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Strategic incentives in intermediary markets: Field-experimental evidence*

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Abstract

We investigate how to strategically motivate sales agents in intermediary markets. In collaboration with a large travel company, we run a field experiment with more than $1,200$ independently owned intermediaries that sell our study firm's own products as well as products from competitors to end customers. The intermediaries employ sales agents responsible for customer interaction. We compare the impact of different forms of monetary incentives with non-monetary incentives provided through direct support to reduce the sales agents' effort costs. We develop a conceptual formal model hypothesizing that incentives for intermediaries (i) generally increase sales, and are more effective when targeting (ii) sales agents rather than owners of the intermediaries, (iii) intermediaries with weaker monetary incentives prior to the intervention, and (iv) products where the firm has no competitive advantage. We find that providing sales-agent support increases sales, while higher commission payments to the agencies' owners has no discernible effects. Directly incentivizing sales agents through vouchers raises sales for agencies with low prior commission rates. The incentive effects are driven by products where the firm has a weaker market position, while they have no discernible effects on product sales where the firm has a strong competitive advantage. We analyze underlying mechanisms using surveys and further administrative data.

JEL Codes: *C93, D23, L21, M52*
Keywords: *Incentives, intermediaries, competitive advantage, strategy, productivity, field experiment*

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1. Introduction

Using intermediaries to sell products to end customers is a standard distribution channel in many industries. For example, in the financial and insurance sector, companies distribute their products via brokers or retailers, travel companies engage travel agencies or online platforms, and real-estate businesses rely on local brokers. Donna et al. (2022) estimate that intermediary markets contribute to more than one third of the US GDP.

From the perspective of upstream firms, using intermediaries as a distribution channel has the advantage that it leads to higher market coverage by increasing accessibility to their products (Rubinstein and Wolinsky 1987, Hagiu and Wright 2015) and limits capital commitment, thereby providing flexibility in response to demand volatility (Lassar and Kerr 1996, Conti et al. 2019). Using this channel comes with the disadvantage that intermediaries typically sell products from various competing upstream firms, potentially providing them with a strong bargaining position due to their local market power. In general, intermediaries limit an upstream firm's level of control over the distribution of its products and the interaction with end customers. In such circumstances, for upstream firms, understanding the strategic behavior of intermediaries is essential to foster a profitable business relationship.

One common strategic contracting approach that upstream firms use to steer sales behavior of intermediaries is pay-for-performance schemes. There is a broad consensus in the literature that pay-for-performance schemes are a powerful tool to steer the behavior of workers (e.g., Yanadori and Marler 2006, Obloj and Sengul 2012, Chung et al. 2014, Cobb and Lin 2017, Chung and Narayandas 2017, Nyberg et al. 2018, Khashabi et al. 2021).[1] However, in intermediary markets, firms do not pay for the performance of workers, but for the performance of legally and organizationally independent intermediaries, causing multiple layers of complexity (see Caldieraro and Coughlan 2007). First, the intermediaries have autonomy over how to pay the workers employed by them; in particular, if an upstream firm pays the intermediary based on performance, it is the intermediaries' choice to what extent these payments are passed on to their workers. This can cause inefficiencies due to the "double marginalization of rents", as intermediaries have to be motivated to motivate their workers (see, e.g., Barron and Umbeck 1984, Mookherjee and Tsumagari 2004, Mookherjee 2006). Second, intermediaries often sell products of different competing upstream firms. Thus, when selling products to end customers, intermediaries take the product-specific degree of differentiation, costs of effort required to sell, and profit margins into account.

We conduct a field experiment in collaboration with one of the largest European travel companies. The firms' revenue – and the ones of the major competitors – mainly stems from the sale of package bookings to popular travel destinations. One important channel the firm uses to sell its travel products to end customers are travel agencies, i.e., legally and organizationally independent intermediaries (more than $1,200$ of which were part of our study). Our study firm is challenged

[1] In field experiments within firms, several studies in economics have analyzed various design aspects of incentive pay, such as team work and collaboration (Friebel et al. 2017, Lee and Puranam 2017, Delfgaauw et al. 2022), learning (Manthei et al. 2021), and interaction effects of incentives with other management practices (Lourenço 2016, Englmaier et al. 2017, Manthei et al. 2023a,b).

with finding ways to motivate intermediaries to sell its products. In our study, we analyze and compare the effects of various monetary and non-monetary incentive tools on intermediaries' sales behavior.

Specifically, while for a control group of agencies business operations continued as usual (including the pre-existing pay-for-performance system), our study firm implemented three distinct additional incentives (treatments) in randomly selected travel agencies. The first *Agent support* treatment reduces the intermediaries' sales agents' cost of effort to sell our study firm's products. Sales agents often face the problem that customers ask for specific adjustments to their package bookings (e.g., flying from a specific airport, (not) favoring a particular airline), which have to be coordinated with and approved by our study firm. Prior to our intervention, sales agents often complained about long waiting times when coordinating adjustments with our study firm (e.g., via the firm's call center, delayed e-mail responses, etc.). Our treatment offers randomly selected agencies access to a service hotline providing support for bookings to strategic target destinations. The key feature of the service hotline is an extremely short waiting time. The *Agent voucher* treatment introduces a monetary incentive targeted at the agency's sales agents. For travel bookings to strategic target destinations, the agents receive travel vouchers, which they can use themselves for products offered by our study firm. Although the vouchers are formally handed over by our study firm to the owners of the agencies, the vouchers are designed in such a way that they can only be used by the sales agents, and owners are nudged to forward them to their employees.[2] The third *Reseller payment* treatment introduces a monetary incentive for travel bookings to strategic target destinations, paid directly to the owners of the travel agencies.

The design of our intervention is grounded in a conceptual framework. Our first hypothesis is that all three treatments lead to an increase in bookings. Second, we hypothesize that, because of double marginalization, incentives in our setup are more effective when targeting sales agents rather than owners of the agencies. Third, we hypothesize that incentives are more effective for agencies with weaker monetary incentives prior to the intervention. Our setup allows us to study the role of prior monetary incentive strength by exploiting that the study firm distinguishes agencies with high and low sales volumes, and pays larger commissions to the former ones. Agencies with high sales volumes at the outset are limited in their leeway to generate additional bookings. Fourth, we hypothesize that additional incentives are less effective for products where the firm has a competitive advantage as agencies are more likely to sell products from our study firm anyway when it holds a strong market position. This limits the scope to generate further bookings. To test this hypothesis we incentivized products (i.e. travel destinations) where the study firm has a competitive advantage as well as products where this is not the case. Our framework does not provide a sharp hypothesis concerning the comparison between directly targeting sales agents either through payments (vouchers) or lowering their costs of effort required to sell by providing support, but we study this question in an exploratory manner.

[2] As our study firm does not have (employment) contracts with the intermediaries' sales agents, it could not hand over the vouchers or cash directly to the sales agents. This is a common characteristic of intermediary markets.

Our main findings are as follows: First, the *Agent support* treatment increases the total number of bookings to the destinations targeted by our field experiment; in contrast, for the other two treatments we find no significant average effects. Second, the positive effect of the *Agent support* treatment is mainly driven by agencies with weak monetary incentives prior to the intervention. For this type of agencies, we also observe an increase in bookings for the *Agent voucher* treatment. Third, both the *Agent support* treatment and the *Agent voucher* treatment significantly increase bookings of products for which our study firm has no competitive advantage. Overall, we thus find strong evidence for the role of double marginalization and that incentives can compensate a lack of strategic advantage. We, however, find no evidence that stronger monetary payments to the intermediary owners drive additional sales.

Our results have three core managerial implications for upstream firms designing incentive schemes in intermediary markets: First, our results suggest that incentives are more effective when they target the intermediaries' sales agents directly and not the intermediaries' owners. Second, we find that non-monetary incentives facilitating the daily work routine of sales agents are highly effective; in our setup, they were even more effective than monetary incentives. Third, when implementing incentives it can be rational for upstream firms to focus on products and intermediaries with the highest leeway for sales increases. In our setup, this comprises intermediaries with weak monetary incentives and products for which our study firm has no competitive advantage.

Our results highlight the importance for upstream firms to strategically align their incentives with their product strategies. This is consistent with studies stressing the importance of a firm's competitive strategy for the design of systems of control of distributors (Lassar and Kerr 1996) and compensation schemes (Conyon 2006, Yanadori and Marler 2006).

In addition, we contribute to the literature that theoretically analyzes the challenges faced by upstream firms when designing incentives in intermediary markets (e.g., Lafontaine and Slade 2007, Inderst and Ottaviani 2009, 2012 and Honda et al. 2024).[3] To the best of our knowledge, ours is the first paper to validate empirically the challenges faced by upstream firms in intermediary markets and to design and evaluate new incentive tools aimed at addressing these issues.

The structure of the paper is as follows. In Section 2, we describe the experimental design and provide detailed description of the study background. In Section 3, we present the conceptual framework guiding our empirical analysis. We proceed in Section 4 with the main findings of our empirical analysis. Section 5 provides further results and discusses potential mechanisms. Section 6 discusses the managerial implications of our findings. Lastly, Section 7 concludes.

2. Experimental design

2.1. Background and environment

We collaborate with one of Europe's leading travel companies/tour operators (study firm), which sells its products online, but also through many stationary travel agencies (agencies). Agencies can

[3] Other studies focus on the empirical investigation of welfare aspects in intermediary markets, e.g., Stanton and Thomas (2015), Anagol et al. (2017), Robles-Garcia (2019), and Biglaiser et al. (2020).

be categorized by the degree of bonding to our study firm. There are agencies directly owned by the study firm, others are part of its franchise network, but the majority are independently owned. In particular the latter agencies offer products of many competing tour operators. These tour operators pay the agencies through commission payments defined as percentages of sales (commission rates) which are typically set once a year and communicated to the agency. The commission rates a tour operator pays to the agencies may vary between agencies and in general are higher the closer an agency is to a tour operator, i.e., the higher the revenue from selling the respective products of this operator has been in the past.

Figure 1 illustrates the distribution structure focusing on an exemplary agency. The agency's owner, i.e., the reseller, has a contractual agreement with the respective tour operators on selling their products while receiving commission payments as described above in return. Note that the reseller can be a natural person as well as a corporation. The reseller employs sales agents who receive a fixed wage and possibly some variable compensation, i.e., a bonus.

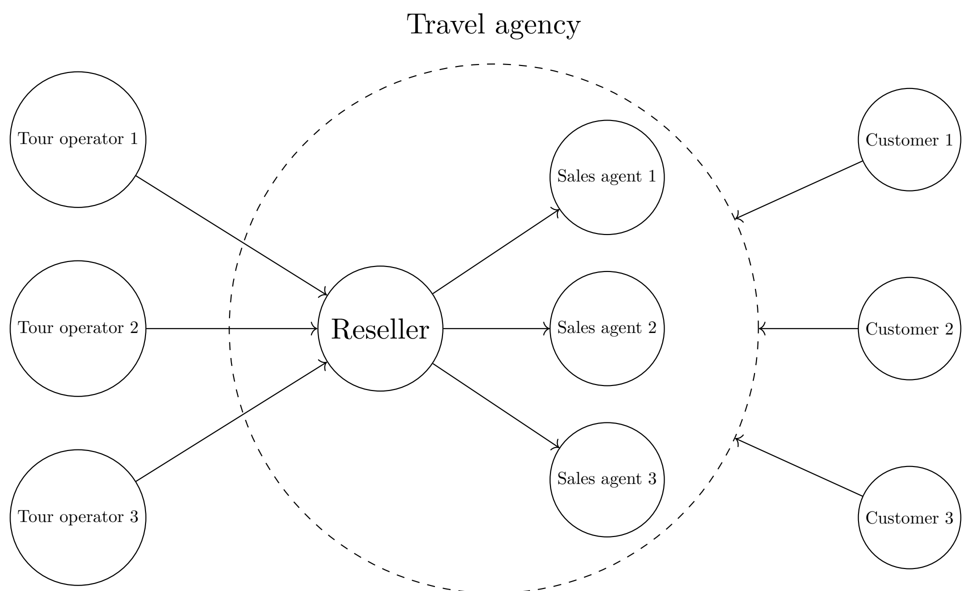


Figure 1: Distribution structure

The experiment took place among independently owned agencies located all over Germany. Our final sample includes $1,257$ agencies organized in six different purchasing pools ('chains').[4] With regard to the commission rates, the participating agencies are segmented into two tiers based on their prior sales. Tier-1 agencies receive a commission rate of 10%, and the rate for tier-2 agencies is 8%. Approximately 80% of the participating agencies belong to the latter group.

[4]In the travel industry, many of the small independently owned agencies organize themselves in larger purchasing pools. The aim is to increase the bargaining power against the tour operators when it comes to purchasing or negotiations about commissions.

2.2. Treatments

An essential step in developing the treatments involved gaining a comprehensive understanding of the firm's business model, the operations of travel agencies, and the primary tasks of their sales agents. To achieve this, we engaged in discussions with company board members and middle management and conducted thorough interviews with agency owners and sales agents. We observed not only the sales process within these agencies, but also the challenges they encountered when dealing with customers. It became apparent that both the product-specific costs of effort required to sell and the monetary incentives provided by the upstream firms play an important role for the agencies' decisions on which products to promote to customers. The overall process resulted in two core questions needing further investigation: (i) To which extent can non-monetary incentive tools, like reducing sales-effort costs, steer sales behavior in contrast to traditional monetary incentive tools? (ii) How do incentives provided to the sales agents compare to incentives provided to the owners of the agencies? Consistent with the approach of Camuffo et al. (2023), we built on these questions to develop treatments that, based on our conceptual framework, should be effective and provide important insights for the firm, while also making an important contribution to the literature.

The agencies are assigned to one of three treatments or to the control group. All of the treatments are designed to motivate bookings to four specific target destinations. The chosen destinations vary with regard to the study firm's strategic position in the industry, a fact that we explore in detail in Section 4.4. According to the study firm's top management as well as the surveyed agencies, our study firm possesses a competitive advantage for products in two target destinations (henceforth named destinations 3 and 4). In contrast, the study firm's market position is relatively weaker for products with the target destinations 1 and 2. One reason is that far more tour operators sell products with target destinations 1 and 2 and thus competition is generally more intense.[5]

In the *Agent support* treatment, we target the non-monetary selling effort cost side by providing sales agents with a better service lowering their effort costs when selling the study firm's products. The treated agencies receive priority access to a newly established service hotline that they can consult in case of booking changes, inquiries, customer complaints or any other questions related to bookings for the four specified target destinations.

Beyond that, we consider two treatments targeting the monetary benefits of selling the study firm's products.

In the *Reseller payment* treatment, we study the effect of a top-up payment, i.e., an additional commission of 6€ per booked customer, which is paid to the reseller.[6]

In the *Agent voucher* treatment, the agencies receive the top-up payment of 6€ per booked customer in form of a travel voucher for products of the study firm. Importantly, the vouchers

[5] As we show in in Section 4.4, the quality of the firm's products is also rated as substantially higher for destinations 3 and 4.

