# THE INCENTIVE AND SELECTION ROLES OF SALESFORCE COMPENSATION CONTRACTS

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## ABSTRACT

Designing compensation plans with appropriate level of incentives is a key decision faced by managers of direct salesforces. The authors use data on individual salesperson compensation contracts to show that firms design their pay plans to both discriminatingly *select*, i.e. attract and retain, salespeople and provide them the right level of *incentives*. Consistent with standard agency arguments, the authors find that firms use higher-powered incentives as the importance of agent effort increases. At the same time, the authors find strong support for the selection role of these contracts. Specifically, agents with greater selling ability and lower risk aversion are associated with jobs offering higher-powered incentives. Finally, consistent with past findings on incentive contracts, the authors find no support for the insurance implication of the typical agency model. The authors rule out alternative explanations for this anomalous result and find that the selection role of contracts best explains the result in our context.


**Keywords**: Salesforce Compensation, Agency Theory, Incentives, Selection, Retention, Survey Research.

## INTRODUCTION

Designing compensation plans with an appropriate level of incentives is an important decision faced by managers of direct salesforces. Per one estimate, companies in the United States spend more than $200 billion on just incentive compensation for their direct salesforces – almost as much as they spend on advertising (Zoltners, Sinha, and Lorimer 2006, p.2). While designing these compensation plans, firms have to take into consideration two critical issues: How to (a) *attract* and *retain* salespeople with characteristics the firm desires (the *selection* problem) and (b) *incentivize* the salespeople to undertake desired, but unobserved, effort on behalf of the firm (the *moral hazard* problem)? Empirical research in this area, relying on agency-theoretic arguments (e.g., Holmstrom 1979; Basu et al. 1985) and using a variety of methodologies (surveys, experiments, secondary data) and data (within versus across industries, firm versus individual level), has primarily focused on investigating the ramifications of the *incentive* role of such plans – i.e., the role of pay-for-performance in resolving the moral hazard, or agent shirking, problem. In contrast, despite observations in the sales management (e.g., Oliver 1974; Zoltners, Sinha, and Lorimer 2006, Ch.5, in particular p.156) and labor economics (e.g., Lazear 2000; Balmaceda 2009) literature, scant attention has been paid to the equally important *selection* role of compensation plans – i.e. their role in enabling firms to recruit *and* retain salespeople with characteristics desired by the firm (Prendergast 1999).

The selection problem is especially acute in the context of industrial sales where complex technical knowledge, fast pace of technical change, and variation in customer types and needs combine to create a challenging environment for the salesperson. Moreover, salespeople themselves vary in their ability to conduct various non-selling (e.g., gathering information, understanding customer needs, designing and recommending customer-specific solutions) and selling (e.g., negotiating and completing the sale) tasks, as well as in their preferences for income stability, i.e., their risk aversion. Salespeople with different ability levels and/or risk preferences would be differentially attracted to jobs with different job/task characteristics and to pay plans with different incentive levels. From the firm's point-of-view, the crucial selection problem then becomes: How to design compensation plans that sort from this heterogeneous pool, and retain, the salespeople that are best suited to the job?

We develop a framework that shows how firms design pay plans to simultaneously resolve the moral hazard and selection problems, i.e. discriminatingly *select* salespeople and provide them with the right level of *incentives*. We argue that based on the job/task profile, firms choose the incentive rate in pay plans that are attractive to salespeople with traits the firm perceives fit these task characteristics. After observing the compensation plan as well as the task characteristics, agents self-select into, and stay with, firms that offer combinations of pay plans and job profiles that suit them. This process then results in an overall fit between task characteristics, agent characteristics, and incentive rates.

We test the implications of this equilibrium matching in the context of industrial sales. This setting has three appealing features. First, technical job requirements and variation in customer profiles imply that salespeople must not only be well versed in product features, but also be skilled in initiating, conducting, and completing the sales. This makes the problem of securing the services of agents with characteristics that fit the job particularly salient. Second, unlike executive pay contracts which tend to be customized to individual agents, pay schemes for industrial salespeople are relatively simple and rarely tailor-made for each agent. Instead, firms generally design pay plans at the level of a salesforce and offer take-it-or-leave-it contracts (e.g., John and Weitz 1989; Joseph and Kalwani 1995), keeping in mind the profile of the average salesperson they seek. Thus pay plans and job profiles are indeed observable to agents when choosing their jobs. Third, given that pay plans are uniform within a sales group, the individual salesperson-level compensation data that we collected from a cross-section of industrial equipment manufacturers provides cross-firm variation in pay that we can associate with cross-firm differences in job profiles and agent traits to test the predictions of our model.

Our study makes three key contributions. First, we show that the incentive rate offered by firms in these non-customized pay plans indeed serves as a selection device. Using individual-level data we show that agents with high ability and low risk aversion work in firms that offer higher-powered incentives, providing evidence that the incentive rates help firms to sort amongst heterogeneous agents and match them to task/job profiles as well as retain them. Furthermore, high ability and less risk-averse agents also work at firms that offer incentives that are higher-powered relative to their peers.

Second, we find that this incentive rate is endogenous to the job profile, particularly to characteristics such as customer heterogeneity and firm reputation that affect the difficulty of the sales job, supporting the claim that compensation plans are also designed to provide incentives for unobserved agent effort. In other words, firms offer higher-powered incentives when the salesperson's effort is more important in achieving sales. Taken together, to the best of our knowledge, we provide the first evidence on the simultaneous use of compensation contracts as both selection and incentive devices *across* heterogeneous agents and job profiles (i.e. firms). Our results complement work in labor economics (e.g., Lazear 2000) that has relied on longitudinal data to show selection and incentive effects within a firm.

Finally, consistent with prior work (e.g., John and Weitz 1989; Krafft, Albers, and Lal 2004), we find no support for the classic insurance implications of agency models, i.e., the prediction that as uncertainty increases firms should offer lower-powered incentives.[1] Specifically, we find no impact of either technological or product demand uncertainty on the incentive rate. This lack of effect remains even after we control for agent risk aversion to avoid omitted variable bias, as suggested by Joseph and Kalwani (1995) and Ackerberg and Botticini (2002). While the literature provides many explanations for this anomalous risk effect, we argue that it arises in our setting as a result of the explicit role of contracts in selecting agents. In particular, rather than simply reacting to uncertainty and agent traits such as risk aversion, firms operating in more volatile environments purposefully look for ways to manage this uncertainty and deliberately devise pay structures that encourage less risk-averse agents to join and remain with the firm. Pay plans thus not only serve the role of encouraging effort and allocating risk, but also have large efficiency implications in terms of total compensation paid to the agent, controlling for task characteristics. For example, in volatile settings, firms would have to pay large risk premia to risk-averse agents. However, if pay plans with high incentive rates help firms attract and retain agents who are more willing to bear risk, the required risk premia – holding constant the strength of incentives – are reduced. This contrast between our explanation and others, such as Ackerberg and Botticini (2002), highlights the importance of the context in which pay contracts are established as a central ingredient to understanding their role and effects. Specifically, the fact that the pay plans are offered on a non-customized basis is crucial to our analysis. As such, our work shows the importance of institutional context for understanding the role of compensation contracts generally.

The paper is organized as follows. In the next section, we present a simple agency model, develop the incentive and selection effects, and draw testable implications. We follow that with a description of our data and empirical results and conclude with implications for research and practice.

## THEORY

We begin with an agency model to show how optimal compensation schemes respond to incentive requirements and uncertainty. We then extend it to show how they also may be used to induce salespeople to self select into, and stay, with firms that offer particular combinations of work environments and incentive pay.

### *A Basic Agency Model*

In the spirit of standard agency models (e.g., Lal and Srinivasan 1993; Lafontaine and Slade 2007), we assume that a principal needs an agent to put forth some effort (a), to generate output (q), according to a production function given by:

$$q = g(a, \varepsilon)$$

where $\varepsilon$ is an error term with known distribution that indexes some level of uncertainty. While output (q) is observable (and verifiable), agent effort (a) is not, and its level cannot be inferred from observed output given the error term in the production function. For a normally distributed error term with variance $\sigma^2$ and an agent with a constant absolute risk aversion utility function of parameter $\rho$, the agent chooses effort to maximize his certainty equivalent income given by $CE = E(y) - (\rho/2)Var(y)$. For a pay scheme with a base salary plus sales-based incentive rate, $y = B + bq$, where y is agent income, B is the base salary, and b is the incentive rate, the principal chooses the parameters B and b to maximize total surplus subject to the contract being incentive compatible and meeting the agent's participation constraint. Note that the incentive rate b is a proportion of the output, or *sales revenue* generated by the agent. This has implications for measures to capture b, an issue we will revisit below.

If the agent's cost of effort is quadratic, i.e., $C(a) = ca^2/2$, and the production function is linear in effort (a), i.e. $q = \theta a + \varepsilon$, the model yields a closed-form solution:

$$b^* = \theta^2/(\theta^2 + \rho c \sigma^2)$$

where b* is the optimal sales-based incentive rate. This equation embodies the following testable implications, all of which are related to the *incentive effect* of b:

- The incentive rate should be negatively related to environmental uncertainty, $\sigma^2$ (e.g., Stiglitz 1974; Holmstrom 1979; Basu et al. 1985). Environmental uncertainty here refers to shocks that are *exogenous* to the agent's sales effort. We operationalize this as technological uncertainty, which refers to shocks arising from frequent and rapid changes in the product and associated technology, and as product demand uncertainty at the industry level.
- The incentive rate should be positively related to the importance of agent effort in the production process, $\theta$, which itself will to be a function of the task profile. This effort includes non-selling and selling efforts that contribute to generating sales. The value of the sales effort is expected to be greater when customer needs are non-standard. Likewise, it is easier to sell products of firms that enjoy a strong reputation in their customer markets; hence, the agent's sales effort is likely to be more valuable for firms that do not enjoy such a reputation. Thus $\theta$, and consequently b*, is expected to be positively correlated with customer heterogeneity, but negatively correlated with firm reputation.
- The incentive rate should be negatively related to the degree of agent risk aversion, $\rho$ (Stiglitz 1974; Holsmstrom 1979; Basu et al. 1985).
- The incentive rate should be negatively related to the agent's cost of effort, *c*. Previous research (e.g., Lazear 2000) has argued that high-ability agents have a lower cost of effort. This yields the prediction that the incentive rate should be positively correlated with agent ability.

Although the model above is developed for a particular dyad, namely one principal and a particular single agent, it easily can be interpreted in terms of an "average" agent for a given principal (firm). In that case, $\sigma^2$ becomes the average level of uncertainty encountered by agents in the firm, $\theta$ is the average importance of agent effort, and the optimal average incentive rate for agents with average characteristics $\rho$ and c is given by b*. This reinterpretation of the standard dyadic agency model has two key implications for empirical work in field settings where firms offer contracts at a salesforce (not sales agent) level, as is the case here. First, the model can be tested using salesforce level data under the assumption that these plans are designed taking into account the average skill and/or risk preferences of a *homogeneous* salesforce that deals with average conditions. Past empirical research (e.g., John and Weitz 1989; Joseph and Kalwani 1995) has exploited this fact. Second, managers design their salesforce compensation plans based on their *perceptions* of the risk attitude of the average salesperson the firm employs or seeks to employ.[2] The model thus can be tested using data obtained from firms/managers on pay plans, job/task characteristics, and perceived agent traits.

***Selection***

While the literature on salesforce compensation has focused primarily on agency costs and the uncertainty-incentive trade-off described above, a related literature in salesforce management (e.g., Lal and Staelin 1986; Albers 1996; Joseph and Thevaranjan 1998) and personnel economics (e.g, Hallagan 1978; Brown 1990, 1992; Lazear 1999, 2000; Balmaceda 2009) has emphasized the selection role of pay schemes, i.e. their ability to attract and retain the right type of agent. Agents are known to vary in their ability to, amongst other things, (a) initiate and close a sale, (b) extract valuable information on customer requirements, (c) propose appropriate solutions, (d) negotiate skillfully with customers, and (e) learn from past experience and adapt to new circumstances. They also differ along another important dimension, namely their preferences vis-à-vis variability in their compensation.

