Relationships as an Incentive and Price Discriminating Tool*

Maria Dolores Palacios†

August 3, 2018

Abstract

I explore the importance of employee-customer relationships as an incentive and price discriminating tool. The model assumes that customers differ in their valuations and on their probability of returning (q). The distribution of valuations and q are known, and in each interaction the sales agent exerts effort to learn the customer's valuation. The agent earns a commission based on the client's payment and has full pricing flexibility. The two main insights are, first that when the valuation is unknown, effort is increasing in q. Second, that a commission raise increases the learning speed, and under certain conditions the learning speed on customers with higher q's increases more. Average prices should be increasing in effort. Using administrative data from an electrical wholesale company, I show that the data supports the theoretical insights.

*I am grateful to Kevin Lang, Andrew Newman, and Marc Rysman for their comments and suggestions.
†Boston University. email: doloresp@bu.edu.

1 Introduction

This study highlights two matters: first the importance of sales agent-client relationships as an incentive tool (that complements pay-for-performance), and second, the relevance of these relationships for price discrimination when the firm delegates pricing to the salesforce due to information asymmetries. The paper has a theoretical framework and an empirical section that tests the model's predictions. The model developed has the spirit of the framework used in Lo et al. (2016) where the price sensitivity of clients is better observed by the salesperson, but not influenced by the effort choices of the salesperson (as in Joseph, 2001; Hansen et al., 2008; and Palacios, 2018). However, in Lo et al. (2016) the authors focus on a static setting, whereas I set up a dynamic context, which is essential to understand the relevance of customer-employee relationship for agents' incentive provision.

In the model, customers differ in their valuations of goods and in the probability of coming back. The distribution of customers' valuations and the probability of returning for each customer is known. In addition, in each interaction the customer wants to buy one unit and the sales agent can exert some unobservable effort to learn the customer's valuation. Once the agent learns a customer's valuation she knows that information forever. I also assume that the sales agent earns a commission based on the client's payment and decides the price the customer pays. The theoretical framework provides two main insights. First, the probability of learning the client's valuation each period is increasing in the probability of returning. If the sales agent expects to have a recurrent client (and thus a long-term relationship), then by learning the customer's valuation she (and the firm) will benefit from extracting more of the buyer's surplus in several interactions. So, assigning customers to sales agents and allowing them to have a relationship incentivizes agents to exert higher effort and results in a more accurate price discriminating strategy for the firm. The second insight is that a higher commission increases the probability of learning customers' valuation and that the probability of learning increases more for recurrent clients. This suggests that customer-employee relationships complement commission based incentive schemes, which is the most prevalent form of sales agent compensation.

The main purpose of the model is to get testable predictions and guide the empirical section of the paper. To link theory and data, I note that expected price is higher when the sales agent knows the customer's valuation. Using administrative data from an electrical wholesaler that includes information about prices, sales agents and customers of each sale, I test the four predictions derived from the model.

First, I show that average weekly prices and customers' buying frequency (that I use as the empirical approximation of customers' probability of returning) are positively correlated. Second, I provide evidence that average prices within clients increase with interactions, in line with the intuition that sales agents learn from their customers and use this private information to increase prices (and thus their earnings and the firm's profits). Third, I show that the price spread is increasing in the number of interactions, supporting the view that agents are acquiring more information in each interaction and using it to price discriminate.

In 2008, the firm changed its commission scheme, resulting in an increase in the commission rate for most transactions. I use this contract change to test the fourth prediction regarding learning effort being increasing in the commission and how the effect of a commission raise is different among customers. The announcement of the new scheme was rolled out in two stages allowing identification of its effect by difference-in-differences. Not surprisingly, the price increases when the new contract is announced. I also find evidence that the effect of a commission raise has an inverted-U relation with the customers' buying frequency. On the one hand, with a higher commission sales agents increase effort on high-frequency customers more than on low-frequency customers. On the other hand, it is more likely that sales agents already know the valuation of high-frequency customers.

This paper is related to different literatures. It contributes to the literature on incentives well described in Prendergast (1999), Oyer and Schaefer (2011) and Lazear and Oyer (2013). Following the seminal paper by Lazear (2000), I use administrative data from a firm to test the predictions of the model developed. However, the main focus of my paper differs from Lazear's and previous studies. I do not focus on the effect of financial incentives. In this paper, I show that customer-employee relationships complement financial incentives and are relevant for motivating sales agents' effort for information acquisition.

I also contribute to the marketing literature on delegating pricing responsibility to the salesforce. To motivate my theoretical framework, I use the intuition that information asymmetry is a necessary condition for delegation to be preferred (proposed in Lal, 1986; Bhardwaj, 2001; and Mishra and Prasad, 2004, for instance). I do not model the choice of the firm to delegate pricing decisions to sales agents, but given that there is pricing delegation I assume that it is more profitable for the firm than centralization. This is true according to Lal (1986) when the salesperson's information is superior. To support the model, I provide evidence that sales agents adjust prices when they interact more with clients. This suggests that there is learning and that sales agents can use the new information because of the pricing flexibility they are allowed. This also speaks to the results from Lo et al. (2016), the authors argue that pricing flexibility is more valuable when the salesperson is more knowledgeable about customers' valuations.

The previous point is related to price discrimination. Because of information asymmetries, sales agents are better at price discrimination than the firm.[1] I contribute to the extensive literature on price discrimination by highlighting the interaction between price discrimination and customer-employee relationships. I also emphasize as in Palacios (2018) how the organization within the firm matters for the final price offered.

Finally, this paper is also related to the marketing literature on customer relationships.[2] However, it differs from previous studies which suggest that trust, customer loyalty or switching costs are the most important outcomes of customer-employee relationships. As previously stated, I focus on how relationships act as an incentive for sales agents.

[1] "One way to look at delegation of the pricing decision is that it helps eliminate complex specifications of the pricing policy (as is the case in nonlinear pricing schemes) and can lead to higher profits if it is less expensive for the firm to design salesforce compensation plans which will induce the salesperson to charge the maximum price (a customer is willing to pay) rather than designing nonlinear pricing schemes to motivate the customer to self-select truthfully." (Lal, 1986)

[2] See for instance Swan and Nolan (1985), Dwyer et al. (1987), Frankwick et al. (2001), Sharma (2001), and Guenzi et al. (2009).

2 Model

I start by describing a simple theoretical framework. I assume that customers value consumption differently and that this is private information. The firm assigns sales agents to customers because they can work more closely with customers and learn about their valuation. The sales agents can learn with some probability about customers' private information and decide what payment to ask for. The probability of learning depends on some unobservable effort that is costly for the agents.

2.1 The Basic Model

Sales agents are forward-looking. When choosing their actions in period t, they take into account not only the one-period utilities associated with the choices but also their effect on future earnings.

Assumptions:

1. **Competition**: the firm is a monopoly.

2. **Probability of returning**: each customer has a different probability of returning (q).

3. **Customers' valuation**: the customer's type or valuation can be low (θ_L) or high (θ_H). The proportion of low types is β. Customers only buy in period t if the payment (P_t) they have to make is less or equal to their valuation (i.e., if $P_t \leq \theta$).[3]

4. **Agents' utility**: the one period utility function for the sales agent is earnings minus cost of effort: $u(a_t, s_t) = \alpha P_t - g(\lambda_t)$, where a_t are the choice variables, s_t is the state of the world, α is the commission paid to the sales agent, and $g(\lambda_t) = \frac{k\lambda_t^2}{2}$ is the cost of providing effort λ_t.

5. **Choice variables**: $a_t = \{\lambda_t, P_t\}$ are the effort, and the payment requested.

[3] An alternative is to think that customers have a low or a high outside option.

6. **State variable**: the state s_t is whether the sales agent is informed ($s_t = i$) about the customer type or not informed ($s_t = -i$). Knowing the valuation is an absorbing state; once the sales agent learns the customer's valuation in period t, she is informed in all subsequent periods.

