Workplace Knowledge Flows

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Abstract

How large are the gains from knowledge sharing among co-workers? What frictions prevent the spread of information, and what management practices overcome these frictions? We conducted a field experiment with three active treatments in a sales company to address these questions. (1) Encouraging workers to talk about their sales techniques with a randomly chosen partner during short meetings substantially lifted average sales revenue during and after the experiment. (2) Worker-pairs given incentives to increase joint output increased sales during the experiment, but not afterwards. (3) Worker-pairs given both treatments realized small incremental sales gains over the meetings treatment alone. Providing encouragement for workers to initiate conversations resulted in knowledge exchange; incentives were insufficient. Our results highlight the importance of managerial interventions in facilitating knowledge spillovers.

Keywords: management practices; spillovers; peer effects; organizational design; randomized controlled trial (RCT).
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1 Introduction

The best workers in many firms substantially outperform others (Lazear, 2000; Mas and Moretti, 2009; Bandiera et al., 2007; Lazear et al., 2015; Lo et al., 2016). Is this the result of variation in natural abilities or do frictions that limit the spread of best practices between coworkers contribute to productivity differences? In the spirit of Bloom and Van Reenen's (2011) survey on human resources, performance gaps may arise from the slow diffusion of people management practices.[1] Contributing to this slow diffusion is the conflicting advice in academic articles and executive-focused publications about what practices best enable knowledge sharing (Earl, 2001; Myers, 2015). For example, open office spaces that were intended to facilitate collaboration and information sharing appear ineffective or counterproductive (Bernstein and Turban, 2018). To better understand workplace knowledge flows, we investigate the frictions to knowledge sharing and whether management interventions may reduce them.

The substantial literature on peer effects suggests various spillovers may be powerful forces for driving productivity gains (Mas and Moretti, 2009; Bandiera et al., 2010; Shue, 2013), but limited evidence exists on knowledge sharing inside firms. This sparsity in research is likely due to the empirical challenge of using observational data to study workplace interactions, as omitted variables may drive a positive association between peer connections and performance (Manski, 1993; Glaeser et al., 2003; Guryan et al., 2009). These difficulties arise because it is rare to have exogenous variation that shocks frictions to knowledge exchange. We conducted a field experiment inside a sales firm to create this exogenous variation. We find that simple management practices encouraging workers to ask peers about their own sales techniques substantially improved individual performance during and after the experiment.[2]

[1] A common view is that firms exist to facilitate knowledge spillovers (Grant, 1996). These spillovers have been shown to drive productivity growth (Marshall, 1890; Glaeser, Kallal, Scheinkman, and Shleifer, 1992; Barro, 1991; Romer, 1990), but the foundations for how spillovers happen inside the firm are less clear.

[2] In other contexts, cities are thought to create similar benefits because they increase the probability of encountering new practices (Jacobs, 1969; Glaeser et al., 1992).

The experiment occurred in a sales call center where workers sell television, phone, and internet packages from multiple large providers to customers calling from across the United States. Calls are allocated to salespeople randomly, meaning that each salesperson faces the same distribution of opportunities, and compensation depends on individual sales performance. Sales productivity varies dramatically across workers. Prior to the experiment, salespeople at the 75th percentile brought in 70 percent more revenue per call than those at the 25th percentile of the distribution. This dispersion in productivity is driven, in part, by varying mastery of sales techniques.[3] For example, if a customer does not qualify for a product because of credit check requirements or geographic restrictions, an above-average salesperson would likely know how to re-direct that customer to more appropriate products; less-knowledgeable agents may give up on the sale or frustrate the customer with infeasible recommendations. The most successful agents understand when to ask about customer qualifications in the flow of the conversation, and they weave in product explanations appropriate for the individual caller.

Our treatments isolated frictions to knowledge seekers and providers. We illustrate these frictions and how our treatments target them in a theoretical model. *Initiation costs* reduce the likelihood that individuals will seek information from others. Initiation costs include social concerns (e.g., reluctance to approach unfamiliar coworkers or a fear of signalling incompetence by asking for help), coordination difficulties (e.g., setting up meetings), and search frictions (e.g., knowing whom to ask) (Chandrasekhar et al., 2016; Edmondson and Lei, 2014; Cai and Szeidl, 2017). *Contracting costs*, capture the possibility that knowledge providers lack the incentives necessary to overcome the coordination and opportunity costs associated with knowledge transmission.[4]

[3] Variation in task-specific knowledge to complete a sale is akin to task-specific human capital as discussed in Gibbons and Waldman (2004).

[4] Many models of person-to-person knowledge transfer assume that knowledge sharing and mentoring is difficult to contract over (Morrison and Wilhelm Jr, 2004; Garicano and Rayo, 2017; Fudenberg and Rayo, 2017). In related work, Becker (1962) discusses the contracting costs associated with a firm sharing knowledge with employees. Specifically, trainees disproportionately benefit in the long run, while firms pay an up-front cost, leading to an under-provision of general skills training in firms.

We designed the experiment to distinguish between long-term changes in sales arising from knowledge transmission as opposed to short-term increases due to changes in effort. Over 650 salespeople in the firm's two main offices were assigned to four treatment cells, based on the identity of their sales manager; an additional 83 salespeople located in a third office 600 miles from the two main offices provide an *External Control* group that was unaware of the experiment.[5] For employees eligible for treatment assignment and aware of the experiment, we define three treatments as active and the fourth as an *Internal Control* group. Treatments took place over four weeks. We then estimate how treatments affect output, focusing on the firm's main performance measure, revenue-per-call (RPC). Following the pre-registration protocol, which calls for a four-week treatment period and at least three months of post-treatment data, we use four weeks of pre-treatment data, the four-week treatment period itself, and 20 additional weeks of data after treatments end.[6]

The treatments targeted frictions that potentially inhibit knowledge transfer. Sales agents in all treatments were randomly assigned a partner at the beginning of each week. Different treatments then targeted initiation costs, contracting costs, or both. The first treatment, labeled *Structured-Meetings*, lowered initiation costs by encouraging worker-pairs to meet early in the week to fill out a worksheet that discussed their sales techniques.[7] Salespeople who filled out the worksheet were encouraged to follow up with their partner over a free lunch toward the end of the week. The second treatment, labeled *Pair-Incentives*, reduced contracting costs by providing incentives to pairs of workers to increase their joint production. The third treatment, labeled *Combined*, included all elements of both the *Structured-Meetings* and the *Pair-Incentives* treatments. Sales agents in the *Internal Control* group

[5]The RCT Registry notes 650 treatment eligible staff and 44 clusters. We use slightly different numbers here, reflecting updated data given to us by the firm. The RCT Registry sample size does not include the *External Control* group because these employees were not treatment eligible.

[6]We extended the analysis to 20 weeks of post-treatment data, beyond the original plan to analyze three months of post-treatment data, in response to seminar questions about whether the findings persist even longer than the pre-registered analysis period.

[7]One side of the worksheet asked agents to reflect on their performance that week (e.g., their most difficult call and how in hindsight it could have been improved), and the other side had agents solicit the same responses from their partner.

were randomly paired and knew about the experiment, but they were not given additional instructions or incentives.

Our experimental findings show that barriers to knowledge exchange are empirically relevant and that productivity improves when these barriers are lowered. It was not necessary to compensate coworkers to help others, suggesting frictions exist largely with those who lack knowledge. This within firm evidence complements results in influential studies showing that productivity differences across firms arise from managers' own failure to adopt best practices (Bloom et al., 2017, 2016, 2014, 2012; Bloom and Van Reenen, 2011, 2010, 2007). We find individuals improved their sales, suggesting that they were not previously at their productivity frontier, which parallels evidence from randomized controlled trial evidence between firms (Bloom et al., 2013). The estimates yield the following results.

1. The *Structured-Meetings* treatment was particularly effective in raising sales. Relative to the control groups, the *Structured-Meetings* treatment yielded a 24% increase in revenue-per-call during the treatment period, compared to a 13% increase in the *Pair-Incentives* treatment. The per-person cost of implementing the *Structured-Meetings* treatment was also approximately 50% lower than that of the *Pair-Incentives* treatment, resulting in higher accounting profit margins.[8] Results are similar along every measure tracked by the firm, including revenue-per-hour (RPH) and total revenue-per-week. The return-on-investment (ROI) from the *Structured-Meetings* treatment was approximately 500% over just the four-week treatment period. The other two active treatments—the *Pair-Incentives* and *Combined* treatments—had positive, albeit smaller, ROIs during the same four-week period. Results are not due to attrition or drop-out differences across treatments.

2. Sales agents in the *Combined* treatment had similar gains during the treatment period

[8]While the experiment had two levels of incentive compensation ($0 and a prize worth about $50 per person), extrapolation based on a linearity assumption suggests it would have taken a prize of about $100 per person to replicate the *Structured-Meetings* results. This extrapolation, however, is not experimentally identified, nor does it distinguish between individual effort and learning.

to those in the *Structured-Meetings* treatment. Adding incentives to lower contracting costs had a positive but small effect in addition to the reduction in initiation costs.[9]

3. Treatments involving structured meetings induced knowledge transfers between peers, while pair incentives alone did not.

   (a) The *Structured-Meetings* and *Combined* treatments yielded persistent performance increases through the 20-week post-treatment period. Twenty weeks after treatments formally ended, average sales in the *Structured-Meetings* and *Combined* treatments remained between 15% and 20% higher than the control groups.

   (b) Sales agents in the *Pair-Incentives* treatment had post-treatment productivity that was statistically indistinguishable from either control group.

   (c) Heterogeneous effects by partner ability distinguish knowledge transfers from self-improvement and sentiment explanations. Salespeople in the *Structured-Meetings* and *Combined* treatments performed better across the treatment and post-treatment periods when they were paired with stars—agents with pre-treatment productivity above the median. Star salespeople themselves improved in the *Structured-Meetings* and *Combined* treatments only when paired with other stars.

   (d) Survey responses and interviews of participants and managers indicate that the *Structured-Meetings* and *Combined* treatments induced partners to share best practices during the treatment period, while the *Pair-Incentives* treatment did not. Management believed that knowledge sharing continued between past partners in the *Structured-Meetings* and *Combined* treatments after the active treatments ended.

[9] There is a large literature in economics and psychology investigating the crowd-out effects of monetary incentives; see Bénabou and Tirole (2006), Ederer and Manso (2013), Titmuss (1970), Frey and Oberholzer-Gee (1997), Ariely et al. (2009a), Ariely et al. (2009b), Gneezy et al. (2011). Other literature considers how incentives and other practices should be bundled (Athey and Stern, 1998; Ichniowski and Shaw, 2003). The evidence suggests that, in this setting, the *Pair-Incentives* and *Structured-Meetings* treatments are substitutes, not complements.

Survey responses suggest that social costs, rather than search or coordination costs, were the most limiting friction. Specifically, salespeople report that (1) they can identify star agents and (2) they believe that help from star agents would improve their sales and hence their compensation. In fact, the average salesperson estimates that interacting with a top sales agent would result in a 12% sales lift and that top agents would likely be willing to help if approached. Still, many individuals largely could not overcome, in the words of one interviewee, an "intimidation factor" that prevented them from asking co-workers to share tips and techniques. The treatments lowering initiation costs involved managerial directions for workers to talk through problems that they encountered in their own sales process, which may indicate that simply providing opportunities to interact (like through open space and light touch interactions) is not sufficient to overcome the main hindrances to knowledge spillovers.

By relaxing initiation costs, the *Structured-Meetings* and *Combined* treatments increased individual workers' earnings by between $27 to $35 per week and firm revenues by between $530 and $700 per agent-week. Given these magnitudes, why were these practices not attempted earlier? First, the outcomes were not obvious to management (nor to the authors). In particular, many leaders on the sales teams believed that providing joint incentives to overcome contracting costs would be sufficient to induce knowledge transfers. Human resource managers, on the other hand, were intrigued by the potential efficacy of using interventions to increase peer-to-peer interactions, but these had not been tested. Second, experimentation was necessary to uncover these findings, and formal experiments had not been attempted within this firm.[10] The average gains from experimenting with different practices were substantial.

In addition to measuring average sales gains, we also (per the pre-registration) explored

[10] Similarly, Jackson and Schneider (2015) find large and unanticipated productivity gains in an experiment on the introduction of checklists in auto repair shops. The results across numerous studies underscore that field experiments are a useful tool to test new practices prior to firm-wide adoption (Carpenter et al., 2005). Based on the favorable outcomes of our experiment, the firm's management has replaced its traditional on-boarding process with a mentoring program to increase knowledge exchange between newly hired sales agents and seasoned workers.

heterogeneous effects based on partner rotation, experience, and worker characteristics. In the experimental design, half of the subjects in each treatment were randomly assigned to rotate partners each week, allowing us, in principle, to identify whether exposure to multiple partners or repeated interactions with a single partner differentially affects sales.[11] Borrowing from the machine learning literature, we estimate heterogeneous treatment effects based on individual and partner characteristics, using a LASSO approach for variable selection. Sales agents randomly paired with a star partner are found to have the largest post-treatment gains from the *Structured-Meetings* and *Combined* treatments, even after penalizing the model to avoid overfitting. Highly tenured workers have somewhat smaller gains from these treatments.

