Commission-Based Pay – Three Essays on German Insurance Tied Agents

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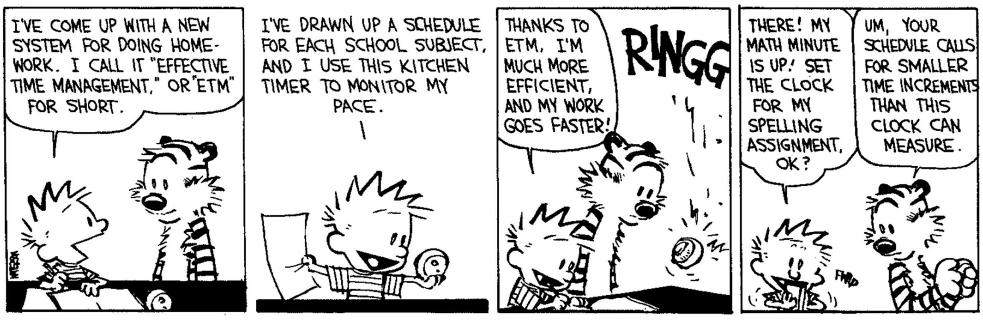
Introduction



(*Calvin and Hobbes, Watterson (2006)*)

This comic-strip by *Calvin and Hobbes* is an example for the intrinsic effort-allocation of an "agent" not always being in line with the desired allocation by the "principal". The basic but crucial question of how to design an incentive scheme that endorses a certain agent behavior has given rise to extensive economic research in the past. To understand and describe the influence of incentives properly, the individual characteristics of each worker (e.g., ability, age, labor-market experience) have to be considered. Cognitive and motivational mechanisms also play an important role in determining how a certain level of compensation translates into job- and pay-satisfaction.

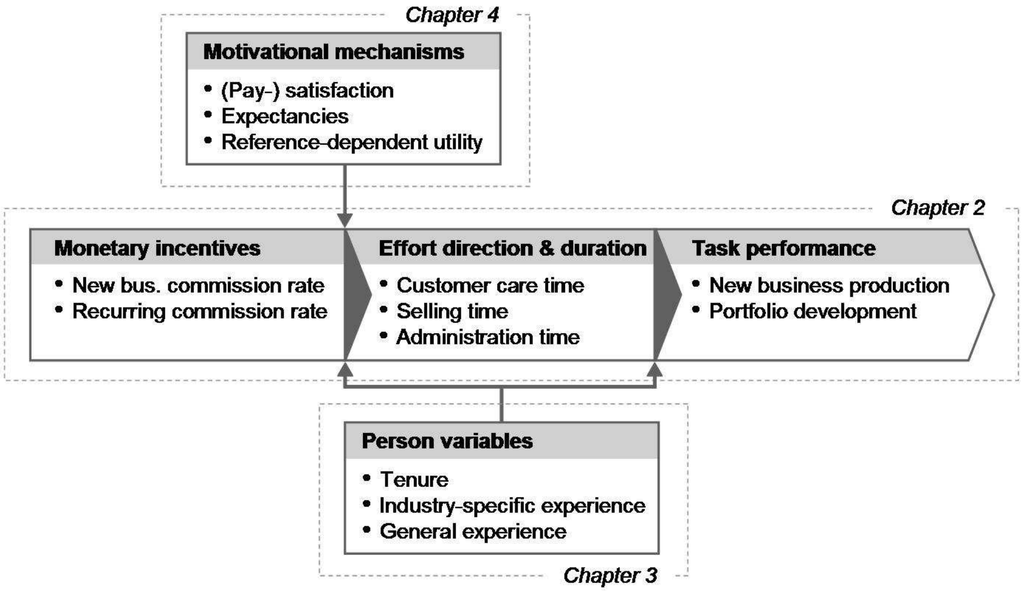


Figure 1.1: Guiding framework of my thesis (based on Bonner & Sprinkle (2002))

Figure 1.1 summarizes this diverse set of effects and mechanisms, based on a framework suggested by Bonner & Sprinkle (2002). My thesis is structured along this framework and consists of three main building blocks. The first of these is the relationship between incentives, allocation of effort, and task performance. Second, I will analyze how person variables, i.e., different forms of labor-market experience, influence the agent's performance. Finally, I discuss the effect of compensation on agent satisfaction, using a model of expectancies and reference-point dependent utility. I discuss the findings of each of the three chapters in more detail below, after giving a brief introduction to the data-set I use throughout my work. The data is on German insurance tied agents[1] and was collected in the first half of 2006. It is based on an online questionnaire among German insurance companies. A total of 9,386 insurance tied agents from 10 large German insurance companies participated in the survey (for more infor-

[1] An "official" definition can be found in the German commercial code (HGB, §84 Abs. 1), which defines tied agents as "independent tradesmen that act as an agent for another company. "Independent" means someone, who is generally free to decide which tasks to perform and how to spend his time" (see also Heinz (1999))

mation regarding set-up and concept of the questionnaire, see also Vogler (2009)). The data was sanitized, meaning that both the agents and the companies remained anonymous. As the level of information provided differs among the ten companies, not all observations could be used in the analyses, depending on the research question under consideration. Each chapter therefore contains a section in which I describe the subset of data used for the specific analysis. Overall, though, the findings presented in this work are based on a comparably large number of observations and therefore can be said to be representative.

One major difference to most of the other works that have been published in the past is that this focuses on one single industry in one country. The concentration on this specific industry and occupation, enables us to study in detail the effects under consideration due to the special nature of the compensation scheme of insurance agents, which is almost entirely variable, based on commission rates. Therefore, a clear link exists between performance and pay. This is a big advantage compared to other studies that cover a broad range of occupations and industries. As already stressed by Goette et al. (2004), an environment in which workers are free to choose when and how much to work and where a salient relationship between their effort and their income exists, is the ideal context in which to test the standard, neoclassical model of intertemporal labor supply. In this sense, I do not consider insurance tied agents an artificial case, but rather a job and industry that is perfectly suited for economic research.

As we will refer to the compensation system applicable to German insurance tied agents frequently in the subsequent chapters, I will now briefly present the general set-up of their compensation system.

The four components of the agents compensation are (i) new business commissions, (ii) recurring commissions, (iii) bonification and (iv) fixed salary and subsidies.[2] The insurance company pays these components to the agent, with the commissions directly related to new business generated and the total portfolio managed, whilst the bonification is paid for

[2] I will refer to these four components also as NBC, RC, Boni and Sal throughout the text, especially in the column-headers of regression tables

achieving or surpassing previously agreed goals. The fixed salary/subsidies component is usually paid only in the first couple of years after an agent joins the insurer, in order to help the agent sustain a minimal level of earnings (see Beenken (2003) and Damm (1993)). Apart from these purely monetary incentives, there can also be non-monetary rewards, e.g., travel vouchers, a watch, or some form of public recognition. Although there is evidence that these non-financial rewards can be very motivating, as they conspicuously recognize the agent's achievements (Dorfman (1976)), this type of bonification is outside the scope of this work (in line with Coughlan & Narasimhan (1992)). More information on the compensation systems of German insurance agents can be found in Cummins & Doherty (2006) (who focus on non-tied insurance intermediaries), Cupach & Carson (2002), Heinz (1999), Ludwig (1994) and Dorfman (1976).

I will now give a brief outline of the chapters of this thesis, including the main findings of the analyses.

Chapter 2 focuses on the question of how incentives can influence agents' time allocation and whether they can lead to a change in performance. Many recent studies have suggested that incentives matter, and that piece-rates are the best way to endorse the desired behavior (see e.g., Shearer (2004), Paarsch & Shearer (2000), Lazear (2000) or Lazear (1986)). Empirical evidence that supports this hypothesis, however, is scarce (see Bonner et al. (2000)). Alongside the problem of if and how incentives increase the amount of effort exerted by the agent, there is also the question of how the effort is allocated. A common hypothesis among practitioners is that there is always a trade-off between acquiring new customers and caring for existing ones (see Albers (2006), Cupach & Carson (2002), Albers (1996) or Sautter (1980)). I use the concept of a multi-task model based on the seminal work by Holmstrom & Milgrom (1991) to describe this trade-off between selling and customer care. Initially, I develop a simple one-period multi-task model and derive hypotheses regarding the influence of effort allocation on performance and how commission rates can be used to steer this allocation. This model is then extended to a 2-period setting where we include the intertemporal dependencies arising from the portfolio-effect

(i.e., that extending effort on selling also increases future recurring commissions and that a higher retention of customers via an increase in customer care effort is also beneficial in the next period). We revisit our hypotheses from the one-period model using simulated data and find that they generally hold for the 2-period case. Second, I test the hypotheses using data on auto insurance sales of three German insurance companies. I find a significant positive effect of the time spent on customer care activities both on the portfolio size and new business production. The new business commission rate has a positive effect on selling and a negative effect on customer care time. The results for the recurring commission rate are mixed.
In Chapter 3, I turn towards the influence of individual characteristics of each worker. The human capital theory is well-known and seeks to explain the relationship between experience and pay, stating that more experience makes the employee more valuable and should thus lead to higher wages. Previous research has cast some doubts on this simple relationship and suggested that the type of experience needs to be differentiated from the total sum of experience. The analysis presented here leans on the work by Parent (2000), who found that three categories of experience can be distinguished: industry-specific, job-specific and general labor-market experience (the works by Kambourov & Manovskii (2009), Poletaev & Robinson (2008) and Gibbons & Waldman (2006) suggest an even finer differentiation into occupational-, skill- or task-specific experience, respectively). Based on the standard wage model, I test the influence of experience using the data on tied agents. I find both the expected strong effect of tenure on pay due to the special structure of agent compensation in this industry, and that general- and industry-specific labor market experience also have positive effects. The latter deviate is dependent on the agent's tenure: it is strong for agents with low tenure, but becomes rather weak or even negative for high-tenure agents. A detailed look into the effects on different compensation components reveals a high degree of diversity in the size and direction of the experience-related influence on wage. By applying an instrumental variable (IV) approach (based on Altonji & Shakotko (1987))

and introducing proxy variables for the job- and industry-match, the chapter also contributes to the discussion regarding the omitted-variable bias that can arise from using simple OLS instead of IV.

Finally, Chapter 4 discusses the motivational aspects of compensation. Camerer et al. (1997) found (using data on taxicab drivers) that the *expected* wage acts as a reference-point and that performance drops after that target is met. Similarly, Groot & van Maassen den Brink (1999), found that the positive effect of higher wages on job satisfaction wears off after some time (called ”preference drift”). Recent works have found such a reference-dependent utility not only in employer-employee relationships but also in other areas of public life (see Clark et al. (2009), Luttmer (2005) and Stutzer (2004)). One of the most often analyzed phenomena in the context of reference points is ”loss aversion”: people usually feel that a loss reduces their utility far more than a comparable gain would increase it (see Fehr & Goette (2007), Goette et al. (2004), Tversky & Kahneman (1991) and Kahneman & Tversky (1979)). Based on this line of thought, I present empirical evidence for the existence of a reference-point for satisfaction with compensation. Information on the satisfaction (both with pay, and overall) of the tied agents is used to test the hypotheses. An ordered probit regression and a subsequent analysis of the marginal effects is applied to investigate the influence of compensation on the satisfaction score. I find a relationship between the agents’ deviation from peer-group compensation and their satisfaction with pay. Surprisingly, the analysis shows a positive relation with satisfaction for deviations above the peer-group median but no statistically significant relation for deviations below the median. These results run contrary to the common notion of loss aversion presented in other publications. In line with previous work, no relation is found between compensation and overall satisfaction.

Overall, the results as presented in the following three chapters support the notion that there are many influencing factors in the context of pay and performance. Due to the analysis of one single job and industry, it is possible to combine different theories that have been proposed in the past to explain many aspects of human behavior. Further research is needed to understand in depth how the findings translate to other industries and jobs and how social (non-quantitative) preferences may interact with the evidence presented here.

Chapter 2

The Relation Between Incentives, Effort and Performance

2.1 Introduction

A basic assumption in principal-agent problems is that compensation systems reward the agent for his output and provide a premium for the risk he accepts. If there is only one task the agent can potentially perform, then the challenge for the principal is to provide incentives so that the amount of effort exerted by the agent is maximized (assuming that the effort efficiency is unchanged). In such situations, piece rates are generally found to be superior to fixed wages (e.g., Shearer (2004), Paarsch & Shearer (2000), Lazear (2000), or Lazear (1986)). Similar results were already obtained and summarized by Prendergast (1999) so it seems reasonable to assume that agents do respond to incentives.

Intuition would suggest that higher incentives lead to higher effort and therefore higher performance, but there is a lack of empirical evidence and results of laboratory studies have been quite mixed. Bonner et al. (2000) state that only half of the studies analyzed showed a significant positive effect of incentives on performance (a similar result was also found by Camerer & Hogarth (1999)). Gneezy & Rustichini (2000) found a positive effect of higher compensation on performance relative to lower pay (but the overall performance level may be lower because of the introduction of compensation, i.e., motivation crowding out, see also Sliwka (2003)). Camerer et al. (1997) on the other hand find a negative effect of wage increase on the working hours of cab drivers. The studies by Pritchard & Leo (1973) and Tomporowski et al. (1993) also suggest a negative correlation between incentives and performance.

Recent research has presented an agent-specific, preference-based solution to those counter-intuitive results. Fehr & Goette (2007) argue that loss-averse agents have a reference income level, and failure to reach this level is experienced as a loss (see also Chapter 4 where I investigate the existence of a reference-point in the case of insurance tied agents). On the other hand, the marginal utility of income above the reference-point decreases discontinuously. As a consequence, one could argue that after incentives are increased, this reference-point is achieved with even less effort and thus the overall performance drops. Fehr & Goette (2007) find that in the case of bike messengers (who are paid on a commission-only basis), effort duration increases whilst the effectiveness decreases. Although the overall performance still increased in this example, these findings point towards potential negative effects of an increase of incentives. In general, it must be said that the effect of the incentive changes seem to depend heavily on the nature of the task to be performed (see Camerer & Hogarth (1999)).

A recent theory to explain the rather weak relation between incentives and performance uses the concept of "fairness". Fehr et al. (2009) argue that a wage increase leads to an increased effort only if the wage is perceived as fair (see also Akerlof & Yellen (1990)). Similarly, MacLeod (2007) suggests that fairness may be more important than pure profit maximization.

These models, although already quite instructive, lack an important link to reality: in modern work environments, the agent rarely has only one task to perform; in most cases, workers are in charge of a broad variety of tasks. Thus, in contrast to the one-task situation, where the emphasis is mainly put on effort duration, there is now an additional challenge to influence the direction of effort (see Bonner & Sprinkle (2002)). This may lead to incentives that increase the effort duration, but shift the effort direction towards those tasks that can be clearly measured (Brüggen & Moers (2007), Fehr & Schmidt (2004)).

As outlined by Holmstrom & Milgrom (1991), the multi-task approach can be applied to production workers as well as to teachers and many other jobs. To my knowledge, there is only limited empirical evidence from real data (i.e., not from laboratory experiments) on how incentives influence the allocation of time and effort among different tasks. One of the few works regarding effort direction comes from Brickley & Zimmerman (2001) who analyzed the effect of a change in organizational incentives on the teaching ratings and the research output at a top-tier business school. They find that, after putting more emphasis on teaching ratings, the overall score in the classroom evaluations went up whilst the average research output went down.

I contribute to this new empirical field first by developing a model that accounts for repeated interactions between the agent and customers over multiple periods and secondly by analyzing the effect of varying incentive levels on the effort duration and direction using data on German insurance agents. As already described in Chapter 1, the largest component of variable compensation is commission that is paid for (i) new contracts sold by the agent and (ii) customers with a multi-year contract that remain with the insurance company without cancelation of their policy within this period. Furthermore, depending on the overall performance and the targets set by the Insurance company, a bonification may be paid out at the end of the accounting period. This bonification can be either a cash amount or a non-cash reward. There is evidence that non-financial rewards can be very motivating, as they conspicuously give the recipient recognition that they have met their performance objectives (Dorfman (1976)), this type of bonification is outside the scope of this work.

I focus on commissions, as they account for more than 80%, on average, of the agent's total annual compensation (see also Damm (1993)). As commission rates vary significantly between an insurer's different products, I focus on product-specific data. I use auto insurance products as they can be assumed to be fairly standardized and thus the data from different insurance companies can be used without large company-specific differences in the products.

A common hypothesis among practitioners is that there is always a trade-off between acquiring new customers and caring for existing ones. As outlined for example by Sautter (1980), it is either that agents lose sight of their existing customers in order to have more time to sell products to new ones (see Cupach & Carson (2002) or Albers (1996)) or that those agents with a broad customer base stop writing new business as they are already well paid by the recurring commissions (see Albers (2006)). Based

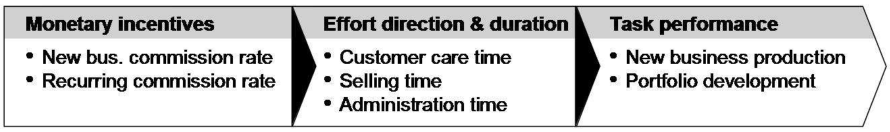


Figure 2.1: Framework for the effects of monetary incentives on effort and task performance (see also Figure 1.1)

on Figure 1.1, Figure 2.1 shows the different quantities I will analyze in this chapter and gives a first indication of the potential causal relations based on the literature review. I will treat the new business and recurring commission rates as the only steering instruments the principal has available. Companies seem to be able to influence their agents' time allocation between three tasks: customer care, selling and administration.[3] Finally, the way the agent splits his time between the tasks should influence his performance, which I measure in terms of new business production and portfolio development.

Understanding the causal relation between incentives, effort allocation and performance has the potential to improve the effectiveness of com-

[3] I will disregard the impact of effort spent on administration in the model, as I assume that the agent cannot directly influence the amount of administrative work to be performed. In the empirical results, I control for administrative tasks but focus on interpreting the effects from customer care and selling

pensation schemes, not only in the sense of efficiency gains for the principal but also in terms of the agent's well-being. Survey results by Graf & Keese (2000) show that 43% of agents perceive their current compensation system as "unfair".

In the next section, I develop a formal model and derive specific hypotheses regarding the different effects just discussed using both closed-form solutions (2.2.1) and simulated data (2.2.2). In Section 2.3, I give a brief introduction into the data-set (2.3.1), test the hypotheses (2.3.2 and 2.3.3) and discuss the robustness of the results (2.3.4). Section 2.4 summarizes the findings and concludes.

2.2 The Model

2.2.1 Theoretical Predictions

In this section, I develop a model to derive the optimal effort allocation of an agent that has the choice between multiple tasks. The model specification leans heavily on the seminal work by Holmstrom & Milgrom (1991). As in their work, I also focus on a linear-contract, normal-noise, CARA[4]-preference setting. Based on the theoretical results, I formulate hypotheses regarding the influence of effort and commission rates on performance that I test in Section 2.3 with the data-set. I am interested in the optimal effort allocation of the agent, so I do not discuss the principal's problem here and assume that the commission rates are externally set.

I start with a 1-period model (assuming that the agent is completely myopic). In the second stage, I extend the model into multiple periods, where I focus on the 2-period case for the sake of traceability. A closed-form solution for the optimal effort levels of the agent is derived and I discuss the differences between the 1- and 2-period model based on simulated data.

[4] Constant absolut risk aversion

In all cases, the contract specifies the recurring commission rate α_P and the new business commission rate α_N. The environment is assumed to be static and the firm cannot directly verify the agent's effort level but the outcomes are observed by both the company and the agent (compare Daido (2006)).
In the description of the model, I will rely on the following nomenclature:

N_t	≥ 0	New business of the agent at the end of period t
P_t	≥ 0	Portfolio of the agent at the end of period t
e_N^t	$\in [0,1]$	Agent's effort on selling during period t
e_P^t	$\in [0,1]$	Agent's effort on customer care during period t
τ	$\in [0,1]$	Natural churn rate
a_t	≥ 0	Agent's fixed salary at the end of period t
α_N	$\in [0,1]$	New business commission rate
α_P	$\in [0,1]$	Recurring commission rate
w_t	≥ 0	Agent's total compensation at the end of period t
β_N	> 0	Scaling factor - Sales effectiveness
κ	≥ 1	Scaling factor - Churn avoidance
c_N, c_P	> 0	Scaling factors - Cost function
s	$0 \leq s < \sqrt{c_N c_P}$	Scaling factor - Effort substitution

With this nomenclature at hand, I describe the model as follows:

$$N_t = \beta_N e_N^t + \epsilon_N \tag{2.1}$$

$$P_t = N_t + [1 - \tau(\kappa - e_P^t)]P_{t-1} + P_{t-1}\epsilon_P \tag{2.2}$$

The new business production N_t at the end of period t is assumed to depend on the amount of effort spent on selling by the agent during time period t subject to some error term $\epsilon_N \sim \mathcal{N}(0, \sigma_N^2)$.
The portfolio size P_t at the end of period t depends on the amount of new business generated during the same period and the remainder of the previous period's portfolio (P_{t-1}). I assume that there is a natural churn rate τ (due to customers changing their insurance company, removing the in-

sured risk or death of the policyholder). Depending on the amount of effort the agent invests in customer care, the effect of this churn factor can be reduced. As effort is scaled to be between 0 and 1, κ in the equation defines how much of the churn rate can be compensated (i.e., if $\kappa = 1$, the agent could completely neutralize the negative effect of churn on the portfolio by choosing the maximum customer care effort of 1).[5] The introduction of κ also allows us to account implicitly for "word-of-mouth" effects (see, e.g., Rob & Fishman (2005), Vettas (1997), Dodson & Muller (1978); for ways to efficiently solve the advection-diffusion problems that often arise in these settings, see also Widura et al. (2008)). This suggests that an increase of the customer base should lead to additional new business as existing customers recommend the product to their family and friends. Thus, if we assume that there is a positive relationship between customer base and new business production, we can write (introducing the new variables η as the word-of-mouth effect and $\bar{\kappa}$ via $\tau\kappa = \tau\bar{\kappa} - \eta$):

$$P_t = \underbrace{\beta_N e_N^t + \eta P_{t-1}}_{=:\tilde{N}_t} + [1 - \tau(\bar{\kappa} - e_P^t)]P_{t-1} + P_{t-1}\epsilon_P$$

Here, $\tilde{N}_t$ denotes new business production adjusted for the word-of-mouth effect. For the sake of traceability, I will not use this explicit form but the one of equation (2.2) with the word-of-mouth parameter being implicitly defined via κ.

As in the case of the new business production, I assume that the development of the portfolio is not completely deterministic but depends on some random error term $\epsilon_P \sim \mathcal{N}(0, \sigma_P^2)$. In this case, however, the size of this disturbance will clearly depend on the portfolio size (more customers means greater volatility in the number of retained customers). I therefore scale the error term using the portfolio size of the previous period. Regarding the covariance between ϵ_N and ϵ_P, I assume that $\sigma_{NP} = 0$.

After describing the mechanisms of new business production and port-

[5] Due to this notation, the effective churn rate is not τ but $\tau \cdot \kappa$. I nevertheless usually refer to τ as the churn rate, slightly abusing the notation here

folio development, we can easily derive the formulation for the agents' compensation scheme. I introduce a compensation scheme based on a certain amount of fixed salary (a_t) and commissions.[6] I allow both the fixed part and the commissions to vary over time[7] and write:

$$w_t = a_t + \alpha_N N_t + \alpha_P (P_t - N_t) \tag{2.3}$$

The term $(P_t - N_t)$ accounts for the assumption that new business is not subject to recurring commissions in the year the new business was generated (i.e., that the agent gets not paid twice in one year for the same contract). Following Bolton & Dewatripont (2005), I define the cost function for the agent as

$$C(e_N^t, e_P^t) := C(e_N^t, e_P^t; s) = \frac{1}{2}(c_N (e_N^t)^2 + c_P (e_P^t)^2) + s \cdot e_N^t e_P^t \tag{2.4}$$

with $0 \leq s < \sqrt{c_N c_P}$ representing the degree of cost substitution between two actions.[8]

Finally, I assume a negative exponential utility function for the agent (compare Holmstrom & Milgrom (1991)). Introducing r as the constant risk aversion of the agent, we can write his utility as $U(w_t, C(e_N^t, e_P^t)) = -\exp[-r(w_t - C(e_N^t, e_P^t))]$.[9]

Corollary 2.1 *The agent's certainty equivalent compensation is given by*

$$CE_t := a_t + \alpha_N N_t + \alpha_P (P_t - N_t) - C(e_N^t, e_P^t) - \frac{r}{2}(\alpha_N^2 \sigma_N^2 + \alpha_P^2 P_{t-1}^2 \sigma_P^2)$$

[6] This is the most common form of compensation in insurance companies

[7] Usually, the amount of fixed salary decreases over time as it is directed at new agents who naturally lack a strong customer base

[8] If $s = 0$, the two efforts are independent; if $s > 0$, raising effort on one task raises the marginal cost of the other task

[9] Due to the assumption that both effort types induce costs and rewards at the same time (i.e., at the end of the current period), we can avoid disturbances from present-biased preferences (see O'Donoghue & Rabin (1999)) that give stronger relative weight to the earlier reward as it gets closer

Proof. I define $w_t^0 = E[w_t]$ to be the expected compensation (with the expectation being subject to ϵ_N and ϵ_P) the agent receives. Let Π be the risk premium such that the agent is indifferent between the (risky) compensation w_t and the ensured one. Then holds that $E[U(w_t^0 - \Pi)] = E[U(w_t)]$ (I drop the second argument, i.e., the cost, from the utility function for the sake of ease of presentation). Using a first-order Taylor approximation of the utility on the left hand-side of the equation yields: $U(w_t^0 - \Pi) \approx U(w_t^0) - \Pi U'(w_t^0)$. Similarly, second-order Taylor approximation of the utility on the right hand side gives: $U(w_t) \approx U(w_t^0) + (w_t - w_t^0)U'(w_t^0) + \frac{1}{2}(w_t - w_t^0)^2 U''(w_t^0)$. Taking the expected value of both equations and using that $U(w_t^0), U'(w_t^0), U''(w_t^0)$ are not stochastic (i.e., they are invariant under the application of the expected value) and that therefore $E[w_t - w_t^0] = 0$, yields: $\Pi \approx -\frac{U''(w_t^0)}{U'(w_t^0)} \cdot \frac{E[(w_t - w_t^0)^2]}{2}$. With $E[(w_t - w_t^0)^2] = E[(\alpha_N \epsilon_N + \alpha_P P_{t-1} \epsilon_P)^2] = \alpha_N^2 \sigma_N^2 + \alpha_P^2 P_{t-1}^2 \sigma_P^2$ (using the assumption that ϵ_N and ϵ_P are uncorrelated) and $r = -\frac{U''(w_t^0)}{U'(w_t^0)}$, we see that $\Pi \approx -\frac{r}{2}(\alpha_N^2 \sigma_N^2 + \alpha_P^2 P_{t-1}^2 \sigma_P^2)$. ■

Due to the exponential form of the utility function (i.e., it is strictly monotonously increasing), it suffices to find the maximum of the certainty equivalent defined in Corollary 2.1.

By introducing a (constant) factor δ that is used to discount future earnings, we can now formulate the agent's maximization problem.

The agent's problem at the beginning of period t can be written as:

$$\max_{\substack{(e_N^t, \ldots, e_N^T), \\ (e_P^t, \ldots, e_P^T)}} \left[\sum_{i=0}^{T-t} \delta^i \, CE_{t+i} \right] \tag{2.5}$$
$$\text{s.t.} \sum_{i=0}^{T-t} \delta^i \, CE_{t+i} \geq \bar{u}$$

where T defines the end of the agents' planning horizon and $\bar{u}$ being the agents' reservation utility.[10]

The first step is to examine the one-period case. This means that the agent maximizes his expected utility based only on the outcomes of the current

[10] As the fixed salary is independent of the chosen effort, I assume that the participation constraint in equation (2.5) is alwas fulfilled as the principal could set a_t accordingly without changing any of the subsequent results

period. I summarize the optimal effort from the agent's perspective for this case in the following theorem.

Theorem 2.2 *In the case of a purely myopic agent, i.e., if $T = t$ the optimal levels of effort are*

$$e_N^t = \frac{c_P \alpha_N \beta_N - s\alpha_P \tau P_{t-1}}{c_N c_P - s^2}$$
$$e_P^t = \frac{c_N \alpha_P \tau P_{t-1} - s\alpha_N \beta_N}{c_N c_P - s^2}$$

Proof. By solving the first order conditions of the agent's problem from equation (2.5) for the case $T = t$ for e_N^t and e_P^t and solving the resulting two equation system, the expressions above can easily be derived. ■

Based on the specification just presented, we can now formulate our main hypotheses:

Hypothesis 2.1 *The effort spent on selling has a positive effect on the new business production (see equation* (2.1)*).*

As similar hypothesis can be stated for the portfolio development:

Hypothesis 2.2 *The effort spent on customer care has a positive effect on the portfolio size (see equation* (2.2)*).*

And thirdly, regarding the ability of the company to influence the allocation of the agent's effort across different tasks, we formulate:

Hypothesis 2.3 *The agent exerts more effort on selling the higher α_N, the lower α_P and the lower the initial portfolio size P_{t-1} is. He invests more in customer care the higher α_P, the lower α_N and the higher P_{t-1} is (see Theorem 2.2).*

These hypotheses are built on the myopic case, I will now turn to the multi-period version of the agent-problem and discuss how far this extension affects our above statements.
For the sake of traceability, and to be able to derive a closed-form solution, I will discuss the case of an agent over two periods. This is, of course, a limitation to the general case but as the work by Frederick et al. (2002) has shown, the concept of discounted utility on multiple periods is usually not supported by empirical data. For insurance agents in particular, where the overall business is subject to many external factors, it seems to be reasonable to assume that the planning horizon is limited to a couple of years. Conceptually, however, the same methods also apply to higher-period models, although they quickly become computationally very involved.
Rewriting equation (2.5) for the 2-period case gives

$$\max_{\substack{(e_N^t, e_N^{t+1}),\\ (e_P^t, e_P^{t+1})}} [CE_t + \delta CE_{t+1}] \tag{2.6}$$
$$\text{s.t. } CE_t + \delta CE_{t+1} \geq \bar{u}$$

Again, I summarize the solution of this 2-period agent's problem into a Theorem.