7. **Transition probabilities**: the probability of finding out the customer type is $\pi(\lambda) = 1 - e^{-\lambda}$. So, with no effort ($\lambda = 0$) the probability of finding out the customer's valuation is equal to zero.

8. **Rejected offers**: if the customer rejects an offer there are no future interactions. Under the outside option interpretation of customers' type, one could think that after receiving an offer higher than the outside option, the customer concludes that the outside option is cheaper and quits the relationship.

9. **Valuations and proportion**: $\theta_L/\theta_H > 1 - \beta$.[4]

The sales agent weights the consequences of her decisions for future utility. She maximizes expected utility with each customer given the vector of state variables and the client's probability of returning

$$E\left(\sum_{j=0}^{\infty}(\delta q)^j u(a_{t+j}, s_{t+j})|a_t, s_t\right)$$

where δ is the discount factor. By Bellman's principle of optimality the value function can be obtained using the recursive expression

$$\begin{aligned} V(s_t) &= \max_{a\in A} \{u(a, s_t) + \delta E[V(s_{t+1})|s_t, a_t = a]\} \\ V(s_t) &= \max_{a\in A} \{\alpha P - g(\lambda) + \delta \cdot q \cdot E[\pi(\lambda|s_t)V(s_{t+1} = i) + (1 - \pi(\lambda|s_t))V(s_{t+1} = -i)]\} \end{aligned}$$

The following Lemmas describe the payment requested by the agent in both states of the world (proofs can be found in the Appendix).

[4] If I do not impose this condition, the agent can set prices such that $P_t = \theta_H \quad \forall t$, and the paper provides no insights about the value of relationships for price setting and effort (see Lemma 2).

Lemma 1 *When the agent is informed she will ask for a payment* $P_\theta = \theta$*.*

Lemma 2 *When the agent is not informed she will ask for a payment* $P^{-i} = \theta_L$*.*

Some simplifications of the problem are worth pointing out. When the agent is informed, effort does not bring any additional benefits (the probability of knowing the customer's type in period $t+1$ given that it is known in period t is equal to one; i.e., $\pi(\lambda|s_t = i) = 1 \ \forall \lambda$). Thus, if the agent is informed she will always choose to exert no effort ($\lambda = 0$) and ask for a payment $P_\theta = \theta$ for customer with valuation θ. On the other hand, when the agent is not informed she requests a payment P^{-i} and chooses how much effort to exert depending on the expected benefits of this effort. To analyze the evolution of effort choices, a first relevant point stated in Lemma 3 is that there are expected benefits for the agent of being informed. Let the expected revenue be $P^i \equiv E[P_\theta]$ when the agent is informed.

Lemma 3 *The sales agent's expected earnings in a given period are higher when she has information (*$w^i \equiv \alpha P^i$*) than when she does not (*$w^{-i} \equiv \alpha P^{-i}$*).*

Customers differ in their valuations and in their probability of returning. Sales agents benefit more from knowing the valuations of frequent buyers. Therefore, conditional on not having yet learned the client's type, a sales agent exerts more effort to learn the valuation of customers with high q's. This intuition is stated more formally in Theorem 1.

Theorem 1 *The probability that an uninformed sales agent learns the client's valuation in interaction* t *is increasing in the customer's probability of returning (*q*).*

Another relevant matter is to consider how effort responds to changes in the commission rate and if the probability of returning matters. In the uninformed state, both the effort and the learning speed are increasing in the commission. Also, the effect is heterogeneous among customers with different probabilities of returning. Learning effort and speed increase more for customers with a larger probability of returning after a commission raise than for customers with a small probability of returning.

Lemma 4 *The probability that an uninformed sales agent learns the customer valuation is increasing in the commission. Moreover, changes in the probability of learning the customer valuation when there is a commission change are stronger for customers with larger probabilities of returning.*

The cost function ensures that the agent always exerts some effort. So, the probability of learning is non-zero in every period during which the agent is uninformed.

Lemma 5 *The probability of knowing the customer's valuation goes to one as t goes to infinity.*

Putting Lemmas 4 and 5 together gives us that the learning speed is increasing in the commission and increases more for customers with a larger probability of returning after a commission raise than for customers with a small probability of returning.

Proposition 1 *If the commission increases, then the sales agent learns the customer's valuation faster than before and even faster for customers with larger probabilities of returning.*[5] *In terms of the rate of convergence (μ) of the probability of knowing the customer valuation to one*

$$\begin{aligned} \frac{\partial \mu}{\partial \alpha} &< 0 \\ \frac{\partial^2 \mu}{\partial \alpha \partial q} &< 0. \end{aligned}$$

Therefore, the probability of knowing the customer valuation converges faster to one as α increases and converges even faster to one for customers with high probabilities of returning as α increases.

[5] This last proposition cannot be tested with the data currently available, but will be explored and tested in future drafts.

2.2 Predictions

If the intuition of this model is correct, what should we observe across clients with different probabilities of returning? How do prices respond to changes in the commission rate? Is the response different depending on the probabilities of returning q? I describe four predictions drawn from the model outlined that I then test using an administrative dataset (proofs can be found in the Appendix).

Prediction 1 *The average price is higher for clients with a higher probability of returning.*

Prediction 2 *The average price increases with the number of past interactions.*

Prediction 3 *The spread of clients' average prices increases with the number of past interactions.*

Prediction 4 *If the commission increases, then the average price: (a) increases and (b) the increase has an inverted-U relation with the probability of returning.*

The intuition for the second part of the last prediction comes from putting together Theorem 1 and Lemma 4. On the one hand, with a higher commission sales agents increase effort on customers with a high probability of returning more than on customers with a low probability of returning. On the other hand, it is more likely that sales agents already know the valuation of customers with a high probability of returning. If the sales agent already knows the client's valuation, a commission increase has no effect on the prices charged. That means that there could be a group of customers with $\hat{q} < 1$ for which the effect of a commission raise is the highest.

3 Data and patterns

To test the predictions previously described I use data from a branch of an international company specialized in distribution of electrical products and related services. An important characteristic of this firm is that sales agents set the prices. There is a list price for each product. In theory, sales agents can go above the list price, yet in practice, they never do. The only restriction agents have is that the price has to be greater than or equal to the cost of the product.

I merge information from the commissions and sales records. The data compiled contains detailed information on every transaction for 2008 and 2009, including a product ID number, the revenue made, price-cost margin, price and quantity of each transaction, employee, commission earned, customer, invoice number, invoice date, and payment date. I define interactions on a weekly basis. That is, the number of interactions increases by one in a given week if I observe any transaction in that week and stays the same otherwise. I define the probability of returning q as the buying frequency: the ratio of sum of all interactions observed for each customer and the total number of weeks (103).[6] So, customers that buy every single week have a q equal to one and those that buy only once in the two years observed have a q lower than 0.01.

Figure 1 shows a histogram of customers by their buying frequency. There are 9,055 customers and the average q is 0.12. About half of the customers have fewer than 4 interactions in 2008 and 2009 and only 20 customers buy every single week. Figure 2 shows that even when excluding the customers with few interactions the distribution of clients by their buying frequency is very skewed to the right.

3.1 Prediction 1: price and the buying frequency

Figure 3 supports Prediction 1. It shows that there is a positive relation between average price and customer's buying frequency. Customers that buy every single period are paying twenty dollars more per item than those that buy only once. This comes both from customers paying different prices per product and buying different products. To analyze how the prices paid on the same products differ by customers' buying frequencies we can look at Figure 4. This figure shows the relation between the residuals (of a regression of the log prices and

[6] I drop the first week of 2008 because information is incomplete for many transactions.

product fixed effects) and the buying frequency. For clients with $0 < q < 0.75$ there is a positive relation between the per product prices and the buying frequency. Customers with a buying frequency of 0.7 pay on average about 1 percent more for the same products than customers that have low buying frequencies. However, for customers with $q > 0.75$ there is a negative relation between the per product average prices and the buying frequency. There are 236 customers with $q > 0.75$ (2.6 percent of customers), that account for 35 percent of the transactions and 40 percent of the firm's sales in 2008 and 2009.

