Shaping interfirm relationships in intermediary markets: Evidence from a field experiment*

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Abstract

Prior work highlights the value of relation-specific assets and knowledge-sharing routines in interfirm relationships, but little is known about how short-term interventions can build these resources. We propose that temporary transactional benefits encourage engagement, leading to accumulated firm-specific knowledge and relational assets. In a field experiment with a travel company that distributes products via intermediaries, 253 of 757 independent agencies were randomly granted access to a service hotline, lowering transaction costs for frontline agents and facilitating knowledge transfer about the firm's products and processes. Sales increase in response to the intervention, in particular among agencies with weaker prior ties, showing such initiatives help cultivate new relationships. The treatment effects persist beyond the period of the intervention and extend to non-targeted products, indicating durable relational resources.

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INTRODUCTION

In their seminal article, Dyer and Singh (1998) argue that a firm's resources extend beyond its boundaries, with competitive advantages embedded in interfirm relationships. A substantial body of literature has since elaborated on this *relational view* and examined its specific implications (e.g., Dyer et al., 2018; Kale et al., 2002; Lavie, 2007; Lavie et al., 2012; Mesquita et al., 2008; Zollo et al., 2002). However, comparatively less research has focused on the micro-level dynamics, exploring whether and how relational resources such as relation-specific assets and interfirm knowledge-sharing routines can be actively shaped through strategic interventions. This paper aims to address that gap by showing that short-term transactional interventions can effectively shape such relational resources.

This question is particularly important when firms use intermediaries (e.g., brokers, retailers) to sell their products to end customers. In many industries – such as financial services, insurance, real estate, travel, and consumer goods – firms indeed often rely heavily on intermediaries to distribute their products. Donna et al. (2022) estimate that intermediary markets account for more than one third of the US GDP. While using intermediaries allows upstream firms to expand market coverage (Hagiu and Wright, 2015; Rubinstein and Wolinsky, 1987) with minimal capital investment and greater flexibility in responding to demand volatility (Conti et al., 2019; Lassar and Kerr, 1996), it also presents specific challenges. Given that intermediaries operate beyond a firm's boundaries, firms must actively manage relational resources to maintain a competitive edge. First, because intermediaries typically offer products from multiple competing firms, upstream firms must develop relation-specific assets (such as firm-specific product knowledge and knowledge-sharing routines) to ensure preferential promotion of their own products. Second, existing ties between intermediaries and competing firms may constrain new sales opportunities, necessitating strategic interventions to reshape relational dynamics. Third, relationship-specific knowledge often resides with sales agents employed by intermediaries who operate outside the direct control of upstream firms. These factors underscore the importance of actively shaping interfirm relationships and knowledge-sharing routines to mitigate the risks associated with intermediary-based distribution while strengthening the firm's competitive advantage.

To investigate this idea, we theorize that interventions providing short-term transactional benefits may serve as deliberate triggers for the development of relation-specific assets. By temporarily reducing transaction costs, such interventions can increase the interfirm engagement. If this engagement enables firm-specific knowledge accumulation by means of knowledge transfer and experiential learning, it generates idiosyncratic relational resources. To illustrate this, our theoretical framework combines insights from theories of the relational view, transaction cost economics, and organizational learning to explain how targeted transactional benefits can initiate such trajectories. To test the developed hypotheses empirically, we conduct a large-scale field experiment in collaboration with a travel company. We demonstrate that an intervention which facilitates knowledge transmission to intermediaries' sales agents leads to a substantial increase in sales of the upstream firm's products. Importantly, the positive outcomes are not confined to the scope of the intervention, but spill over beyond the intervention period and to non-targeted products. This highlights that the intervention catalyzed deeper interfirm engagement and knowledge accumulation, thereby contributing to the formation of relation-specific assets that continue to deliver value beyond the immediate intervention.

Upstream firms relying on intermediaries to distribute their products face a value-capture challenge (Bennett, 2013; Brandenburger and Stuart, 1996, 2007; Gans and Ryall, 2017; Obloj and Zemsky, 2015) when these intermediaries sell also competing products. This requires strategic management of relational resources. A key relational asset is the sales agents' familiarity with a firm's products, which enhances efficiency in the direct relationship and increases switching costs when considering marketing competitors' products. Agents who regularly sell a firm's offerings become more adept at promoting them, reinforcing long-term engagement. Convex commission schemes frequently used by the upstream firm to compensate resellers (Jansen et al., 2024; Pierce et al., 2025) further entrench this dynamic by disproportionately rewarding intermediaries based on past sales.[1] These incentives further foster lock-in effects, as intermediaries with strong historical sales of a firm's products receive increasingly favorable contract terms, reducing their likelihood of reallocating sales to competitors. This interplay of relational resources driven by product familiarity and financial incentives underscores the need for strategic interventions to shape and sustain such relational resources within intermediary-based distribution networks.

Our large-scale field experiment is run in collaboration with one of Europe's largest travel companies, whose revenue (like that of its major competitors) primarily stems from selling package bookings to popular travel destinations. To reach end customers, the firm relies on legally and organizationally independent travel agencies, more than 750 of which were part of our study. Our intervention grants randomly selected travel agencies priority access to a newly established service hotline, providing direct booking support from the study firm for selected travel destinations. The intervention serves two key purposes: (i) reducing sales agents' workload when selling the firm's strategically important products and (ii) fostering knowledge-sharing to build firm-specific human capital among these agents. We assess the effectiveness of this intervention by comparing the performance of treated agencies with a control group where business operations continued as usual.

We document three primary findings. First, the intervention is highly effective in increasing sales of the study firm's products during its implementation, leading to a significant rise in both the total number of bookings by treated travel agencies to the targeted destinations and the resulting revenue. Second, we find strong evidence supporting the view that the intervention also generates relational resources, as there are positive spillover effects beyond the targeted products. These effects manifest in two ways: (i) a significant increase in bookings for destinations not included in the intervention, and (ii) a sustained impact beyond the experimental period. Although access to the hotline ended after nine months, bookings

[1] As it is common that marginal commission rates increase with (past) sales, intermediaries have a stronger incentive to sell more of the products of those upstream firms whose products they have mostly sold in the past.

remained significantly higher for travel agencies in the treatment group compared to those in the control group in the post-treatment phase.

Our experimental setup also allows us to examine how the strength of prior ties between intermediaries and the upstream firm influences the effectiveness of the intervention. In our theoretical framework, we hypothesize that additional sales are harder to achieve for agencies with already strong pre-existing ties to the firm. For these agencies, the firm likely benefits already at the outset from lock-in effects driven by relational assets such as product familiarity and stronger monetary incentives due to convex commission schemes. In other words, if an agency predominantly recommends the study firm's products to customers at the outset, the potential for further sales growth through intervention is naturally more limited. Conversely, agencies with weaker prior ties present greater opportunities to shift sales behavior. When product and process-specific knowledge is fostered through intervention, these agencies' sales agents may become more inclined to promote the firm's offerings, creating future lock-in effects. To test this, we leverage the study firm's categorization of travel agencies based on past sales volumes, which pays higher commissions to firms with higher past sales. Our findings show that the effect of the treatment is in fact mainly driven by agencies with lower prior sales volumes, highlighting the fact that short-term knowledge-sharing initiatives can be especially powerful in cultivating new relational assets where ties are underdeveloped.