Given this heterogeneity in skills and preferences, firms can – and will want to – use the incentive intensity of their pay plans to *sort* amongst such agents (Lal and Staelin 1986; Brown 1990; Lazear 2000). For instance, Bishop (1987) argues that incentive-laden pay has three primary benefits: incentivizing the employees to work harder, attracting a higher caliber workforce, and reducing the attrition of good performers for better jobs elsewhere. Likewise, the sales management literature has argued that output-based rewards improve self-esteem and lead to higher performance (Bagozzi 1978) and impact motivation (Darmon 1974), amount and quality of effort (Lal, Outland and Staelin 1994), and willingness to take challenging jobs (Oliver 1974). Using compensation data for 3000 workers from a large auto-glass firm over a 19-month period within which the firm started offering piece rates, Lazear (2000) found that half of the observed improvement in productivity due to output-based piece rates resulted from the selection and retention of higher-skill employees while the other half was attributable to the pure incentive-to-work-harder effect.[3]

Following Brown (1990) and Lazear (2000), in what follows we illustrate graphically the basic selection argument for different compensation schemes. We begin with selection on agent ability.

<u>Selection on Ability:</u> Consider Figure 1. Here, we have two types of agents, namely low- and high-ability agents. Low-ability agents have steeper indifference curves than high-ability agents in the effort/compensation space because effort is more costly to them. Thus for any given increase in effort, they require greater increases in expected compensation to bring them back to their original utility level than high-ability agents do. Figure 1 also shows two pay schemes offered by two different firms. The first firm offers a constant salary, $w_0$. The second firm offers a lower base salary, $w_1$, combined with output-based pay, resulting in a linear upward sloping compensation scheme. Finally, there is a minimum effort level, $e_0$. We assume that the firms can discern whether workers exert at least this level of effort, and if not, terminate their contract.

************ Insert Figure 1 about here *****************

The separating equilibrium combination of effort and pay has the low-ability agents choosing to work with Firm 1, putting in exactly effort level $e_0$ and getting paid $w_0$. The high-ability agents, in contrast, find it advantageous to choose the combination of lower base salary and output-based pay offered by Firm 2 and exert more than the minimum effort, i.e. they choose $e_h$ and get paid $T_h$ in expectation. This allows them to attain a higher level of utility, $u_h$', than the fixed wage/minimum effort option ($u_h$). This is a separating equilibrium in that the low-ability types have no reason to imitate the high-ability types – their indifference curve through the combination of $e_h$ and $T_h$ is lower than what they can achieve with $e_0$ and fixed wage, $w_0$ ($u_l' < u_l$).

Selection on Risk Aversion: A similar argument can be made for selection on agent preferences for income stability, i.e. their degree of risk aversion. And just like firms benefit if they employ higher-ability agents – as long as the cost of more productive workers is not too high – firms that offer an environment where salespeople are exposed to volatility might find it beneficial to attract and retain individuals who are not very risk averse. This is because more risk-averse individuals demand a higher level of expected compensation when exposed to uncertainty. A firm then has two choices. It can isolate its agents from such uncertainty by paying them more on a fixed wage basis. Or, it can devise contracts that encourage less risk-averse workers – who require less compensation to bear risk – to work at the firm. Not only does selecting such workers reduce the risk premium the firm needs to pay the agents, it also relaxes the constraint on the incentive power that can be offered. Thus firms operating in uncertain environments may have strong incentives to select workers on risk preferences.[4]

We argue that firms characterized by more uncertain work environments for sales agents benefit from *purposefully* setting the incentive rate to select the right kind of salesperson. Just as more able agents find higher incentive rates attractive, more risk-averse agents find higher incentive rates unattractive. This is illustrated in Figure 2. Here a risk-averse, low-ability salesperson would choose the ($e_0$, $w_0$) combination just like his risk-neutral counterpart: as his wages are fixed under this contract, he obtains full insurance and thus his degree of risk aversion does not affect his choice of compensation scheme or effort level. Among high-ability salespeople, however, only those with low risk aversion would choose the output-based compensation contract.

************ Insert Figure 2 about here *****************

To see this, consider the utility a high-ability salesperson derives from a particular expected total compensation in Figure 2. For a given level of uncertainty, the more risk-averse individual will value the same expected compensation less than the less risk-averse agent will. This is captured in Figure 2 by the certainty equivalent curves for high and low risk aversion individuals with high ability.

The more risk-averse, high-ability individual's CE curve is $CE_{high}$ which lies below the CE curve of the low risk agent $CE_{low}$. This more risk-averse agent will choose low effort and the fixed-wage contract since that contract allows him to achieve a higher utility curve than the output-based contract ($u_h > u_{h0}$). However, the less risk-averse, high-ability individual – whose CE curve is $CE_{low}$ – will find it best to choose the contract with the lower fixed wage and output-based pay and put in a higher level of effort as this gives him a greater level of utility ($u_h' > u_h$). In that sense, an output-based contract would lead to sorting among high-ability types along the risk-aversion characteristic. Thus, in our empirical analyses, we should find that controlling for agent ability, less risk-averse agents will opt for higher output-based incentive contracts.

The two CE curves in Figure 2 not only can be interpreted as those of different individuals with different levels of risk aversion, but instead as representing the CE income of agents with the same degree of risk aversion facing different levels of uncertainty. The $CE_{low}$ would then represent a situation where uncertainty is low, while the $CE_{high}$ represents a higher level of uncertainty. Under this interpretation, the firm operating in a highly uncertain environment would not successfully separate the high and low-ability salespeople if it offered the pay schemes in Figure 2. In this case, the high-ability worker would opt for ($e_0$, $w_0$) as it yields a higher level of utility than ($e_h$, $T_h$) does (i.e., it yields $u_h$ rather than $u_{h0}$). To induce separation along the ability dimension, the firm operating in a more uncertain environment would need to offer a steeper pay scheme than the one depicted in Figure 2. In other words, firms operating in more uncertain environments can be expected to choose higher incentive rates to encourage less risk-averse agents to join. Further, for a given level of risk aversion, these firms will need to offer higher incentive rates to select high-ability agents.

Accordingly, we offer the following testable predictions concerning the *selection effect*:

- All else equal, salespeople with higher ability levels will be associated with jobs that offer higher incentive rates.
- All else equal, salespeople with higher levels of risk aversion will be associated with jobs that offer lower incentive rates.

***Incentives, Selection, and the Insurance Effect***

Prendergast's (2002) survey of studies across four categories of occupations – executives, franchisees, sharecroppers, and salesforce and others – not only concludes that there is no clear evidence of an uncertainty-incentive trade-off, but finds that the number of studies finding the opposite, namely a positive relationship between uncertainty and incentives is higher than the number supporting the theoretically predicted negative relationship. Our model provides a rationale for this anomaly. Specifically, consider firms operating in highly uncertain environments (e.g., unpredictable changes in industry-level product demand). These firms would desire salespeople who have low risk aversion as these individuals would demand a lower level of compensation for the risk they bear. Such selection can be accomplished by offering higher incentive rates, resulting in a positive association between uncertainty and incentive pay.

Alternative explanations have been proposed for this anomalous risk effect. First, Lafontaine and Bhattacharyya (1995) note that measures of uncertainty used in many studies not only capture exogenous uncertainty but also reflect variation in outcomes that is due to agent behavior. The use of such endogenous measures of uncertainty bias estimates of the effect of uncertainty on incentive rates upwards. To avoid this bias, we focus on measures of exogenous uncertainty in our study.

Second, Ackerberg and Botticini (2002) offer a conceptually different model of matching (Figure 3-II), which they refer to as "endogenous matching," where less risk-averse agents gravitate toward more uncertain job environments and pay plans are set *after* this matching occurs. The level of uncertainty in such a setting would be negatively correlated with the level of risk aversion of the agents who choose to work in that job. As a consequence, regression analyses of the power of incentives on uncertainty that do not control for agent risk aversion - as is the case in many empirical studies - would suffer from omitted variable bias. Specifically, the coefficient on uncertainty would be biased upward, thereby potentially explaining why the expected negative relationship between risk and power of incentives has eluded empirical verification to date. The authors show that risk aversion and riskiness both matter for contract choice, and that matching indeed affects the strength of these relationships in their data. Joseph and Kalwani (1995) show similar effects in a salesforce context.

Ackerberg and Botticini (2002) also make clear that this "endogenous matching" argument can be extended to any unobserved, latent trait of agents that would lead them to match to particular types of tasks, yielding biased coefficients unless those agent traits are controlled for in the "contract term" regressions. For instance, higher ability agents may opt for more challenging jobs involving more heterogeneous customers. If ability is not controlled for in regression analyses considering the effect of customer heterogeneity on incentive rates, the coefficient on the customer heterogeneity variable will be biased as well.

In our selection model, in contrast, the firm considers the job profile and purposely chooses the terms of its take-it-or-leave-it pay plan to attract and retain a type of salesperson whom it *perceives* fits the particular job and task characteristics at the firm. In the context of industrial sales, as pay plans are set at the sales-tier level and not customized to individual agents, we formulate our estimation strategy based on this purposeful selection mechanism, as depicted in Figure 3-I. Concurrently, these pay plans also incentivize salespeople to undertake unobservable effort as well. We now turn to test our theoretical framework which implies that pay plans can serve as both selection and incentive provision mechanisms using individual-level compensation data for industrial salespeople.

************ Insert Figure 3 about here *****************

## METHOD

A test of the equilibrium outcomes for the selection mechanism requires a context where firms design pay plans to attract and retain agents with certain skills and risk preferences from a pool of heterogeneous salespeople. The context of industrial equipment sales has two appealing features that make it ideal for this purpose. First, the technical nature of the product and significant variation in customer requirements on product specifications and configuration implies that salespeople must not only be well versed in product features and their fit with customer needs, but also have considerable skills in conducting the sales. As salespeople themselves vary in their ability to conduct various non-selling and selling tasks, as well as in their risk preferences, the firm's problem of attracting and retaining agents with characteristics that fit the job becomes particularly salient. Second, as was noted in our in-depth interviews, industrial firms design the pay plans for their salespeople at the level of a sales group, keeping in mind the profile of the average salesperson they want to attract. Thus pay plans and job profiles are observable to agents at the time they choose their jobs.

We gathered individual salesperson-level data on compensation, and the firm's/manager's perceptions of the job profile and the salesperson's traits, from a cross-section of manufacturers selling complex industrial equipment, to obtain between-firm variation in pay plans. These manufacturers operate in four sectors: non-electrical machinery (SIC35), electrical and electronic machinery (SIC36), transportation equipment (SIC37), and instruments (SIC38). As adequate measures of the key variables are unlikely to be available from secondary sources, we chose to obtain our data via a primary survey administered to sales managers of these firms. To ensure data quality, we took a number of steps that included conducting in-depth interviews with field sales managers to ascertain the relevance of our theoretical framework, choosing appropriate key informants, and constructing appropriate measures for our variables. We describe each of these steps below.

***Pilot Study***

To improve our understanding of the issues firms face while designing compensation plans, we conducted on-site field interviews with sales managers at 16 firms. Each manager was directly responsible for managing the firm's direct salesforce. These interviews lasted for an average of about 3 hours each. We also pre-tested our survey instrument in some of these interviews. Insights from this pilot study were then used to refine the questionnaire and generate the final survey instrument.

