This final draft was published in *Journal of Marketing Research*, LIII (April 2016), 199-206. It is fully accessible to all users at libraries and institutions that have purchased a license. If you do not have access, please send an email to [jhess@uh.edu](mailto:jhess@uh.edu) and we will gladly provide a copy of the published version.

**Can Sales Uncertainty Increase Firm Profits?**

Niladri Syam\*

Department of Marketing

University of Missouri

Columbia, MO 65211

Email: syamn@missouri.edu

Phone: 573-882-9727

James D. Hess

Department of Marketing and Entrepreneurship

University of Houston

Houston, TX 77204

Email: jhess@uh.edu

Phone: 713-743-4175

Ying Yang

Department of Marketing

Stetson University

Email: yyang@stetson.edu

Phone: 386-822-7435

**May 13, 2015**

\*Corresponding Author

Do not cite without permission

**Can Sales Uncertainty Increase Firm Profits?**

**Abstract:** We add to the sales management literature in three ways. First we demonstrate that a firm can benefit from higher sales uncertainty. This is contrary to the finding in the standard principal-agent models that more sales uncertainty hurts the firm when agents are risk-averse. Second, we also find that the risk-averse agent’s total pay can increase in uncertainty, and this too is contrary to the standard principal-agent model. Third, we provide intuition for our surprising result by showing that it holds when the slope of the sales response function is random but not when the intercept is random. When the responsiveness (slope) of sales to a decision variable (of the firm or the agent) is random then information about randomness becomes decision-relevant and the firm can exploit learnt information. In our model, the agent and firm can receive noisy signals of random demand. When the customers’ response to effort (or price) is random the decision about effort (price) responds optimally to information in a way that benefits the firm. When uncertainty is high there is more information potential for the firm to exploit profitably owing to the convexity of the sales with respect to the uncertainty parameter. This is enough to dominate the negative impact that uncertainty has owing to agents’ risk-aversion. When randomness only affects baseline sales (intercept), received signals are not decision-relevant. In this case, higher uncertainty only has a negative impact just as in standard principal-agent models.

Keywords: principal-agent, uncertainty, signals, information, sales force

**1. Introduction**

The role of uncertainty has received much attention in the sales force management literature which has studied it both from theoretical and empirical perspectives. In the sales force management context, the risk-averse salespeoples’ incentives are crucial since risk-aversion creates costs for the firm that employs them. In other contexts, such as in finance, it has been suggested that uncertainty could be beneficial, implying that firms may voluntarily want to expose themselves to risk (Buehler and Pritsch, 2003; Hartford, 2011). Importantly, studies in these other contexts set aside employee attitudes toward risk. Thus, two questions for sales force management are: Can the firm benefit from uncertainty when it must incentivize a risk-averse salesperson? How does the risk-averse salesperson’s total compensation respond to larger uncertainty?

The theoretical sales management literature, which uses the principal-agent model as the workhorse, unambiguously predicts that higher sales uncertainty should reduce firm profits (Bolton and Dewatripont, 2005, p. 139; Salanie, 1997, p. 133; Lal and Srinivasan 1993). We have two main results. First, contrary to the standard principal-agent model, information about sales randomness can be extracted and used in a way that the firm can actually benefit from higher uncertainty even though it needs to incentivize a risk-averse agent. Second, we show that, also contrary to the standard principal-agent model, the agent’s total pay can increase with higher uncertainty. The standard principal-agent model predicts that sales uncertainty decreases total pay (Bolton and Dewatripont, 2005, p. 139; Coughlan and Narasimhan, 1992, p. 96; Basu, Lal, Srinivasan, Staelin, 1985, p. 282, etc.) Related to our first result, in the finance literature Alexandrov (2011) theoretically shows that firms could benefit from cost uncertainty, but this work is not in the principal-agent framework and ignores the added complexity of motivating a risk-averse agent. Related to our second result, Misra, Coughlan and Narasimhan (2005) theoretically show that the agent’s total pay can increase in uncertainty, but only when the firm is sufficiently risk-averse. Consistent with the standard, and the most commonly used, principal-agent models we have assumed a risk-neutral principal.