Our work connects the large literature on the effectiveness of specific management practices (Bloom and Van Reenen, 2011) with "social learning" (Conley and Udry, 2010; Hanna et al., 2014), showing how different organizational policies may overcome widespread social costs that limit information sharing (Bursztyn and Jensen, 2017). These results have obvious connections to the substantial literature on peer effects and mentoring in the workplace (Lyle and Smith, 2014; Lazear et al., 2015) but also relate to the challenges for policymakers to design institutions that facilitate peer spillovers (Garlick, 2014; Carrell et al., 2013).[12]

Our findings suggest that individuals stand to gain significantly from peer-knowledge transmission, but they often fail to do so because of frictions that prevent them from asking for information. Organizational policies can help overcome these frictions. In our setting, simple yet deliberate interventions bred knowledge exchange between individuals by breaking down barriers to productive interactions. For university departments, this means that encouraging professors and students to get coffee together might be enough to unlock otherwise unrealized knowledge spillovers (Catalini, 2017; Cai and Szeidl, 2017; Hasan and Koning,

[11] We find that partner rotations mattered little, relative to baseline effects.

[12] Most of the literature on peer effects largely focuses on settings with significant group-level components, including effort externalities (Mas and Moretti, 2009), production coordination (Friebel et al., 2017), internal competition (Chan et al., 2014), and social spillovers associated with choosing one's coworkers (Bandiera et al., 2005, 2013). The peer knowledge flows that we induced yield measurable value despite the lack of production interdependencies (workers sell autonomously).

2017; Boudreau et al., 2017). For firms, these results may help explain the relatively limited takeup of the gig economy or remote hiring (Katz and Krueger, 2019), because spillovers from co-workers are important even for individual work. We conclude that within firms, organizational practices may unlock the same benefits from personal interactions that have been documented in cities and other contexts with spillovers.

2 Experimental Setting

2.1 The Study Firm and Performance Metrics

The experiment took place in an inbound-sales call center from July to August of 2017, with subsequent data collection for an additional 20 weeks after the conclusion of the experiment. At the time of the experiment, the firm employed over 730 salespeople across three geographically separate offices.[13] It contracts with television, phone, and internet providers to market and sell their services. Sales agents are tasked with answering inbound calls from potential customers, determining customer needs, and explaining the benefits of premium service packages (up-selling) when appropriate. Such third-party sales contracting is common in the United States, especially for nationwide service providers. The sales department of the firm consists of six large divisions and several smaller divisions. Divisions are headed by one or two division presidents and are uniquely characterized by the bundles of products, services, and brands offered for sale.[14] Divisions are comprised of multiple subgroups consisting of approximately 10 to 15 sales agents led by a single manager.

The firm collects detailed metrics about a variety of activities. Sales agents spend over 80% of their workday on the phone or waiting to field a call, and the data contain agents' *Adherence* measures, which track their ability to take calls as well as the actual time spent

[13]The two offices involved in the experiment are within 50 miles of one another, whereas the third office is located over 600 miles away.

[14]For example, one division might only sell internet packages from provider A, while another might sell internet packages from provider B *and* satellite television packages.

talking to customers. When not receiving phone calls, salespeople participate in group- and division-wide meetings as well as in one-on-one discussions with managers. Most agents, 87%, work full-time.[15] The sales floor is predominately male, 68%, and is relatively young, with an average age of 26. In a given week, the average agent takes 62 calls, approximately two calls for every hour available to answer the phone. To filter variation in the number of calls, the firm primarily focuses on revenue-per-call (RPC), which is based on each agent's sales per opportunity. The firm also collects data on revenue-per-hour (RPH) and total revenue-per-week (Revenue). Random assignment of calls to salespeople allows us to use these metrics to measure the effects of treatments on individual sales productivity.[16]

Salespeople are compensated in three ways. (1) They receive an hourly wage. The base wage starts at approximately 150% of minimum wage, with small hourly raises for every three months of tenure. Hourly wages are capped at approximately 200% of minimum wage. (2) They receive a weekly commission[17] based on multiple performance measures: the revenue they generate from sales (revenue-per-call is the primary driver of the commission rate, but it also depends on revenue-per-hour worked),[18] their selling efficiency relative to their peers, and the audited quality of their customer service. (3) They are eligible to receive bonuses from temporary promotional sales activities.

[15]The threshold for full-time employment at the firm is 32 hours per week. The maximum number of weekly hours observed in our data is 46.

[16]See Table 1 for additional detail about agent demographics and sales, split by eventual treatment assignment.

[17]The average (median) sales agent earns \$217.78 (\$185.45) per week in commissions.

[18]Partners pay the firm for every sale in accordance with pre-negotiated schedules—some of which vary with the total number of products or services sold by the firm. To insulate the sales agents from the uncertainty surrounding aggregate sales and periodic contractual negotiations, the firm posts relatively fixed "transfer prices" that form the base revenue upon which agents are paid commissions. All use of the term "revenues" in this paper refers to sales priced in accordance with the internal transfer price schedule.

2.2 Training, Development Practices, and Productivity Dispersion

When hired, salespeople are enrolled in a formal two-week, on-site sales training regimen. Throughout training, agents receive information largely through lectures and by listening in on other agents' phone calls. Trainees then spend up to four weeks in a hands-on training program, taking calls under the supervision of a temporary training manager. The training manager oversees all agents as they learn to sell effectively, both by familiarizing them with the process of selling and by educating them on the products being sold. Once trainees reach a threshold level of revenues, they join a permanent group on the sales floor, where they continue to sell the same products and services on which they were trained. Agents who fail to reach the threshold levels of performance within a designated number of weeks after training are usually let go. After training, salespeople report that their primary point of contact for solving problems is their direct sales manager.

There is substantial dispersion in sales among the agents. Using data from the four weeks preceding treatment, we estimate the overall dispersion in residual sales, after controlling for time-by-sales division fixed effects. We decompose this variation further to extract agent fixed effects, which proxy for skill differences.[19] Figure 1 shows that differences across agents explain a significant fraction of the total variation in sales. The interquartile range of log revenue-per-call (RPC) residuals, due to agent effects, suggests that, on a random call, an agent at the 75th percentile of the fixed effects distribution generates about 52 log points (70%) more revenue than an agent at the 25th percentile.[20]

In survey questions designed to assess why agents believe that top performers have higher sales than other agents, 32% of respondents attribute these agents' success to their superior

[19] We shrink the fixed effects to reduce the influence of sampling error using the procedure of Lazear et al. (2015).

[20] The agent fixed effects, as reported, capture experience effects and cross-sectional skill or knowledge differences. We explore the extent to which this dispersion changes with tenure by zooming in on highly tenured agents. The productivity dispersion remains significant for agents with greater than 38 weeks of tenure (the median). For these experienced agents, the interquartile range of their fixed effects is about 40 log points. Firm-specific experience reduces some of the productivity gap but much remains.

ability to learn and respond to the customers' needs. Similarly, 29% of respondents attribute success to a better sales process—knowing when to suggest products, how to overcome objections, and how to use the computer system. A further 29% of respondents report that superior product knowledge gives top performers an edge. All of these factors point to differences in knowledge and skill being the main drivers of the observed dispersion in sales productivity.

2.3 Pre-Experiment Collaboration Among Agents

At first glance, two features of the environment potentially reduce agent collaboration. First, peer-learning requires inter-agent communication; yet any time away from the phone results in fewer revenue generating opportunities for an agent, which directly decreases their pay (total commissions). However, our observations of agent behavior and the data suggest that there is substantial downtime between calls. The average agent spends about half of his or her work time on the phone with customers; the lag between calls is somewhat predictable, and agents often talk to co-workers between calls. Second, agents' commission rates—i.e., the fraction of their earned revenue paid out as commission—is a weakly decreasing function of their co-workers' success. However, the probability that providing help to a coworker meaningfully shifts one's own compensation is small.[21] Still, we did not observe significant knowledge sharing between salespeople prior to the experiment.

[21] Commission rates are bucketed into four to five coarse categories that depend on relative performance on revenue-per-call and revenue-per-hour. For the same level of sales revenue, moving from the bottom bucket to the top bucket, changes take-home commissions by about 10 percent. Employees are fully aware of the incentive structure, but pre-experiment interviews suggested that employees would be willing to collaborate with others if encouraged to do so. This is likely because the probability of changing categories after helping one other person is small. In particular, agents described these categories as if they were relatively fixed.

3 Experimental Design

The design was pre-registered before beginning the experiment.[22] All agents in the six largest sales divisions working in the firm's two largest offices were eligible for treatment, resulting in 653 workers assigned to a treatment cell. Workers in the third location, 83, were not eligible for assignment to a treatment group, constituting a hold-out control group.[23] Because there is minimal interaction between workers at different locations and because the hold-out location is geographically distant, workers at the third location were unaware of the experiment.

All agents assigned to a treatment cell received four common changes. First, all agents were randomly paired with a single partner each week. Second, pairs were randomly designated as stable-pairs or rotating-pairs, such that roughly half of all agents had a single partner throughout the entire four-week intervention and the other half were randomly paired with a new partner each week (repeat assignments permitted).[24] Third, all pairs had joint performance scores, tracking pair-gains in RPC during the experiment, published daily on TV monitors and on their internal messaging platform. This joint performance score normalized the *change* in the pair's average revenue-per-call (RPC), relative to their RPC in the four weeks immediately preceding the pre-treatment period, allowing for inter-divisional comparisons.[25] Finally, all agents in these four cells were notified that their and their partners'

[22]The RCT registry number is AEARCTR-0002332. The IRB approval at the University of Utah is IRB 00098156.

[23]As noted in the introduction, there are three more workers than what was logged in the pre-registration. The third location was not pre-registered, because we did not have the ability to interact with these agents. The pre-registration was based on having 44 sales managers. We had an accurate forecast of the number of sales agents during our planning period, but the number of manager clusters increased slightly from what was anticipated, due to new managers being added and the replacement of some managers. In our final sample for the two main locations, we observe 52 different managers during the pre-treatment and treatment periods and 54 managers over the entire sample period.

[24]As new agents entered the sample (e.g., newly trained agents or agents moving in from other divisions), they too were randomly paired with a coworker and the pair was randomly designated to remain unchanged or to be repaired in subsequent weeks. Some pairs were dissolved as one or both agents left the sample (e.g., termination of employment, moved to a different division, took a leave of absence, etc.); the partners of these departing agents were paired with a new randomly chosen partner.

[25]Management advised us to avoid displaying negative scores. Hence scores were normalized around 100, where 100 reflected pre-treatment productivity levels. Employees who joined the sales floor during the treatment period were tagged with the median pre-treatment RPC.

individual productivity was being shared with a team of university researchers.

The experiment was a clustered design, with agents allocated into one of the four cells in Figure A based on the identity of their sales manager. This ensured overlap in the sales tasks and minimized spillovers across treatments.

	No Meetings Prompted	Meetings Prompted
No Pair Incentives	*Internal Control* Group	*Structured-Meetings* Treatment
Pair Incentives	*Pair-Incentives* Treatment	*Combined* Treatment

Figure A: Treatment Assignment Matrix for Agents in Active-Treatment Eligible Locations

Each treatment cell was designed to target different frictions to knowledge exchange. In particular, the *Structured-Meetings* treatment lowered the initiation costs facing knowledge seekers, the *Pair-Incentives* treatment targeted knowledge providers' potential contracting costs, and the *Combined* treatment explored whether both frictions jointly limit knowledge transfers. We refer the interested reader to Appendix A.1 where we provide a parsimonious model of knowledge transfers, frictions, and treatments.

3.1 Structured-Meetings Treatment

Pairs in the *Structured-Meetings* treatment were encouraged to complete the following tasks: (1) fill out an individual self-reflective worksheet to prompt discussion prior to meeting with their partner,[26] (2) converse with their partner and record their partner's self-reflective responses on the backside of their own worksheet, and (3) return completed worksheets to management by Wednesday each week. Completion of these tasks was optional but motivated by the receipt of a free catered lunch on Wednesday or Thursday of the same week. During this lunch, agent-pairs were provided with high-end, local sandwiches[27] and were asked to

[26]Example question: "Think about the least successful sales call you've had in the last week. How could you have done better?" These worksheets were (ex-ante) viewed as a necessary step to make the ensuing conversations more salient; points of emphasis on the worksheets were sourced from the firm's leadership to maximize the expected gains from focusing agents' attention. Documentation of this worksheet can be found in Appendix B.

[27]Price for the sandwiches was about $7.

discuss several points related to the worksheets.[28]

Note that, while the *Structured-Meetings* treatment was largely self-guided, agents were provided with directions to focus their conversations. The distinction is important because, relative to the *Pair-Incentives* treatment discussed below, the *Structured-Meetings* treatment directly targeted initiation costs through nontrivial managerial attention; e.g., creating the worksheets, coordinating and administrating lunch, etc.

3.2 Pair-Incentives Treatment

Agents in the *Pair-Incentives* treatment were given an incentive valued at approximately $50 per person to increase their joint production. Agent-pairs' probability of achieving the incentive was a function of their joint percentage increase in RPC, relative to a pre-treatment baseline. This ensured agents were not disadvantaged by being randomly paired with a less productive partner. Further details are provided in Sections 4.5 and 4.7.