Our interviews provided some fascinating insights into how and why pay plans are designed as they are. First, the managers mentioned that though it might be appealing in theory to design individual-specific pay plans (two of them specifically called this the *agency problem*), it was impractical to do so for two key reasons – the *computational* problem as in "How do I know what all is necessary to make these precise calculations?" and the *ex post conflict management* problem as in "I don't want petty jealousies between my salespeople for getting paid differently from their peers … this could backfire." As a consequence, pay plans are structured at the level of the salesforce or sales group. In particular, salespeople within an identifiable group/tier (e.g., selling similar products to customers with similar profiles; operating within similar geographies; etc.) are offered the same pay plan. Of course, this does not necessarily translate into the same level of total pay for the salespeople within the group. Different sales output levels under the same salary and incentive rate structure lead to differences in total pay. The fixed part of the pay plan might also include cost of living adjustments. Finally, salespeople selling similar products to different customer profiles (e.g., selling information storage and computing devices to key-account retail chain stores versus individual stores) usually operate under different pay plans because the job profiles are very different. In other words, these are different sales groups and, as such, they are paid according to different formulas.

Second, managers indicated that pay plans are designed keeping in mind the type of agent the firm perceives would best fit with the task at hand. For example, they consider the variation in customer needs, the technical complexity of the product line(s) and other environmental factors as well as what type of salesperson is most likely to do well in all aspects of industrial sales (e.g., understanding customer needs and recommending appropriate solutions, negotiating, closing, etc). In effect, as expected from our framework, the managers suggested that pay plans are designed to attract and retain a certain type of salesperson, and that they are indexed to and reflect exogenous heterogeneity in the work and task environment.

Third, and finally, managers noted that the core components of their pay plans were base salary and sales commission with the revenues generated by the salesperson being the predominant metric used to calculate the commissions. The key reason for using revenues (instead of gross margins generated by the salesperson) was that revenues are easier to observe and less likely to be distorted, or, as one manager stated, "margins can be easily manipulated … the salesperson would not know if he is cheated on and worse he would never believe he is not cheated on … we don't want such headaches".[5]

The ease of implemention of sales-based incentives has also been noted in previous research on salesforce compensation (Albers 1996, p.5) as a factor leading to its popularity in practice.

***Data Collection Procedure***

We used the key informant methodology (Campbell 1955) to identify individuals who were closely involved in the decision making and knowledgeable about the context being investigated. We used a two-stage procedure to reach our survey participants. We first obtained a list of sales managers of manufacturing firms in the industrial sector with sales exceeding $100 million from two list brokers – the American List Council and Dunn and Bradstreet. These 1470 individuals were then contacted by phone to qualify them as key informants. To qualify, they had to meet three criteria: (a) be involved in managing the salesforce for their division/firm in a well-defined customer, product, or geographic market, (b) be knowledgeable about the customers and environment in this market, and (c) their firm had to be using a direct salesforce rather than contract dealers in those markets. Four telephone calls on average were required to qualify each informant. To elicit cooperation, we offered each participating manager a customized report that summarized the findings from our survey and compared their profile to the average patterns across all firms in the data. Of the initial 1470 individuals, 869 indicated that they use a direct salesforce and agreed to participate in the survey. In the second stage, questionnaires were mailed to these 869 respondents. After two reminders, we received 264 responses. Three of these were discarded for missing data, for a final sample of 261 responses (or a response rate of 30%).

The survey questions were specific to a particular salesperson that these sales managers were currently supervising. To minimize selection bias on the salesperson, we asked the sales manager to identify a customer who had procured their company's product over the previous fiscal year and then identify the salesperson who was responsible for making that particular sale. We then requested that the manager give responses pertaining to this and only this salesperson. Hence, our *unit of analysis is an individual salesperson*, with each salesperson, or data point, representing a different firm.

***Measures***

Table 1 shows the measures as well as the fit indices. Table 2 shows the descriptive statistics and inter-measure correlation coefficients. We describe each measure below.

************ Insert Tables 1 and 2 about here *****************

Compensation: For each salesperson, we obtained their base salary, total compensation, and the sales revenue they generated during the relevant year. *Base Salary* is the dollar amount of fixed pay received by this salesperson in the previous fiscal year. *Total Compensation* refers to the sum of the base salary and performance-based pay received in the same fiscal year. The performance-based pay is computed by subtracting the base salary from the total compensation. In our data, the proportion of performance-based (i.e. variable) to total compensation is around 30% which is similar to the 29% ratio in the John and Weitz (1989) sample. Using this measure of total variable compensation and the *Sales Revenue*, in U.S. dollars, generated by the salesperson in the same fiscal year, we calculate the incentive rate as:

*Incentive Rate = (Total Variable Compensation)/Sales Revenue*

Three aspects of this measure should be noted. First, consistent with past research (John and Weitz 1989; Coughlan and Narasimhan 1992; Joseph and Kalwani 1995), this measure includes all types of performance-based pay (e.g., lump-sum bonus). Managers we interviewed indicated that the dominant part of their salesforce' incentive pay was direct commissions and not bonuses. This is consistent with Coughlan and Narasimhan's (1992) observation that the most frequent pay plans are either commission-plus-salary or commission-only plans. There is also recent evidence on bonuses themselves being revenue-based (Misra and Nair 2009). In the presence of non-revenue-based bonus pay, even though our measure of incentive rate will overestimate the actual incentive power *at the margin*, it can be considered to be a good first-order approximation for actual sales-based incentive pay, or b* per the canonical agency model above, since bonuses are comparatively small in our setting.

Second, consistent with the incentive structure observed in other industries, and the managerial insight that incentive schemes should be simple to implement and hard to manipulate, our incentive rate is based on revenues and not on the gross margins generated by the salesperson.

Third, our incentive rate measure is conceptually different from that typically used in sales compensation studies, namely *Total Variable Compensation*/*Total Compensation*. Using our measure, it is possible that the incentive rate is lower for a salesperson whose total pay is 100% variable than for a salesperson whose total pay is say 30% variable. However, unlike other studies (e.g., John and Weitz 1989), our interest is not in assessing the appropriate proportion of salary versus variable pay. Rather, our focus is on explaining the level of incentive intensity that we observe in sales compensation plans. Given this context, and our theoretical framework, our measure has two main advantages. First, by highlighting the link between variable pay to an observable (by the firm and agent) outcome, sales output, our measure represents an index of *pay-for-performance*. This measure corresponds directly to, or is a first-order approximation for, the concept of incentive intensity in our and other agency-theoretic models (i.e., b*). Per figures 1 and 2, it is also the appropriate measure for the selection argument, where the intercept of the compensation line is the base salary, B, and its slope is the incentive rate (b*). Second, in contrast with the traditional measure, our measure is consistent with the notion of *ex ante* incentives per agency-theoretic models and thus is not susceptible to distortions arising from *ex post* realizations of outcomes (including both chosen effort level a and random shock ε).[6]

<u>Salesperson Characteristics</u>: We assessed two key characteristics of the focal salesperson, namely, the sales manager's perceptions of the salesperson's ability level and attitude towards risk. Given that managers design the pay plans to entice, retain, and motivate a certain type of salesperson who they *perceive* fits the job/task profile (Krafft 1999), we believe it is worthwhile measuring these perceptions to test our equilibrium "fit" prediction between incentive rate, agent traits, and job profile. The *Salesperson's Ability* scale measures the manager's perceptions of the salesperson's skill and competence in selling (e.g., negotiating and completing a sale) and non-selling (e.g., information gathering, understanding and adapting to customer needs, recommending solutions) tasks, both of which generate sales in the long-run. This measure was derived from Cravens et al. (1993). The *Salesperson's Risk Aversion* scale measures the manager's perceptions of the focal salesperson's preference for income stability and aversion to variations in outcomes and pay. This scale was adapted

from Oliver and Weitz (1991) who also found that this measure had a very significant negative correlation (-.51) with agent's actual preference for high-powered incentives, suggesting that this perceptual measure is a good proxy for "true" risk preferences. Our measure is again consistent with Krafft's (1999) assertion that real-world sales control systems are designed by executives based on their perceptions of risk attitudes rather than actual measures of such preferences.

<u>Task Characteristics</u>: We have several measures of the characteristics of the salesperson's job. *Product-Demand Uncertainty* is measured using a single item to capture the volatility of demand at the industry level for the product category sold by the focal salesperson. The item is adapted from John and Weitz (1989). *Technological Uncertainty* is measured using a 4-item scale that maps onto the manager's perception of the speed and predictability of technological advances in the product category. These measures are adapted from Heide and John (1990). Note that the salesperson's actions are very unlikely to impact either of these forms of uncertainty; hence, these measures capture "exogenous" rather than "endogenous" uncertainty. As mentioned previously, this is crucial for conducting tests of agency models (Lafontaine and Bhattacharyya 1995; Godes 2004). *Customer Heterogeneity* is measured using a 3-item scale that was developed *de novo* to assess the variation in customer types, profiles, and needs faced by the salesperson. *Firm Reputation* was a 4-item scale adapted from Mishra, Heide, and Cort (1998) to measure the extent to which the salesperson's firm is held in high esteem for its products and services, and the extent to which its products command a price premium. The salesperson's job is likely to be easier when they sell the products of a more reputable firm. Finally, the *Difficulty of Monitoring* scale, adapted from John and Weitz (1989), measures the difficulty of assessing the salesperson's performance using only data on activity and sales call reports.

Finally, we use a number of control variables in our regressions. In particular, we measure (a) *Firm Size* as total revenues for the firm/SBU (in millions of dollars) for the fiscal year, in natural log; (b) *Competition* as the potential number of competitors for the firm's product-line(s); (c) *Product-line Margin* as the operating margin, as a percentage of sales, the firm earns on the product-line(s); (d) the formal education of the focal salesperson in engineering (*Engineering Degree*) and/or in business

(*Business Degree*), both of which are coded as binary variables; and (e) "*Peer Incentive Rate*" and "*Peer Salary*" which are the mean incentive rate (salary, respectively) offered by all other firms in our sample that operate in the same SIC sector as the focal firm.

***Assessing Data Quality, Non-Response and Response Bias, and Measure Validity***

To assess informant quality, we use 2 self-reported items – "How involved are you personally in this salesperson's dealings in his/her sales territory?" and "How knowledgeable are you about this salesperson and his/her sales territory?" The responses, on a 7-point scale (1 = "not much"; 7 = "very much"), averaged 6.25 (SD = .47) and 6.48 (SD = .38) for involvement and knowledge respectively. None of the informants rated below 5 on either scale. Overall, it appears that our manager informants were capable of shedding light on the context. We assessed non-response bias using the Armstrong and Overton (1977) technique. 68% of our responses were received within 3 weeks of mailing the initial survey; these were classified as early respondents and the rest as late respondents. The two groups were compared on various demographic characteristics, using MANOVA. The test revealed no statistical difference suggesting that non-response bias is not a significant issue in our data.

We undertook several analyses to rule out response bias in our perceptual measures. First, given our survey procedure, it is possible that informants strategically chose customers and/or sales agents. To test this, we assessed two customer-side measures – the profitability of the customer to the firm and the firm's satisfaction with this customer relationship, and the two salesperson characteristics – ability and risk aversion, for distribution bias. The data[7] exhibits large variation along these measures and it does not seem as though the manager-informants strategically chose to report on their most profitable customers or their most able salespeople. Second, informants might have inferred a salesperson's risk aversion (or ability) based on whether the job is risky, or on her total compensation or revenue generated. The pair-wise correlations in Table 2 show no evidence of this bias. Indeed, the correlation of risk aversion with technological uncertainty and total compensation are opposite to what one would predict under the conjecture of inference bias.

Third, to test whether measures of risk aversion and ability vary systematically across the different industries , as defined by the SIC classification, we estimated a measurement model where each item was loaded on the corresponding construct and each of the four SIC codes among which our firms can be classified. The industry factor loadings were small and insignificant, suggesting that individual item measures are not systematically different across the industries represented in our data. This was as expected given that, while they belong to four different SIC codes, firms in our data all face similar salesforce management challenges and hire from a reasonably similar pool of technically proficient salespeople. Finally, to test for common method bias, we conducted Harman's one factor test by loading all the items of our scales on a single latent factor. The fit indices (RMSEA = .21, CFI = .18, IFI = .22, NFI = .23) were significantly lower than acceptable levels, suggesting that one factor cannot adequately account for the observed variance in the measures. Overall, our tests revealed no evidence of significant response bias in our data.