[6] As the average number of customers per booking is 2.5 the average top-up payment is about 15€, which corresponds to an increase of the commission rate by 0.75ppt, or about 9.4% for 80% of the participating agencies that receive a commission rate of 8%.

cannot be used by the agency's owner or manager, but only by the sales agents. Furthermore, the vouchers cannot be forwarded to customers.

Due to a technical limitation in the booking software, the sets of affected products differ to some degree between the first two treatments, on the one hand, and the third treatment, on the other hand. We therefore focus on all bookings to the four target destinations in our main analysis.[7]

We compare all treatments to an unaffected control group.

2.3. Data and primary outcome variables

From our study firm, we obtain sales data on a booking level from December 2022 to October 2023. One observation contains the booking's characteristics, such as tour operator, booking type (e.g., package booking, flight, rental car, city tour), booking date, travel date, gross revenue (i.e., booking price), commission payment, gross and net margin, destination, duration, number of passengers, and a numerical indicator for the agency making the booking. Furthermore, the data contain the agencies' commission rates and chains they belong to.[8]

Our primary outcome variable is the number of incentivized bookings, i.e., the number of bookings to the four incentivized target destinations, as the most important variable for detecting behavioral shifts of the reseller or sales agents. To evaluate how changes in agents' selling behavior translate to profits, we also consider the effect on the net contribution stemming from the incentivized products. Furthermore, we investigate heterogenous effects on the number of incentivized bookings with respect to the market position for the different target destinations. For robustness, we also consider the effects on the total number of bookings to the non-incentivized destinations. This allows us to evaluate whether potential treatment effects also cause shifting between destinations.

We also collect survey data for parts of the agencies. The survey is conducted with the participating agencies, and it elicits perceptions about the study firm and working practices within the agencies, the relevance of product quality, commissions and service quality when choosing the tour operator in order to study underlying behavioral mechanisms.[9]

To gain a deeper understanding of the mechanisms behind the *Agent support* treatment, we make use of three further data sources. First, we have access to detailed call-center data on a call level including the calling agency, the month and year in which the call occurred, the matter at hand (categories are, e.g., payment, booking changes, cancellations), the duration of the call, and the destination with which the matter is associated. Second, we get information about the usage

[7] In the *Reseller payment* and *Agent voucher* group, all new bookings of a specific type ("package booking") to the four specified target destinations were incentivized in such a way that they 1) were booked at one of the study firm's tour operators, 2) had a booking price of at least 1,000€ and 3) had a travel date up to October 31, 2023. The *Agent support* group encompasses all new bookings to the four specified target destinations that were booked with the main tour operator. We also analyze the treatment effects on the intersection of both sets. The results are similar to our findings in Section 4.2. For the detailed regression output, we refer to Section 8.3 in the Appendix.

[8] For the agencies that do not appear in the sales data, the information about commission rates and chains was provided by the study firm.

[9] The summary statistics are presented in Section 8.5 in the Appendix. The response rate is 20%. The detailed questionnaire is available from the authors upon request.

of our newly established hotline, i.e., the monthly number of calls per destination, the average duration of the respective calls, as well as the average waiting time before the call is answered by a call-center agent. To compare, we receive the same data for agencies who are not part of the *Agent support* treatment. Finally, we conduct a survey with the employees operating the service hotline, i.e., the call-center agents.[10]

2.4. Randomization

We used sales data from December 2022 and January 2023 to assign the agencies randomly to the treatment groups or the control group. The randomization was stratified with regard to the chains within which the agencies are organized.[11] Pre-experimental summary statistics for the outcome variables on booking as well as revenue and the final assignment are presented in Table 1. The groups are balanced with regard to all of our main outcome variables, as defined in Section 2.3.[12] Due to financial constraints, the control group had to be twice as large as each of the treatment groups.

Note that six additional agencies had been assigned to one of the groups, but as the cooperation with our study firm was terminated during the field experiment, we do not include them in our analysis.

2.5. Experimental timeline

The field experiment started for all groups on 1 February 2023. The agencies receiving a treatment were informed via e-mail as well as a physical letter about their respective treatments as well as the end of the project. For the *Reseller payment* and *Agent voucher* group the project ended on 30 April 2023. The *Agent support* group had priority access to the hotline until 31 October 2023. We aimed to ensure in this way that agents were also be able to reach the hotline around the time of the customers' departure date.[13]

During the field experiment the agencies received a biweekly reminder, again informing them about the treatments and, if applicable, the amount of additional commission or voucher value gathered by the respective agency up to this date.

On 10 May 2023, all agencies that gathered top-up payments or a voucher during the field experiment were informed about the final amount. The agencies in the *Agent voucher* group were additionally asked to state how many vouchers of which value they would like to receive, i.e., to split up the voucher's total amount into several vouchers.[14] Agencies in the *Agent support* group were informed about their treatment as before. Furthermore, we announced the forthcoming survey. The

[10]The key insights are presented in Section 8.6 in the Appendix. The response rate is 92%. The detailed questionnaire is available from the authors upon request.

[11]The randomization procedure was conducted using the Stata module *randomize* as provided by Kennedy and Mann (2015).

[12]In the Appendix in Section 8.2, we present the results of multiple multinomial logistic regressions, showing that none of the key outcome variables has the potential to predict an agency's assignment.

[13]However, we will see later that the hotline is mostly used for questions at the time the customer decides about the booking.

[14]The vouchers were distributed to all qualified agencies on 5 June 2023.

Table 1: Balance table

Treatment	Agent support	Agent voucher	Reseller payment	Control	All
	(1)	(2)	(3)	(4)	(5)
No. of Agencies	253	250	250	504	1,257
			Bookings		
Total	6.46	6.85	7.59	7.16	7.05
	(6.90)	(7.98)	(9.56)	(7.84)	(8.06)
Incentivized	2.63	2.62	2.90	2.72	2.72
	(2.95)	(3.35)	(3.61)	(3.32)	(3.31)
Other	3.83	4.23	4.69	4.44	4.33
	(4.74)	(5.39)	(6.74)	(5.42)	(5.58)
Strong	1.19	1.30	1.42	1.20	1.26
	(1.67)	(1.96)	(2.34)	(1.91)	(1.95)
Weak	1.45	1.32	1.47	1.52	1.46
	(1.89)	(1.95)	(2.21)	(2.05)	(2.03)
			Revenue		
Total	14.74	14.81	16.07	15.29	15.24
	(16.49)	(18.44)	(18.00)	(17.60)	(17.62)
Incentivized	6.58	6.81	7.30	6.74	6.83
	(7.96)	(9.28)	(9.27)	(8.80)	(8.83)
Other	8.16	8.00	8.78	8.55	8.41
	(10.47)	(11.10)	(10.55)	(10.68)	(10.69)
Strong	3.09	3.30	3.57	3.14	3.25
	(4.49)	(5.12)	(5.67)	(5.20)	(5.14)
Weak	3.49	3.51	3.73	3.60	3.59
	(4.92)	(5.90)	(5.88)	(5.33)	(5.48)
			Commission rate		
Share tier 1	0.21	0.21	0.24	0.19	0.21

Notes: The table provides a summary of the agencies' pre-experimental number of bookings and the corresponding revenue, i.e., the sum of bookings (revenue) in December 2022 and January 2023, by treatment groups and the control group. 'Total' refers to (revenue from) all bookings, 'Incentivized' to (revenue from) all bookings to the four incentivized target destinations, 'Other' to (revenue from) all other bookings, 'Strong' to (revenue from) bookings to the incentivized destinations with a stronger market position (i.e., 3 and 4), and 'Weak' to (revenue from) bookings to the incentivized destinations with a weaker market position (1 and 2). Revenues are in thousands of euros. Furthermore, the table presents the allocation of tier-1 and tier-2 agencies across the groups. Columns 1 to 5 show sample means. Standard deviations are in parentheses.

agencies that did not gather any top-up payments or a voucher were informed about the upcoming survey on 16 May 2023. The agencies in the control group were not informed about the upcoming survey.

The first survey with the travel agencies was conducted online and all agencies (including the control group) were informed and asked to participate via e-mail on 15 June 2023. Agencies that had not participated yet were reminded to do so on 22, 26 and 30 June, as well as on 6 July 2023. The survey ended on 9 July 2023.

The second survey with the employees operating the service hotline set up for the *Agent support* treatment was conducted online as well. The link for participating in the survey was distributed by the call-center management on July 31, 2023. The survey was closed on October 12, 2023.

3. Conceptual framework

Before delving into our empirical findings, we introduce an illustrative conceptual framework to formulate hypotheses related to the average treatment effects. Moreover, this framework guides us in identifying relevant mechanisms and potential effect heterogeneities. In this section, we focus on presenting testable hypotheses and their intuition. These findings are derived from a formal model, which we relegate to the Appendix (see Section 8.1).

Consider the following framework, which reflects the market environment we study: Firms sell their products via resellers (i.e., intermediaries) who employ sales agents. The agents sell the products of these firms to end customers. A sales agent can either choose actively to promote a product, making it more attractive to customers and thus reducing the relative attractiveness of the other firms' products, or not to promote any product actively. However, active promotion comes with personal effort costs to the sales agent. For each product sold, the corresponding firm pays a commission to the reseller. The reseller, in turn, can provide incentives to the sales agent to sell the firms' products actively. The reseller's profit depends on the commissions received from the firms and the bonuses paid to the sales agents. The agents' utility is determined by the bonus payments from the reseller and personal selling costs. An agent will choose active promotion only if the bonus from the reseller is large enough compared to the personal selling costs.

The profits of the reseller change positively with an increase of the commission payments made by the firm, and the utility of the sales agent increases with additional bonus payments by the reseller. Thus, increasing compensation for either party is expected to provide stronger incentives and thus an increase in sales. In our experiment, the *Reseller payment* treatment increases the payments to the reseller, and the *Agent voucher* treatment increases the direct bonus for the sales agents. Therefore, we hypothesize that both treatments positively affect sales on average.

Hypothesis 1a. *On average, the Agent voucher treatment and the Reseller payment treatment should increase sales.*

In our conceptual framework, the *Agent support* treatment corresponds to a decrease in the personal selling costs that the sales agent incurs when actively promoting a product. By reducing these costs, promoting the company's product becomes more attractive to the agent. Thus, we expect that the *Agent support* treatment will positively affect sales behavior. We summarize this in the following hypothesis.

Hypothesis 1b. *We expect that, on average, the Agent support treatment will lead to an increase in sales.*

One important objective of our experiment is to compare the performance effects of commission payments from the firm to a reseller to those of direct payments to the resellers' sales agents. If a company wants to induce an active promotion of its products, it needs to motivate the reseller to provide sufficiently strong incentives to its sales agents. This, in turn, requires a sufficiently high commission to the reseller to motivate the latter to incentivize its agents properly. A key observation is that the minimum payment necessary to motivate the reseller to provide incentives to the sales agent is larger than the minimum payment needed to incentivize the agent directly.

The intuition is the following: When intermediaries pass through all commission payments received by the firms fully to their sales personnel, they make no additional profits. In turn, an intermediary has an incentive to keep part of the commissions. Hence, a direct payment to a sales agent naturally has a stronger incentive effect.[15] Thus, it is less costly for companies to engage with sales agents directly whenever possible.

In our experiment, the *Reseller payment* treatment and the *Agent voucher* treatment have identical payment structures. Thus, we hypothesize that the *Agent voucher* treatment will have a stronger average effect on sales than the *Reseller payment*.

Hypothesis 2. *On average, the Agent voucher treatment should increase sales more than the Reseller payment treatment.*

Our conceptual framework does not allow us to derive clear ex-ante hypotheses with regard to the relative effectiveness of the *Agent support* treatment in comparison to the *Reseller payment* and *Agent voucher* treatment. The reason is that the metrics for the payments and the cost reductions are not comparable. As outlined in the introduction, a further key aim of our experiment is to compare the effectiveness of monetary with non-monetary incentives. However, the answer to this question is up to the empirical investigation.

Next, we discuss effect heterogeneities. The formal model implies that any additional incentives only have an effect if the product of the respective company has not already been promoted sufficiently at the outset. As laid out above, the firm segments the participating agencies into two tiers based on their prior sales. Tier-1 agencies receive a commission rate of 10%, and the rate for tier-2 agencies is 8%. Hence, tier-1 agencies (i) have sold more of the firm's products in the past and (ii) have stronger incentives to sell these products at the outset. Therefore, we expect that all our treatments will have a stronger effect on tier-2 agencies, as there is a larger scope to additionally promote the firm's products. We summarize this in the following hypothesis.

[15] This phenomenon is akin to the "double marginalization" issue discussed in the introduction.

Hypothesis 3. *On average, all treatments are expected to have a stronger positive effect on sales for agencies with a lower commission rate.*

In Section 2, we have discussed the market position of our study firm with regard to the incentivized products. Our study firm has a competitive advantage and provides superior quality for travel products to specific destinations (destinations 3 and 4) when compared to competitors. However, it possesses a weaker market position for travel products to destinations 1 and 2. Considering this, it appears likely that agencies have stronger incentives to sell travel products to destinations 3 and 4 already at the outset (i.e., before our interventions). Therefore, additional incentives should provide smaller increases in sales for these products. Hence, we predict that the impact on sales of all treatments will be stronger for bookings to destinations where the firm has no competitive advantage. This leads us to the following hypothesis.

Hypothesis 4. *We expect all treatments to cause a stronger increase in sales for travel products for which the firm has a weaker competitive advantage.*

4. Main empirical analysis

In this section, we discuss our identification strategy and then proceed to present our main results. More precisely, we investigate how the treatments affect our main outcome variable, namely, the number of incentivized bookings, and discuss their effects on profits. Finally, we analyze effect heterogeneity with regard to the agencies' closeness and the firm's market positioning for the different incentivized products. Our goal is to determine whether the effects of incentives vary depending on whether the firm has a competitive advantage for these products.

4.1. Identification strategy

In our analysis, we employ a difference-in-differences approach. As our main outcome variable, the number of bookings to incentivized destinations, is a count variable, we use both (i) a Poisson regression and (ii) an OLS fixed-effects regression.[16] Our estimations include two observations per agency: one in the pre-experimental period and another one in the experimental period.[17]

In the main specifications, we consider the core experimental period from February 2023 to April 2023. Given that all treatments started in February 2023 and two of the three ended in April 2023, this time frame ensures a clean comparison between treatments.[18]

[16]Specifically, due to overdispersion and the presence of inflated zeros, we rely on the Poisson Pseudo Maximum Likelihood estimator. The estimation is implemented in Stata using the *ppmlhdfe* command from the *ppml* package; see Correia et al. (2020).

[17]We drop those bookings from our analyses that have a net margin of less than -150 euros. The net margin is defined as revenue minus purchasing costs and commission payment. According to the study firm's management, these bookings are typically characterized by cancellations, internal allocation or payment defaults. These bookings account for about 5% of all bookings.

[18]Effects of the *Agent support* group beyond April 2023 are presented in the Appendix, in Section 8.4. We observe qualitatively the same effect for the *Agent support* group over the full time period of the treatment. However, interpreting these effects is challenging due to the concentration of most sales between January and April. Moreover, the full benefit of the *Agent support* group is contingent on the operational status of the service hotline during customers' travel dates. Consequently, the treatment effect is expected to decrease after April 2023, as booking volume decreases and the hotline's closing date approaches.