The negative relation between the per product average prices and the buying frequency for customers with $q > 0.75$ is probably due to quantity discounts that the model does not consider (because I am assuming that customers buy one unit in each interaction). Figure 5 shows that per interaction clients with $q > 0.75$ on average buy more of the same products than clients with lower buying frequencies. However, as seen in Figure 6 even with this discount, the value added (i.e., (price-cost)$\times$quantity) is increasing in the buying frequency. The same is true for the sales agents' earnings, suggesting that the sales agents are optimizing when deciding whether to give quantity discounts. However, we would need a more complex model to also include this behavior.

In addition to the figures described, I test the prediction using the following regression

$$log(p_{ijt}) = \beta_1 \cdot q_i \beta_2 \cdot int_{it} + \psi X_i + \phi_t + \mu + u_{ijt} \tag{1}$$

where p_{ijt} is the average price paid by customer i on product j in week t, q_i is the buying frequency for customer i, int_{it} is the number of past interactions that customer i has in period t, X_i are covariates from the sales agent that sold the products to client i (age, age squared, gender and tenure), ϕ_t are a full set of week time effects and μ are either sales agent, customer and/or product fixed effects, depending on the specification. Finally, the u_{ijt} are identically distributed error terms with mean zero. I cluster the standard errors at the sales agent level to account for correlation among the customers of a same agent.

The results in Table 1 are consistent with the figures. The correlation between log prices and buying frequency is positive except when we include product fixed effects (Column (4)). Still, the result in Column (4) indicates that customers that buy every single week are paying only a price 0.3 percent lower than customers that buy only once.

We might think that causality would go from price to customers returning. Yet that would mean that we would consistently observe the opposite relation from the one predicted in the model[7] and estimated across products and within products for customers with $q < 0.75$.

3.2 Prediction 2: price and the number of past interactions

To test Prediction 2 I use Equation 1. Prediction 2 states that price is increasing not only in the buying frequency but also in the length of the relationship or number of past interactions.

The evidence in Table 1 supports this prediction. The point estimates of the five specifications are positive and statistically significant. Average per product price is between 0.09 and 0.03 percent higher for each additional interaction. That means that after the customer has purchased between 11 and 33 times from the sales agent she pays a price one percent higher than in the first purchase.

3.3 Prediction 3: price spread and the number of past interactions

Figure 7 provides evidence that the spread of clients' average prices is increasing in the number of past interactions t. In this figure, we see that the average range of product prices increases as the number of past interactions increases. For this figure I am only using the customers with a buying frequency greater or equal to 0.99 in order to depict the within customer changes. This way, the evolution of the price range is only due to changes in the same group of customers and not due to changes in the composition of customers.

In the next section I analyze how a change in the commission structure affected the different customers and test Prediction 4.

[7]Suggesting that because sales agents are offering lower prices to some customers, these clients are the ones that have the higher probability of returning.

4 A commission change

As in many companies, sales workers of this firm receive a fixed salary and a commission on the revenues they make from sales. Commissions are an important component of sales agents' income, they represent around one third of total wages. Before mid-2008, the commission percentage was one. That is, sales employees earned one percent of revenues. In 2008, this scheme changed. After mid-2008, the commission percentage could take four different values (0.375%, 0.75%, 1.125% and 1.5%) depending on the price-cost margin of the transaction. More details can be found in Palacios (2018).

Let s represent the fixed component of the wage $w(p, q)$ that agents receive, and, p_j and q_j the price and quantity, respectively, of each transaction j. Finally, α_j is the commission percentage or commission rate. Then

$$w(p,q) = s + \sum_{j=1}^{J} \alpha_j (p_j q_j).$$

With the old contract

$$\alpha_j = 1\%, \quad \forall j.$$

With the new contract, the commission percentage is a piecewise linear function that depends on the price-cost margin of each transaction

$$\alpha_j = \begin{cases} 0.375\% & \text{if } \frac{p_j - c_j}{p_j} < 0.05 \\ 0.75\% & \text{if } 0.05 < \frac{p_j - c_j}{p_j} \leq 0.11 \\ 1.125\% & \text{if } 0.11 < \frac{p_j - c_j}{p_j} \leq 0.14 \\ 1.5\% & \text{if } 0.14 < \frac{p_j - c_j}{p_j}. \end{cases}$$

With the new contract, transactions with a price-cost margin less or equal than 0.11 receive a lower commission than before. However, even when the old contract was in place, around 94% of transactions (that represented 83% of revenues) registered a margin above this threshold. In the months after the announcement of the new contract, 91% of transactions (representing 82% of revenues) had a margin at least equal to 0.11. This implies that for most sales the change in the compensation scheme involved an increase of the commission rate.

The announcement of the new contract scheme was rolled out in two stages. This allows me to implement a difference-in-differences analysis using the two announcement dates. The firm divides its sales employees in regions. Sales agents do not interact with anyone outside their region. They report to a regional manager and have a portfolio of customers assigned to them. This avoids competition for clients between employees. In 2008, the firm divided its sales employees in twelve regions. At the end of June 2008, the human resources team announced the new contract to agents of three regions. I will refer to this set of agents as group one. In the other nine regions, the new policy was announced and explained to the sales workforce by the end of September of the same year. I will refer to this set of agents as group two.

A caveat is that the announcement dates did not coincide with the actual implementation dates. The plan, and what the sales agents were told, was that in the month following the announcement, the new scheme would be in place. However, the new contract was gradually introduced and it was not until December 2008 that all workers were generating commissions according to the piecewise scheme. Still, employees were not aware that the introduction of the new payment scheme would be gradual. In addition, they received their commissions after customers paid and on average it took customers 60 days to pay after a transaction. So, sales agents did not expect to perceive an immediate change in their paycheck after adjusting their behavior. Therefore, we would anticipate to have a sustained change in agents' effort in the weeks following the announcement.[8]

[8] For a more detailed explanation of the dataset and the announcement see Palacios (2018).

4.1 Prediction 4(a): price and a higher commission

Again aggregating the transactions at the customer i product j week t, I use the following specification to test Prediction 4(a)

$$log(p_{ijt}) = \tau D_{it} + \psi X_i + \phi_t + \mu + u_{ijt} \tag{2}$$

where D_{it} is a dummy variable equal to one after the announcement of the new contract was made in the region to which customer i belongs, and zero otherwise. When there are no sales agent or client fixed effects I also include a dummy variable for group.

Table 2 shows the effect of the announcement of the new contract on average weekly prices. The point estimates of the five specifications are positive (but only statistically significant for Columns (1), (4) and (5)). According to Column (1), average weekly prices per customer increase 2 percent with the announcement of the new contract. However, when we include product fixed effects as shown in Columns (4) and (5) the increase is less than 1 percent, suggesting that with a higher commission sales agents are changing both the prices and the product mix offered to customers.

4.2 Prediction 4(b): a higher commission and the heterogeneous effect on customers

The second part of Prediction 4 states that the price increase caused by a commission raise will have an inverted-U relation with the customers' probability of returning. To test this I run the following regression

$$log(p_{ijt}) = \tilde{\tau}(q_i \times D_{it}) + \tilde{\tilde{\tau}}(q_i^2 \times D_{it}) + \tau D_{it} + \gamma q_i + \tilde{\gamma} q_i^2 + \psi X_i + \phi_t + \mu + u_{ijt}. \tag{3}$$

The results in Table 3 confirm Prediction 4(b): there is an inverted-U relation between the price increase and customers' buying frequency. The estimates from the first three columns suggest that for customers with a buying frequency of around 0.4 the effect of a commission increase is higher than for any other customer. The estimates from Columns (4) and (5), when including product fixed effects, suggest that for customers with a buying frequency above 0.74 the effect of a commission increase is higher than for any other customer. Finally, Figures 8, 9, and 10 confirm the view that there is an inverted-U relation between the price increase and customers' buying frequency allowing for a more flexible specification. I divide customers into five groups according to their buying frequency and estimate the effect of the new contract announcement on the average prices paid by the five groups of customers. These five figures consider the specifications with different fixed effects shown in Table 3.