Theorem 2.3 *In the case of an agent that optimizes his effort allocation based on the current and the next period, i.e., if $T = t+1$ the optimal levels of effort are:*

$$\begin{aligned}
e_N^t B(\alpha_P, P_{t-1}) = &\quad \beta_N \tau^2 P_{t-1}^2 K \alpha_P^3 \\
&+ K P_{t-1} \left[(1-\kappa\tau)(c_P\beta_N - s\tau P_{t-1}) - \alpha_N \beta_N P_{t-1}\tau^2\right] \alpha_P^2 \\
&+ \left[\delta(s\tau P_{t-1} - \beta_N c_P)(1 - \kappa\tau + \frac{\alpha_N \beta_N s\tau}{D}) - s\tau P_{t-1}\right] \alpha_P \\
&+ c_P \alpha_N \beta_N \\
e_P^t B(\alpha_P, P_{t-1}) = &- \beta_N^2 \tau P_{t-1} K \alpha_P^3 \\
&+ K P_{t-1} \left[(1-\kappa\tau)(c_N \tau P_{t-1} - s\beta_N) - \alpha_N \beta_N^2 \tau\right] \alpha_P^2
\end{aligned}$$

$$+\left[\delta(c_N\tau P_{t-1}-\beta_N s)(1-\kappa\tau-\frac{\alpha_N\beta_N s\tau}{D})+c_N\tau P_{t-1}\right]\alpha_P$$
$$-s\alpha_N\beta_N$$

with $K := \delta(\frac{c_N\tau^2}{D} - r\sigma_P^2)$, $D = c_N c_P - s^2$ *and the polynomial* $B(\alpha_P, P_{t-1}) := K(2\beta_N s\tau P_{t-1} - \beta_N^2 c_P - c_N\tau^2 P_{t-1}^2)\alpha_P^2 + D$. *For* e_N^{t+1} *and* e_P^{t+1}*, Theorem 2.2 applies.*

Proof. As I assume the agent to behave rationally, we can apply the first order conditions for (e_N^t, e_P^t) in (2.6), conditional on (e_N^{t+1}, e_P^{t+1}) being optimal in the sense of Theorem 2.2. Accounting for the P_t-dependency (and consequentially, the (e_N^t, e_P^t)-dependency) of the optimal effort at time $t+1$, we obtain the expressions above. ■

Although the expressions for e_N^t and e_P^t are more complex than those for the 1-period case seen earlier, there are still some interesting conclusions we can draw from these results. First, we see that both efforts are linear in the new business commission rate (we will have a closer look at the effect-direction of an increase/decrease in the new business commission rate on the selling effort and the customer care effort later). Second, the influence of the recurring commission rate is non-linear with a third-order polynomial in the nominator and a second-order polynomial in the denominator.[11] This complex structure makes it difficult to derive analytical expressions such as the derivative with respect to the recurring commission rate and we will thus rely on the results we will obtain from the simulated data in order to make predictions regarding our hypotheses. What we can see, though, is that the variance of the customer retention activity σ_P plays an important role as it determines the magnitude of the variable K. Furthermore, we can see that Theorem 2.3 reduces to Theorem 2.2 if $\delta = 0$.

We will now turn to the analysis of the effect from changes in the new business commission rate.

[11] The notation with the polynomial $B(\alpha_P, P_{t-1})$ being multiplied with the corresponding effort level has been chosen for presentational purposes only

Theorem 2.4 *The new business commission rate has a linear effect on both the optimal selling and customer care effort. If $B(\alpha_P, P_{t-1}) > 0$ and $K > 0$, the direction of the effect can be evaluated depending on the recurring commission rate α_P:*

$$\frac{\partial e_N^t}{\partial \alpha_N} > 0 \quad \text{if } \alpha_P < \phi_N$$
$$\frac{\partial e_P^t}{\partial \alpha_N} < 0 \quad \text{if } \alpha_P < \phi_P$$

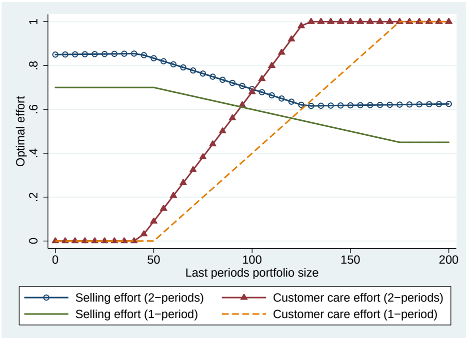
with $\phi_N = \frac{\delta P_{t-1} s^2 - \beta_N c_P \delta s + \sqrt{4 c_P P_{t-1}^2 D^2 K + \delta^2 P_{t-1}^2 s^4 \tau^2 - 2\beta_N c_P \delta^2 P_{t-1} s^3 \tau + \beta_N^2 c_P^2 \delta^2 s^2}}{2 P_{t-1}^2 \tau D K}$ *and* $\phi_P = \frac{c_N \delta P_{t-1} s \tau^2 - \beta_N \delta s^2 \tau + \sqrt{4\beta_N P_{t-1} s \tau D^2 K + c_N^2 \delta^2 P_{t-1}^2 s^2 \tau^4 - 2\beta_N c_N \delta^2 P_{t-1} s^3 \tau^3 + \beta_N^2 \delta^2 s^4 \tau^2}}{2\beta_N P_{t-1} \tau D K}$. *If $B(\alpha_P, P_{t-1}) < 0$, the effect direction is inverted. For $K < 0$, the same qualitative effect direction applies only with different values for ϕ_N and ϕ_P. The effect of α_N on (e_N^{t+1}, e_P^{t+1}) has already been summarized in Hypothesis 2.3.*

Proof. Calculating the first derivatives with respect to α_N of the optimal effort levels as given in Theorem 2.3, we see that if $B(\alpha_P, P_{t-1}) > 0$, the nominator of $\frac{\partial e_P^t}{\partial \alpha_N}$ ($\frac{\partial e_N^t}{\partial \alpha_N}$) is of (inverse) U-shape in α_P. Calculating the roots of the nominator results in expressions with different signs. Thus, we can conclude that the derivative of e_P^t with respect to α_P is negative as long as α_P is smaller than the (positive) root. The same argument can be used to show the claim for e_N^t. ■

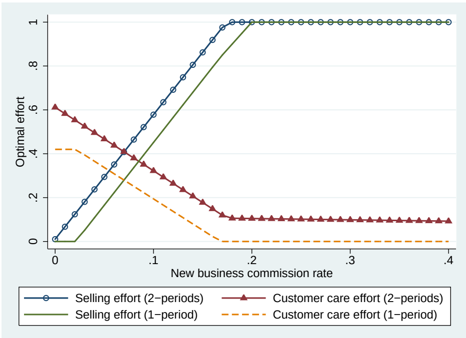
In other words, the result of Theorem 2.4 indicates that in the 2-period case, an increase of the new business commission rate has a positive effect on the sales effort and a negative effect on the customer care effort unless the recurring commission rate raises beyond a certain critical value. Beyond this point, an increase in the new business commission rate leads to a decrease in the selling effort, resulting in the opposite effect to that presumably desired. Instead, the effort spent on customer care increases. Even if α_P is still below the critical point, the higher the recurring commission rate, the smaller the marginal effect of an increase in the new business commission rate. This result is in line with general intuition, as the agent probably feels less willing to spend additional effort on selling if the recurring commission rate is comparably high (and thus, the financial loss of not retaining a customer is quite severe).

2.2.2 Predictions from Simulated Data

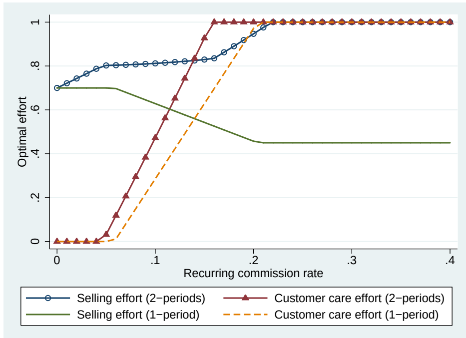
As already pointed out above, it is impossible to calculate closed-form solutions for the marginal effect of the recurring commission rate or the last year's portfolio on the optimal effort choice of the agent. I will now, therefore, discuss the effects of changes in α_P and P_{t-1}, respectively, using simulated data. It should be noted that the discussion of the 2-period results based on the simulated data is not meant to be a rigorous proof regarding the properties of the solution given in Theorem 2.3. Due to the dependency between the optimal effort and the chosen parametrization, some scenarios (e.g., that the root of the first derivative of the agent's problem with respect to e_N^t or e_P^t does not mark a maximum but a minimum) are not discussed here. Instead, I will focus on those settings that resemble a "real-life" scenario, disregarding some theoretical artifacts that may occur. In Figure 2.2, we see the results of the numerical calculations, i.e., the formulas derived above were used to calculate the optimal selling and customer care effort under different scenarios. In order to calculate these values, I make some assumptions regarding the input-parameters. The choice was based on considerations regarding an appropriate relative relation between the parameters, although the overall level is fairly arbitrary as one could easily scale all parameters up or down without changing the qualitative, relational shape of the curves. As I assume the effort to be between 0 and 1, I chose the set of parameters to be close to 1 in order to maintain a common effect-level. Furthermore, if possible, I also tried to lean on the data-set I will use in the next section. In particular, I chose $\tau = 0.1$, $\kappa = 1.1$, $\delta = 0.5$, $c_N = 2$, $c_P = 1$, $s = 0.5$, $\sigma_P^2 = 0.1$, $\beta_N = 10$ and $r = 0.1$. Thus, I assume a churn rate of 10%, which the agent can reduce (assuming a customer care effort of 1) to 1% (i.e., $10\% * (1.1 - 1)$) due to



(a) Portfolio variation ($\alpha_N = 0.14$, $\alpha_P = 0.07$)



(b) New bus. com. rate variation ($\alpha_P = 0.07$, $P_{t-1} = 60$)



(c) Rec. com. rate variation ($\alpha_N = 0.14$, $P_{t-1} = 60$)

Figure 2.2: Results from simulated data with $\beta_N = 10$, $\tau = 0.1$, $\delta = 0.5$, $s = 0.5$, $\kappa = 1.1$, $c_N = 2$, $c_P = 1$, $\sigma_P^2 = 0.1$, $r = 0.1$

the choice of $\kappa = 1.1$. I assume that the agent values the expected return of the next period with one-half. The cost associated with exerting effort on selling is assumed to be twice as large as the customer care effort (e.g., due to required customer visits prior to the signing of a contract and administrative one-off costs). The cost substitution factor is set to 0.5 which is roughly one-third of the maximal, full-substitution value of $\sqrt{2}$. I base this on the assumption that agents are not always in an "either/or" situation regarding how they spend their time but rather have some flexibility in their daily schedule. The uncertainty regarding the portfolio development is set to 10% of the portfolio managed. As unexpected changes in the portfolio development are rare and small, this value seems reasonable.

As the variance of the new business production error term is not required for the calculations, I omit it here. Regarding the scaling factor of the new business production β_N, I try to be close to the data-set I will use in the next section. As we can see in Table 2.3, the average new business production is around EUR 14,000 and the average portfolio size is EUR 75,000. To keep a similar ratio in the simulated data, I set $\beta_N = 10$ in all cases and $P_{t-1} = 60$ in those cases where we analyze the commission rate variations (see Figures 2.2(b) and 2.2(c)). Also the choice of α_N and α_P draws on the field data. In Figure 2.2(a), I set the commission rates to 14% and 7% for the new business and the recurring commission rate, respectively. In Figures 2.2(b) and 2.2(c), the same values are used for the non-variable commission rate (i.e., $\alpha_P = 0.07$ in 2.2(b) and $\alpha_N = 0.14$ in 2.2(c)).
As the optimal effort levels given in Theorem 2.2 and 2.3 are not restricted to values between 0 and 1, I set negative values to zero and values above one to 1. I will now show that this method (in most cases) leads to the unique maximum within the interval. As we will need the first order conditions of the agent's problem that were already implicitly used for the proofs of Theorem 2.2 and 2.3, I will now explicitly state them here. The first order conditions for the 1-period case are

$$e_N^t = \frac{\alpha_N \beta_N - s e_P^t}{c_N} \tag{2.7}$$

$$e_P^t = \frac{\alpha_P \tau P_{t-1} - s e_N^t}{c_P} \tag{2.8}$$

and for the 2-period case

$$e_N^t = \frac{B_1 e_P^t + \beta_N(\alpha_N + \alpha_P B_2)}{c_N - \beta_N^2 K \alpha_P^2} \tag{2.9}$$

$$e_P^t = \frac{B_1 e_N + \tau P_{t-1}(\alpha_P + \alpha_P B_2)}{c_P - \tau^2 P_{t-1}^2 K \alpha_P^2} \tag{2.10}$$

with $B_1 = \beta_N \alpha_P^2 \tau P_{t-1} K - s$ and $B_2 = \frac{(1-\kappa\tau)(\delta + \alpha_P P_{t-1} K)}{c_N c_P - s^2}$.
With these preliminaries at hand, I summarize in Table 2.2.2 the rules on how to project the different possible effort levels into the interval of al-

		e_N^t		
		< 0	$\in [0,1]$	> 0
e_P^t	< 0	$e_N^t = e_P^t = 0$	(2.10) with $e_N^t = 0$	$\approx e_N^t = 0, e_P^t = 1$
	$\in [0,1]$	(2.9) with $e_P^t = 0$	Theorem 2.3	(2.9) with $e_P^t = 1$
	> 0	$\approx e_N^t = 1, e_P^t = 0$	(2.10) with $e_N^t = 1$	$e_N^t = e_P^t = 1$

Table 2.1: Decision rules how to project the calculated optimal effort into the interval of [0,1] for the 2-period case

lowed values. Although I am interested mainly in the "inner solutions" of the agent's problem, i.e., where Theorem 2.3 applies, I will briefly discuss why the projection rules as described in Table 2.2.2 lead to the optimal effort allocation within the given interval. Due to the inverted U-shape with respect to e_N^t or e_P^t of the agent's problem, it is clear that if the vertex of the parable lies outside of [0,1], the maximum within this interval is attained at the boundaries, i.e., at 0 for negative optimal effort values and at 1 for positive optimal effort values. By setting the effort to values other than the calculated optimum, the equilibrium effort as given in Theorem 2.3 is no longer attained. Instead, if only one of the two effort values is set to its boundary value, we can use equation (2.9) or (2.10), respectively, to calculate the corresponding optimal effort. If both calculated optimal efforts are above (below) the upper (lower) boundary, setting one of them to one (zero) increases (decreases) the corresponding other effort level (as for most parameter constellations, $B_1 < 0$ and the denominators are positive, there is a negative relation between e_N^t and e_P^t as one would expect due to the cost substitution between the two tasks. Therefore, decreasing (increasing) one of the efforts increases (decreases) the other one. Only in those cases where one value is above the upper and the other is below the lower boundary, might there be two "second best" optima, depending on which of the two values is set to the boundary first (as the decrease (increase) of one effort could theoretically lead to the other value being pushed above (below) the boundary). As these nonetheless lie close together due to the continuous nature of the equations, this does not change the qualitative direction of the results. The same argument applies to the 1-period case.

Interpreting Figure 2.2, we start with 2.2(a) where both the selling and the customer care efforts are shown for the 1- and the 2-period model for different levels of (last periods) portfolio P_{t-1}. The optimal selling effort in the 2-period model is higher at the beginning compared to the 1-period model. This is in line with the expectations as the agent not only receives the utility of the resulting new business for the current period but also for the subsequent one. For the same reason, the customer care effort is also higher. Due to the change of the calculation method for boundary-solutions, as described above, the resulting graphs are continuous but not continuously differentiable. In the 2-period case, if the customer care effort is set to one of the boundaries, the selling effort slightly increases as new business effort is linearly dependent on the portfolio size if the customer care effort is held constant (compare equation 2.9). As $K > 0$, the slope is positive in these cases. In those cases where we have an inner solution as given in Theorem 2.3, we see the expected effort substitution as the expected utility of customer care increases with portfolio size (as the amount of commission at stake due to potential customer-churn increases).
In Figure 2.2(b), we clearly see the linear dependency between effort and the new business commission rate. As $\phi_N = 3.1$ ($\phi_P = 1.4$), we see from Theorem 2.4that the slope of the selling (customer care) effort has to be positive (negative). Again, as expected, the level of effort in the 2-period case is higher than for 1-period. The marginal effect of an increase in new business commission rate, however, is quite similar between the two models.[12]
Figure 2.2(c) describes the influence of the recurring commission rate on the agent's effort. The 1-period case shows the behavior as described in Hypothesis 2.3. In the 2-period model, however, we observe a positive relation between α_P and the selling effort. This is contrary to the hypothesis derived from the 1-period model. Nevertheless, this result is probably more in line with the rational behavior one might expect: the higher the

[12] Note that in the 1-period case, we observe the scenario of opposed boundary-hitting described above. As already pointed out, I set the optimal values to be zero and one, although there might be two different optimum values which oscillate closely around zero and one

utility of (the future) portfolio (due to an increase of the recurring commission rate), the more incentive the agent has to exert effort on selling today in order to increase the customer base, as it will pay-off later through the subsequent recurring commissions. Whether, and how strongly, the selling effort will increase (together with the effort spend on customer care) clearly depends on the level of cost substitution between the two tasks. For high values of s, we would expect a negative relation while for low values of s, the relation should be positive.[13]

To summarize, as all other results are quite robust to changes in the parametrization, we conclude that the hypotheses 2.1-2.3 also hold for the 2-period case with the exception of the influence of the recurring commission rate. For the relation between the recurring commission rate and the selling effort, we can make no clear predictions due to the strong dependency of the effect direction on the parametrization of the model.

I am aware that both the time allocation and the compensation of an agent are affected by many other external factors such as personal preferences and ability which I do not cover in the model. I restrict myself to quantitative analyses on the performance and compensation levels based on the agents' time split, age and tenure. Thus, I do not draw on the behavioral or managerial literature on sales-force management for the hypotheses (in line with Coughlan & Narasimhan (1992)). This approach has been chosen in other works, e.g., in Mohnen & Schmidtlein (2008) where behavioral aspects such as altruistic behavior or fairness are excluded in order to simplify the model. Nevertheless, some works found certain evidence for the influence of social incentives and personal preferences (see Brüggen & Moers (2007), Bonner & Sprinkle (2002), Sprinkle (2000)).

In the next section, I will describe the data-set and test the four hypotheses using the given sample.

[13] This intuition is also substantiated by using an appropriate parametrization of the simulated data (not shown here)

2.3 Empirical Results

2.3.1 Data Description

I use a database containing performance and compensation data as well as additional, survey-based personal information at the agent level for the year 2005.[14] The data was collected from three German insurance companies. As the data does not contain explicit information on the new business and recurring commission rates specified within the contract, I calculate the corresponding commission rate for each agent by dividing the recurring (new business) commissions by the portfolio (new business production) size.

I exclude observations with an unreasonably high or low commission rate (i.e., all those with a commission rate below 0% or above 40%). Furthermore, I only consider full-time agents, i.e., agents who work more than 20 hours per week, which leaves us with a total of 1,504 observations.

To determine how the agent splits the time between customer care activities, selling and administrative tasks, I use a question from the survey. The agent was asked to distribute his time over eight activities such that the total is 100%. To simplify the analysis, I clustered those eight activities into the three categories ″selling″, ″customer care″ and ″administration″ as shown in Table 2.2.[15] Furthermore, the agent was asked to provide the average number of working hours per week. From this information, I derived the number of hours spent on each task, referred to as ″effort″ in this paper.

An important caveat of the study is that the time split and the working hours were not asked for individual products. Therefore, I assume that

14 In addition, I also use data on new business and portfolio from 2004 as control variables

15 See also Table 2.8 for a regression with all tasks. Especially the high correlation of 0.29 between claims and customer advisory indicates that it seems to be reasonable to combine both tasks. Also, anecdotic evidence suggests that good claims-handling is often perceived as a strong retention reason for the customer

Table 2.2: Definition of selling, customer care and administrative tasks

Selling	Customer care	Administration
• Scheduling and preparation of appointments • Appointments (incl. travel time) • Tender preparation	• Advice, customer care • Claims management	• Trainings, coaching, organization, leadership • Office and administrative tasks

the effort is evenly distributed between the products offered.
Table 2.3 gives a basic description of the key variables used in this work. As outlined above, the most frequently used performance measures in the insurance industry are new business and portfolio size. Looking at the average time split and the split of the commission per agent, we find that almost 80% of the total commission comes from the portfolio (i.e., recurring commission) with only 20% of the time being spent on customer care. On the other hand, with 60% of the time spent on selling, only 20% of the total commissions are generated for auto policies. This indicates that the recurring commissions are almost treated as a ”fixed salary” that needs minimal if any attention from the agent.
The new business commission rate is quite high, with a mean of 14.3% and a standard deviation of 6.7. The recurring commission rate on the other hand is much lower: 7.3% on average, with a standard deviation of 2.6, is paid to the agents.[16] So, although the incentive to focus on new business is clearly visible, the majority of the money is still earned via the portfolio as seen above. Means reveal very little about potential causal effects between the level of the commission rate and the production or the time spent on a specific task, so I will use a more direct approach to investigate this issue.
Table 2.4 presents some means of the key variables as in Table 2.3 but contains the data for only two groups. One group contains those agents that

16 These values are quite customary in this particular market (see, e.g., Beenken (2003)) with the new business commission rate being slightly above-average

Table 2.3: Mean and standard deviation of key variables (N=1,504)

Variable	**Mean**	**(Std. Dev.)**
Hrs. selling	31.6	(9.0)
Hrs. cust. care	9.4	(5.4)
Hrs. admin	10.0	(6.1)
New business ('000)	13.6	(13.5)
Portfolio ('000)	74.5	(61.0)
Last periods new bus. ('000)	15.2	(14.9)
Last periods portf. ('000)	77.5	(62.6)
New business commission	1,701.2	(1,428.3)
Recurring commission	5,701.2	(5,097.2)
New bus. commission rate	14.3	(6.7)
Rec. commission rate	7.3	(2.6)
Age	44.1	(9.6)
Tenure	11.3	(8.6)
No. employees	1.4	(0.9)

spend an extraordinarily large amount of time selling. The other group has those agents that similarly focus instead on customer care. By "extraordinarily", I mean that the time spent on selling or customer care is above the mean plus one standard deviation. These means are, therefore, quite instructive in helping identify some basic features of multi-tasking, which we investigate in more detail below. We find that agents focusing mainly on customer care generate new business worth EUR 20,300 whilst those that focus on selling get only EUR 12,200. One reason for this surprising result may be the difference in tenure between the two groups: The customer care focused agents have a mean tenure of 14 years compared to 9 years for those that spend most time selling. Thus, one aspect of the difference in performance may be a simple experience-driven effect that leads to more efficient and effective selling practice in the customer care group. Furthermore, due to the lower tenure of the first group, these are probably mainly agents that have recently started and are therefore still in the process of building-up their customer base. Thus, they naturally have to focus on selling as there are only a few existing customers need their attention. A similar result was also found by Beenken (2003), who states

Table 2.4: Summary of key variables for agents specialized on selling (N=235) and customer care (N=249)

	Selling		Customer care	
Variable	**Mean**	**(SD)**	**Mean**	**(SD)**
Hrs. selling	46.1	(5.3)	28.5	(7.8)
Hrs. cust. care	7.7	(4.8)	18.6	(4.3)
Hrs. admin	7.6	(5.4)	9.8	(5.4)
New business ('000)	12.2	(11.2)	20.3	(21.0)
Portfolio ('000)	61.2	(51.2)	110.7	(83.9)
Last periods new bus. ('000)	14.5	(16.0)	21.2	(19.6)
Last periods portf. ('000)	65.4	(59.4)	111.6	(78.8)
New bus. com.	1,513.8	(1,323.2)	2,388.2	(1,917.8)
Rec. com.	4,529.2	(4,262.6)	8,544.3	(6,623.1)
New bus. com. rate	14.2	(7.1)	14.1	(6.4)
Rec. com. rate	7.0	(3.5)	7.5	(2.1)
Age	43.7	(10.2)	45.5	(8.8)
Tenure	9.1	(7.6)	13.5	(8.3)
No. employees	1.5	(0.9)	1.6	(0.9)

that agents with 500 or more customers are forced to work mainly on customer care.

Nevertheless, we do see a slightly higher recurring commission rate for the group that is more customer care oriented, therefore this could also be a driver that enforces a retention-based approach.

2.3.2 Effect of Effort Allocation on Performance

With these first indications in mind, I now run an OLS regression[17] to test hypotheses 2.1 and 2.2 from Section 2.2. Besides the main explanatory variables used in the model, I also control for age and tenure to account for the potential experience-driven effects just mentioned. Furthermore, I include the number of employees and company effects and use the log-transformed values for new business and portfolio size for an easier interpretation. The results of the regression are shown in Table 2.5.

17 I always use robust standard errors in this work

Table 2.5: Influence of effort allocation on (log) new business production and portfolio development

	New bus.	New bus.	Portf	Portf.
Hrs cust. care	0.0371***	0.0114***	0.0416***	0.00725***
	(7.41)	(3.07)	(7.97)	(2.71)
Hrs selling	0.000413	0.000635	-0.00543*	-0.00247*
	(0.14)	(0.29)	(-1.77)	(-1.65)
Hrs admin	0.0239***	0.0138***	0.0251***	0.00914***
	(5.63)	(4.09)	(6.21)	(4.22)
Last periods new bus. ('000)		0.0190***		0.00375***
		(9.55)		(3.16)
Last periods portf. ('000)		0.00484***		0.00876***
		(10.18)		(28.66)
Age		-0.0100***		-0.000498
		(-4.48)		(-0.30)
Tenure		0.00337		0.00831***
		(1.23)		(4.51)
No. employees		-0.132***		-0.182***
		(-5.08)		(-8.45)
Company effect	No	Yes	No	Yes
Observations	1504	1504	1504	1504
Adjusted R^2	0.062	0.501	0.078	0.758

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Constant not shown

The first two columns contain the regression results with new business, and the third and fourth columns show portfolio as the dependent variable. We see a positive relation both for customer care and selling time with new business. This relation gets weaker as we add more control variables, but is still maintained (with the coefficient for selling time being small in magnitude and statistical significance). Similarly, there is also a strong positive relation between customer care time and the size of the portfolio. An increase in the weekly time spent on customer care by one hour corresponds to a portfolio increase of approximately 0.7%. For selling, we see a negative relation of approximately -0.3%.

Overall, we find some evidence for both the first and second hypothesis, although the support of the relation between selling time and new business is small in magnitude and significance.

Regarding the influence of the control variables, we find a strong positive relationship between the last period's portfolio and the new business production of approximately 5% which might hint at some word-of-mouth effects as discussed in Section 2.2. The negative effect from age might indicate the influence of fatigue or energy levels that are too low for a sales-job, while the strong negative coefficient of the number of employees clearly stems from some commission-sharing agreements with sub-agents.

Furthermore, we also see that the time spent on administration has a positive, statistically significant effect. One reason for this somewhat surprising result may be that it also contains some effects from more managerial tasks that go along with larger agencies, which we do not fully capture via the tenure variable.

2.3.3 Effect of Incentives on Effort Allocation

We will now turn to the third and last hypothesis: the influencing factors of the agent's time allocation. Table 2.6 summarizes the OLS regression results with the time allocated to customer care and selling, as well as the total working time as dependent variables. We also included squared

Table 2.6: Influence of commission rates and last periods portfolio on the agent's effort allocation

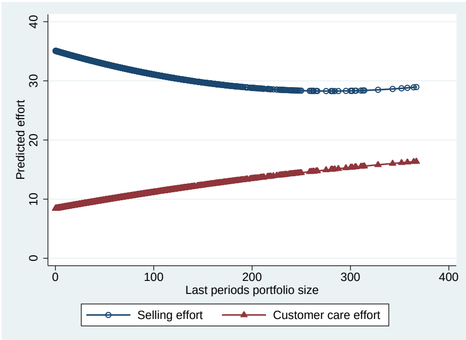
	Hrs selling	Hrs cust. care	Total hrs
New bus. com. rate	0.255**	-0.0169	-0.157
	(2.45)	(-0.23)	(-0.94)
sq(New bus. com. rate)	-0.00587**	-0.000506	0.00370
	(-2.06)	(-0.26)	(0.80)
Rec. com. rate	-0.238	0.248**	-0.384
	(-1.61)	(2.37)	(-1.52)
sq(Rec. com. rate)	0.0129***	-0.0113***	0.00768
	(2.62)	(-3.31)	(0.67)
Total hrs	0.620***	0.183***	
	(31.53)	(12.00)	
Last periods new bus. ('000)	-0.0441	-0.0126	0.0804
	(-1.33)	(-0.47)	(1.62)
sq(Last periods new bus.)	0.000761**	-0.0000292	-0.000464
	(2.32)	(-0.09)	(-1.09)
Last periods portf. ('000)	-0.0488***	0.0296***	0.0195
	(-4.83)	(3.55)	(1.29)
sq(Last periods portf.)	0.0000875***	-0.0000217	-0.00000472
	(2.87)	(-0.77)	(-0.11)
Age	0.00296	-0.0156	0.0824***
	(0.14)	(-1.04)	(2.63)
Tenure	-0.130***	0.0432**	-0.0398
	(-5.07)	(2.22)	(-1.03)
No. employees	-1.139***	0.423**	1.482***
	(-4.78)	(2.49)	(4.35)
Constant	32.17***	10.50***	48.97***
	(39.36)	(17.40)	(42.91)
Observations	1504	1504	1504
Adjusted R^2	0.474	0.215	0.040

t statistics in parentheses

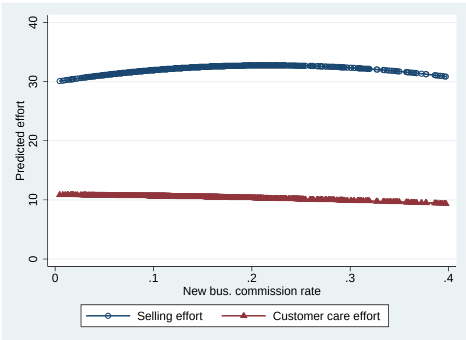
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Company-effects included

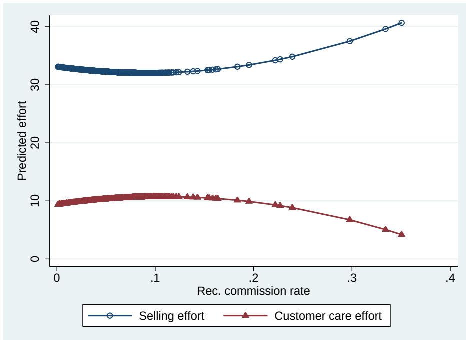
terms to be in line with the model, so interpreting the coefficients is quite tedious. Therefore, I interpret only the qualitative results based on the Table and discuss the details based on Figure 2.3, which allows for an easier comparison with the model. Starting with the first column of Table 2.6, we



(a) Estimated portfolio variation



(b) Estimated new bus. com. rate variation



(c) Estimated rec. com. rate variation

Figure 2.3: Predicted effort levels based on regression results from field-data

find a positive (negative) relation between the new business (recurring) commission rate and the time spent on selling. Similarly, we have the same but inverted effect for customer care time, although the coefficients of the new business commission rate are statistically not significant. The third column shows that both commission rates have a negative relationship with the total number of working hours. Even though the effect is statistically not significant, this might be an indicator of a reference-point dependent preference of the agent (see Fehr & Goette (2007)).