To operationalize this incentive, we followed the related literature to properly distribute the bonus. Specifically, pairs were bracketed with two other randomly chosen pairs, and the pair with the highest percent increase in joint RPC was awarded the weekly prize. To discourage agent-pairs from giving up, we did not tell pairs whom they were paired with until a random drawing at the end of the work week. We created new groups of pairs each week. We find no evidence that agent-pairs gave up or that losing in one week had a negative impact in subsequent weeks. To increase the salience of the incentive, we followed the suggestion of management and used prizes such as golf vouchers, on-site massages, and tickets to other extra-curricular activities. These prizes had the advantage of immediacy—allowing us to deliver the prizes every week instead of making agents wait two weeks to receive the bonus in a pay check. In surveys, agents reported an average valuation for prizes of $40, which equates to an 18% (22%) increase in weekly commission pay for the average (median) agent. The expected prize values were equal to over 8% of the median agent's take-home pay.

[28]Documentation of these talking-points can also be found in Appendix B.

Far weaker group incentives have been found to generate meaningful productivity increases, albeit in a setting with complementarity among workers (Friebel et al., 2017).

While agents in the *Pair-incentives* treatment were not explicitly encouraged to transfer knowledge with their partners, they were free (and able) to do so.

3.3 Combined Treatment

Pairs in the *Combined* treatment were given both the *Structured-Meetings* and *Pair-Incentives* treatments exactly as they were administered separately.[29]

3.4 Control Groups

Agents in the *Internal Control* group were assigned a partner and the pair had their joint change in productivity score published publicly (as with all pairs), but they did not receive worksheets or guided directions to meet. When designing the experiment, we expected rank incentives to be minimal, but the design does, in principle, allow us to test for the effect of rank incentives.[30] The *External Control* group, or hold-out group, allows a comparison of each of these cells, relative to agents with no pairings, no knowledge of the experiment, nor any prompts to collaborate. In practice, trends in the *Internal Control* group tracked those in the *External Control* group throughout the experimental period.

3.5 Allocation of Agents to Treatments and Implementation Procedures

Figure B, located at the end of the section, illustrates the allocation of agents to treatments and provides descriptions of the treatments. Table 1 describes the demographics and pre-

[29]Their bonus eligibility was only defined based on other groups in the *Combined* treatment.

[30]While other studies have found that the introduction of public rank data (sometimes called rank incentives) may cause deviations from prior productivity (e.g. Bandiera et al. (2013)), rank incentives for individual agents were already present at this firm, because commission rates partially depend on relative—albeit private—comparisons of agents. According to the contingency results of Blader et al. (2016), rank displays comported with prior practices and therefore may have had minimal effects, relative to the baseline.

treatment performance of the participating sales agents. All treatment group characteristics and performance averages in the pre-treatment period are *not* statistically different from one another in these four cells (see the p-values column).[31] The agents in the three treatment groups are relatively similar to each other and to those in the *Internal Control* group. Agents in the *External Control* group are, on average, less productive. We test for, and find, common pre-period trends in productivity between the agents assigned to different treatment arms and agents in the *External Control* group, giving rise to a difference-in-differences estimator.

Appendix A.2 describes communication of the experiment and further implementation procedures.

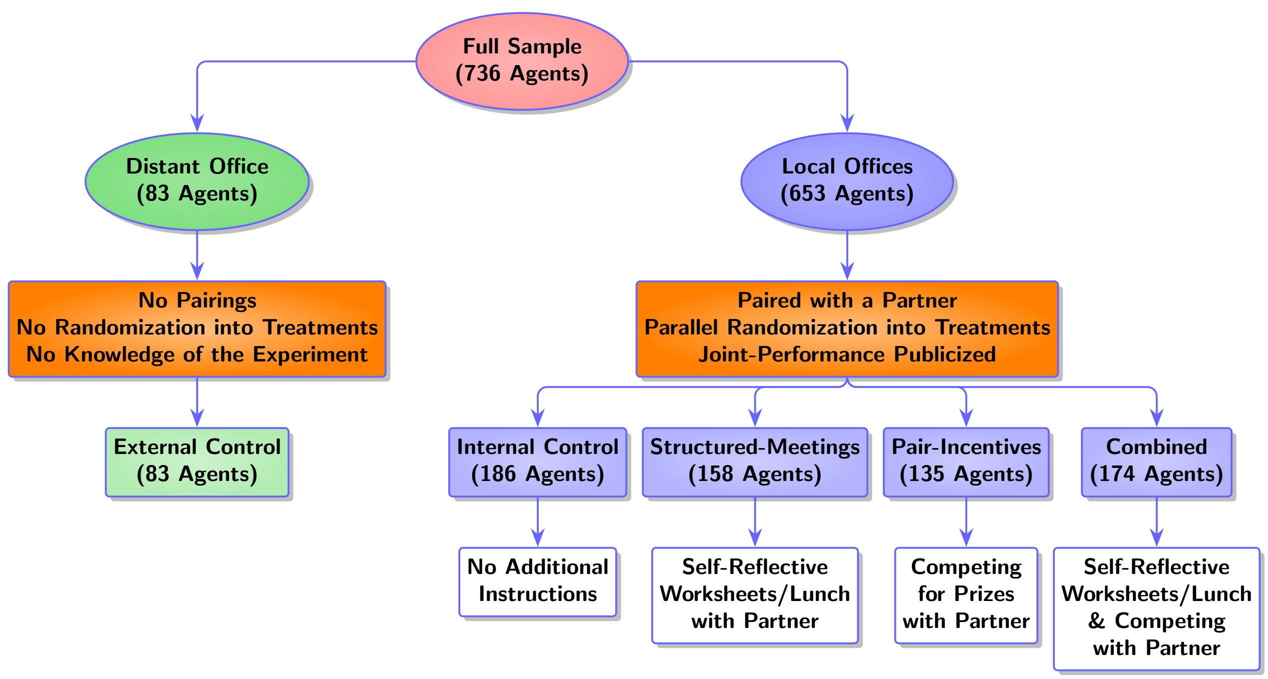

Figure B: Allocation of Agents to Treatments and Treatment Descriptions

[31]P-values of randomization tests of mean differences in the *Internal Control* and active treatment columns are reported. These tests are computed as the joint-hypothesis test of equality of treatment groups from a regression of the variable of interest on treatment assignment dummies after clustering standard errors based on manager identity (the level of assignment).

4 Results

We develop a formal model in Appendix A.1, where agents combine effort and knowledge to generate revenue. The model allows for knowledge to flow freely between paired agents provided the two have made sufficiently large, relationship-specific investments ahead of time. Hindering such flows are initiation and contracting costs, though the magnitude of these costs and who bears them are empirical questions that the experimental results help to uncover.

We first present the results by comparing simple averages in the firm's main performance measure, revenue-per-call (RPC), across treatment groups.[32] Subsequent difference-in-differences estimations, comparing the pre-treatment and later periods, reinforce the findings obtained using simple unconditional means. We also consider how the treatments affected revenue-per-hour (RPH), revenue-per-agent-week (Revenue), and worker turnover.[33] Revenue-per-hour, revenue-per-agent-week, and turnover measures jointly capture the possibility that the firm realized other distortions or benefits from the treatments. Analyses of these other measures in Section 5.2 yield similar conclusions to the baseline results focusing on revenue-per-call.

Panel A of Figure 2 shows that during the treatment period, revenue-per-call is greater in all three treatment groups, relative to the control groups. Later regression-based analyses present standard errors confirming that differences are precisely estimated.[34] Beginning with a pre-treatment baseline of \$61, RPC climbed by \$11 (17%) for agents in the *Pair-Incentives* treatment, whereas the *Structured-Meetings* and *Combined* treatments yielded

[32]The RPC measure also aligns revenue with per-call customer acquisition costs used internally for accounting purposes. The firm did not change its customer acquisition strategy at any point throughout the entire 28-week data collection window. Therefore relative RPC increases among treated agents represents incremental profits, net of treatment costs (discussed below).

[33]Revenue-per-hour aligns revenue with the labor cost of staffing agents, while total revenue accounts for changes in hours worked or hours off the phone.

[34]Figure 2 displays RPC (normalized to the grand-mean in the pre-treatment period) by treatment group in the four-week pre-treatment period and the four-week treatment period. The normalization is to present a consistent scale for comparison of trends in Panel B of Figure 2. Table 1 presents the non-normalized, average log RPC for each group in the pre-treatment period.

a revenue increase of \$15 (23%). Performance stayed relatively constant for agents in the control groups. Panel B of Figure 2 shows RPC by week for each treatment group. Positive effects are present for all three active treatments in week one, the first week of treatment, and these effects increase for the *Structured-Meetings* and *Combined* treatments throughout the treatment period. The effect dissipates somewhat but remains positive over the four weeks of treatment for the *Pair-Incentives* group. Although active interventions ended after week four, RPC remained elevated for agents in the *Structured-Meetings* and *Combined* treatments, whereas it quickly collapsed to the control mean for agents in the *Pair-Incentives* treatment.[35]

The persistent increases in the *Structured-Meetings* and *Combined* groups, along with the collapse in sales after week four for agents in the *Pair-Incentives* group, suggest that the sales gains observed during the treatment were achieved through different channels. The persistent gains realized by agents in the *Structured-Meetings* and *Combined* treatments suggest that agents who were instructed to exchange job-specific tips with their partner increased their human capital. Agents in the *Pair-Incentives* treatment, on the other hand, likely increased sales through transitory increases in effort. Figure 3 zooms out, plotting average RPC for each treatment group throughout the entire sample period (over 28 weeks of data). Sales gains in the *Structured-Meetings* and *Combined* treatments are long-lasting. We subsequently provide evidence in favor of a knowledge exchange interpretation by showing that agents matched with above-median partners had the largest persistent sales gains.

4.1 Productivity During the Treatment Period

Table 2 presents difference-in-differences regressions of log RPC on treatment group indicators interacted with indicators for the *Treatment-Period*, allowing for formal statistical tests

[35] Figure 2 also demonstrates parallel trends before the experiment, enabling subsequent analysis with a difference-in-differences estimator. The figure also highlights that neither the *Internal* nor *External Control* groups reacted to the onset of the active treatments.

of differences between treatments.[36] The sample contains the four weeks of data in the pre-treatment period and the four weeks of data concurrent with treatments. The estimating equation is:

$$\begin{aligned}\log(\text{RPC})_{i,t} =& \beta_0 + \beta_1 \text{Structured-Meetings}_i \text{ x Treatment-Period}_t \\ &+ \beta_2 \text{Pair-Incentives}_i \text{ x Treatment-Period}_t \\ &+ \beta_3 \text{Combined}_i \text{ x Treatment-Period}_t + \lambda_t + \theta_g + \varepsilon_{i,t},\end{aligned} \tag{1}$$

where i represents an agent, t represents a week, g represents sales manager group, λ_t and θ_g are week and sales manager fixed effects, respectively, and $\varepsilon_{i,t}$ is an idiosyncratic error term. The variables *Structured-Meetings x Treatment-Period*, *Pair-Incentives x Treatment-Period*, and *Combined x Treatment-Period* are set to one during weeks one through four (the treatment period) for those agents randomly assigned to the treatment and to zero otherwise. The level effects of each treatment are subsumed by the sales manager fixed effects, because all agents reporting to a sales manager are assigned to the same treatment.[37] Week fixed effects remove common time shocks that affect all treatments. Specifications in Columns (1) to (3) are relative to the *Internal Control*; Column (4) replaces the *Internal Control* group with the *External Control* as the baseline; Column (5) includes the *Internal Control* and tests for changes in the *Internal Control*, relative to the *External Control*.

Consistent with the graphical results, the estimates indicate that the active treatments resulted in large increases in average sales. Table 2 shows that agents in the *Structured-Meetings* treatment increased sales by about 24%, relative to either control group. Agents who were in the *Pair-Incentives* treatment increased performance by about 13%–14%. The difference between the sales gains in the *Structured-Meetings* and *Pair-Incentives* treatments

[36] Table A.2 reports similar results, using log revenue-per-hour and total revenue per week as dependent variables. Across different measures, results are similar.

[37] The standard errors are clustered at the sales manager level to allow for arbitrary correlation within a sales manager group, due to the clustered assignment rule. Standard errors are clustered at the sales manager group level in all subsequent specifications, and, for brevity, we do not continue to reiterate this in the text.

is statistically significant, as indicated by the p-value from the Wald test of equality in the penultimate row. As expected in a randomized experiment, the addition of agent or partner demographic controls across these columns minimally changes the estimates. Furthermore, the results are invariant to the choice of control group.

An important result from Column (5) is that the *Internal Control* group (with agents in the same locations as the active treatments, who had an assigned partner, and who had their sales gains published) performed similarly to the (off-site) *External Control* group that was unaware of the experiment. Agents in the *Internal Control* were aware of the experiment (see Appendix Table A.1, Panel B) but did not change their sales. The sales increases in the active treatments are thus unlikely to be driven by Hawthorne effects or by the publication of agents' paired productivity scores. Merely displaying performance information was not sufficient to improve sales, likely because most agents were aware of their place in the sales distribution already (see Appendix Figure A.3).

The larger gains from the *Structured-Meetings* and *Combined* treatments underscore the value of deliberately guiding agents to interact. Agents complied with this guidance, as over 80% of the agents in the *Structured-Meetings* and *Combined* treatments completed the worksheets used to direct conversations with their partner (see Appendix Table A.1).[38] The additional incentives provided in the *Pair-Incentives* treatment did not deliberately target meetings, and we have little evidence to suggest that these agents met with their partners.