5 Conclusion

Aligning sales agents' incentives with the firm's objectives is crucial for businesses success. I develop a simple theoretical model in which customer-employee relationships are a tool for motivating sales agents. Sales agents put more effort into learning the customer's type if they know there is a higher probability that the customer will buy from them again. By assigning sales agents to customers, the firm increases this probability and helps set up the basis for the customer-employee relationship. With the right financial incentives in place, relationships allow sales agents to learn the customer's valuation and incite them to use this information to charge the maximum price the customer is willing to pay. Relationships act as an incentive and price discriminating tool.

Using administrative data from an electrical wholesaler I test four predictions drawn from the model. I find that customers' probability of returning (customers' buying frequency) and average weekly prices are positively correlated. This finding supports the view that sales agents exert more effort to learn customer's valuation when they know there is a higher probability that the customer will buy from them again and use the information to increase the price charged. Additionally, weekly average prices within clients increase with the number of past interactions, in line with the intuition that the customer type is unknown and learning can occur in every interaction.

I also take advantage of a change in the commission scheme that increased the commission rate of most transactions to estimate the effect of a commission increase on weekly average price. Not surprisingly, I find that with the announcement of the new scheme average weekly prices increased. In addition, I find that the effect was heterogeneous for customers with different buying frequencies. The evidence demonstrates that there is an inverted-U relation between the price increase caused by the commission change and customers' buying frequencies.

References

Bhardwaj, Pradeep, "Delegating Pricing Decisions," *Marketing Science*, 2001, *20* (2), 143–169.

Dwyer, F Robert, Paul H Schurr, and Sejo Oh, "Developing Buyer-Seller Relationships," *The Journal of marketing*, 1987, pp. 11–27.

Frankwick, Gary L, Stephen S Porter, and Lawrence A Crosby, "Dynamics of Relationship Selling: A Longitudinal Examination of Changes in Salesperson-Customer Relationship Status," *Journal of Personal Selling & Sales Management*, 2001, *21* (2), 135–146.

Guenzi, Paolo, Laurent Georges, and Catherine Pardo, "The Impact of Strategic Account Managers' Behaviors on Relational Outcomes: An Empirical Study," *Industrial Marketing Management*, 2009, *38* (3), 300–311.

Hansen, Ann-Kristin, Kissan Joseph, and Manfred Krafft, "Price Delegation in Sales Organizations: An Empirical Investigation," *Business Research*, 2008, *1* (1), 94–104.

Joseph, Kissan, "On the Optimality of Delegating Pricing Authority to the Sales Force," *Journal of Marketing*, 2001, *65* (1), 62–70.

Lal, Rajiv, "Delegating Pricing Responsibility to the Salesforce," *Marketing Science*, 1986, *5* (2), 159–168.

Lazear, Edward P., "Performance Pay and Productivity," *American Economic Review*, 2000, *90*, 1346–1361.

_ **and Paul Oyer**, "Personnel Economics," *Handbook of Organizational Economics*, 2013, pp. 479–519.

Lo, Desmond, Wouter Dessein, Mrinal Ghosh, and Francine Lafontaine, "Price Delegation and Performance Pay: Evidence from Industrial Sales Forces," *The Journal of Law, Economics, and Organization*, 2016, *32* (3), 508–544.

Mishra, Birendra K. and Ashutosh Prasad, "Centralized Pricing versus Delegating Pricing to the Salesforce under Information Asymmetry," *Marketing Science*, 2004, *23* (1), 21–27.

Oyer, Paul and Scott Schaefer, "Personnel Economics: Hiring and Incentives," *Handbook of Labor Economics*, 2011, *4*, 1769–1823.

Palacios, Maria D., "Price Setting and Multitasking: Evidence from a Contract Change," 2018.

Prendergast, Canice, "The Provision of Incentives in Firms," *Journal of economic literature*, 1999, pp. 7–63.

Sharma, Varinder M, "Industrial and Organizational Salesforce Roles: A Relationship-Based Perspective," *Journal of Marketing Theory and Practice*, 2001, *9* (3), 44–60.

Swan, John E and Johannah Jones Nolan, "Gaining Customer Trust: A Conceptual Guide for the Salesperson," *Journal of Personal Selling & Sales Management*, 1985, *5* (2), 39–48.

Appendix A

A.1 Proof of Lemma 1

Suppose for a contradiction this is not true. Then, if the agent requests a higher payment $P_t > \theta$ the customer rejects the offer and all future interactions are lost. If $P_t < \theta$, the agent could ask for $P_t + \epsilon$ (with $\epsilon > 0$); the customer still buys and the agent's earnings are higher. So, the agent is better off asking for $P_t = \theta$.

A.2 Proof of Lemma 2

Suppose for a contradiction this is not true. If $P_t < \theta_L$, the agent could instead ask for $P_t + \epsilon$ (with $\epsilon > 0$); the customer still buys and the agent's earnings are higher. If $P_t > \theta_L$, the agent loses the low valuation customers and thus automatically transitions into an informed state; if there are future interactions it is because the customer has a high valuation. Therefore, $P_t = \theta_H$ (Lemma 1). She is better off than requesting θ_L in period t if and only if the utility from this strategy is higher than the utility from requesting θ_L for any effort sequence

$$\begin{aligned} \iff \quad & (1-\beta)\alpha\theta_H \sum_{j=0}^{\infty} (\delta q)^j > \ldots \\ & \alpha\theta_L - g(\lambda_t) + \delta q E[\pi(\lambda_t|s_t)V(s_{t+1} = i) + (1 - \pi(\lambda_t|s_t))V(s_{t+1} = -i)] \end{aligned}$$

Take $\lambda = 0 \quad \forall t$, then we have

$$\begin{aligned} & (1-\beta)\alpha\theta_H \sum_{j=0}^{\infty} (\delta q)^j > \alpha\theta_L \sum_{j=0}^{\infty} (\delta q)^j \\ \iff \quad & (1-\beta) > \frac{\theta_L}{\theta_H} \quad \Rightarrow\Leftarrow \text{ which contradicts Assumption 9.} \end{aligned}$$

A.3 Proof of Lemma 3

$P^{-i} = \theta_L$ and $P^i = \beta\theta_L + (1-\beta)\theta_H$

$\theta_H > \theta_L \Rightarrow \beta\theta_L + (1-\beta)\theta_H > \theta_L \Rightarrow P^i > P^{-i} \Rightarrow w^i > w^{-i}$.

A.4 Proof of Theorem 1

Since the informed state is an absorbing state we know that $V(s_t = i) = \sum_{j=0}^{\infty}(\delta q)^j w^i$. Let $V(s_t = -i) \equiv V_{t+1}$. Sales agent's first order condition is

$$-k\lambda_t + \delta q \cdot e^{-\lambda_t}\left[\sum_{j=0}^{\infty}(\delta q)^j w^i - V_{t+1}\right] = 0.$$

First, we want to show that effort is not zero; then, that the marginal benefit of effort is increasing in q. Together these two imply that agents will exert more effort when q is larger and therefore that the probability of learning the client's valuation in interaction is increasing in the customer's probability of returning (q).