Interestingly, the number of employees in an agency has a very significant effect on the time allocation. This may be explained by the fact that agents with a large customer base employ sub-agents who carry out the time-consuming customer-acquisition work, leaving the senior agents to focus on the relationships with his customer base.
These first impressions are backed up by Figure 2.3. Here, I have used the corresponding linear and squared coefficients of Table 2.6 to predict the effort allocation of each agent (with each dot representing one observation). Comparing these graphs with those in Figure 2.2, we see that in the case of portfolio and new business commission rate variations (Figures 2.2(a) and 2.3(a) as well as 2.2(c) and 2.3(c)), the shapes are qualitatively the same. In the case of the recurring commission rate, however, the slope of the curves resembles the 1-period model for the first part (up to approx $\alpha_P = 10\%$) but then, the effect is inverted, i.e., the amount of time spent on selling increases, while the customer care time decreases. As we already saw in Section 2.2, the direction of the effect on selling was quite sensitive to the chosen specification. This could be one reason for the observed U-shape. For the customer care effort, the decreasing slope may again indicate some degree of the reference-point dependency. Due to the limited number of observations on the right-hand side of the curve, however, the unexpected slope might also be an artifact driven by outliers.
To summarize, I found clear support of the predicted influence of the last period's portfolio and the new business commission rate as outlined in hypothesis 2.3. Regarding the relation between recurring commission rate and effort allocation, I find some evidence for the predictions derived from the 1-period model for small to medium values of α_P. For large recurring commission values, the findings do not support this particular part of hypothesis 2.3.

2.3.4 Robustness

I will now discuss the robustness of the results under different specifications. First of all, a test reveals that we can clearly reject the hypothesis of homoscedastic error terms. I therefore use robust standard errors throughout this work. The use of log-transformed new business and portfolio values should further reduce this problem.

As already pointed out in Section 2.3.1, I had to use an estimation of the commission rates to perform the analyses. Running a correlation analysis, we see a high correlation of 0.82 /0.95) for new business production compared to new business commissions (portfolio and recurring commissions). The lower correlation in the former may be due to the fact that the new business data is net of churn, i.e., in case of mid-term cancelations, the new business figures are already reduced by this amount. The new business commission, though, is not necessarily corrected for churn. Thus, the commission rates I calculate may not fully represent the true commission rates as they were agreed in the agent's contract. Nonetheless, the high correlation values indicate that the approximation is reasonable.

Another critical question is the validity of the task-clustering as shown in Table 2.2. Running a correlation analysis supports this clustering. Furthermore, performing the same analyses with the full set of tasks gives comparable results to the clustered case (see Table 2.8).

One could question the overall relationship between incentives and performance (see Camerer et al. (1997) and Section 2.1 for more details). In fact, running a regression of new business production and portfolio size on the commission rates, we also get mixed results as can be seen in Table 2.7. In a simple specification, the relation between both new business and recurring commission rate with new business production and portfolio is positive (see columns (1) and (3)). Adding further control variables, however, leads to a negative relation of both commission rates with new business (whereas the relation with the portfolio remains positive). This surprising result should probably be attributed to the approximation of the new business commission rate as discussed above. Specifically, as there may be cases in which the new business figures are corrected for churn whereas the commissions paid are not, we could have a bias towards higher commission rates. This would, in turn, correspond to comparably lower new business values, thus explaining the result in Table 2.7. This should be kept in mind when interpreting the results regarding new business.

Finally, the time-allocation I use here is not product-specific. Thus, to understand better the effect of the commission rates on the effort direction, I included also the property & casuality commission rates as independent variables. The results (see Table 2.9) are almost the same as in Table 2.6 so that we can suppose the effects we measure are not just artifacts from other commission rates that were omitted.

Overall, we find that the results presented in the previous section are rather robust under different specifications.

2.4 Discussion and Conclusion

In this work, I analyzed the relation between incentives, effort allocation and performance using the example of insurance tied agents.
First, I set up the mathematical model and derived three hypotheses regarding the expected effects of variations in the effort allocation and incentives. Second, I used a data-set of German insurance agents to test the hypotheses.
I found that time spent on customer care has a positive effect both on the auto portfolio and new business production. Surprisingly, though, I did not find a statistically significant effect of the selling-time on new business. Regarding the influence of the new business commission rate on the agent's time allocation, the results are in line with the model, i.e., there should be a positive (negative) relation with the selling (customer care) time. In the case of the recurring commission rate, however, I obtained mixed results, suggesting that for low to medium rates, the effect is in line with the predictions (i.e., positive on customer care, negative on selling) whereas for high rates, the effect is inverted.
Finally, regarding the influence of the last period's portfolio on the effort allocation, I again find support for the hypothesis that it is positive for customer care and negative for selling.
To further refine the results, a next step would be to test the results with product-specific effort-levels. As I use data from general insurance companies, this data was not available. Therefore, future research could focus on, e.g., monoline insurance companies to avoid cross-product interdependencies.
The main contribution of this work is two-fold. Firstly, by developing a 2-period model that accounts for portfolio effects, I present a theoretical framework that captures many of the influencing factors in the context of insurance tied agents. The limitation to two periods might actually be a more appropriate approach than the general multi-period setting (compare Frederick et al. (2002)). The closed-form solution presented may therefore be used as a starting-point for further research regarding

the optimal time-allocation also from the principal's point of view (which I excluded in this work as I purely focused on the agent). Secondly, by using a large data-set, I added another piece of empirical evidence to the discussion regarding the influence of incentives. I was able to show that there is indeed a relation between incentives, effort allocation and performance, indicating that a thorough choice of an appropriate incentive level is crucial to steer the sales force in the desired direction.

2.5 Appendix to Chapter 2

Table 2.7: Direct influence of commission rates on (log) new business and portfolio

	New bus.	New bus.	Portf.	Portf.
New bus. com. rate	0.00971	-0.0324**	0.0990***	0.0419***
	(0.53)	(-2.19)	(5.09)	(3.21)
sq(New bus. com. rate)	-0.00142***	-0.000334	-0.00257***	-0.00115***
	(-3.17)	(-0.91)	(-5.05)	(-3.43)
Rec. com. rate	0.102**	-0.0357	0.286***	0.0966***
	(2.38)	(-1.13)	(5.88)	(3.40)
sq(Rec. com. rate)	-0.00564**	-0.000576	-0.0121***	-0.00530***
	(-2.18)	(-0.39)	(-3.89)	(-3.69)
Age		-0.00698***		-0.00314
		(-2.69)		(-1.37)
Tenure		0.0275***		0.0333***
		(8.77)		(11.94)
No. employees		-0.186***		-0.231***
		(-6.03)		(-9.06)
Company effect	No	Yes	No	Yes
Observations	1504	1504	1504	1504
Adjusted R^2	0.112	0.319	0.194	0.509

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Constant not shown

Table 2.8: Influence of effort allocation on (log) portfolio and new business using the detailed tasks for customer care

	New bus.	New bus.	Portf.	Portf.
Hrs. preparation	-0.0323***	-0.0182**	-0.0355***	-0.0112**
	(-3.09)	(-2.56)	(-3.44)	(-2.22)
Hrs. appointment	0.00372	0.00217	-0.00112	-0.000861
	(1.03)	(0.82)	(-0.30)	(-0.46)
Hrs. tender prep.	-0.00487	0.00197	-0.0145	-0.00405
	(-0.48)	(0.29)	(-1.31)	(-0.77)
Hrs. service	0.0352***	0.00869	0.0429***	0.00794**
	(4.73)	(1.62)	(5.50)	(2.14)
Hrs. claims	0.0565***	0.0246**	0.0567***	0.0133
	(3.56)	(2.31)	(3.10)	(1.57)
Hrs. training	-0.000715	-0.00335	0.0159	-0.00324
	(-0.04)	(-0.27)	(0.84)	(-0.31)
Hrs. office tasks	0.0251***	0.0125***	0.0292***	0.00912***
	(5.04)	(3.14)	(6.04)	(3.60)
Last periods new bus. ('000)		0.0201***		0.00442***
		(9.32)		(3.27)
Last periods portf. ('000)		0.00466***		0.00873***
		(8.90)		(25.52)
Age		-0.00963***		-0.000511
		(-4.10)		(-0.29)
Tenure		0.00295		0.00920***
		(0.95)		(4.21)
No. employees		-0.160***		-0.198***
		(-5.49)		(-8.23)
Company effect	No	Yes	No	Yes
Observations	1316	1316	1316	1316
Adjusted R^2	0.072	0.506	0.088	0.757

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Constant not shown

Table 2.9: Influence of commission rates and last periods portfolio on the agent's effort allocation, including property and casuality commission rates

	Hrs selling	Hrs cust. care	Total hrs
New bus. com. rate	0.237**	-0.0108	-0.155
	(2.25)	(-0.14)	(-0.93)
sq(New bus. com. rate)	-0.00558*	-0.000639	0.00365
	(-1.95)	(-0.32)	(0.78)
Rec. com. rate	-0.108	0.230**	-0.294
	(-0.69)	(2.11)	(-1.15)
sq(Rec. com. rate)	0.00995*	-0.0107***	0.00644
	(1.96)	(-3.19)	(0.57)
dmN_ratio_S	0.000135	0.000315	-0.00639**
	(0.07)	(0.17)	(-2.31)
dmN_ratio_S2	1.52e-08	-2.40e-11	-0.000000480***
	(0.11)	(-0.00)	(-2.65)
dmB_ratio_S	-0.411***	0.0807	-0.246
	(-2.96)	(0.78)	(-1.24)
dmB_ratio_S2	0.00555***	-0.00116	0.00370
	(2.74)	(-0.79)	(1.25)
Total hrs	0.618***	0.183***	
	(31.23)	(11.86)	
Last periods new bus. ('000)	-0.0408	-0.0142	0.0758
	(-1.22)	(-0.53)	(1.52)
sq(Last periods new bus.)	0.000738**	-0.0000155	-0.000430
	(2.22)	(-0.05)	(-1.02)
Last periods portf. ('000)	-0.0440***	0.0287***	0.0208
	(-4.34)	(3.41)	(1.37)
sq(Last periods portf.)	0.0000775**	-0.0000195	-0.00000559
	(2.55)	(-0.69)	(-0.13)
Age	0.00748	-0.0160	0.0850***
	(0.36)	(-1.06)	(2.73)
Tenure	-0.115***	0.0388*	-0.0280
	(-4.37)	(1.93)	(-0.71)
No. employees	-1.068***	0.442**	1.580***
	(-4.31)	(2.52)	(4.56)
Constant	32.27***	10.48***	48.37***
	(37.46)	(16.55)	(40.84)
Observations	1501	1501	1501
Adjusted R^2	0.475	0.214	0.042

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Company-effects included

Chapter 3

The Effect of Tenure, Industry- and General-Experience on Compensation

3.1 Introduction

Many studies have tried to understand and explain the effect of tenure, industry-, and general labor-market experience on the wage development of employees. One of the best-known theories regarding the relation between experience and wage is the human capital theory. This states that additional years of work experience increase the general human capital, which makes the employee more valuable, and thus lead to higher wages in all jobs. This implies that employees' performance improves over time. Unfortunately, as past empirical research has shown, the link between pay and performance is rather weak. The main advantage of this work compared to previous research is that it uses a data-set containing information on German insurance agents whose compensation is mainly based on commission.[18] Thus, I can circumvent the issue of both a clear link between pay and performance and the required voluntariness of the effort exerted (see Goette et al. (2004)). In this way, I also avoid disturbances of the experience-performance curve that can arise if earnings are measured instead (e.g., due to cost of training associated with the build-up of skills within a firm, see Hashimoto (1981)). Furthermore, as the works by Parent (2009) and Lemieux et al. (2009) show, the prospect of ”commission pay” enhances the quality of the worker-firm match, i.e., it induces a certain selection effect that pulls more productive workers into these kinds of jobs. As a consequence, we can at least assume that the variation in worker-specific heterogeneity is smaller compared to a set of employees with very different kinds of jobs.

I will now give a brief overview of the literature concerning experience and pay. Marshall & Zarkin (1987), Altonji & Shakotko (1987), Abraham & Farber (1987) and Williams (1991) were the first to question the human capital theory. They argued that the effect of experience on the current job is biased because other relevant variables are omitted in the OLS regressions used. They claim that the tenure variable is not exogenous but rather correlated with the error term in the regression. The rationale behind this is that the error term contains the effects of ability and other personal preferences of the employee that can not be controlled for. By introducing the concept of a match variable to account for the goodness-of-fit between the employee and his current job, they capture all the potential effects that could be related with tenure in one construct. By assuming that tenure is correlated with this matching variable (which seems quite reasonable, as employees that match well with their job also tend to stay longer with their employer, thus leading to higher tenure), it is obvious that a simple OLS regression would deliver a biased estimate of the tenure-variable as it would also include those effects from the matching variable.

Altonji & Shakotko (1987) show that this bias can be quite substantial and they provide an instrumental-variable (IV) approach to circumvent these

[18] As shown by MacLeod & Parent (1999), this payment method is characteristic for basically all sales workers (they analyzed NLSY data from 1988-90)

issues (see Section 3.2 for further details). Based on their work, others picked-up on this issue and a variety of extensions were developed (e.g., Lillard (1999) by modeling the wage dynamics within and between jobs, and testing for exogeneity of job number and tenure in the wage equation, or Parent (2000) by distinguishing between job- and industry-match).
Topel (1991) suggested a different, two-stage approach to reduce the bias from endogeneity of the tenure variable, and finds a rather large return of 25% for 10 years of tenure with a firm. Reassessments in recent years, however, provided evidence that the instrumental variable approach gives more reliable results (see, e.g., Altonji & Williams (2005)).
The question of the influence of job- and industry-match has been widely discussed. Ruhm (1990) found that the differences in match-quality appear to be less important, but the more recent publications by Kim (1998), Parent (2000), Dustmann & Meghir (2005) and Woodcock (2008) all emphasized the importance of match-specific effects on the wage determination of the employee, so this concept is now well established.
Of course, other influencing factors have also been discussed. In Topel (1991), Topel & Ward (1992) and Dustmann & Pereira (2005), the importance of job mobility on wage growth is discussed, suggesting that many job changes are due to the prospect of receiving higher wages with the new employer. Another reason for the link between tenure and wage growth may be due to firm-specific human capital that is built up by the employer through on-the-job-training. The paper by Barth (1997), however, shows no support for this theory as they find that higher levels of firm specific training requirements are associated with less steep wage-tenure profiles. Another factor is analyzed in the work of Bronars & Famulari (1997) who find that education, experience and tenure are highly correlated within a company. They conclude that employees at high wage-growth firms tend to have longer tenure.
The majority of the literature has focused on inter-industry effects, i.e., it has analyzed data-sets that captured all industries of one or multiple countries. Examples are Abraham & Farber (1987) (PSID[19]: US), Kletzer

[19] Panel Study of Income Dynamics

(1989) (CPS[20]: US), Ruhm (1990) (PSID: US), Topel (1991) (PSID: US), Topel & Ward (1992) (LEED[21]: US), Neal (1995) (DWS[22]: US), Kletzer (1996) (CPS: US), Margolis (1996) (DAS[23]: France), Kim (1998) (DWS: US), Parent (2000) (NLSY[24], PSID: US), Burda & Mertens (2001) (GSOEP[25]: Germany), Haynes et al. (2002) (NESPD[26]: UK), Huang (2003) (TWFS[27]: Taiwan), Chuang & Lee (2004) (MPUS[28]: Taiwan), Munasinghe & Sigman (2004) (NLSY: US), Dustmann & Pereira (2005) (GSOEP: Germany, BHPS[29]: UK).

In these studies, information on (forced) job-displacement was usually used to estimate an effect of past (industry-specific) experience on the future wage either within the same or a different industry.[30] Neal (1995) and Parent (2000) report that the industry-specific experience plays an important role in determining the employee's wage. On the other hand, Kletzer (1996) finds that the effect depends on the industry under consideration. In Haynes et al. (2002), and more recently Kambourov & Manovskii (2009), occupational-specific experience is reported to be more important than industry-specific experience. Gibbons & Waldman (2006) even proposed that a main driver of performance is task-specific human capital. Similarly, the recent work by Poletaev & Robinson (2008) suggests that human capital is not narrowly specific to either industries or occupations, but rather to a limited number of basic skills.[31]

As the differences between industry-, occupation-, and task-specific human capital might be very sensitive to changes in terminology and specification, this study focuses on one task/occupation (the tied sales agent)

20 Current Population Survey
21 Longitudinal Employee-Employer Data
22 Displaced Worker Survey
23 Déclaration Annuelles de Salaire
24 National Longitudinal Survey
25 German Socio-Economic Panel
26 New Earnings Survey Panel Dataset
27 Taiwan Women and Family Survey
28 Manpower Utilization Surveys
29 British Household Panel Survey
30 Oyer (2004) discusses potential issues regarding the reliability of reported pre-displacement wages in the DWS
31 A related approach was proposed even earlier by Lazear (2003) who suggests, that the importance of prior experience varies with how firms weight certain skills

in one specific industry (German insurance).
Many of the empirical studies referenced here were based on large panels (e.g., the PSID). As outlined by Brown & Light (1992), the effect from job changes in particular seems to be very sensitive to the specification of the analysis. One of the general limitations when using this or comparable data sets is that they cover a broad range of very different jobs and industries. This of course helps to uncover the overarching mechanics of experience and wage, but provides no conclusions for individual industries or job profiles.
As already pointed out, the results from the more overarching inter-industry analyses (see Kletzer (1996)) showed that the observed effects depend heavily on the industry being considered. Surprisingly, though, very few works have tried to narrow the scope of analysis to a specific industry or sector (see also Baker et al. (1994*a*)).
One of the few job-specific analyses stems from Coughlan & Narasimhan (1992). Here, only employees identified as part of the sales force were used to investigate compensation plans. The study covers 286 firms across 39 industries, but narrows the focus of the research to a specific job profile. They find that a one-year increase in the average number of years of service in the sales force is associated with a USD 300 pay increase when controlling for industry pay. In other specifications, however, this tenure effect becomes statistically insignificant.
Another, even more specific analysis was presented by Bratsberg et al. (2003) who investigated the effect of seniority on the pay of academic researchers. They found a negative relationship and report that the effect is even stronger when controlling for match-quality. The work by Huckman & Pisano (2003), on the other hand, reports a positive effect between seniority and performance of surgeons in a hospital. No relation, though, is found between prior experience and performance.
The works by Medoff & Abraham (1980) and Medoff & Abraham (1981), based on three manufacturing companies, found that the increase in wage with seniority cannot be explained by an increase in productivity. Similarly, the more recent work by Flabbi & Ichino (2001) reproduced the re-

sults at a large Italian bank. Again, they find that the observed effect of seniority on wage is not reflected in a higher level of productivity (except at the lowest hierarchy-levels) and thus that the observed positive relation between seniority and wages must be due to other reasons (e.g., deferred incentives or insurance).

In the work by Baker et al. (1994*b*), the wage policy of a single firm[32] is analyzed over a period of 20 years. Again, they find no clear evidence for a single theory to explain the wage variation within and across hierarchy-levels in the firm. Overall, we see that there is a lack of industry-specific empirical evidence for the relation between experience and wage.

With this work, I will contribute to the research on the field of pay and experience in three different ways.

First, by using a data-set containing information on insurance agents that are primarily compensated via commissions, I am in the rare position to test the pure economic effects in the spirit of Goette et al. (2004) (see also Chapter 1). Furthermore, by focusing on one industry, I add another case-example to the scarce literature of industry-specific wage and employer-employee matched analysis (see Lazear & Oyer (2004)).

Second, I contribute to the literature not only by modeling an averaged influence of the two distinct experience measures but also by providing the effects for discrete levels of prior experience, revealing a more accurate shape compared to studies where only quadratic/cubic representations are given. In addition, I distinguish different forms of compensation of the agent (i.e., new business and recurring commissions, bonification and salary/subsidies) and therefore provide further insights into the differences of compensation components.

Third, I distinguish the effects from prior (non-)agent work experience for different tenure levels. As we have seen, this approach leads to interesting results, and is in line with the intuitive notion that skills gained on previous jobs are especially beneficial at the start of a new job, with the effect wearing off some years into the new role.

Quite naturally, the insurance company has an interest to motivate the

[32] The industry was not disclosed for confidentiality purposes

agent both to produce new business and to exert a sufficient effort in customer care in order to increase the likelihood of retaining customers. Therefore, one of the very specific questions in this industry is whether the agents can increase their new business production (and, therefore, new business commissions) while gaining additional experience (see Ingraham (1973)). Thus, when analyzing the effect of tenure and experience on agents' compensation, both the total compensation should be considered as well as the part generated by new customers. Ingraham (1973) finds a mixed answer to this question by stating that production seems to plateau after the third calendar year under contract. A similar finding is also presented by Dorfman (1976) who states that an agent should be able to increase the amount of new business as the agent's skill, knowledge, reputation, average policy-size and referred leads increases. The rate of growth will decrease as the agent reaches the limits of effort he is willing to make.

Finally, also the recent publication by Vogler (2009) provides some evidence that the number of years worked as insurance agent has a positive effect on sales success. In contrast to my work, he operationalizes work experience only using different job types but not the actual length of work experience. In addition, he summarizes all agent-related work experience, without distinguishing between tenure and industry-experience. Therefore, even though based on the same data-set, the analysis presented here goes beyond the scope of his publication.

The remainder of this paper is structured as follows. In the next section, I develop the model and discuss the application of the IV estimator. In Section 3.3, I briefly describe the data-set used to test the experience effects before presenting the outcomes of the IV estimation and discussing the robustness of the results. In the last section, I summarize the findings and discuss their implications.

3.2 The Model

Many different models to describe the relationship between wage and experience have been developed and proposed in the past. I will base this work on the model suggested by Parent (2000) in which he introduces a new variable called industry-specific experience. This variable measures the amount of time a person has spent in the industry in which he is currently employed. He concludes that industry-specific skills play a larger role than firm-specific skills in the wage growth process. One aspect, however, that is not part of his study, is whether the measured effect really is an industry- or rather an occupation-effect. This is because the two are usually closely related. As I focus only on experience that has been gathered as an insurance agent, I can ensure that I measure only the effect from both the same industry and occupation. This makes the interpretation of the results even more clear-cut.
As a starting point, I adopt the model by Parent (2000) and consider the following log wage equation:[33]

$$\begin{aligned} \ln(W_{it}) = &\beta_0 OJ_{it} + \beta_1 T_{it} + \beta_2 Exp_{it} + \beta_3 Expind_{it} \\ &+ \alpha_i + \theta_i + \gamma_i + \epsilon_{it} \end{aligned} \tag{3.1}$$

where W_{it} represents the compensation of agent i in year t. T is tenure, $Expind$ is the experience of the agent collected when working as tied agent for a different insurance company and Exp is the general labor market experience excluding both the current job and any previous jobs as a tied agent. Furthermore, I include the dummy variable OJ_{it} (for old job) of 1 for agents with a tenure larger or equal to one (see Altonji & Shakotko (1987), Parent (2000)) to capture the particularly strong increase in compensation within the first year of employment. All other independent variables, including higher order terms of tenure and experience, portfolio, year and company effects will be included in the regression, but are

[33] As I consider only agents working in the insurance industry, I drop the job- and industry-indices compared to the work by Parent (2000)

omitted here for the ease of presentation.

In addition to the explanatory variables, I also include four different error terms. Besides the general error term ϵ_{it} that captures the unobserved heterogeneity, I separate α_i to capture the person-specific effects (e.g., ability), θ_i that corresponds to the job-match effects (i.e., how well the agent performs in this specific job-employer constellation) and γ_i which contains those effects that are related to the industry-match of the agent (i.e., how well the agent performs as insurance tied agent per se).

As already seen in Section 3.1, the concept of such a matching variable has been widely discussed. As pointed out by Lazear & Oyer (2007), the importance of the match-effects mainly arises from the heterogeneity of labor in the firm's production function. They conclude that matching the right firm to the right worker creates enormous economic value.[34]

One of the main reasons to split the error term in such a way is to identify those aspects that potentially correlate with the explanatory variables in the regression using equation (3.1). The problem arising from this potential endogeneity is best discussed by using the form

$$\alpha_i = a_1 T_{it} + a_2 Exp_{it} + a_3 Expind_{it} + \xi_{it}^{\alpha} \tag{3.2}$$

$$\theta_i = b_1 T_{it} + b_2 Exp_{it} + b_3 Expind_{it} + \xi_{it}^{\theta} \tag{3.3}$$

$$\gamma_i = c_1 T_{it} + c_2 Exp_{it} + c_3 Expind_{it} + \xi_{it}^{\gamma} \tag{3.4}$$

which says that both the job- and the industry-match effects can depend on tenure, general labor market experience and industry-specific experience.

When estimating equation (3.1) using OLS and considering the relationships described in equations (3.2)-(3.4), the estimator would produce results with $\beta_1^{OLS} = \beta_1 + a_1 + b_1 + c_1$, $\beta_2^{OLS} = \beta_2 + a_2 + b_2 + c_2$ and $\beta_3^{OLS} =$

34 The findings by Neal (1999) suggest, that employees use a two-stage approach to find their optimal job. They first look for their most suitable career (i.e., industry/occupation) and then for the best-matched employer. Similar findings are reported by Gathmann & Schönberg (2007). Regarding the second-stage of job search, Altonji & Paxson (1986) find that there is a match between the number of working hours the employee is willing to invested and the job chosen

$\beta_3 + a_3 + b_3 + c_3$ for the partial effects of the three different experience types. As pointed out in Dustmann & Pereira (2005), the sign of the bias can be assessed under certain constraints but is generally ambiguous. If the coefficients a_i, b_i or c_i are not zero (see Section 3.3.4 for a discussion of endogeneity tests and robustness) the most common solution is to use instrumental variables.

The basic idea of instrumental variables is to predict the value of the (potentially) endogenous explanatory variable with a set of instruments and use these predicted values as regressors in the original model (instead of the endogenous ones).

More precisely, if we have N observations and k explanatory variables, we define $\mathbf{X} \in \mathbb{R}^{N\times k}$ to be the matrix of all explanatory variables in equation (3.1) and $\mathbf{u} \in \mathbb{R}^{N\times 1}$ the vector of all error terms (where I lump-summed all four different error components into a single one for the ease of presentation), we can define a new matrix $\mathbf{Z} \in \mathbb{R}^{N\times k}$ in which the endogenous variable T_{it} is being replaced by an instrument z_{it}. There are two properties this instrument has to satisfy in order to derive consistent estimates. First, it must be highly correlated with the endogenous variable but must be uncorrelated with with the error term. If we have found such an instrument, we can write (see also Baum (2006)):

$$\begin{aligned}
&\mathbf{y} = \mathbf{X}\beta + \mathbf{u} \\
\Leftrightarrow\ &\mathbf{Z}'\mathbf{y} = \mathbf{Z}'\mathbf{X}\beta + \mathbf{Z}'\mathbf{u} \approx \mathbf{Z}'\mathbf{X}\hat{\beta}^{IV} \\
\Leftrightarrow\ &\hat{\beta}^{IV} = (\mathbf{Z}'\mathbf{X})^{-1}\mathbf{Z}'\mathbf{y}
\end{aligned}$$

where $\mathbf{Z}$ is unrelated to $\mathbf{u}$ (following from the assumption that $\mathbf{z}$ is uncorrelated with the error term and, as it substitutes the only endogenous variable, that the whole matrix is uncorrelated) and therefore $(\mathbf{Z}'\mathbf{u})/N \rightarrow 0$ as N becomes large.

The second required property of the instrument is a high correlation between instrument and endogenous variable. This ensures that the resulting estimate $\hat{\beta}_T^{IV}$ of the corresponding variable $\mathbf{T}$ has a small standard error. The asymptotic variance of $\hat{\beta}_T^{IV}$ can be calculated as $\sigma^2/(N\sigma_T^2\rho_{T,z}^2)$ with

$\sigma^2 = E(\mathbf{u}'\mathbf{u}|\mathbf{z})$, σ_T^2 the variance of $\mathbf{T}$ and $\rho_{T,z}^2$ the square of the correlation between $\mathbf{T}$ and $\mathbf{z}$ (see Wooldridge (2006)). From this, we see that weak correlation between the endogenous variable and its instrument leads to a high variance and thus a large standard error.