We estimate the following equation in our main analyses:

$$y_{it} = \alpha_i + \lambda_t + \beta_{AS} AgentSupport_{it} + \beta_{RP} ResellerPayment_{it} + \beta_{AV} AgentVoucher_{it} + \epsilon_{it} \quad (1)$$

Here, y_{it} denotes our outcome variable. The variables $ResellerPayment_{it}$, $AgentVoucher_{it}$, and $AgentSupport_{it}$ are dichotomous and equal to one in the experimental period if store i belongs to the *Reseller payment*, *Agent voucher*, or *Agent support* group. The variable λ_t accounts for time fixed-effects, α_i denotes the individual agency fixed-effects, and ϵ_{it} denotes the error term.[19]

4.2. Main results

Table 2 presents the estimation results from Equation (1) using a Poisson regression, and Table 3 presents the results using an OLS fixed-effects regression.[20] In both tables, Column 1 displays results for all agencies, Column 2 for tier-2 agencies, and Column 3 for tier-1 agencies, as defined in Section 2.1. For ease of interpretation, Table 2 also shows the incidence ratios (IR) of the estimates obtained from the Poisson regression as additional statistics. The incidence ratio, being the exponential of the coefficient, indicates the factor by which the average of the dependent variable changes for a specific treatment group. The outcome variable is defined as the number of bookings to the four incentivized destinations.

The results for both the Poisson and the OLS regressions are very similar: The strongest performance gains are achieved by the *Agent support* treatment: It increased bookings by about 16% overall and by about 25% (both in Poisson and OLS) among the tier-2 agencies.

For the *Agent voucher* treatment, we find no significant average treatment effect (Column 1), but a significant and sizeable treatment effect for tier-2 agencies, which corresponds to an increase in the number of bookings by about 20% (Poisson) or 17% (OLS) in this group.

The treatment effect of the *Reseller payment* group is not significantly different from zero, neither on average (Column 1) nor in one of the subgroups of agencies (Columns 2 and 3).

To test Hypothesis 2, i.e., the presence of *double marginalization*, we report p-values of F-tests for the hypothesis that the *Agent voucher* treatment is equally effective as the *Reseller payment* treatment, i.e., $\beta_{AV} = \beta_{RP}$. For both the Poisson and the OLS specifications, we can reject the Null $\beta_{AV} = \beta_{RP}$ at the 5% level for tier-2 agencies. For these agencies, it is more effective to pay the sales agents in form of vouchers compared to making same-sized monetary payments to the

[19] Regarding the robustness of our main results, we provide checks with regard to the estimation procedure, time aggregation and outcome variable. Therefore, we first investigate the effects of our interventions on the incentivized bookings using an ANCOVA approach. Second, we study the treatment effects using a different form of time aggregation by re-estimating Equation (1) with data aggregated on a monthly level. Finally, as the sets of products affected by the treatment differ between the *Reseller payment* and *Agent voucher* treatment, on the one hand, and the *Agent support* treatment, on the other, due to a technical limitation, we also analyze the treatment effects on the intersection of both sets. All results are qualitatively similar to our findings in Section 4.2. For the detailed regression outputs of our robustness checks, we refer to Section 8.3 in the Appendix.

[20] The estimations are based on data from $1,008$ agencies, as we need to discard observations from 252 agencies due to the well-known separation problem in non-linear estimations. These agencies lack variation, making their inclusion in the estimation impossible. However, as Correia et al. (2020) suggest, these observations can be safely discarded, as they do not provide identifying information for the estimators.

Table 2: Effect on incentivized bookings (Poisson)

	Incentivized bookings		
Agencies	All	Tier 2	Tier 1
	(1)	(2)	(3)
Agent support	0.146*	0.220**	0.036
	(0.077)	(0.107)	(0.106)
Agent voucher	0.039	0.185**	-0.163
	(0.074)	(0.089)	(0.119)
Reseller payment	-0.027	-0.061	-0.000
	(0.073)	(0.099)	(0.107)
p value $\beta_{AV} = \beta_{RP}$	0.44	0.02	0.22
IR Agent support	1.16	1.25	1.04
IR Agent voucher	1.04	1.20	0.85
IR Reseller payment	0.97	0.94	1.00
Observations	2016	1508	508
No. of Clusters	1008	754	254

Notes: The table shows the impact of the treatments on the number of bookings to the incentivized destinations using a difference-in-differences approach. The estimates in Columns 1 to 3 are obtained using a Poisson Pseudo Maximum Likelihood estimator. Column 2 only includes tier-2 agencies. Column 3 only includes tier-1 agencies. All specifications include time and store fixed-effects. Standard errors are clustered on store level in parentheses. The incidence ratios of the estimators are presented as additional statistics in the regression table. The incidence ratio is the exponential of the coefficient and is interpreted as the factor by which the average of the dependent variable approximately changes upon belonging to a specific treatment group.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

Table 3: Effect on incentivized bookings (OLS)

	Incentivized bookings		
Agencies	All	Tier 2	Tier 1
	(1)	(2)	(3)
Agent support	0.490*	0.546**	0.190
	(0.261)	(0.274)	(0.690)
Agent voucher	0.107	0.383*	-1.025
	(0.229)	(0.217)	(0.727)
Reseller payment	-0.053	-0.141	-0.028
	(0.231)	(0.219)	(0.665)
p value $\beta_{AV} = \beta_{RP}$	0.55	0.04	0.22
Observations	2514	1986	528
No. of Clusters	1257	993	264

Notes: The table shows the impact of the treatments on the number of bookings to the incentivized destinations using a difference-in-differences approach. The estimates in Columns 1 to 3 are obtained using a standard OLS fixed-effects estimator. Column 2 only includes tier-2 agencies. Column 3 only includes tier-1 agencies. All specifications include time and store fixed-effects. Standard errors are clustered on store level in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

agency owners.

To test Hypothesis 3 – according to which the treatments have a stronger positive effect on sales for tier-2 agencies with a lower prior commission – we compare the treatment effects between Columns 2 and 3. More precisely, we conduct a one-sided t-test. For the *Agent voucher* treatment, we can reject the Null $\beta_{\text{AV}}^{\text{T2}} < \beta_{\text{AV}}^{\text{T1}}$ with a p-value of 0.0315 (where the superscript denotes the tier). For the *Agent support* and *Reseller payment* treatments, we cannot reject the corresponding null hypotheses.[21] This means that, even though some of the evidence is mixed, overall the results support Hypothesis 3.

4.3. Effect on profits

Our analysis thus far has focused on behavioral changes induced by the treatments by examining the impact on the number of bookings to the specified destinations as the incentivized key performance indicator. Given that profitability and product margins are not directly observable by agents, and resellers are incentivized based on sales volume in terms of number of bookings, these factors are likely not of primary relevance for the resellers' or agents' decisions. However, these effects are of course very relevant for firms.

We thus now turn to the bottom-line effects of the treatments on profits generated from bookings to the incentivized destinations.[22] For this purpose, we re-estimate equation (1) using an OLS fixed-effects estimator and define the outcome variable as the net profit contribution. The net profit contribution obtains as follows:

$$NPC_{it} = R_{it} - PC_{it} - CP_{it} - HotlineCosts_{it} - ResellerPayments_{it} - AgentVouchers_{it}. \quad (2)$$

Here, R_{it} denotes the revenue generated from the bookings to the incentivized destinations, PC_{it} denotes the corresponding purchasing costs, and CP_{it} denotes the corresponding commission payments made to the agencies. The variable $HotlineCosts_{it}$ obtains as the total number of minutes an agency used one of the study firm's hotlines multiplied with the study firm's internal transfer price per minute of hotline usage. The variable is defined for both the pre-experimental and the experimental period and for all treatment groups as well as the control group. On the contrary, the variables $ResellerPayments_{it}$ and $AgentVouchers_{it}$ are only defined for the experimental period and agencies that are part of the respective treatment group. $ResellerPayments_{it}$ obtains as the sum of top-up payments gathered by the respective agency in the experimental period. $AgentVouchers_{it}$ obtains as the sum of vouchers that has already been redeemed by the respective agency.[23]

[21]The p-value for the Null $\beta_{\text{AS}}^{\text{T2}} < \beta_{\text{AS}}^{\text{T1}}$ is 0.3155, and for the Null $\beta_{\text{RP}}^{\text{T2}} < \beta_{\text{RP}}^{\text{T1}}$ it is 0.436.

[22]We also consider the effect on the revenue stemming from the corresponding bookings. The results are comparable to the effect on profits presented in Table 4 and are presented in Section 8.3 of the Appendix.

[23]Up to February 2024, 22% of the distributed vouchers had been redeemed by the agencies. Notice that our study firm does not operate a full cost accounting process or allocate full costs on a product basis. However, the remaining costs are primarily overhead and not product-specific. Thus, the net profit contribution directly translates to an increase in profits.

Table 4 presents the results. Here the results are very clear: Both monetary treatments (i.e., the *Reseller payment* and the *Agent voucher* treatment) do not refinance themselves, but the *Agent support* has a substantial return on invest.

Table 4: Effect on profits

	Profit contribution		
Agencies	All (1)	Tier 2 (2)	Tier 1 (3)
Agent support	82.80*	118.58**	-63.80
	(49.59)	(54.09)	(121.60)
Agent voucher	-40.26	-22.06	-120.01
	(47.97)	(48.92)	(137.26)
Reseller payment	-45.18	-31.57	-120.07
	(48.59)	(53.09)	(117.52)
Observations	2514	1986	528
No. of Clusters	1257	993	264

Notes: The table shows the impact of the treatments on the net profit contribution using a difference-in-differences approach. The estimates in Columns 1 to 3 are obtained using a standard OLS fixed-effects estimator. Column 2 only includes tier-2 agencies. Column 3 only includes tier-1 agencies. All specifications include time and store fixed effects. Standard errors are clustered on store level in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

First, we observe that the *Agent support* treatment increases net profits by 83 euros per agency on average across the two tiers and by 119 euros in tier 2. The estimated annual profit impact of extending the *Agent support* treatment across all participating agencies amounts to approximately $360,000$ euros.[24] Notably, this is an average figure, with the point estimate in Column 2 suggesting even stronger returns for tier-2 agencies.

The results for the *Agent voucher* group are less robust. While there is a behavioral change in terms of an increase in bookings, it does not translate into a significant profit increase. This result is mainly attributed to the strong promotion of particularly cheap products with low margins, paired with an absence of positive demand shifts for products with relatively high margins.

The *Reseller payment* group shows no significant results.

4.4. Heterogeneity with regard to market position

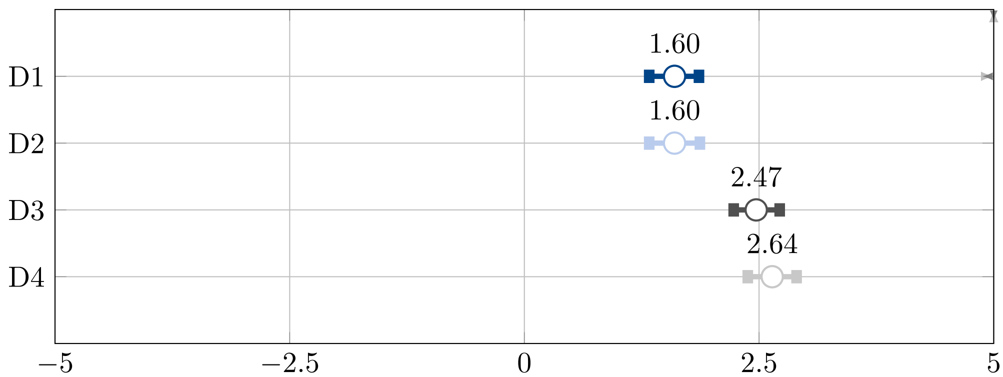
In this subsection, we separate the treatment effects according to the firm's relative standing to its competitors. More precisely, we divide the products with regard to whether the firm has a competitive advantage (Porter 1985).

Due to its ownership structure, our study firm maintains strong ties to Destination 3 and Destination 4, particularly benefiting from an excellent political and business network in these

[24] The average net profit contribution per agency during the main treatment period (February to April 2023) is 83 euros. Considering that this period accounts for about 29% of annual bookings to the four target destinations, we extrapolate the total annual net profit contribution to be around $83 \times \frac{100}{29} \times 1257 \approx 359,762$ euros.

regions. This enables the firm to offer high-quality products at lower costs, giving it a competitive advantage over the biggest competitors. In contrast, the market for travel products to Destination 1 and Destination 2 is more competitive in general. This competitiveness stems from the larger and more homogeneous offerings of competitor firms. Hence, our study firm does not hold a competitive advantage for Destinations 1 and 2. This information was primarily gathered through conversations with board members and high-level managers. To validate this claim, we asked participating agencies in our survey to rank the product quality offered by our study firm relative to competitors in all four destinations. As Figure 2 shows, the quality of the study firm's products is indeed perceived as higher compared to the relevant competitors for all four destinations, but especially for Destination 3 and Destination 4.

Figure 2: Perception of study firm's product quality by destination



Notes: The figure presents the mean and 95% confidence interval of the agencies' perception of the study firm's product quality across the incentivized destinations. The exact question within the survey reads as follows: 'How do you rate the study firm's product quality in general and for the following destinations compared to other relevant competitors on a scale from -5 to +5? Please refer only to the product quality and not to the service quality!' Only the difference between Destination 1 and Destination 2 is not statistically significant.

Table 5 displays the results from a re-estimation of Equation (1), where we split the total number of bookings to the incentivized destinations into two categories. For each agency, we have two observations for the pre-experimental and the experimental period. The specification includes an interaction term indicating whether the bookings stem from destinations with a competitive advantage or not. More precisely, the variable 'Strong' is dichotomous and equal to one in case of a booking to Destination 3 or 4 and zero otherwise. Column 1 comprises the entire sample, Column 2 focuses solely on tier-2 agencies, and Column 3 presents effects for tier-1 agencies. All estimates are obtained using a standard OLS fixed-effect regression.

The baseline estimates demonstrate the effects for products with 'no competitive advantage'. Here, we see a pattern similar to our main results: The point estimates indicate an average increase of 0.43 bookings for the *Agent support* group and an increase of 0.28 for the *Agent voucher* group, and these are mainly driven by the tier-2 agencies.