Measure Validity: The 6 items salesperson's ability measure is treated as a formative scale as the items touch on different facets of the salesperson's skill set. To validate our other multi-item scales, which we treat as reflective scales, we first computed the item-to-total correlations and dropped items with estimates below .30. We then used LISREL 8.0 to estimate con-generic models for each set of items and compute the scale reliability estimates. These are reported in Table 1. All the factor loadings were significant and the fit indices (NFI, CFI, and RMSEA) met the fit requirements, suggesting a satisfactory level of internal consistency and unidimensionality. To assess discriminant validity, we used the Fornell and Larcker (1981) procedure. Specifically, we calculated the average variance extracted for each multi-item scale and compared its square root (SQAVE) with the inter-construct correlations. These are reported in Table 1. We found that SQAVE exceeds the inter-construct correlations in all cases; hence, each construct shares more variance with its own measures than with other constructs. We conclude that the traits are sufficiently discriminated from each other.

***Results***

We begin by investigating the incentive and insurance roles of salesforce pay plans. Moreover, given the Ackerberg and Botticini matching argument above, we explore in particular how controlling for perceived agent traits affects the observed relationship between incentive rate and uncertainty in our data. We then turn to analyses of the selection (and retention) role of these compensation plans.

<u>The Incentive Effect</u>: We first test the hypotheses concerning the effects of uncertainty, importance of agent effort, and difficulty of monitoring on incentive rates per classical agency models. Table 3 shows the OLS results for these incentive rate equations. In Model 1 we show results for the basic agency theory considerations, excluding controls for agent risk aversion and agent ability. We then add these agent traits separately in Models 2 and 3 and then simultaneously in Model 4. In Model 5, we further add a number of control variables capturing both task (or firm) and individual characteristics. These include firm size, number of competitors, and product-line margin, each of which is expected to be positively related to compensation within the firm and thus potentially to the incentive rate. Model 4 also includes two dummy variables capturing whether or not the salesperson has advanced degrees in engineering and/or business. As these can be viewed as measures of human capital, we expect them to have a positive effect on compensation and thus potentially on the incentive rate. Finally, in Model 6, we control for peer incentive rates, which is the average incentive rate of all other firms in the same industry as firm *i*. Given that this measure was constructed for each industry, we have high correlation between the peer incentive rates and our industry dummy variables; hence, we cannot estimate Model 6 unless we exclude the latter from this specification.

************ Insert Table 3 about here *****************

Results are very consistent across all our specifications. They show first that, as predicted by agency theory, incentive rates are higher when agent effort is more important. Specifically, higher incentive rates are offered when customer heterogeneity is high. This is consistent with Lal and Staelin (1986)'s argument that higher incentive intensity aligns the goals of principal and agent when the information asymmetry between the salesperson and the manager regarding local conditions, as well as the importance of agent effort, are high. Likewise, higher incentive rates are offered when firm reputation is low – a situation where agent effort again is more important to the sales generation process (high θ). Models 2 through 4 also show that, per the model's prediction, incentive rates are positively correlated with agent ability and negatively correlated with agent risk aversion. This last result is supportive of the insurance role of compensation schemes in the sense that more risk-averse agents are associated with jobs offering lower incentive rates.  Note that the inclusion of these agent traits changes the coefficients and statistical significance of effects for customer heterogeneity and firm reputation to some degree, providing hints of the validity of our selection argument. In addition, in all cases, we find that monitoring difficulty has a negative but insignificant effect on incentive rates.  As predicted, we find that firm size, product-line margins and salesperson education – at least in engineering - have a positive effect on the incentive rate. Likewise, the positive effect of competition is consistent with theory because the value of agent effort becomes more important as competitive intensity increases; hence, firms would like to attract and retain good salespeople and share the risks by paying them higher incentive rates. Finally, peer incentive rates have the expected positive effect on incentive rates, but this effect is not statistically significant.  A comparison of results from Models 5 and 6 also confirms that industry effects are a more flexible way to control for peer incentive rates and other industry characteristics, and hence Model 5 yields a better fit.

Consistent with results in previous studies (e.g., John and Weitz 1989; Coughlan and Narasimhan 1992), we find no support in our data for a key prediction of standard agency models – the negative effect of uncertainty on incentive power. Neither technological uncertainty nor product demand uncertainty has a significant impact on the incentive rate, regardless of whether we control for agent risk aversion or ability. Recall that the basic premise of the endogenous matching argument (Ackerberg and Botticini 2002) is that if agents match themselves to jobs based on risk aversion or other traits, excluding this trait from the contract term regressions would cause an omitted-variable bias in the relationship between uncertainty and the intensity of incentives offered to agents. Models 2 through 6, however, show that controlling for agent risk aversion and ability, separately or together, still does not lead to the expected "negative" effect of technological or product demand uncertainty on the incentive rate.

Note that our measures of technological uncertainty and product demand uncertainty are clearly outside the scope of agent control and independent of agent effort. In essence, these are measures of exogenous risk. The absence of the negative effect of uncertainty in our context thus cannot be explained away by the endogenous measurement issues described in Lafontaine and Bhattacharyya (1995), Gaba and Kalra (1999), and Godes (2004). We argue that in our context, contract terms are set before the agents choose their jobs, and thus these terms *together* with environmental uncertainty yield the actual level of risk that the agent faces. As a result, there need not be a negative effect of uncertainty on incentive rates.

<u>The Selection Effect</u>: As shown in Figure 3-I, selection involves a two-step process. In the first stage, based on the exogenous task profile and environmental factors, firms choose contract terms to attract salespeople with desirable traits. In the second stage, agents observe contract terms and the task and environmental characteristics and self-select into, or choose to stay with, jobs that match their particular traits. In contrast to regressions that focus on incentive effects, investigating the selection effect thus mandates that task characteristics and incentive rate should be included as regressors in regressions where either agent ability or risk aversion is the regressand. The results of such estimations are shown in Tables 4 and 5 for ability and risk aversion respectively. In these tables, Models 1 through 4 show the OLS results, where the incentive rate is assumed to be exogeneous, or fully determined by factors that are controlled for in our ability and risk aversion regressions. Model 5 gives results for instrumental variable (IV) regressions, which are appropriate if there are unobservable factors that affect both the incentive rate and base salary on the one hand, and the salesperson ability or risk aversion on the other hand, and that are not controlled for in our regressions. In this case, we treat the system of equations as recursive (Wooldridge 2001, p. 228) and adjust standard errors to reflect the degrees of freedom accordingly (Wooldridge 2001, p. 95-101). We provide a brief description of the procedure used to adjust these standard errors in the Appendix.

************ Insert Tables 4 and 5 about here *****************

In the first three columns of Tables 4 and 5 we include an increasing number of (control) variables. We begin with only industry fixed effects in Model 1, followed by a specification that includes all the variables from our basic model above, and then finally by our most general specification, where we also control for the task and individual characteristics described above (i.e. firm size, product-line margins, competition, and education). Theoretically, we would not expect firm size and product-line margins to affect ability or risk aversion directly and the statistically insignificant effects in Model 3 of Tables 4 and 5 are consistent with this rationale. At the same time, from Table 3 we see that product-line margins is strongly related to incentive rate; moreover, product-line margins and firm size are strongly related to base salary (results are not shown). Hence, we use product-line margins and firm size as our excluded instruments for IV regressions where we treat both incentive rate and base salary as endogenous. This is reported in Model 5 of Tables 4 and 5. We find that according to the standard Hausman tests, we cannot reject the null hypothesis that these variables in fact are exogenous once we include all the control variables in our model. In other words, while there may be factors that affect both the terms of the pay scheme as well as the ability and risk aversion of salespeople, which would mean that we need to rely on an IV approach, it appears that the inclusion of our control variables eliminates the sources of bias for the incentive rates and base salary coefficients in our regressions. Consequently, in our discussion of results below, we focus mostly on our most general OLS regressions (Model 3). For comparison purposes, we also include Model 4, which has the same set of regressors as in Model 3, but excludes the two variables used to instrument the contract terms in Model 5. The OLS results in Models 3 and 4 are robust to the inclusion of product-line margins and firm size in our regression. Consistent with the results of our Hausman tests, Models 4 and 5 also show that the results are quite similar whether we use an IV or an OLS approach.

Finally, in OLS Models 2, 3 and 4, and in our IV regressions, we control for base salary (or instrument it in our IV regression). Controlling for base salary allows the selection effect to depend specifically on the extent to which salespeople expect their pay to vary. Of course, since the firm chooses the base salary as well as the incentive rate to ensure that the participation constraint of the salesperson is satisfied, the base salary is an endogenous variable and a function of the incentive rate. As such, it is implicitly included in our selection equations once we control for the incentive rate (see Figure 1). However, we control for base salary explicitly in Models 2, 3 and 4, and instrument for it in Model 5, to make sure we take into account the full range of what salespeople select on. Per the theory, once we include the incentive rate, base salary has no significant separate effect in the selection equations for risk aversion (see Table 5). It has a positive and significant effect in our ability regressions, suggesting that there remains some component of the salary that compensates for unobserved heterogeneity among salespeople in our data (i.e. firms that want to attract higher ability salespeople offer higher total pay, and our other control variables do not fully capture this) leaving base salary to show this effect in these regressions.

*Agent Ability*. The OLS results (Models 1 through 4 of Table 4) provide strong evidence that high-ability salespeople work at firms that offer high incentive rates. They also show that controlling for the incentive rate, high-ability individuals are attracted to more challenging environments, namely ones where firm monitoring is costly and, though this effect is not statistically significant, where customer heterogeneity is high. Such individuals, however, also seem to be attracted to firms with high reputation, even though, per the effect of this variable on incentive rates, this reputation may reduce the importance of their effort (see Table 3). This result suggests that working for a high-reputation firm is a reward onto itself, quite independent of the effect this has on compensation. Thus, controlling for compensation, high reputation firm indeed can attract higher-ability salespeople. When we include our other control variables, we also find that high ability salespeople select firms that have fewer competitors. Finally, as expected, high ability is positively correlated with education.

In sum, when it comes to agent ability, our results provide strong evidence that firms in industrial markets use pay plans as a selection devices as high ability salespeople are found to react positively to high incentive rates (and base salary) in addition to being responsive to some of the task characteristics directly.

*Agent Risk Aversion*. Consistent with expectations, the OLS estimates in Models 1 through 4 in Table 5 provide strong evidence that more risk-averse individuals are associated with jobs that offer lower incentive rates. This is true regardless of whether we only allow for industry differences (in Model 1) or we control for the job characteristics in Model 2, or add other control variables in Models 3 or 4. In our IV regression, we find this effect is still negative but not statistically significant. As increased standard errors are a usual consequence of using an IV approach, and our Hausman tests indicate that we should focus on our OLS results, we view our results on the negative incentive rate effect on risk aversion as both strong and robust. We also find that controlling for the incentive rate, more risk-averse individuals are attracted to jobs where technological uncertaintly, product demand uncertainty, and customer heterogeneity, are high. In other words, these individuals seem to like challenging environments as well – they simply do not desire the income variability that can result from the uncertainty that makes their work interesting when their pay involves a high incentive rate. We also find that more risk-averse individuals are attracted to jobs at highly reputed firms. This is expected because a firm's good reputation provides some form of insurance to the salespeople. At the same time, as mentioned above, perhaps it is simply rewarding to all salespeople to be considered good enough to work at highly reputed firms. Contrary to high-ability salespeople, more risk-averse salespeople do not systematically work for firms that face greater levels of competition or offer jobs where monitoring is difficult. Finally, risk aversion is positively correlated with education in engineering, but negatively related to the decision to obtain business degrees.