Interestingly, empirical tests of the principal-agent model regarding the effect of uncertainty on agent’s total pay seem to support our theoretical prediction. The standard PA model predicts that agent’s total pay should decrease in uncertainty, but consistent with our prediction, Coughlan and Narasimhan (1992) empirically find that higher uncertainty increases agent’s total pay (although not statistically significant). Similarly, Joseph and Kalwani (1995) investigate the effect of uncertainty on total pay and proportion of incentive pay and note that “for both of these comparisons, the observed effects are in a direction opposite to that hypothesized” (pp. 194). Misra, Coughlan and Narasimhan (2005) analyze two data sets and find no effect of uncertainty on salesperson’s total pay in one data set and a statistically significant positive effect in the other data set. Interestingly, unlike the field evidence provided by these above mentioned papers, Umanath, Ray and Campbell (1993) test the principal-agent model’s predictions in an experimental setup. Thus, these authors are able to ensure that they remain true to the theoretical model’s assumptions of a risk-neutral principal and a risk-averse agent. They find that, contrary to the model’s prediction, there is a positive and significant effect of uncertainty on agent’s total pay. Lal, Outland and Staelin (1994) offers significant supporting evidence for the theoretically predicted effects of uncertainty on salary and on the ratio of salary to total pay, but they do not study the effect on total pay alone. In sum, the bulk of empirical evidence runs counter to the theoretical prediction that total pay should decrease in uncertainty.

As will be clear below, our results above hold where the slope of the sales response function is random. Whereas most theoretical principal-agent models assume a random intercept (Basu, Lal, Srinivasan, Staelin; Lal and Srinivasan 1993, etc.), Godes (2003) is one of the few models where the effectiveness of effort (that is, the slope of the response function) is random.

The sales management literature recommends that salespeople should avoid uncertainty, perhaps driven by a mistaken belief about the impact of uncertainty as mentioned above. Among other things, this is especially harmful for a critical success factor for firms, which is new product success, since uncertainty avoidance induces salespeople to shy away from selling new products in favor of serving established products and customers. Hultink and Atuahene-Gima (2000) state that, “With increasing *market uncertainties* [our italics] and the rapid pace of technological change, new product marketing poses unique challenges to market participants.” In a similar vein, Ahearne, Rapp, Hughes and Jindal (2010) mention that, “They [salespeople] may even be unwilling to expend the energy necessary to sell a new product… preferring instead to focus on selling established products because this requires less effort and engenders *greater certainty* [our italics] than attempting to generate interest in a new product.”

The key managerial message of our paper is that both sales managers and salespeople can benefit from greater uncertainty if the following conditions hold: (a) managers/salespeople possess or can install information systems designed to generate accurate, decision-relevant information about the sales environment and (b) sales processes are flexible and adaptive, so that agents can nimbly adjust their selling efforts and/or managers can adjust the marketing mix (prices, advertising, etc.) to reflect the acquired information.

Why are sales higher with greater uncertainty? The critical driver is the salesperson’s ability to adapt her efforts, or other decisions, to the acquired information. For example, the salesperson may discuss the customer’s needs and concerns and then adjust the frequency of sales calls or price discounts to reflect these assessments. Consider uncertainty regarding consumers’ preference for a product. A higher uncertainty implies a higher variance around typical consumer preferences: more consumers love the product and more hate the product. In such cases there is more of a potential upside, and the acquired information allows the salesperson to benefit from it by increasing her effort. Of course, there is also more of a potential downside, but now acquired information allows the salesperson to decrease her effort and thereby reduce costs without substantially effecting sales. This minimizes the negative effect of the potential downside. Thus, this type of ‘adaptive selling’, where effort adapts to information, ensures that the salesperson and firm benefit more from the upside of uncertainty while not suffering as much from the downside.

We demonstrate our findings with two important selling decisions, the salesperson’s effort (as in the principal-agent model) and product’s price (as a representative of a variety of other marketing mix variables). First, when demand responds only to salesperson’s effort, we show that the expected profit can increase in uncertainty when the effectiveness of effort is random (slope), but not when baseline demand (intercept) is random. Second, when the sales response function also includes price, profit can increase in uncertainty even when randomness enters additively (see also, Weinberg 1975; Bhardwaj 2001; Joseph 2001; Kalra, Shi and Srinivasan 2003). The critical driver of our result is thatthe sensitivity of the firm’s profit to a choice variable of the firm *and/or* the agent is the source of uncertainty*.* In both cases, adaptive selling convexifies the sales with respect to uncertainty, and therefore, higher uncertainty implies more information potential in the system for the firm to benefit from.

Our model resembles Godes (2003) where sales randomness pertains to the effectiveness of effort and noisy signals of effort effectiveness are received by the agent. However, unlike his model, we assume the firm and the agents have the same information and thus signaling by the agents to the firm is moot. Our research connects to the rich literature in marketing that investigates the role of sales uncertainty in various aspects of interest to a selling organization (Godes 2004). Other researchers (Lal et al. 1994; Joseph and Kalwani 1995; Krafft et al. 2004) have studied how sales uncertainty affects the firm’s compensation decision. We also connect to the literature on informational aspects of principal-agent models (Nalebuff and Stiglitz 1983; Singh 1985; Sobel 1993).