The point estimates of the interaction terms of the treatment dummies and the dummy for Destinations 3 and 4 for the *Agent support* and *Agent voucher* group are negative and statistically significant. The magnitude suggests that the average treatment effect for products with a compet-

Table 5: Heterogeneous effects with respect to market position

	Incentivized bookings		
Agencies	All (1)	Tier 2 (2)	Tier 1 (3)
Agent support	0.434**	0.428**	0.412
	(0.172)	(0.182)	(0.446)
Agent voucher	0.277*	0.382**	-0.165
	(0.161)	(0.158)	(0.486)
Reseller payment	-0.091	-0.208	0.125
	(0.149)	(0.142)	(0.416)
Agent support × Strong	-0.379**	-0.310*	-0.633
	(0.174)	(0.178)	(0.488)
Agent voucher × Strong	-0.447**	-0.381**	-0.695
	(0.173)	(0.168)	(0.532)
Reseller payment × Strong	0.129	0.276*	-0.278
	(0.155)	(0.152)	(0.427)
Observations	5028	3972	1056
No. of Clusters	1257	993	264

Notes: The table shows the impact of the treatments on the number of bookings to the incentivized destinations using a difference-in-differences approach. We split the bookings into two different categories according to the market position of the study firm with regard to the products. The outcome variable is the number of bookings. The data set consists of two observations for each agency in the pre-experimental and experimental period. The variable 'Strong' is dichotomous and equal to one if the observations stem from bookings to Destinations 3 and 4 and zero otherwise. All estimates are obtained using a standard OLS fixed-effects estimator. Column 2 only includes tier-2 and Column 3 only includes tier-1 agencies. All specifications include time and store fixed-effects. Standard errors are clustered on store level in parentheses.

$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

itive advantage is close to zero. Consistent with previous results, we observe no significant results for the *Reseller payment* group.

In conclusion, our main analysis results appear to be strongly driven by products for which our study firm lacks a competitive advantage. This aligns with our conceptual framework, particularly with Hypothesis 4. The underlying intuition is akin to the observed heterogeneity in commission rates. Products where our study firm lacks a competitive advantage are less likely to be promoted by sales agents at the outset. Consequently, a more substantial behavioral change upon all treatments regarding these products is relatively more likely, as there is a greater scope for improvement.

5. Further results and discussion

In this section, our analysis is segmented into two distinct parts. First, we discuss specific behavioral mechanisms behind our main findings using survey data and additional administrative data. Second, we discuss the impact on other outcome variables of interest.

5.1. Behavioral mechanisms

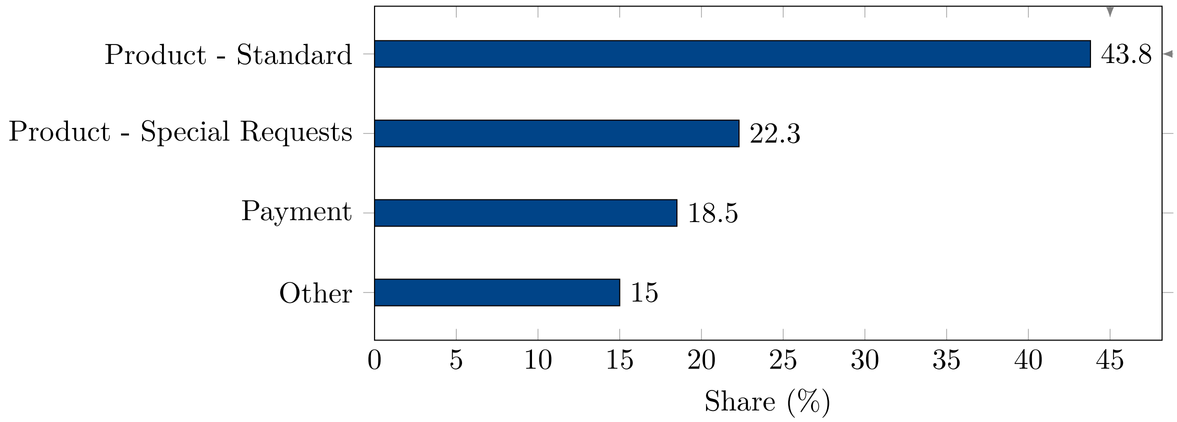
5.1.1. Agent support

We now discuss the behavioral mechanisms driving the positive effect of the *Agent support* treatment. The primary conceptual distinction between this treatment and the other two is twofold. First, the treatment facilitates the daily work routine of the sales agents instead of rewarding performance. Second, the *Reseller payment* or *Agent voucher* are contingent upon a successful sale, while the hotline offers support to sales agents, irrespectively of converting customers. The hotline thus serves to reduce the costs associated with sales efforts and simplifies the selling and consulting process of the agents. Therefore, it appears likely that the *Agent support* treatment effectively lowers the marginal costs of effort, as assumed in our conceptual framework. In this section, we provide multiple sources of evidence to support and illustrate this claim.

First, we offer an overview of how agents use the call center and provide the reasons behind their calls. Figure 3 displays the distribution of call reasons, manually aggregated by us from over 120 more specific categories. These finer categories are created by call-center agents, who classify the reason for each call upon completion. ‘Product - Standard’ typically involves requests for detailed information about a particular product, often in response to customer queries. ‘Product - Special Requests’ includes calls where sales agents seek to accommodate specific changes to bookings, such as using a preferred airline or departure airport or require special dietary restrictions for customers. ‘Payment’ encompasses various queries or issues related to the payment and billing process. The ‘Other’ category captures all other types of calls, including general inquiries about the study firm or complaints. The figure reveals that the majority of calls are product-related, directly linked to the booking process.[25] Additional insights into the call center’s usage by agents, derived from our survey with call-center agents, are provided in Section 8.6 of the Appendix.

[25]The figure represents the share of calls across all groups. There are no statistically significant differences in the distribution of categories between treatment groups.

Figure 3: Distribution of inbound calls among categories



In order to understand the drivers behind the positive effects of the *Agent support* treatment, it is important to study whether the hotline indeed led to a reduction in the personal selling costs of the agent as was the basis of our key hypothesis. An alternative explanation is that the hotline increased sales through an increase in customer value.

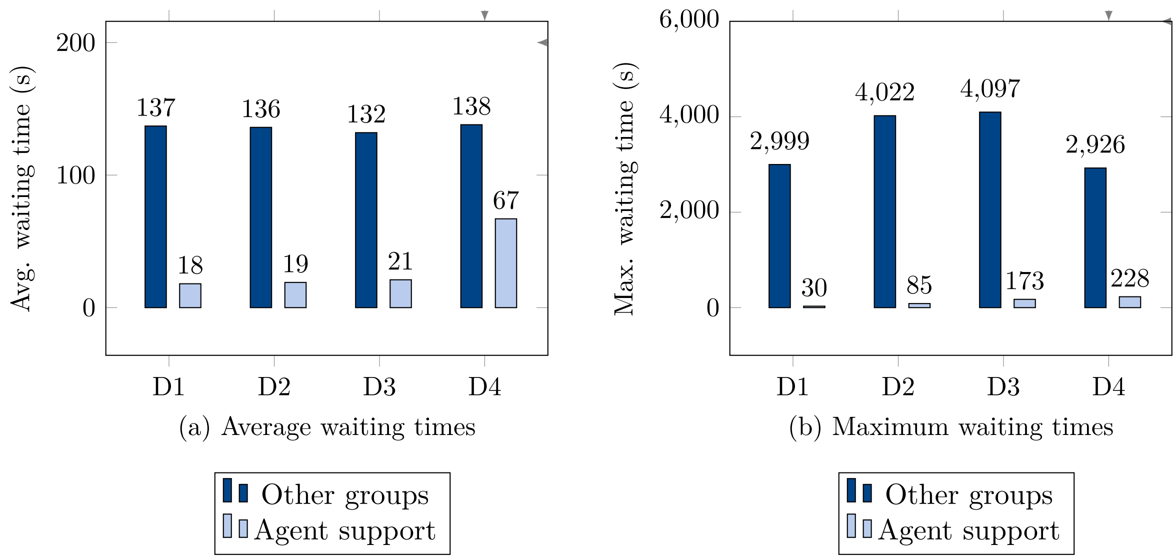
Agents can benefit from the hotline access particularly at two distinct points in time. The first is a reduction in waiting time when contacting the study firm by phone with customer queries or special requests about the products at the time of purchase. The second is the ability to contact the study firm for customer requests around the time of departure or during the vacation. Given that our observation period primarily covers the booking phase, the first point is the primary driver of the observed effects. However, the second point, serving as a form of insurance for unforeseen circumstances or problems, might be important as well.[26]

The key difference in the experimental environment is the substantial reduction in waiting time when agents contact the study firm. Figure 4 (a) compares the average waiting times (in seconds) for the other groups (in blue) and the *Agent support* group (in red), showing a substantial reduction in average waiting times by about 52% to 87% depending on the destination.[27] However, there is huge heterogeneity in waiting times, as they can increase rapidly during busy periods, as shown in Figure 4 (b). This figure displays the maximum waiting times, with reductions ranging from 94% to 99% depending on the destination. Such significant reductions during peak periods highlight the time-saving benefits for agents, clearly substantiating our claim that the hotline access causes personal cost reductions for the sales agents.

[26] In Section 8.6.2, Figure A.8 illustrates the total minutes of inbound calls over time, with peaks in February, March, and from September onwards, aligning with high-booking seasons. This pattern supports our assertion that sales agents primarily use the call center for booking-related inquiries.

[27] We only have aggregated data available to measure waiting times. Thus, we can only distinguish between the *Agent support* group and all other agencies. However, there is no reason to believe there are differences between other treatment and the control groups. Further, note that shifts and the number of call-center agents on each shift were adjusted in preparation of the experiment. Therefore, the *Agent support* group did not exhibit negative spillover effect in terms of waiting times on other groups.

Figure 4: Waiting time - Agent support vs. Other groups

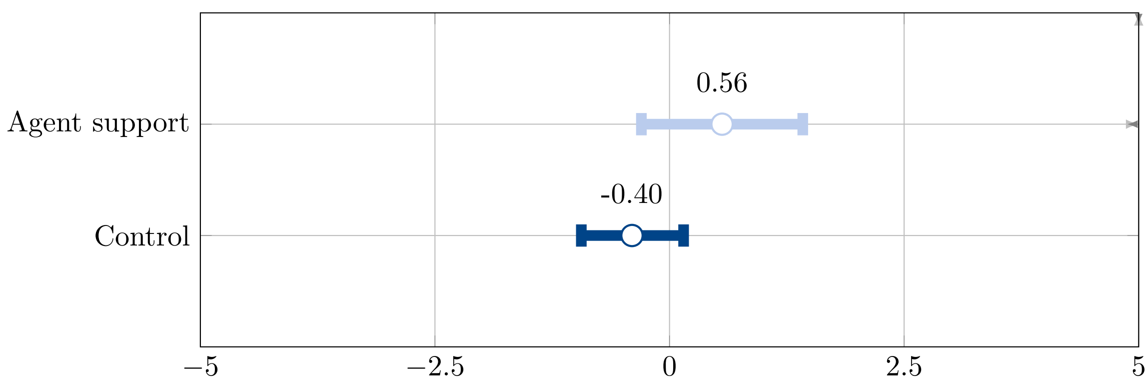


(a) Average waiting times

(b) Maximum waiting times

Lastly, we provide further supporting evidence from our survey.[28] We asked survey participants from agencies to rate the service quality provided by our study firm. These ratings were on a scale from -5 to $+5$ relative to the firm's most relevant competitors, with zero meaning equal quality. Figure 5 summarizes the responses. We observe that agencies in the *Agent support* group perceive the service quality provided by our study firm as significantly better than the control group. Hence, it is again very likely that the sales agents profited from the treatment in form of a reduction of their cost of effort.

Figure 5: Perception of quality of service provided by study firm



Notes: The figure presents the mean and 95% confidence interval of the agencies' perception of the study firm's service quality for the *Agent support* group and the control group. The exact question within the survey reads as follows: 'It is common knowledge that bookings can get quite complicated due to special customer wishes, cancellations, booking changes or the like. How do you rate the service quality (especially availability and competence) of the study firm compared to other relevant competitors on a scale from -5 to +5?'. The observed difference is statistically significant with the null $\mu_{\text{supp}} \leq \mu_{\text{control}}$ being rejected with p-value of *0.0343*.

[28]The survey's response rate was 20%. We cannot exclude selection biases with respect to key performance variables. Therefore, we do not want to overemphasize these findings, but we consider them as complementary evidence.

5.1.2. Reseller payment vs. Agent voucher

We proceed by providing further evidence for the role of 'double marginalization' that we illustrated in our conceptual framework: As shown there, resellers have an incentive not to forward all payments to their sales agents, leading to weaker effective selling incentives.[29] In contrast, when paying the sales agents directly, the reseller can be circumvented, and the direct incentives for the sales agents who manage the customer contact get stronger.

Considering our empirical results, it is important to note that paying the agent in form of a voucher is not the same as a cash payment. The consumption opportunities with a direct cash payment would be richer, while a voucher can only be used for travel products offered by our study firm. Thus, it is reasonable to assume that the cash equivalent of the voucher is below its value. Moreover, for legal reasons vouchers have to be handed over to the reseller and it is not allowed to give them to the sales agents directly. Hence, it is still at the resellers' discretion whether to forward them or not.[30] As outlined in Section 2, we sent reminders about the program on a bi-weekly basis to the e-mail address of the agency, informing the whole team that the program is in place. This would admittedly make it difficult for the reseller to keep all received vouchers. Nevertheless, it is reasonable that the effect is at least partially reduced to the fact that there is no legal claim of the sales agents.

Taking both points together, one could probably expect the effect sizes to be stronger with actual cash payments to sales agents. We thus cannot rule out that this partly explains why we do not observe a significant change in profits or overall stronger effects. But by the same token, the fact that for the tier-2 agencies the *Agent voucher* treatment significantly outperforms the *Reseller payment*, despite the fact that the actual payout is more valuable in the latter, further substantiates the importance of 'double marginalization'.

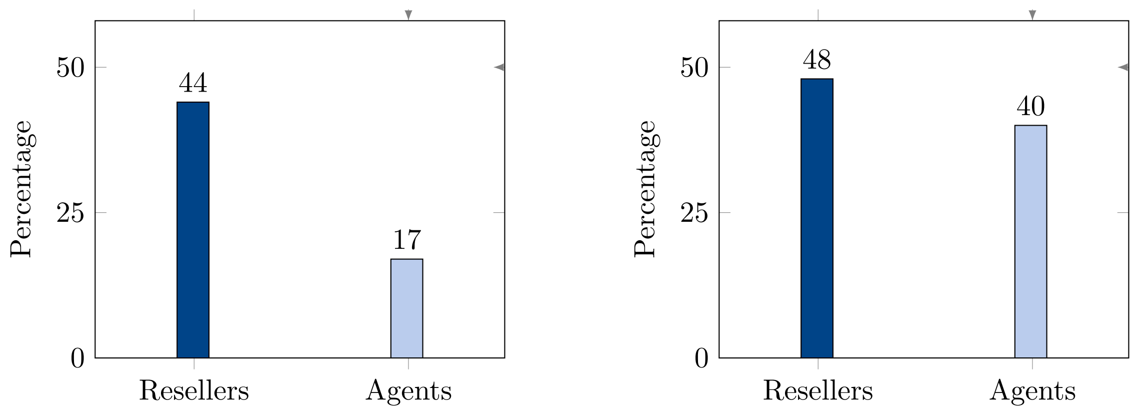
We can further illustrate this issue based on the survey data collected from the agencies. We elicited a rating from the resellers to which extent either the reseller himself or his sales agents profited from the incentive programs. The results are shown in Figure 6. While for the *Agent voucher* group the share of resellers stating that the reseller profited from the program is very similar to the share stating that the sales agents profited (48% vs. 40%), this is not the case for the *Reseller payment*. For the *Reseller payment* treatment 44% of the resellers stated that they benefited from the program, while only 17% stated that their sales agents benefited. This clearly suggests that many resellers did not forward the additional top-up payment. For the *Agent voucher* group, however, the majority (73%) of resellers who participated in our survey stated that they had already forwarded the vouchers to their sales agents or planned to do so soon.