Step 1: show that $\left[\sum_{j=0}^{\infty}(\delta q)^j w^i - V_{t+1}\right] > 0$. Suppose for a contradiction that

$$\begin{aligned} w^i \sum_{j=0}^{\infty}(\delta q)^j &\leq V_{t+1} \\ &\Rightarrow \text{the sales agent exerts no effort} \lambda_t = 0 \; \forall t \\ &\Rightarrow w^i \sum_{j=0}^{\infty}(\delta q)^j \leq w^{-i} \sum_{j=0}^{\infty}(\delta q)^j \\ &\Rightarrow w^i \leq w^{-i} \;\; \Rightarrow\Leftarrow \end{aligned}$$

Step 2: show that $\frac{\partial}{\partial q} MgB \equiv \frac{\partial}{\partial q}\left\{\delta q \cdot e^{-\lambda_t}\left[\sum_{j=0}^{\infty}(\delta q)^j w^i - V_{t+1}\right]\right\} > 0$. Suppose for a contradiction that $\frac{\partial}{\partial q} MgB \leq 0$, then

$$\left[1 + \frac{\delta q}{1-\delta q} - \frac{\delta q \pi}{1 - \delta q + \delta q \pi} - \frac{\delta^2 q^2 \pi}{(1-\delta q)(1-\delta q + \delta q \pi)}\right] V(s_t = i) \leq \left[1 + \frac{\delta q - \delta q \pi}{1 - \delta q + \delta q \pi}\right] V(s_t = -i).$$

Since $V(s_t = i) > V(s_t = -i)$ the constant term on the left hand side would have to be less than the constant term on the left hand side

$$1 + \frac{\delta q}{1-\delta q} - \frac{\delta q \pi}{1-\delta q+\delta q \pi} - \frac{\delta^2 q^2 \pi}{(1-\delta q)(1-\delta q+\delta q\pi)} < 1 + \frac{\delta q - \delta q \pi}{1-\delta q+\delta q\pi}.$$

Simplifying we get

$$\begin{aligned} 1 - \frac{1-\delta q+\delta q\pi}{1-\delta q+\delta q\pi} &< 0 \\ 1-1 &< 0 \Rightarrow\Leftarrow \end{aligned}$$

A.5 Proof of Lemma 4

The marginal cost of effort does not depend on the commission. So, if the marginal benefit of effort increases with the commission, then effort is increasing in the commission and therefore the probability of learning the customer valuation is increasing in the commission.

$$\begin{aligned} \frac{\partial MgB}{\partial \alpha} &= \delta q \cdot e^{-\lambda_t} \left[\sum_{j=0}^{\infty} (\delta q)^j P^i - \frac{\partial V_{t+1}}{\partial \alpha} \right] \\ &= \delta q e^{-\lambda_t} \left[\frac{P^i}{1-\delta q} - \frac{(1-\delta q)P^{-i} + \delta q \pi P^i}{(1-\delta q)(1-\delta q+\delta q\pi)} \right] \\ &= \frac{\delta q e^{-\lambda_t}(P^i - P^{-i})}{1-\delta q+\delta q\pi} \\ &= \frac{\delta q e^{-\lambda_t}(P^i - P^{-i})}{1-\delta q e^{-\lambda_t}} > 0. \end{aligned}$$

Moreover, the changes in the probability of learning the customer valuation when there is a commission change are stronger for customers with larger probabilities of returning.

$$\frac{\partial \frac{\partial MgB}{\partial \alpha}}{\partial q} = \frac{\delta e^{-\lambda_t}(P^i - P^{-i})(1 - \delta q e^{-\lambda_t}) + \delta^2 e^{-2\lambda_t}(P^i - P^{-i})}{(1 - \delta q e^{-\lambda_t})^2}$$
$$= \frac{\delta e^{-\lambda_t}(P^i - P^{-i})}{(1 - \delta q e^{-\lambda_t})^2} > 0.$$

A.6 Proof of Lemma 5

The probability of knowing the customer's valuation in period t is $prob(s_t = i) = 1 - \prod_{j=1}^{t}(1 - \pi(\lambda_j))$. Let $\pi(\lambda_j) = \pi \quad \forall j$, then $prob(s_t = i) = 1 - (1 - \pi)^t$. Since $(1 - \pi) < 1$, then $lim_{t \to \infty}[1 - (1 - \pi)^t] = 1$.

A.7 Proof of Proposition 1

From Lemma 4 we know that the probability of learning the customer valuation is increasing in the commission and that the probability of knowing the customer's valuation goes to one as $t \to \infty$. Thus, it follows that if the commission increases, the sales agent knows the customer's valuation faster. Also, since changes in the probability of learning the customer valuation when there is a commission change are stronger for customers with larger probabilities of returning, the sales agent learns the valuation of customers with larger probabilities of returning even faster than of customers with small probabilities of returning. The rate of convergence μ is

$$\mu = \lim_{t \to \infty} \frac{|1 - (1 - \pi(\lambda))^{t+1}|}{|1 - (1 - \pi(\lambda))^t|} = 1 - \pi(\lambda) = e^{-\lambda}.$$

Then,

$$\frac{\partial \mu}{\partial \alpha} = -e^{-\lambda}\frac{\partial \lambda}{\partial \alpha} < 0$$
$$\frac{\partial^2 \mu}{\partial \alpha \partial q} = e^{-\lambda}\left[\frac{\partial \lambda}{\partial \alpha}\frac{\partial \lambda}{\partial q} - \frac{\partial^2 \lambda}{\partial \alpha \partial q}\right] < 0.$$

Therefore, the probability of knowing the customer valuation converges faster to one as α increases and converges even faster to one for customers with high probability of returning as α increases.

A.8 Proof of Prediction 1

From Lemma 3 we know that $P^i > P^{-i}$. From Theorem 1 we know that the probability of discovering the client's type in interaction t is increasing in the probability of returning q. Thus, the probability of being in the informed state in every period is higher for customers with a higher q. Therefore, expected prices in period t are higher for customers with a higher q. This is true for all periods, thus average prices are higher for clients with a higher q.

A.9 Proof of Prediction 2

With more interactions, agents are more likely to know the customer's valuation. In period t the agent does not know customer's valuation with probability $\prod_{j=1}^{t}(1-\pi(\lambda_j))$. The probability of not learning the customer's valuation is less than one $\forall t$ so $\prod_{j=1}^{t}(1-\pi(\lambda_j)) > \prod_{j=1}^{t+1}(1-\pi(\lambda_j))$. The likelihood of being in the uninformed state decreases with the number of interactions and $P^i > P^{-i}$. Therefore, the average per period price increases with the number of interactions.

A.10 Proof of Prediction 3

In the first period, the agent has no information about any customer so payments are $P^{-i} = \theta_L$ for all customers. The probability of knowing the customer's valuation goes to one as $t \to \infty$ (Lemma 5), therefore the range goes to $\theta_H - \theta_L > 0$ as $t \to \infty$.

A.11 Proof of Prediction 4

(a) $P^i > P^{-i}$ and effort is increasing in the commission for all periods. So, if the commission increases, effort in all periods increases which in turn increases the probability of receiving P^i and lowers the probability of receiving P^{-i}. Therefore, the expected price increases.

(b) How much a commission increase will affect prices depends on how much it will affect the probability of learning given that the sales agent is in the uninformed state which is $\pi(\lambda|s_t = -i) = (1 - e^{-\lambda}) \cdot e^{\lambda_0 \cdot t}$, where λ_0 is the effort provided in every interaction up to period t and λ is the effort the sales agent will provide from period t on. Then

$$\frac{\partial^2 \pi(\lambda|s_t = -i)}{\partial\alpha\partial q} = \frac{\partial^2(1 - e^{-\lambda})}{\partial\alpha\partial q} e^{\lambda_0 \cdot t} + \frac{\partial e^{-\lambda_0 \cdot t}}{\partial q}(1 - e^{-\lambda}).$$

The first term is positive and the second one is negative. This implies that there exists a q for which the derivative of $\frac{\pi(\lambda|s_t=-i)}{\partial\alpha}$ with respect to q is equal to zero. This is a maximum if

$$\frac{\partial^2 \frac{\partial\pi(\lambda|s_t=-i)}{\partial\alpha}}{\partial q^2} < 0$$

$$\frac{\partial^2 \frac{\partial\pi(\lambda|s_t=-i)}{\partial\alpha}}{\partial q^2} = \frac{\partial^2 \frac{\partial(1-e^{-\lambda})}{\partial\alpha}}{\partial q^2} e^{-\lambda_0 \cdot t} + \frac{\partial^2(1 - e^{-\lambda})}{\partial\alpha\partial q}\frac{\partial e^{-\lambda_0 \cdot t}}{\partial q} + \frac{\partial^2 e^{-\lambda_0 \cdot t}}{\partial q^2}(1 - e^{-\lambda}) + \frac{\partial^2 e^{-\lambda_0 \cdot t}}{\partial q}\frac{\partial(1 - e^{-\lambda})}{\partial q}.$$

The four terms of this expression are negative. Therefore, if the commission increases, the effect on prices has an inverted-U relation with the probability of returning.