Our results contribute to the literature on the relational view of competitive advantage by showing that short-term transactional benefits can serve as triggers for the development of relation-specific assets (e.g., Dyer and Singh, 1998; Dyer et al., 2018; Williamson, 1985). Dyer and Singh (1998, p. 661), for instance, argue that competitive advantages often stem from resources beyond firm boundaries, particularly from *"idiosyncratic interfirm linkages that may be a source of relational rents[..]"*. Our study supports this view and shows that those interlinkages can be actively fostered through short-term interventions, yielding spillover effects on non-targeted products and sustained higher sales beyond the intervention period. The treatment particularly allows intermediaries with weaker prior ties to gain experience with our study firm, thus highlighting the importance of interfirm knowledge-sharing (Asanuma, 1989; Dyer and Nobeoka, 2000; Dyer and Hatch, 2006) to accumulate specialized information, know-how, and leading to improved communication.

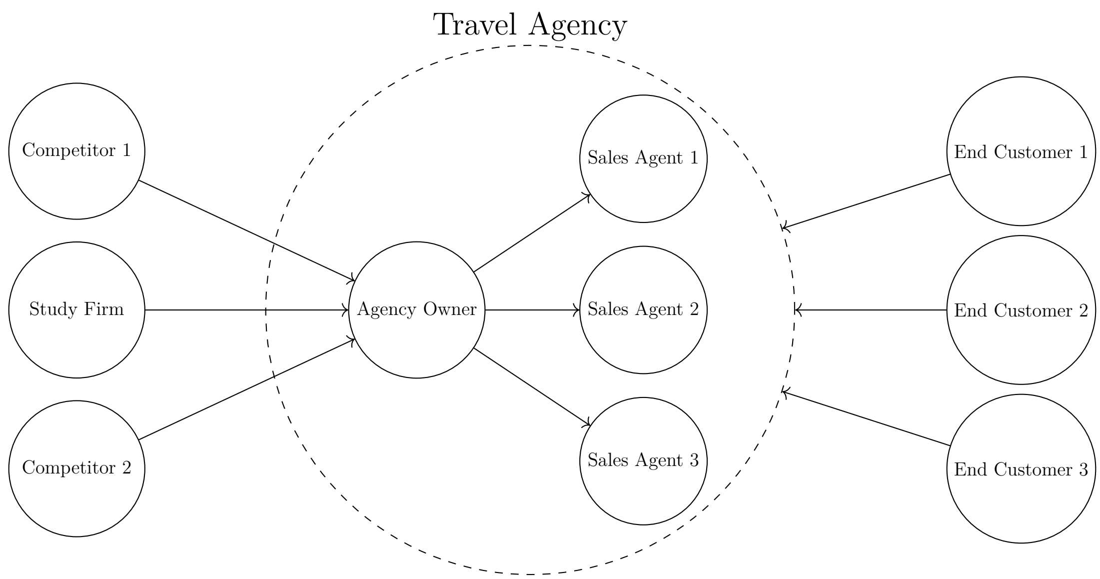
Our study also adds to the discussion on resource allocation and strategy (Coen and Maritan, 2011; Klingebiel and Rammer, 2014; Maritan and Lee, 2017; Noda and Bower, 1996). The results underscore the importance of strategically channeling resources within vertical relationships toward areas that allow firms to establish new connections, rather than distributing them broadly without accounting for existing ties. The effects on bookings and revenue observed in the treatment group were mainly driven by agencies with weaker prior relationships, while agencies with stronger ties exhibited no significant impact.

Moreover, we contribute to the literature analyzing the challenges faced by upstream firms when designing incentives in intermediary markets (e.g., Biglaiser et al., 2020; Honda et al., 2024; Inderst and Ottaviani, 2009; Jansen et al., 2024; Lafontaine and Slade, 2007; Pierce, 2012; Pierce et al., 2025). While monetary incentives have played a dominant role in previous work, we show that a non-monetary strategy fostering knowledge-sharing can be more effective than an increase in commission rates. More generally, our paper relates to the literature on managing contractors. There are a few recent studies focusing on gig workers and investigating how these can be tied more closely to the firm (e.g., Burbano, 2016; Teodorovicz et al., 2024). Our study is related, in that tools are considered that aim to tie intermediaries more closely to our study firm.

FIELD SETTING

Our study firm is one of Europe's leading travel companies/tour operators. At the time of the intervention, the company employed around $11,000$ people. The firm offers a wide range of travel products to customers (e.g., flights, hotels, individualized tours). The main product of the firm is so-called "package bookings", i.e., bookings that bundle different travel components such as flights, accommodation, etc. While the study firm offers tours all over the world, the Mediterranean countries and the Middle East are the most popular destinations. A key distribution channel is through stationary travel agencies (agencies), which are independently owned and offer products of many competing tour operators to the end customers. Figure 1 illustrates the distribution structure.

FIGURE 1 Distribution structure



The industry is generally competitive as tour operators sell rather similar products. But two key factors shield operators from too intense price competition and cause relational assets leading to (local) competitive advantages when selling through the agencies as intermediaries: (i) Sales personnel within the agencies have different levels of experience with, and thus knowledge of, operator-specific product characteristics and processes (in particular the use of the operator's booking platform). (ii) Commission rates paid by tour operators vary between travel agencies, and in general these rates are higher the higher the revenue an agency has generated for a tour operator in the previous year. These two factors generate lock-in effects and reinforce persistent ties between travel agencies and specific tour operators, as the agencies have an interest to sell more products of operators whose products they have favored in the past.

Price competition is much fiercer in online sales, where products and prices are more directly compared by end customers. Still, a large share of end customers uses travel agencies, as these provide specific travel planning services and advice.[2] But, in particular, the provision of these services to end customers requires operator-specific product and process knowledge.

Our study firm pays a commission rate of 8% to agencies with a yearly total past revenue up to 150k Euros (called tier-2 agencies in the following) and a commission rate of 10% for agencies with a larger past revenue (called tier-1 agencies in the following).[3] Approximately 80% of the agencies that are part of our study belong to the former group of tier-2 agencies. The commission systems of the competitors are fairly similar.

The central questions we explore in our research project are whether upstream firms can increase sales through a short-term intervention reducing sales agents' workload and fostering knowledge-sharing and, moreover, whether the intervention also serves to strengthen relationships with resellers (agency owners) and their sales agents beyond the targeted time frame and products.[4] Our intervention is conducted among 757 independently owned agencies located all over Germany. This corresponds to approximately 10% of all stationary travel agencies in Germany (German Travel Association, 2025).

An essential step in developing our experiment involved gaining a comprehensive understanding of the industry structure, 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.

THE INTERVENTION

A key role of the independent travel agencies is the provision of specific travel-planning services and advice to end customers which requires operator-specific product and process

[2]According to the German Travel Association, more than 50% of all travel bookings are made via stationary travel agencies (German Travel Association, 2025).

[3]There is a third revenue tier with a 12% commission rate. However, this high threshold is only reached by a few agencies owned directly by the study firm or franchisees. Beyond the commission rate, the study firm sometimes pays additional top-up commissions for particular products.