[29] One may argue that a simple solution to make the *Reseller payment* work is just elevating the amount. However, margins in the travel business are not high and this would substantially lower the profitability. To account for a different strength of incentives, we additionally ran experiments where we paid the Reseller 3 and 9 euros (instead of 6 euros as in our main experiment). Both experiments yielded null results. Therefore, just increasing the amount until a positive effect occurs is no reasonable strategy in such a market environment. The results are available from the authors upon request.

[30] Recall that resellers cannot redeem the vouchers themselves.

Figure 6: Rating of Resellers about which groups benefit from the incentive program.

(a) Who profited from the Reseller payment? (b) Who profited from the Agent voucher?



Notes: The left graph shows the share of resellers stating that they (their sales agents) profited from the *Reseller payment* treatment. The difference is significantly different from zero. The right graph shows the share of resellers stating that they (their sales agents) profited from the *Agent voucher* treatment. The corresponding difference is not significantly different from zero. The exact questions within the survey read as follows: 'Did you (your employees) profit from those additional incentives?' Participants could choose between 'Yes' and 'No' when asked about themselves and between 'Yes', 'No' and 'I do not know' when asked about their employees. Answers from survey participants with other positions than agency owner, i.e., reseller, were excluded from this specific analysis.

5.2. Other outcomes

Lastly, we present the effects of our interventions on other outcome variables of interest.

As the additional top-up payments and vouchers are determined via the total number of passengers per booking, one can also analyze the treatment effects on the average number of passengers per booking. However, as travel products typically require advanced planning and commitment by the customers, there is no reason to expect sales agents to be able to upsell in terms of the number of passengers. The results are presented in Table 6.

We observe negative treatment effects on the average number of passengers per booking to the incentivized destinations for the *Agent voucher* group. This is stemming from the fact that the additional sales were mainly generated by bookings with fewer than three passengers and thereby changing the distributional composition. Also, the decline in average passenger numbers does not translate into profits as evaluated in 4.3.

Furthermore, a remaining key question is whether the treatments may have caused a shift between destinations. It appears conceivable that sales agents nudged customers with no or only weak preferences regarding the target destination towards the incentivized destinations. Then, the treatment effect would not result from additional bookings, but only from shifting customers from a non-incentivized to an incentivized destination. We therefore consider the effect on the number of bookings to all but the incentivized destinations and do not find any statistically significant effect and mostly positive point estimates. The results are presented in Table 7.[31]

[31] The results regarding the corresponding revenue are presented in Section 8.3 in the Appendix. Again, we do not find any notable effect.

Table 6: Effect on passengers per incentivized booking

	Passengers per incentivized booking		
Agencies	All (1)	Tier 2 (2)	Tier 1 (3)
Agent support	-0.04	-0.07	0.04
	(0.11)	(0.13)	(0.16)
Agent voucher	-0.21**	-0.30**	-0.00
	(0.10)	(0.13)	(0.12)
Reseller payment	-0.18*	-0.20	-0.13
	(0.10)	(0.13)	(0.12)
Observations	1426	994	432
No. of Clusters	713	497	216

Notes: The table shows the impact of the treatments on the average number of passengers per booking to the incentivized target destinations using a difference-in-differences approach. The estimates in Column 1 to 3 are obtained using a standard OLS fixed-effects estimator. Column 2 only includes tier-2 agencies. Column 3 only includes tier-1 agencies. Agencies without bookings to the incentivized destinations are excluded from the regression. All specifications include time and store fixed-effects. Standard errors are clustered on store level in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

Table 7: Effect on other bookings

	Other bookings		
Agencies	All (1)	Tier 2 (2)	Tier 1 (3)
Agent support	0.390	0.450	0.121
	(0.341)	(0.349)	(0.981)
Agent voucher	0.146	0.148	0.100
	(0.408)	(0.406)	(1.226)
Reseller payment	0.126	-0.393	1.612
	(0.404)	(0.360)	(1.248)
Observations	2514	1986	528
No. of Clusters	1257	993	264

Notes: The table shows the impact of the treatments on the number of bookings to the non-incentivized destinations using a difference-in-differences approach. The estimates in Columns 1 to 3 are obtained using a standard OLS fixed-effects estimator. Column 2 only includes tier-2 agencies. Column 3 only includes tier-1 agencies. All specifications include time and store fixed-effects. Standard errors are clustered on store level in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

6. Managerial implications

Strategic tools such as incentives are important to steer the behavior of people. However, when badly designed, they can backfire, e.g., by causing gaming (Larkin 2014), reducing collaboration (Siegel and Hambrick 2005), or increasing absenteeism (Alfitian et al. 2023). As discussed before, designing strategic tools aimed at increasing sales can be particularly challenging in markets in which firms sell their products via intermediaries, for example because of contractual constraints and as intermediaries are legally and organizationally independent. Our study provides a number of implications for the design of strategic tools in such intermediary markets aimed at improving sales behavior.

Which unit or individual should be incentivized? In our study, we find that tools that directly benefit an intermediary's sales agents are most effective, while providing the owner with an incentive has no significant effect – arguably because the owner does not transfer the entire incentive to the sales agents. This implies that – if possible – firms that sell products via intermediaries should directly provide the intermediary's sales agents with the incentive, and by doing so avoid a 'double marginalization' problem. Therefore, incentives should specifically target the individuals responsible for customer interaction.

However, in intermediary markets, providing the intermediary's sales agents with incentives or other benefits is often challenging, in particular because of regulation, contractual or organizational restrictions (e.g., owners have an incentive to mitigate direct interaction between the sales agent and the upstream firm). In our field experiment, we implemented one treatment (*Agent voucher* treatment) in which we used three methods to increase the probability that sales agents are indeed incentivized. First, we informed the intermediaries in letters and e-mails about the additional compensation, being aware that it is likely that sales agents read the messages. The increased transparency made it difficult for owners to keep agents uninformed about the additional incentives. Second, we nudged the owners (via a letter) to transfer the additional compensation – in our case, the voucher – to the sales agents. Third, we limited the usefulness of the compensation for the owner by ensuring that only sales agents can redeem the voucher (although owners still had the discretion whether and when to allocate the voucher to the sales agents). Indeed, in our study, we find that a significant share of the owners transferred the voucher to the sales agents, and there are some effects of the intervention on sales. This implies that transparency, nudges and limiting the use of the compensation for the owner can be methods that firms selling products via intermediaries can use to circumvent the owner, and at least partly benefit the sales agents.

Should effort costs be reduced or monetary rewards be increased? The *Reseller payment* and *Agent voucher* treatments are conceptually different from the *Agent support* treatment. While the *Reseller payment* and *Agent voucher* treatments benefit intermediaries by increasing rewards for the reseller and/or agent, the *Agent support* treatment reduces the effort costs for agents. This approach effectively bypasses the reseller, ensuring that the full benefit reaches the agent. Moreover, it appears that reducing effort costs benefits the sales agent more comprehensively. The *Reseller payment* and *Agent voucher* treatments yield benefits only upon successful customer conversion. In contrast, the *Agent support* treatment facilitates the sales agents' work even if customer conversion is ultimately unsuccessful. This approach has proven to be the most effective in directing sales behavior and increasing profits in our setting. However, various alternative strategies that directly simplify the sales personnel's handling of the firm's products could yield similar benefits, such as reducing bureaucratic hurdles (see Friebel et al. 2023), improving sales-force automation systems (see Speier and Venkatesh 2002, Johnson and Bharadwaj 2005) or offering specialized training (see Chung et al. 2021), among other initiatives.

In our case, increasing service quality to facilitate daily work routines likely was particularly effective, as it also supported further task dimensions. The key objective of additional incentives is to convert more customers, which typically includes customers who would not purchase the firm's product otherwise. Therefore, it is plausible that the effort costs in these cases are relatively higher.[32] While the *Reseller payment* and *Agent voucher* treatments distribute their benefits uniformly, without accounting for the varying amounts of work required by the agent, the *Agent support* treatment provides the highest benefit when sales effort costs are high. Sales agents have the autonomy to utilize the tool when they believe it is most needed. We further observe that positive treatment effects are predominantly driven by tier-2 agencies, which interact less frequently with the company's products and are less familiar with booking procedures compared to tier-1 agencies. Again, the *Reseller payment* and *Agent voucher* treatments offer uniform monetary benefits, regardless of the agency's familiarity or booking frequency. In contrast, the *Agent support* treatment provides the greatest benefit to those agencies with the least knowledge.

Where can the highest benefits be achieved? We observe that both the *Agent voucher* and the *Agent support* treatments were more effective for tier-2 agencies as well as for products where the firm holds a relatively weak market position. Importantly, both contexts provide a large scope for a change in sales behavior. This is because tier-2 agencies are less likely to sell the study firm's product in general, and products with a weak market position are less likely to be sold initially as well. Often, firms follow a cost-based approach when deciding on the size of incentives. Products where firms are particularly strong provide higher margins, making larger incentives more affordable. Similarly, higher payments are likely made to intermediaries who perform well. While this approach is not inherently wrong, as it is necessary to pay sufficiently to maintain sales volume, firms need to be aware that the marginal benefit of additional incentives is likely weaker in these cases. The reason is that products with a strong market position – due to superior quality – are more likely to be sold by intermediaries without further inducements. An analogous reasoning applies to intermediaries with stronger ex-ante ties to the upstream firm. Managers are advised to identify the subgroups of intermediaries and products with the greatest potential for sales increases and to adjust additional incentives accordingly.

[32] As highlighted by Chen (2005), most compensation schemes for sales agents do not account for differences in sales effort.

7. Conclusion

In conclusion, we observe that directly targeting sales agents by providing better service to them can be a simple, cost-effective way to increase sales generated through intermediaries: In our setting, the *Agent Support* treatment led to the strongest performance gains.

Although the *Agent voucher* treatment did not translate into significant profit increases, our results here validate the critical assumption that 'double marginalization' may prevent that simple monetary incentives from effectively being forwarded by intermediary owners to their sales personnel. Even though the vouchers generated less fungible rewards than direct monetary payments, they outperformed such payments made to owners in the *Reseller payment* treatment and influenced agent behavior. Similar instruments, potentially being targeted even more specifically to particular products and agencies, appear promising to achieve further profit increases and strengthen the firm's market position. However, this needs to be investigated in future research.

References

Alfitian, J., D. Sliwka, and T. Vogelsang (2023). When bonuses backfire: Evidence from the workplace. *Management Science (forthcoming).*

Anagol, S., S. Cole, and S. Sarkar (2017). Understanding the advice of commissions-motivated agents: Evidence from the Indian life insurance market. *Review of Economics and Statistics 99*(1), 1–15.

Barron, J. M. and J. R. Umbeck (1984). The effects of different contractual arrangements: The case of retail gasoline markets. *The Journal of Law and Economics 27*(2), 313–328.

Biglaiser, G., F. Li, C. Murry, and Y. Zhou (2020). Intermediaries and product quality in used car markets. *The RAND Journal of Economics 51*(3), 905–933.

Caldieraro, F. and A. T. Coughlan (2007). Spiffed-up channels: The role of spiffs in hierarchical selling organizations. *Marketing Science 26*(1), 31–51.

Camuffo, A., A. Gambardella, and A. Pignataro (2023). Theory-driven strategic management decisions. CEPR Discussion Paper DP17664 (v.2).

Chen, F. (2005). Salesforce incentives, market information, and production/inventory planning. *Management Science 51*(1), 60–75.

Chung, D. J., B. Kim, and B. G. Park (2021). The comprehensive effects of sales force management: A dynamic structural analysis of selection, compensation, and training. *Management Science 67*(11), 7046–7074.

Chung, D. J. and D. Narayandas (2017). Incentives versus reciprocity: Insights from a field experiment. *Journal of Marketing Research 54*(4), 511–524.

Chung, D. J., T. Steenburgh, and K. Sudhir (2014). Do bonuses enhance sales productivity? A dynamic structural analysis of bonus-based compensation plans. *Marketing Science 33*(2), 165–187.

Cobb, J. A. and K.-H. Lin (2017). Growing apart: The changing firm-size wage premium and its inequality consequences. *Organization Science 28*(3), 429–446.

Conti, R., A. Gambardella, and E. Novelli (2019). Specializing in generality: Firm strategies when intermediate markets work. *Organization Science 30*(1), 126–150.

Conyon, M. J. (2006). Executive compensation and incentives. *Academy of Management Perspectives 20*(1), 25–44.

Correia, S., P. Guimarães, and T. Zylkin (2020). Fast Poisson estimation with high-dimensional fixed effects. *The Stata Journal 20*(1), 95–115.

Delfgaauw, J., R. Dur, O. Onemu, and J. Sol (2022). Team incentives, social cohesion, and performance: A natural field experiment. *Management Science 68*(1), 230–256.

Donna, J. D., P. Pereira, T. Pires, and A. Trindade (2022). Measuring the welfare of intermediaries. *Management Science 68*(11), 8083–8115.

Englmaier, F., A. Roider, and U. Sunde (2017). The role of communication of performance schemes: Evidence from a field experiment. *Management Science 63*(12), 4061–4080.

Friebel, G., M. Heinz, M. Hoffman, T. Kretschmer, and N. Zubanov (2023). Is this really kneaded? Identifying and eliminating potentially harmful forms of workplace control. Discussion Paper.

Friebel, G., M. Heinz, M. Krueger, and N. Zubanov (2017). Team incentives and performance: Evidence from a retail chain. *American Economic Review 107*(8), 2168–2203.

Hagiu, A. and J. Wright (2015). Marketplace or reseller? *Management Science 61*(1), 184–203.

Honda, J., R. Inderst, and M. Ottaviani (2024). When liability is not enough: Regulating bonus payments in markets with advice. *Management Science 70*(2), 1301–1314.

Inderst, R. and M. Ottaviani (2009). Misselling through agents. *American Economic Review 99*(3), 883–908.

Inderst, R. and M. Ottaviani (2012). Competition through commissions and kickbacks. *American Economic Review 102*(2), 780–809.

Johnson, D. S. and S. Bharadwaj (2005). Digitization of selling activity and sales force performance: An empirical investigation. *Journal of the Academy of Marketing Science 33*(1), 3–18.

Kennedy, C. and C. B. Mann (2015). Randomize: Stata module to create random assignments for experimental trials, including blocking, balance checking, and automated rerandomization.

Khashabi, P., M. Heinz, N. Zubanov, T. Kretschmer, and G. Friebel (2021). Market competition and the effectiveness of performance pay. *Organization Science 32*(2), 334–351.

Lafontaine, F. and M. Slade (2007). Vertical integration and firm boundaries: The evidence. *Journal of Economic literature 45*(3), 629–685.

Larkin, I. (2014). The cost of high-powered incentives: Employee gaming in enterprise software sales. *Journal of Labor Economics 32*(2), 199–227.