As already mentioned, in this paper we distinguish between uncertainty that affects the intercept of the sales response function and uncertainty that affects the slope. The former is more commonly used in the principal-agent literature and can be thought of as uncertainty about market size. That is, there is randomness about how many customers the salesperson will be able to sell to but the response of any given customer to salesperson’s effort is known. The counter-intuitive result that we present in this paper occurs when there is uncertainty about the slope, and this can be thought of as uncertainty about customers’ response to salesperson’s effort. This could be related to the customer’s unknown preference for the product. Clearly, if the customer likes the firm’s product more, the agent’s effort will lead more easily to sales. Therefore, in practical terms, the uncertainty can be thought of as the firm’s and agent’s uncertainty about how much the customer likes the product.

Our theory is relevant to situations where a product is being sold to new customers and the firm and agent are unaware of the customer’s liking for the product. If the compensation plan period is shorter than the sales cycle, then the agent’s compensation can be changed in the next plan period to reflect the new information. For instance, in complex sales (e.g., in ‘solution’ selling) the product-and-service combination is novel and therefore the customer’s preference is unknown. Moreover, the longer sales cycles of these complex sales implies that the firm has ample opportunities to customize the marketing mix (e.g. the price) and/or the agent’s compensation depending on what is learnt about the customer’s preference for the product. As is quite common, the firm does ride-alongs with the agent, especially at the beginning when the company is establishing rapport with the customer. Through these joint visits both the manager and agent receive signals about the customer’s preference. The firm’s compensation in the next plan period, the agent’s efforts and the firm’s marketing mix (or a subset of these) can be conditioned on information received. Usually there is no ‘list-price’ for such complex offerings; prices are negotiated with buyers and can be conditioned on new information. Our theory also holds when marketing mix elements can be adapted in light of new information.

**2. Profit Can Increase in Sales Uncertainty in a Principal-Agent Model**

2.1 Random slope

Consider a firm (firm plays the role of the principal in the principal-agent model) that sells its product through a sales agent. Let the sales response function be

|  |  |  |
| --- | --- | --- |
|  |  | ( |

As is common in principal-agent models, the sales s are random and here randomness is given by the coefficient θ, whose mean is 1 and variance is V. We could interpret θ as the effectiveness, or productivity, of sales effort. The sales response function in (1) captures a situation where the uncertainty is about the customers’ response to the sales agent’s effort. On average the sales will increase 1 unit for every extra unit of effort, but the customers’ response to effort may exceed or fall short of this at random (see Godes 2003 for a different approach to this). We take the variance of  as the measure of sales uncertainty (Lal and Srinivasan 1993). In subsection 2.2, we analyze the more common sales response function where uncertainty concerns the demand intercept rather than slope. The contrasting effects of sales uncertainty on expected profit when the slope versus the intercept is random is the major insight of this paper.

Prior to the agent choosing effort and the principal choosing its compensation, suppose both principal and agent receive a signal  about θ. Others scholars have used this idea of imperfect signals about consumers being available in the system. Like Godes (2003), we model a situation where the effectiveness/productivity of effort is random (the randomness could be interpreted as the customer’s response to effort for example). He models the randomness as discrete where effort is either “effective” or “ineffective.” Similar to our setup, the agent in Godes’ analysis chooses action after receiving a noisy signal about the effectiveness of her effort and Joseph (2001) analyzes a situation where salespeople gather customer information through prospecting.

Specifically, suppose the joint distribution of productivity and signal is Normal:

|  |  |  |
| --- | --- | --- |
|  |  | ( |

Obviously the covariance matrix can be parameterized in different, equivalent ways, but we have expressed the covariance matrix in terms of correlation ρ for a very specific purpose: as we change the uncertainty V we would like to keep the accuracy of the signal constant. We use the squared correlation ρ2 as a measure of the accuracy, or information quality, of the signal (like the coefficient of determination in regression analysis). The conditional distribution of customers’ response given the signal is

|  |  |  |
| --- | --- | --- |
|  | . | ( |

The signal allows the agency to reduce the prior variance of θ, which is V, to the posterior variance V(1- ρ2). The absolute reduction in the variance Vρ2 depends upon the initial uncertainty V, but the *proportional* reduction in variance Vρ2 /V=ρ2 is constant across initial uncertainty. Thus, ρ2, which is the squared correlation of θ and  is a measure of the accuracy of the signal , with ρ2 =1 implying that the signal is completely accurate and ρ2 =0 implying that the signal is completely inaccurate; we assume that 2<1 because the basic issue of agency theory is uncertainty. We explore the effect of higher uncertainty V on firm profits keeping the signal accuracy, i.e., the proportional reduction in uncertainty, constant.