For the firm, the sales increases through structured meetings were less costly than those arising from *Pair-Incentives*. The variable cost of the *Structured-Meetings* treatment was simply the $7 catered lunch ($14 total) for the agent-pairs who complied. In comparison, the *Pair-Incentives* treatment relied on prizes costing approximately $50, which were awarded to a third of the participating agents. Thus the cost per six agents was $42 in the *Structured-Meetings* treatment and $100 in the *Pair-Incentives* treatment. Nonetheless, the *Structured-*

[38]However, we avoid inferences based on the text of the worksheets. Partner pairs who filled out sparse worksheets were frequently observed to have meaningful conversations and follow-up interactions after their initial meetings. The worksheets served as a prompt rather than a complete record of information exchange. Later we do discuss content from the worksheets, recognizing that reporting is incomplete.

Meetings treatment induced sales gains that were 10 percentage points higher than the *Pair-Incentives* treatment, while costing only 40% as much.[39]

These results and those from Figures 2 and 3 provide several insights. First, the performance increase among agents in the *Pairs-Incentives* treatment is consistent with previous findings on the effectiveness of group-based incentives to increase effort (Friebel et al., 2017; Bandiera et al., 2013). Second, the *Structured-Meetings* intervention, meant to reduce initiation costs, resulted in larger productivity increases than the *Pair-Incentives* treatment alone. Third, the estimated treatment effects are not due to differential turnover (discussed in Section 5.2.2) and are robust to the inclusion of agent fixed effects (Table A.2). Fourth, and finally, the persistent gains among agents in the *Structured-Meetings* and *Combined* treatments suggest knowledge flows occurred between partners.

4.2 Persistence of Productivity Gains in the Post-Treatment Period

Figures 2 and 3 show that the gains observed during the treatment period for agents in the *Pair-Incentives* treatment collapsed once the treatment period ended. Yet agents in the *Structured-Meetings* and *Combined* treatments saw persistent sales gains. Persistent gains are possible indicators of agent learning and knowledge transfer. Turning to the formal statistical results, we examine the persistence of the observed sales gains, using data from the four-week pre-treatment period and the post-treatment period between weeks five and 24. The model compares the entire post-treatment period with the pre-treatment period.

[39] A different back-of-the-envelope calculation estimates the value that the incentives in the *Pair-Incentives* treatment would have to be to induce the same productivity increase as the *Structured-Meetings* treatment if the treatment effect was linear. Accordingly, if a \$50 incentive resulted in a 14% increase in RPC, relative to the control group, then to achieve the same 24% increase realized by agents in the *Structured-Meetings* treatment, the incentives would have to be approximately $\$86 \approx (.24 \times \$50)/.14$ per agent. We postpone a full return-on-investment discussion to section 5.5.

The estimating equation is:

$$
\begin{aligned}
\log(\text{RPC})_{i,t} \quad = \quad & \beta_0 + \beta_1 \text{Structured-Meetings}_i \text{ x Post-Period}_t \qquad (2) \\
& + \beta_2 \text{Pair-Incentives}_i \text{ x Post-Period}_t + \beta_3 \text{Combined}_i \text{ x Post-Period}_t \\
& + \lambda_t + \theta_g + \varepsilon_{i,t},
\end{aligned}
$$

where each of the treatment indicators equals one in the post-treatment period for agents originally assigned to that treatment cell and zero otherwise. The specification mirrors that of Table 2, except we omit the treatment period and include the post-treatment period.

The results, reported in Table 3, are consistent with Figures 2 and 3. Specifically, agents in the *Structured-Meetings* treatment continue to have sales that remain over 17% higher than agents in either control group after the treatment period ends. This increase is precisely estimated. In contrast, agents in the *Pair-Incentives* treatment have changes in post-treatment sales that are indistinguishable from either control group. The *Pair-Incentives* treatment yielded increased effort during the treatment period, but the lack of persistent changes in sales suggests that reducing contracting costs did little to stimulate knowledge transfers. Finally, the *Combined* treatment had positive gains of about 20% after the treatment ended. In the *Combined* group, once the firm provided agents with the framework used in the *Structured-Meetings* treatment, the incentives *may* have reinforced learning, but effect sizes are not statistically distinguishable, relative to the estimates for *Structured-Meetings*. More detail about persistent gains over different post-treatment horizons is provided in Appendix Table A.3, which varies the number of weeks included in the post-treatment window.

That gains remain for at least 20 weeks may be surprising, given the relatively light-touch nature of the interventions. In line with the "insider econometrics" approach to assess the credibility of results (Bartel et al., 2004), subsequent interviews with a number of sales, operations, and HR executives at the firm reveal that managers believe the *Structured-Meetings* treatment provided a pathway for agents to continue asking questions and gaining knowledge from their partners, even after the formal meetings and lunches ceased.

4.3 Partner Quality and Knowledge Transfer

To further delineate learning from alternative channels, we leverage random agent pairings with star partners to assess how heterogeneity in partner quality affects treatment gains. For this analysis, we create a binary classification, sorting agents based on their sales productivity in the eight weeks preceding treatment. Agents are labelled "stars" if their productivity is above the median in the eight weeks prior to treatment for their sales division. We estimate how being paired with a star partner affects productivity in the different treatments. We also assess whether treatments and partner quality pairings differ as a function of an agent's own human capital, allowing us to recover the directional nature of who is gaining in a partner pairing.

The estimating equation is

$$\begin{aligned}\log(\text{RPC})_{i,t} \;=\;& \beta_0 + \beta_1\text{Structured-Meetings}_i \text{ x } \text{T}_t + \beta_2\text{Pair-Incentives}_i \text{ x } \text{T}_t \\ &+\beta_3\text{Combined}_i \text{ x } \text{T}_t + \gamma_1\text{Structured-Meetings}_i \text{ x } \text{T}_t \text{ x Star-Partner}_t \\ &+\gamma_2\text{Pair-Incentives}_i \text{ x } \text{T}_t \text{ x Star-Partner}_t + \gamma_3\text{Combined}_i \text{ x } \text{T}_t \text{ x Star-Partner}_t \\ &+\gamma_4\text{T}_t \text{ x Star-Partner}_t + \gamma_5\text{Ever-Star-Partner}_i + \lambda_t + \theta_g + \varepsilon_{i,t},\end{aligned} \tag{3}$$

where the variable T_t is interacted with treatments as a placeholder to indicate either the treatment period or the post-treatment period. The parameters of interest are γ_1, γ_2, and γ_3, comparing how star partners affect sales productivity in different treatments. The parameter γ_4 captures the baseline effect of having a star partner for agents in the *Internal Control* group. A further test of random assignment comes through γ_5, which is an indicator that the agent was ever paired with a star partner.

Table 4 shows that agents randomly paired with a star partner in the *Structured-Meetings* and *Combined* treatments were more productive in both the treatment and post-treatment periods, supporting our hypothesis of knowledge transfer.[40] Agents in the *Pair-Incentives* treatment did not perform differently when paired with a star partner. In the first three columns, star partners are defined based on the concurrent identity of the partner; i.e., the *Star Partner* dummy variable is applied to agent-weeks. Column (1) is the baseline specification, which includes the pre-experimental and treatment periods. While all active treatments show sales gains for agents with non-star partners, agents paired with a star partner increased sales by an additional 15% in the *Structured-Meetings* treatment and by an additional 14% in the *Combined* treatment.

Not all agents can be paired with star partners, but some assignment rules may fare better than others to realize aggregate gains. We ask whether the difference in being paired with a star partner depends on the identity of an agent. Columns (2) and (3) split the sample, based on whether the agent is himself or herself a star. Comparing these columns, all non-star agents in active treatments benefited, even when paired with non-star partners (baseline estimates in Column 2). When paired with a star partner, captured through the interaction terms in Column (2), non-star agents had additional positive gains in the *Structured-Meetings* and *Combined* treatments. When the agent in question is a star (Column 3), his or her sales only increased when the partner was also a star. Said another way, no treatment induced sales gains for star agents when they were paired with non-star partners. Importantly, stars themselves did not see a decrease in RPC during treatment, suggesting that the opportunity cost of helping others was not large. The direction of this result suggests that *star agents provided knowledge to non-stars, while stars only learned from other stars.*

Further evidence of knowledge transfer can be found in Column (4), which only examines the post-treatment period, relative to the pre-treatment period. In our post-treatment analysis, the star partner interaction equals one for an agent who was ever paired with a star partner. Past pairing with a star partner is responsible for most of the detectable sales

[40] In Section 4.5, we test for several heterogeneous effects, using a machine learning procedure for variable selection and regularization. The star partner effect survives and has the largest heterogeneous effect for explaining variation in sales within treatment groups that included structured meetings.

increases from the *Structured-Meetings* treatment in the post-treatment period. Taken together, these results further confirm knowledge transfer between more and less skilled agents. In Section 4.5, we analyze partner pairing in the post-treatment period in more detail and show that the largest persistent gains arose from non-star agents paired with star partners. This motivates an intermediate investigation of the consequences of each treatment over quantiles of the distribution of sales.

4.4 Changes in the Distribution of Sales after the Experiment

The evidence on who benefits from treatments suggests that the *Structured-Meetings* and *Combined* treatments disproportionately affected agents at the bottom of the distribution. Figure 6 confirms this by plotting how quantiles of the sales distribution change for different treatments. To construct the figure, we compute the log RPC for each treatment at 100 quantiles in the post-treatment period (weeks five through 24) and in the pre-treatment period. For each quantile, we then take the difference in post-treatment log RPC and pre-treatment log RPC. Quantiles one through 17 show substantial gains in sales through the post-treatment period in the *Structured-Meetings* and *Combined* treatments. Gains were smaller but remain positive across the remainder of the distribution for these treatments, suggesting that more productive agents either benefited (or at least were not harmed) from these interventions. Quantiles are little changed across the distribution of sales among agents in the *Pair-Incentives* treatment and the *Internal Control*.

4.5 Other Heterogeneous Responses

There are several potential heterogeneous responses, beyond the effect of partner pairings. For example, did older or longer tenured agents have different gains from structured meetings? Perhaps these agents forecast a greater likelihood of remaining with the firm, so they had already self-organized to realize the benefits of peer-learning. Perhaps gains are concentrated among new agents, who have yet to learn tips and tricks that come from being exposed to a variety of different calls. Or perhaps some agents are already well-connected within the firm, so they benefit less from our exogenously imposed connections.

To discipline our examination of heterogeneity, we employ a machine learning approach for variable selection and regularization that penalizes overfitting. In particular, the LASSO procedure that we use penalizes adding dimensions of heterogeneity (see Friedman et al. (2010)). We cross-validate the penalty term from the data, and this allows us to consider a large number of interactions for heterogeneous characteristics of agents or their partners in a difference-in-differences model between the post-treatment period and the pre-treatment period.

Table 5 reports the heterogeneous treatment effects after the LASSO, with some estimates set to zero. Most importantly, ever having a star partner provides the largest source of heterogeneous gains in the *Structured-Meetings* and *Combined* treatments. Long tenured agents have smaller gains from all treatments, whereas star agents have minimal baseline responses in the *Combined* treatment, which only increase if they have a star partner (taking the sum of the three interaction terms). One word of caution involves interpretation, as some interactive effects may be difficult to parse (like the inconsistent signs on age interactions in the *Structured-Meetings* and *Combined* treatments), due to the lack of orthogonality between characteristics like age and tenure. We thus focus on the fact that the star partner effects survive the LASSO, which is specifically designed to penalize overfitting or allowing too many heterogeneous characteristics. Also note that, due to random assignment of partners, the effect of ever having a star partner is easily interpretable, because it is orthogonal to all the other heterogeneous characteristics that we estimate (other than the interactions for agents who were re-paired weekly, which have a small effect in all specifications).

5 Discussion

While we find evidence that each treatment improved performance via different margins of adjustment, several questions remain. This section considers alternative explanations, provides evidence on the mechanism, and discusses to what extent our findings generalize.

5.1 Evidence on the Mechanism

5.1.1 Worksheet and Survey Responses

Agents in the *Structured-Meetings* and *Combined* treatments largely complied with the instructions to meet and fill out the worksheets, as over 80% of agents completed a worksheet every week (see Appendix Table A.1). But because agent-pairs also frequently met after their structured time, the worksheets contain an incomplete accounting of partner interactions. Still, the worksheets capture instances of specific knowledge being transferred between agents. For example, one agent shared with her partner that she could help customers overcome their initial skepticism by discussing two unique add-on features of the product. Another agent shared that her customer wanted a very specific but unavailable product mix; using product knowledge and techniques to pivot to different solutions, she explained the problem and sold the customer an alternative bundle of products. Many worksheets contained tips about the best time over the course of a call to inquire about the caller's credit qualifications or to offer details about pricing and promotions. The worksheets conveyed job-specific knowledge that could immediately be used by the agents' partners to better interact with customers.

Why was the intervention required to realize these gains? Survey results allow us to rule out agent skepticism over peer-learning and search costs. Specifically, agents themselves estimate positive treatment effects from asking others for help (see Figure A.2). Agents also know their relative standing, compared to top agents (see Figure A.3), and 93% of survey respondents can name three agents in the top 10% of the sales distribution for their division and location.