<u>Additional Investigations</u>: We conducted additional analyses to ensure that our results were robust. In particular, we estimated our models with different subsets of regressors, with and without industry effects, and also examined the relationship between risk aversion and ability in our selection equations.[8] We found throughout that our results were robust to these alternative specifications. Finally, we conducted two sets of additional investigations. First, we estimated our incentive and selection models using two alternative measures that tap into *ex post* realizations of variable versus fixed pay (in contrast to our *ex ante* measure of incentive power). We found that our results were

robust to these alternative measures.[9] Second, we considered the possibility that what matters for selection is how a firm's compensation plan differs from that of its industry peers, as detailed in the remainder of this section.

*Relative Peer Effects*. The main selection results show the effect of differences in the level of the incentive rate on the ability and risk aversion of the salespeople in the firm. It is possible, however, that agents self-select into firms based on the *relative* incentive rate, i.e. the difference between the incentive rate offered by the focal firm to that offered by other firms in the same industry. To test this possibility we construct a measure of $\textit{Relative Incentive Rate}_i = \textit{Incentive Rate}_i - \textit{Peer Incentive Rate}_i$, where the peer incentive rate is as defined earlier, i.e. it is the average of the incentive rates for all *other* firms in the *same* SIC sector as firm *i*. Similarly, we construct $\textit{Relative Base Salary}_i = \textit{Base Salary}_i - \textit{Peer Base Salary}_i$, where the peer base salary is the average of the *Base Salary* for all *other* firms in the *same* SIC as firm *i*. Table 6 shows results corresponding to Models 3, 4 and 5 of Tables 4 and 5 respectively where we allow the selection to operate based on relative incentive rate and base salary. Consistent with what our model predicts, we find that high-ability salespeople are more likely to work in firms that offer a higher incentive rate relative to their peers, while more risk-averse salespeople are more likely to work in firms that offer a lower incentive rate than their peers do. These results confirm the value of a competitively superior incentive rate on a firm's ability to attract and retain the right type of salespeople. More generally, we find that our results are very consistent, whether we measure the incentive rate and base salary in absolute levels or in terms of differences with peer firms.

************ Insert Table 6 about here *****************

## CONCLUSION

Salespeople are the key bridge between a firm and its customers. Given that agents are heterogeneous in their abilities and risk preferences, firms will benefit if they purposefully attract and retain the desired types of salespeople as well as incentivize them to take productive actions. These are the classic *selection* and *moral hazard* problems of salesforce compensation design (Bergen, Dutta, and Walker 1992). We offer a framework that simultaneously incorporates these two issues and shows how firms use the incentive rate, a direct index of pay for performance in pay plans, to discriminatingly select and retain salespeople as well as incentivize them. Specifically, we argue that the firms choose their incentive rates purposefully so that it contributes to the sorting of heterogeneous salespeople to heterogeneous jobs.

Using individual salesperson-level data from firms that manufacture complex industrial products, we show that firms base their choice of incentive rates on the underlying characteristics of the job. In particular, they use higher-powered incentive contracts when salesperson effort is more important, i.e. when customer heterogeneity is high and firm reputation is weak. In turn, salespeople choose combinations of jobs and pay contracts that match their heterogeneous traits. In particular, agents with high ability work for firms that, everything else equal, offer jobs with higher incentive rates while agents with high risk aversion work for firms that, everything else equal, offer jobs with lower incentive rates. Furthermore, there seem to be different purposes for selecting agents on these two traits. While higher ability agents seem to be selected to lower the cost of effort under conditions of costly monitoring, less risk-averse agents are selected to reduce the risk premium that would have to be paid to agents working in more volatile environments (high technological uncertainty or volatile demand). This latter effect in particular is consistent with the predictions of Joseph and Thevaranjan's (1998) model. We also find that high-ability and less risk-averse salespeople work in firms that offer an incentive rate that is higher than that of their peers. This novel result highlights the impact of a competitively superior incentive rate on a firm's ability to attract and retain the right type of salesperson from a pool of heterogeneous agents. We conclude that firms selling complex industrial products through their direct salesforce offer higher incentive rates not only for incentive purposes but also to secure the employment of high ability and low risk-averse agents when this is particularly valuable to them.

Consistent with previous findings, we find no evidence of the classic insurance-uncertainty effect in our data. Though we find that incentive rates are negatively related to risk aversion, as the canonical principal-agent model suggests they should be, increased uncertainty – in terms of technology or demand – is not associated with reduced incentive rates. Two prominent explanations have been proposed to explain this lack of insurance effect: endogenous measurement (Lafontaine and Bhattacharyya 1995; Godes 2004) and endogenous matching (Ackerberg and Botticini 2002). Our data, however, provides no support for either of these explanations. In particular, to address the endogenous measurement issues, we used measures of uncertainty that were outside the control of agent effort. Similarly, to address the omitted variable bias issue raised by endogenous matching, we included measures of agent risk aversion and/or ability. Yet, even with these adjustments, we found no support for the predicted insurance effect in our incentive rate equations (as well as for other measures of variable pay). Instead, our analyses and data suggest that the anomalous relationship between uncertainty and incentives could result from the explicit selection role of contracts. In other words, instead of simply reacting to agent characteristics (say risk aversion), firms that operate in more volatile contexts devise their pay plans to encourage less risk-averse agents to join. In essence, our results imply that compensation contracts not only serve the role of allocating risk and encouraging effort, but may also have large efficiency implications in that they allow firms that operate in volatile environments to attract salespeople who are not very sensitive to this volatility, and thus do not seek as high a level of compensation as more risk-averse individuals would prefer. Thus our analyses and results complement Lazear's (2000) selection and incentive results *within* a firm by providing evidence that selection occurs on risk aversion as well as ability, and that it takes place *across* firms as well.

Finally, our work highlights the importance of understanding institutional context when examining the role of contracts in a given setting. To wit, an intriguing finding from Prendergast's (2002) survey is that the uncertainty-incentive trade-off prediction receives its best support (relatively) in contexts where compensation contracts are customized for individual agents (e.g., executive compensation). Of course, contracts are unlikely to serve as selection devices in these contexts. Rather, in such cases, per the Ackerberg and Botticini (2002) logic, agents choose jobs that match their risk profiles and pay contracts are then customized to suit these characteristics (as well as the characteristics of the work). In contrast, in contexts like salesforce compensation and franchising, firms do not devise customized contracts. Thus, pay plans can serve as explicit selection devices in addition to their role as incentive devices. Moreover, ignoring the selection role of contracts obfuscates the real uncertainty-incentive relationship in these settings. Our selection regressions on risk aversion, however, show clearly that the effect of uncertainty can be mitigated via the incentive rate.

Similarly, our results rule out another alternative explanation for the anomalous uncertainty effect on incentive rates. Allen and Lueck (1999) had proposed the "measurement of output" argument to explain such anomalous results in the sharecropping literature. This logic, however, does not apply in our context simply because, unlike sharecroppers who can keep the output they hide from their landlords, our salespeople are paid only *after* the sales output (revenues) is revealed to the firm. Hence, the institutional setting, and in particular the process by which output is accounted for and shared in our context, precludes reliance on this logic to explain the anomalous risk effect in our context.

***Limitations***

Like all studies, ours has a number of limitations. First, our results are context dependent; hence caution should be exercised in attempting to generalize our insights to other contexts. Second, some of our key constructs are obtained from key informants using perceptual scales. For instance, measuring agent risk preferences in field settings using survey instruments is a tricky task, such that measurement issues can cloud our results. Our measure of risk aversion, however, was based on Oliver and Weitz (1991), who also found a very significant negative correlation between risk aversion and preferences for high-powered incentives in their data (-.51). This gives us some confidence that our own measure taps into some significant aspect of risk preferences. Yet, we cannot rule out that given our survey method and perceptual measures, certain biases might exist in our data. For instance, even though the positive correlation between customer heterogeneity and salesperson ability is consistent with our selection model, we cannot rule out the possibility that managers perceived the particular salesperson to be more able because he managed a more heterogeneous customer base. A third limitation of our study is that we focus explicitly on the role of the pay plan as an instrument for selection and incentive effects, and do not consider directly the impact of other potentially related incentive and screening mechanisms that managers could use. Our results relative to firm reputation, for example, suggest that it is also a significant factor affecting the types of salespeople that individual firms can attract. While we controlled for this effect, it is beyond the scope of this paper to analyze the reputation effect more directly. Similarly, using high-ability agents in volatile environments would not be useful unless the firm is willing to delegate some decision making authority to these agents (Prendergast 2002). Considering how delegation interacts with incentives is beyond the scope of the present study but points out avenues for future research. Finally, most sales agents in industrial markets have to multitask (Holmstrom and Milgrom 1991). For instance, each salesperson has to manage time and effort allocation between short-term (harvesting) and long-term (prospecting) activities. Our study does not parse out the nuances associated with such multi-tasking decisions. We hope that future research will address these issues.

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## TABLE 1: OPERATIONAL MEASURES OF CONSTRUCTS[a]

| Descriptive and Confirmatory Fit Statistics | Item Description and Response Format |
|---|---|
| *Base Salary* | What was the total fixed compensation (i.e. base salary) that was received by this salesperson in the last fiscal year? (In thousands of dollars) |
| *Total Compensation* | What was the total compensation (base salary plus performance based compensation - commissions, quotas etc.) received by this salesperson in the last fiscal year? (In thousands of dollars) |
| *Sales Revenue Generated* | What was the total revenue, in thousands of dollars, generated by this salesperson in the last fiscal year? |
| *Product Demand Uncertainty* | The total demand in this product category is very predictable. (reverse coded) |
| *Technological Uncertainty*<br><br>Reliability = .91<br>SQAVE = .87 | 1. Significant technological advances in this product category are very unpredictable and fast.<br>2. The machine/equipment in this product category becomes obsolete very fast.<br>3. There are frequent and significant changes in the technical features of machines in this product category.<br>4. In this product category new technologies follow each other very quickly. |
| *Customer Heterogeneity*<br><br>Reliability = .89<br>SQAVE = .82 | 1. Our product can be used in manufacturing/administrative/operational activities that vary widely from customer to customer.<br>2. Our customers for this product themselves operate in a wide variety of industry sectors.<br>3. Our product is most useful for a narrow range of operational tasks (reverse coded). |
| *Firm Reputation*<br><br>Reliability = .88<br>SQAVE = .81 | 1. Our company has a good standing in the business world for providing quality products and services.<br>2. Customers are willing to pay a high premium for our products and services.<br>3. Our company is held in high esteem for being able to provide products that mirror customer needs and specifications.<br>4. Our company is highly regarded for providing good service support to our customers. |
| *Monitoring Difficulty*<br><br>Reliability = .82<br>SQAVE = .77 | 1. It is not possible to supervise the salesperson's activities closely.<br>2. It is difficult for us to evaluate how much effort this salesperson really puts into her/his job.<br>3. It is relatively easy for this salesperson to turn in falsified sales call reports.<br>4. Our evaluation of this salesperson cannot be based on his/her activity and sales call reports. |

| | |
|---|---|
| *Salesperson's Ability*[b] | 1. This salesperson has a high degree of competence in tailoring his/her sales approach to the specific situation on hand.<br>2. This salesperson has been very creative in designing relevant solutions to customers' problems.<br>3. This salesperson is a skilled and persuasive negotiator.<br>4. This salesperson is capable of closing a deal in a tough selling situation.<br>5. This salesperson is able to learn from past experiences and adapt them to current circumstances.<br>6. This salesperson is skilled in extracting the unique problems faced by and the requirements of his/her customers. |
| *Salesperson's Risk Aversion*<br><br>Reliability = .85<br>SQAVE = .76 | 1. In my opinion, this salesperson prefers predictable outcomes to unpredictable ones.<br>2. In my opinion, this salesperson does not prefer variation in her/his compensation from one month to the next.<br>3. In my opinion, this salesperson would be willing to sacrifice some "top-end" variable pay to assure himself/herself of a steady compensation (i.e. base salary). |
| *Education – Engineering Degree* | Does this salesperson have a degree in engineering or technical sciences (e.g., B. Engg)? |
| *Education – Business Degree* | Does this salesperson have a degree in business administration (e.g., MBA)? |
| *Product-line Margin* | What is the operating margin as % of sales that your company earns for this product line? |
| *Competition* | What is the potential number of competitors for this product-lines/equipment? |
| *Firm Size* | Log(Total firm or SBU revenues for the year)<br>(revenue is in millions) |

a: Unless otherwise indicated, the anchors for the scale points are 1 = strongly disagree and 7 = strongly agree.

b: This 6 item measure is treated as a formative scale.