The most commonly used instrument for the case under consideration in this paper is the one proposed by Altonji & Shakotko (1987) and I will also adopt their approach here. I compute $\widetilde{T_{it}} = T_{it} - \overline{T_i}$, $\widetilde{(T_{it}^2)} = T_{it}^2 - \overline{T_i^2}$ and $\widetilde{OJ_{it}} = OJ_{it} - \overline{OJ_i}$ with $\overline{X_i}$ being the average of variable X of person i over the whole period consisting of H years. I then use $\widetilde{T_{it}}$, $\widetilde{(T_{it}^2)}$ and $\widetilde{OJ_{it}}$ together with the other explanatory variables as instrumental variables for T_{it}, T_{it}^2 and OJ_{it}. As the sum of each of these instruments is zero over the sample years and the individual-specific, the job and the industry error terms α_i, θ_i and γ_i are constant over all H years, we find that for each person i: $\sum_{t=1}^{H}(\alpha_i + \theta_i + \gamma_i)\widetilde{T_{it}} = (\alpha_i + \theta_i + \gamma_i)\sum_{t=1}^{H}\widetilde{T_{it}} = 0$, thus the instrument is orthogonal to these three errors by construction. In addition, by assumption, the instrument is also supposed to be uncorrelated with the remaining unobserved heterogeneity ϵ_{it}. Overall, we can conclude that the instrument is valid under the above assumptions.

With this methodology, we have taken care of the potential bias stemming from the endogeneity of the tenure variable and its higher order terms. Unfortunately, the problem with the unobserved matching variables still remains. In the past, this was usually solved by introducing appropriate instrumental variables (see, e.g., Parent (2000)). These approaches, though, all rely on the diversity of industries and past job-changes to derive the different instruments. As I focus on only one industry and one job, these methods would produce perfectly collinear instruments to the ones constructed above, and are therefore of no use.

Instead, I solve this problem by directly introducing a proxy variable for job- and industry-match, i.e., instead of equation (3.1), we estimate:

$$\begin{aligned}\ln(W_{it}) = &\beta_1 T_{it} + \beta_2 Exp_{it} + \beta_3 Expind_{it} \\ &+ \beta_4 Matchjob_i + \beta_5 Matchind_i + \alpha_i + \epsilon_{it}\end{aligned} \tag{3.5}$$

with the two new explanatory variables $Matchjob$ and $Matchind$ corresponding to the job- and industry-match-quality, respectively. Together with the IV-approach described above, we have now captured all the sources of potential bias as described in equations (3.2)-(3.4) and therefore, expect consistent estimates of the different experience effects.
With the design of the compensation system of tied agents in mind (as described in Chapter 1), we can already suppose that the effect on tenure in the data will be large and positive as the portfolio develops with tenure in a firm and thus also the (log) wage of the agent will increase accordingly. The question of interest in this study will therefore be mainly on the effect of the two different kinds of prior work experience (tied agent experience and non-tied agent experience) on the agent's wage. Furthermore, we will investigate if and how tenure influences the *rate* of increase, i.e., if the predictions by Ingraham (1973) and Dorfman (1976) that the increase will eventually plateau are correct.
Besides analyzing the overall effect of the experience, we will also investigate how far the potential (dis-)advantage of prior labor market experience of either type may change depending on the tenure of the agent. For this purpose, I will include interaction terms of tenure with (non-) tied agent work-experience. This important aspect is usually not analyzed (see, e.g., Parent (2000) who includes only the pure effects as explanatory variables), although it is very instructive in providing further insights into the influence of experience.

3.3 Empirical Results

3.3.1 Data Description

For this analysis, I use a subset of the original data-set containing compensation information for agents for the years 2003 to 2005. The data stems from six German insurance companies with a total of 6,890 observations over this period. I considered only those agents with a tenure below 40 years and total prior experience of less than or equal to 30 years.[35] As only those agents that were employed in 2005 are captured, the data-set is unbalanced and contains 2,838 agents in 2005, 2,314 in 2004 and 1,738 in 2003 (see also Tables 3.4 - 3.6). As data on the sub-categories of compensation was not available for all companies in all years, the actual number of observations may vary in those analyses where I looked into those sub-components. This is also the reason why the means presented in Table 3.1 do not perfectly add up. To control for company- and year-specific effects, I include corresponding indicator variables in this analysis.

A basic description of the key variables used in this analysis appears in Table 3.1. All wage-related numbers are measured as yearly income.[36] We see that the average total income is about EUR 53,000. Agents' main source of income is commission for new contracts and for customer retention. They earn approx. EUR 52,000 in commissions, 59% of which comes from new business commissions. Regarding bonification, we see an average of EUR 4,200, but we have to consider that this is the average over *all* agents whereas one can suppose that only some agents will achieve their full goals and therefore receive even higher bonification. Similarly, the amount of EUR 5,600 we observe as a mean of salary/subsidies may be higher for those agents that receive the payments with others receiving almost nothing. To account for differences in the way agents are subsidized in the first years, I include dummy variables for different levels of initial portfolio.[37]

The average tenure in the sample is 10.6 years with a prior experience as an insurance tied agent of 2.0 years. This is quite low compared to the mean

35 This restriction ensures that the sample-sizes in the analyzes where I introduce experience-clusters are not getting too small, as this would lead to extreme bias from outliers

36 This way, we avoid disturbances from intra-year-effects (e.g., due to deferred contracts to reach certain quotas) as described by Oyer (1998)

37 Instead of paying subsidies, some insurers provide the agent with a certain number of existing customers (e.g., the customer base from a retired agent), which results in recurring commissions serving as subsidies

of prior work experience *excluding* any tied agent-related work, which is 11.0 years on average. Furthermore, we see that 90% of the agents have worked at least one year with their current employer.

The corresponding figures for the each year can be found in the Appendix (see Tables 3.4 - 3.6). The higher levels of new business commissions in the years 2003 and 2004 have to be attributed mainly to the increased demand for life insurance products in these years due to a change in regulation by the German government.

The figures for prior experience as insurance agent, other prior work experience, initial portfolio and job- and industry match are derived from a questionnaire the agents voluntarily filled-in. The value for general labor market experience, though, was not explicitly asked for. Instead, I use a proxy to construct a numerical value (in years) for this variable. Depending on the highest degree of education of the agent (given from the questionnaire), I assume a fixed starting age into the labor market. The following choices were available with the corresponding assumed start-age given in parentheses: middle school (17), high school (20), apprenticeship (20), university degree (26). The total work-experience is thus simply the current age minus the labor-market start age. From this total work-experience, we can derive the non-agent experience by subtracting the current tenure and the agent experience.[38] From the assumed job-start age, it is also straight-forward to calculate the total years of education per agent which is approx. 13 years in the sample. In order to model the job- and industry-match variables as outlined in Section 3.2, I use two more items from the questionnaire. As a proxy for job-match, I use the answer to the question *"How satisfied are you overall with <Company name>?"*.[39] For industry-match, I use the answers to *"Would you recommend a friend or col-*

[38] In those cases where the resulting non-agent experience happened to be between -5 and 0, I assume that it is due to deviations from the job starting age and set the experience to zero. In the cases where the difference was below -5, I set the experience to be missing as the large difference implies that there is some potential mis-classification in the data

[39] translated from the German question *"Wie zufrieden sind Sie insgesamt mit <Firmenname>?"*

Table 3.1: Mean and standard deviation of key variables (2003-2005)

Variable	Mean	(Std. Dev.)	N
Total commission	53,062.4	(38,258.5)	6,890
Total new business commission	30,596.6	(22,571.2)	4,523
Total recurring commission	21,240.6	(15,823.9)	5,525
Bonification	4195.6	(4,824.1)	3,179
Fix salary/subsidies	5,613.8	(5,592.4)	4,014
Tenure	10.6	(8.2)	6,890
Prior agent labor experience	2.0	(4.1)	6,890
Non-agent labor experience	11.0	(7.2)	6,890
OJ	0.9	(0.2)	6,890
Years of education	12.9	(2.9)	6,890
Job-match	3.4	(0.9)	6,890
Industry-match	3.0	(1.2)	6,890

league to work as insurance agent?".[40] In both cases, the answer could be given on a Lickert scale ranging from 1 (Not at all) to 5 (Very much). The correlation between the two variables is 0.35. This value is rather high but reflects the intuition that job- and industry-match cannot be fully disentangled. To improve this proxy, I use another item from the questionnaire: information on satisfaction with pay. By regressing overall satisfaction on pay-satisfaction (using bootstrapping), calculating the predicted values and using the residuals instead of the initial total satisfaction variable, I excluded the effect from compensation and thus a potential source of endogeneity in the regression. The correlation between the two match-variables is now 0.30. The sample averages of job- and industry-match are 3.4[41] and 3.0, respectively.

It should be noted that as the questionnaire was filled-in only once (early 2006), the job- and industry-match variables are time-invariant in this analysis. Although not optimal, in the light of the variables regarding previous experience (Exp and $Expind$) also being time-invariant, it seems reason-

[40] translated from the German question *"Würden Sie einem Freund oder Kollegen empfehlen, als Versicherungsvertreter zu arbeiten?"*

[41] Here I used the pre-transformation value of the overall satisfaction for the sake of comparison with the industry-match variable

able to treat them in a similar way and use them in the regression. Furthermore, due to the voluntary character of the questionnaire, there is a certain danger of selection-bias.

3.3.2 Effect of Experience on Total Wage

I will now turn to the analysis of the effects of experience on the wage of insurance tied agents as outlined in Section 3.2. In a first step, I estimate equation (3.5) using different regression methods.[42] I also include a linear version in the case of OLS and IV to get a better understanding of the net-effects of the experience variables. The results are shown in Table 3.2. In line with our expectations, we find a strong positive influence of the old job indicator variable OJ, which shows that agents who have been with their company for more than a year earn significantly more than those who have just started. For the other independent variables, we see strong differences between OLS, random effects GLS and IV estimation. As we will see in Section 3.3.4, there is strong evidence that an IV approach is appropriate in this case. Thus, we can conclude from the differences shown in Table 3.2, that the wrong specification of the regression can indeed lead to serious bias in the results.

In line with previous literature, we expect non-linearity of the experience effects. Alongside the most common approach of including squared and cubic terms for industry- and general experience (see Table 3.2), I also divide them into ranges of five years, and include indicator variables to measure the effects of prior experience at these discrete knot-points (see Table 3.7 and 3.8). This gives us a more accurate view on the change of influence these variables have as they increase. This analysis is conducted (i) for all agents in the sample (ii) for agents with a tenure above nine years (which is the median of the sample) and (iii) for agents with a tenure less or equal to 9 years (see Figure 3.1(b) and 3.1(c)). This lets us determine if and how

[42] I use robust standard errors in all regression types to account for heteroscedasticity, see also Section 3.3.4

Table 3.2: Comparison of tenure-effect on log(wage) using **OLS**, **random effects GLS**, and **Instrumental variables (2SLS) (with and without higher order terms)**

	(1) OLS	(2) OLS	(3) GLS	(4) IV	(5) IV
OJ	1.259***	1.014***	0.845***	0.856***	0.832***
	(15.87)	(12.37)	(11.22)	(7.81)	(7.52)
Tenure	0.0275***	0.0799***	0.0984***	0.0870***	0.106***
	(21.13)	(20.38)	(16.02)	(9.29)	(5.43)
Sq(Tenure)x100		-0.178***	-0.219***		-0.0915
		(-15.89)	(-12.94)		(-1.05)
Prior agent labor experience	0.00422*	-0.0105	-0.0129	0.0291***	0.0283*
	(1.90)	(-1.07)	(-0.72)	(6.19)	(1.94)
Sq(Prior agent lab.ex.)x100		0.119	0.139		-0.0928
		(0.95)	(0.61)		(-0.62)
(Prior agent lab.ex.3)x1000		-0.0154	-0.0177		0.0450
		(-0.40)	(-0.26)		(0.99)
Non-agent labor experience	0.00320**	-0.0158*	-0.0135	0.0238***	0.0340**
	(2.19)	(-1.83)	(-0.90)	(6.63)	(1.96)
Sq(Non-agent lab.ex.)x100		0.135*	0.153		-0.0819
		(1.75)	(1.14)		(-0.78)
(Non-agent lab.ex.3)x1000		-0.0289	-0.0347		0.0118
		(-1.48)	(-1.03)		(0.50)
Years of education	-0.00478	-0.0151	-0.0165	0.0249***	0.106**
	(-1.39)	(-0.54)	(-0.35)	(4.41)	(2.42)
Sq(Yrs. edu)		0.000166	0.000280		-0.00301**
		(0.17)	(0.17)		(-2.28)
Job-match	-0.121***	-0.116***	-0.131***	-0.102***	-0.103***
	(-10.61)	(-10.47)	(-6.93)	(-7.66)	(-8.15)
Industry-match	-0.00161	0.00339	0.00236	0.0354***	0.0332***
	(-0.20)	(0.43)	(0.17)	(3.26)	(3.08)
Observations	6890	6890	6890	6890	6890
Adjusted R^2	0.514	0.530		0.362	0.415

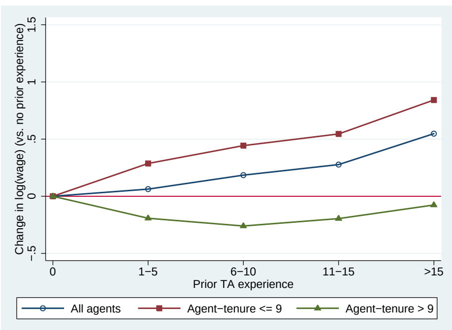
t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

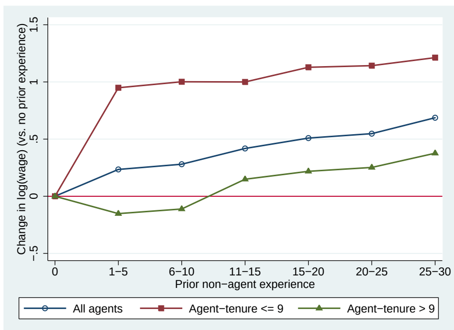
Note: Constant not shown; company-, initital portfolio- and years effects included

the effect from prior agent-/general-experience is different for new starting agents compared to longer-serving agents.
For presentational purposes, I multiplied the effects of the squared (cubic) terms with 100 (1000) in order to reduce the number of leading zeros of the coefficients. Furthermore, in all regressions, I control for company, initial portfolio and year effects but do not report the results here. I will

(a) Influence of tenure, tied agent experience, and non-agent experience on log(total wage) (see Table 3.2, column(5))



(b) Tenure-dependency of effect from prior tied agent experience



(c) Tenure-dependency of effect from prior non-agent experience

Figure 3.1: Effect of the different experience-types on log(wage)

first focus on the overall effect of the different kinds of experience on the wage development of the agent shown in Table 3.2. I will consider only the estimates from the IV estimation as shown in columns (4) and (5) of Table 3.2. As expected, we find a large positive and statistically significant effect of tenure on the log(wage) of the agent both in the linear case and also after inclusion of the quadratic term. Similarly, also the prior agent- and general-experience have a positive relationship with log(wage). In the linear version of the regression, the influence from agent-experience is slightly higher than the one from general labor-market experience. After inclusion of the higher order terms, however, the relations are inverted. The development of the effects over the years can easily be examined by looking at Figure 3.1(a). Here, I plotted the polynomial functions for tenure, agent-experience and general labor-market experience based on the coefficients given in Table 3.2, column (5).

As we can see, the effect of tenure slightly flattens as tenure increases. This is in line with Ingraham (1973) and Dorfman (1976) although the effect does not occur as early as predicted (Ingraham (1973) states that a plateau would be reached after the third year). His focus, though, was on production only. We will investigate this in Section 3.3.3. [43]

I now turn to the effects of agent-experience and general labor-market experience. Again, for the sake of interpretation, I present the coefficients from Table 3.2, column (5), by plotting the corresponding graphs. The resulting curves are shown together with the tenure-development in Figure 3.1(a). We see that the positive relation between agent/non-agent experience and log(wage) is almost identical and linear up to 15 years of each experience-type. Beyond this, the non-agent experience effect remains quasi-linear while the agent-experience related influence increases quite significantly. The surprising conclusion we can draw from this is that, for the agent, it does not make much difference whether he has worked as an

[43] In any case, we have to keep in mind that due to the logarithmic scale we use here, a certain flattening of the wage curve can be expected as otherwise, the (real) wages and linked to that, also the portfolios and new business Figures would increase exponentially till infinity what seems quite unreasonable given the effort-restrictions of each agent

insurance agent before, or whether he gathered experience in a different industry. Only if he has worked for more than 15 years as an insurance agent before, a slight advantage can be observed. Overall, we see that each of the two experience components leads to an increase of total wage by roughly 25% for 10 years of experience.

Up to now, we have looked only at the total of all agents, independent of their tenure. Quite intuitively, one could suspect that the benefit the agents have from prior (agent-)experience wears off after some time; i.e., the specific job-experience they gain on their current job becomes more and more important, making the experience gained from prior jobs almost insignificant. To test this hypothesis, I divide the two experience-variables into clusters of five years[44] (and an additional cluster for agents with zero experience which serves as a reference category). The results from this piecewise-regression are shown in Figures 3.1(b) and 3.1(c) as "all agents". The shape of these piecewise regressions is in line with the continuous version seen in Figure 3.1(a).

To investigate the influence of tenure on the effect from (non-)agent experience, I introduce an interaction term between the experience-clusters and an indicator variable for above/below nine years[45] of tenure. The results we see in Figures 3.1(b) and 3.1(c) clearly show that what drives the positive effect seen when looking at all agents are the agents with a below-median tenure. In fact, agents with a tenure above nine years have negative returns from prior experience. This relation is especially severe in the case of prior agent-experience where the effect is negative on all experience levels, whilst for general labor-market experience, there is a positive effect at least for those agents with more than 11 years' experience. Furthermore, in Figure 3.1(b), we see that for agents with low tenure, the positive effect is almost linearly increasing with the number of years. On the other hand, for non-agent experience, we see a steep increase for those agents with at least one year of experience compared to those with no ex-

[44] In the case of prior TA (Tied Agent)-experience, I use fewer categories than for non-agent experience as the number of samples per cluster would otherwise become very small, leading to large bias from outliers

[45] The sample median

perience at all, but then the effect remains almost unchanged.
Overall, we can conclude that the influence of prior experience significantly depends on the tenure of the agent and that the positive relation between experience and wage is mainly observed in the first years of tenure and the relation can even become negative for agents with higher tenure.

3.3.3 Effect of Experience on Sub-Components of Wage

We have already developed some initial insights into the effects of experience on total wage. We now drill down into the four sub-categories of agent compensation to find potential reasons for the observations made so far.
Starting with the new business commissions, we see the results from the regression in column (2) of Table 3.3 (for comparability with the previous results, I also included the corresponding regression for total wage in the first column of this Table). For tenure, we see a lower coefficient in the linear part but a slightly more curved shape of the parabola due to the more negative coefficient of the squared term as we can see in Figure 3.2(a). As already outlined, we can confirm a similar shape as seen in the total wage case. Thus, we can partially support the findings of Ingraham (1973) and Dorfman (1976) regarding the shape of the production curve of an agent, although we find that the flattening of the curve is observed at a much higher tenure than stated in their works. The coefficient of the linear prior-agent experience term is small both in size and statistical significance. The two higher order terms are both almost twice as large as for the total wage case. This leads to a strong increase of the positive effect for large values of prior agent-experience as we can see in Figure 3.2(a). In the case of non-agent experience, we actually see a negative effect, although again statistically not significant. From Figures 3.3(a) and 3.3(b), we see that this general shape is also confirmed by the more detailed, tenure-specific analysis. Here, we see that the extreme increase in the positive effect from high levels of prior agent experience stems from those agents with low tenure.

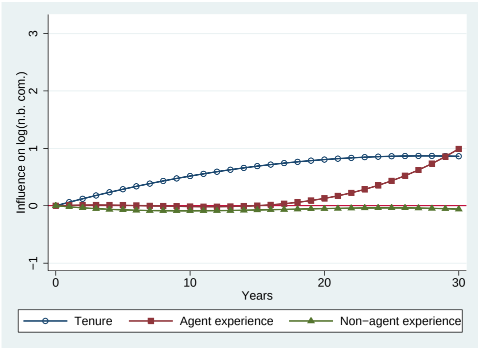
Table 3.3: Comparision of experience influence onto different compensation components

	(1) Total	(2) NBC	(3) RC	(4) Boni	(5) Sal
OJ	0.832***	1.083***	1.133***	1.560***	0.426***
	(7.52)	(9.13)	(6.25)	(6.77)	(3.74)
Tenure	0.106***	0.0633***	0.194***	0.230***	-0.0811***
	(5.43)	(3.43)	(7.40)	(6.95)	(-3.46)
Sq(Tenure)x100	-0.0915	-0.115	-0.285***	-0.651***	0.194*
	(-1.05)	(-1.58)	(-2.64)	(-6.48)	(1.92)
Prior agent labor experience	0.0283*	0.00946	0.0548***	0.0516	0.0431**
	(1.94)	(0.66)	(3.00)	(1.57)	(2.15)
Sq(Prior agent lab.ex.)x100	-0.0928	-0.203	-0.313	-0.726	-0.540*
	(-0.62)	(-1.15)	(-1.37)	(-1.37)	(-1.79)
(Prior agent lab.ex.3)x1000	0.0450	0.0938	0.106	0.243	0.175
	(0.99)	(1.57)	(1.40)	(1.20)	(1.50)
Non-agent labor experience	0.0340**	-0.0211	0.0541**	-0.0373	-0.0279
	(1.96)	(-1.04)	(2.16)	(-1.52)	(-1.08)
Sq(Non-agent lab.ex.)x100	-0.0819	0.152	-0.192	0.0811	0.166
	(-0.78)	(1.16)	(-1.20)	(0.36)	(1.01)
(Non-agent lab.ex.3)x1000	0.0118	-0.0295	0.0351	0.00641	-0.0259
	(0.50)	(-0.96)	(0.95)	(0.11)	(-0.69)
Years of education	0.106**	0.0330	0.0586	-0.0947	-0.00584
	(2.42)	(0.68)	(1.00)	(-1.24)	(-0.10)
Sq(Yrs. edu)	-0.00301**	-0.00155	-0.00108	0.00210	-0.000375
	(-2.28)	(-1.05)	(-0.61)	(0.80)	(-0.21)
Job-match	-0.103***	-0.121***	-0.121***	-0.151***	-0.0909***
	(-8.15)	(-8.75)	(-7.19)	(-4.69)	(-5.09)
Industry-match	0.0332***	0.0436***	0.0191	0.0874***	0.0122
	(3.08)	(3.85)	(1.38)	(4.05)	(0.93)
Observations	6890	4521	5483	3176	3990
Adjusted R^2	0.415	0.399	0.322	0.127	0.245

t statistics in parentheses

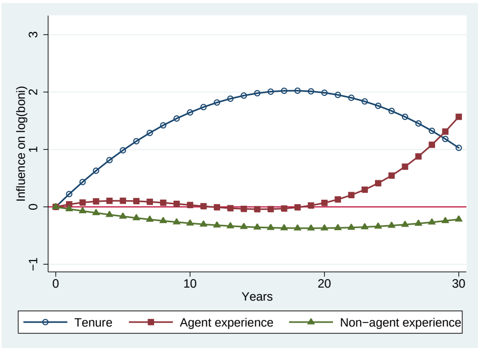
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Constant not shown; company-, initital portfolio- and years effects included

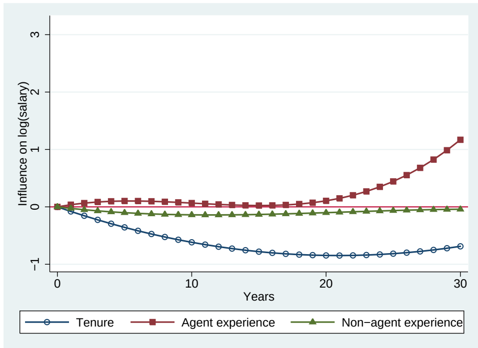


(a) New business commissions

(b) Recurring commissions



(c) Bonification



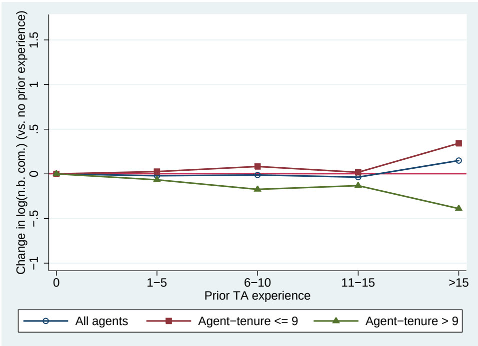
(d) Salary/subsidies

Figure 3.2: Influence of tenure, tied agent experience, and non-agent experience on the four sub-categories of compensation (see Table 3.3)

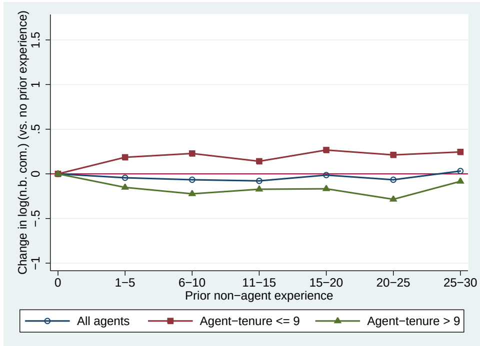
On the other hand, although not visible from the aggregated view, we now also find a positive relationship between prior non-agent experience and new business commissions, at least for agents with low tenure. This again shows how important such a differentiated view is, although it is lacking in most publications.

Looking at recurring commissions, the positive effect of tenure is much stronger than in the case of new business, which is in line with our expectations formulated in Section 3.1. Again, we see a flattening log(wage) curve in tenure.

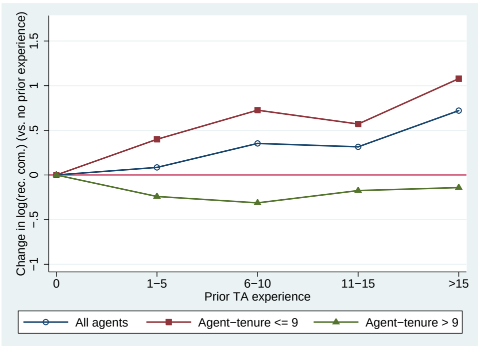
Both types of prior experience have a large positive relation with the logarithm of recurring commissions and are almost of the same size (5% per year for the linear components as we can see from column (3) of Table



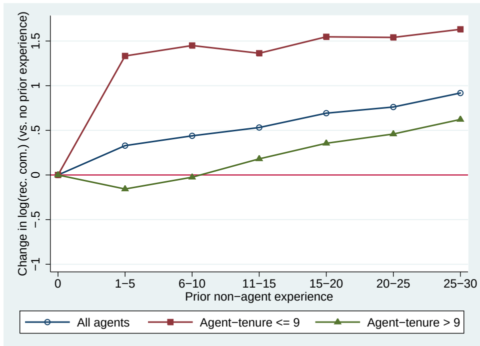
(a) New bus. com. (prior agent-exp.)



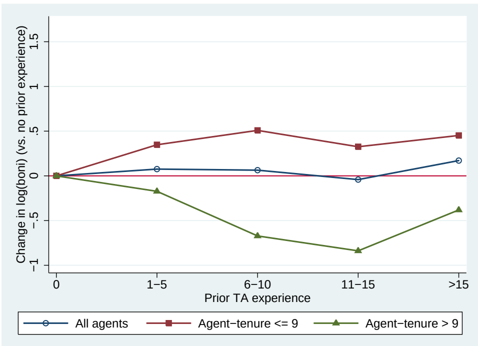
(b) New bus. com. (non-agent-exp.)



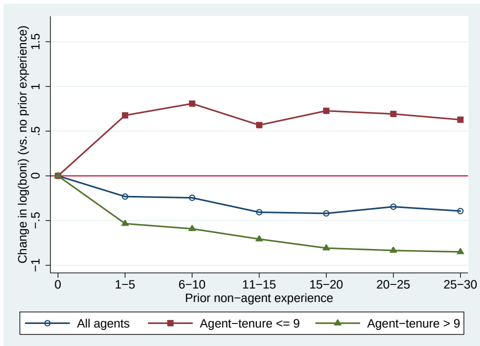
(c) Recurring com. (prior agent-exp.)



(d) Recurring com. (non-agent-exp.)



(e) Bonification (prior agent-exp.)



(f) Bonification (non-agent-exp.)

Figure 3.3: Discrete-estimation effect of prior agent and non-agent experience for different tenure levels on compensation components (see Tables 3.9 and 3.10)

3.3). These effects are therefore stronger than for the total wage, which can potentially be attributed to the fact that previous labor-market experience (whether job-specific or general) helps the agent to organize himself, gives him an air of seniority and thus makes him seem more trustworthy from a customer's perspective. These effects might lead to a reduced churn rate and, as a consequence, to higher recurring commissions. Overall, the shape of the tenure and the experience curves in Figure 3.2(b) resemble that of the total wage regression curve. Also when looking at the tenure-differentiation of the effects, we conclude from Figures 3.3(c) and 3.3(d) that the effects are again similar to those observed for total wage. This is quite reasonable, as we have seen already in Section 3.3.1 that the recurring commissions account for a large part of the total compensation of the agents. The size of all effects, however, is larger than in the total wage case due to the logarithmic scale.