[4]In a different set of experiments, we investigate monetary strategies that increase material sales incentives and target either the agency owners or sales agents. See Gürtler et al. (2025) for details.

knowledge. Our intervention is designed to reduce the workload of sales agents at the intermediaries in this process when selling the study firm's products, thus lowering their transaction costs.

Agencies in our treatment group receive priority access to a newly established service hotline that they can consult in case of booking changes, inquiries, customer complaints, and any other questions related to bookings to four target destinations. It is important to recall that most customers book a combination of different products (such as flights, hotel, rental cars, insurance policies, etc.), and sales agents usually book these products through platforms offered by tour operators. A key task for sales agents is to translate specific customer requests into bookings made on these platforms, which requires effort from the agents. The hotline now aims to reduce this selling-effort burden for products offered by the study firm. Pre-treatment interviews with management, agency owners, and sales agents within the agencies supported us in developing this treatment, as (i) sales management executives have emphasized that the service provided by tour operators to support the agencies is an important factor in sales agents' selling decisions and (ii) agency owners have stated that it takes a long time to onboard new sales agents due to the sometimes complex processes involved in making bookings or adjusting package bookings (e.g., an end customer wants to change the departure airport or times, upgrade her / his room category or flight class, or change her / his surname on a flight ticket shortly before going on honeymoon).

The hotline is available for all questions regarding new bookings to four specific target destinations. The travel destinations were selected based on the firm's strategic goal to focus and expand bookings in the four countries. The bookings to these target destinations account for approximately a third of all bookings.

Even before our intervention, the agencies had the opportunity to contact the study firm by phone.[5] However, the waiting time for support via telephone was quite long, especially during peak booking times, where waiting times for sales agents – and the end customers

[5] Agencies can also contact the study firm via e-mail. We do not have access to these data, and according to sales agents this is usually the least preferred option because of long reply times.

waiting in the travel agency – can exceed an hour. Our intervention reduced the average and maximum waiting times for the treated agencies by around 90% (for more details, see Section **RESULTS**)

The field experiment started on 1 February 2023. The agencies assigned to the treatment were informed via e-mail and a physical letter about the treatment and received priority access to the hotline until 31 October 2023, which ensures that agents were able to reach the hotline not only during the main booking period, but also around the time of the customers' departure date. All treated agencies received a biweekly reminder informing them about the availability of the hotline. During the field experiment, we conducted surveys with the agencies and call-center agents operating the hotline. The survey with the travel agencies was conducted online in June and July 2023. The second survey with the call-center agents was conducted online in August and September 2023.

THEORY AND HYPOTHESES

There is a rich literature on interfirm relational resources and capabilities (Dyer and Singh, 1998; Dyer and Hatch, 2006; Dyer et al., 2018). While much of this work emphasizes their strategic importance, relatively few studies address the dynamic *development* of these resources. Existing research points to factors such as iterative interaction (Gulati, 1995), the evolution of trust (Zhong et al., 2017), relational learning (Cheung et al., 2011; Kale et al., 2000), and the emergence of mutual dependency (Casciaro and Piskorski, 2005) as key to this process. Typically, these relational resources accumulate gradually and often emerge at critical junctures such as the initiation of strategic partnerships, responses to operational shocks (Keller et al., 2021), or investments in joint problem-solving routines (Dyer and Hatch, 2006), which may shift governance mechanisms from transactional to relational. However, comparatively little attention has been paid to whether and how such resources can be purposefully developed, and specifically, whether they can be actively *induced*. This section develops the theoretical rationale for the idea that initial transactional benefits may serve as deliberate triggers for increased interfirm engagement and knowledge exchange, thereby laying the groundwork for the emergence of relation-specific assets.

In our setting, upstream firms sell their products through resellers who employ sales agents. These agents play a pivotal role, as they offer products from multiple upstream firms to end customers. While agency owners can attempt to influence which products their agents promote, the agents retain substantial discretion in their customer interactions. When recommending a product, an agent incurs personal selling costs associated with explaining product details, addressing customer needs, and navigating upstream firms' booking platforms when assembling tailored bundles that include flights, accommodation, car rentals and the like. These selling costs constitute transaction costs in the classical sense (Williamson, 1985), and sales agents aiming at minimizing these costs tend to favor products that are less burdensome for them to sell. Our intervention is designed to lower these firm-specific transaction costs. By providing support to agents in advising customers, the treatment eases the effort involved in selling the study firm's offerings during the time of the intervention. As agents weigh the relative personal costs and benefits associated with promoting products from different providers, our intervention should make it more attractive to sell the study firm's products for which the hotline provides targeted support (Ahearne et al., 2008). We therefore hypothesize:

Hypothesis 1. *The treatment will lead to an increase in average sales of the targeted products during the time of the intervention via a reduction in transaction costs.*

However, our intervention extends beyond pure transactional benefits. The reason is that the effectiveness of the intervention is inherently connected with preexisting organizational ties.

The selling costs and benefits of upstream firms' products vary substantially ex ante, due in part to established knowledge-sharing routines. As the literature on inter-organizational competitive advantage suggests (e.g., Dyer and Singh, 1998; Dyer et al., 2018), intermediaries often build stronger relationships with firms they have dealt with frequently in the past. In our context, higher past sales contribute to deeper knowledge of a firm's products and processes, which reduces effort in subsequent transactions (Peng and York, 2001). Switching to another firm's offerings incurs adjustment costs for the agents, who are less familiar with that firm's tools and procedures (e.g., Cabral, 2016; Klemperer, 1987b,a; Sengupta et al., 1997). Additionally, as is common in vertical channels with resellers (e.g., Chung et al., 2021b; Jansen et al., 2024; Misra and Nair, 2011), commission structures reward higher historical sales. Agencies with greater past sales receive more favorable commission rates, incentivizing agency owners to direct agents toward upstream firms with which they have stronger prior ties.

Thus, when an agency has previously favored the study firm's products, two key relational assets are already in place: (i) sales agents possess relationship-specific human capital, having developed familiarity with the firm's offerings and processes; and (ii) commission rates are more favorable due to historical sales volume. The result is a substantial lock-in effect, implying that the additional support provided by our intervention is unlikely to yield significant incremental gains in sales.[6] In contrast, for agencies with weaker initial ties, i.e., those that have not historically promoted the study firm's products, the intervention has greater potential to shift sales behavior. As described earlier, the study firm segments agencies based on prior sales: tier-1 agencies earn a 10% commission rate, while tier-2 agencies receive 8%. Tier-1 agencies have both higher prior sales and stronger initial incentives to promote the firm. Hence, we expect the intervention to have a stronger impact on tier-2 agencies, where more scope exists to build new relational assets.