## TABLE 2: CORRELATION MATRIX AND DESCRIPTIVE STATISTICS

| Construct | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. *Base Salary*[a] | 1.00 | | | | | | | | | | | | | | | |
| 2. *Total Compensation*[a] | .74 | 1.00 | | | | | | | | | | | | | | |
| 3. *Sales Revenue*[a] | .10 | .16 | 1.00 | | | | | | | | | | | | | |
| 4. *Incentive Rate*[b] | -.32 | .12 | -.36 | 1.00 | | | | | | | | | | | | |
| 5. *Product Demand Uncertainty* | -.10 | -.00 | .00 | .02 | 1.00 | | | | | | | | | | | |
| 6. *Technological Uncertainty* | -.10 | -.01 | .03 | .05 | -.26 | 1.00 | | | | | | | | | | |
| 7. *Customer Heterogeneity* | -.03 | .07 | -.07 | .12 | -.04 | -.09 | 1.00 | | | | | | | | | |
| 8. *Firm Reputation* | .03 | -.14 | .07 | -.15 | -.05 | -.21 | -.05 | 1.00 | | | | | | | | |
| 9. *Monitoring Difficulty* | -.25 | -.14 | -.06 | .07 | .02 | .22 | .16 | -.30 | 1.00 | | | | | | | |
| 10. *Salesperson's Ability* | -.08 | .09 | -.05 | .27 | -.04 | .03 | .16 | .27 | .19 | 1.00 | | | | | | |
| 11. *Salesperson's Risk Aversion* | .03 | .17 | -.00 | -.29 | -.02 | .12 | .01 | .17 | -.03 | -.15 | 1.00 | | | | | |
| 12. *Engineering Degree* | -.24 | -.09 | -.10 | .23 | .08 | .00 | .05 | -.06 | .18 | .19 | .10 | 1.00 | | | | |
| 13. *Business Degree* | -.11 | .12 | .10 | .12 | .00 | .10 | -.06 | -.10 | .03 | .33 | -.25 | .01 | 1.00 | | | |
| 14. *Firm Size* | .31 | .47 | .08 | .19 | .04 | -.02 | .02 | -.04 | -.13 | .11 | -.08 | -.02 | .16 | 1.00 | | |
| 15. *Product-line Margin*[c] | -.14 | .00 | -.04 | .20 | .05 | .04 | -.08 | .02 | -.05 | .00 | -.03 | -.06 | -.01 | .07 | 1.00 | |
| 16. *Competition* | .05 | .15 | .01 | .15 | .13 | -.03 | -.01 | -.18 | .01 | -.19 | -.14 | -.18 | .01 | .14 | .12 | 1.00 |
| Mean | 82.65[a] | 117.03[a] | 1705[a] | 2.39[b] | 3.36 | 3.88 | 3.66 | 4.33 | 3.69 | 28.50 | 3.46 | .54 | .47 | 2.81 | 13.97 | 8.96 |
| Standard Deviation | 15.06 | 21.69 | 1845 | .97 | 1.45 | 1.45 | 1.39 | 1.35 | 1.19 | 7.33 | 1.16 | .50 | .50 | .48 | 8.75 | 4.84 |
| Minimum | 52.50 | 73.00 | 580 | .00 | 1 | 1 | 1 | 1.5 | 1 | 12 | 1 | 0 | 0 | 2.01 | -15 | 2 |
| Maximum | 118.50 | 170.00 | 24000 | 5.16 | 7 | 7 | 6.67 | 7 | 6.25 | 41 | 6.33 | 1 | 1 | 4.92 | 45 | 40 |

Matrix represents pair-wise correlations. All correlations above |.12| are significant at the .05 level. [a]: In thousands of dollars; [b]: Expressed as a percentage of revenue generated; [c]: Expressed as percentage of product-line sales.

## TABLE 3: INCENTIVE EFFECT OF INCENTIVE RATE

### Dependent Variable – Incentive Rate

| Independent Variables | Basic Model (1) | Effect of Matching on Risk Aversion (2) | Effect of Matching on Ability (3) | Effect of Matching on Risk Aversion and Ability (4) | Controlling for Other Firm and Individual Characteristics (5) | Controlling for Peer Incentive Rate (6) |
|---|---|---|---|---|---|---|
| **Task Characteristics** | | | | | | |
| *Customer Heterogeneity* | .09** | .11** | .06* | .08** | .08** | .07* |
| | (.04) | (.04) | (.04) | (.04) | (.04) | (.04) |
| *Firm Reputation* | -.12*** | -.07* | -.22*** | -.17*** | -.12** | -.10** |
| | (.04) | (.04) | (.04) | (.04) | (.05) | (.04) |
| *Monitoring Difficulty* | -.00 | -.01 | -.09 | -.08 | -.07 | -.07 |
| | (.05) | (.05) | (.06) | (.05) | (.05) | (.05) |
| *Technological Uncertainty* | -.01 | .05 | -.01 | .03 | .05 | .05 |
| | (.04) | (.04) | (.04) | (.04) | (.04) | (.04) |
| *Product Demand Uncertainty* | .00 | .03 | .01 | .03 | .00 | -.01 |
| | (.05) | (.05) | (.05) | (.05) | (.04) | (.04) |
| **Agent Characteristics** | | | | | | |
| *Salesperson's Risk Aversion* | | -.24*** | | -.18*** | -.21*** | -.21*** |
| | | (.05) | | (.04) | (.05) | (.05) |
| *Salesperson's Ability* | | | .29*** | .25*** | .23*** | .22*** |
| | | | (.05) | (.05) | (.05) | (.05) |
| **Control Variables** | | | | | | |
| *Firm Size* | | | | | .18 | .20 |
| | | | | | (.12) | (.12) |
| *Competition* | | | | | .09** | .11** |
| | | | | | (.04) | (.04) |
| *Product-line Margin* | | | | | .02*** | .02*** |
| | | | | | (.01) | (.01) |
| *Engineering Degree* | | | | | .49*** | .48*** |
| | | | | | (.10) | (.10) |
| *Business Degree* | | | | | -.15 | -.14 |
| | | | | | (.13) | (.13) |
| *Peer Incentive Rate* | | | | | | .16 |
| | | | | | | (.22) |
| *SIC 35* | -.17 | -.21 | -.24 | -.26* | -.33** | |
| | (.17) | (.16) | (.16) | (.15) | (.14) | |
| *SIC 36* | -.09 | -.26* | -.26 | -.37** | -.26* | |
| | (.16) | (.15) | (.16) | (.15) | (.15) | |
| *SIC 37* | -.58*** | -.43*** | -.64*** | -.52*** | -.39*** | |
| | (.13) | (.12) | (.14) | (.13) | (.12) | |
| *Constant* | 2.78*** | 3.09*** | 2.31*** | 2.61*** | 1.12*** | .47 |
| | (.36) | (.35) | (.33) | (.30) | (.54) | (.52) |
| $R^2$ | .07 | .14 | .18 | .21 | .33 | .31 |
| *n* | 261 | 261 | 261 | 261 | 261 | 261 |

Robust standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%.

## TABLE 4: SELECTION ON AGENT ABILITY
## Dependent Variable – Salesperson's Ability

| | OLS | OLS | OLS | OLS | IV Regression |
|---|---|---|---|---|---|
| **Independent Variables:** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)[i]** |
| **Pay Structure** | | | | | |
| *Incentive Rate* | .34*** | .43*** | .37*** | .39*** | .47** |
| | (.06) | (.08) | (.08) | (.08) | (.23) |
| *Base Salary* | | .007 | .010* | .011** | .018 |
| | | (.006) | (.005) | (.005) | (.011) |
| **Task Characteristics** | | | | | |
| *Customer Heterogeneity* | | .04 | .05 | .06 | .05 |
| | | (.04) | (.04) | (.04) | (.04) |
| *Firm Reputation* | | .41*** | .37*** | .37*** | .39*** |
| | | (.06) | (.05) | (.05) | (.06) |
| *Monitoring Difficulty* | | .32*** | .30*** | .30*** | .32*** |
| | | (.08) | (.07) | (.07) | (.08) |
| *Technological Uncertainty* | | .03 | -.03 | -.03 | -.01 |
| | | (.06) | (.06) | (.06) | (.06) |
| *Product Demand Uncertainty* | | -.02 | -.02 | -.02 | -.00 |
| | | (.05) | (.04) | (.04) | (.04) |
| **Control Variables** | | | | | |
| *Competition* | | | -.16*** | -.16*** | -.16*** |
| | | | (.04) | (.04) | (.04) |
| *Firm Size* | | | .11 | | |
| | | | (.13) | | |
| *Product-line Margin* | | | .00 | | |
| | | | (.01) | | |
| *Engineering Degree* | | | .27** | .28** | .27 |
| | | | (.13) | (.13) | (.18) |
| *Business Degree* | | | .85*** | .86*** | .87*** |
| | | | (.11) | (.11) | (.13) |
| *SIC 35* | .39 | .29 | .26 | .25 | .24 |
| | (.24) | (.21) | (.18) | (.18) | (.19) |
| *SIC 36* | .45** | .57*** | .54*** | .54*** | .50*** |
| | (.22) | (.21) | (.19) | (.19) | (.19) |
| *SIC 37* | .21 | .47** | .27 | .27 | .33 |
| | (.24) | (.20) | (.22) | (.21) | (.25) |
| *Constant* | 3.66*** | -.31 | -.15 | -.02 | -.95 |
| | (.26) | (1.06) | (1.12) | (1.09) | (1.66) |
| $R^2$ | .09 | .30 | .46 | .46 | .40 |
| Heteroskedasticity Test [ii] | | | | | Sig.*** |
| Hausman Test of Exogeneity [iii] for | | | | | |
| *Incentive Rate* | | | | | p=.67 |
| *Salary* | | | | | p=.49 |
| n | 261 | 261 | 261 | 261 | 261 |

[i] Incentive rate and Base Salary are instrumented. First-stage regressions: Incentive rate and Base Salary regressed on customer heterogeneity, firm reputation, monitoring difficulty, technological uncertainty, product demand uncertainty, competition, engineering degree, business degree, industry dummy variablesi, firm size, and product-line margin. The predicted values from the first stage are used as regressors in the second stage regressions. Adjusted standard errors reported (see Appendix).

[ii] See Appendix for details.

[iii] Hausman test, as described in Cameron and Trivedi (2005, p.276).

* significant at 10%; ** significant at 5%; *** significant at 1%.

