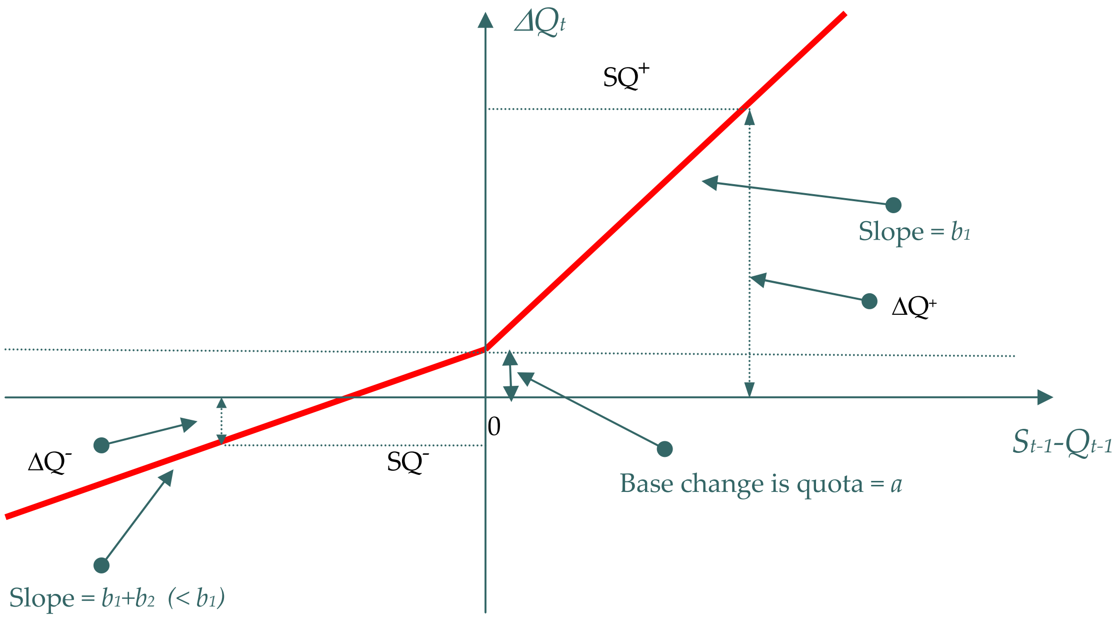

Figure 4

Posterior Estimates of Individual Asymmetric Quota Updating Parameter (b_2)