Hypothesis 2. *The treatment will have a stronger positive effect on sales performance for agencies with weaker prior ties to the study firm (tier-2 agencies) than for agencies with stronger prior ties (tier-1 agencies), as the former have more scope to increase sales of the study firm's products through improved knowledge transfer and reduced selling costs.*

There is growing evidence that short-term interventions can generate lasting effects across a variety of domains and for different reasons (Argyres et al., 2020; Portocarrero and Burbano, 2024; Volpp and Loewenstein, 2020; Wood and Rünger, 2016). However, few studies

[6] Overall customer demand is largely driven by foot traffic into the agency and is difficult to increase directly. As such, a central role of sales agents is to determine which tour operator's products to promote.

examine this phenomenon in the context of interfirm relations, and the underlying mechanisms remain both theoretically (Eisenhardt and Martin, 2000; Thatchenkery and Piezunka, 2025) and empirically understudied. This raises an important question: Under what conditions can short-term interventions shape interfirm relationships and yield enduring benefits, such as persistent behavioral change and strengthened ties that extend beyond the immediate scope of the intervention?

If such interventions fail to provide lasting value, any observed effects may rather reflect transactional incentives or temporary distortions (e.g., "Hawthorne" or novelty effects). However, we argue that, in our setting, the intervention has the potential to create durable impact because it facilitates the accumulation of firm-specific knowledge, thereby fostering the development of relationship-specific assets.

As outlined above, upstream firms in our setting sell their products through resellers, whose agents retain substantial discretion over which products to promote to customers. While the intervention can temporarily boost sales due to lower personal transaction costs of selling the upstream firm's products, we propose that such a transactional intervention can also enable more enduring benefits due to firm-specific knowledge accumulation. Specifically, the intervention should foster two types of learning: (1) direct knowledge transfer through interpersonal contact (Argote and Ingram, 2000; Argote, 2024; Miller et al., 2006; Myers, 2021; Sandvik et al., 2020), and (2) experiential learning-by-doing through repeated transactions (e.g., Chan et al., 2014; Epple et al., 1991; Lieberman, 1987; Musaji et al., 2020). As agents become increasingly familiar with the study firm's offerings and support infrastructure, either through direct interaction with its support staff or through more frequent transactions prompted by reduced selling costs, they develop human asset specificity (Williamson, 1985): firm-specific knowledge that is not easily transferable to other upstream firms. This accumulated expertise creates switching costs and may contribute to the formation of competitive barriers (Dyer and Hatch, 2006; Peng and York, 2001).

Hypothesis 3a. *The treatment will have a positive effect on sales performance after the end of the intervention, because accumulated firm-specific knowledge makes it easier and more* *attractive for agents to continue promoting the study firm's products.*

Our argument thus integrates insights from both transaction-cost theory and the literature on interfirm relational resources. From the transactional perspective, the hotline lowers the immediate costs of selling by reducing the effort required from agents yielding short-term gains in sales performance. However, beyond these immediate effects, the intervention also facilitates firm-specific knowledge accumulation through repeated interactions and support, which deepens agents' familiarity with the study firm's products and processes. This process fosters the development of relationship-specific assets, which may increase switching costs and promote ongoing collaboration. We therefore propose a bridging mechanism: When a transactional intervention is intentionally designed to support learning and knowledge transfer, it can initiate a shift from transactional to relational governance, setting the stage for sustained interfirm advantage.

Based on an analogous argument we also hypothesize that the benefits of such learning can extend not only over time, but also across the product scope of the firm. That is, we expect the intervention to influence not only the targeted products but also other, non-targeted offerings.[7] This expectation is grounded in established theory on knowledge transfer and reuse within organizations. Specifically, the knowledge acquired through the intervention, such as how to navigate the booking platform, understand product configurations, or decode firm-specific abbreviations, constitutes partially transferable know-how (Garud and Nayyar, 1994; Nonaka, 1994). Prior research shows that knowledge transfer is more likely when tasks are cognitively similar or rely on shared routines (Argote and Fahrenkopf, 2016; Nonaka, 1994; Zander and Kogut, 1995). For example, a sales agent who learns to configure bundles or resolve issues for one product line may apply that knowledge to other products of the same firm, especially when supported by a common platform or customer interface. From a knowledge-based view of the firm, such routines represent modular knowledge that can be redeployed across related tasks and products (Grant, 1996). Consequently, we expect that

[7] Recall that the hotline access offered to sales agents covered only a subset of the products, i.e., bookings to four target destinations.

the benefits of the treatment will not be limited to the products directly addressed during the intervention, but will also spill over to related offerings of the study firm.

Hypothesis 3b. *The treatment will have a positive effect on sales of other products not directly targeted by the intervention, because agents acquire transferable knowledge, such as platform skills and routine familiarity, that facilitates the promotion of related offerings from the study firm.*

METHODS

Data and randomization

From our study firm, we obtained sales data on a booking level from December 2022 to December 2023. One observation contains the booking's characteristics, such as booking type (e.g., package booking, flight, rental car, city tour), booking date, travel date, gross revenue (i.e., booking price), destination, duration, number of passengers, and the agencies' commission rates.

Our primary outcome variable is the number of targeted bookings, i.e., the number of bookings for which the hotline can be consulted, as the most important variable for detecting behavioral shifts of the reseller or sales agents. Furthermore, we investigate potential spillover effects on the number of non-targeted bookings as well as the resulting effect on total bookings. To investigate whether our intervention strengthened relational ties between the intermediaries and our study firm, we use data on bookings from the post-experimental period. In addition to the number of bookings, we have information about the revenues from these bookings, and we use these in our analyses as well.

We complement the data on bookings with survey data. The survey is conducted with all agencies of the treatment group and the control group, and it elicits perceptions about the study firm and working practices within the agencies, as well as the relevance of product quality, commissions, and service quality when choosing the tour operator in order to study underlying behavioral mechanisms.[8]

[8]The summary statistics as well as the detailed questionnaire are available upon request. The response rate is 16%.

To gain a deeper understanding of the mechanisms through which the treatment affects sales and the formation of relational assets, we make use of two further data sources. First, we have information about the usage of the 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. Second, we conduct a survey with the employees operating the service hotline, i.e., the call-center agents.[9]

To perform a stratified randomization procedure assigning the agencies to the treatment and control group, we used prior sales data from December 2022 and January 2023.[10] Pre-experimental summary statistics for our main outcome variables in terms of bookings as well as revenues and the final assignment are presented in Table 1. The groups are balanced with regard to all of our main outcome variables, as defined above. Due to financial constraints, the control group had to be twice as large as the treatment group.

Empirical strategy

We employ a difference-in-differences approach. As our main outcome variables are count variables and we are particularly interested in relative effect sizes, we estimate Poisson regressions, but we also report OLS fixed-effects regressions (partly in the main text and in the Appendix).[11] Our estimations include monthly observations per agency. In a first step, we estimate the following equation:

$$y_{it} = \alpha_i + \lambda_t + \beta\, Treatment_{it} + \epsilon_{it}.$$

Here, y_{it} denotes our outcome variable. The variable $Treatment_{it}$ is dichotomous and equal to one in the experimental period, i.e., February to October 2023, if agency i belongs

[9]The key insights as well as the detailed questionnaire are available upon request. The response rate is 92%.

[10]In the travel industry, many of the small independently-owned agencies organize themselves in larger purchasing pools. In our randomization, we stratified with regard to the purchasing pools within which the agencies are organized.

[11]Specifically, due to overdispersion and the presence of inflated zeros, we rely on the Poisson Pseudo Maximum Likelihood estimator.