This and other evidence suggests that treatments with structured meetings helped agents overcome the social costs of peer-learning. In line with the findings of Chandrasekhar et al. (2016), where advice seeking is limited to a personal network, a sales agent in the *Structured-Meetings* treatment expressed her excitement to us when she learned that she had been paired with a very skilled coworker. Specifically, she said: "I would never have had the courage to approach him for help or advice. But since we are paired together for lunch, I get to learn from one of the best sales agents in the company!"

Proximity also appears to influence initiation costs, suggesting that some barriers to communication increase with physical distance. Survey responses show that, when asking peers for help, agents turn to those who sit nearby. Twenty-five percent of survey respondents report that "When I ask other agents for help, I always (100% of the time) look for someone seated beside me." Another 36% of agents report, "When I ask other agents for help, I usually (greater than 75% of the time) look for someone seated beside me." This tendency suggests that coordinating with non-proximate agents may limit conversations.

5.1.2 Partner Rotations and Worker Connections

Half of all agent-pairs were stable during the entire treatment period, while the other half rotated partners each week. We find small effects of weekly partner rotations on long-run sales, and the effects have inconsistent signs across treatments, relative to the control groups. These results are presented in Table 5. Given the effect sizes, our tests lack power to distinguish between the hypothesis that exposure to varied techniques is valuable, compared to the hypothesis that repeated exposure helps with the adoption of tips or provides an outlet for future discussions.

We also test whether agents who are better "connected" to their peers have different treatment effects. We estimate heterogeneous effects based on whether the agent in question has an above-median number of work-related conversations per week (5). The results on connectedness indicate that effects for these agents differ little from the baseline. Said differently, agents' social networks at the firm largely did not alter the effectiveness of treatments.

5.2 Alternative Explanations

5.2.1 Did Treatments Detract from Taking Calls?

There is no evidence to suggest that the treatments themselves left the agents with less time to accept calls. Anecdotally, the agents only allowed the treatments to impinge on their slack time. Agents have about 50% slack time, on average (approximately 20% of their time on the clock is built-in slack, and the rest is spent waiting for calls in a predictable queue). The data confirms that an increase in RPC did not mask a change in time spent selling. Appendix Table A.2 shows that the treatment effects are similar when looking at either log revenue-per-call, log revenue-per-hour, or weekly total revenue. Appendix Table A.2 also shows that the active treatments increased total revenue in levels.[41] Furthermore, Appendix Table A.5 shows that there was no discernible difference in adherence, defined as the time an agent is on the phone or in the queue divided by the time an agent *should* be on the phone or in the queue. Importantly, while we have no evidence to suggest that our treatments reduced agents' time on the phones, any disruption due to treatments was more than offset by increases in sales revenue.

5.2.2 Are Turnover Differences Responsible for the Results?

Adding agent fixed effects in Table A.2 allows a preliminary assessment of whether turnover differences drive the results. The similarity of the estimates suggests that the productivity gains are due to within-worker changes, rather than differential turnover of unproductive agents across the different treatments.

A more direct examination of turnover shows that the propensity for agents to leave the

[41] The total revenue figure must be imputed for the *External Control* group, due to reporting differences across establishments.

sample did not change for those in the *Structured-Meetings* or *Combined* treatments, relative to those in the *Pair-Incentives* treatment or *Internal Control* group. These results are in Appendix Table A.4. We focus on turnover among agents in the two offices that were aware of the experiment, as there are seasonal differences in staffing across locations.[42]

5.2.3 Did the Pair-Incentives Treatment Discourage Agents?

High-powered contests may induce some participants to forego effort provision (Brown, 2011). We observed no evidence from managers or agents to suggest that agents in either the *Pair-Incentives* or *Combined* treatments became discouraged.[43] To test for the possibility of withholding effort or quitting the contest, we assess how agents' performance responded to past wins or losses of incentives. Winners in the prior week did slightly less well than non-winners in the prior week (see Table A.6). This might be due to mean reversion after a win or possibly to income effects. The excluded category is past losers, so this evidence is inconsistent with agents quitting by means of reducing effort in response to competitive cues.

Another possibility is that some agents simply did not engage with the treatment. The *Pair-Incentives* treatment was designed to provide every agent-pair with equal opportunities to win by filtering pre-treatment productivity. That is, the contest rankings were based on gains, relative to pre-treatment performance. Star performers may find it more difficult to improve their own performance, but our pre-experiment discussions with management suggested this design would best encourage overall participation. If stars found it difficult to improve on their own, a more productive path would have been to help their partners.

[42]In particular, locations with active treatments relied more heavily on seasonal hiring and had (predictably) higher natural attrition during the post-treatment period as summer was ending. There are, however, no differences in turnover between active treatments and the *Internal Control* group.

[43]While agents were provided with daily updates of their pair's relative ranking, membership in each three-team contest was randomly determined ex-post.

5.3 The Mix of Management Practices: Complements or Substitutes?

Our experiment is also set up to test spillovers across treatments. Managerial practices may be more or less effective when paired with other practices (Athey and Stern, 1998; Ichniowski and Shaw, 2003). If practices are complements, they will have a larger impact when bundled than the sum of their individual treatment effects. In this case, the bundle is the optimal mix. If, on the other hand, managerial practices are substitutes, then the sum of the individual treatments is greater than the bundled effect.

We examine whether lowering initiation and contracting costs are complements or substitutes. During the treatment period, when these practices are active, we reject the null hypothesis that the *Combined* treatment effect is larger than the sum of the *Pair-Incentives* and *Structured-Meetings* treatment effects (reported in the last row of Table 2). Still, the bundled practices may be optimal, even when they are substitutes. Evaluating the difference in productivity between agents in the *Combined* treatment and those in the *Structured-Meetings* treatment at the point estimates, while recognizing the sampling variance associated with these estimates, yields that the *Combined* treatment was optimal for the firm. The *Combined* treatment increased productivity by about 1% per call, which would have resulted in about $40.00 per week in additional revenue for each agent. Given that the per-agent cost of the *Pair-Incentives* treatment was about $17 per week, the marginal gain from adding incentives appears to outweigh the incremental cost.

5.4 Comparing the Pair-Incentives Treatment to Estimates of Other Incentive Changes

Sandvik et al. (2018) analyze sales changes after two divisions of the firm reduced agents' effective incentive pay by altering the mapping between sales and commission-eligible revenue. The reduction occurred in the fall/winter of the prior year and was not concurrent with this experiment. Sandvik et al. (2018) primarily find effects on which sales agents leave the firm, while sales effort responses to commission reductions were muted.[44] The elasticity of effort with respect to incentive changes differs somewhat across the two studies. What may explain the differences? First, the pair incentives were transitory and avoided the income effects typically associated with permanent wage changes (Ashenfelter and Heckman, 1974). Second, Sandvik et al. (2018) focus on the limited long-run response to the commission reduction, whereas the effort response to the *Pair-Incentives* treatment is short-term (and begins to fade out during the treatment period).[45] Hence the parameters across the two papers capture different timeframes for effort adjustment. Finally, the *Pair-Incentives* treatment may have had a social component that increased the salience of the incentives, relative to individual incentive changes in Sandvik et al. (2018).

5.5 The Firm's Return on Investment

The economic significance of our findings was apparent to the firm. The firm previously relied exclusively on short-term, transitory changes to monetary incentives to influence agents' performance. Interviews with management suggested that, while these interventions generally led to short-term increases in productivity, all associated gains would evaporate as soon as the incentives were removed. Tests of other practices to influence performance, especially around knowledge sharing, had not been performed.

Using the estimated treatment effects, we find that the experiment resulted in significant additional revenue generation for the firm. Overall, sales increased during the treatment period by over $1 million. At the intervention level, we find that the *Structured-Meetings*

[44] Although the *Structured-Meetings* and *Combined* treatments raised agent earnings, the results on the turnover response to earnings changes across papers are not directly comparable. The earnings reductions in the prior paper came about because of a contractual change, rather than through a change in sales productivity. The increase in sales productivity from the experiment may have very different effects on the external market. In addition, the earnings gains are concentrated on a different part of the distribution; changes in turnover propensity in Sandvik et al. (2018) were concentrated among the most productive sales agents; here, the largest changes in earnings occur for non-star agents.

[45] Examining the short term responses in the Sandvik et al. (2018) data, we do observe a limited-term reduction in sales, but there is insufficient power to conclude that the short-run effect differs from zero.

treatment resulted in a return on investment (ROI) of over 530%, where the investment base was the cost of having catered meals delivered to the firms' campuses and the top-line value was the sales-margin multiplied by the extra revenue recorded exclusively during the treatment period. (All ROI details can be found in Appendix A.4.) We estimate the ROI from the *Pair-Incentives* treatment at approximately 61%, as the estimated profits therein outperformed the *Internal Control* group but the associated incentives were more costly—at least double those of the *Structured-Meetings* treatment. Finally, the *Combined* treatment had an estimated ROI of nearly 130%. This intervention was the most costly, as both lunches and additional incentives were provided, but these sales agents outperformed the control group by the largest margin; hence the relatively large ROI. We stress that the reported ROI values do not impound the persistent, relative revenue gains identified in the *Structured-Meetings* and *Combined* treatments. Doing so would cause the reported ROIs to increase further.

Taken together, the increased productivity resulting from our relatively low-cost interventions made the randomized control trial a success with management. Pursuant to sharing our results, management has prioritized supporting future randomized control trials for organizational design.

6 Conclusion

In many workplaces, output varies dramatically across individuals. Managers are quick to credit workplace interactions—and their effort to stimulate such interactions—as a driving force behind employee productivity. Careful examination surfaces a host of economic questions. In particular, which economic costs prevent workers from acquiring knowledge from coworkers in the absence of organizational practices to stimulate knowledge flows? Two theorized frictions are contracting difficulties and initiation costs, with the latter defined as barriers that prevent one from finding or asking for help. Contracting difficulties concern the lack of incentives for others to share information, and the extensive literature on team incentives illuminates this constraint (Bandiera et al., 2013; Friebel et al., 2017). Initiation costs are less studied inside firms, but several literatures suggest they may be important. In urban economics and the economics of innovation, distance is one such barrier to finding information (Glaeser and Gottlieb, 2009; Glaeser et al., 1992; Catalini, 2017); search costs are another (Boudreau et al., 2017). A newer literature studies the (micro) social frictions which may burden those seeking help (Chandrasekhar et al., 2016).

Within firms, little evidence exists on the role of management practices to overcome frictions and spark knowledge sharing. We ran a field experiment that randomly paired more than 650 call center sales agents and then assigned the pairs to treatments that addressed different frictions to knowledge flows. One treatment, *Structured-Meetings*, targeted initiation costs by guiding randomly paired workers to have targeted, work-related conversations. A second treatment, *Pair-Incentives*, targeted contracting frictions by tying partners' expected earnings together. A third treatment, *Combined*, simultaneously addressed both frictions.

Although all treatments raised individual sales relative to the control groups, workers in the *Structured-Meetings* treatment had persistent performance gains, while the performance gains from the *Pair-Incentives* treatment subsided at the end of the treatment period. A number of additional results suggest that the management-lead approach to breaking down initiation costs resulted in knowledge transfers from highly skilled workers to less skilled ones. These findings add to a small but growing set of studies showing that simple management interventions can dramatically raise productivity (Bloom and Van Reenen, 2011; Bloom et al., 2015b, 2013, 2015a; Jackson and Schneider, 2015; Haynes et al., 2009; Englmaier et al., 2018), while highlighting the role of social factors in the adoption of best practices (Shue, 2013).

While our setting provides a nearly ideal environment for measuring the effects of co-worker knowledge spillovers, lessons for practices that overcome impediments to knowledge flows are likely much more general (Chandrasekhar et al., 2016). In other settings, the gains from peer-learning will likely exceed those reported here when job roles involve non-zero collaboration. Many settings provide performance incentives and opportunities to interact with other individuals, such as classrooms, cities, or academic departments. A fruitful area of future research surrounds how to match individuals to maximize the likelihood of productive spillovers.