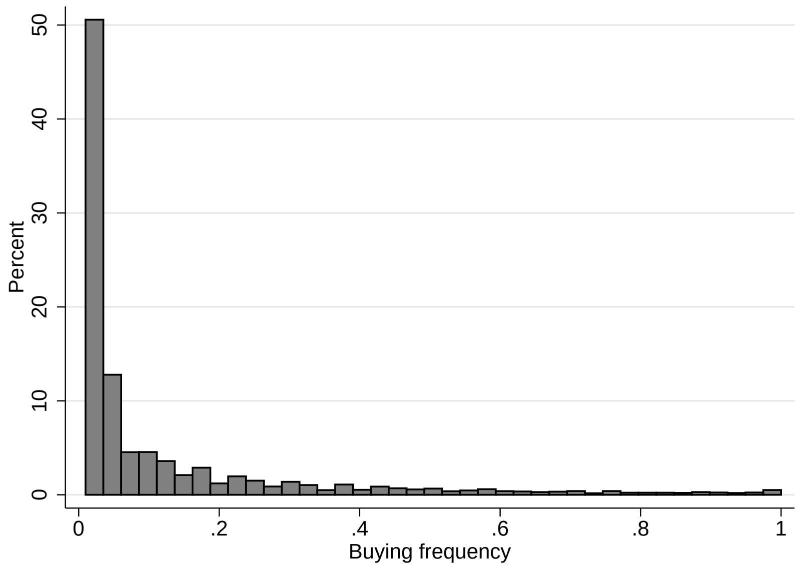


Figure 1: Histogram of customers by their buying frequency (q)

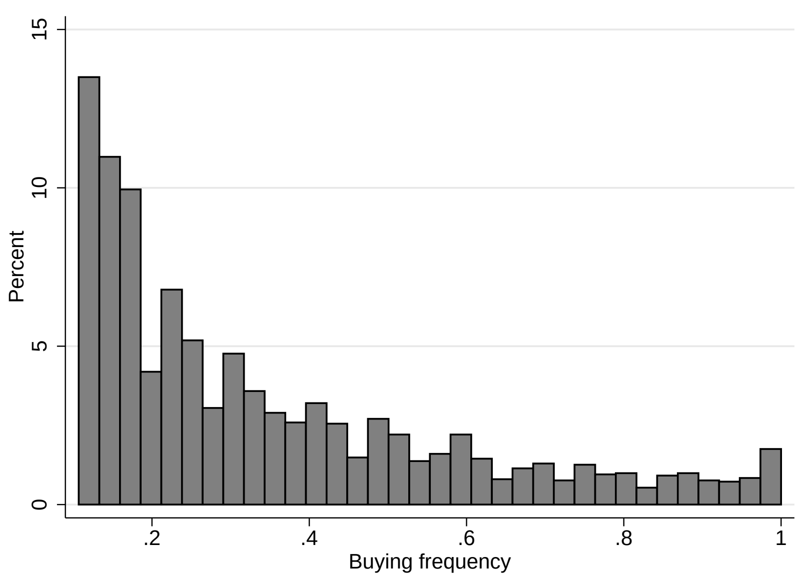


Figure 2: Zoom-in of histogram of customers by their buying frequency (for q>0.1)

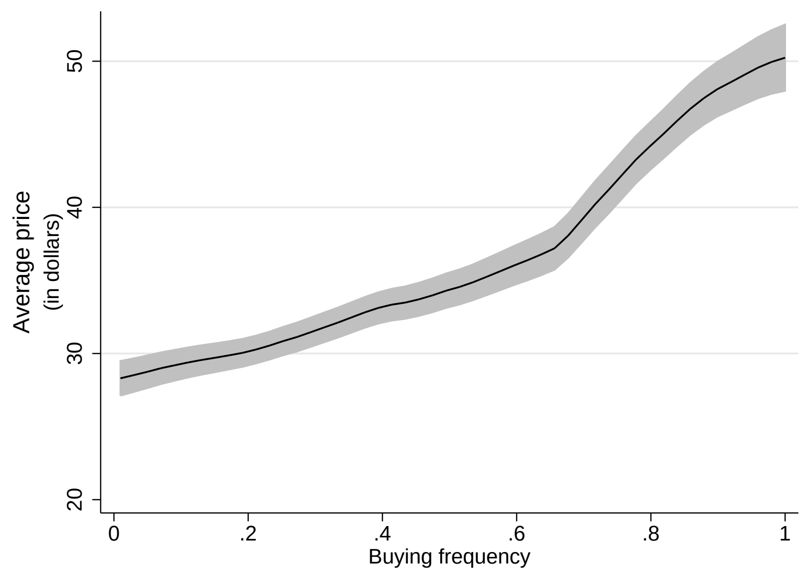


Figure 3: Average price by customers' buying frequency (q)

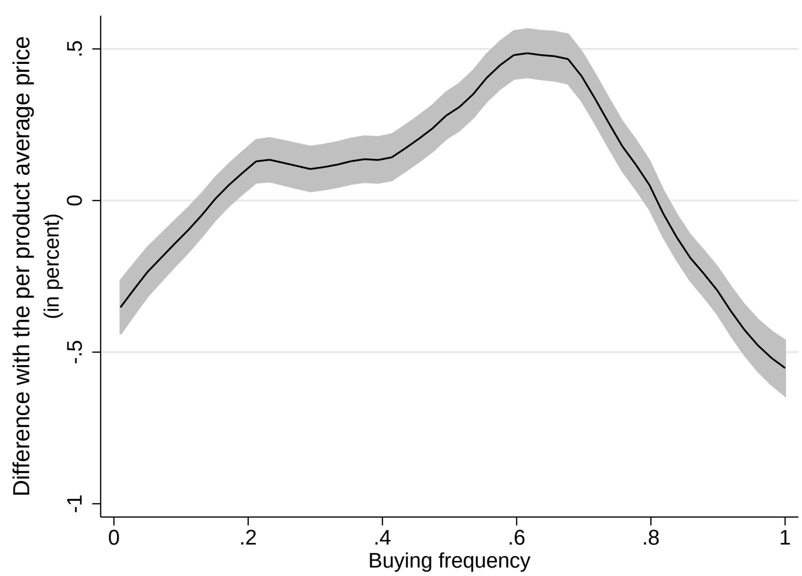


Figure 4: Percent difference with the per product average price by customers' buying frequency (q)

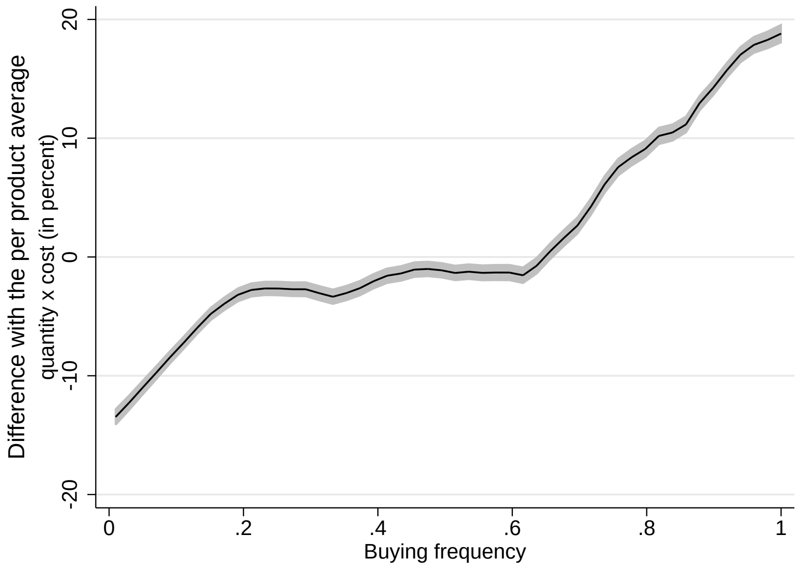


Figure 5: Percent difference with the per product average quantity×cost by customers' buying frequency (q)