As bonification is usually linked to certain goals that need to be achieved, one could assume that there should also be a positive effect from tenure on bonification, as higher tenure leads to larger portfolios (as seen above) and thus should ease the ability to reach sales goals. In line with this expectation, we indeed find a positive relation between tenure and bonification (see column (4) in Table 3.3), with the linear part being by far the largest among all compensation components. When looking at the plotted development in Figure 3.2(c), however, we see that the quite large negative coefficient of the squared term leads to a peak at 18 years of tenure. Beyond that, the size of the effect decreases. We may regard this as a sign of agents tending to be ever more successful in achieving their goals that lead to these bonification with rising tenure but, at some point (maybe due to a certain degree of fatigue) they reduce their effort and thus earn less money from these contests.

For both the non-agent labor experience and the tied-agent experience, the coefficients in the regression are statistically not significant. Thus, we can not reject the hypothesis that there is no influence of these two kinds of experience on the amount of bonification received by the agent. Nonetheless, we see a rather large coefficient of 5% in the linear part of the agent-experience compared to a negative coefficient of -3.7% for the non-agent experience. This may indicate that prior experience as an insurance agent at least slightly increases the likelihood of successfully participating in these contests. This seems reasonable as this form of on-top compensation might be more familiar to those who have already worked in the industry.

On the other hand, when looking at the tenure-differentiated Figures 3.3(e) and 3.3(f), we observe again that low-tenured agents enjoy a positive effect from both kinds of pre-experience, with the magnitude of the non-agent experience being even higher for this group, whilst high-tenured agents suffer quite severe losses.

Finally, when looking at the effect of experience on salary and subsidies in column (5) of Table 3.3, we see a statistically significant negative effect of the linear tenure coefficient. This translates into a U-shaped curve in Figure 3.2(d) which is in line with our expectations as subsidies and (fixed) salary are usually paid only within the first couple of years after joining the insurance company.

Regarding prior agent experience, we see a large positive relation of 4.3% in the linear term with log(salary/subsidies). Although the coefficient of the squared term is negative, we still see an increase of the agent-experience curve in Figure 3.2(d). This is surprising, but might give an indication of the nature of the recruiting practices of some insurance companies. In order to lure tied agents away from their current jobs, hiring companies can provide them with a higher fixed salary in the first years which is usually seen as a prudent practice (see Churchill et al. (1985)). Again, the coefficient of the non-agent labor experience is negative but statistically not significant.

In the case of salary/subsidies, the tenure-based analysis as conducted for the other components does not provide further insights, as there is a natural difference in how much is paid to low- compared to high-tenure agents, so I omit it here.

To summarize, we find that the largest influence both of tenure and of the other experience-types is observed on recurring commissions. Quite surprisingly, we found no significant advantage of prior agent experience above non-agent experience for new business commissions, although one might have expected that this job-specific experience would enable agents to perform better at this sales-directed activity. Prior agent-experience, however, does seem to enhance the likelihood of being successful in contests leading to higher average bonification.

As with the total wage case, we also see a clear difference in the effects for low-tenured agents and high-tenured agents. In all cases, the effects are positive and stronger for those agents that have not been with the firm for very long. Again, this seems to be a reasonable result, assuming that skills gained on previous jobs are especially helpful at the beginning of a new job. This beneficial effect might then be overridden by the experience gained as tenure increases. Another reason for the strong difference between the two tenure-clusters might be that those with higher tenure are also older.[46]

Both in the total wage and the compensation-component regressions, the coefficient of the job-match variable is significantly negative. This surprising result might be attributed to a problem in the causality between wage and the job-match proxy that was constructed from the job-satisfaction score. In Chapter 4, I investigate the relation between income and job-satisfaction. On the other hand, the industry-match variable gives quite reasonable results and is in line with Parent (2002), who finds that the matching-effect is usually of a smaller magnitude than the human capital effects.

3.3.4 Robustness

As pointed out earlier, the IV-approach is widely accepted in the context of estimating the influence of seniority and experience on wages. Nonetheless, from the short description of the workings of the IV estimator in Section 3.2, it is also clear that the IV estimator is less efficient that an OLS approach and thus should be used only if it is really required (see

46 As age is highly correlated with years of education, tenure, agent- and non-agent experience I omit it in this regression, in line with Parent (2000)

Wooldridge (2006)). The most common test that compares IV and OLS estimates is the Durbin-Wu-Hausman test[47], which I will use here. The aim is to fit both models and then compare the resulting coefficient vectors. More precisely (following the description in Baum (2006)), if I denote the estimation results from OLS and IV with β^{OLS} and β^{IV}, respectively, we derive the test statistic as

$$(\beta^{IV} - \beta^{OLS})' \left[\text{Var}(\beta^{IV}) - \text{Var}(\beta^{OLS})\right]^{-1} (\beta^{IV} - \beta^{OLS}) \sim \chi^2(k_1)$$

with k_1 being the number of regressors tested for endogeneity. The null hypothesis of this test is that the difference in the coefficients of the two estimators is not systematic. In this case, due to higher efficiency, the OLS estimator should be used. In our case (with $k_1 = 3$ as we test OJ, tenure and tenure^2 for endogeneity), we obtain a $\chi^2(3)$ of 88.7 and thus can clearly reject the null hypothesis. Thus, we conclude that the IV estimation is the more appropriate estimator to be used in this case.

Another important factor to be tested is the question of heteroscedasticity. Based on the work by Pagan & Hall (1983), many tests have been developed in the past that are also suitable for instrumental variable estimations (I have used the STATA command `ivhettest`). With a Pagan-Hall general test statistic of $\chi^2 = 310.4$, we can clearly reject the null hypothesis of homoscedasticity. The standard Breusch-Pagan-test (Breusch & Pagan (1979)) gives an even higher test score of 2,635.9. Therefore, I use robust standard errors in all the estimations in order to correct the bias from heteroscedasticity in the sample.

After running a test on autocorrelation (see Wooldridge (2006)), we can not reject the null-hypothesis of no autocorrelation. Thus, we assume that there are no severe issues from autocorrelation present in our results.[48]

Finally, I also briefly discuss the question of how appropriate the chosen instruments are. As already outlined, the choice of the instruments (the deviation from the individual mean) has been well-tested in the past and

47 See also Hausman (1978) for further reading on this test

48 Running the regressions with autocorrelation robust estimators consequently leads to very similar standard errors (results are not reported here)

proved to deliver meaningful results. Nonetheless, as we have seen in Section 3.2, if the correlation between the instrument and the underlying variable is weak, the standard errors may become very large, leading to a huge sampling variance of the IV estimator. Based on the suggestion by Bound et al. (1995), I report here the partial R^2 and F-statistic values for the three variables to be instrumented: OJ (Partial $R^2 = 0.72$, F-statistic $= 1,509.4$), tenure (Partial $R^2 = 0.09$, F-statistic $= 422.9$) and tenure^2 (Partial $R^2 = 0.04$, F-statistic $= 115.0$). The partial R^2 values are of interest as they show the correlation between the variable and its instrument. They are large enough to keep the bias at a reasonable level, given the comparably large sample size. Furthermore, Bound et al. (1995) point out, that F-statistics close to 1 should be a cause for concern. Staiger & Stock (1997) report that a common rule of thumb for a single endogenous regressor is an F-statistic of 10. In our case, all F-statistics are far above this threshold. The critical values provided in Stock et al. (2002) are also well below the F-statistics reported here.[49]

Finally, also running the regressions described here with additional control variables leads to very similar results. Table 3.11 shows the results of the regressions using number of employees as additional control variable. We see that there is almost no difference to Table 3.3. Thus, the observed effects do not seem to stem from managerial effects that may go along with higher tenure or experience.

Overall, the robustness tests conducted show that the IV method and its specifications should yield consistent estimates of the effects under consideration.

[49] As pointed out by Shea (1997), the partial R^2 value can be misleading in the case of multiple endogenous variables. The reason being, that even if just one of the instruments would be a valid one for the endogenous variables (i.e., the model would basically be underspecified), the partial R^2 by Bound et al. (1995) could still be high. In our case, the proposed "Shea partial R^2" values, that take care of this potential underspecification, are 0.41, 0.05 and 0.03 for OJ, tenure and tenure^2, respectively. We therefore conclude, that there is only a small danger of underidentification

3.4 Discussion and Conclusion

In this work, I investigated the effects of different kinds of experience on the wage of tied agents in the German insurance industry. I started off defining an equation to describe the mechanics of the log(wage) estimation both with and without an explicit inclusion of matching variables. Adopting the approach by Parent (2000), I not only considered a term for general labor-market experience but also for industry-specific experience (i.e., past experience as insurance tied agent at another company).
There is indeed a significant effect of all kinds of experience on the wage of an agent, in line with the findings of McDaniel et al. (1988). Regarding tenure, the increase of wage is very steep at the beginning as the agent builds up his customer base but eventually flattens albeit at a much later tenure than suggested in Ingraham (1973) and Dorfman (1976). For prior agent- and general-labor experience, there is a significant positive effect, which is of a similar magnitude to the overall wage level. This is quite a different result to that of Dustmann & Meghir (2005), who report that the general labor-experience effect is much higher than the industry-specific one. Nonetheless, for very high levels of prior agent experience, its effect increases strongly compared to non-agent experience. Therefore, it seems that there is indeed a certain advantage of agent-specific experience above general labor-market experience. This is in line with the finding by Churchill et al. (1985) who suggest that such people are more likely to have developed the necessary skills and may be less likely to suffer from inaccurate or ambiguous role perception. By investigating the causal reasons for this effect, we find that the main driver for the increase is a higher level of bonification as well as salary and subsidies. We therefore suspect that prior agent experience mainly leads to higher subsidies being paid in order to lure agents away from their current employer.
Furthermore, I present one of the first studies that distinguishes the effect from past experience for different tenure levels. We see that the two kinds of experience (agent and non-agent experience) both have a significant positive effect for low-tenured agents. This is observed for the total

wage as well as for its sub-components. On the other hand, high-tenured agents can even suffer losses due to their greater prior experience. This surprising result may be attributable to age-effects.

Although the results of this work seem to be quite robust to changes in the specification, there are some caveats mainly attributable to the data-set. A major source of bias may be that the set contains only those agents that were still employed in 2005, i.e., agents that might have been with the firm in 2003 but who quit in 2004 are not captured in the sample. Therefore, we face a certain selection bias, which may lead to errors when calculating the returns on experience.

Furthermore, the proxies used for the matching variables could be, due to the fact that they have been collected via a questionnaire, subject to bias driven by the overall satisfaction of the agent with the company. Thus, it may well be that an agent who is unhappy with his current employer would also deem the whole industry as not being a good match for him. In addition, these variables are time-invariant and, therefore, do not reflect potential changes within the three year period of observation.

In addition, effects from job mobility and other fixed individual effects cannot be controlled for. As outlined by Altonji & Williams (1998), this is certainly a cause for concern. They propose a first-differencing approach that would eliminate these fixed-effects. This method, however, requires some variance in general- and industry-specific labor market experience on an individual level over time. Given the structure of the data-set, this is unfortunately not the case. Nonetheless, as already pointed out, the results by Parent (2009) and Lemieux et al. (2009) suggest, that these individual fixed-effects might have only a comparably small variance as I focus on sales workers with "commission pay", only.

With these limitations in mind, I think that this work adds a new angle to the discussion as to how experience influences wages. The distinction between different tenure-groups to analyze the effect of prior experience for these groups individually, has, to my knowledge, not been used before. Given the instructive results, I feel that these new techniques are very helpful in better understanding the effects at work.

3.5 Appendix to Chapter 3

Table 3.4: Mean and standard deviation of key variables (**2003** only)

Variable	Mean	(Std. Dev.)	N
Total commission	62,127.4	(36,951.5)	1,738
New business commission	34,160.1	(22,724.0)	1,318
Recurring commission	23,255.5	(16,402.9)	1,310
Bonification	6,092.6	(5,485.2)	176
Fix salary/subsidies	5,943.8	(5,748.8)	1,273
Tenure	10.7	(8.5)	1,738
Prior agent labor experience	2.2	(4.3)	1,738
Non-agent labor experience	10.4	(7.0)	1,738
OJ	0.9	(0.2)	1,738

Table 3.5: Mean and standard deviation of key variables (**2004** only)

Variable	Mean	(Std. Dev.)	N
Total commission	56,568.4	(41,665.5)	2,314
New business commission	39,412.1	(25,339.3)	1,393
Recurring commission	21,546.3	(15,283.4)	1,874
Bonification	4,012.3	(5,034.8)	1,304
Fix salary/subsidies	5,867.9	(5,591.3)	1,347
Tenure	10.8	(8.2)	2,314
Prior agent labor experience	1.8	(3.9)	2,314
Non-agent labor experience	11.0	(7.2)	2,314
OJ	1.0	(0.2)	2,314

Table 3.6: Mean and standard deviation of key variables (**2005** only)

Variable	Mean	(Std. Dev.)	N
Total commission	44,652.4	(34,231.5)	2,838
New business commission	21,227.5	(15,691.0)	1,812
Recurring commission	19,868.4	(15,792.4)	2,341
Bonification	4,139.7	(4,538.8)	1,699
Fix salary/subsidies	5,067	(5,408.3)	1,394
Tenure	10.3	(8.1)	2,838
Prior agent labor experience	2.0	(4.1)	2,838
Non-agent labor experience	11.3	(7.3)	2,838
OJ	0.9	(0.2)	2,838

Table 3.7: Comparison of effect of **prior agent-experience** for above- and below-median tenures

	(1) IV-all	(2) IV-tenure
OJ	0.830***	0.821***
	(7.48)	(7.32)
Tenure	0.106***	0.117***
	(5.43)	(5.61)
Sq(Tenure)x100	-0.0920	-0.105
	(-1.05)	(-1.16)
TA-exp_1	0.0625	0.287***
	(1.58)	(3.40)
TA-exp_5	0.185***	0.443***
	(2.98)	(4.80)
TA-exp_10	0.277***	0.545***
	(3.17)	(4.73)
TA-exp_15	0.547***	0.842***
	(4.21)	(5.44)
(TA-exp_1)x(tenure $>$ 9)		-0.479***
		(-4.14)
(TA-exp_5)x(tenure $>$ 9)		-0.703***
		(-5.85)
(TA-exp_10)x(tenure $>$ 9)		-0.740***
		(-5.91)
(TA-exp_15)x(tenure $>$ 9)		-0.918***
		(-5.94)
Non-agent labor experience	0.0311*	0.0300*
	(1.83)	(1.71)
Sq(Non-agent lab.ex.)x100	-0.0621	-0.0693
	(-0.60)	(-0.65)
(Non-agent lab.ex.3)x1000	0.00765	0.0131
	(0.33)	(0.54)
Years of education	0.106**	0.123***
	(2.42)	(2.68)
Sq(Yrs. edu)	-0.00303**	-0.00359***
	(-2.29)	(-2.59)
Job-match	-0.101***	-0.105***
	(-7.97)	(-8.28)
Industry-match	0.0326***	0.0260**
	(3.04)	(2.54)
Observations	6890	6890
Adjusted R^2	0.413	0.403

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Constant not shown; company-, initital portfolio- and years effects included

Table 3.8: Comparison of effect of **non-agent-experience** for above- and below-median tenures

	(1)	(2)
	IV-all	IV-tenure
OJ	0.833***	0.748***
	(7.55)	(6.34)
Tenure	0.106***	0.166***
	(5.46)	(6.70)
Sq(Tenure)x100	-0.0912	-0.175**
	(-1.04)	(-2.00)
non-TA-exp_1	0.235**	0.949***
	(2.52)	(3.92)
non-TA-exp_5	0.280**	1.001***
	(2.57)	(4.11)
non-TA-exp_10	0.418***	1.000***
	(2.99)	(3.98)
non-TA-exp_15	0.509***	1.128***
	(3.21)	(4.30)
non-TA-exp_20	0.548***	1.142***
	(3.23)	(4.33)
non-TA-exp_25	0.687***	1.213***
	(3.58)	(4.26)
(non-TA-exp_1)x(tenure $>$ 9)		-1.101***
		(-4.41)
(non-TA-exp_5)x(tenure $>$ 9)		-1.113***
		(-4.97)
(non-TA-exp_10)x(tenure $>$ 9)		-0.851***
		(-4.50)
(non-TA-exp_15)x(tenure $>$ 9)		-0.910***
		(-5.26)
(non-TA-exp_20)x(tenure $>$ 9)		-0.890***
		(-5.50)
(non-TA-exp_25)x(tenure $>$ 9)		-0.836***
		(-4.70)
Prior agent labor experience	0.0287**	0.0233
	(1.98)	(1.57)
Sq(Prior agent lab.ex.)x100	-0.0964	-0.102
	(-0.64)	(-0.65)
(Prior agent lab.ex.3)x1000	0.0461	0.0550
	(1.03)	(1.16)
Years of education	0.0978**	0.0824**
	(2.34)	(2.04)
Sq(Yrs. edu)	-0.00272**	-0.00200
	(-2.15)	(-1.64)
Job-match	-0.102***	-0.106***
	(-8.07)	(-8.12)
Industry-match	0.0345***	0.0205**
	(3.15)	(2.10)
Observations	6890	6890
Adjusted R^2	0.412	0.377

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Constant not shown; company-, initital portfolio- and years effects included

Table 3.9: Comparison of effect of **prior agent-experience** for above- and below-median tenures for the four different compensation sub-categories

	(1) NBC	(2) RC	(3) Boni	(4) Sal
OJ	1.079***	1.105***	1.536***	0.426***
	(9.00)	(6.03)	(6.58)	(3.68)
Tenure	0.0664***	0.208***	0.250***	-0.0806***
	(3.33)	(7.38)	(6.84)	(-3.30)
Sq(Tenure)x100	-0.119	-0.304***	-0.686***	0.194*
	(-1.64)	(-2.73)	(-6.47)	(1.93)
TA-exp_1	0.0257	0.400***	0.348***	0.0554
	(0.28)	(3.55)	(3.05)	(0.57)
TA-exp_5	0.0827	0.726***	0.509***	0.101
	(0.83)	(6.10)	(3.61)	(0.89)
TA-exp_10	0.0178	0.571***	0.326**	0.0839
	(0.14)	(3.21)	(2.20)	(0.51)
TA-exp_15	0.342**	1.079***	0.452*	0.241
	(2.13)	(5.78)	(1.65)	(1.08)
(TA-exp_1)x(tenure $>$ 9)	-0.0922	-0.640***	-0.521***	0.00763
	(-0.70)	(-4.02)	(-3.16)	(0.06)
(TA-exp_5)x(tenure $>$ 9)	-0.256**	-1.038***	-1.180***	-0.0184
	(-1.97)	(-6.54)	(-4.98)	(-0.13)
(TA-exp_10)x(tenure $>$ 9)	-0.150	-0.745***	-1.164***	-0.187
	(-0.98)	(-3.66)	(-3.96)	(-1.00)
(TA-exp_15)x(tenure $>$ 9)	-0.731***	-1.219***	-0.833**	-0.577**
	(-4.24)	(-5.83)	(-2.49)	(-2.47)
Non-agent labor experience	-0.0220	0.0569**	-0.0325	-0.0301
	(-1.03)	(2.18)	(-1.32)	(-1.12)
Sq(Non-agent lab.ex.)x100	0.156	-0.239	0.0290	0.182
	(1.10)	(-1.42)	(0.13)	(1.05)
(Non-agent lab.ex.3)x1000	-0.0291	0.0510	0.0228	-0.0292
	(-0.87)	(1.30)	(0.39)	(-0.73)
Years of education	0.0431	0.0922	-0.0358	-0.00430
	(0.81)	(1.47)	(-0.47)	(-0.07)
Sq(Yrs. edu)	-0.00188	-0.00220	0.000158	-0.000416
	(-1.16)	(-1.15)	(0.06)	(-0.21)
Job-match	-0.123***	-0.127***	-0.161***	-0.0904***
	(-8.94)	(-7.53)	(-5.02)	(-5.11)
Industry-match	0.0423***	0.00988	0.0783***	0.0124
	(3.90)	(0.75)	(3.64)	(0.97)
Observations	4521	5483	3176	3990
Adjusted R^2	0.399	0.311	0.124	0.244

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Constant not shown; company-, initital portfolio- and years effects included

Table 3.10: Comparison of effect of **non-agent-experience** for above- and below-median tenures for the four different compensation sub-categories

	(1) NBC	(2) RC	(3) Boni	(4) Sal
OJ	1.049***	0.998***	1.367***	0.437***
	(8.08)	(5.14)	(5.58)	(3.49)
Tenure	0.0875***	0.279***	0.307***	-0.0899***
	(3.23)	(7.83)	(6.94)	(-3.08)
Sq(Tenure)x100	-0.152**	-0.413***	-0.727***	0.206**
	(-2.15)	(-3.93)	(-6.66)	(2.13)
non-TA-exp_1	0.186	1.333***	0.677***	-0.223
	(0.68)	(3.84)	(3.10)	(-0.76)
non-TA-exp_5	0.228	1.450***	0.808***	-0.180
	(0.84)	(4.20)	(3.73)	(-0.60)
non-TA-exp_10	0.141	1.363***	0.568***	-0.222
	(0.50)	(3.88)	(2.58)	(-0.72)
non-TA-exp_15	0.267	1.548***	0.727***	-0.144
	(0.94)	(4.35)	(3.16)	(-0.47)
non-TA-exp_20	0.212	1.541***	0.692***	-0.0510
	(0.74)	(4.25)	(2.86)	(-0.16)
non-TA-exp_25	0.245	1.631***	0.628**	-0.0802
	(0.72)	(4.10)	(2.11)	(-0.23)
(non-TA-exp_1)x(tenure $>$ 9)	-0.337	-1.490***	-1.211***	0.251
	(-1.19)	(-4.32)	(-4.90)	(0.88)
(non-TA-exp_5)x(tenure $>$ 9)	-0.452*	-1.475***	-1.400***	0.156
	(-1.82)	(-4.91)	(-5.90)	(0.62)
(non-TA-exp_10)x(tenure $>$ 9)	-0.313	-1.183***	-1.275***	0.157
	(-1.43)	(-4.43)	(-5.09)	(0.69)
(non-TA-exp_15)x(tenure $>$ 9)	-0.434**	-1.192***	-1.535***	0.0399
	(-2.24)	(-5.16)	(-6.24)	(0.21)
(non-TA-exp_20)x(tenure $>$ 9)	-0.497***	-1.082***	-1.527***	-0.120
	(-2.60)	(-4.78)	(-5.36)	(-0.64)
(non-TA-exp_25)x(tenure $>$ 9)	-0.329	-1.009***	-1.478***	-0.211
	(-1.43)	(-3.99)	(-3.99)	(-0.85)
Prior agent labor experience	0.00430	0.0413**	0.0383	0.0426**
	(0.31)	(2.34)	(1.16)	(2.18)
Sq(Prior agent lab.ex.)x100	-0.146	-0.160	-0.571	-0.539*
	(-0.83)	(-0.70)	(-1.06)	(-1.79)
(Prior agent lab.ex.3)x1000	0.0774	0.0443	0.200	0.183
	(1.31)	(0.59)	(0.97)	(1.57)
Years of education	0.0346	0.0263	-0.0698	0.00502
	(0.80)	(0.49)	(-0.91)	(0.09)
Sq(Yrs. edu)	-0.00154	0.000354	0.00164	-0.000779
	(-1.19)	(0.22)	(0.62)	(-0.48)
Job-match	-0.121***	-0.126***	-0.149***	-0.0916***
	(-8.77)	(-7.23)	(-4.61)	(-5.15)
Industry-match	0.0385***	-0.000676	0.0664***	0.0148
	(4.03)	(-0.06)	(3.16)	(1.24)
Observations	4521	5483	3176	3990
Adjusted R^2	0.399	0.296	0.140	0.246

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Constant not shown; company-, initital portfolio- and years effects included

Table 3.11: Comparision of experience influence onto different compensation components including number of employees as control variable

	(1) Total	(2) NBC	(3) RC	(4) Boni	(5) Sal
OJ	0.853***	1.097***	1.161***	1.576***	0.432***
	(7.78)	(9.54)	(6.48)	(6.94)	(3.84)
Tenure	0.108***	0.0671***	0.198***	0.232***	-0.0783***
	(5.65)	(3.76)	(7.67)	(7.15)	(-3.38)
Sq(Tenure)x100	-0.0991	-0.127*	-0.296***	-0.660***	0.186*
	(-1.15)	(-1.79)	(-2.78)	(-6.66)	(1.86)
Prior agent labor experience	0.0248*	0.00589	0.0504***	0.0490	0.0410**
	(1.71)	(0.42)	(2.81)	(1.50)	(2.06)
Sq(Prior agent lab.ex.)x100	-0.0911	-0.184	-0.288	-0.717	-0.528*
	(-0.60)	(-1.06)	(-1.28)	(-1.36)	(-1.76)
(Prior agent lab.ex.3)x1000	0.0503	0.0901	0.102	0.242	0.173
	(1.08)	(1.53)	(1.38)	(1.20)	(1.49)
Non-agent labor experience	0.0346**	-0.0234	0.0522**	-0.0402	-0.0283
	(2.03)	(-1.18)	(2.10)	(-1.63)	(-1.11)
Sq(Non-agent lab.ex.)x100	-0.106	0.153	-0.194	0.0912	0.158
	(-1.03)	(1.18)	(-1.22)	(0.41)	(0.97)
(Non-agent lab.ex.3)x1000	0.0179	-0.0295	0.0358	0.00411	-0.0239
	(0.76)	(-0.97)	(0.98)	(0.07)	(-0.64)
Years of education	0.0993**	0.0299	0.0536	-0.0991	-0.00668
	(2.31)	(0.63)	(0.93)	(-1.30)	(-0.11)
Sq(Yrs. edu)	-0.00277**	-0.00146	-0.000918	0.00224	-0.000338
	(-2.13)	(-1.01)	(-0.52)	(0.85)	(-0.19)
Job-match	-0.117***	-0.125***	-0.133***	-0.156***	-0.0918***
	(-9.28)	(-9.39)	(-8.03)	(-4.84)	(-5.19)
Industry-match	0.0456***	0.0540***	0.0353**	0.0972***	0.0186
	(4.33)	(4.85)	(2.57)	(4.47)	(1.44)
No. employees	-0.163***	-0.182***	-0.210***	-0.147***	-0.111***
	(-12.55)	(-12.19)	(-11.99)	(-4.55)	(-6.91)
Observations	6890	4521	5483	3176	3990
Adjusted R^2	0.434	0.431	0.345	0.132	0.255

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Constant not shown; company-, initital portfolio- and years effects included

Chapter 4

Reference-Point Dependency of Pay Satisfaction

4.1 Introduction

In most of today's work relationships, the satisfaction of the worker with his or her employer has become an important aspect. As a consequence, many employers have started to launch surveys on employee satisfaction to make this very subjective, short-lived and fuzzy concept become more tangible.

Even though interpreting the results of such a subjective variable causes certain difficulties, it is a valuable source for new insights (see e.g., Lévy-Garboua & Montmarquette (2004), Freeman (1978)). It has to be noted that there are many factors that influence employee satisfaction, including job location, training offered, career aspects, job security and compensation. With such a broad range of levers, it can become quite difficult to distinguish individual effects. Nevertheless, anecdotal evidence as presented in Rees (1993) shows that this topic is far more than just an academic artifact.

In this work, I therefore focus on the influence of compensation on satisfaction. More precisely, I investigate both the effect of absolute compensation on satisfaction and whether there are any reference points that employees use to benchmark their own compensation. To avoid having to consider (and measure) a wide variety of potentially influential intrinsic and extrinsic variables, I take advantage of the data-set as described in Chapter 1, that asked not only for overall satisfaction with the employer but also for satisfaction with the total compensation. Thus, I can concentrate on the pure compensation effects.

There have been numerous publications regarding the influence of compensation on employee satisfaction in the past.[50] I will give a brief overview on those publications that seem to be most relevant in this context.

The recent work by Köszegi & Rabin (2006) suggests that the reference-point is endogenously determined by the rational expectation of the agent's outcomes. I will pick-up this point later when formulating my own hypothesis regarding the applicable reference-point in the model.

One of the empirical proofs for the reference-dependency of wages is reported by Clark & Oswald (1996) who investigated 5,000 British employees and found that the overall satisfaction of the workers did in fact depend on the ratio of actual income and a "reference income" derived using fitted values of a wage regression equation.[51] Furthermore, they found little support that worker's satisfaction is a function of absolute income. They also investigated the effects on satisfaction with pay. Here, naturally a much stronger positive effect of absolute income on pay satisfaction was reported but the negative effect of the reference income remained. A similar effect was found by Nguyena et al. (2003) who used the National Educational Longitudinal Study to investigate the drivers of job satisfaction, splitting it into four different sub-categories of satisfaction. Their data sug-

50 The recent publications by Clark et al. (2009), Luttmer (2005) and Stutzer (2004) find, that a reference-dependency does not only exist in the employer-employee relationship but also among people living in the same neighborhood

51 Although they include a total of 77 occupation- and 61 industry-dummies, there are no further details given regarding the differences in the effects across occupations/industries

gested that the influence of relative income on satisfaction with compensation is small compared to the effect of the absolute wage level.
Empirical evidence for reference-dependent preferences is also given in Camerer et al. (1997). This work argues that the *expected* wage acts as a reference-point and that taxicab drivers usually make labor supply decisions one day at a time, and set a loose daily income target and quit working once they reach that target. Interestingly, in the work by Groot & van Maassen den Brink (1999), it is found that the positive effect of higher wages on job satisfaction wears off after some time as the employee gets accustomed to this level of compensation (called ”preference drift”). More evidence for the importance of expected wages as a reference-point is found in the work by Mas (2006) who showed that in the case of police officers, their performance significantly increased (decreased) if the wage-raise as demanded by their union was accepted (not accepted). Thus, even in those cases when the absolute wage in fact increased, their performance nevertheless dipped.
Some research reports that utility from a job is determined largely by wage changes over time (see, e.g., Rees (1993)). Similar findings are found by Grund & Sliwka (2005) who use 19 waves of the German Socio-Economic Panel (GSOEP), a large representative German survey. There, a positive relationship between monthly wage and overall satisfaction and a negative relationship between the previous year's wage and overall satisfaction is reported. This supports the assumption that the previous year's income is seen as a reference income for many employees. In addition, they predict and also find in the data a negative effect of tenure on overall satisfaction. An interesting different spin to this topic is given by Brown et al. (2008) who suggest that it is not even the relative amount of money the employer earns that influences the satisfaction level but rather the *ranking* among his co-workers. They support this claim with data both from a laboratory setting and the analysis of 16,000 British employees.
One of the most often analyzed phenomenon in the context of reference points is ”loss aversion”. Due to its intuitive nature, it has been a vast field of research in the past years. Generally it means that people feel that

a loss reduces their utility far more than a comparable gain would increase it. The seminal work by Tversky & Kahneman (1991) develops a strong reference-dependency model, based on their prospect theory described in Kahneman & Tversky (1979). Another approach was suggested by Gul (1991) who develops an axiomatic model of ”disappointment aversion” that generalizes the expected utility model. Empirical evidence for the theoretic base is presented by Heath et al. (1999). Using several fictitious scenarios with participants in a laboratory experiment, they found that there is a strong notion of people feeling that they failed when they did not meet their (self- or externally-imposed) goals even if, objectively, they performed better than before. This underlines the perception of people not always being completely rational but rather comparing their achievements with ”what should be” states. This behavior was found in all areas of business and private life (e.g., seller behavior in residential real estate markets, see Genesove & Mayer (2001) or behavior of bettors in horse races, see Jullien & Salanié (2000)). The work by Herweg et al. (2008) suggests that to deal with loss aversion of an agent, a pure bonus contract would be optimal, which would specify a certain amount of money to be paid to the agent upon achieving the set goals.