# TABLE 5: SELECTION ON AGENT RISK AVERSION
## Dependent Variable – Salesperson's Risk Aversion

| | OLS | OLS | OLS | OLS | IV Regression |
|---|---|---|---|---|---|
| **Independent Variables:** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)[i]** |
| **Pay Structure** | | | | | |
| *Incentive Rate* | -.31*** | -.28*** | -.32*** | -.30*** | -.20 |
| | (.06) | (.06) | (.07) | (.07) | (.25) |
| *Base Salary* | | .003 | .001 | .002 | .010 |
| | | (.004) | (.004) | (.004) | (.012) |
| **Task Characteristics** | | | | | |
| *Customer Heterogeneity* | | .12*** | .10** | .11** | .10* |
| | | (.05) | (.05) | (.05) | (.05) |
| *Firm Reputation* | | .15*** | .15*** | .15*** | .17*** |
| | | (.06) | (.06) | (.06) | (.06) |
| *Monitoring Difficulty* | | -.03 | -.04 | -.05 | -.02 |
| | | (.05) | (.05) | (.05) | (.07) |
| *Technological Uncertainty* | | .26*** | .27*** | .27*** | .29*** |
| | | (.05) | (.05) | (.05) | (.05) |
| *Product Demand Uncertainty* | | .11** | .10** | .10** | .12** |
| | | (.05) | (.05) | (.05) | (.05) |
| **Control Variables** | | | | | |
| *Competition* | | | .04 | .04 | .04 |
| | | | (.04) | (.04) | (.05) |
| *Firm Size* | | | .12 | | |
| | | | (.15) | | |
| *Product-line Margin* | | | .00 | | |
| | | | (.01) | | |
| *Engineering Degree* | | | .29** | .29** | .28 |
| | | | (.15) | (.15) | (.20) |
| *Business Degree* | | | -.52*** | -.50*** | -.50*** |
| | | | (.13) | (.13) | (.14) |
| *SIC 35* | -.11 | -.21 | -.24 | -.25 | -.26 |
| | (.18) | (.18) | (.17) | (.16) | (.20) |
| *SIC 36* | -.54*** | -.75*** | -.70*** | -.70*** | -.74*** |
| | (.20) | (.19) | (.19) | (.19) | (.19) |
| *SIC 37* | .30 | .75*** | .46* | .45* | .52** |
| | (.24) | (.19) | (.25) | (.24) | (.26) |
| *Constant* | 4.37*** | 1.77** | 1.71*** | 1.85*** | .76 |
| | (.20) | (.72) | (.76) | (.74) | (1.59) |
| $R^2$ | .15 | .25 | .31 | .31 | .25 |
| Heteroskedasticity Test [ii] | | | | | Not sig. |
| Hausman Test of Exogeneity [iii] for | | | | | |
| *Incentive Rate* | | | | | p=.65 |
| *Salary* | | | | | p=.47 |
| n | 261 | 261 | 261 | 261 | 261 |

[i] Incentive rate and Base Salary are instrumented. First-stage regressions: Incentive rate and Base Salary regressed on customer heterogeneity, firm reputation, monitoring difficulty, technological uncertainty, product demand uncertainty, competition, engineering degree, business degree, industry dummy variables, firm size, and product-line margin. The predicted values from the first stage are used as regressors in the second stage regressions. Adjusted standard errors reported (see Appendix).

[ii] See Appendix for details.

[iii] Hausman test, as described in Cameron and Trivedi (2005, p.276).

* significant at 10%; ** significant at 5%; *** significant at 1%.

# TABLE 6: SELECTION WITH RELATIVE INCENTIVE RATE

| | Ability | | | Risk Aversion | | |
|---|---|---|---|---|---|---|
| | **OLS** | **OLS** | **IV Regression** | **OLS** | **OLS** | **IV Regression** |
| **Independent Variables:** | **(1)** | **(2)** | **(3)[i]** | **(4)** | **(5)** | **(6)[i]** |
| **Pay Structure** | | | | | | |
| *Relative Incentive Rate=( Incentive Rate – Peer Effect)* | .37*** | .38*** | .47** | -.31*** | -.30*** | -.19 |
| | (.08) | (.07) | (.22) | (.07) | (.07) | (.25) |
| *Relative Base Salary=(Base Salary – Peer Effect)* | .009* | .011** | .017 | .000 | .002 | .010 |
| | (.005) | (.005) | (.011) | (.004) | (.004) | (.012) |
| **Task Characteristics** | | | | | | |
| *Customer Heterogeneity* | .05 | .06 | .05 | .10** | .11** | .10* |
| | (.04) | (.04) | (.04) | (.05) | (.05) | (.05) |
| *Firm Reputation* | .37*** | .37*** | .39*** | .15*** | .15*** | .17*** |
| | (.05) | (.05) | (.06) | (.06) | (.06) | (.06) |
| *Monitoring Difficulty* | .30*** | .30*** | .32*** | -.04 | -.04 | -.02 |
| | (.07) | (.07) | (.08) | (.05) | (.05) | (.07) |
| *Technological Uncertainty* | -.03 | -.03 | -.01 | .27*** | .27*** | .29*** |
| | (.06) | (.06) | (.06) | (.05) | (.05) | (.05) |
| *Product Demand Uncertainty* | -.02 | -.02 | -.00 | .10** | .10** | .12** |
| | (.04) | (.04) | (.04) | (.05) | (.05) | (.05) |
| **Control Variables** | | | | | | |
| *Competition* | -.16*** | -.16*** | -.16*** | .04 | .04 | .04 |
| | (.04) | (.04) | (.04) | (.04) | (.04) | (.05) |
| *Firm Size* | .11 | | | .12 | | |
| | (.13) | | | (.15) | | |
| *Product-line Margin* | .00 | | | .00 | | |
| | (.01) | | | (.01) | | |
| *Engineering Degree* | .27** | .28** | .27 | .29** | .29** | .28 |
| | (.13) | (.13) | (.18) | (.15) | (.15) | (.20) |
| *Business Degree* | .85*** | .86*** | .87*** | -.52*** | -.50*** | -.50*** |
| | (.11) | (.11) | (.13) | (.13) | (.13) | (.14) |
| *SIC 35* | .22 | .21 | .19 | -.20 | -.21 | -.23 |
| | (.18) | (.18) | (.17) | (.17) | (.17) | (.19) |
| *SIC 36* | .60*** | .60*** | .60*** | -.71*** | -.71*** | -.71*** |
| | (.18) | (.18) | (.18) | (.19) | (.19) | (.18) |
| *SIC 37* | .09 | .07 | .09 | .60** | .58** | .60*** |
| | (.21) | (.20) | (.21) | (.24) | (.24) | (.23) |
| *Constant* | 1.56* | 1.83** | 1.64* | .96 | 1.28** | 1.07 |
| | (.86) | (.75) | (.84) | (.70) | (.60) | (.75) |
| $R^2$ | .46 | .46 | .40 | .31 | .31 | .25 |
| Heteroskedasticity Test [ii] | | | Sig.*** | | | Not sig. |
| Hausman Test of Exogeneity [iii] for | | | | | | |
| *Incentive Rate* | | | p=.67 | | | p=.65 |
| *Salary* | | | p=.48 | | | p=.47 |
| n | 261 | 261 | 261 | 261 | 261 | 261 |

[i] Incentive rate and Base Salary are instrumented. First-stage regressions: Incentive rate and Base Salary regressed on customer heterogeneity, firm reputation, monitoring difficulty, technological uncertainty, product demand uncertainty, competition, engineering degree, business degree, industry dummy variables, firm size, and product-line margin. The predicted values from the first stage are used as regressors in the second stage regressions. Adjusted standard errors reported (see Appendix).

[ii] See Appendix for details.

[iii] Hausman test, as described in Cameron and Trivedi (2005, p.276).

* significant at 10%; ** significant at 5%; *** significant at 1%.