How can uncertainty about selling effectiveness increase in such a way that the agent gets signals of effectiveness that proportionately reduce uncertainty? The initial uncertainty about the two customers A and B is based on a history of calls. Suppose the agent has M and 2M historical observations of sales calls and resulting purchases, respectively, so there is greater initial uncertainty about customer A, who has a shorter history compared to customer B. Subsequently, assume the salesperson asks questions and records the customers’ reactions in a pattern that mirrors previous sales calls.  Let the number of question-and-answer interactions with A and B be N and 2N times. This difference could be because the salesperson feels comfortable asking more questions of a customer with whom he has had more previous interactions. These Q&A interactions could generate signals that reduce the uncertainty by the same proportion for customers A and B.[[1]](#footnote-1) In sum, even though the a priori uncertainty is greater for customer A, the signals are equally accurate.

Suppose the agent is paid a salary and commission on sales, Pay=S+Cs, a common system both in practice and in analytical models of sales force compensation (Joseph and Thevarajan 1998; Kalra, Shi and Srinivasan 2003). Further, let the agent’s cost of effort be . A constant risk-averse salesperson’s utility is , where a and b are arbitrary positive constants, so expected utility equals, where the subscript θ│makes it clear that the expectation is taken with respect to the conditional distribution.

The certainty equivalent (CE) of the job is the certain payment that gives identical expected utility:[[2]](#footnote-2)

|  |  |  |
| --- | --- | --- |
|  | . | ( |

Conditional upon the signal, the effort that maximizes the agent’s certainty equivalent is

|  |  |  |
| --- | --- | --- |
|  | . | ( |

It is important to note that in this case where the uncertainty is about the customers’ response to effort, the optimal effort adjusts to the productivity signal, . Information is decision-relevant.[[3]](#footnote-3) The principal chooses the salary and commission rate so that the agent’s certainty equivalent equals that of the second best possible alternative employment. Conditional upon the signal, the expected profit of the principal is the expected sales (normalized price is 1) minus salary and commission,

|  |  |  |
| --- | --- | --- |
|  | . | ( |

The optimal commission rate C\* is the solution of the first order condition

|  |  |  |
| --- | --- | --- |
|  | . | ( |

Clearly C\* does not depend upon the value of the signal, . One can easily see that the commission rate increases if the information system is more accurate (2 increases), because information reduces the perceived risk that the risk-averse agent must bear.

The principal must calculate the *unconditional* expected profit as anticipated prior to observing the signal. Since C\* is independent of  and ~N(0, ), this calculation leads to

|  |  |  |
| --- | --- | --- |
|  | . | ( |

How does this ex-ante expected profit respond to an increase in the uncertainty about the agent’s effort effectiveness?

**Theorem 1:** If the sales response function is such that the customers’ response to effort is random, s=1+e, then as sales uncertainty V increases, the expected profits of the firm increases if signals are sufficiently accurate (2 large enough).

(All proofs are found in the Appendix.) Theorem 1 offers the main theoretical insight of this paper. Contrary to the finding in the standard principal-agent models (Bolton and Dewatripont, 2005, p. 139; Salanie, 1997, p. 133; Lal and Srinivasan 1993), information extraction can imply that the firm’s profits increases with higher sales uncertainty. Why does this happen?

Risk aversion corresponds to a utility function that bends concavely downward as realized pay increases, such that expected utility is below the utility function. This disutility implies that when the environment is more uncertain, it imposes a larger cost on the firm and this has the effect of reducing sales and profits.

However, if the effectiveness of effort is random and if signals of this effectiveness are available, there is a counter-balancing effect. When signals of effectiveness are available, the agent increases effort if the observed signal is better (see (5)), and this dependence is stronger if the uncertainty is larger (for sufficiently accurate signals, i.e., for 2 large enough). The expected value of the effectiveness of effort  also increases with the signal  (see (3)), and this dependence too is stronger if uncertainty is larger. Thus, the expected sales becomes convex in the signal (see (1)), and is more convexly curved for higher uncertainty. Higher uncertainty might increase both effort and expected effectiveness by 10% for a *given* signal but this would increase expected sales by 1.10×1.10, or 21%. So, averaging across all possible signals can increase the expected sales as uncertainty increases. Crucially, and pertinent to the sales force management context, this convexifying force is enough to counteract the negative effect of risk aversion of the employees. Of course, uncertainty is beneficial only when information is accurate.[[4]](#footnote-4) If the latent component of sales is not decision relevant, convexifying is not created by an effort-moderation and expected sales drop with uncertainty.