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7 Tables and Figures

Figure 1: **Dispersion in Residual log Revenue Per Call**

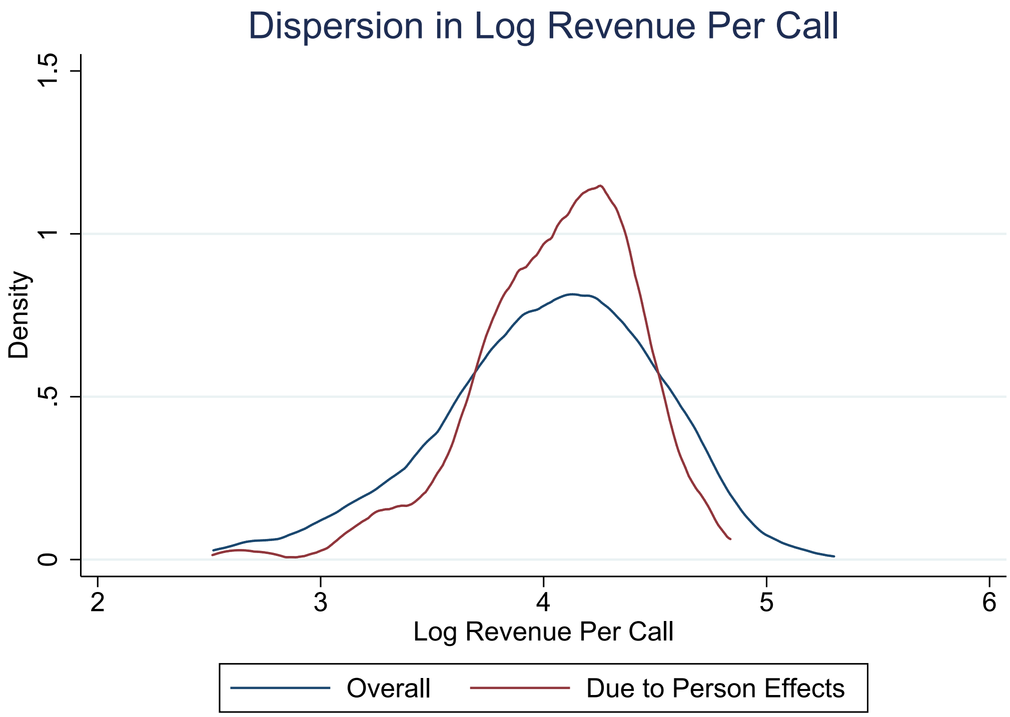
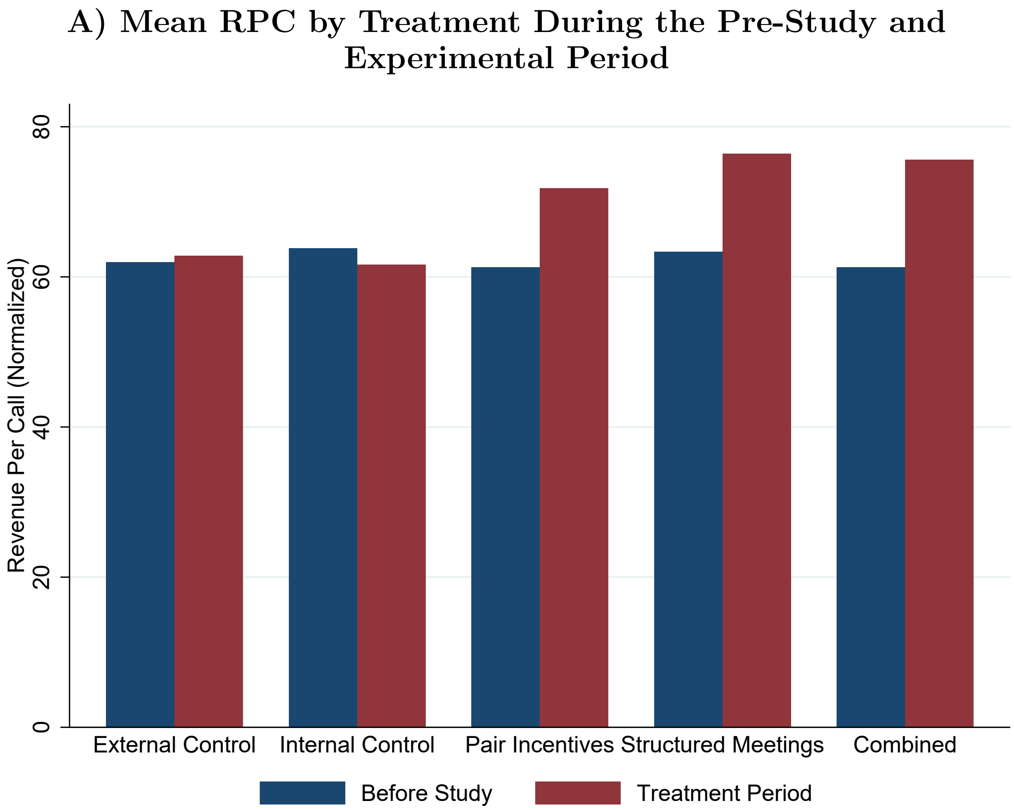
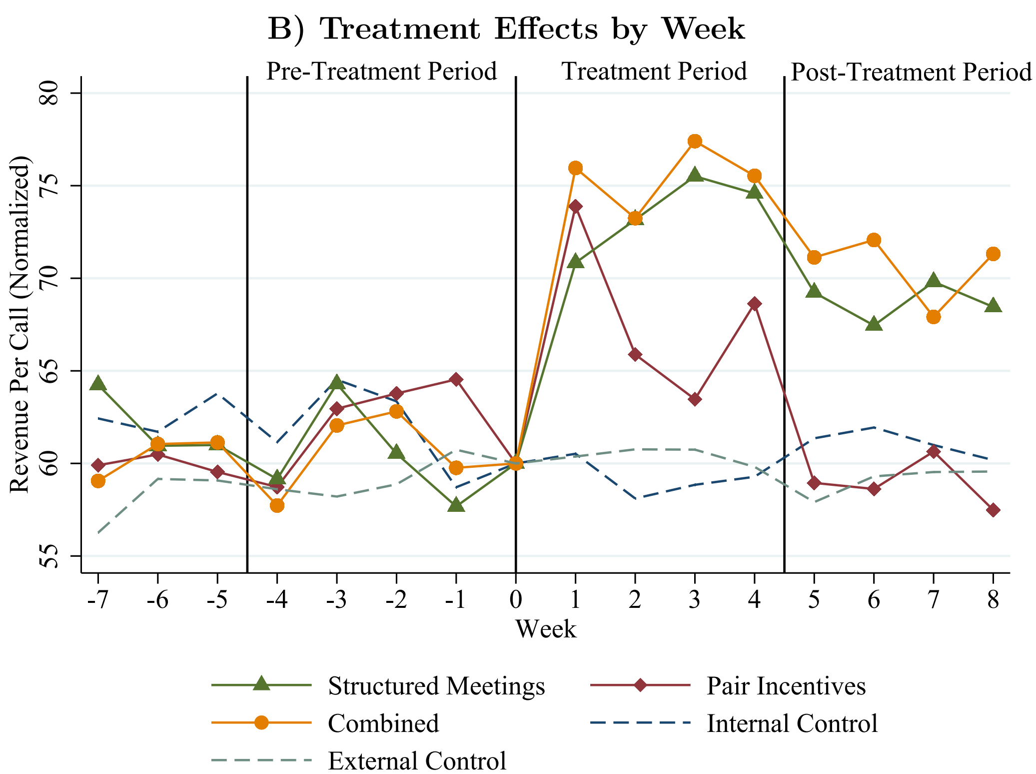


Figure displays overall residual log RPC and the component attributable to person fixed effects after applying the shrinkage procedure in Lazear et al. (2015). The residuals come from a regression using pre-experiment data and net out sales division, office location, and tenure with the firm. The interquartile range of residual log RPC attributable to person effects is 0.6.

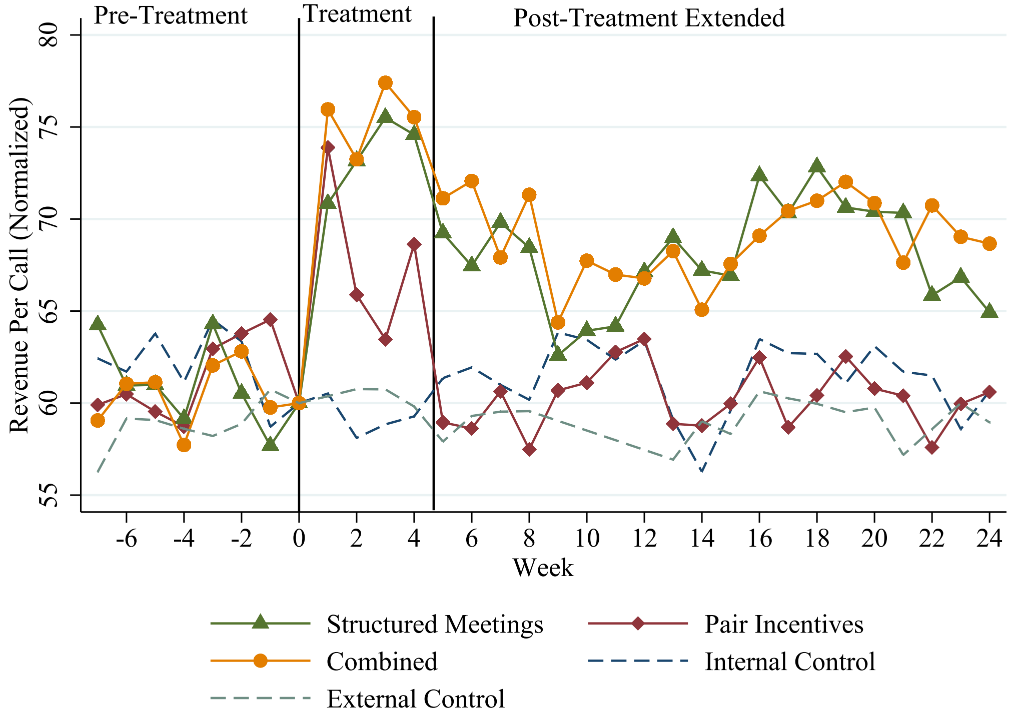
Figure 2: **Treatment Effects**





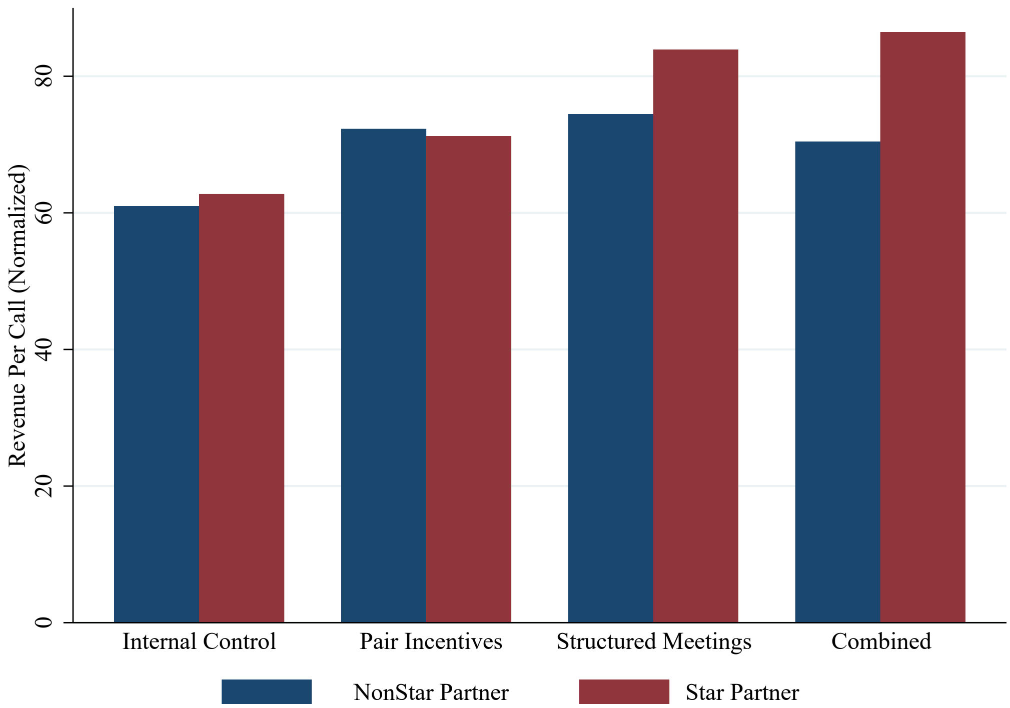
Average revenue-per-call (RPC) by week and treatment group. The external control is normalized to the grand-mean of RPC in week 0 for the other groups. The experimental intervention begins in week 1 and continues to week 4.

Figure 3: **Treatment Effects Over Entire Post Treatment Period**



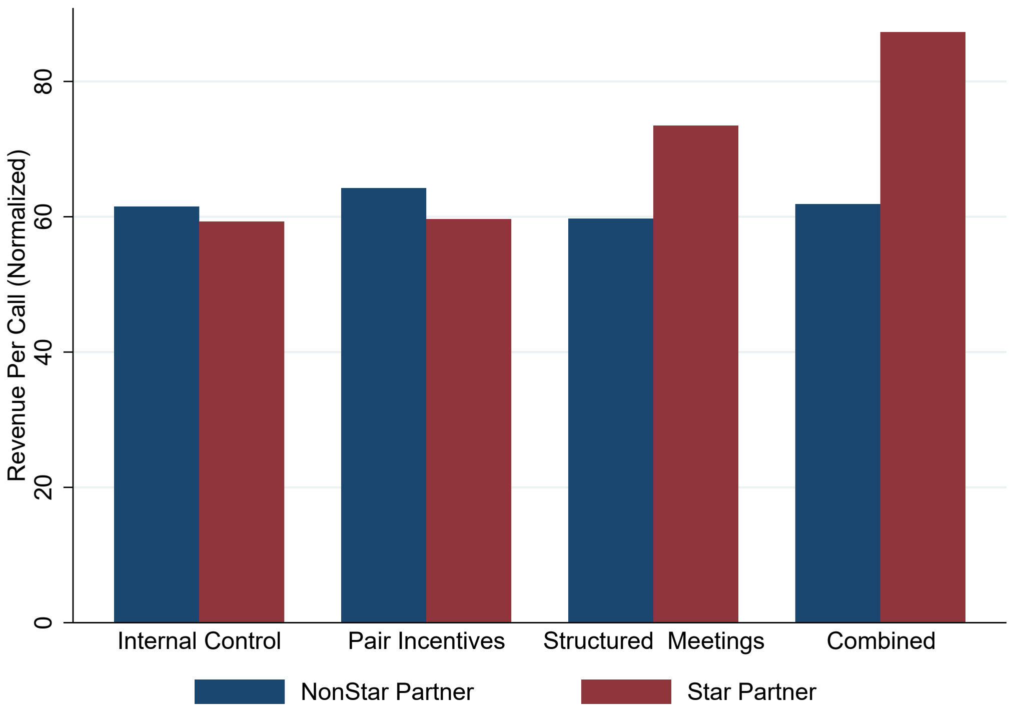
Average revenue-per-call (RPC) by week and treatment group. Each series is normalized to the grand-mean of RPC in week 0. The experimental intervention begins in week 1 and continues to week 4.