**FIGURE 1: THE SELECTION MECHANISM UNDER AGENT RISK NEUTRALITY**

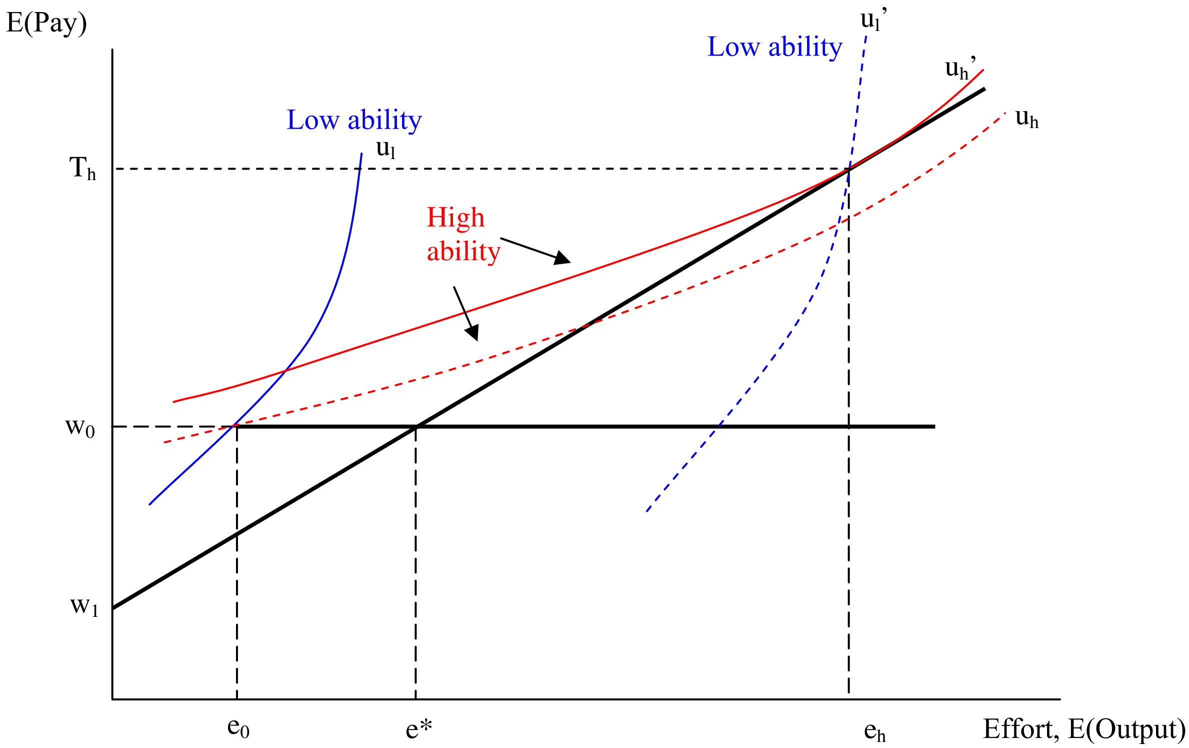



**FIGURE 2: THE SELECTION MECHANISM UNDER AGENT RISK AVERSION**

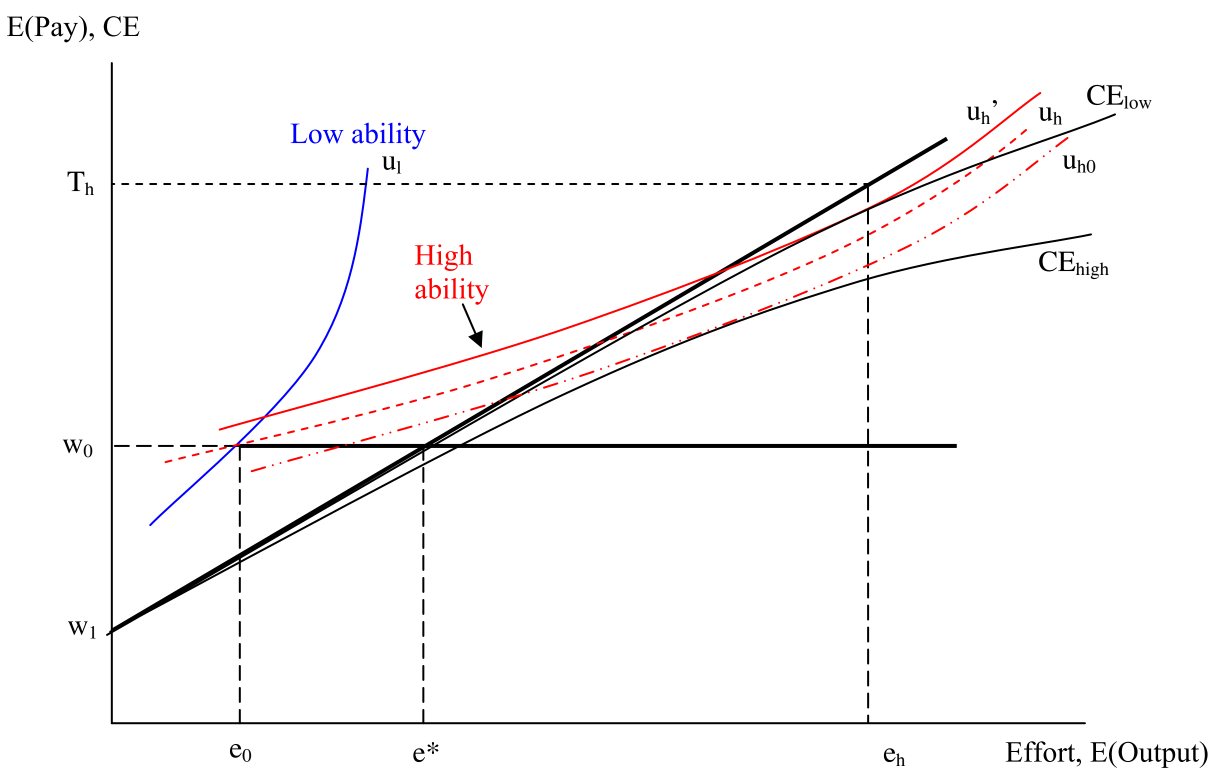
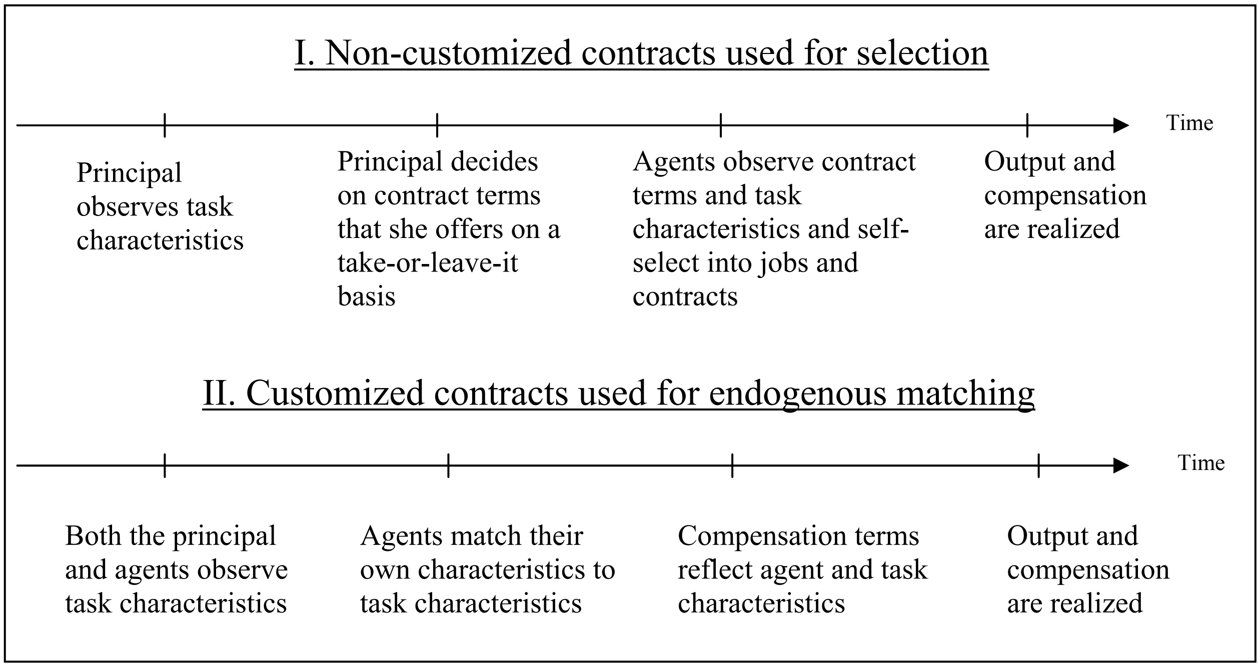


**FIGURE 3: SELECTION VERSUS MATCHING TIME LINES**



# APPENDIX

## RECURSIVE SYSTEM FOR SELECTION EFFECTS

We estimate the selection effect of incentive rates using a recursive system of equations (http://www.stata.com/support/faqs/stat/ivr_faq.html. See also Wooldridge (2001), p.228 and Greene (2003), sections 5.4 and 15.5.3). In what follows, we illustrate our estimation technique by using column 5 in Table 4 as an example.

(1) $$y_1 = Z\delta_1 + e_1, \qquad e_1 \sim N(0, \sigma_1^2)$$

(2) $$y_2 = f(y_1) + \varepsilon = Z\delta_2 + e_2, \qquad e_2 \sim N(0, \sigma_2^2)$$

(3) $$y_3 = \gamma_1 y_1 + \gamma_2 y_2 + X\delta_3 + e_3, \qquad e_3 \sim N(0, \sigma_3^2)$$

where equation (1) and (2) are the first-stage regressions and equation (3) is the ability selection regression, $y_1$ is the incentive rate, $y_2$ is base salary, $y_3$ is the salesperson's ability, Z is a vector of exogenous variables that are listed at the bottom of Table 4 (viz., technological uncertainty, product demand uncertainty, customer heterogeneity, firm reputation, monitoring difficulty, firm size, product-line margin, competition, engineering degree, business degree, and industry dummy variables), X is a set of control and exogenous variables (viz., technological uncertainty, product demand uncertainty, customer heterogeneity, firm reputation, monitoring difficulty, competition, engineering degree, business degree, and industry dummy variables), $\delta_1$, $\delta_2$, $\delta_3$, $\gamma_1$, and $\gamma_2$ are parameters to be estimated, and the e's are error terms. Note that firm size and product-line margin are the two excluded instrumental variables.

Since we assume that firms first choose their incentive rates and base salary and agents then self-select into jobs based on observed incentive rates and base salaries and task characteristics, it is possible that $cov(e_1, e_3) \neq 0$ and $cov(e_2, e_3) \neq 0$. Since $cov(y_1, e_1) \neq 0$ and $cov(y_2, e_2) \neq 0$, if $cov(e_1, e_3) \neq 0$ and $cov(e_2, e_3) \neq 0$ then $cov(y_1, e_3) \neq 0$ and $cov(y_2, e_3) \neq 0$, which would lead to inconsistent estimates for $\gamma_1$ and $\gamma_2$. Substituting the predicted values of the incentive rate and salary from estimating (1) and (2) into (3) we have

(4) $$y_3 = \alpha_1 \hat{y}_1 + \alpha_2 \hat{y}_2 + X\beta_3 + e_4 .$$

Under our assumptions, $cov(\hat{y}_1, e_4) = cov(\hat{y}_2, e_4) = 0$ such that $\hat{\alpha}_1$, $\hat{\alpha}_2$, and $\hat{\beta}_3$ are consistent estimators of $\gamma_1$, $\gamma_2$ and $\delta_3$ respectively.

However, the sample variance formed by the residuals $\hat{e}_4$ from estimating (4) is not a consistent estimator of $\sigma_3^2$, the population variance in the original selection equation (3). This is because in regression (3), it is $y_1$ and $y_1$ rather than $\hat{y}_1$ and $\hat{y}_2$ that are on the right-hand side of the equation. Directly using residuals obtained from (4), or $\hat{e}_4$, to construct an estimate for the population variance for hypothesis testing is incorrect. To obtain a consistent estimator for $\sigma_3^2$, we follow these steps:

(i) Estimate (1) and (2) to obtain $\hat{y}_1$ and $\hat{y}_2$;

(ii) Estimate (4) to obtain $\hat{\alpha}_1, \hat{\alpha}_2$, and $\hat{\beta}_3$ which are consistent estimators of $\gamma_1, \gamma_2$ and $\delta_3$ respectively;

(iii) Calculate $\hat{e}_3 = y_3 - \hat{\alpha}_1 y_1 - \hat{\alpha}_2 y_2 - X\hat{\beta}_3$. Note that all estimators on the right-hand side of this equation are consistent.

Then $\frac{\hat{e}_3^2}{n-k}(W'W)^{-1}$, where n is the number of observations, k is the number of regressors, and $W = [y_1, y_2, X]$, is a consistent estimate of $\sigma_3^2$. If the variance of $e_3$ is heteroscedastic, then its corresponding sample variance, V = (W'W) $(S)^{-1}$ (W'W), where S= $W'\hat{e}_3^2 W$ , is a consistent estimator of $\sigma_3^2$.

## END NOTES

[1] Support for the uncertainty-incentive trade-off is decidedly mixed. Some have found support (e.g., Lal, Outland, and Staelin 1994; Joseph and Kalwani 1995; Ghosh and John 2000; Aggarwal and Samwick 2002) but others have either found insignificant (e.g., John and Weitz 1989; Allen and Lueck 1999; Krafft, Albers, and Lal 2004) or opposite results (e.g., Coughlan and Narasimhan 1992; Umanath, Ray, and Campbell 1993). The results are mixed regardless of the setting (within versus cross-industry studies), methodology (field surveys versus experiments versus secondary data) and level of analysis (firm-level versus individual-level data). Lafontaine and Bhattacharyya (1995) and Prendergast (2002) offer extended reviews of this empirical controversy.

[2] Krafft (1999, p.126) makes this point clear when he states, " … it is the perceived rather than the actual risk preference that has an impact on the design of a sales organization's control system … the actual risk attitude is usually unknown, only its perception by executives can influence the design of control systems."

[3] This increased productivity does not imply that all firms are better off using incentive pay. For instance, when output is difficult to measure (e.g., quality is more important than quantity or salespeople primarily prospect new customers rather than farm existing ones), the costs under an incentive pay contract that emphasizes some measure of output at the expense of other dimensions would be higher and firms might prefer a fixed wage contract. See Brown (1990) for more on this issue.

[4] Joseph and Thevaranjan (1999) offer a model where firms choose agents to minimize their expected compensation costs. They show how increased monitoring allows firms to offer low-powered incentives to more risk-averse salespeople and hence lower their total compensation.

[5] The use of incentives based on generated sales is consistent with observations in franchising (Lafontaine 1992), movie distribution (Gil and Lafontaine 2009), trucking (Lafontaine and Masten 2002), and video rentals (Mortimer 2008) sectors. As Prendergast (2002) argues, incentives are likely to induce effort when performance measures are easily observable and not subject to manipulation. Theory models (e.g., Holmstrom and Milgrom 1987) also show that linear pay schemes are robust and optimal when the agent's strategy space is rich.

[6] Consider two equally able and hard-working salespeople within a firm who are paid per the same linear contract: $B + b\,q$. Suppose that because of some pure random shock, Agent 1 generates revenues that are 5% higher than Agent 2. This will not change our incentive rate parameter $b$, but will make the variable pay to total pay ratio (as well as the variable pay to fixed pay ratio) for Agent 1 to be higher than that for Agent 2, even though they work under the *same* contract structure.

[7] The details of these data and additional analyses are available upon request.

[8] For each selection equation, we also estimated models that controlled for the other agent characteristic. The core results remain unchanged. However we do find a significant negative relationship between risk aversion and ability, a result that is not altogether surprising.

[9] The two alternative measures were: the traditional measure used in past sales compensation studies, i.e. *Total Variable Compensation/Total Compensation* and a new measure given by *Total Variable Compensation/Base Salary*. For both variables the results stay qualitatively consistent with those using our incentive rate measure for the incentive and selection effects. In addition, we find that for both the alternative measures, technological and product demand uncertainty have a significant positive impact on incentive rate regardless of whether or not we control for the agent characteristics. These latter results are inconsistent with standard agency predictions but in-line with the findings of past studies (e.g., Coughlan and Narasimhan 1992). These analyses are available upon request. We thank an anonymous reviewer for suggesting these analyses.