Lassar, W. M. and J. L. Kerr (1996). Strategy and control in supplier–distributor relationships: An agency perspective. *Strategic Management Journal 17*(8), 613–632.

Lee, S. and P. Puranam (2017). Incentive redesign and collaboration in organizations: Evidence from a natural experiment. *Strategic Management Journal 38*(12), 2333–2352.

Lourenço, S. M. (2016). Monetary incentives, feedback, and recognition – complements or substitutes? Evidence from a field experiment in a retail services company. *The Accounting Review 91*(1), 279–297.

Manthei, K., D. Sliwka, and T. Vogelsang (2021). Performance pay and prior learning – Evidence from a retail chain. *Management Science 67*(11), 6998–7022.

Manthei, K., D. Sliwka, and T. Vogelsang (2023a). Information, incentives, and attention: A field experiment on the interaction of management controls. *The Accounting Review 98*(5), 455–479.

Manthei, K., D. Sliwka, and T. Vogelsang (2023b). Talking about performance or paying for it? A field experiment on performance reviews and incentives. *Management Science 69*(4), 2198–2216.

Mookherjee, D. (2006). Decentralization, hierarchies, and incentives: A mechanism design perspective. *Journal of Economic Literature 44*(2), 367–390.

Mookherjee, D. and M. Tsumagari (2004). The organization of supplier networks: Effects of delegation and intermediation. *Econometrica 72*(4), 1179–1219.

Nyberg, A. J., M. A. Maltarich, D. D. Abdulsalam, S. M. Essman, and O. Cragun (2018). Collective pay for performance: A cross-disciplinary review and meta-analysis. *Journal of Management 44*(6), 2433–2472.

Obloj, T. and M. Sengul (2012). Incentive life-cycles: Learning and the division of value in firms. *Administrative Science Quarterly 57*(2), 305–347.

Porter, M. E. (1985). *Competitive advantage: Creating and sustaining superior performance.* New York, London: Free Press, Collier Macmillan.

Robles-Garcia, C. (2019). Competition and incentives in mortgage markets: The role of brokers. Working Paper.

Rubinstein, A. and A. Wolinsky (1987). Middlemen. *The Quarterly Journal of Economics 102*(3), 581–593.

Siegel, P. A. and D. C. Hambrick (2005). Pay disparities within top management groups: Evidence of harmful effects on performance of high-technology firms. *Organization Science 16*(3), 259–274.

Speier, C. and V. Venkatesh (2002). The hidden minefields in the adoption of sales force automation technologies. *Journal of Marketing 66*(3), 98–111.

Stanton, C. T. and C. Thomas (2015). Landing the first job: The value of intermediaries in online hiring. *The Review of Economic Studies 83*(2), 810–854.

Yanadori, Y. and J. H. Marler (2006). Compensation strategy: Does business strategy influence compensation in high-technology firms? *Strategic Management Journal 27*(6), 559–570.

8. Appendix

8.1. Conceptual framework

Consider a setting in which two firms $F \in \{1,2\}$ sell products through an independent reseller S who employs a sales agent A. The sales agent sells the firms' products to a customer. Product prices π are identical and exogenously given. The agent chooses a sales action $a \in \{0,1,2\}$ where action $a = 0$ represents no active selling of either product, in which case a customer buys the product from firm 1 and firm 2 with the same probability $p_M < \frac{1}{2}$, respectively. When choosing $a > 0$, the agent actively sells the product of firm $F = a$, increasing the likelihood that the customer buys the respective product to $p_H > p_M$ and reducing the probability of buying the respective other product to $p_L < p_M$.[33] The agent incurs personal selling costs c_a where $c_0 = 0$ and $c_1, c_2 > 0$. Assume that $p_H + p_L > 2p_M$ such that active selling increases the total probablity of a sale.

For a product sold, each firm pays a commission $B_F > 0$ to the reseller, and the reseller can pay a bonus $b_F \geq 0$ to the sales agent.

8.1.1. Analysis

For given bonuses (b_1, b_2), the agent chooses active selling of one product $a = i$ with $i \in \{1,2\}$ rather than choosing $a = 0$ or actively selling the respective other product $a = j$ iff

$$\begin{aligned} p_H b_i + p_L b_j - c_i &\geq p_M b_i + p_M b_j \text{ and} \\ p_H b_i + p_L b_j - c_i &\geq p_H b_j + p_L b_i - c_j \end{aligned}$$

hold. Rearranging terms directly yields the following result:

Proposition 1. *The agent actively sells product $a = i$ iff*

$$b_i \geq \max\left\{\tfrac{p_M - p_L}{p_H - p_M} b_j + \tfrac{c_i}{p_H - p_M}, b_j + \tfrac{c_i - c_j}{p_H - p_L}\right\}. \tag{3}$$

From this result it is straightforward to note that the least costly way for the reseller to implement an action $a = i$ is to set the bonus of the non-favored action $b_j = 0$ and set b_i to the lowest payment that satisfies condition (3):

Corollary 1. *If the reseller wants to implement action $a = i$, he will set $b_i = \frac{c_i}{p_H - p_M}$ and $b_j = 0$.*

[33] This structure, for instance, follows from a simple model of idiosyncratic tastes: Suppose the customer has prior preferences for each of the two products (v_1, v_2), where the valuations are independently drawn from a cdf F_v. When $a = 0$, the customer will buy product 1 if and only if $v_1 \geq \pi$ and $v_1 \geq v_2$. When selling efforts increase customer value v by V, then

$$\begin{aligned} p_L &= \Pr(v_1 \geq \pi; v_1 \geq v_2 + V) \\ p_M &= \Pr(v_1 \geq \pi; v_1 \geq v_2) \\ p_H &= \Pr(v_1 + V \geq \pi; v_1 + V \geq v_2). \end{aligned}$$

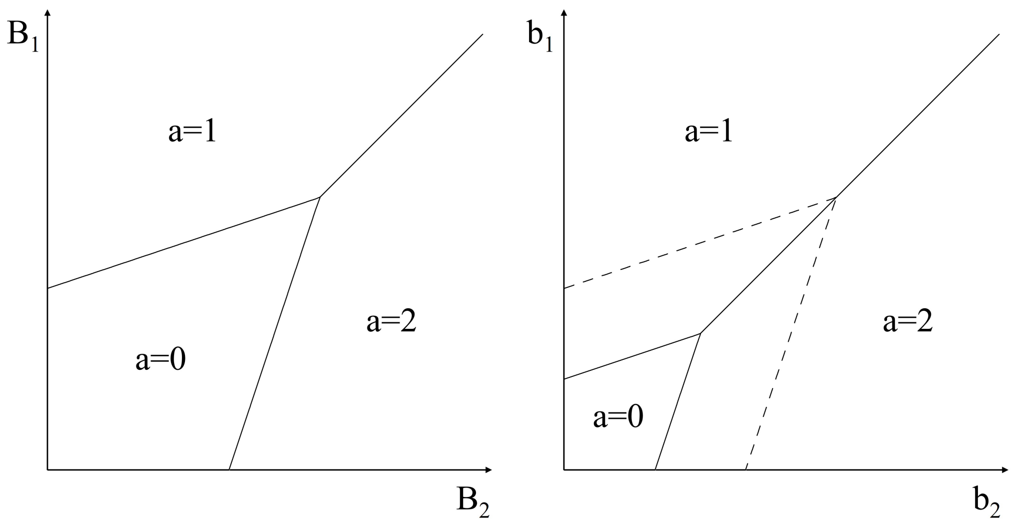


Figure A.7: Comparison of reseller and agent payment

Next, we consider the action the reseller optimally implements. When implementing $a = i$, the reseller's profits are

$$p_H \left(B_i - \frac{c_i}{p_H - p_M} \right) + p_L B_j.$$

He will implement action $a = i$ iff it is more profitable than both (i) no active selling, which will yield $p_M (B_i + B_j)$ at no costs (as no active selling does not require any bonus to the sales agent), and (ii) implementing active selling of the respective other product j, i.e.,

$$\begin{aligned} p_H \left(B_i - \frac{c_i}{p_H - p_M} \right) + p_L B_j &\geq p_M (B_i + B_j) \text{ and} \\ p_H \left(B_i - \frac{c_i}{p_H - p_M} \right) + p_L B_j &\geq p_H \left(B_j - \frac{c_j}{p_H - p_M} \right) + p_L B_i \end{aligned}$$

, which by rearranging terms yields the following result:

Proposition 2. *The reseller will implement action $a = i$ iff*

$$B_i \geq \max \left\{ \tfrac{p_M - p_L}{p_H - p_M} B_j + \tfrac{p_H}{(p_H - p_M)^2} c_i, B_j + \tfrac{p_H (c_i - c_j)}{(p_H - p_M)(p_H - p_L)} \right\}. \tag{4}$$

The result is illustrated in the left panel of Figure A.7. When both commission rates are small, the reseller implements no active selling of either product. When bonuses are large enough, the reseller will always implement active selling of one of them. When selling costs are identical (as illustrated here), the reseller will then always implement incentives for the product with the higher commission.

To illustrate the problem of 'double marginalization', it is instructive to consider the single firm case where $B_2 = 0$ such that the reseller only considers the products of firm $i = 1$. The conditions from Proposition 2 simplify to

$$B_1 \geq \frac{p_H}{(p_H - p_M)^2} c_1.$$

Now note that this smallest commission necessary to induce the reseller to implement $a = 1$ is strictly greater than the smallest direct bonus $\frac{c_1}{p_H - p_M}$ (obtained from Corollary 1) necessary to get the agent to choose $a = 1$. Hence, the firm always has to pay the reseller strictly more money than the amount necessary to incentivize the sales agent directly. This effect is similar to the double marginalization issue in vertical chains. It is due to the following: When a firm sets the commission to the lowest level necessary to incentivize the agent, then the reseller would make no profit when handing over this commission as a bonus to the sales agent. The reseller will then be better off keeping the money and achieving positive profits from the non-active sales that occur with probability p_M. A higher commission payment to the reseller is necessary to motivate him to hand over a sufficiently high bonus to the agent. In other words, providing direct incentives to the agent is always cheaper than incentivizing the reseller to incentivize the agent.

This mechanism is illustrated in the right-hand panel of Figure A.7. The solid lines show the lowest direct bonus payments (b_1, b_2) necessary to induce active sales from the agent (Proposition 1), and the dashed lines the respective commission payments that need to be paid to the reseller (Proposition 2). As the figure illustrates, it requires lower sales-agent bonus payments than reseller commissions to induce active selling of either product.

8.1.2. The interventions

We can now analyze the effects of the three interventions on the reseller's and agent's actions. For the following analyses, we assume that the costs of selling for both products are symmetric and equal to c. The three treatments correspond to the following effects in the model.

- *Reseller payment*: B_i raised by $\Delta > 0$
- *Agent voucher*: $\Delta > 0$ is directly paid to the agent
- *Agent support*: The costs c_i are lowered to $c_i - \delta$, with $0 < \delta \leq c$.

We assume that $\Delta < \frac{c}{p_H - p_M}$. This means that the voucher alone is insufficient to motivate the agent.

First, note the following:

Lemma 1. *When* $B_i \geq \max\left\{\frac{p_M - p_L}{p_H - p_M} B_j + \frac{p_H}{(p_H - p_M)^2} c, B_j\right\}$, *none of the three interventions increases sales.*

The intuition is simple: When firm i provides higher-powered incentives already at the outset and thus resellers implement active selling of i's products, neither intervention can have an additional effect. However, if this condition is not met, the treatments can affect sales behavior.

8.1.3. Reseller commissions or direct payments to the agent?

Next, we compare the effects of the *Reseller payment* and *Agent voucher* treatments for a given payment size $\Delta > 0$.

We begin by analyzing the effect of an increase of the *Reseller payment*. Similar to before, the reseller implements action $a = i$ iff it is more profitable than no active selling and active selling of the respective other product $a = j$. To determine the exact conditions, we can simply replace B_i by $B_i + \Delta$ in (4). Rearranging for Δ yields the following result:

Lemma 2. *The reseller implements action $a = i$ iff*

$$\Delta \geq \max\left\{\frac{p_M - p_L}{p_H - p_M}B_j - B_i + \frac{p_H}{(p_H - p_M)^2}c, B_j - B_i\right\}. \tag{5}$$

Similar to the result in Proposition 2, the reseller implements action $a = i$ in case the additional cash payment is large enough. How large it needs to be depends on the difference of the current reseller payments, i.e., B_i, B_j. The closer they are, the smaller is the necessary increase to induce active selling of the product of firm $F = i$.

Next, we consider the *Agent voucher* treatment, which corresponds to an increase in b_i. To determine under which conditions the increase induces the agent to sell product $a = i$ actively, we can rely on our results from Proposition 1. Replacing b_i with $b_i + \Delta$ yields the following condition. Iff

$$b_i + \Delta \geq \left\{\frac{p_M - p_L}{p_H - p_M}b_j + \frac{c}{p_H - p_M}, b_j\right\} \tag{6}$$

holds, the agent actively sells the product of firm $F = i$.

The least costly way for the reseller to implement action $a = i$ is to offer $b_j = 0$ and $b_i = \frac{c}{p_H - p_M} - \Delta$. Now, assume the reseller would like to implement action j. The least costly way to induce active selling of j is to offer $b_i = 0$ and $b_j = \frac{p_M - p_L}{p_H - p_M}\Delta + \frac{c}{p_H - p_M}$. In case the reseller wants to implement no active selling, he offers $b_i = b_j = 0$. Considering the offered contracts highlights a crucial difference between the impact of the *Reseller payment* and *Agent voucher* treatments. While the cash payment to the reseller does not affect the payments made to the agent, the payment to the agent does. In case the reseller would still like to implement action j, he needs to compensate the agent for the foregone bonus payment.

The reseller implements action $a = i$ in case profits are higher than both no active selling and implementing active selling of the respective other product of firm $F = j$. This is true iff

$$\begin{aligned}
p_H\left(B_i - \frac{c}{(p_H - p_M)} + \Delta\right) + p_L B_j \quad &\geq \quad p_H\left(B_j - \frac{c}{(p_H - p_M)} - \frac{p_M - p_L}{p_H - p_M}\Delta\right) + p_L B_i \text{ and} \\
p_H\left(B_i - \frac{c}{(p_H - p_M)} + \Delta\right) + p_L B_j \quad &\geq \quad p_M(B_i + B_j)
\end{aligned}$$

hold. Rearranging for Δ yields the following result:

Lemma 3. *In case the payment to the agent increases by $\Delta > 0$, the reseller implements action $a = i$ iff*

$$\Delta \geq \frac{p_H - p_M}{p_H} \cdot \max\left\{\frac{p_M - p_L}{p_H - p_M} B_j - B_i + \frac{p_H}{(p_H - p_M)^2} c, B_j - B_i\right\}. \tag{7}$$

Next, we want to discuss under which circumstances both treatments have an effect. As shown in Lemma 1, when action $a = i$ is already implemented at the outset, both treatments have no effect. However, in case either no active selling or selling the respective other product j is implemented at the outset, both treatments may cause a behavioral shift. In case Δ is (i) paid to the reseller and fulfills condition (5) or (ii) paid to the agent and fulfills condition (7), the payment causes a behavioral shift of the reseller to implement action $a = i$.