Figure 4: **Mean Productivity During the Experimental Period by Star Partner Assignment**



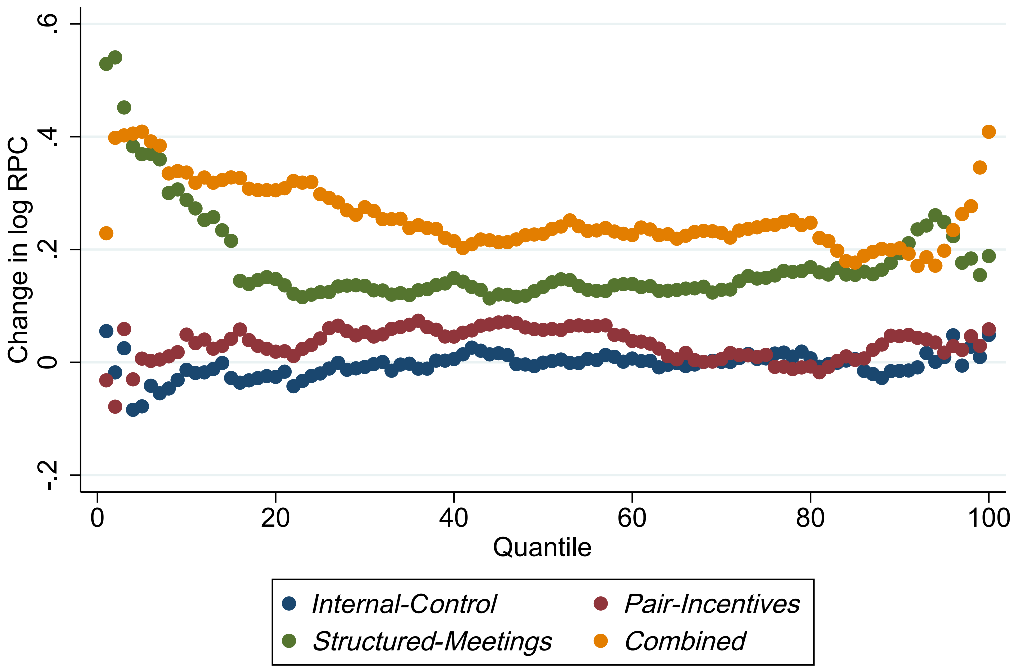
Average revenue-per-call (RPC) by treatment group during the treatment period based on whether the concurrent partner is a Star agent (defined as above median productivity in the pre-treatment period).

Figure 5: **Mean Productivity During the Post-Experimental Period by Star Partner Assignment**



Average revenue-per-call (RPC) by treatment group during the post-treatment period based on whether the agent was ever partnered with a Star (defined as above median productivity in the pre-treatment period).

Figure 6: **Log RPC Changes By Quantile Post-Experiment**



To construct this figure, we compute log RPC for 100 quantiles by treatment in the post-treatment period (weeks 5 through 24) and the pre-treatment period. For each quantile, we then take the difference in post-treatment log RPC and pre-treatment log RPC. The figure plots these differences at each quantile by treatment.

Table 1: **Agent Demographics and Sales Prior to the Experiment**

	Full Sample	Structured Meetings	Pair Incentives	Combined	Internal Control	External Control	P-Value
Age (yrs.)							
Mean	26.08	25.76	26.61	26.43	25.14	27.19	0.62
Median	23.39	22.51	23.55	24.02	22.97	24.63	
Std Dev.	8.14	8.20	9.61	8.10	6.66	8.41	
Tenure (log days)							
Mean	5.25	5.14	5.38	5.59	5.18	4.67	0.61
Median	5.15	4.62	5.40	5.37	4.62	5.18	
Std Dev.	1.18	1.12	1.07	1.10	1.22	1.24	
Percent Female							
Mean	0.32	0.32	0.31	0.33	0.34	0.25	0.95
Revenue per Call (log)							
Mean	3.92	3.90	4.06	3.94	3.92	3.62	0.69
Median	3.97	4.04	4.09	3.99	3.99	3.69	
Std Dev.	0.49	0.52	0.37	0.47	0.55	0.33	
Revenue per Hour (log)							
Mean	4.51	4.48	4.69	4.56	4.51	4.11	0.54
Median	4.62	4.64	4.78	4.65	4.63	4.18	
Std Dev.	0.60	0.69	0.45	0.59	0.59	0.46	
Commission							
Mean	217.78	202.65	230.41	230.64	202.31		0.75
Median	185.45	168.42	192.28	209.73	169.73		
Std Dev.	155.61	159.99	156.09	157.73	147.70		
Total Calls							
Mean	61.53	57.56	64.16	65.81	58.89		0.33
Median	60.43	57.22	62.41	65.29	58.63		
Std Dev.	21.32	19.16	22.02	20.81	22.43		
Phone Hours							
Mean	32.61	32.52	33.76	33.17	31.22		0.32
Median	34.05	34.08	34.77	33.33	33.75		
Std Dev.	7.36	7.01	6.09	6.74	8.95		
Adherence							
Mean	0.80	0.80	0.84	0.79	0.77		0.19
Median	0.83	0.83	0.85	0.83	0.82		
Std Dev.	0.14	0.11	0.07	0.14	0.21		
Attrition							
Turnover Rate	0.22	0.22	0.18	0.24	0.24		0.19
N Agents	736	158	135	174	186	83	

Notes. Sales agent demographic information (age, tenure with the firm, and gender) and performance measures are listed below for the full sample of agents, broken out by treatment group. Except for attrition, statistics for time-varying measures are derived from a four-week average immediately before the experiment began. A *Phone Hour* is a measure of time an agent is logged into the phone system, and *Adherence* is calculated as the sum of an agent's time available to receive a call and his time on calls, all divided by the total time he is logged into the phone system. *Attrition* is calculated as the number of agents that turnover during the pre-experimental period, treatment period, and post-treatment period divided by the total number of agents in that treatment. P-values of randomization tests of mean differences in the *Internal Control* and active treatment columns are reported. These tests are computed as the joint-hypothesis test of equality of treatment groups from a regression of the variable of interest on treatment assignment dummies after clustering standard errors based on manager identity (the level of assignment).

Table 2: **Difference-in-Differences Estimates of log Revenue-Per-Call Changes During the Treatment Period**

Control Group:	Internal (Passive Pairs)			External (No Pairs)	Both
	(1)	(2)	(3)	(4)	(5)
Structured-Meetings	0.241***	0.241***	0.241***	0.247***	0.244***
	(0.045)	(0.044)	(0.044)	(0.073)	(0.071)
Pair-Incentives	0.131***	0.136***	0.136***	0.124*	0.134*
	(0.048)	(0.047)	(0.047)	(0.071)	(0.071)
Combined	0.255***	0.258***	0.256***	0.259***	0.259***
	(0.043)	(0.044)	(0.044)	(0.069)	(0.069)
Internal Control					0.004
					(0.065)
Demographics		✓	✓	✓	✓
Partner Demo.			✓		
Manager FE (θ_g)	✓	✓	✓	✓	✓
Week FE (λ_t)	✓	✓	✓	✓	✓
Adj. R-Square	0.470	0.482	0.483	0.459	0.476
Observations	3,418	3,418	3,418	2,856	3,821
Agents	653	653	653	580	736
Managers	52	52	52	45	58
P-Values:					
H_0: Meetings = Incent.	0.048	0.051	0.049	0.033	0.050
H_0: Meetings+Incent.$\leq$Comb.	0.049	0.042	0.039	0.110	0.094

Notes. This table reports regression estimates of log revenue-per-call using data from the 4 weeks before and 4 weeks during the treatment period. The variables *Structured-Meetings*, *Pair-Incentives*, and *Combined* are shorthand for "Structured-Meetings x Treatment-Period," "Pair-Incentives x Treatment-Period," and "Combined x Treatment-Period" and are set to 1 in the treatment period for those randomly assigned to those treatments, and zero otherwise. Using the abbreviated variable names, the baseline estimating equation is:

$$\log(\text{RPC})_{i,t} = \beta_0 + \beta_1 \text{Structured-Meetings}_{i,t} + \beta_2 \text{Pair-Incentives}_{i,t} + \beta_3 \text{Combined}_{i,t} + \lambda_t + \theta_g + \varepsilon_{i,t}$$

where i represents an agent, t represents week, g represents sales manager group, λ_t and θ_g are week and sales manager fixed effects, and $\varepsilon_{i,t}$ is an idiosyncratic error term. Indicators for treatment assignment in the pre-period are absorbed by θ_g as randomization is at the sales manager group level. In Columns (1)–(3) the *Internal Control* (passive pairs) is the omitted category. Column (4) omits the *Internal Control* group and instead uses the *External Control* group (that was not aware of the experiment and had no partner pairing) as the excluded category. Column (5) includes both control groups, with an indicator for the *Internal Control* during the experimental period. Specifications with agent or partner demographics include age, gender, and tenure with the firm. The p-values in the bottom rows report results from Wald tests of two null hypotheses: i) equality of effects between *Pair-Incentives* and *Structured-Meetings* and ii) that the *Combined* group had sales gains that exceed the sum of the gains in the *Structured-Meetings* and *Pair-Incentives* groups. Standard errors are clustered at the sales manager level and are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively.

Table 3: **Agents in the Structured-Meetings and Combined Treatments had Persistent Sales Gains**

Control Group:	Internal (Passive Pairs)			External (No Pairs)	Both
	(1)	(2)	(3)	(4)	(5)
Structured-Meetings	0.189**	0.170**	0.172**	0.201**	0.200**
	(0.077)	(0.073)	(0.075)	(0.091)	(0.095)
Pair-Incentives	0.069	0.067	0.066	0.103	0.105
	(0.052)	(0.046)	(0.046)	(0.095)	(0.093)
Combined	0.210***	0.202***	0.205***	0.218**	0.218**
	(0.078)	(0.069)	(0.065)	(0.095)	(0.096)
Internal Control					0.011
					(0.093)
Demographics		✓	✓	✓	✓
Partner Demo.			✓		
Manager FE (θ_g)	✓	✓	✓	✓	✓
Week FE (λ_t)	✓	✓	✓	✓	✓
Adj. R-Square	0.351	0.365	0.367	0.341	0.347
Observations	6,236	6,236	6,236	6,026	7,334

Notes. This table reports regression estimates of log revenue-per-call using data from the 4 weeks before the experiment and from the post-treatment period after active interventions ceased (between 5 and 24 weeks after the experiment began). The variables *Structured-Meetings*, *Pair-Incentives*, and *Combined* are shorthand for "Structured-Meetings x Post-Period", "Pair-Incentives x Post-Period", and "Combined x Post-Period." They are set to 1 in the post-experimental period for those randomly assigned to the treatment and are zero otherwise. The baseline estimating equation is the same as in Table 2 except the treatment period is omitted and the post-treatment period is included. Standard errors are clustered at the sales manager level and are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively.