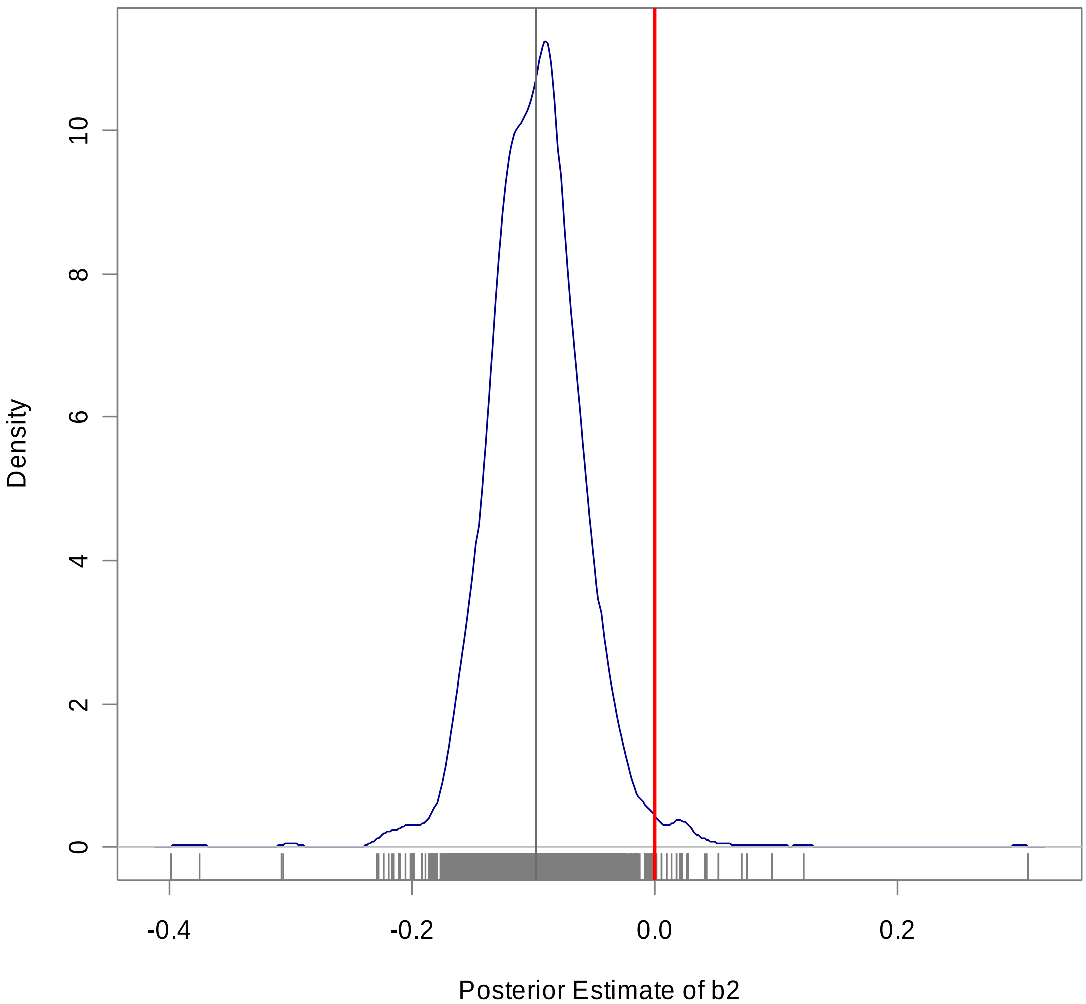

Figure 5
Posterior Estimates of Individual Quota Updating Parameter (b)