Prendergast (1999) already stated that real-life contracts are usually far less sophisticated and complex than those derived from common economic methods. Lazear & Oyer (2007) reiterates this point, and the question remains unresolved. In general, there is even a question as to whether incentives really do have a positive effect on performance (e.g., Gneezy & Rustichini (2000), Camerer & Hogarth (1999)).

Goette et al. (2004) suggest that workers have behaviorally relevant income targets that act as a reference-point for their daily labor supply. The work by Fehr & Goette (2007) gives some empirical evidence to support this hypothesis. They investigated the amount of effort employees provide if their income is increased. Here, they find that the bike messengers under consideration would increase the number of shifts they work but reduce the effort made during each shift. They conclude that this may be a sign of their loss aversion and that once they have reached their respective reference income they see no need to work as hard. The notion that increased wage has no effect on daily effort was also reported in Goette & Huffman (2003) who use data from two different firms. Shalev (2000) showed existence of a myopic loss-aversion equilibrium by using methods of game theory.

In many of the cited analyses, the effect of wage on total job satisfaction was found to be rather limited if statistically significant at all. One explanation for these findings is provided by Lydon & Chevalier (2002) who claim that wage is not usually an exogenous variable, as assumed in many models. They show that using an instrumental variable approach on wage doubles its effect.

Meza & Webb (2007) explicitly model employer loss aversion in the context of executive compensation and find that this can lead to pay being insensitive to performance differences (at a certain performance-interval). Neuman & Neuman (2008) try to substantiate the theoretical aspects of loss aversion with another empirical study. Using discrete choice experiments (giving candidates different scenarios to choose from, thus deriving their utility-maximizing choice) in the medical sector, they find evidence for loss aversion among the candidates.

Overall, a broad range of literature has been published that deals with various aspects of (pay) satisfaction and reference points. I contribute to this discussion by providing empirical evidence for a peer-group-specific reference-point.

The remainder of this paper is structured as follows: The model is described in Section 4.2 where I also introduce the peer-groups used to test the reference-dependency of the pay satisfaction. Section 4.3 gives a short introduction to the statistical methods used in this work, with a focus on how to interpret the coefficients of the ordered probit regression. In Section 4.4, I describe the data-set used in this chapter, the results and the derived implications regarding the influence of different wage forms on job satisfaction. Section 4.5 discusses the findings and gives an outlook on future research questions.

4.2 The Model

To estimate the influence of compensation on satisfaction with pay, we have to control both for the different salary-related variables captured in a vector $\vec{S}_i$ and the individual characteristics $\vec{X}_i$ of an agent i in order to isolate the effects. Thus, I estimate the satisfaction with pay using a latent variable model:

$$Y_i = \vec{\beta}^T \vec{S}_i + \vec{\gamma}^T \vec{X}_i + \epsilon_i$$

where Y_i is the pay satisfaction score of agent i.
In the first specification of Section 4.4.2, I use only total compensation or the four sub-categories of compensation as the independent salary-related variables. In a second step, when testing for reference-point dependency of pay satisfaction, I add the relative deviation of each agent from a "peer-group specific median" and test their influence using indicator variables for discrete ranges of deviation (see Section 4.4.3). In all cases, I use age, tenure and company indicator variables to describe the agents' individual characteristics.
In order to construct meaningful peer-groups, I specify multiple tenure clusters. To account for newly hired agents, one cluster contains agents with a tenure of zero. The next cluster contains agents with a tenure of one to five years, and so on, with the last two clusters being those with a tenure of 36 to 40 years and above 40 years.[52] I then calculate the median (to reduce bias from outliers) of the corresponding compensation component for each tenure cluster in each company and the relative deviation of each individual from this median (i.e., the absolute deviation divided by the corresponding median). This relative deviation is split into a set of dummy variables to indicate how much (and in which direction) the individual agent deviates from the peer-group median.

52 I obtain similar results when introducing clusters for each individual year although this comes at the cost of reduced statistical significance as some of the "company-tenure-deviation" triples contain no or only very few observations

This means, we can write for the definition of N tenure-clusters T_j:

$$T_1 = \{i : i \in \mathbb{N}_0 \wedge i \leq L_1\}$$
$$T_j = \{i : i \in \mathbb{N}_0 \wedge L_{j-1} < i \leq L_j\} \quad , j = 2, \dots, N-1$$
$$T_N = \{i : i \in \mathbb{N}_0 \wedge i > L_N\}$$

with L_j being the cut-off levels that limit a tenure cluster. In this case, we have $N = 9$ and, as outlined above, $L_1 = 0$, $L_2 = 5$, $L_3 = 10$, ..., $L_9 = 40$. Then, assuming that we have M companies identified via a unique company ID running from $1, \dots, M$ attached to each agent i via c_i^{ID} , the definition of the peer-group median P_{kj} and the individual agents absolute deviation D_i and relative deviation R_i are:

$$P_{kj} = \text{Med}(s_i) \quad \text{if } c_i^{\text{ID}} = k \wedge t_i \in T_j$$
$$D_i = s_i - P_{kj} \quad \text{if } c_i^{\text{ID}} = k \wedge t_i \in T_j$$
$$R_i = \frac{D_i}{P_{kj}} \quad \text{if } c_i^{\text{ID}} = k \wedge t_i \in T_j$$

with s_i being the salary component of the vector $\vec{S_i}$ and t_i being the tenure of agent i being analyzed.

For my analysis, I use indicator variables for discrete ranges of the deviation variable under consideration with $K - 1$ knots denoted $B_1 < B_2 < \dots < B_{K-1}$:

$$\mathbf{I}_1 := \begin{cases} 1 : R_i \leq B_1 \\ 0 : \text{else} \end{cases}$$
$$\mathbf{I}_j := \begin{cases} 1 : B_{j-1} < R_i \leq B_j \\ 0 : \text{else} \end{cases} \quad , j = 2, \dots, K-1$$
$$\mathbf{I}_K := \begin{cases} 1 : R_i > B_{K-1} \\ 0 : \text{else} \end{cases}$$

With this formal notation defined, we can formulate the latent variable model we will test in the course of the reference-dependency analysis:

$$Y_i = \sum_{j=2}^{K} \eta_j \mathbf{I}_j + \vec{\beta^*}^T \vec{S_i^*} + \vec{\gamma}^T \vec{X}_i + \epsilon_i$$

where the star denotes that we reduced the dimension of the salary-related vector $\vec{S_i}$ by one (being the variable now being modeled via the indicator functions). Without loss of generality, I dropped the first indicator function to act as a reference.

In my calculations, I chose the following 11 knots B_j that divide the relative deviation into $K = 12$ ranges: -90%, -70%, -50%, -30%, -10%, 0%, 10%, 30%, 50%, 70%, 90%. If not stated otherwise, I used the category 0% to 10% as well as Company C as reference categories in the regression.[53]

4.3 Methodological Background

To avoid the complications that accompany survey data on job satisfaction, I apply the ordered probit model (see, e.g., McKelvey & Zavoina (1975)). The downside of the ordered probit regression is that it can be quite cumbersome to interpret the results correctly (see LeClere (1999) or Anderson (1984) for several methods). This is also the reason why in many scientific publications, only the sign of the coefficients of an ordered probit analysis is considered whilst the magnitude of the effect is neglected. However, this way valuable information is lost. Therefore, I will not only conduct the ordered probit regression, but also attach a marginal effects analysis to understand the changing effect that compensation has on satisfaction depending on the level of compensation.

Before interpreting the results of my analysis, I give a brief overview on the

53 The reason why the middle categories have been chosen in 10% rather than 20% steps is to have a finer grid around the expected reference-point

theoretical background of the ordered probit model to better understand the meaning of the results. A good introduction into how to implement these methods with Stata is given in Long & Freese (2006), from which I also draw in the introduction to the multinomial regression model.
Running an ordered probit regression of independent variables $\vec{X}$ on a dependent categorial variable Y, we get a set of coefficients β for the independent variables as well as $k-1$ cut points $\mu_1, \ldots, \mu_{k-1}$ that divide the curve of the density function into k sections. These cut points are usually automatically calculated by the statistical program using the maximum likelihood procedure. Using a latent variable model, as in the previous section, we can calculate a prediction of the z-score by $Y^* := \vec{\beta}^T \vec{X} + \alpha$ with α being the identically and independently distributed error term. Now, if $Y^* < \mu_1$, we would predict $Y = 1$, if $\mu_1 < Y^* < \mu_2$, $Y = 2$, ..., if $Y^* > \mu_{k-1}$, $Y = k$. Given the density function of the error term α, Φ, we find that:[54]

$$\begin{aligned}
\Pr(Y=1) &= \Pr(Y^* < \mu_1) = \Pr(\vec{\beta}^T \vec{X} + \alpha < \mu_1) \\
&= \Pr(\alpha < \mu_1 - \vec{\beta}^T \vec{X}) = \Phi(\mu_1 - \vec{\beta}^T \vec{X}) \\
\Pr(Y=2) &= \Pr(\mu_1 \leq Y^* < \mu_2) = \Pr(\mu_1 \leq \vec{\beta}^T \vec{X} + \alpha < \mu_2) \\
&= \Pr(\alpha < \mu_2 - \vec{\beta}^T \vec{X}) - \Pr(\alpha < \mu_1 - \vec{\beta}^T \vec{X}) \\
&= \Phi(\mu_2 - \vec{\beta}^T \vec{X}) - \Phi(\mu_1 - \vec{\beta}^T \vec{X}) \\
&\vdots \\
\Pr(Y=k) &= \Pr(Y^* \geq \mu_{k-1}) = \Pr(\vec{\beta}^T \vec{X} + \alpha \geq \mu_{k-1}) \\
&= \Pr(\alpha \geq \mu_{k-1} - \vec{\beta}^T \vec{X}) = 1 - \Pr(\alpha < \mu_{k-1} - \vec{\beta}^T \vec{X}) \\
&= 1 - \Phi(\mu_{k-1} - \vec{\beta}^T \vec{X})
\end{aligned}$$

Now, we can see what the effect of a shift in one of the independent variables means: An increase by 1 unit of the variable X_1 leads to an increase of the z-score by $\beta_1 X_1$. This means that for a discrete change in the inde-

54 Here, the parallel regression assumption is required (compare Long & Freese (2006)), stating that the coefficient vector β is the same for all possible outcomes of the categorical variable. See also the discussion regarding the robustness of the model in Section 4.4.4

pendent variable X_j from a to b and holding all other variables constant, the predicted probability of the outcome $Y = m$ changes according to:

$$\frac{\triangle \text{Pr}(Y = m|\vec{X})}{\triangle X_j} = \text{Pr}(Y = m|\vec{X}, X_j = b) - \text{Pr}(Y = m|\vec{X}, X_j = a)$$

The marginal effect then is basically only the infinitesimal change if we let the difference between a and b go to zero.
Using the notation above, we can write

$$\begin{aligned}\frac{\triangle \text{Pr}(Y = 1|\vec{X})}{\triangle X_j} &= \Phi(\mu_1 - \vec{\beta}^T\vec{X}|X_j = b) - \Phi(\mu_1 - \vec{\beta}^T\vec{X}|X_j = a) \\ &= \Phi(\mu_1 - \vec{\beta}^T\vec{X} - \beta_j(b-a)|X_j = b) - \Phi(\mu_1 - \vec{\beta}^T\vec{X}|X_j = b)\end{aligned}$$

If we assume a discrete change by one unit, i.e., $b - a = 1$, then the above equation simplifies to (dropping the conditionality condition):

$$\frac{\triangle \text{Pr}(Y = 1|\vec{X})}{\triangle X_j} = \Phi(\mu_1 - \vec{\beta}^T\vec{X} - \beta_j) - \Phi(\mu_1 - \vec{\beta}^T\vec{X})$$

From this equation, we can see that if the coefficient of the independent variable X_j is positive (i.e., $\beta_j > 0$), the difference $\Phi(\mu_1 - \vec{\beta}^T\vec{X} - \beta_j) - \Phi(\mu_1 - \vec{\beta}^T\vec{X})$ is negative, given the fact that the probability density function Φ is monotonously increasing and therefore a shift by β_j to the left of the density curve reduces the probability of $Y = 1$. Conversely, if $\beta_j < 0$, the probability of being in the first category increases.
In an analogue way, a similar expression can be derived for the highest category (i.e., for $Y = k$), which shows that a positive coefficient increases the probability of being in this category whilst a negative coefficient decreases this probability.
No general interpretation is possible for the intermediate categories, as the direction of the effect depends on the shape of the density function as well as on the position of the cut-off points.
Nonetheless, keeping these limitations in mind, we can at least get a rough intuition regarding the direction of the effect from the coefficients derived

from the ordered probit regression.
Having said this, it is also clear why the interpretation of even the discrete/ marginal effects is still a challenge. Given the fact that these effects change depending on the value of the other (fixed) independent variables, it is necessary to evaluate the discrete/marginal effects at meaningful values. In the case of dummy variables (the company indicators in my case), neither calculating the marginal effect nor evaluating these variables at their mean/median is meaningful. Thus, I will set them either to zero or one and calculate the discrete change between these two values, accordingly. In the case of the other independent variables, we will have to restrict ourselves to a set of cases where we would expect major changes in the effects to occur, knowing that it is impossible to describe all possible combinations of the variables. For this purpose, I define ideal types of agents in Section 4.4.2 and compare the probability distribution regarding their pay satisfaction scores.
As the marginal effects of a certain variable X_i change not only depending on the level of the other independent variables (which are held constant), but also on the starting point from where an additional unit of X_i is added, I will use graphs that show the marginal effects of a certain variable for each value of this variable. This enables us to evaluate the change of the effect this specific variable has on the satisfaction score for different levels of magnitude (see Figure 4.2).
Furthermore, I conduct some goodness-of-fit analyses regarding the predictions of the model. I will use the coefficients from the ordered probit regression to calculate the predicted probabilities. Then, using the value for satisfaction with the highest predicted probability, I compare this "model-satisfaction" with the actual satisfaction value given in the survey (see Baum (2006)). Furthermore, I include several competing goodness-of-fit methods as described by Long & Freese (2006) and discuss their differences in the course of the robustness discussion in Section 4.4.4.

4.4 Empirical Results

4.4.1 Data Description

In this chapter, I use a subset of the database described in Chapter 1 that contains the answers to the question regarding the agents' overall satisfaction and satisfaction with pay. In total, I have data from three German insurance companies with 1,558 observations in this period. As data was not available for all agents in both years, the actual number of observations in Table 4.1 slightly varies. To control for company-effects, I include corresponding dummies in my analysis.

Table 4.1: Mean and standard deviation of key variables (2005)

Variable	Mean	(Std. Dev.)	N
Overall satisfaction	3.5	(0.8)	1,558
Satifsfaction with compensation	2.9	(1.0)	1,558
Total comp. 2005	58,124.5	(37,251.8)	1,558
New bus. com. 2005	25,852.9	(19,646.5)	1,558
Rec. com. 2005	23,000.6	(16,587.8)	1,558
Bonif. 2005	4,265.8	(4,697.3)	1,558
Fix/subsidies 2005	5,005.2	(5,371.5)	1,558
Age	44.0	(9.2)	1,558
Tenure	11.6	(9.0)	1,558
Diff. total comp. 2005-2004	-13,825.5	(25,371.4)	1,513
Diff. n.b. com. 2005-2004	-14,274.1	(17,794.8)	1,511
Diff. rec. com. 2005-2004	1,040.1	(7,953.0)	1,508
Diff. bonif. 2005-2004	9.1	(4,756.0)	1,410
Diff. Fix/subs. 2005-2004	-988.0	(3,351.1)	1,469

The values for overall satisfaction and satisfaction with compensation are derived from a questionnaire the agents voluntarily filled-in. The question regarding overall satisfaction was *"How satisfied are you overall with <Company name>?"*.[55] The question regarding satisfaction with compensation was *"How satisfied are you with your current total compensation? (Total*

[55] translated from the German question *"Wie zufrieden sind Sie insgesamt mit <Firmenname>?"*

compensation means the included compensation as new business commission, recurring commission, bonification or subsidies)". [56] In both cases, the answer could be given on a Likert-scale from 1 (not at all satisfied) to 5 (completely satisfied). Overall satisfaction is, with a mean of 3.5, slightly higher than satisfaction with pay, which has a mean of 2.9. The distribution of the answers is shown in Figure 4.1, from which we can see that overall satisfaction is indeed skewed to higher satisfaction values compared to compensation satisfaction.

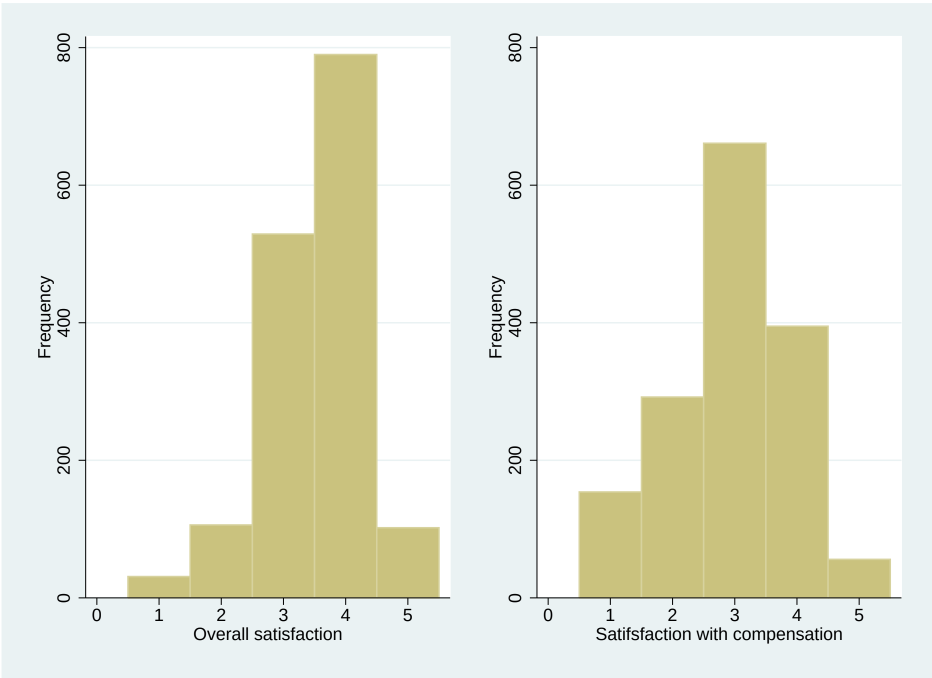


Figure 4.1: Survey answer frequency regarding overall satisfaction (left) and satisfaction with pay (right)

The other key variables used in this work are shown in Table 4.1. We see that the average total income is EUR 58,125, of which approximately EUR 49,000 comes from commission (53% from new business commission). Average bonifications are EUR 4,300, but this is the average over *all*

[56] translated from the German question *"Wie zufrieden sind Sie mit Ihrer jetzigen Gesamtvergütung? (Gesamtvergütung meint dabei alle erhaltenen Vergütungen wie Abschlussprovisionen, Bestandspflegeprovisionen, Bonifikationen oder Zuschüsse)"*

agents and one must suppose that not all agents will achieve their goals, so those that do will receive even higher bonification. Similarly, the average salary/subsidies of EUR 5,000 may be higher for those agents that receive the payments with others receiving almost nothing. In both cases, this also explains the fairly high standard deviation.
The average tenure and age in the sample are 11.6 and 44 years, respectively. The high average tenure may seem surprising, but we must keep in mind that only the agents who were still with their company at the time the survey was conducted are represented.
Table 4.1 also lists the average deviation of the compensation components between 2004 and 2005. It is striking that the total compensation dips significantly between these two years, driven by a reduction in new business commission. This has to be attributed mainly to the increased demand for life insurance products in 2004, due to a change in regulation by the German government. The total sum of bonification paid is unaffected by this trend. As pointed out above, I only consider those agents who worked in both years, i.e., excluding agents that joined in 2005, and thus would expect the total amount of subsidies to decrease.
As the questionnaire was filled-in only once (in 2006), I was not able to conduct a panel-analysis. Furthermore, due to the voluntary character of the questionnaire, there is a certain danger of selection-bias which one needs to keep in mind when interpreting the results.

4.4.2 Effect of Absolute Compensation on Satisfaction

Initially, I will try to validate a finding reported in existing literature. Therefore, I formulate my first hypothesis based on results from Clark & Oswald (1996):

Hypothesis 4.1 *Agents' compensation has a strong positive relation with pay satisfaction and a weak positive one with overall satisfaction*

Table 4.2 shows the results of the ordered probit regression of wage on overall satisfaction (columns (1) and (2)) and satisfaction with compensation (columns (3) and (4)). These and all subsequent results are obtained using robust standard errors. In each case, I ran one regression using only the total compensation as the independent variable and one with the more detailed split of the four different compensation components.

Table 4.2: Effect of absolute wage level on compensation satisfaction

	(1) Tot. sat.	(2) Tot. sat.	(3) Pay sat.	(4) Pay sat.
Total comp. 2005 ('000)	-0.000734		0.00700***	
	(-0.97)		(7.29)	
New bus. com. 2005 ('000)		-0.000162		0.00692**
		(-0.07)		(2.49)
Rec. com. 2005 ('000)		-0.00401		0.00407
		(-1.63)		(1.28)
Bonif. 2005 ('000)		0.00911		0.0246**
		(1.23)		(2.43)
Fix/subsidies 2005 ('000)		-0.00219		-0.00509
		(-0.37)		(-0.81)
Age	0.00781**	0.00823**	-0.0153***	-0.0148***
	(2.19)	(2.30)	(-4.38)	(-4.24)
Tenure	-0.0137***	-0.0125***	0.0158***	0.0157***
	(-3.41)	(-2.93)	(4.24)	(3.92)
Company A	0.0974	0.112	0.349***	0.365***
	(1.15)	(1.24)	(3.54)	(3.42)
Company B	0.602***	0.667***	0.631***	0.751***
	(6.12)	(5.01)	(5.58)	(4.54)
N	1558	1558	1558	1558
Log-Likelihood	-1763.1	-1761.8	-2061.7	-2057.2
Count R^2	0.508	0.507	0.432	0.433
Adj. Count R^2	0.00260	0	0.0134	0.0156
McKelvey/ Zavoina's R^2	0.0444	0.0463	0.107	0.112
AIC	3544.3	3547.7	4141.3	4138.4
BIC	3592.4	3611.9	4189.5	4202.7

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: Constant not shown

There is no statistically significant influence of absolute wage on overall satisfaction (neither in the aggregated nor in the split version of the regression) which supports at least the notion of the second part of the above hypothesis.[57] Also running a Wald-test on the coefficients of the four compensation components yields a p-value of 0.48 and we can not reject the

57 When running the peer-group deviation-dependent analysis, as presented below, with overall satisfaction as a dependent variable, no statistically significant effects are observed

null-hypothesis. Therefore, I will focus mainly on the effect of compensation on satisfaction with pay. In a first step, we evaluate the results pre-

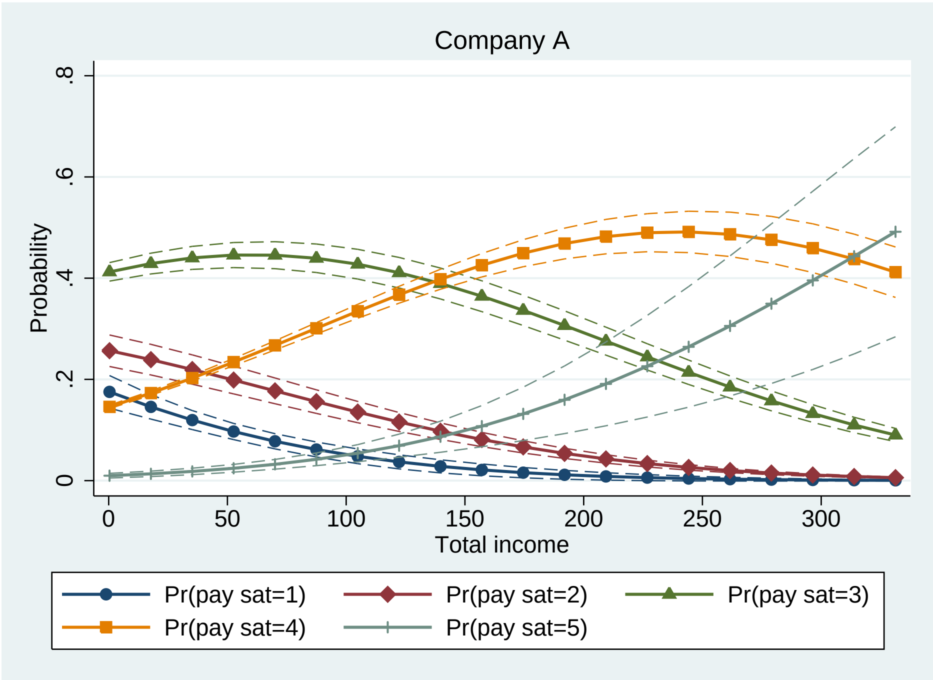


Figure 4.2: Marginal effects plot (including 95% confidence-intervals) of total compensation on satisfaction with pay at the example of Company A; variables set to their median: Age = 44, Tenure = 10 (compare column (3) of Table 4.2)

sented in the latter two columns of Table 4.2 based only on the sign of the coefficients. From the discussion in Section 4.3, we know that care must be taken when interpreting the coefficient of the different variables. Nevertheless, we can say that there is a statistically significant influence of compensation on agents' satisfaction with pay. In line with common intuition, an increase in compensation leads to a higher chance of the agent choosing the highest category of satisfaction instead of the lowest. Interestingly, when splitting the total compensation into the four sub-categories, we find a positive effect only for the new business commissions and the bonification with the coefficient of the latter being almost three-times as high. This could already be an indication that agents see bonification as an additional payment and are therefore more satisfied with their overall pay. Surprisingly, there is no statistically significant effect coming from the recurring commissions. With a share of almost 50% of total compensation, we would expect satisfaction to exhibit a significant dependency on this type of pay. One explanation might be that the agents are already confident about receiving their recurring commissions, and therefore react to the driver of the change (mainly new business), than to the actual change itself.

To understand these first results in more detail, I plot the marginal effects of different levels of total compensation for Company A in Figure 4.2, with the other dependent variables from the regression (column (3), Table 4.2), set to their median being age = 44 and tenure = 10. To get an impression of the robustness of the results, I also include the upper and lower bounds of the 95% confidence interval for each of the five satisfaction scores. We see that, except for satisfaction 5 in the case of high total compensation, the confidence interval is quite narrow.

From the graph, we can conclude, that the (predicted) probability of an agent choosing one of the two lowest categories of pay satisfaction becomes almost nil as the total compensation increases. At the same time, the probability of the highest category increases and ends up at almost 50%. The two middle-categories show an inverse bell-shape curve with peaks at roughly EUR 60,000 and EUR 180,000 for 3 and 4, respectively. These results further substantiate the first conclusions we drew from looking at the ordered probit regression and add a notion of the steepness and dynamics of the changes for different levels of total compensation.

Comparable results are achieved when running the same analysis for the two other companies (see Figures 4.5 and 4.6). The main differences are in the intercepts and the peak-points of the two middle-categories, but the overall shape is similar to that discussed above.

Overall, we can support the first part of the hypothesis, as we see a clear positive relationship between total compensation and satisfaction with pay. Again, running a Wald test shows that we can reject the null hypothesis that all coefficients are zero.

Having assessed the effect of compensation on satisfaction, we will now consider more closely the combined effects of changes in several of the independent variables. For this purpose, I define ideal types of agents, based on different specifications of the independent variables. As outlined in Section 4.3, the influence of changes in the independent variables is not linear and thus this method will help us understand how the distribution of satisfaction scores may change for different types of agents. I will conduct this analysis using the model-specification as in column (3) of Table 4.2. I define a total of eight ideal types to capture a wide range

Table 4.3: Predicted probabilities for the average agent and differences for selected "ideal types"

	Pay satisf. probabilities				
Ideal types	1	2	3	4	5
Avg. Company A	**10.08%**	**20.24%**	**44.51%**	**22.85%**	**2.32%**
△ Young Rookie	4.28%	3.52%	-1.52%	-5.34%	-0.95%
△ Old Rookie	14.73%	8.19%	-8.03%	-13.05%	-1.84%
△ Rich Retiree	-9.42%	-16.61%	-19.14%	25.97%	19.20%
△ Avg. Low Performer	3.37%	2.87%	-1.09%	-4.36%	-0.80%
△ Avg. High Performer	-4.92%	-6.13%	-1.37%	9.68%	2.74%
△ Avg. Company B	-4.14%	-4.94%	-0.71%	7.74%	2.05%
△ Avg. Company C	7.58%	5.48%	-3.33%	-8.37%	-1.36%

"△" indicates the change in probabilities compared to the average model, shown in the first row

of cases. The details on the definition can be found in Table 4.5. I use an average agent (i.e., with median tenure, age and total pay) from Company A as the reference.[58] The calculated probabilities for each of the five possible survey scores are given in the first row of the Table. We find that the middle-category 3 is the most likely to be chosen, with a 45% chance that an average agent would choose it whilst the top score of 5 is the least probable, at roughly 2%. Choosing the lowest category 1 has a probability of 10%. By calculating the same set of probabilities for the next ideal type (the Young Rookie) and subtracting the first row, I derive the change in probabilities for young agents with no income that just started their job. We find that they are more likely to chose one of the lowest categories.