It is important to note two aspects of Theorem 1. First, our result is not merely a statement about the value-of-information: that additional information is valuable to the principal. Value-of-information refers to the levels of profits when more accurate information is available (2 is larger). This obviously holds in our model. From the profit expression in (8), and because (7) implies that  >0, the profit clearly increases with information quality . Instead, Theorem 1 demonstrates how the firm can exploit greater sales uncertainty, so our result is about the *marginals* of profit with respect to uncertainty when the firm can and cannot exploit information about randomness – the marginal is positive in the former case and negative in the latter. Second, our result is independent of the level of risk-aversion. Because r enters the optimal profit only indirectly through C\* and (7) implies that<0, the profit decreases with risk-aversion, consistent with expectation. Instead, Theorem 1 shows that the benefit of reflecting learnt information in optimal decisions is large enough to overcome the drag due to risk-aversion for all levels of risk-aversion r.

What about the agent’s total pay? One can show that *total pay* of the agent is expected to equal. Differentiating this with respect to variance V and evaluating it when 2 approaches 1, one can see that the total pay increases as uncertainty rises.

**Theorem 2:** If the sales response function is such that the customers’ response to effort is random, s=1+e, then as sales uncertainty V increases, the total pay of the agent increases if signals are sufficiently accurate (2 large enough).

Interestingly, Theorem 2 also is the opposite of that in the standard principal-agent model where the agent’s total pay decreases in uncertainty (Bolton and Dewatripont, 2005, p. 139; Coughlan and Narasimhan, 1992, p. 96; Basu, Lal, Srinivasan, Staelin, 1985, p. 282 etc.). In Table 1, inaccurate information, the lower row, corresponds to the standard finding: as variance increases, reliance on commissions to motivate effort is diminished and total pay is expected to fall. However, with accurate decision-relevant information, top row of Table 1, expected sales increase with variance and this leads to an increase of total pay for the agent.

**Table 1. Response to Greater Uncertainty, V**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  |   Profits | S+C×Sales  Total Pay | e  Agent Effort | C  Commission Rate | S  Salary | 1+e  Sales | C×Sales  Commission |
| Accurate Signal,  2 near 1 | **+** | **+** | **–** | **–** | **–** | **+** | **+** |
| Inaccurate Signal,  2 near 0 | **–** | **–** | **–** | **–** | **+** | **–** | **–** |

This implication of our model is important for two reasons. First, unlike the other literatures which have investigated the effect of uncertainty on the profits of the risk-neutral firm, the incentives of the risk-averse agent are critical in the sales management context. In fact, one would expect the risk-averse agent to dislike higher uncertainty. We have shown that *both* the firm’s profit and the risk-averse agent’s total pay can increase with higher uncertainty. Second, the finding in Theorem 1 is consistent with empirical evidence. As mentioned in the introduction, Coughlan and Narasimhan (1992) and Joseph and Kalwani (1995) have found a positive but insignificant relationship of variance and total pay, whereas Umanath, Ray and Campbell (1993) and Misra, Coughlan and Narasimhan (2005) have found a positive and significant relationship, contradicting the traditional theory but supporting ours.

We show in the next sub-section that when the randomness in sales response is additive, information is not decision relevant and greater uncertainty is injurious to the agency. In general, these results can provide one rationalization for why the empirical evidence regarding various aspects of principal-agent models has been at odds with theoretical predictions. The contrasting implications of the random slope versus random intercept forms underscores the fact that functional assumptions about the sales response functions are consequential when testing agency theory. Most of the empirical studies on the effects of sales uncertainty are survey-based investigations and their conclusions are very divergent (John and Weitz 1988). Survey-based studies face some internal validity threats. As Ghosh and John (2000) state, “To make exact predictions (for testing) *both* technology and (risk) preferences must be known.” (pp. 350). Technology refers to the form of the sales response function and, as we have demonstrated, the theoretical predictions can change depending on the functional form.

2.2 Random intercept

In a contrast to randomness of slope in (1), consider the more traditional case of the additive random term in the sales response function:

|  |  |  |
| --- | --- | --- |
|  |  | ( |

Here, the intercept of demand, 1+, is random but the customers’ response to effort is fixed (Lal and Staelin 1986; Joseph and Thevarajan 1998; Kalra and Shi 2001).

As in sub-section 2.1, prior to the agent choosing effort and the firm choosing its compensation both firm and agent receive a signal  about demand fluctuations, ε. Suppose the joint distribution of level of demand and signal is Normal, similar to distribution (2). The expected sales are 1+e, the same as with the response function in (1). The analysis of this case is similar to that in sub-section 2.1 and is relegated to the Appendix.

**Theorem 3:** If the sales response function has a random intercept, s=1++e, then as sales uncertainty V increases, the expected profits of the firm decreases regardless of the accuracy of signals about the level of demand.