TABLE 1 Balance table

Agencies	All $N = 757$ (1)	Treatment $N = 253$ (2)	Control $N = 504$ (3)	p-value $\mu_T = \mu_C$ (4)
Targeted bookings	1.19	1.15	1.21	0.50
	(1.86)	(1.83)	(1.88)	
Non-targeted bookings	2.48	2.32	2.56	0.21
	(3.51)	(3.41)	(3.56)	
Total bookings	3.67	3.47	3.77	0.23
	(4.73)	(4.60)	(4.79)	
Targeted revenue	3.02	2.88	3.09	0.46
	(5.06)	(4.99)	(5.10)	
Non-targeted revenue	4.88	4.89	4.87	0.98
	(7.36)	(7.96)	(7.05)	
Total revenue	7.90	7.77	7.96	0.75
	(10.84)	(11.16)	(10.68)	
Share tier-1 agencies	0.18	0.19	0.18	0.81

Notes: The table provides a summary of the agencies' pre-experimental number of bookings and the corresponding revenue, i.e., sample means of bookings (revenue) in December 2022 and January 2023, in the treatment group and the control group (Columns 1 to 3, standard deviations are in parentheses). "Targeted" refers to (revenue from) all bookings to the four specified target destinations, "Non-targeted" to (revenue from) all non-targeted bookings, and "Total" to (revenue from) all bookings. Revenues are in thousands of Euros. Furthermore, the table presents the share of tier-1 agencies across the groups. Column 4 reports the p-values of the two-sided t-test of equality of the means of treatment and control group. In the case of the commission rate, we rely on a two-sided test for equality of proportions.

to the treatment group. The variable λ_t accounts for time fixed-effects, α_i denotes the individual agency fixed-effect, and ϵ_{it} denotes the error term. The pre-experimental period contains the observations from December 2022 and January 2023. For analyzing spillover effects to later periods, we will include data from the post-experimental period and modify our main specification accordingly.

RESULTS

Directly targeted outcomes

We start by presenting the estimation results of our main specification, where the dependent variable is the number of targeted bookings. The results are reported in Table 2. Columns 1 and 2 present the treatment effect on the number of targeted bookings, using both a Poisson regression (Column 1) and an OLS regression (Column 2).[12] For ease of interpretation, Table 2 (and all further tables showing Poisson regressions) also shows the incidence ratios (IR) of the estimates obtained from the Poisson regression as additional statistics. The IR, being the exponential of the coefficient, indicates the factor by which the average of the dependent variable changes for a specific treatment group. Column 3 displays the results concerning the revenue stemming from the targeted bookings.

TABLE 2 Treatment effects

	Targeted bookings		*Targeted revenue*
	Poisson	OLS	OLS
	(1)	(2)	(3)
Treatment	0.16^{**}	0.16^{**}	456.28^{**}
	(0.07)	(0.08)	(219.30)
IR	1.18	–	–
Control mean	0.86	0.86	2138.99
Observations	7084	8327	8327
No of Clusters	644	757	757
No of Months	11	11	11

Notes: The table shows the impact of the treatment on the number of targeted bookings and the corresponding targeted revenue, using a difference-in-differences approach. The estimate in Column 1 is obtained using a Poisson Pseudo Maximum Likelihood estimator. The estimates in Columns 2 and 3 are obtained using a standard OLS fixed-effects estimator. 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. Due to lack of interpretation, we do not present incidence rations for the OLS estimates. Standard errors are clustered on agency level in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

The results strongly support Hypothesis 1: The treatment increased the monthly number of targeted bookings substantially by about 18% (both in Poisson and OLS), and the revenue stemming from these bookings by about 456 Euros (or 21%).

[12] Note that the Poisson estimations discard some clusters, i.e., agencies, due to the well-known separation problem in non-linear estimation. These agencies lack variation across all levels of fixed-effects, making their inclusion in the estimation impossible. However, as Correia et al. (2020) argue, these observations can be safely discarded, as they do not provide identifying information for the estimators.

The role of prior ties

Next, we turn to Hypothesis 2 according to which the treatments have a stronger positive effect on sales for tier-2 agencies (i.e., those with weaker prior ties to the firm and thus lower commission rates). As Columns 1 and 3 from Table 3 show, we indeed find a significant treatment effect on the booking level of about 22% (23% for OLS) for the tier-2 agencies. According to Columns 2 and 4, the effect is smaller at about 12% (11% for OLS) and noisier among the tier-1 agencies (i.e., those with stronger prior ties). However, the difference between the two coefficients is not statistically significant (one-sided test, $p = .27$). When considering the corresponding revenues (Columns 5 and 6), we find a significant treatment effect of 550 Euros (+36%) for the tier-2 agencies. This provides partial support for Hypothesis 2.

TABLE 3 Effect heterogeneities regarding prior ties

	Targeted bookings				*Targeted revenue*	
	Poisson		OLS		OLS	
Agencies	Tier 2 (1)	Tier 1 (2)	Tier 2 (3)	Tier 1 (4)	Tier 2 (5)	Tier 1 (6)
Treatment	0.20**	0.11	0.15**	0.21	550.16***	94.04
	(0.09)	(0.11)	(0.07)	(0.25)	(209.73)	(709.15)
IR	1.22	1.12	–	–	–	–
Control mean	0.65	1.82	0.65	1.82	1573.45	4671.61
Observations	5621	1463	6787	1540	6787	1540
No of Clusters	511	133	617	140	617	140
No of Months	11	11	11	11	11	11

Notes: The table shows the impact of the treatment on the number of targeted bookings and the corresponding targeted revenue, using a difference-in-differences approach. The estimates in Columns 1 and 2 are obtained using a Poisson Pseudo Maximum Likelihood estimator. The estimates in Columns 3 to 6 are obtained using a standard OLS fixed-effects estimator. Columns 1, 3 and 5 only include tier-2 agencies. Columns 2, 4 and 6 only include tier-1 agencies. All specifications include time and agency fixed-effects. 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. Due to lack of interpretation, we do not present incidence rations for the OLS estimates. Standard errors are clustered on agency level in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

Spillover effects and persistence

Before turning to Hypothesis 3a, we now first consider Hypothesis 3b and investigate whether our treatment led to spillover effects on non-targeted bookings during the experimental period. To do so, we re-estimate our main specification and use the number of non-targeted bookings as the dependent variable. Furthermore, we also consider the effect on the number of total bookings.

As Table 4 shows, we indeed find evidence in line with our Hypothesis 3b, i.e., we observe positive spillover effects for the tier-2 agencies. The treatment significantly increased the number of non-targeted bookings by 14% (see IR of Column 2), leading to an increase in total monthly bookings per tier-2 agency by 16% (see IR of Column 5).[13] The effect on total bookings is again larger for tier-2 agencies compared to tier-1 agencies. The difference between the two coefficients is (marginally) significant (one-sided test, $p = .09$), providing further support for our Hypothesis 2. On average, total monthly bookings per agency increased by 9%.