[58] The absolute probabilities for the average agents of each of the three companies corresponds to the graphs in Figures 4.2, 4.5 and 4.6 when looking at the intercept of a (theoretical) line at $income = 50$ (being the median) and the five curves, respectively

Even more striking is the result when looking at old agents (50 years) that just started their job and have no income. In line with intuition, we see a steep increase in the probability of the lower two categories. Quite contrarily, we have the rich retirees next who earn a total of 200,000 EUR per year and are 65 years old. Here, we have an increase in the probability of choosing the highest satisfaction category by 19% and even 25% of the second highest category. The next two ideal types earn half (low performer) and twice (high performer) as much as the average whilst keeping age and tenure at their median. We see a modest increase in the lower categories for the low and an increase in the upper categories for the high performer. Finally, the last two ideal types tell us, that, given median age, tenure and pay, agents working for Company B are more likely to chose a high satisfaction whilst agents of Company C rather chose a low satisfaction score.

Table 4.4: Effect of absolute wage level on compensation satisfaction

	Predicted sat. with compensation			
Satifsfaction with compensation	3	4	5	Total
1	152	2	0	154
2	284	8	0	292
3	624	37	0	661
4	345	49	1	395
5	45	11	0	56
Total	1,450	107	1	1,558

To assess the quality of the model, we compare the predicted survey answers with the actual ones. I assign the agent the answer that has the highest predicted probability (compare Baum (2006), Long & Freese (2006)). Table 4.4 shows both the actual and the predicted answers in one matrix and we see that the simple model with the total compensation as independent variable gives us 673 correct predictions out of a total of 1,558 observations (a hit-rate of 43.2%). The same result is provided by the Count R^2 measure provided at the bottom of the regression tables. In addition, following Long & Freese (2006), I also report the adjusted count R^2 measure which compares the number of correct predictions with the scenario where all agents are predicted to have the satisfaction score with the high-

est frequency in the sample. Similarly, McKelvey & Zavoina's R^2, Akaike's information criterion (AIC), and the Bayesian information criterion (BIC) give other indications regarding the goodness-of-fit. I will use these different measures to compare the different models when discussing the robustness of the results (4.4.4).
The analysis thus far has focused mainly on compensation-related effects on satisfaction. However, the coefficients from age and tenure show a remarkably high statistical significance. Turning back to the regression with overall satisfaction as dependent variable (columns (1) and (2) of Table 4.2), we see a positive effect from age and a negative effect from tenure. This is in line with the findings by Grund & Sliwka (2005). For pay satisfaction, the effect is opposite.

4.4.3 Reference-Point Dependent Satisfaction

The findings thus far are already quite instructive, but we have not yet investigated the question of a potential reference-point. Due to the special structure of the insurance sales process, and the fact that agents are primarily paid based on commissions, it seems odd to assume that agents would chose their previous year's total compensation as a reference-point. Agents with a low tenure strive to increase their own profit by generating a lot of new business and expanding their customer stock. In addition, as already mentioned in Section 4.4.1, the external shock due to the change in German legislation in 2004 that pushed life insurance sales, makes it as good as impossible to choose a meaningful baseline in the years 2003–2005.[59]
Instead, I use anecdotal evidence that agents of the same company are usually well-informed as to on the average income of their peers and therefore

[59] A test on the influence of deviations from the previous year's total compensation is shown in Figure 4.4. As can be seen, no reference-point pattern can be observed. Running the same analysis for the four compensation categories also yields no positive results

have an approximate idea on what they should earn based on their tenure (some of this information is even made public via company-intern sales competitions). This is also in line with the approach taken by Köszegi & Rabin (2006), who propose that agents' expectation forms a reference-point. Assuming that this expectation is driven mainly by the income observed at other agents within the same peer-group, we can view the peer-group-specific reference-point as a special case of an expectation-reference-point. I therefore formulate the second hypothesis that I will try to validate with the data:

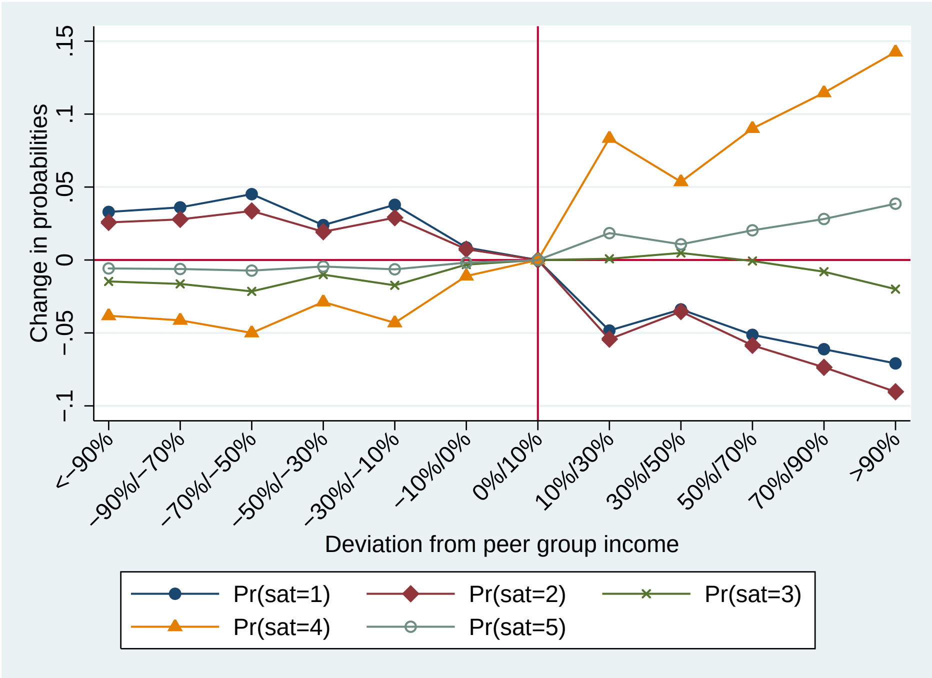
Hypothesis 4.2 *The average income of agents from the same company and the same peer-group acts as a reference-point for those agents*

I first conduct an ordered probit regression (the results are shown in Table 4.6).[60] Here, the independent variables Δ always refer to the peer-group deviation regarding the compensation component as indicated at the top of each column whilst controlling for the absolute level of all four compensation categories. This means that the first number in column (1) represents the coefficient of the dummy variable "Less than 10% of the peer-group median of total compensation", the first number in column (2) represents the coefficient of the dummy variable "Less than 10% of the peer-group median of new business commissions" and so on. From this, we see that mainly those dummies that indicate a positive deviation from the peer group have a statistically significant coefficient. In line with the previous regression using the continuous absolute compensation data, we again see no statistically significant influence of salary/subsidies on the satisfaction with pay. In the case of bonification, the only significant coefficient comes from the highest possible, positive category "$> 90\%$". This seems reasonable given the fact that bonification is usually paid to only a few agents and, therefore, the deviation of those that receive it compared

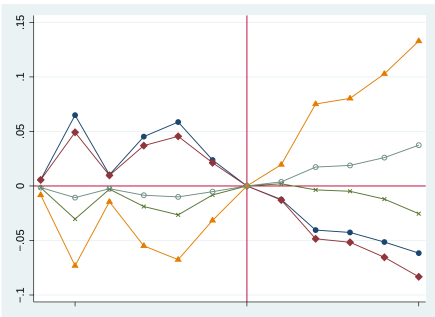
[60] An alternative specification with the deviation from the peer-group median included in the list of independent variables gives similar results and is not shown here

to the, rather low, median is quite high.
With the inclusion of the reference-point, we now also see a statistically significant effect of the recurring commissions, which is reassuring as we would expect it to play an important role in pay satisfaction due to its high share of total compensation.
For ease of presentation, I have combined the marginal effects of total compensation and the four sub-categories for Company A in Figure 4.3. Similar results are found for the other two companies (see Figures 4.8 and 4.9, only the effect of the total compensation dummies is shown).
In Figure 4.3(a), we see that the probability of choosing one of the top two satisfaction categories significantly increases beyond the reference-point and is almost 15 percentage points higher for those agents that have a more than 90% higher income compared to their peer-group median.[61] In contrast, the probability decreases by only 4 percentage points for agents with a total compensation below 10% of the peer-group income (i.e., $\triangle < -90\%$). Furthermore, the coefficients of those dummies indicating negative deviation are statistically not significant. Running a joined Wald test on all the indicator variables yields a p-value of 0.0002, showing that we can indeed reject the hypothesis of no influence from the deviation dummies. Virtually the same result is obtained when comparing the nested models (column (4) of Table 4.2 and column (1) of Table 4.6) via a Likelihood ratio-test. Applying the Wald test only to those dummies indicating negative deviation, however, results in a p-value of 0.74, and thus we cannot reject the null hypothesis. On the other hand, the p-value of only the dummies indicating positive deviation yields a p-value of 0.0118, and we therefore reject the null hypothesis. Hence, we conclude that the results support our above hypothesis for positive deviations from the reference-point.
As outlined in Section 4.1, a common theme accompanying reference points is the notion of loss aversion. From the results, we see that the data is not

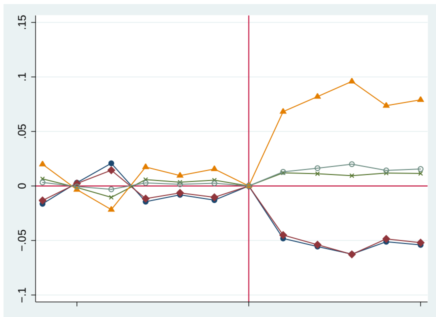
[61] An alternate visualization of the results is shown in Figure 4.7. Here, I used the average predicted satisfaction score on the vertical axis. We again see that positive deviations result in an increase of up to 0.4 satisfaction points whilst negative deviations have almost no effect



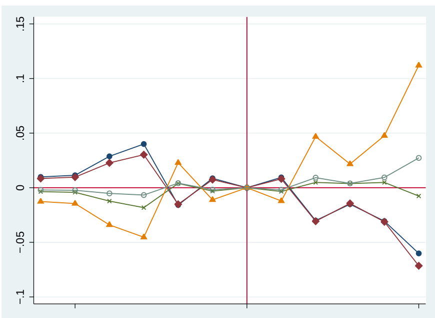
(a) Total commissions



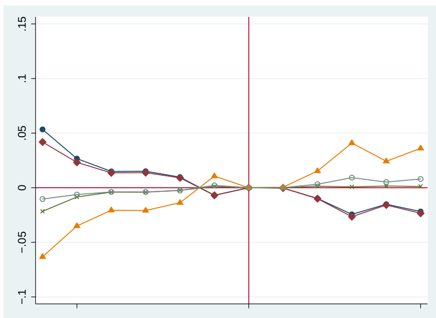
(b) New business



(c) Recurring commissions



(d) Bonification



(e) Salary/subsidies

Figure 4.3: Effect of deviation from peer compensation on satisfaction with pay (Company A)

in line with this finding but rather shows that only positive deviations have a significant influence on the agents' pay satisfaction. I will discuss potential explanations for this surprising result in Section 4.5.

When looking at the four compensation components, we find that the main drivers of the development described for the total compensation are new business and recurring commissions. The recurring commission curve in 4.3(c) shows a very characteristic reference-point pattern, as we see a strong increase of the top three satisfaction categories and a strong decrease of the bottom two beyond the assumed reference-point of 0% to 10% deviation from the peer-group total compensation.

In the case of bonification, we see the strong positive effect of the highest positive deviation category and much lower amplitudes for the others. This again is in line with the explanation given earlier, i.e., that bonification is usually seen as an added extra and thus triggers only positive changes to satisfaction.[62]

When interpreting Figure 4.3(e), we have to keep in mind that the regression showed no statistical significance for any of the dummy variables. This in itself, though, is also a result that could hint at the fact that salary and subsidies do not play a major role in determining agents' satisfaction with pay. One potential explanation might be that the level of fixed salary and subsidies is already defined in the employment contract and thus does not influence the agent's judgement after joining, as his hopes and fears are mainly directed towards the variable part of his compensation.

Regarding the model's goodness-of-fit, we also see an increase in the number of correctly predicted satisfaction levels. Table 4.7 summarizes the actual and predicted satisfaction scores for the different specifications shown in Table 4.6. In direct comparison to the results in Table 4.4, we now find a total of 690 correct predications compared with 673 from the simple model that did not use the reference-point dummy variables. The number of correct predictions of the other compensation components ranges from 675 to 694. The adjusted R^2 values are also higher compared to the previous model.

62 A discussion on how people react to salient events is given in Loewenstein (1996)

4.4.4 Robustness

After presenting the results of the work, I will now briefly discuss the robustness of the findings. As already mentioned in Section 4.4.2, I used robust standard errors throughout this work in order to adjust the results for heteroscedasticity. Besides the Wald- and LR-test results, which I usually reported together with the corresponding discussions of the coefficients, I also conducted the regressions using bootstrapping and jackknife analyses. In both cases, the results remained almost unchanged, with only the p-values changing slightly.

Regarding the goodness-of-fit measures, we see that the (adjusted) count R^2, the McKelvey & Zavoina's R^2, and the AIC, all show that the inclusion of the reference-point dummies increases the model's fit. Only in the case of the BIC, the results indicate a decrease in the goodness-of-fit.

As we have seen, the results remain consistent and quite stable under different specifications of the independent variables. Even running an OLS regression (despite all the caveats of OLS in the case of categorical variables) yields similar results.

Finally, as already indicated in Section 4.3, I also test the parallel regression assumption. As the results show that we can in fact reject the hypothesis that all coefficients are the same for all satisfaction scores (and strictly could not use ordered probit, see Long & Freese (2006)), I also ran the above analyses using a generalized ordered probit regression. Again, we find similar behavior and thus stick to the more common (and easier to interpret) simple ordered probit regression.

Besides these rather technical aspects, we also see that significant results are obtained only when using the *pay* satisfaction scores. This can also be interpreted as a sign of robustness and that the effects observed are indeed specific to compensation.

Overall, I conclude that the results are quite robust as the analysis of various specifications has shown.

4.5 Discussion and Conclusion

In this chapter, I analyzed the influence of compensation on both overall and pay satisfaction. Furthermore, I investigated the existence of a reference-point that drives agents' pay satisfaction.

I use a data-set of German tied insurance agents of three companies and find that, in line with other studies, the absolute level of compensation drives the satisfaction with pay but has no influence on overall satisfaction. Furthermore, I find supporting evidence for the assumption that agents judge their own income based on a reference-point. In spite of the predictions from common labor market literature, this reference-point is not the previous year's income but instead the income of the agent's peer group (which includes agents at the same company and within the same tenure cluster). Surprisingly, I find no evidence for loss aversion of the agent (which would mean a higher sensitivity of pay satisfaction for under-average income compared to above-average income) but instead the opposite. For the two commission types under consideration (new business and recurring commissions), we see a strong positive impact on the upper satisfaction scores of above-average performance and only a moderate (and statistically not significant) influence of below-average performance. Variations in the model specification prove the robustness of the results.

A potential explanation for these unexpected results might lie in the special profession under consideration. As insurance tied agents usually have a strong entrepreneurial spirit, the results might reflect the nature of many sales people to focus on the successes than on the failures of their work. Furthermore, a certain affinity to stick to average scores in questionnaires might have resulted in less satisfied agents to nevertheless give an average score, while very satisfied agents will not shy away from selecting a score from the upper part of the range. Finally, agents probably perceive their achievement/failure against set goals in quite diverse ways. As pointed out in the recent study by Kahneman & Thaler (2006), the choices made by agents depend on expectations as to what their compensation should be. Thus, if there is a systematic bias on how the agents predict or perceive their peers' income development, it might be that they more often feel they are above average, leading to higher pay satisfaction scores.

I contribute to the recent research regarding reference-dependent satisfaction of employees and show that, in this case, a different specification might be a more reasonable reference-point. By focusing on insurance agents, we have a clear link between performance and pay, which enables us to study the pure economic effects under consideration in the spirit of Fehr & Schmidt (2004). Furthermore, I hope to push the use of marginal effects analyses that extend the insights drawn from regression models for categorical dependent variables. The methods presented in this work help develop a better understanding of the dependency of the probabilities for different answer categories.

Even though the concept of peer-group specific reference points seems intuitively reasonable, it should be noted that it implies a rather high degree of transparency on agents' compensation. Even though this is a reasonable assumption in the case of insurance tied agents, one has to be careful when applying this concept to other industries.

Nevertheless, future research should try to validate the findings I present, using data from other industries to either prove or falsify the theory of peer-group-dependent reference points.

4.6 Appendix to Chapter 4

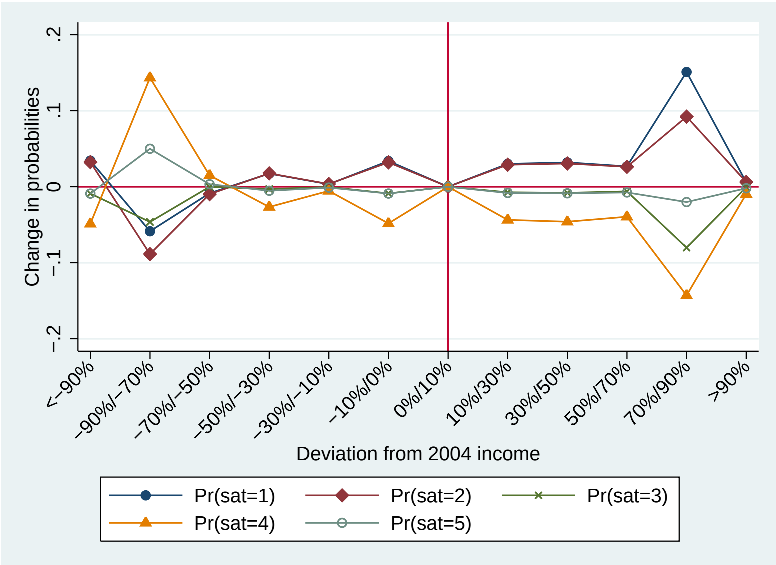


Figure 4.4: Test on last years total compensation as reference-point (Company A); variables set to their median

Table 4.5: Definition of ideal types of agents as used in Table 4.3

Ideal types	**Company**	**Age***	**Tenure***	**Total pay****
Avg. Company A	A	44	10	50
Young Rookie	A	25	0	0
Old Rookie	A	50	0	0
Rich Retiree	A	65	40	200
Avg. Low Performer	A	44	10	25
Avg. High Performer	A	44	10	100
Avg. Company B	B	44	10	50
Avg. Company C	C	44	10	50

* in years, ** in '000 EUR

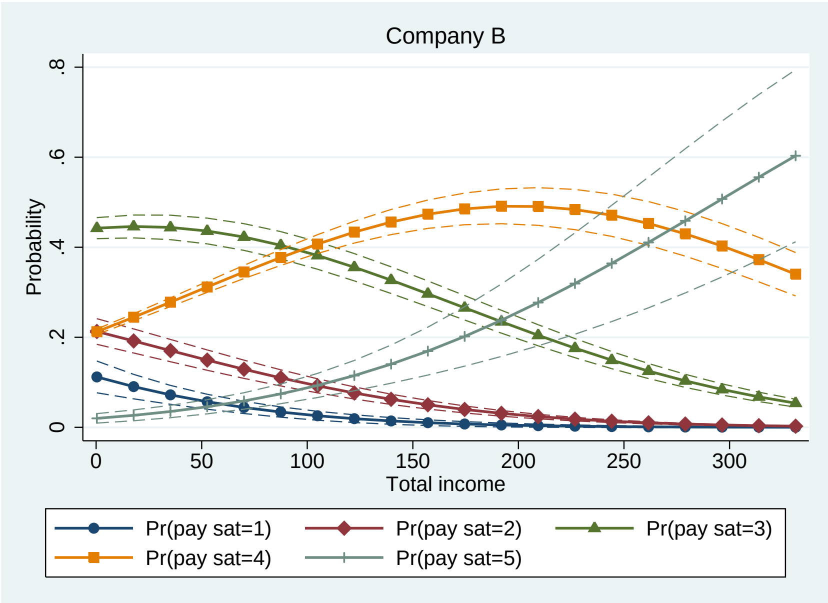


Figure 4.5: Marginal effects plot (including 95% confidence-intervals) of total compensation on satisfaction with pay (Company B); variables set to their median

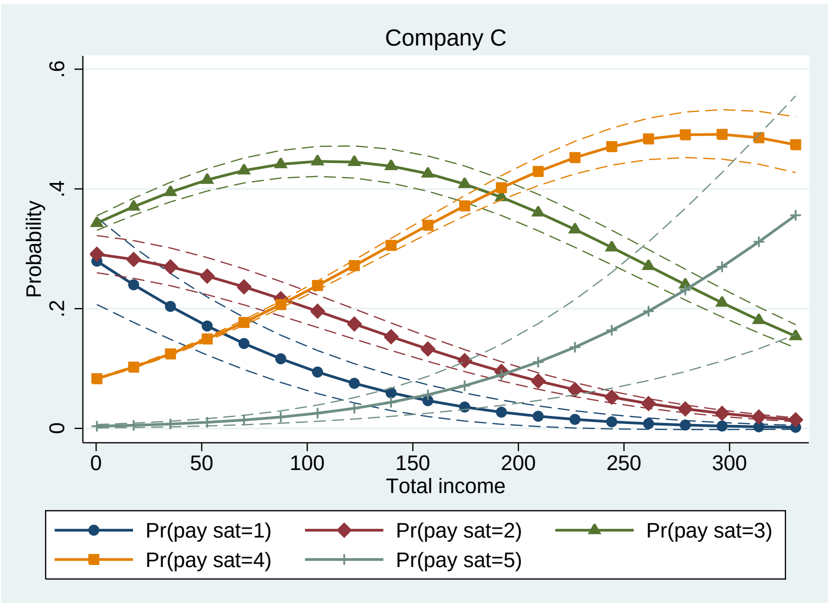
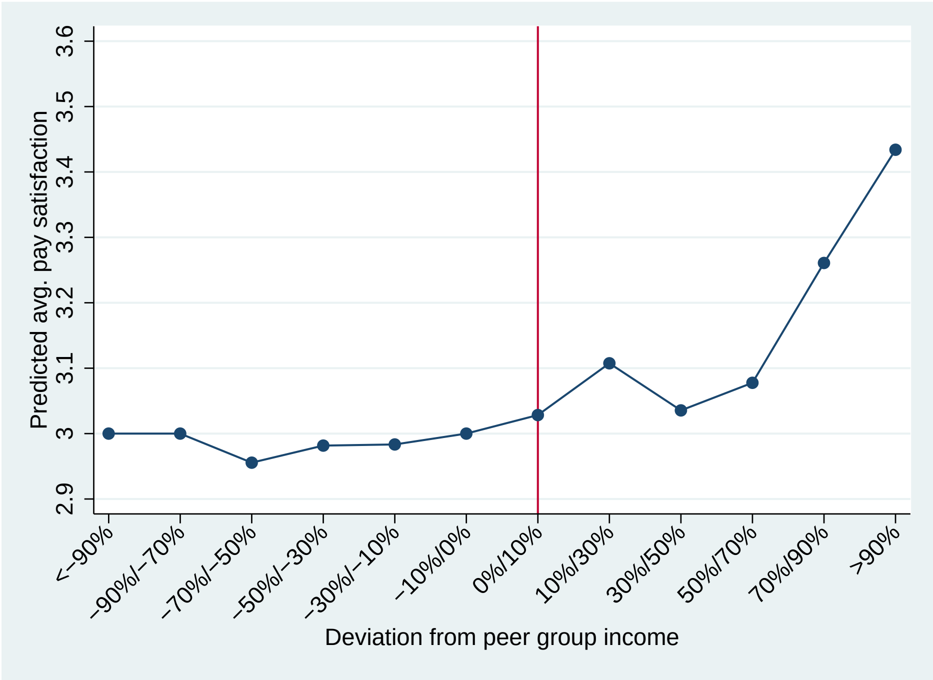
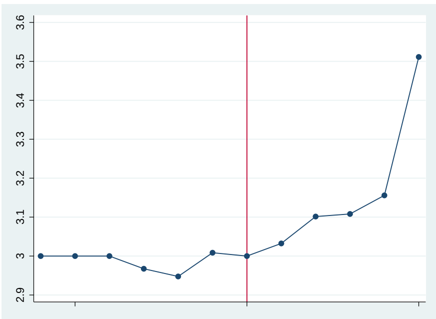


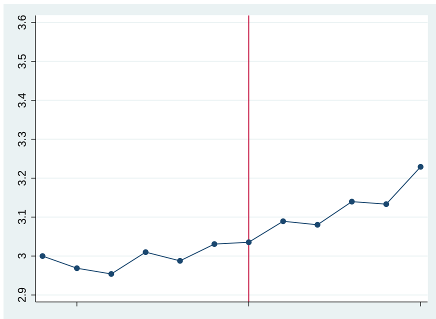
Figure 4.6: Marginal effects plot (including 95% confidence-intervals)of total compensation on satisfaction with pay (Company C); variables set to their median



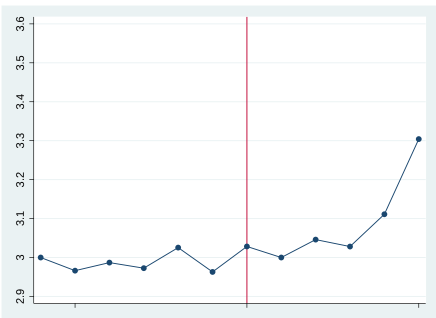
(a) Total commissions



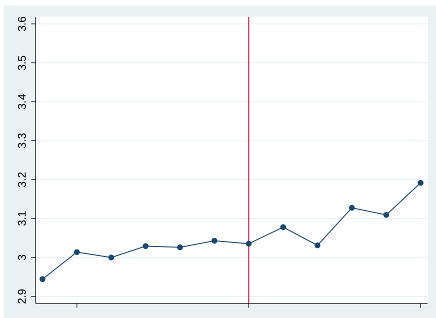
(b) New business



(c) Recurring commissions



(d) Bonification



(e) Salary/subsidies

Figure 4.7: Alternate visualization of Figure 4.3 using averaged predicted pay satisfaction scores

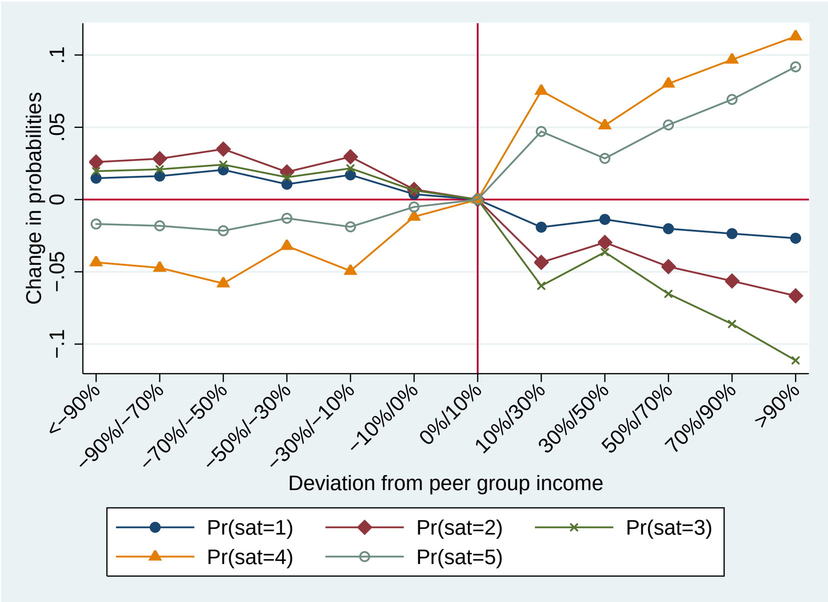


Figure 4.8: Effect of deviation from peer-group total compensation on satisfaction with pay (Company B); variables set to their median

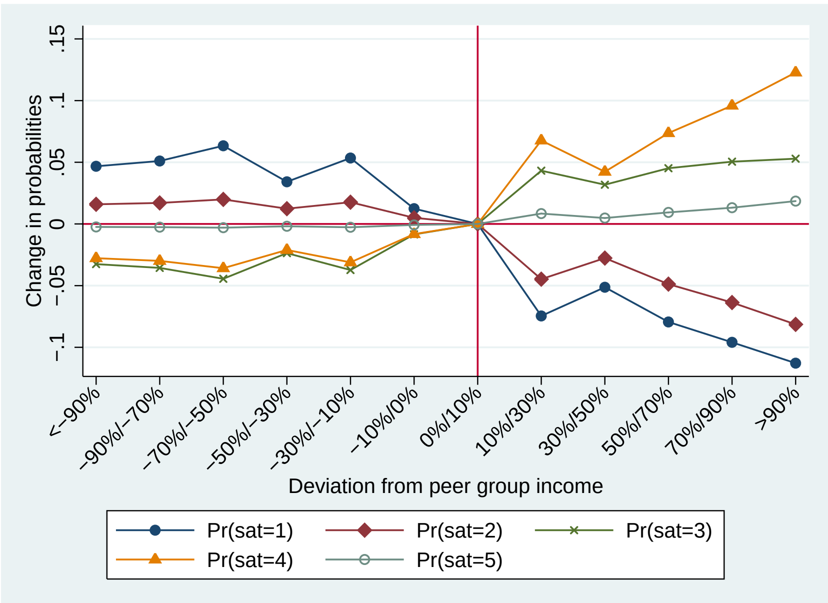


Figure 4.9: Effect of deviation from peer-group total compensation on satisfaction with pay (Company C); variables set to their median