Of course, in standard principal-agent models where there are no opportunities to gather demand signals, increased sales uncertainty *always* decreases expected profits because of the agent’s risk-aversion (see Bolton and Dewatripont, 2005, p.139; Salanie, p.133; Lal and Srinivasan 1993). The analysis in sub-section 2.1 establishes that decision-relevant information can reverse this conclusion. To be decision-relevant, the randomness needs to be about the customers’ response to agent effort, rather than baseline level of sales.[[5]](#footnote-5)

We have focused on the simplest model of an agency, where the only choice that influences demand is the agent’s sales effort. Our result is more general, however. So long as the productivity/effectiveness of a marketing activity is random, a turbulent environment can actually be more profitable than a more stable environment.

Many marketing scholars, including Kalra, Shi and Srinivasan (2003) have incorporated marketing mix variables like price in the analyses of principal-agent models. We will now show that the result of Theorem 1 holds when price is incorporated in the analysis even though the randomness enters additively and the coefficient of effort is constant (customers’ response to effort is not random). This illustration is important because many principal-agent researchers make the assumption that randomness is additive with effort, and extending principal-agent models to include other marketing variables is quite natural.

**3. Incorporating Price and Advertising**

Consider a firm selling a product at a price p with demand in units equal to

|  |  |  |
| --- | --- | --- |
|  |  | ( |

The sales response function (10) is similar to Kalra, Shi and Srinivasan (2003) who have also incorporated price. Notice that quantity demanded falls with price, but otherwise this is the same as (9), with an additive random demand term ε, so the customers’ response to effort is constant. However, the revenue of the firm is the product of unit sales s and price p, so that the revenue has a term ⋅p that interacts the uncertainty about the level of demand with a marketing decision variable, price. Typically, it is assumed that the price is set by the principal (but see Weinberg (1975) and Bhardwaj (2001) for studies of price delegation).

Prior to the agent choosing effort and the firm choosing its compensation and price, suppose both firm and agent receive a signal  about demand fluctuations ε.

We leave the details to the Appendix and state the main result of this section.

**Theorem 4:** If the unit sales response function has a random intercept, s=1++e-p, but the firm can adjust price based upon a sufficiently accurate signal of demand intercept, then as sales uncertainty increases, the expected profits of the firm increases.

The result in Theorem 4 is qualitatively the same as Theorem 1 even though the uncertainty pertains to the level of demand, not the customers’ response to effort.

How does the finding of the traditional principal-agent model flip in this case? Here the signal  is decision relevant for the firm’s price, rather than agent effort. Observe that the profit is sales × price which has the effect of making the randomness multiplicative with price. Thus, the responsiveness of the firm’s profit to a decision variable, price in this case, is random just as we had the responsiveness of profit to effort being random in section 2.1.

There are two differences between the extension presented in the current section and the standard principal-agent model: (1) the firm can obtain signals about the random term, and (2) this information is used to change some element of the marketing mix. Both of these are critical. First, if there is no signal, then in terms of our model it would imply that ρ2=0. As shown in Theorem 4, a signal with ρ2=0 implies that <0. In others words, the firm’s profit would decrease in sales uncertainty consistent with the standard principal-agent model. Second, if price is not endogenized then we can show that the firm’s profit decreases in sales uncertainty, again consistent with the standard principal-agent model. Then the optimal profit of the firm is, which always decreases in sales uncertainty: <0.

We can extend our analysis to incorporate advertising. Suppose the demand is a function of awareness advertising A,  (see Hauser and Shugan 1983). The random variable  multiplies the marketing decision variable A, much like it did price above. This means that signals about demand are decision-relevant for advertising and one could show that the resulting expected profit increases with uncertainty if the information is accurate enough.

**4. Conclusion**

We show that the selling firm’s profit and a risk-averse sales agent’s total pay can increase with greater uncertainty in the selling environment, both of which are contrary to the results in the standard principal-agent model. This occurs when the firm/salesperson can extract and exploit information about sales randomness. The core issue is whether the information is decision relevant, as it would be if the customers’ response to the agent’s effort was random or if the firm could use information about the level of demand to adjust price (or other marketing mix variables). When uncertainty is high there could be both higher upside and higher downside of uncertainty. Adaptive selling ensures that the salesperson and firm benefit more from the upside of uncertainty while not suffering as much from the downside. In this paper we assumed a salary plus commission type of compensation contract, but we have also explored non-linear contract forms, like the bonus-quota contract, and find that the main result of Theorem 1 continues to hold. We have assumed a very standard utility function used in principal-agent models, but one could also do explorations with different utility functions (eg, Kalra and Shi 2001). We leave this to future research.

**References**

Ahearne, Michael, Adam Rapp, Douglas Hughes and Rupinder Jindal (2010), “Managing Sales Force Product Perceptions and Control Systems in the Success of New Product Introductions,” *Journal of Marketing Research*, Vol. XLVII, 764-776.