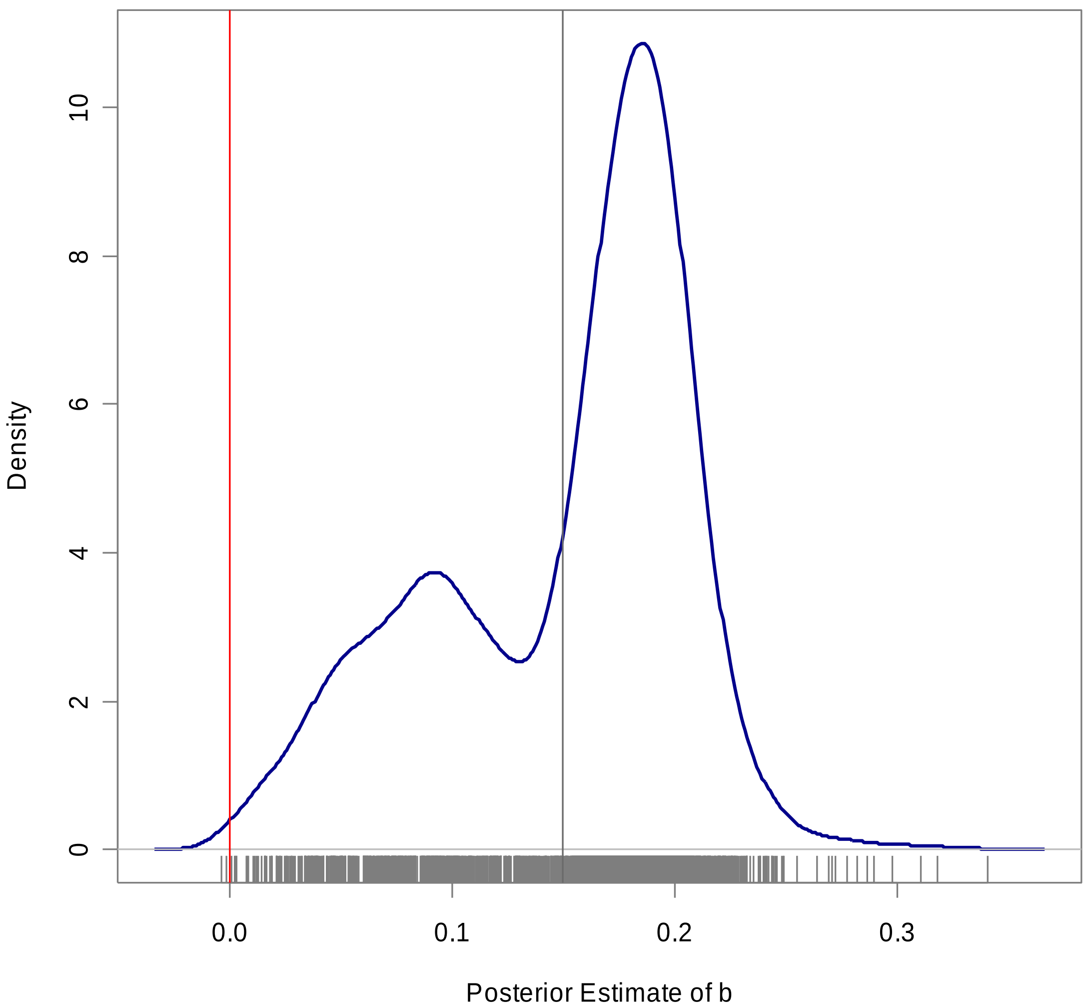

Table 1
Descriptive Statistics

Variable Name	Description	Mean	Std. Dev.	Min	Max
S_t	1996 Actual Sales	$ 3,869,725.35	$ 5,693,563.67	$ 11,281.00	$ 79,293,171.00
	1997 Actual Sales	$ 4,443,491.15	$ 6,270,562.52	$ 11,412.00	$ 53,538,796.00
Q_t	1996 Quota	$ 3,382,584.03	$ 5,009,231.11	$ 198,885.00	$ 69,220,470.00
	1997 Quota	$ 3,834,968.72	$ 5,705,473.55	$ 204,772.00	$ 56,727,842.00
	1998 Quota	$ 4,592,901.05	$ 5,851,174.89	$ 887,048.00	$ 31,150,469.00
ΔQ	Quota 1997-Quota 1996	$ 452,384.69	$ 1,797,824.19	- $ 17,560,023.00	$ 17,636,312.00
	Quota 1998-Quota 1997	$ 757,932.33	$ 3,725,435.66	- $ 28,065,557.00	$ 26,789,655.00
$(S_{t-1}-Q_{t-1})$	Sales 1996-Quota 1996	$ 487,141.32	$ 1,766,546.44	- $ 9,303,012.00	$ 14,304,679.00
	Sales 1997-Quota 1997	$ 608,522.43	$ 2,187,949.17	- $ 15,841,000.00	$ 26,242,761.00
D	Dummy =1 if (Sales 1996<Quota 1996)	0.37	0.48	0	1
	Dummy =1 if (Sales 1997<Quota 1997)	0.38	0.49	0	1
TEN	Tenure (months)	170.99	100.66	19	458
COMP	Competition (1-7 scale)	5.19	1.22	3	7
MSIZE	Market Size (1-7 scale)	5.98	1.46	3	7
VOL	Volatility of monthly sales	5.95	23.3	.002	64.9
	Number of salespeople	1,758			