To understand which treatment is more likely to have an effect, we need to compare the results from Lemmas 2 and 3. Condition (7) from Lemma 3 is similar to condition (5) from Lemma 2, but contains the factor $\frac{p_H - p_M}{p_H}$ on the right-hand side of the inequality. As $p_H - p_M < p_H$, it is therefore straightforward to see that condition (7) is always easier to satisfy than (5). To put it differently, the minimum increase in payments necessary for the reseller to switch to implementing action $a = i$ is always smaller when paid directly to the agent than when paid to the reseller. The next proposition formally summarizes this result.

Proposition 3. *Assume that the reseller implements no active selling, $a = 0$, or active selling of the other product, $a = j$, at the outset. Let $\bar{\Delta}^A > 0$ be the minimum increase in b_i, and $\bar{\Delta}^R > 0$ be the minimum increase in B_i necessary such that the reseller implements action $a = i$. It holds that $\bar{\Delta}^A < \bar{\Delta}^R$.*

The result of Proposition 3 implies the following: When one compares the effect of an increase in B_i or b_i by the same value $\Delta > 0$, the increase in b_i is always more likely to cause a behavioral shift towards implementing action $a = i$ than the increase in B_i. For our experiment, this implies that we expect the *Agent voucher* treatment on average to have a stronger positive effect on sales than the *Reseller payment* treatment. This leads to Hypothesis 2 in Section 3.

8.1.4. Effect of the *Agent support* treatment

To analyze the *Agent support* treatment, we can rely on our earlier analysis. Proposition 2 shows how the decision of the reseller to implement action $a = i$ depends on c_i and c_j. To state the exact conditions under which lowering the selling costs ensures that the reseller implements action $a = i$, we can set $c_i = c - \delta$ and $c_j = c$ in (4). Rearranging for δ yields the following result:

Lemma 4. *The reseller implements $a = i$ iff*

$$\delta \geq \max\left\{\frac{((p_M - p_L)B_j - (p_H - p_M)B_i)(p_H - p_M)}{p_H} + c, \frac{(p_H - p_L)(p_H - p_M)}{p_H}(B_j - B_i)\right\}. \tag{8}$$

The reseller will always implement action $a = i$ in case the cost reduction is large enough.

There are three cases to consider. As discussed in Lemma 1, when action $a = i$ is already implemented, the treatment has no effect. When no active selling ($a = 0$) or active selling of the respective other product ($a = j$) is implemented, the treatment may cause a behavioral shift towards implementing $a = i$. However, one needs to take into account that δ cannot become arbitrarily large, as it is bounded from above by c. The question is whether there exist $\delta \in (0, c]$ such that (8) is fulfilled. The answer is provided by the following proposition.

Proposition 4. *There exist B_i, B_j, and $\delta \in (0, c]$ such that the cost reduction causes the reseller to implement action $a = i$.*

Proof. We consider two different cases with respect to the implemented action at the outset.

1) Assume that $a = j$ is implemented at the outset. This implies that (i) $B_j - B_i \geq 0$ and (ii) $B_j \geq \frac{p_M - p_L}{p_H - p_M} B_i + \frac{p_H}{(p_H - p_M)^2} c$. If δ is large enough, as indicated in (8), the cost reduction leads to implementation of $a = i$. However, δ is bounded from above by c, thus we need to show that the set of δ fulfilling $\delta \leq c$, (8), (i), and (ii) is non-empty. For the first inequality in (8) to hold for some $\delta \leq c$, we require $B_j \leq \frac{p_H - p_M}{p_M - p_L} B_i$ (where we note that $\frac{p_H - p_M}{p_M - p_L} > 1$ so that the inequality can be fulfilled for $B_j \geq B_i$). This inequality and condition (ii) can be jointly fulfilled iff $\frac{p_H - p_M}{p_M - p_L} B_i \geq \frac{p_M - p_L}{p_H - p_M} B_i + \frac{p_H}{(p_H - p_M)^2} c$, which is equivalent to $B_i \geq \frac{p_H (p_M - p_L)}{(p_H - p_M)(p_H - p_L)(p_H + p_L - 2p_M)} c$. For the second inequality in (8) to hold for some $\delta \leq c$, we require $\frac{(p_H - p_L)(p_H - p_M)}{p_H} (B_j - B_i) \leq c$, which is equivalent to $B_j \leq B_i + \frac{p_H}{(p_H - p_L)(p_H - p_M)} c$ (which can again be fulfilled for $B_j \geq B_i$). This inequality and condition (ii) can be jointly fulfilled iff $B_i + \frac{p_H}{(p_H - p_L)(p_H - p_M)} c \geq \frac{p_M - p_L}{p_H - p_M} B_i + \frac{p_H}{(p_H - p_M)^2} c \Leftrightarrow B_i \geq \frac{p_H (p_M - p_L)}{(p_H - p_M)(p_H - p_L)(p_H + p_L - 2p_M)} c$, which is the same condition that we have derived before. We thus observe that there exist B_i, B_j, and δ such that all of the preceding conditions are fulfilled. Therefore, the set of parameter values for which a decrease in c_i leads to a switch from $a = j$ to $a = i$ is non-empty.

2) Suppose that $a = 0$ is implemented at the outset. This implies that (iii) $B_i < \frac{p_M - p_L}{p_H - p_M} B_j + \frac{p_H}{(p_H - p_M)^2} c$ and (iv) $B_j < \frac{p_M - p_L}{p_H - p_M} B_i + \frac{p_H}{(p_H - p_M)^2} c$. We need to show that the set of δ fulfilling $\delta \leq c$, (8), (iii), and (iv) is non-empty. For simplicity, assume that $B_i = B_j = B$. First, note that (iii) and (iv) are then identical and can be written as $B < \frac{p_H}{(p_H - p_M)(p_H + p_L - 2p_M)} c$. We start with the first inequality in (8), which can be rewritten as $\delta \geq c - \frac{(p_H + p_L - 2p_M)(p_H - p_M)}{p_H} B$. As $c - \frac{(p_H + p_L - 2p_M)(p_H - p_M)}{p_H} B < c$, it is clear that there exists $\delta \in (0, c]$ such that the condition holds. The second inequality in (8) always holds for $B_j = B_i$. Thus, we can conclude that there exist B_i, B_j, and δ such that all of the preceding conditions are fulfilled. Therefore, the set of parameter values for which a decrease in c_i leads to a switch from $a = 0$ to $a = i$ is non-empty. □

The proposition states that there exist a δ, which is large enough to cause the reseller to switch to implementing action $a = i$, but is also lower than c. The existence of such a δ requires that $B_j - B_i$ is not too large. Intuitively, this ensures that action $a = j$ is not too profitable relatively to action $a = i$, such that even large cost reductions cannot compensate for the foregone profits.

For our experiment, Proposition 4 implies that we expect the *Agent support* treatment on average to have a positive effect on sales and leads to Hypothesis 1b in Section 3.

8.1.5. Discussion of effect heterogeneity

As stated in Lemma 1, all treatments only have an effect in case the desired action is not already implemented at the outset. In the context of our experiment, our sample differs with regard to stores with a large and a small base commission. The base commission is determined by previous sales volume. This means that stores with a high base commission are already at the outset more likely to sell products offered by our study firm. Therefore, we expect that all treatments are more likely to boost sales in stores with a small base commission. This discussion leads to Hypothesis 3 in Section 3.

Similarly, our incentivized products in the experiment differ with regard to the market position of our study firm. While our study firm possesses a competitive advantage for products with the destinations 3 and 4, this advantage does not exist for products with the destinations 1 and 2. Due to the perceived quality difference indicated by the agencies, we expect that products for which our study firm has a strong market position are more likely to be sold at the outset. Therefore, we expect all treatments to increase sales stronger for products for which our study firm has no competitive advantage, i.e., Destination 1 and Destination 2. This discussion leads to Hypothesis 4 in Section 3.

8.2. Randomization

To check if our random assignment to the treatments worked out succesfully, we rely on multinomial logistic regressions. To be more precise, we investigate whether our primary outcome variables in terms of bookings and revenue have any potential to predict the assignment to the treatments. For bookings as well as revenue, we consider five regressions each. The first focuses on total volumes, the second on volumes from incentivized destinations, the third on volumes from non-incentivized destinations (‘Other’), the fourth on volumes from incentivized destinations with a stronger market position, and the fifth on volumes from incentivized destinations with a weaker market position.

The results are displayed in Table A.8. As none of the coefficients are significantly different from zero, we can conclude that none of our primary outcome variables has predictive power for the assignment to the treatments. In other words, the treatment groups are balanced with regard to our primary outcome variables.

Table A.8: Balance check - Multinomial logistic regressions

	Total (1)	Incentivized (2)	Other (3)	Strong (4)	Weak (5)
			Bookings		
Agent support	-0.012	-0.008	-0.022	-0.005	-0.016
	(0.010)	(0.024)	(0.015)	(0.042)	(0.038)
Agent voucher	-0.005	-0.009	-0.007	0.026	-0.048
	(0.010)	(0.024)	(0.014)	(0.040)	(0.039)
Reseller payment	0.006	0.015	0.007	0.055	-0.010
	(0.009)	(0.023)	(0.013)	(0.038)	(0.038)
			Revenue		
Agent support	-0.002	-0.002	-0.003	-0.002	-0.004
	(0.004)	(0.009)	(0.007)	(0.015)	(0.014)
Agent voucher	-0.002	0.001	-0.005	0.006	-0.003
	(0.004)	(0.009)	(0.007)	(0.015)	(0.014)
Reseller payment	0.002	0.007	0.002	0.015	0.004
	(0.004)	(0.009)	(0.007)	(0.015)	(0.014)
Observations	1257	1257	1257	1257	1257

Notes: The table shows the results of multinomial logistic regressions, where each Column defines one regression. The predictor variable is listed in the top row and defined as the agencies' respective number of bookings (revenue, in thousands of euros) in the pre-experimental period, i.e., the sum of bookings (revenue) in December 2022 and January 2023. The dependent variable is the agencies' assignment and listed in the first Column. The control group serves as the baseline outcome and is therefore omitted. Since the parameter estimates are relative to the baseline outcome, the multinomal logit can be interpreted as follows: For a unit change in the predictor variable, the logit of the respective outcome relative to the baseline outcome is expected to change by its respective parameter estimate (which is in log-odds units). The constants, all statistically significant at the 1% level, are not reported. Standard errors are reported in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

8.3. Robustness of main results

8.3.1. Estimation procedure

Table A.9: Effect on incentivized bookings - ANCOVA

	Incentivized bookings		
Agencies	All	Tier 2	Tier 1
	(1)	(2)	(3)
Agent support	0.476*	0.518*	0.137
	(0.261)	(0.272)	(0.690)
Agent voucher	0.092	0.323	-0.936
	(0.227)	(0.224)	(0.677)
Reseller payment	-0.026	-0.132	-0.050
	(0.224)	(0.203)	(0.642)
p value $\beta_{AV} = \beta_{RP}$	0.66	0.07	0.25
Observations	1257	993	264

Notes: The table shows the impact of the treatments on the number of bookings to the incentivized destinations using an ANCOVA approach. The estimates in Columns 1 to 3 are obtained using a standard OLS estimator. Column 2 only includes tier-2 agencies. Column 3 only includes tier-1 agencies. Robust standard errors are reported in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

Table A.10: Effect on incentivized bookings - Monthly aggregation (Poisson)

	Incentivized bookings		
Agencies	All	Tier 2	Tier 1
	(1)	(2)	(3)
Agent support	0.146*	0.220**	0.036
	(0.077)	(0.107)	(0.106)
Agent voucher	0.039	0.185**	-0.163
	(0.074)	(0.089)	(0.119)
Reseller payment	-0.027	-0.061	-0.000
	(0.073)	(0.099)	(0.107)
p value $\beta_{AV} = \beta_{RP}$	0.44	0.02	0.22
IR Agent support	1.16	1.25	1.04
IR Agent voucher	1.04	1.20	0.85
IR Reseller payment	0.97	0.94	1.00
Observations	5040	3770	1270
No. of Clusters	1008	754	254

Notes: The table shows the impact of the treatments on the number of bookings to the incentivized destinations using a difference-in-differences approach. The dependent variable is the monthly total number of bookings to the four incentivized destinations. The estimates in Columns 1 to 3 are obtained using a Poisson Pseudo Maximum Likelihood estimator. Column 2 only includes tier-2 agencies. Column 3 only includes tier-1 agencies. All specifications include time and store fixed-effects. Standard errors are clustered on store level in parentheses. The incidence ratios of the estimators are presented as additional statistics in the regression table. The incidence ratio is the exponential of the coefficient and is interpreted as the factor by which the average of the dependent variable approximately changes upon belonging to a specific treatment group.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

Table A.11: Effect on incentivized bookings - Monthly aggregation (OLS)

	Incentivized bookings		
Agencies	All (1)	Tier 2 (2)	Tier 1 (3)
Agent support	0.178*	0.202**	0.097
	(0.098)	(0.103)	(0.267)
Agent voucher	0.052	0.173**	-0.398
	(0.093)	(0.080)	(0.317)
Reseller payment	-0.047	-0.054	0.005
	(0.099)	(0.098)	(0.278)
p value $\beta_{AV} = \beta_{RP}$	0.38	0.03	0.25
Observations	6285	4965	1320
No. of Clusters	1257	993	264

Notes: The table shows the impact of the treatments on the number of bookings to the incentivized destinations using a difference-in-differences approach. The dependent variable is the monthly total number of bookings to the four incentivized destinations. The estimates in Columns 1 to 3 are obtained using a standard OLS fixed-effects estimator. Column 2 only includes tier-2 agencies. Column 3 only includes tier-1 agencies. All specifications include time and store fixed-effects. Standard errors are clustered on store level in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

8.3.2. Outcome variable

Table A.12: Effect on incentivized bookings - Intersection (Poisson)

	Incentivized bookings		
Agencies	All	Tier 2	Tier 1
	(1)	(2)	(3)
Agent support	0.199**	0.363***	-0.039
	(0.088)	(0.118)	(0.129)
Agent voucher	0.053	0.165	-0.108
	(0.083)	(0.105)	(0.133)
Reseller payment	-0.008	0.017	-0.071
	(0.085)	(0.113)	(0.127)
IR Agent support	1.22	1.44	0.96
IR Agent voucher	1.05	1.18	0.90
IR Reseller payment	0.99	1.02	0.93
Observations	1792	1306	486
No. of Clusters	896	653	243

Notes: The table shows the impact of the treatments on the total number of bookings in the intersection of all sets of incentivized bookings using a difference-in-differences approach. The estimates in Columns 1 to 3 are obtained using a Poisson Pseudo Maximum Likelihood estimator. Column 2 only includes tier-2 agencies. Column 3 only includes tier-1 agencies. All specifications include time and store fixed-effects. Standard errors are clustered on store level in parentheses. The incidence ratios of the estimators are presented as additional statistics in the regression table. The incidence ratio is the exponential of the coefficient and is interpreted as the factor by which the average of the dependent variable approximately changes upon belonging to a specific treatment group. All specifications include time and store fixed-effects.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