Alexandrov, Alexei (2011), “Firms Should be Risky at the Margin,” *Working Paper*, University of Rochester.

Anderson, Erin and Richard Oliver (1987), “Perspectives on Behavior-Based Versus Outcome-Based Salesforce Control Systems,” *Journal of Marketing*, 51 (Oct), 76-88.

Basu, Amiya, Rajiv Lal, V. Srinivasan and Richard Staelin (1985), “Salesforce Compensation Plans: An Agency Theoretic Perspective,” *Marketing Science*, 4 (4), 267-291.

Bhardwaj, P. (2001), “Delegating Pricing Decisions,” *Marketing Science*, 20(2), 143-169.

Bolton, P. and M. Dewatripont (2005), *Contract Theory*, MIT Press, Cambridge, MA.

Buehler, Kevin S. and Gunnar Pritsch (2003), “Running with risk,” *McKinsey Quarterly*, 4,

40–49.

Coughlan, A. and C. Narasimhan (1992), “An Empirical Analysis of Salesforce Compensation Plans,” *Journal of Business*, 65(1), 93-121.

Ghosh, M. and G. John (2000), “Experimental Evidence for Agency Models of Salesforce Compensation,” *Marketing Science*, 19(4), 348-365.

Godes, D. (2003), “In the Eye of the Beholder: An Analysis of the Relative Value of a Top Sales Rep Across Firms and Products,” *Marketing Science*, 22(2), 161-187.

Godes, D. (2004), “Contracting under Endogenous Risk,” *Quantitative Marketing and Economics*, 2, 321-345.

Hartford, Tim, (2011), “Adapt: Why Success Always Starts with Failure,” *Farrar, Straus and*

*Giroux.*

Hauser, J. R. and S. M. Shugan (1983), “Defensive Marketing Strategies,” *Marketing Science*, 2(4), 319-360.

Hultink, Eric Jan and Kwaku Atuahene-Gima (2000), “The Effect of Sales Force Adoption on New Product Selling Performance,” *Journal of Product Innovation Management*, 17, 435-450.

John, G. and B. Weitz (1988), “Explaining Variation in Sales Compensation Plans: Empirical Evidence for the Basu et al Model,” *Working Paper*, Department of Marketing, University of Minnesota.

Joseph, K. (2001), “On the Optimality of Delegating Pricing Authority to the Sales Force,” *Journal of Marketing*, 65(1), 62-70.

Joseph, K. and A. Thevarajan (1998), “Monitoring and Incentives in Sales Organizations: An Agency Theoretic Perspective,” *Marketing Science*, 17(2), 107-123.

Joseph, K., and M. Kalwani (1995), “The Impact of Environmental Uncertainty on the Design of Salesforce Compensation Plans,” *Marketing Letters*, 6, 183–197.

Kalra, A., and M. Shi (2001), “Designing optimal sales contests: A theoretical Perspective,” Marketing *Science* 20(2), 170-193.

Kalra, A., M. Shi and K. Srinivasan (2003) “Salesforce Compensation Schemes and Consumer Inferences,” *Management Science*, 49(5), 655-672.

Lal R., D. Outland and R. Staelin (1994), “Salesforce Compensation Plans: An Individual Level Analysis,” *Marketing Letters*, 5(2), 117-130.

Lal, R., and V. Srinivasan (1993), “Compensation Plans for Single- and Multi-Product Salesforces: An Application of the Holmstrom-Milgrom Model,” *Management Science*, 39(7), 777-793.

Misra, Sanjog, Anne Coughlan and Chakravarthi Narasimhan (2005), “Salesforce Compensation: An Analytical and Empirical Examination of the Agency Theoretic Approach,” *Quantitative Marketing and Economics*, 3, 5-39.

Salanie, B. (1997), *The Economics of Contracts*, MIT Press, Cambridge, MA.

Sobel, J. (1993), “Information Control in the Principal-Agent Problem,” *International Economic Review*, 34(2), 259-269.

Umanath, Narayan, Manash Ray and Terry Campbell (1993), “The Impact of Perceived Environmental Uncertainty and Perceived Agent Effectiveness on the Composition of Compensation Contracts,” *Management Science*, 39 (1), 32-45.

Ustuner, T. and D. Godes (2006), “Better Sales Networks,” *Harvard Business Review*, July-August, 84(7/8), 102-112.

Weinberg, C. B. (1975), “An Optimal Commission Plan for Salesmen’s Control Over Price,” *Management Science*, 21(8), 937-943.

**Appendix**

**Proof of Theorem 1:**

Differentiating (7) with respect to V gives  Differentiating (8) with respect to V and substituting the above gives .