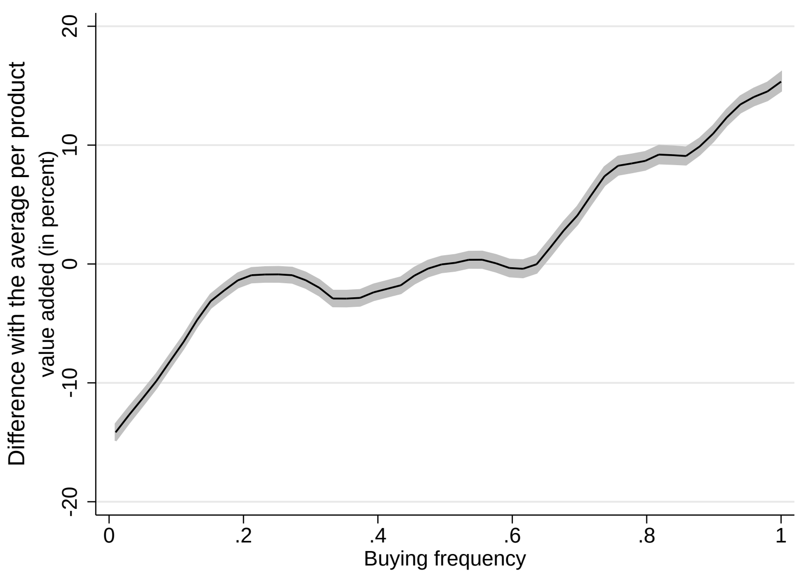


Figure 6: Percent difference with the per product average value added by customers' buying frequency (q)

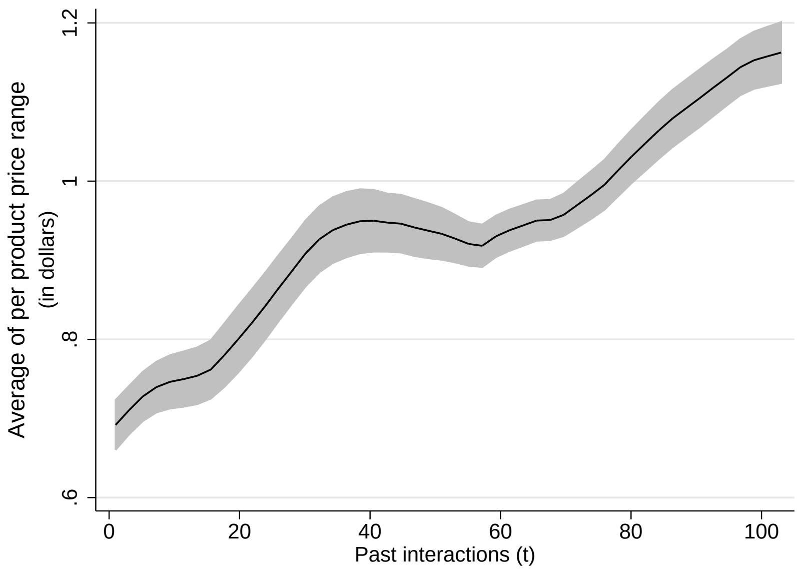
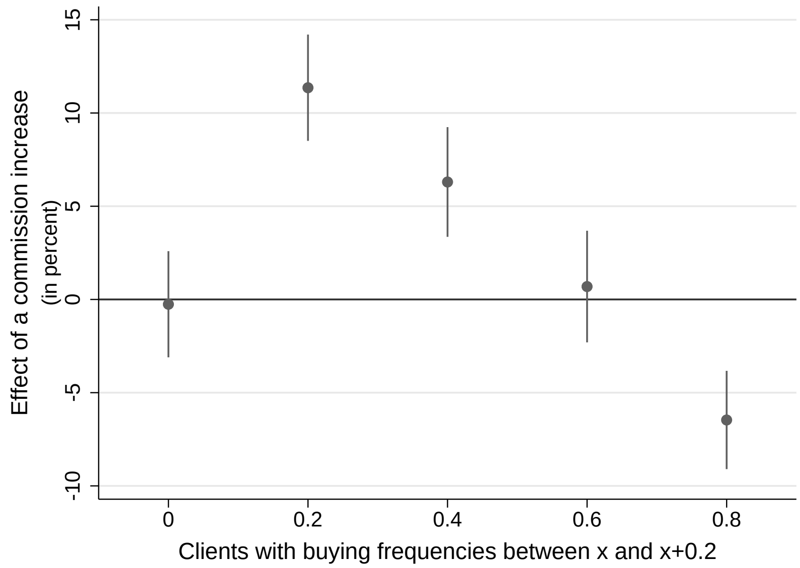
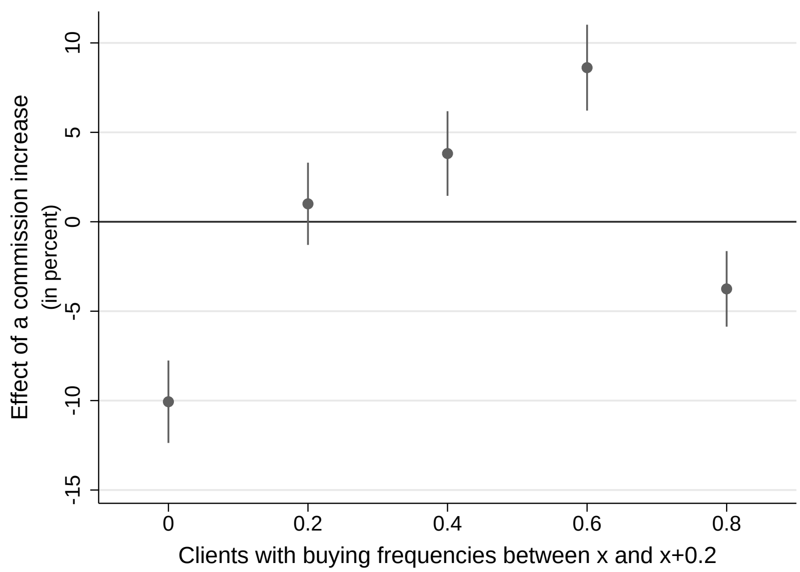


Figure 7: Average range of product prices among clients by the number of past interactions (for clients with q≥ 0.99)