Finally, we examine whether the effect of the treatment persists beyond the experimental period. To do so, we add the data from the post-experimental period, i.e., November and December 2023, and we our main specification by adding the dichotomous variable $\mathit{TreatmentPost}_{it}$ as an additional independent variable, which is equal to one in the post-experimental period if agency i belongs to the treatment group.[14]

As Table 5 displays, the treatment effect persists after the end of the intervention, providing support for Hypothesis 3a.[15] For the tier-2 agencies, we estimate an increase of 17% in monthly total bookings in the post-experimental period. This result indicates that the intervention strengthened the ties of our study firm with the intermediaries, in particular

[13] For the corresponding results of an OLS fixed-effects regression, we refer to Tables A.1 and A.2 in the Appendix.

[14] Our cooperation with the travel company ended on 31 December 2023. We are thus unable to investigate the persistency of the effects beyond December 2023.

[15] For the corresponding results of an OLS fixed-effects regression, we refer to Table A.3 in the Appendix. For the tier-2 agencies, the result also transfers to the corresponding total revenue. The results are presented in Table A.4 in the Appendix.

TABLE 4 Spillover effect on non-targeted bookings and effect on total bookings

Agencies	*Non-targeted bookings* All (1)	Tier 2 (2)	Tier 1 (3)	*Total bookings* All (4)	Tier 2 (5)	Tier 1 (6)
Treatment	0.06	0.13*	-0.03	0.09*	0.15**	0.01
	(0.06)	(0.07)	(0.10)	(0.05)	(0.06)	(0.08)
IR	1.06	1.14	0.97	1.09	1.16	1.01
Control mean	2.23	1.65	4.80	3.08	2.30	6.61
Observations	7711	6182	1529	7832	6292	1540
No of Clusters	701	562	139	712	572	140
No of Months	11	11	11	11	11	11

Notes: The table shows the impact of the treatment on the number of non-targeted bookings (Columns 1 to 3) as well as the number of total bookings (Columns 4 to 6) using a difference-in-differences approach. The estimates in Columns 1 to 6 are obtained using a Poisson Pseudo Maximum Likelihood estimator. Columns 2 and 5 only include tier-2 agencies. Columns 3 and 6 only include tier-1 agencies. All specifications include time and agency fixed-effects. Standard errors are clustered on agency 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.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

those that did not sell many of the firm's products in the past (see Hypothesis 2). The difference between the two coefficients for tier-1 and tier-2 agencies is (marginally) significant for the treatment period (one-sided test, $p = .09$) and also for the post-experimental period (one-sided test, $p = .06$). Thus, we find support for Hypotheses 2 and 3a.

The micro-level effects on sales agents

To understand better how the intervention shaped sales outcomes and relational resource formation, we examine several underlying micro-level mechanisms. These mechanisms shed light on the channels through which the intervention reduced agents' effort costs, enabled knowledge transfer, and ultimately contributed to the development of relation-specific assets. We begin by analyzing waiting time reductions for sales agents, before turning to patterns of knowledge exchange, perceived service quality, and a robustness check addressing potential confounds related to reciprocal behavior.

Reduction in waiting time. In a first step, we analyze the extent to which our

TABLE 5 Persistence of effect on total bookings

	Total bookings		
Agencies	All (1)	Tier 2 (2)	Tier 1 (3)
Treatment	0.09*	0.15**	0.01
	(0.05)	(0.06)	(0.08)
Treatment - Post	0.07	0.16*	-0.05
	(0.07)	(0.09)	(0.10)
IR	1.09	1.16	1.01
IR - Post	1.08	1.17	0.95
Control mean	2.95	2.19	6.34
Observations	9256	7436	1820
No of Clusters	712	572	140
No of Months	13	13	13

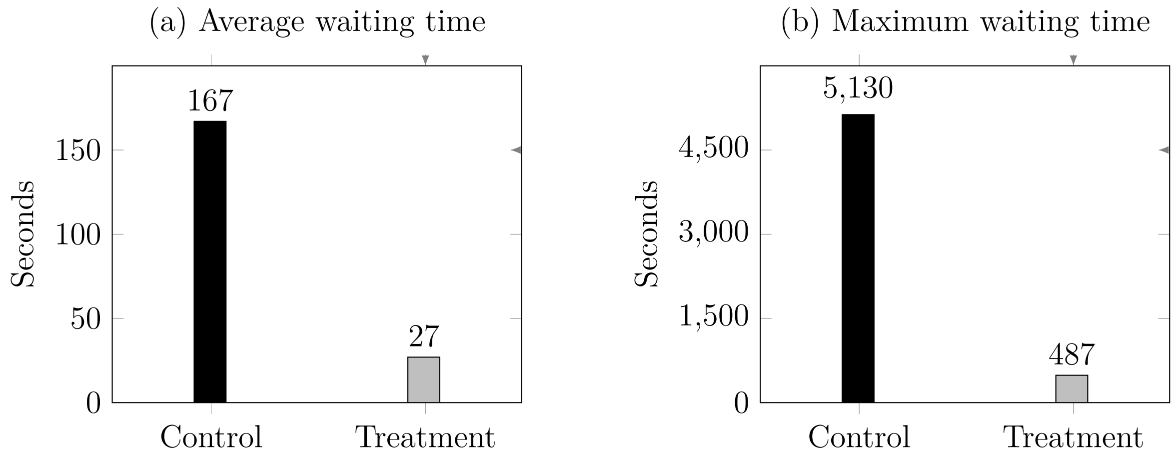
Notes: The table shows the impact of the treatment on the number of total bookings during as well as after the experimental period, using a difference-in-differences approach. The estimates in Columns 1 to 3 are obtained using a Poisson Pseudo Maximum Likelihood estimator. Column 2 only includes tier-2 agencies. Column 3 only includes tier-1 agencies. All specifications include time and agency fixed-effects. Standard errors are clustered on agency 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.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

intervention has reduced the waiting time of sales agents when contacting the study firm on the phone. Figure 2 (a) shows the average waiting times (in seconds) for the treatment group (in grey) and all other agencies of the study firm's sales portfolio (in black). As the waiting times can increase rapidly during busy periods, panel (b) of the figure also shows the respective maximum waiting times.[16] We find that the intervention reduced the average waiting time by 84%, and the maximum waiting time by 91%. Such substantial reductions – particular, during peak periods – highlight the time-saving benefits for agents, substantiating the claim that the intervention reduced the sales agents' workload from selling the study firm's products.

Knowledge transfer to sales agents. In a second step, we identify whether and

[16]During our field experiment, the study firm increased the number of call-center agents significantly. Therefore, the treatment group did not exhibit negative spillover effects in terms of waiting times on other agencies. Note that we cannot distinguish in our dataset between the waiting times of control-group agencies and other non-treated agencies.