Table 4.6: Effect of compensation deviations on compensation satisfaction

	(1) Total	(2) New	(3) Rec.	(4) Boni	(5) Subs.
$\Delta < -90\%$	-0.157	-0.0318	0.0803	-0.0501	-0.257
	(-0.47)	(-0.09)	(0.36)	(-0.30)	(-1.22)
$-90\% \leq \Delta \leq -70\%$	-0.171	-0.305	-0.0139	-0.0576	-0.138
	(-0.73)	(-1.63)	(-0.06)	(-0.39)	(-0.89)
$-70\% \leq \Delta < -50\%$	-0.209	-0.0560	-0.0925	-0.139	-0.0797
	(-1.39)	(-0.39)	(-0.60)	(-0.97)	(-0.61)
$-50\% \leq \Delta < -30\%$	-0.117	-0.223*	0.0703	-0.187	-0.0807
	(-0.96)	(-1.68)	(0.58)	(-1.34)	(-0.61)
$-30\% \leq \Delta < -10\%$	-0.178	-0.279**	0.0390	0.0875	-0.0527
	(-1.63)	(-2.36)	(0.33)	(0.61)	(-0.45)
$-10\% \leq \Delta < 0\%$	-0.0437	-0.125	0.0631	-0.0439	0.0400
	(-0.35)	(-0.90)	(0.48)	(-0.27)	(0.27)
$10\% \leq \Delta < 30\%$	0.308***	0.0734	0.263**	-0.0480	0.00193
	(2.63)	(0.58)	(2.12)	(-0.31)	(0.01)
$30\% \leq \Delta < 50\%$	0.201	0.274*	0.313**	0.176	0.0574
	(1.52)	(1.91)	(2.24)	(1.08)	(0.38)
$50\% \leq \Delta < 70\%$	0.332**	0.292**	0.363**	0.0831	0.151
	(2.25)	(2.04)	(2.39)	(0.48)	(0.98)
$70\% \leq \Delta < 90\%$	0.419***	0.372**	0.283*	0.179	0.0904
	(2.61)	(2.24)	(1.80)	(0.97)	(0.57)
$90\% \leq \Delta$	0.520***	0.480***	0.302*	0.409***	0.134
	(3.12)	(2.87)	(1.88)	(2.64)	(0.95)
New bus. com. 2005 ('000)	0.00239	-0.00120	0.00718***	0.00685***	0.00556*
	(0.83)	(-0.40)	(2.63)	(2.58)	(1.95)
Rec. com. 2005 ('000)	-0.00243	0.00145	-0.00259	0.00429	0.00387
	(-0.74)	(0.48)	(-0.62)	(1.45)	(1.23)
Bonif. 2005 ('000)	0.0223**	0.0253***	0.0268***	-0.00524	0.0259***
	(2.35)	(2.75)	(2.67)	(-0.45)	(2.60)
Fix/subsidies 2005 ('000)	-0.0173**	-0.0133**	-0.00618	-0.00907	-0.0175*
	(-2.55)	(-2.05)	(-0.99)	(-1.44)	(-1.88)
Age	-0.0154***	-0.0143***	-0.0150***	-0.0152***	-0.0148***
	(-4.36)	(-4.06)	(-4.27)	(-4.33)	(-4.25)
Tenure	0.0216***	0.0197***	0.0201***	0.0182***	0.0150***
	(5.29)	(4.88)	(4.62)	(4.48)	(3.72)
Company A	0.369***	0.316***	0.395***	0.369***	0.341***
	(3.39)	(2.90)	(3.65)	(3.39)	(3.14)
Company B	0.935***	0.754***	0.903***	0.870***	0.818***
	(5.64)	(4.67)	(5.13)	(5.33)	(4.87)
N	1558	1558	1558	1558	1558
Log-Likelihood	-2039.1	-2034.4	-2049.3	-2041.7	-2053.9
Count R^2	0.443	0.445	0.436	0.445	0.433
Adj. Count R^2	0.0323	0.0368	0.0212	0.0368	0.0156
McKelvey/ Zavoina's R^2	0.135	0.141	0.123	0.132	0.117
AIC	4124.3	4114.8	4144.7	4129.5	4153.7
BIC	4247.4	4237.9	4267.7	4252.6	4276.8

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: Constant not shown. Agents with a deviation of $0\% - +10\%$
and Company C used as reference categories.
Tenure clusters of 5 years used to calculate median and deviation of this median.

Table 4.7: Predicted compensation satisfaction based on model specifications as outlined in Table 4.6

Based on Table 4.6, Column (1)	Predicted sat. with compensation				
Satifsfaction with compensation	1	3	4	5	Total
1	3	148	3	0	154
2	2	281	8	1	292
3	1	616	44	0	661
4	0	324	71	0	395
5	0	37	19	0	56
Total	6	1,406	145	1	1,558

Based on Table 4.6, Column (2)	Predicted sat. with compensation				
Satifsfaction with compensation	1	3	4	5	Total
1	5	148	1	0	154
2	2	280	10	0	292
3	1	611	49	0	661
4	1	315	78	1	395
5	0	37	19	0	56
Total	9	1,391	157	1	1,558

Based on Table 4.6, Column (3)	Predicted sat. with compensation				
Satifsfaction with compensation	1	3	4	5	Total
1	2	150	2	0	154
2	2	284	5	1	292
3	1	623	37	0	661
4	1	338	55	1	395
5	0	43	13	0	56
Total	6	1,438	112	2	1,558

Based on Table 4.6, Column (4)	Predicted sat. with compensation				
Satifsfaction with compensation	1	3	4		Total
1	4	147	3		154
2	1	276	15		292
3	1	622	38		661
4	1	326	68		395
5	0	40	16		56
Total	7	1,411	140		1,558

Based on Table 4.6, Column (5)	Predicted sat. with compensation				
Satifsfaction with compensation	1	3	4	5	Total
1	0	152	2	0	154
2	0	285	6	1	292
3	1	626	34	0	661
4	1	343	49	2	395
5	0	42	14	0	56
Total	2	1,448	105	3	1,558

References

Abraham, K. G. & Farber, H. S. (1987), 'Job Duration, Seniority, and Earnings', *The American Economic Review* **77**(3), 278–297.

Akerlof, G. A. & Yellen, J. L. (1990), 'The Fair Wage-Effort Hypothesis and Unemployment', *The Quarterly Journal of Economics* **105**(2), 255–283.

Albers, S. (1996), 'Optimization models for salesforce Compensation', *European Journal of Operational Research* **89**, 1–17.

Albers, S. (2006), 'Außendienstentlohnung'.

Altonji, J. G. & Paxson, C. H. (1986), 'Job characteristics and hours of work', *Research in Labor Economics* **8**, 1–55.

Altonji, J. G. & Shakotko, R. A. (1987), 'Do Wages Rise with Job Seniority?', *The Review of Economic Studies* **54**(3), 437–459.

Altonji, J. G. & Williams, N. (1998), 'The Effects of Labor Market Experience, Job Seniority and Mobility on Wage Growth', *Research in Labor Economics* **17**, 233–276.

Altonji, J. G. & Williams, N. (2005), 'Do Wages Rise with Job Seniority? A Reassessment', *Industrial and Labor Relations Review* **58**(3), 370–397.

Anderson, J. A. (1984), 'Regression and Ordered Categorical Variables', *Journal of the Royal Statistical Society. Series B (Methodological)* **46**(1), 1–30.

Baker, G., Gibbs, M. & Holmstrom, B. (1994*a*), 'The Internal Economics of the Firm: Evidence from Personnel Data', *The Quarterly Journal of Economics* **109**(4), 881–919.

Baker, G., Gibbs, M. & Holmstrom, B. (1994*b*), 'The wage policy of a firm', *The Quarterly Journal of Economics* **109**(4), 921–955.

Barth, E. (1997), 'Firm-Specific Seniority and Wages', *Journal of Labor Economics* **15**(3), 495–506.

Baum, C. F. (2006), *An introduction to modern econometrics using stata*, Stata Press, College Station, Tex.

Beenken, M. (2003), *Der Versicherungsvertreter als Unternehmer: Betriebswirtschaftliche Herausforderungen für den Ausschließlichkeitsvertrieb*, Verlag Versicherungswirtschaft GmbH, Karlsruhe.

Bolton, P. & Dewatripont, M. (2005), *Contract theory*, MIT Press, Cambridge, Mass.

Bonner, S. E., Hastie, R., Sprinkle, G. B. & Young, M. (2000), 'A review of the effects of financial incentives on performance in laboratory tasks: Implications for management accounting', *Journal of Management Accounting Research* (12), 19–64.

Bonner, S. E. & Sprinkle, G. B. (2002), 'The effects of monetary incentives on effort and task performance: theories, evidence, and a framework for research', *Accounting, Organizations and Society* **27**(4-5), 303–345.

Bound, J., Jaeger, D. A. & Baker, R. M. (1995), 'Problems with Instrumental Variables Estimation When the Correlation Between the Instruments and the Endogeneous Explanatory Variable is Weak', *Journal of the American Statistical Association* **90**(430), 443–450.

Bratsberg, B., Ragan, J. F. & Warren, J. T. (2003), 'Negative Returns to Seniority: New Evidence in Academic Markets', *Industrial and Labor Relations Review* **56**(2), 306–323.

Breusch, T. S. & Pagan, A. R. (1979), 'A Simple Test for Heteroscedasticity and Random Coefficient Variation', *Econometrica* **47**(5), 1287–1294.

Brickley, J. & Zimmerman, J. (2001), 'Changing incentives in a multitask environment: evidence from a top-tier business school', *Journal of Corporate Finance* (7), 367–396.

Bronars, S. G. & Famulari, M. (1997), 'Wage, Tenure, and Wage Growth Variation within and across Establishments', *Journal of Labor Economics* **15**(2), 285–317.

Brown, G. D., Gardner, J., Oswald, A. J. & Qian, J. (2008), 'Does Wage Rank Affect Employees' Wellbeing?', *Industrial Relations* **47**(3), 355–389.

Brown, J. N. & Light, A. (1992), 'Interpreting Panel Data on Job Tenure', *Journal of Labor Economics* **10**(3), 219–257.

Brüggen, A. & Moers, F. (2007), 'The Role of Financial Incentives and Social Incentives in Multi-Task Settings', *Journal of Management Accounting Research* **19**, 25–50.

Burda, M. C. & Mertens, A. (2001), 'Estimating wage losses of displaced workers in Germany', *Labour Economics* **8**(1), 15–41.

Camerer, C., Babcock, L., Loewenstein, G. & Thaler, R. (1997), 'Labor supply of New York City cabdrivers: One day at a time', *The Quarterly Journal of Economics* **112**(2), 407–441.

Camerer, C. F. & Hogarth, R. M. (1999), 'The Effects of Financial Incentives in Experiments: A Review and Capital-Labor-Production Framework', *Journal of Risk & Uncertainty* **19**(1-3), 7–42.

Chuang, Y.-c. & Lee, C.-y. (2004), 'Industry-specific human capital and the wage profile: Evidence from Taiwan', *Review of World Economics* **140**(1), 110–124.

Churchill, G. A., Ford, N. M., Hartley, S. W. & Walker, O. C. (1985), 'The Determinants of Salesperson Performance: A Meta-Analysis', *Journal of Marketing Research (JMR)* **22**(2), 103–118.

Clark, A. E., Kristensen, N. & Westergård-Nielsen, N. (2009), 'Economic Satisfaction and Income Rank in Small Neighbourhoods', *Journal of the European Economic Association* **7**(2-3), 519–527.

Clark, A. E. & Oswald, A. J. (1996), 'Satisfaction and comparison income', *Journal of Public Economics* **61**(3), 359–381.

Coughlan, A. T. & Narasimhan, C. (1992), 'An Empirical Analysis of Sales-Force Compensation Plans', *The Journal of Business* **65**(1), 93–121.

Cummins, J. D. & Doherty, N. A. (2006), 'The Economics of Insurance Intermediaries', *Journal of Risk and Insurance* **73**(3), 359–396.

Cupach, W. & Carson, J. (2002), 'The Influence of Compensation on Product Recommendations Made by Insurance Agents', *Journal of Business Ethics* **40**(2), 167–176.

Daido, K. (2006), 'Formal and relational incentives in a multitask model', *International Review of Law and Economics* **26**(3), 380–394.

Damm, P. (1993), *Ertragsbarwertbezogene Vergütungspolitik von Versicherungsunternehmen zur Steuerung von Absatzorganen: Dissertation*, VVW, Karlsruhe.

Dodson, J. A. & Muller, E. (1978), 'Models of New Product Diffusion Through Advertising and Word-of-Mouth', *Management Science* **24**(15), 1568–1578.

Dorfman, M. S. (1976), 'Reformation in Life Insurance Agents' Compensation', *Journal of Risk and Insurance* **43**(3), 447–461.

Dustmann, C. & Meghir, C. (2005), 'Wages, Experience and Seniority', *The Review of Economic Studies* **72**(1), 77–108.

Dustmann, C. & Pereira, S. C. (2005), 'Wage Growth and Job Mobility in the U.K. and Germany', *IZA Discussion Paper* **No. 1586**.

Fehr, E. & Goette, L. (2007), 'Do Workers Work More if Wages are High? Evidence from a Randomized Field Experiment', *The American Economic Review* **97**(1), 298–317.

Fehr, E., Goette, L. & Zehnder, C. (2009), 'A Behavioral Account of the Labor Market: The Role of Fairness Concerns', *Annual Review of Economics* **1**(1), 355–384.

Fehr, E. & Schmidt, K. M. (2004), 'Fairness and Incentives in a Multitask Principal-Agent Model', *The Scandinavian Journal of Economics* **106**(3), 453–474.

Flabbi, L. & Ichino, A. (2001), 'Productivity, seniority and wages: new evidence from personnel data', *Labour Economics* **8**(3), 359–387.

Frederick, S., Loewenstein, G. & O'Donoghue, T. (2002), 'Time Discounting and Time Preference: A Critical Review', *Journal of Economic Literature* **40**(2), 351–401.

Freeman, R. B. (1978), 'Job Satisfaction as an Economic Variable', *The American Economic Review* **68**(2), 135–141.

Gathmann, C. & Schönberg, U. (2007), 'How General is Human Capital? A Task-Based Approach', *IZA Discussion Paper* **No. 3067**.

Genesove, D. & Mayer, C. (2001), 'Loss Aversion and Seller Behavior: Evidence from the Housing Market', *The Quarterly Journal of Economics* **116**(4), 1233.

Gibbons, R. & Waldman, M. (2006), 'Enriching a Theory of Wage and Promotion Dynamics inside Firms', *Journal of Labor Economics* **24**(1), 59–107.

Gneezy, U. & Rustichini, A. (2000), 'Pay enough or don't pay at all', *The Quarterly Journal of Economics* **115**(3), 791–810.

Goette, L. & Huffman, D. (2003), 'Reference-dependent preferences and the allocation of effort over time', *Working Paper Mimeo Institute for Empirical Research in Economics* .

Goette, L., Huffman, D. & Fehr, E. (2004), 'Loss Aversion and Labor Supply', *Journal of the European Economic Association* **2**(2-3), 216–228.

Graf, T. & Keese, O. J. (2000), 'Kundenbindung wird noch nicht genügend honoriert', *Versicherungsmagazin* (5), 30–32.

Groot, W. & van Maassen den Brink, H. (1999), 'Job satisfaction and preference drift', *Economics Letters* **63**(3), 363–367.

Grund, C. & Sliwka, D. (2005), 'Reference Dependent Preferences and the Impact of Wage Increases on Job Satisfaction: Theory and Evidence', *IZA Discussion Paper* **No. 1879**.

Gul, F. (1991), 'A Theory of Disappointment Aversion', *Econometrica* **59**(3), 667–686.

Hashimoto, M. (1981), 'Firm-Specific Human Capital as a Shared Investment', *The American Economic Review* **71**(3), 475–482.

Hausman, J. A. (1978), 'Specification Tests in Econometrics', *Econometrica* **46**(6), 1251–1271.

Haynes, M., Upward, R. & Wright, P. (2002), 'Estimating the wage costs of inter- and intra- sectoral adjustment', *Review of World Economics* **138**(2), 229–253.

Heath, C., Larrick, R. P. & Wu, G. (1999), 'Goals as Reference Points', *Cognitive Psychology* **38**(1), 79–109.

Heinz, M. H. (1999), 'Provisionssysteme - Bestimmungsgrößen und Elemente der Vergütung von Ausschließlichkeitsvertretern: Hrsg. von Fred Wagner, Karlsruhe (2000)', *Aktuelle Fragen in der Versicherungswirtschaft* pp. 85–93.

Herweg, F., Müller, D. & Weinschenk, P. (2008), 'The Optimality of Simple Contracts: Moral Hazard and Loss Aversion', *BonnEcon Discussion Paper* (17).

Holmstrom, B. & Milgrom, P. (1991), 'Multitask Principal-Agent Analyses: Incentive Contracts, Asset Ownership, and Job Design: Special Issue: [Papers from the Conference on the New Science of Organization, January 1991]', *Journal of Law, Economics, & Organization* **7**, 24–52.

Huang, L.-H. (2003), 'Industry-Specific Human Capital, Occupation and Firm Size: Evidence from Taiwan', *Small Business Economics* **20**(3), 205–218.

Huckman, R. S. & Pisano, G. P. (2003), 'The Effect of Organizational Context on Individual Performance', *National Bureau of Economic Research Working Paper Series* **No. 10027**.

Ingraham, H. G. (1973), 'Problems in Agents' Compensation', *Journal of Risk and Insurance* **40**(2), 191–208.

Jullien, B. & Salanié, B. (2000), 'Estimating Preferences Under Risk: The Case of Racetrack Bettors', *The Journal of Political Economy* **108**(3), 503–530.

Kahneman, D. & Thaler, R. H. (2006), 'Anomalies: Utility Maximization and Experienced Utility', *The Journal of Economic Perspectives* **20**(1), 221–234.

Kahneman, D. & Tversky, A. (1979), 'Prospect Theory: An Analysis of Decision under Risk', *Econometrica* **47**(2), 263–291.

Kambourov, G. & Manovskii, I. (2009), 'Occupational specificity of human capital', *International Economic Review* **50**(1), 63–115.

Kim, D. I. (1998), 'Reinterpreting Industry Premiums: Match-Specific Productivity', *Journal of Labor Economics* **16**(3), 479–504.

Kletzer, L. G. (1989), 'Returns to Seniority After Permanent Job Loss', *The American Economic Review* **79**(3), 536–543.

Kletzer, L. G. (1996), 'The Role of Sector-Specific Skills in Post displacement Earnings', *Industrial Relations* **35**(4), 473–490.

Köszegi, B. & Rabin, M. (2006), 'A Model of Reference-Dependent Preferences', *The Quarterly Journal of Economics* **121**(4), 1133–1165.

Lazear, E. P. (1986), 'Salaries and Piece Rates', *Journal of Business* **59**(3), 405–431.

Lazear, E. P. (2000), 'Performance Pay and Productivity', *The American Economic Review* **90**(5), 1346–1361.

Lazear, E. P. (2003), 'Firm-Specific Human Capital: A Skill-Weights Approach', *National Bureau of Economic Research Working Paper Series* **No. 9679**.

Lazear, E. P. & Oyer, P. (2004), 'The Structure of Wages and Internal Mobility: Papers and Proceedings of the One Hundred Sixteenth Annual Meeting of the American Economic Association San Diego, CA, January 3-5, 2004', *The American Economic Review* **94**(2), 212–216.

Lazear, E. P. & Oyer, P. (2007), 'Personnel Economics', *National Bureau of Economic Research Working Paper Series* **No. 13480**.

LeClere, M. J. (1999), 'The Interpretation of Coefficients in N-Chotomous Qualitative Response Models', *Contemporary Accounting Research* **16**(4), 711–747.

Lemieux, T., MacLeod, W. B. & Parent, D. (2009), 'Performance Pay and Wage Inequality', *Quarterly Journal of Economics* **124**(1), 1–49.

Lévy-Garboua, L. & Montmarquette, C. (2004), 'Reported job satisfaction: what does it mean?', *Journal of Socio-Economics* **33**(2), 135–151.

Lillard, L. A. (1999), 'Job Turnover Heterogeneity and Person-Job-Specific Time-Series Wages', *Annales d'Économie et de Statistique* (55/56), 183–210.

Loewenstein, G. (1996), 'Out of Control: Visceral Influences on Behavior', *Organizational Behavior and Human Decision Processes* **65**(3), 272–292.

Long, J. S. & Freese, J. (2006), *Regression models for categorical dependent variables using Stata*, 2. ed. edn, Stata Press, College Station, Tex.

Ludwig, R. (1994), *Vergütungssysteme in der Versicherungswirtschaft im Spannungsfeld zwischen Anbieter, Vermittler und Verbraucher: Mitglied der Vorstände der R+V Versicherung Holding AG*, Vol. 22 of *Münsteraner Reihe*, VVW, Karlsruhe.

Luttmer, E. F. P. (2005), 'Neighbors as Negatives: Relative Earnings and Well-Being', *The Quarterly Journal of Economics* **120**(3), 963–1002.

Lydon, R. & Chevalier, A. (2002), 'Estimates of the Effect of Wages on Job Satisfaction', *Centre for Economic Performance Discussion Paper* .

MacLeod, W. B. (2007), 'Reputations, Relationships, and Contract Enforcement', *Journal of Economic Literature* **45**(3), 595–628.

MacLeod, W. B. & Parent, D. (1999), 'Job Characteristics, Wages, and the Employment Contract', *Federal Reserve Bank of St. Louis Review* **81**(3), 13–28.

Margolis, D. N. (1996), 'Cohort Effects and Returns to Seniority in France', *Annales d'Économie et de Statistique* (41/42), 443–464.

Marshall, R. C. & Zarkin, G. A. (1987), 'The Effect of Job Tenure on Wage Offers', *Journal of Labor Economics* **5**(3), 301–324.

Mas, A. (2006), 'Pay, Reference Points, and Police Performance', *The Quarterly Journal of Economics* **121**(3), 783–821.

McDaniel, M. A., Schmidt, F. L. & Hunter, J. E. (1988), 'Job Experience Correlates of Job Performance', *Journal of Applied Psychology* **73**(2), 327–330.

McKelvey, R. & Zavoina, W. (1975), 'A statistical model for the analysis of ordinal level dependent variables', *Journal of Mathematical Sociology* (4), 103–120.

Medoff, J. L. & Abraham, K. G. (1980), 'Experience, Performance, and Earnings', *The Quarterly Journal of Economics* **95**(4), 703–736.

Medoff, J. L. & Abraham, K. G. (1981), 'Are Those Paid More Really More Productive? The Case of Experience', *The Journal of Human Resources* **16**(2), 186–216.

Meza, D. & Webb, D. C. (2007), 'Incentive Design under Loss Aversion', *Journal of the European Economic Association* **5**(1), 66–92.

Mohnen, A. & Schmidtlein, A. (2008), 'Vergütungssysteme im Vertrieb: Eine emprische Untersuchung', *Zeitschrift für Management* **3**(1), 73–95.

Munasinghe, L. & Sigman, K. (2004), 'A hobo syndrome? Mobility, wages, and job turnover', *Labour Economics* **11**(2), 191–218.

Neal, D. (1995), 'Industry-Specific Human Capital: Evidence from Displaced Workers', *Journal of Labor Economics* **13**(4), 653–677.

Neal, D. (1999), 'The Complexity of Job Mobility among Young Men', *Journal of Labor Economics* **17**(2), 237.

Neuman, E. & Neuman, S. (2008), 'Reference-dependent preferences and loss aversion: A discrete choice experiment in the health-care sector', *Judgment and Decision Making* **3**(2), 162–173.

Nguyena, A. N., Taylor, J. & Bradley, S. (2003), 'Relative pay and job satisfaction: some new evidence', *Lancaster University Management School Working Paper* (045).

O'Donoghue, T. & Rabin, M. (1999), 'Doing It Now or Later', *The American Economic Review* **89**(1), 103–124.

Oyer, P. (1998), 'Fiscal Year Ends and Nonlinear Incentive Contracts: The Effect on Business Seasonality', *Quarterly Journal of Economics* **113**(1), 149–185.

Oyer, P. (2004), 'Recall bias among displaced workers', *Economics Letters* **82**(3), 397–402.

Paarsch, H. J. & Shearer, B. (2000), 'Piece Rates, Fixed Wages, and Incentive Effects: Statistical Evidence from Payroll Records', *International Economic Review* **41**(1), 59–92.

Pagan, A. R. & Hall, A. D. (1983), 'Diagnostic tests as residual analysis', *Econometric Reviews* **2**(2), 159–218.

Parent, D. (2000), 'Industry-Specific Capital and the Wage Profile: Evidence from the National Longitudinal Survey of Youth and the Panel Study of Income Dynamics', *Journal of Labor Economics* **18**(2), 306–323.

Parent, D. (2002), 'Matching, human capital, and the covariance structure of earnings', *Labour Economics* **9**(3), 375–404.

Parent, D. (2009), 'The effect of pay-for-performance contracts on wages', *Empirical Economics* **36**(2), 269–295.

Poletaev, M. & Robinson, C. (2008), 'Human Capital Specificity: Evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys, 1984-2000', *Journal of Labor Economics* **26**(3), 387–420.

Prendergast, C. (1999), 'The Provision of Incentives in Firms', *Journal of Economic Literature* **37**(1), 7–63.

Pritchard, R. D. & Leo, P. J. (1973), 'Experimental test of the valence-instrumentality relationshp in job performance', *Journal of Applied Psychology* **57**(3), 264–270.

Rees, A. (1993), 'The Role of Fairness in Wage Determination', *Journal of Labor Economics* **11**(1), 243–252.

Rob, R. & Fishman, A. (2005), 'Is Bigger Better? Customer Base Expansion through Word-of-Mouth Reputation', *The Journal of Political Economy* **113**(5), 1146–1162.

Ruhm, C. J. (1990), 'Do Earnings Increase with Job Seniority?', *The Review of Economics and Statistics* **72**(1), 143–147.

Sautter, H. (1980), *Vergütungen als absatzpolitisches Instrument der Versicherungsunternehmung*, Vol. Bd. 266 of *Europäische Hochschulschriften*, Lang.

Shalev, J. (2000), 'Loss aversion equilibrium', *International Journal of Game Theory* **29**(2), 269–287.

Shea, J. (1997), 'Instrument Relevance in Multivariate Linear Models: A Simple Measure', *Review of Economics and Statistics* **79**(2), 348–352.

Shearer, B. (2004), 'Piece Rates, Fixed Wages and Incentives: Evidence from a Field Experiment', *Review of Economic Studies* **71**(247), 513–534.

Sliwka, D. (2003), 'Anreize, Motivationsverdrängung und Prinzipal-Agenten-Theorie', *Die Betriebswirtschaft* (63-3), 293–308.

Sprinkle, G. B. (2000), 'The Effect of Incentive Contracts on Learning and Performance', *The Accounting Review* **75**(3), 299–326.

Staiger, D. & Stock, J. H. (1997), 'Instrumental Variables Regression with Weak Instruments', *Econometrica* **65**(3), 557–586.

Stock, J. H., Wright, J. H. & Yogo, M. (2002), 'A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments', *Journal of Business & Economic Statistics* **20**(4), 518–529.

Stutzer, A. (2004), 'The role of income aspirations in individual happiness', *Journal of Economic Behavior & Organization* **54**(1), 89–109.

Tomporowski, P. D., Simpson, R. G. & Hager, L. (1993), 'Method of Recruiting Subjects and Performance on Cognitive Tests', *The American Journal of Psychology* **106**(4), 499–521.

Topel, R. (1991), 'Specific Capital, Mobility, and Wages: Wages Rise with Job Seniority', *The Journal of Political Economy* **99**(1), 145–176.

Topel, R. H. & Ward, M. P. (1992), 'Job Mobility and the Careers of Young Men', *The Quarterly Journal of Economics* **107**(2), 439–479.

Tversky, A. & Kahneman, D. (1991), 'Loss Aversion in Riskless Choice: A Reference-Dependent Model', *The Quarterly Journal of Economics* **106**(4), 1039–1061.

Vettas, N. (1997), 'On the Informational Role of Quantities: Durable Goods and Consumers' Word-of-Mouth Communication', *International Economic Review* **38**(4), 915–944.

Vogler, D. (2009), *Personenbezogene Einflussfaktoren für den Vertriebserfolg im Versicherungsvertrieb: Eine empirische Analyse bei Ausschließlichkeitsvertretern: Univ. Diss. – Köln 2009*, Vol. 53 of *Reihe Versicherungswirtschaft*, 1. aufl. edn, Eul, Lohmar.

Watterson, B. (2006), *The complete Calvin and Hobbes*, Andrews McMeel Pub.

Widura, R., Lehn, M., Muralidhar, K. & Scherer, R. (2008), 'Operator splitting approach applied to oscillatory flow and heat transfer in a tube', *Journal of Computational and Applied Mathematics* **211**(2), 115–130.

Williams, N. (1991), 'Reexamining the Wage, Tenure and Experience Relationship', *The Review of Economics and Statistics* **73**(3), 512–517.

Woodcock, S. D. (2008), 'Match Effects', *SSRN eLibrary* **No. 931529**.

Wooldridge, J. M. (2006), *Introductory econometrics: A modern approach*, 3. ed., internat. student ed. edn, Thomson South-Western, Mason, Ohio.