Table 2
Parameter Estimates Specifications based on Models 1 through 6

	Standard		Heteroskedastic		Heterogeneous	
	Weitzman	**Asymmetric**	**Weitzman**	**Asymmetric**	**Weitzman**	**Asymmetric**
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
a (or μ_a)	0.3858***	0.3575***	0.2466***	0.2271***	0.2468***	0.2243***
Intercept	(0.0388)	(0.0456)	(0.0131)	(0.0163)	(0.0131)	(0.0166)
σ_a					0.0073	0.0034
					(0.0123)	(0.0188)
b (or μ_b)	0.2461***		0.1526***		0.1526***	
Total Ratcheting Parameter	(0.0195)		(0.0139)		(0.0140)	
σ_b					0.0021	
					(0.0133)	
b1 (or μ_{b_1})		0.2646***		0.1724***		0.1851***
Symmetric Ratcheting Parameter		(0.0250)		(0.0171)		(0.0201)
σ_{b_1}						0.1058***
						(0.0382)
b2 (or μ_{b_2})		-0.0615		-0.0952**		-0.0993*
Asymmetric Ratcheting Parameter		(0.0523)		(0.0475)		(0.0524)
σ_{b_2}						0.2206***
						(0.0633)
$\tau_1 \left(=1/\sigma_1^2\right)$	0.3784***	0.3774***	0.8060***	0.8059***	0.8062***	0.8068***
	(0.0063)	(0.0064)	(0.0138)	(0.0138)	(0.0138)	(0.0140)
$\tau_2 \left(=1/\sigma_2^2\right)$	0.8141***	0.8167***	3.4119***	3.4138***	3.4116***	3.478***
	(0.0137)	(0.0139)	(0.0765)	(0.0766)	(0.0765)	(0.0830)
η			0.6982***	0.6978***	0.6983***	0.6913***
			(0.0114)	(0.0114)	(0.0114)	(0.0118)
-2LL	7673	7672	3772	3768	3771	3755
AIC	7681	7682	3782	3780	3785	3822

*** Significant at α=0.0001 level, ** Significant at α=0.05 level, * Significant at α=0.1 level
Standard errors are in parentheses.

Table 3
Estimates based on Asymmetric Ratcheting Model with Observed and Unobserved Heterogeneity (Model 7)

Variable	Estimate	Std. Err.	P-Value
μ_a	0.2563	0.0172	<.0001
σ_a	0.0043	0.0182	0.8117
b1 – Intercept (μ_{b_1})	-0.5050	0.1326	0.0001
δ_{b_1} – Volatility	0.0524*	0.0073	<.0001
δ_{b_1} – Competition	-0.0012	0.0162	0.9419
δ_{b_1} – Market Size	-0.0004	0.0131	0.9739
δ_{b_1} – Tenure	-0.0005	0.0006	0.4651
δ_{b_1} – Tenure^2	0.0000	0.0000	0.5636
σ_{b_1}	0.1110	0.0353	0.0017
b2 – Intercept (μ_{b_2})	0.6124	0.2760	0.0266
δ_{b_2} – Volatility	-0.1046	0.0145	<.0001
δ_{b_2} – Competition	0.1209	0.0437	0.0057
δ_{b_2} – Market Size	-0.0203	0.0385	0.5981
δ_{b_2} – Tenure	0.0027	0.0014	0.0577
δ_{b_2} – Tenure^2	0.0000	0.0000	0.1325
σ_{b_2}	0.1827	0.0700	0.0091
η	0.6886	0.0119	<.0001
τ_1 $\left(=1/\sigma_1^2\right)$	0.8151	0.0142	<.0001
τ_2 $\left(=1/\sigma_2^2\right)$	3.5155	0.0840	<.0001
-2LL	3666		
AIC	3704		

The estimated model is $\Delta Q_{it} = a_i + b_i\left(S_{it-1} - Q_{it-1}\right) + h\left(Q_{it-1}\right)\varepsilon_{it}$,

with $b_i = b_{i1} + b_{2i}D_{it}$, $a_i \sim N\left(\mu_a, \sigma_a^2\right)$, $b_{1i} \sim N\left(\mu_{b_1} + Z_i'\delta_{b_1}, \sigma_{b_1}^2\right)$ *and* $b_{2i} \sim N\left(\mu_{b_2} + Z_i'\delta_{b_2}, \sigma_{b_2}^2\right)$