FIGURE 2 Waiting time – Treatment vs. Control group



Notes: The figure shows the average waiting time on the phone (a) and the maximum waiting time (b) during the experimental period for agencies belonging to the treatment group (in gray) and all other agencies of the study firm's sales portfolio (in black). We only have aggregated data available to measure waiting times. Thus, we can only distinguish between the treatment group and all other agencies (i.e., the control group as well as agencies not participating in our experiment).

how the intervention fostered the transfer of firm-specific knowledge and thus the creation of relational assets. To do so, we conducted a survey with the study firm's call-center employees supporting the treated sales agents. In the survey, we asked the employees to provide free-text answers describing the most frequent inquiries of sales agents by destination. We categorized the 148 obtained answers. Most of the inquiries were support requests for either specific *process knowledge* or *product knowledge*. Typical *process knowledge* requests address means to adjust package bookings on the study firm's booking platform, for instance, how to upgrade the hotel room category, change the customer's surname on a flight ticket shortly before going on honeymoon, or change the departure airport or the flight times. *Product knowledge* requests encompass, for instance, questions about whether it is possible for two customers to stay in the same hotel room, but fly from different airports to the destination, or specific inquires from disabled customers or customers with children. We find that 41% of the free text answers are *process knowledge* requests, 45% are *product knowledge* requests, and 9% fall under both categories.[17] We also asked the call-center employees

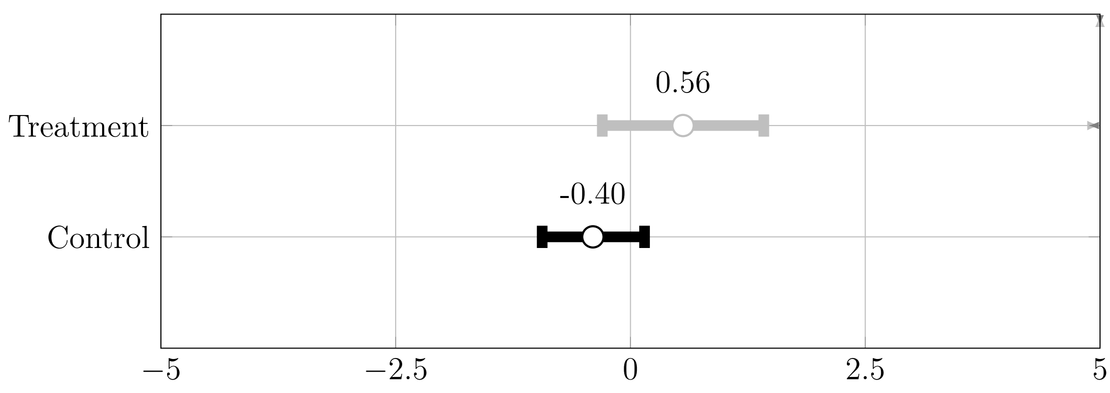
[17] 5% of the requests are classified as *other*.

whether they were able to resolve the inquiries successfully, and they stated that this was the case for about 80% of the requests.

In line with our findings on the role of prior ties, we also find anecdotal evidence that treated agencies with limited experience with the study firm's products and processes benefited the most from the hotline. For example, one call-center employee stated that "*these agencies are not familiar with the specific characteristics of XXX [the study firm] such as codes or requirement abbreviations in the booking system*". Another one said that "*in particular it was easier for them to implement bookings of complex product combinations*".

Perception of service quality. Lastly, we investigate how the sales agencies perceived the quality of the service provided by our study firm in general. In our survey among the participating agencies, we asked to rate the quality of the services provided to the agencies 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 3 summarizes the responses. We observe that agencies in the treatment group perceive the quality of services provided as significantly better than those in the control group ($p = .03$), providing another piece of evidence that the treatment reduced sales agents' costs of effort.

FIGURE 3 Sales agents' perception of service quality provided by our 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 treatment 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 XXX [the study firm] compared to other relevant competitors on a scale from -5 to +5?". The observed difference is statistically significant with the null $\mu_{\text{AS}} \leq \mu_{\text{C}}$ being rejected ($p = .03$).

The role of generosity. Finally, one rival explanation for our findings is that our intervention treated the affected agencies more generously, and that the agencies reciprocated by selling more of our study firm's products. Indeed, a large literature spanning different fields has shown that reciprocity is a key driver of human behavior (e.g., Bosse et al., 2009; Dabos and Rousseau, 2004; Fehr and Gächter, 2000; Hekman et al., 2009). To investigate this, we can compare our treatment effects to those of an intervention where our study firm paid additional commissions to randomly selected agencies. As shown in the Appendix, Table A.5, these top-up payments had no discernible effects on sales, even though this commission increase was much more costly for our study firm than the costs of the support hotline implemented in our treatment.[18] This indicates that it is unlikely that reciprocity is a key driver of the treatment effect.

DISCUSSION

The intervention not only lowered the sales agents' transaction costs but fostered a beneficial direct transfer of firm-specific knowledge to the intermediaries. Moreover, the reduction in the sales agents' personal selling costs led to more bookings during the intervention period and thus likely enabled additional learning-by-doing. The accumulated knowledge appears to be transferable beyond the initially targeted products and time frame as we observe sales increases for non-targeted products and after the end of the intervention. Further supporting this interpretation, the treatment effects are concentrated among tier-2 agencies – those with limited prior experience with the study firm's products and processes – who stand to gain most from knowledge acquisition. If the intervention merely offered transactional benefits, we would expect the greatest impact among tier-1 agencies, whose higher commission rates enhance the returns of making use of the support services to achieve higher sales. Instead, the observed pattern indicates that the hotline acted as a learning mechanism rather than simply as a sales facilitator.

[18]See Gürtler et al. (2025) for more details on the limited effect of increasing commission payments on sales.

As outlined in our theoretical framework, the reduction in personal selling costs acted as a transactional trigger that initiated the development of relationship-specific knowledge. By encouraging use of the support hotline, the intervention facilitated both interpersonal and experiential learning. As agents deepened their familiarity with the study firm's offerings and routines, the interfirm relationship strengthened, yielding spillover benefits across other product categories.

Our findings thus show that interfirm relational capabilities can be purposefully cultivated, not just organically developed. Specifically, we show that a transactional trigger – when directed at strategically positioned intermediaries – can catalyze the formation of relational assets through firm-specific knowledge accumulation. This extends the relational view of competitive advantage by demonstrating that short-term operational interventions can generate durable relational resources when they lower frictions in interfirm collaboration and promote embedded learning (Dyer and Singh, 1998; Grant, 1996).

Another insight from our study is the importance of targeting strategic job families at partner organizations. Individuals in operational roles who influence the selection or delivery of offerings play a critical part in shaping interfirm outcomes. Providing targeted support to these actors can improve performance and strengthen collaborative ties, underscoring the value of interventions that address their practical, day-to-day challenges.

Moreover, our study also contributes to the literature on resource allocation and strategy (Coen and Maritan, 2011; Klingebiel and Rammer, 2014; Maritan and Lee, 2017; Noda and Bower, 1996), underscoring the importance of allocating resources in vertical relationships strategically – specifically to areas where there is potential for forming new connections – rather than distributing them uniformly. The value generated by our intervention was driven by agencies with weaker prior ties to the study firm, suggesting that the marginal return on investment is greatest where relational foundations are still underdeveloped.

Finally, our results emphasize the value of process improvements over merely increasing monetary incentives. This implies that firms may prioritize interventions that enhance operational efficiencies and directly address the needs of employees within key job families at intermediaries, rather than solely raising financial inducements. Future research on intermediaries may learn from related findings on within-firm process improvements for sales tasks, for instance, by reducing bureaucratic hurdles (Friebel et al., 2024), improving sales-force automation systems (Johnson and Bharadwaj, 2005; Speier and Venkatesh, 2002), offering specialized training (Chung et al., 2021a), or fostering communication (Manthei et al., 2023).