Table A.13: Effect on incentivized bookings - Intersection (OLS)

	Incentivized bookings		
Agencies	All	Tier 2	Tier 1
	(1)	(2)	(3)
Agent support	0.41**	0.55***	-0.18
	(0.18)	(0.18)	(0.53)
Agent voucher	0.12	0.25	-0.42
	(0.17)	(0.16)	(0.57)
Reseller payment	-0.01	0.02	-0.32
	(0.17)	(0.16)	(0.52)
Observations	2514	1986	528
No. of Clusters	1257	993	264

Notes: The table shows the impact of the treatments on the total number of bookings in the intersection of all sets of incentivized bookings using a difference-in-differences approach. The estimates in Columns 1 to 3 are obtained using a standard OLS fixed-effects estimator. Column 2 only includes tier-2 agencies. Column 3 only includes tier-1 agencies. All specifications include time and store fixed-effects. Standard errors are clustered on store level in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

8.3.3. Revenues

Table A.14: Effect on incentivized revenue

	Incentivized revenue		
Agencies	All (1)	Tier 2 (2)	Tier 1 (3)
Agent support	2.66	1.74**	5.88
	(1.62)	(0.73)	(7.20)
Agent voucher	-0.29	0.12	-2.09
	(0.65)	(0.59)	(2.19)
Reseller payment	-0.10	-0.18	-0.58
	(0.64)	(0.60)	(1.89)
Observations	2514	1986	528
No. of Clusters	1257	993	264

Notes: The table shows the impact of the treatments on the revenue (in thousands of euros) stemming from the bookings to the incentivized destinations using a difference-in-differences approach. The estimates in Columns 1 to 3 are obtained using a standard OLS fixed-effects estimator. Column 2 only includes tier-2 agencies. Column 3 only includes tier-1 agencies. All specifications include time and store fixed-effects. Standard errors are clustered on store level in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

Table A.15: Effect on other revenue

	Other revenue		
Agencies	All (1)	Tier 2 (2)	Tier 1 (3)
Agent support	0.212	0.551	-1.274
	(0.924)	(0.673)	(3.659)
Agent voucher	-0.233	0.097	-1.678
	(0.794)	(0.687)	(2.836)
Reseller payment	-0.193	-0.624	0.554
	(0.778)	(0.677)	(2.548)
Observations	2514	1986	528
No. of Clusters	1257	993	264

Notes: The table shows the impact of the treatments on the revenue (in thousands of euros) stemming from the bookings to the non-incentivized destinations using a difference-in-differences approach. The estimates in Columns 1 to 3 are obtained using a standard OLS fixed-effects estimator. Column 2 only includes tier-2 agencies. Column 3 only includes tier-1 agencies. All specifications include time and store fixed-effects. Standard errors are clustered on store level in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

8.4. Long-term analysis - Agent support

Table A.16: Effect on incentivized bookings - Long term (Poisson)

	Incentivized bookings		
Agencies	All (1)	Tier 2 (2)	Tier 1 (3)
Agent support	0.16^{**}	0.16^{*}	0.15
	(0.07)	(0.09)	(0.10)
IR Agent support	1.17	1.17	1.16
Observations	1322	1030	292
No. of Clusters	661	515	146

Notes: The table shows the impact of the treatments on the number of bookings to the incentivized destinations using a difference-in-differences approach. The estimates in Columns 1 to 3 are obtained using a Poisson Pseudo Maximum Likelihood estimator. Column 2 only includes tier-2 agencies. Column 3 only includes tier-1 agencies. All specifications include time and store fixed-effects. Standard errors are clustered on store level in parentheses. The incidence ratio of the estimator is presented as an additional statistic in the regression table. The incidence ratio is the exponential of the coefficient and is interpreted as the factor by which the average of the dependent variable approximately changes upon belonging to a specific treatment group.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

Table A.17: Effect on incentivized bookings - Long term (OLS)

	Incentivized bookings		
Agencies	All (1)	Tier 2 (2)	Tier 1 (3)
Agent support	1.221^{*}	0.784	2.312
	(0.670)	(0.570)	(1.999)
Observations	1514	1212	302
No. of Clusters	757	606	151

Notes: The table shows the impact of the treatments on the number of bookings to the incentivized destinations using a difference-in-differences approach. The estimates in Columns 1 to 3 are obtained using a standard OLS fixed-effects estimator. Column 2 only includes tier-2 agencies. Column 3 only includes tier-1 agencies. All specifications include time and store fixed-effects. Standard errors are clustered on store level in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

Table A.18: Effect on profits - Long term

Agencies	*Profit contribution* All (1)	Tier 2 (2)	Tier 1 (3)
Agent support	151.463*	164.575*	48.044
	(90.852)	(97.826)	(208.141)
Observations	1514	1212	302
No. of Clusters	757	606	151

Notes: The table shows the impact of the treatments on the net profit contribution using a difference-in-differences approach. The estimates in Columns 1 to 3 are obtained using a standard OLS fixed-effects estimator. Column 2 only includes tier-2 agencies. Column 3 only includes tier-1 agencies. All specifications include time and store fixed-effects. Standard errors are clustered on store level in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

8.5. Survey among travel agencies

To identify mechanisms better and to be able to study further heterogeneities, we ran a survey with the participating agencies.

The survey consists of five blocks. Block 1 is a general introduction explaining the reasoning and purpose behind the survey. It also mentions the involved parties, explains details about data protection, and informs about the compensation payments.

In Block 2, we aim to identify the travel agencies' perceptions about the study firm relative to the most important competitors. More precisely, we want to gather information on how the agencies rate aspects that are crucial when deciding on which tour operator's product to showcase in the sales talk. Such crucial aspects are the quality of products, the commission system and the service quality. This block is identical for the treatment groups, as well as for the control group.

Block 3 asks questions about the working routines within the travel agencies. After evaluating the crucial aspects when it comes to selling in Block 2, we now want to identify the relative importance of those aspects within the decision which tour operator's product to showcase. Furthermore, we want to analyze if the relative importance of those aspects differs between executives and sales agents. This block is again identical for all groups.

Block 4 is different for each of the three treatment groups and the control group. Block 4A (*Reseller payment*), 4B (*Agent voucher*) and 4C (*Agent support*) were asked to the three treatment groups. They contain questions aimed at measuring the knowledge among the survey participants as well as sales agents about the treatments, which behavioral changes occurred upon introducing the treatment, as well as some hypothetical choice questions aimed at measuring the attractiveness of the treatment. The control group was only asked hypothetical choice questions aimed at identifying the relative attractiveness between additional monetary top-up payments and access to a service hotline. The questions should help to quantify the agencies' willingness to pay for better service quality.

Block 5 is the final block of the survey and identical for the treatment groups and the control group. It elicits reciprocity, asks for open feedback to our study firm and for the payment details for the compensation payment.

The detailed questionnaire containing all questions asked in the course of the survey is available from the authors upon request, whereas the most important summary statistics are presented in Tables A.19 and A.20.

Table A.19: Summary statistics from survey with participating agencies (1)

Question	N	Mean	SD	Min	Max
		Block 2			
Product quality overall	204	1.75	1.94	-4	5
Product quality - Destination 1	204	1.60	1.92	-4	5
Product quality - Destination 2	204	1.60	1.96	-4	5
Product quality - Destination 3	204	2.47	1.78	-3	5
Product quality - Destination 4	204	2.64	1.90	-5	5
Commission model	202	-0.85	2.89	-5	5
Service quality overall	202	-0.17	2.51	-5	5
Service quality - Destination 1	51	0.49	2.11	-3	5
Service quality - Destination 2	49	-0.31	2.23	-5	4
Service quality - Destination 3	103	0.48	2.08	-5	5
Service quality - Destination 4	37	0.81	2.36	-4	5
		Block 3			
Number of employees (FTE)	175	2.09	1.30	0	11
Knowledge commission	175	8.40	2.19	1	10
Service very time-consuming	175	7.96	2.33	1	10
Relevance service quality	175	8.35	2.11	1	10
Relevance commission	175	8.22	2.14	1	10
Knowledge commission employees	162	6.88	2.79	1	10
Service very time-consuming for employees	162	8.12	2.21	1	10
Relevance service quality for employees	162	8.27	2.13	1	10
Relevance commission for employees	162	7.42	2.48	1	10
Employees steering towards incentives	162	7.94	2.30	1	10
		Block 4C			
Hotline led to better service/product quality	22	4.91	2.91	1	10
Hotline helped to win additional customers	23	3.96	2.69	1	10
		Block 5			
Reciprocity	174	8.99	1.67	2	10

Notes: The table displays the summary statistics for all questions of survey with numeric response options. With the exception of “Number of employees (FTE)”, answers could be given either on an 11-point Likert scale ranging from -5 to +5 or a simple 1-to-10 scale. The statistics include all recorded answers.

Table A.20: Summary statistics from survey with participating agencies (2)

Question	N	Shares "Yes!"
	Block 3	
Internal incentive scheme	174	0.10
	Block 4A	
Received information	36	0.75
Employees received information	26	0.92
Changed personal sales behavior	27	0.07
Changed instructions for employees	26	0.08
Incentives advantageous	27	0.41
Incentives advantageous for employees	26	0.12
Hotline instead of top-up payment (6€)	27	0.22
	Block 4B	
Received information	39	0.97
Employees received information	33	0.79
Changed personal sales behavior	38	0.18
Changed instructions for employees	33	0.09
Incentives advantageous	38	0.45
Incentives advantageous for employees	33	0.39
Vouchers forwarded	33	0.61
Vouchers fully forwarded	20	0.80
Hotline instead of voucher	38	0.58
Top-up payment (6€) instead of voucher (6€)	38	0.79
	Block 4C	
Received information	26	0.92
Employees received information	23	0.91
Changed personal sales behavior	24	0.13
Changed instructions for employees	23	0.04
Top-up payment (9€) instead of hotline	24	0.58
Top-up payment (6€) instead of hotline	14	0.79
Top-up payment (3€) instead of hotline	11	0.55
	Block 4D	
Top-up payment (9€) instead of hotline	73	0.55
Top-up payment (15€) instead of hotline	33	0.27
Top-up payment (21€) instead of hotline	24	0.21
Top-up payment (27€) instead of hotline	19	0.32

Notes: The table displays the summary statistics for all questions of survey with non-numeric response options. The statistics include all recorded answers.

8.6. Call center

8.6.1. Survey among call-center agents: Structure and summary statistics

To gain a better understanding of the mechanisms behind the treatment effects for the *Agent support* treatment, we conduct a survey with the call-center agents operating the newly established service hotline. It shall be noted that the hotline is operated by two different call centers. The first call center manages inquiries concerning three of the four incentivized destinations, and the second call center manages the respective inquiries of the other incentivized destination.

The survey consists of three blocks. The first block gives an introduction to the background of the survey and provides information about the compensation payment. Furthermore, participants are asked to state which destinations they were primarily occupied with. In the second block, we ask for each of our four incentivized destinations what the most common concerns for this destination are. If the most common concerns are rather homogeneous across destinations, we can dismiss the possibility that the hotline is only valuable for certain inquiries. Survey participants are only asked about destinations they chose in the first block. Furthermore, we ask about the participants' beliefs as to how often the customer is still in the agency while the sales agent calls. In doing this, we wish to obtain an idea if the sales agents actively use the hotline as a signal of good service and competence towards the customer. Lastly, participants shall state which other destinations are similar to the one asked about and estimate how successful their help was for the agencies. The latter aims at investigating if the utility of the service hotline for the agencies differs across destinations. Block 3 is the final block of the survey, just asks for the compensation details, and provides contact information of the researchers in case there are any questions.

The detailed questionnaire for the survey that we ran among the call-center agents is available from the authors upon request. Table A.21 provides a summary of the most important information gathered.

Table A.21: Survey among call-center agents - Main results

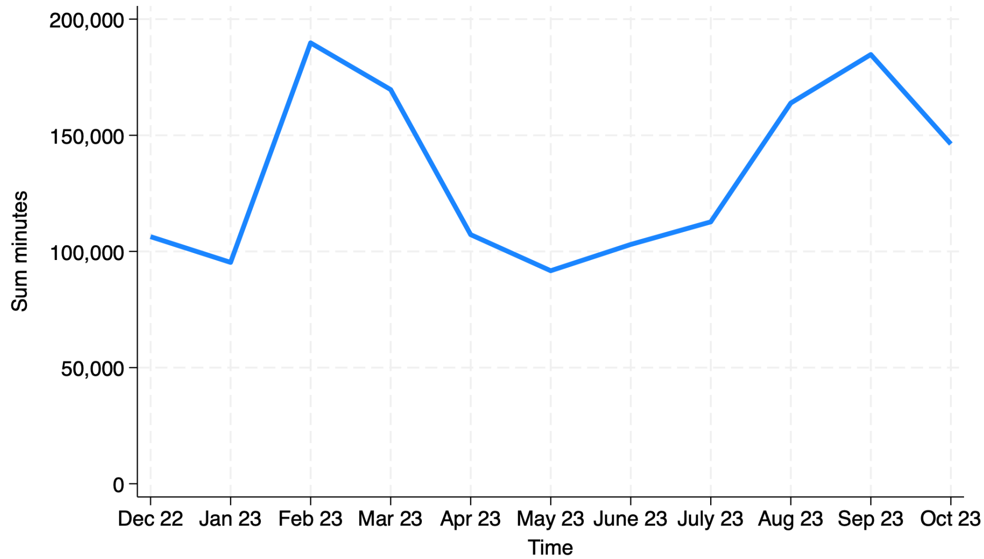
Destination 1	
No call-center agents	15
Most frequent inquiries	Questions regarding hotels and rooms, Booking changes, Private transfer
Similar target destinations	Other destinations, Destination 2
Successful consultations	Mean: 75%, Range: 40-98%
Destination 2	
No call-center agents	16
Most frequent inquiries	Questions regarding hotels and rooms, Flight-related issues, Private transfer
Similar target destinations	Other destinations, Destination 1
Successful consultations	Mean: 74%, Range: 20-98%
Destination 3	
No call-center agents	18
Most frequent inquiries	Questions related to river cruises, Sightseeing packages, Booking changes
Similar target destinations	Other destinations, Destination 2, Destination 1
Successful consultations	Mean: 83%, Range: 40-100%
Destination 4	
No call-center agents	11
Most frequent inquiries	Questions regarding hotels and rooms, Booking changes, Flight-related issues
Similar target destinations	Other destinations
Successful consultations	Mean: 91%, Range: 68-100%

Notes: The table summarizes the most important information gathered from the survey with the call-center agents. In total, 34 of 37 responsible call-center agents participated in our survey, yielding a response rate of 92%.

8.6.2. Call-center usage

Figure A.8 illustrates the total minutes of inbound calls over time, with peaks in February, March, and from September onwards, aligning with high-booking seasons. This pattern supports our assertion that sales agents primarily use the call center for booking-related inquiries. Note that this concerns the usage of the call center over all agencies (also those not participating in the A/B test and without access to the premium hotline). It serves merely as a representative statistic to illustrate the timing of usage.

Figure A.8: Distribution of inbound call volume over time



Notes: This graph shows the total inbound call volume of the call center coming from all agencies over time in minutes.