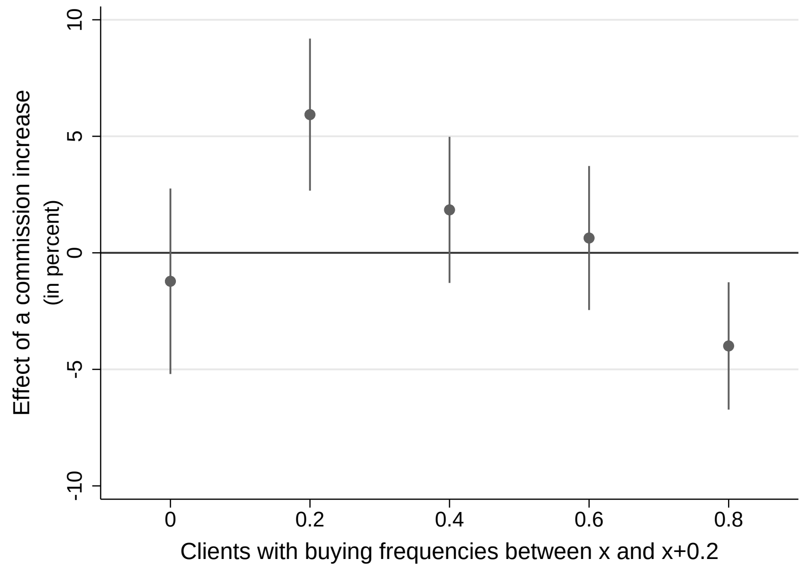
(a) No additional fixed effects



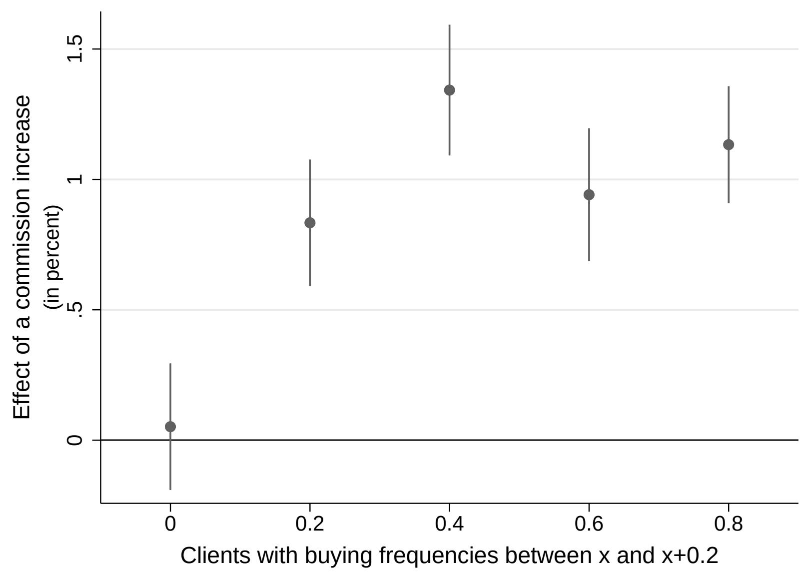
(b) Sales agent fixed effects

Figure 8: Heterogeneous effect of a commission increase on prices*

**Both figures include week fixed effects.*



(a) Client fixed effects



(b) Product fixed effects

Figure 9: Heterogeneous effect of a commission increase on prices*

**Both figures include week fixed effects.*

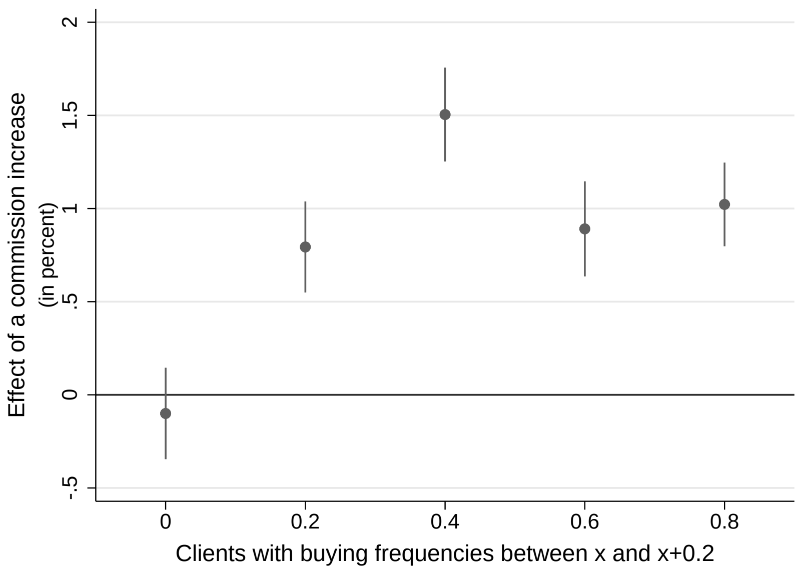


Figure 10: Heterogeneous effect of a commission increase on prices*

**Includes client, product and week fixed effects.*

Table 1: Correlation between log prices, frequency and past interactions

	(1)	(2)	(3)	(4)	(5)
Frequency	0.0467***	0.0094		-0.0030***	
	(0.0110)	(0.0115)		(0.0009)	
Past interactions	0.0004**	0.0008***	0.0007**	0.0003***	0.0003***
	(0.0002)	(0.0002)	(0.0003)	(0.0000)	(0.0000)
Age	0.0140***			-0.0007***	
	(0.0017)			(0.0001)	
Age (sqrd)	-0.0001***	-0.0007***	-0.0012***	0.0000***	-0.0001***
	(0.0000)	(0.0002)	(0.0002)	(0.0000)	(0.0000)
Male	-0.1426***			0.0027***	
	(0.0078)			(0.0007)	
Tenure	0.0020***			-0.0010***	
	(0.0005)			(0.0000)	
Employee fixed effects		✓			
Client fixed effects			✓		✓
Product fixed effects				✓	✓
R-squared		0.0074	0.0799	0.9931	0.9931

Notes: *** denotes significance at 1 percent, ** at 5 percent and * at 10 percent. Standard error are clustered at the employee level (i.e., there are 75 clusters). Estimates are calculated using data for years 2008 and 2009. All regressions have week fixed effects. Number of observations: 1,099,108.

Table 2: Effect of a commission increase on log prices

	(1)	(2)	(3)	(4)	(5)
New contract	0.0209*	0.0165	0.0024	0.0088***	0.0085***
	(0.0113)	(0.0114)	(0.0118)	(0.0010)	(0.0010)
Group 1	0.0000			-0.0024***	
	(0.0058)			(0.0005)	
Age	0.0148***			-0.0007***	
	(0.0017)			(0.0001)	
Age (sqrd)	-0.0001***	-0.0005***	-0.0012***	0.0000***	-0.0001***
	(0.0000)	(0.0002)	(0.0002)	(0.0000)	(0.0000)
Male	-0.1375***			0.0013**	
	(0.0078)			(0.0007)	
Tenure	0.0033***			-0.0012***	
	(0.0007)			(0.0001)	
Employee fixed effects		✓			
Client fixed effects			✓		✓
Product fixed effects				✓	✓
R-squared	0.0021	0.0073	0.0798	0.9931	0.9931

Notes: *** denotes significance at 1 percent, ** at 5 percent and * at 10 percent. Standard error are clustered at the employee level (i.e., there are 75 clusters). Estimates are calculated using data for years 2008 and 2009. All regressions have week fixed effects. Number of observations: 1,099,108.

Table 3: Heterogeneous effect of a commission increase on log prices

	(1)	(2)	(3)	(4)	(5)
New contract × frequency	0.4200***	0.3628***	0.1898**	0.0206***	0.0339***
	(0.0590)	(0.0599)	(0.0862)	(0.0050)	(0.0051)
New contract × frequency (sqrd)	-0.5042***	-0.4262***	-0.2281***	-0.0104**	-0.0229***
	(0.0538)	(0.0544)	(0.0716)	(0.0046)	(0.0046)
New contract	-0.0134	-0.0154	-0.0117	0.0017	-0.0011
	(0.0169)	(0.0172)	(0.0248)	(0.0014)	(0.0015)
Group 1	-0.0053			-0.0015***	
	(0.0058)			(0.0005)	
Frequency	-0.3900***	-0.3516***		-0.0096**	
	(0.0500)	(0.0512)		(0.0043)	
Frequency (sqrd)	0.5065***	0.4403***		-0.0099**	
	(0.0459)	(0.0468)		(0.0039)	
Age	0.0138***			-0.0006***	
	(0.0017)			(0.0001)	
Age (sqrd)	-0.0001***	-0.0003*	-0.0010***	0.0000***	-0.0001***
	(0.0000)	(0.0002)	(0.0002)	(0.0000)	(0.0000)
Male	-0.1449***			0.0025***	
	(0.0078)			(0.0007)	
Tenure	0.0023***			-0.0009***	
	(0.0007)			(0.0001)	
Employee fixed effects		✓			
Client fixed effects			✓		✓
Product fixed effects				✓	✓
R-squared	0.0024	0.0075	0.0799	0.9931	0.9931

Notes: *** denotes significance at 1 percent, ** at 5 percent and * at 10 percent. Standard error are clustered at the employee level (i.e., there are 75 clusters). Estimates are calculated using data for years 2008 and 2009. All regressions have week fixed effects. Number of observations: 1,099,108.