These mechanisms are most likely to operate in contexts that are characterized by discretionary agent behavior, informational asymmetries, and product complexity. In contrast, in environments where products are commoditized, sales are highly standardized, or agent discretion is minimal, the marginal value of firm-specific knowledge is likely to be lower, and behavior may be more tightly governed by formal incentives or pricing alone. Similarly, in more volatile or transactional markets, where switching among upstream partners is frequent, relationship-specific knowledge may be less durable or relevant.

Although we find evidence for the persistence of treatment effects beyond the intervention period, data-access limitations prevent us from studying longer-term outcomes. Additionally, while the strategic focus on sales agents is promising, it may be subject to imitation by competitors. Future research should therefore examine how such interventions play out in more competitive or dynamic environments, and also take into account potential rival responses. Still, our findings suggest that first-movers who develop effective relational strategies to engage key intermediary roles may gain durable advantages in shaping interfirm ties.

CONCLUSION

Our study demonstrates that an intervention aimed at reducing transaction costs for frontline employees at intermediaries can foster knowledge-sharing and, in turn, strengthen relational resources. By lowering personal selling costs and facilitating firm-specific knowledge transfer, the intervention not only delivered immediate performance gains, but also generated persistent benefits that extended beyond the experimental period and to non-targeted products, providing evidence of relational resource formation.

These findings underscore the broader strategic importance of deliberately managing relational assets in competitive markets. Rather than relying solely on financial incentives to influence intermediary behavior, firms can benefit from targeted, low-cost interventions that deepen engagement, enable learning, and gradually embed routines and preferences within their partners' operations.

More broadly, our results suggest that even short-term interventions, when designed to lower friction and enable capability-building, can catalyze longer-term shifts in interfirm collaboration. This adds nuance to theories of relational advantage by showing that such advantages can be actively nurtured and not just passively accumulated.

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APPENDIX

Further results

TABLE A.1 Spillover effect on non-targeted bookings and effect on total bookings (OLS)

	Non-targeted bookings			*Total bookings*		
Agencies	All (1)	Tier 2 (2)	Tier 1 (3)	All (4)	Tier 2 (5)	Tier 1 (6)
Treatment	0.16 (0.14)	0.23* (0.12)	-0.08 (0.53)	0.32* (0.17)	0.37** (0.15)	0.12 (0.63)
Control mean	2.23	1.65	4.80	3.08	2.30	6.61
Observations	8327	6787	1540	8327	6787	1540
No of Clusters	757	617	140	757	617	140
No of Months	11	11	11	11	11	11

Notes: The table shows the impact of the treatment on the number of non-targeted bookings (Columns 1 to 3) as well as the number of total bookings (Columns 4 to 6) using a difference-in-differences approach. The estimates in Columns 1 to 6 are obtained using a standard OLS fixed-effects estimator. Columns 2 and 5 only include tier-2 agencies. Columns 3 and 6 only include tier-1 agencies. All specifications include time and agency fixed-effects. Standard errors are clustered on agency level in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

TABLE A.2 Spillover effect on non-targeted revenue and effect on total revenue

	Non-targeted revenue			*Total revenue*		
Agencies	All (1)	Tier 2 (2)	Tier 1 (3)	All (4)	Tier 2 (5)	Tier 1 (6)
Treatment	132.84 (342.47)	367.27 (266.13)	-802.01 (1360.78)	589.12 (447.72)	917.42** (358.48)	-707.97 (1708.75)
Control mean	4140.72	3014.86	9182.58	6279.70	4588.31	13854.20
Observations	8327	6787	1540	8327	6787	1540
No of Clusters	757	617	140	757	617	140
No of Months	11	11	11	11	11	11

Notes: The table shows the impact of the treatment on the revenue stemming from the non-targeted bookings (Columns 1 to 3) as well as on total revenue (Columns 4 to 6) using a difference-in-differences approach. The estimates in Columns 1 to 6 are obtained using a standard OLS fixed-effects estimator. Columns 2 and 5 only include tier-2 agencies. Columns 3 and 6 only include tier-1 agencies. All specifications include time and agency fixed-effects. Standard errors are clustered on agency level in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

TABLE A.3 Persistence of effect on total bookings (OLS)

	Total bookings		
Agencies	All (1)	Tier 2 (2)	Tier 1 (3)
Treatment	0.32*	0.37**	0.12
	(0.17)	(0.15)	(0.63)
Treatment - Post	0.28	0.39**	-0.08
	(0.21)	(0.18)	(0.64)
Control mean	2.95	2.19	6.34
Observations	9841	8021	1820
No of Clusters	757	617	140
No of Months	13	13	13

Notes: The table shows the impact of the treatment on the number of total bookings during as well as after the experimental period 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 agency fixed-effects. Standard errors are clustered on agency level in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

TABLE A.4 Persistence of effect on total revenue

	Total revenue		
Agencies	All (1)	Tier 2 (2)	Tier 1 (3)
Treatment	589.12	917.42**	-707.97
	(447.75)	(358.50)	(1709.23)
Treatment - Post	707.41	1197.33**	-1193.41
	(531.76)	(475.63)	(1626.31)
Control mean	6026.85	4413.82	13250.42
Observations	9841	8021	1820
No of Clusters	757	617	140
No of Months	13	13	13

Notes: The table shows the impact of the treatment on total revenue during as well as after the experimental period 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 agency fixed-effects. Standard errors are clustered on agency level in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

More on the role of generosity

In Gürtler et al. (2025) we study the role of commissions in the considered setting in more detail. More precisely, randomly selected agencies received a top-up payment for specific bookings to the same four target destinations for which the hotline was available. In the most generous treatment, the agencies received a top-up payment of 9 Euros per booked customer, which corresponds to an increase of the commission rate by about 1ppt, or 12.5% for the tier-2 agencies that receive a commission rate of 8%. The top-up payment was paid directly to the agency owner. Starting in February 2023, the treatment was implemented for three months. Table A.5 presents the results. We observe no effect on the key outcome variables. Additionally, it should be stressed, that while the top-up payment did not have any effect on sales, it was much more costly for our study firm than our main intervention, i.e., the hotline. On average, the hotline resulted in additional monthly costs of approximately 1.01 Euros per agency, whereas the top-up payment incurred monthly costs of about 19.06 Euros per agency.

TABLE A.5 Treatment effects (Top-up payment)

	Targeted bookings		*Targeted revenue*
	Poisson	OLS	OLS
	(1)	(2)	(3)
Top-up payment	-0.02	-0.02	-111.60
	(0.07)	(0.09)	(260.84)
IR	0.98	–	–
Control mean	1.07	1.07	2879.43
Observations	2905	3755	3755
No of Clusters	581	751	751
No of Months	5	5	5

Notes: The table shows the impact of the top-up payment on the number of targeted bookings and the corresponding targeted revenue, using a difference-in-differences approach. The estimate in Column 1 is obtained using a Poisson Pseudo Maximum Likelihood estimator. The estimates in Columns 2 and 3 are obtained using a standard OLS fixed-effects estimator. 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. Due to lack of interpretation, we do not present incidence rations for the OLS estimates. Standard errors are clustered on agency level in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$