The marginal expected profit is a weighted average of a positive term and a negative term, with weights 2 and 1-2. If signal accuracy 2 is near 1, the weighted average is positive. 

**Proof of Theorem 2:** Differentiate  with respect to V to get . The derivative of C\* is found in the proof of Theorem 1, so after substitution, .

The marginal expected pay is a weighted average of a positive term and a negative term, with weights 2 and 1-2. If signal accuracy 2 is near 1, the weighted average is positive. 

**Proof of Theorem 3:** The distribution of intercept and signal is

|  |  |  |
| --- | --- | --- |
|  |  | ( |

As before, the squared correlation of ε and , ρ2, is a measure of the accuracy of the signal . The conditional distribution of ε given  is

|  |  |  |
| --- | --- | --- |
|  | . | ( |

The risk-averse agent has a certainty equivalent

|  |  |  |
| --- | --- | --- |
|  |  | ( |

The effort that maximizes this certainty equivalent is

|  |  |  |
| --- | --- | --- |
|  | e\*=C. | ( |

Unlike the optimal effort when slope is random, here the effort is independent of the signal. This decision-irrelevance is a crucial difference from the random slope model; contrast (14) and (5).

The principal will choose compensation to hold the agent’s certainty equivalent constant:

|  |  |  |
| --- | --- | --- |
|  |  | ( |

Notice that compensation is independent of the signal about demand level, contrary to the finding for random slope. The expected profit conditional on the observed signal  is

|  |  |  |
| --- | --- | --- |
|  | . | ( |

The profit maximizing commission rate is

|  |  |  |
| --- | --- | --- |
|  | , | ( |

independent of the signal about demand level, . The optimized profit conditional on  is

|  |  |  |
| --- | --- | --- |
|  | . | ( |

The principal must calculate the *unconditional* expected profit anticipated prior to observing .

|  |  |  |
| --- | --- | --- |
|  | . | ( |

The signal is not “decision relevant” and greater uncertainty reduces expected profit. 

**Proof of Theorem 4:** Suppose the random demand and signal are distributed as in (11). The agent’s certainty equivalent is

|  |  |  |
| --- | --- | --- |
|  | , | ( |

and the effort that maximizes it is the same as (14) , independent of the signal .

To hold the agent’s certainty equivalent to zero, the salary of the agent is set equal to

|  |  |  |
| --- | --- | --- |
|  |  | ( |

The firm’s expected profit conditional on the observed signal is

|  |  |  |
| --- | --- | --- |
|  |  | ( |

The profit maximizing price and commission rate are

|  |  |  |
| --- | --- | --- |
|  | and | ( |
|  | . | ( |

Notice that both price and commission rate depend on the value of the signal, . In other words, the signal  is decision-relevant for the firm. With the appropriate substitutions the optimal expected profit in terms of  is

|  |  |  |
| --- | --- | --- |
|  | . | ( |

The firm’s *unconditional expected* profit anticipated prior to observing signal  is

|  |  |  |
| --- | --- | --- |
|  | . | ( |

The response of the expected profit (26) to increasing sales uncertainty V is clearly a function of the accuracy of the information, ρ2. The derivative is the same as the sign of, which is negative if ρ2=0 and positive if ρ2=1. 

1. The prior uncertainty for A is proportional to 1/M and, after N question and answer sessions, the posterior uncertainty is proportional to 1/(M+N). The proportional reduction in uncertainty for A is [M-1- (M+N)-1]/M-1. Similarly, the proportional reduction in uncertainty for B is [(2M)-1- (2M+2N)-1]/(2M)-1, but the 2s cancel.  [↑](#footnote-ref-1)
2. This uses the fact that if X~N(,2) the moment generating function is E[exp(tX)]=exp(t+ ½ t22). [↑](#footnote-ref-2)
3. In contrast, when uncertainty is about the baseline level of sales, effort is independent of the signal which is decision-irrelevant; see equation (14) in Appendix. [↑](#footnote-ref-3)
4. The simple form of the sales response function in equation (1) could be easily generalized, so long as there is an interaction of effort and uncertainty, and Theorem 1 will be applicable. For example, one could show that it is also true for a sales response function , which has the property that the marginal productivity of effort is influenced by the magnitude of the random term. We thank an anonymous reviewer for this suggestion. [↑](#footnote-ref-4)
5. A reviewer of this paper pointed out that it is possible for an increase in the variance of a random variable to automatically increase its mean, making expected sales increase with variance. For example, if  was distributed 2 with k degrees of freedom, its mean is k and its variance is 2k. Theorem 3 applies when random sales has a mean that is independent of its variance as is assumed in the standard PA model. [↑](#footnote-ref-5)