Table 4: **How do Partner and Agent Baseline Productivity Influence Treatment Outcomes?**

	Baseline	Non-Star Agents	Star Agents	Post-Period
	(1)	(2)	(3)	(4)
Meetings × Star Partner	0.150***	0.210**	0.147*	0.114***
	(0.054)	(0.087)	(0.078)	(0.031)
Incentives × Star Partner	-0.021	-0.031	0.069	0.001
	(0.067)	(0.088)	(0.085)	(0.038)
Combined × Star Partner	0.136**	0.250***	0.206**	0.162***
	(0.063)	(0.071)	(0.077)	(0.033)
Structured-Meetings	0.222***	0.241***	0.068	0.145***
	(0.055)	(0.075)	(0.072)	(0.028)
Pair-Incentives	0.105*	0.290***	-0.012	0.028
	(0.061)	(0.064)	(0.082)	(0.066)
Combined	0.190***	0.372***	0.061	0.143***
	(0.057)	(0.064)	(0.062)	(0.031)
Manager FE (θ_g)	✓	✓	✓	✓
Week FE (λ_t)	✓	✓	✓	✓
Adj. R-Square	0.488	0.491	0.450	0.367
Observations	3,287	1,465	1,818	6,236

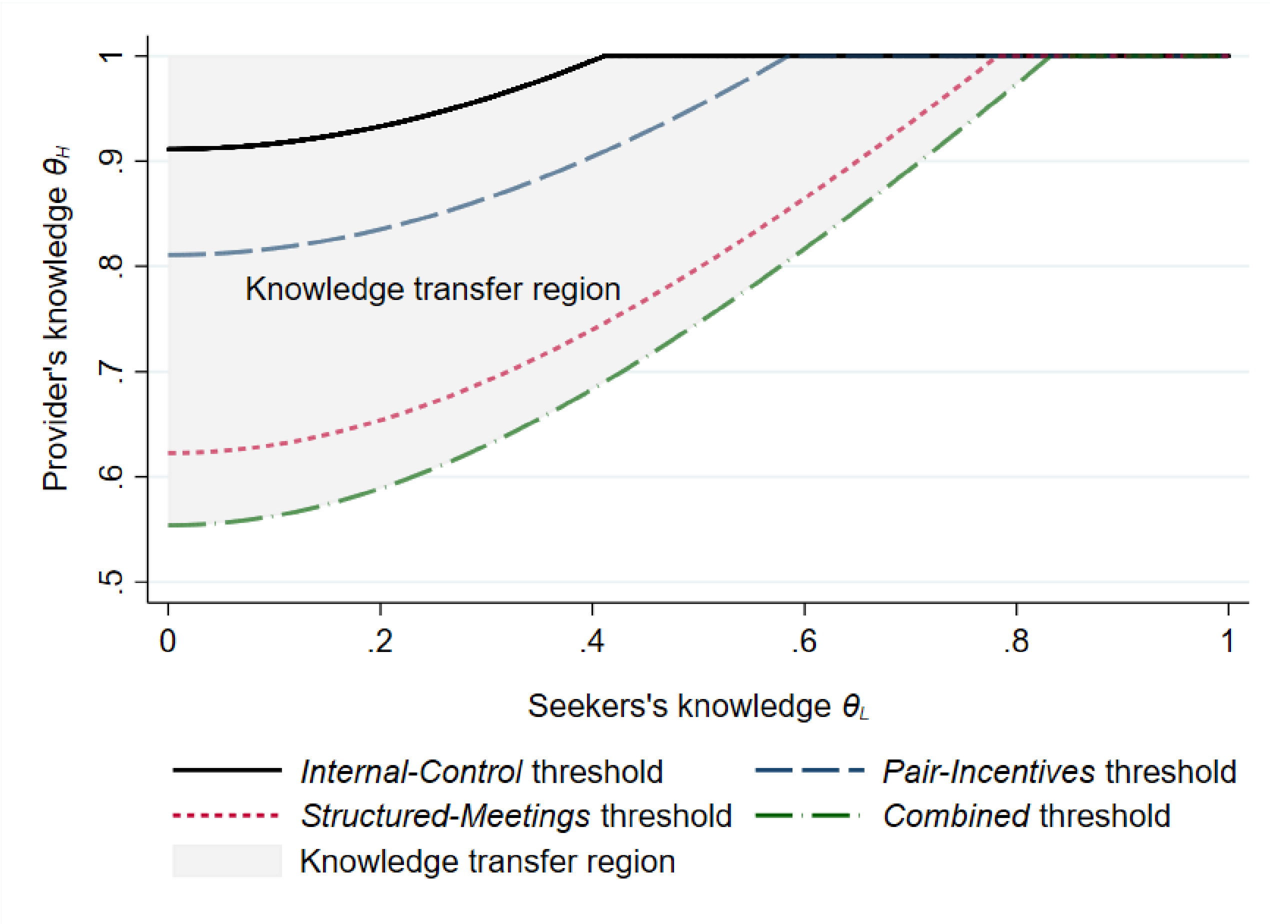
Notes. This table examines the effect of star partners on treatment outcomes. An agent is defined as a star if they are an above median performer within their own division 0 to 8 weeks before the beginning of active treatments. The table reports regressions of $log(RPC)$ that add interactions for treatment assignment and being paired with a star partner. The *Internal Control* group is the excluded category. Columns (1)—(3) include the pre-period and treatment period while Column (4) includes the pre-period and post-treatment period. During the treatment, star partner assignment is defined based on the concurrent partner. For the post-experimental period, *Star Partner* is defined based on whether the agent was ever paired with a star. The variable "Star Partner x Study/Post" is set to 1 if the agent is paired with a star partner. The variable *Ever Star Partner* is set to one during the entire sample if the agent was ever paired with a star, serving as a test of non-random partner assignment. Columns (2) and (3) condition on the productivity of the agent in question and examine heterogeneous effects of star partnership by agent productivity. Each regression includes time fixed effects and sales manager group fixed effects. Note that observation counts differ due to agents whose assigned partner was not available or was absent that week. These agents are included in prior tables, but based on lack of pair data, are not included in this subsample. Standard errors are clustered at the sales manager level and are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively.

Table 5: **Estimates of Heterogeneous Treatment Effects from LASSO**

	Structured-Meetings	Pair-Incentives	Combined
Baseline	0.216	0.041	0.13
High Tenure	-0.156	-0.14	-0.021
High Age	0.089	0.084	-0.179
Male	-0.139	0.029	0.114
Star Partner	0.194	0.051	0.123
Star Agent	0.016	0	-0.267
Star Agent and Star Partner	-0.145	-0.168	0.16
High Baseline Connections	0.052	-0.036	0
Re-paired Each Week	-0.063	0	0.1

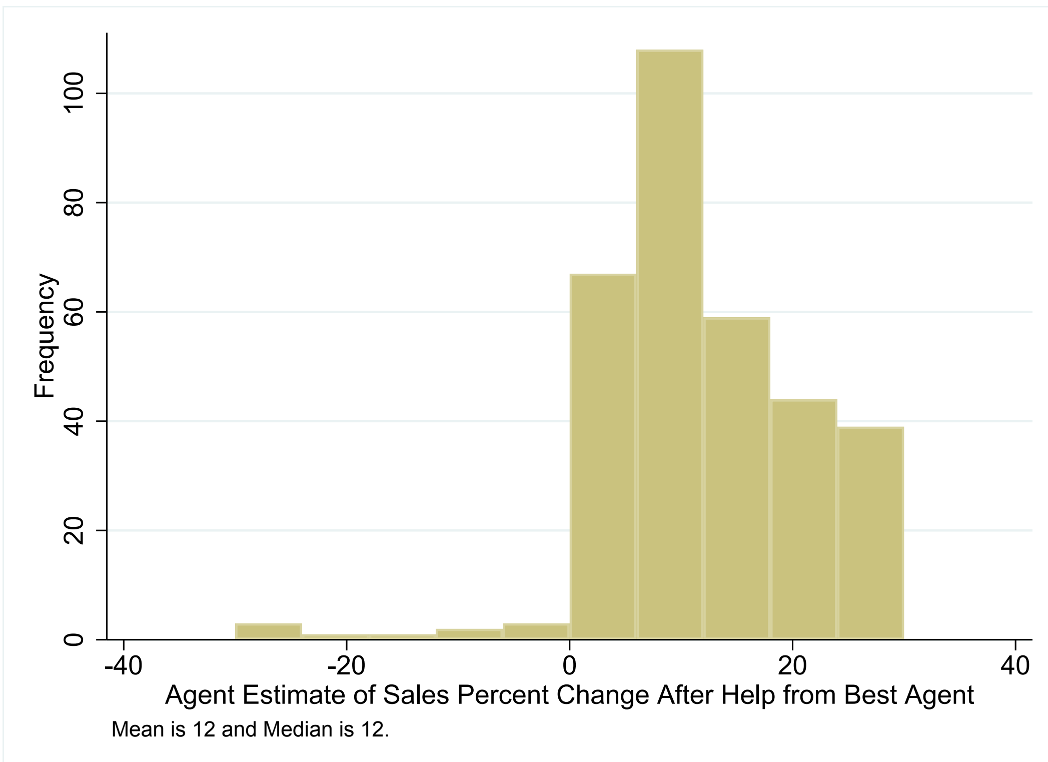
Notes. This table displays point estimates of persistent treatment effects for log RPC in the post-treatment period after fitting the LASSO procedure for variable selection and regularization. The cells are the coefficients on interaction terms. We use 10-fold cross-validation to set $\lambda = .0003$ (the penalty term). The baseline is for a young, non-star, female, agent with under 9 months of tenure. Highly tenured agents have above median (about 9 months) of tenure. Old agents are above median age. Star agents or partners have above median RPC in the pre-treatment period, and the star partner indicator is set to 1 for agents who are ever paired with a star partner. Connected agents are those who report 5 or more work-related conversations in a week on pre-experimental surveys. Agents who are repaired rotate partners every week during treatment.

Figure A.1: **Knowledge Transfer Region**



This figure plots the region in which knowledge transfers will occur in the knowledge seeker - knowledge provider spaces. All curves reflect a baseline commission of $B = 0.425$, and the underlying cost threshold is given by $K = 0.075$ (see Theory Appendix for definitions). The solid curve plots the provider's level of knowledge, θ_H, required by the knowledge seeker as a function of his own knowledge level, θ_L for the internal control group. The long dashed curve (*Pair-Incentives* threshold) reflects the knowledge seeker's reduced requirements vis-à-vis the knowledge provider when both earn a marginal commission of $b = 0.05$ on their joint output. The small dashed curve (*Structured-Meetings* threshold) reflects a reduced threshold cost, $K' = 0.035$, which further reduces the knowledge seeker's requirements regarding the knowledge provider's knowledge level. Finally, the dashed and dotted curve reflects the *Combined* threshold with $b = 0.05$ and $K' = 0.035$.

Figure A.2: **Agents' Reported Estimates of Treatment Effects after Help from Sales Stars**



This figure plots agent's responses to a survey question asking for their estimated percentage change in RPC if they were to receive help from the top agent on their team. This measure was collected in a followup survey done over a year after the end of treatment. Prior to the experiment, agents responded positively on a Likert scale survey question asking about the effects of receiving help from coworkers.

Figure A.3: **Perceived and Actual Differences Between Individual and the Top Sales Agents**

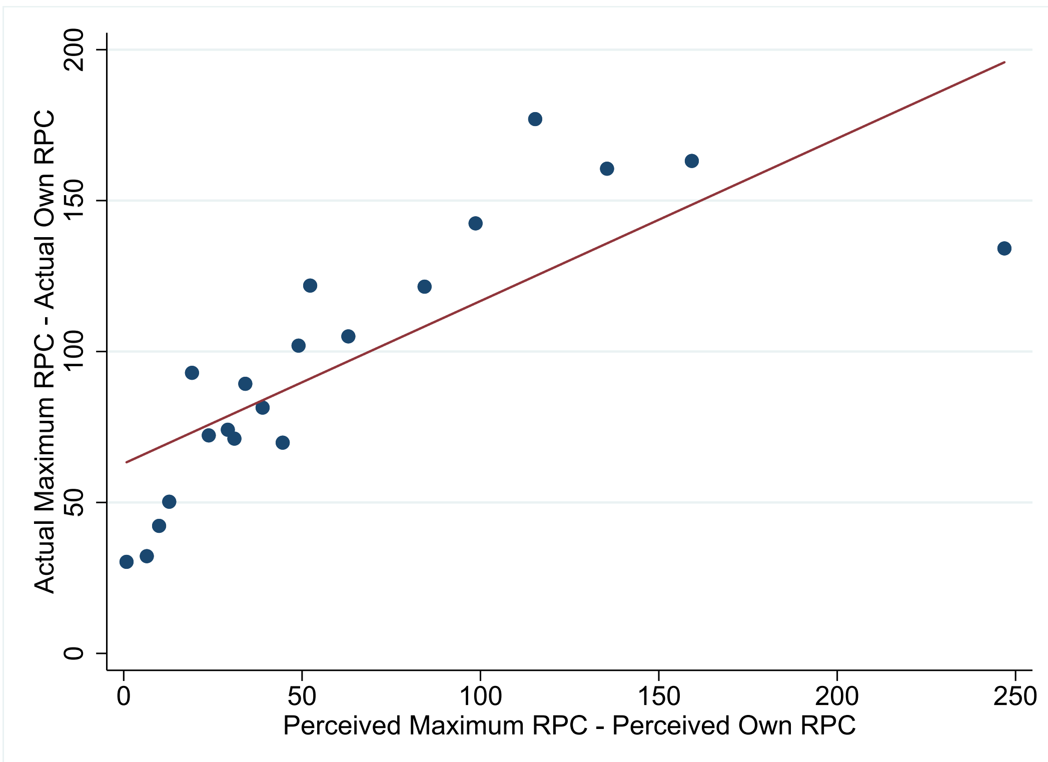


Figure plots the actual deviation between the maximum RPC in a division/office and the agent's own RPC against the agent's reported perceived maximum RPC and their own RPC. These measures were collected in a followup survey done over a year after the end of treatment.

Table A.1: **Pre-Experiment and Post-Experiment Survey Responses for Treatment-Eligible Agents**

	Full Sample	Internal Control	Pair-Incentives	Structured-Meetings	Combined
		Panel A: Pre-Experiment Survey			
On a scale of 1-5, how connected do you feel to others within the firm?	3.7	3.7	3.4	3.7	3.8
How many work-related interactions do you initiate in an average work week?	5.8	5.0	5.3	7.1	6.1
On a scale of 1-5, how beneficial are these interactions to you personally?	3.9	3.9	3.9	4.0	4.0
What dollar value would you be willing to spend on the proposed incentives?	$40.20				
		Panel B: Post-Experiment Survey			
I was aware of the treatment that took place this past month.	82.5%	77.4%	78.3%	84.8%	92.0%
We turned in a completed worksheet each week.				82.6%	88.2%
I spent [ ] minutes with my partner on the worksheet.				6.3	7.3
These interactions with my partner were beneficial.				78.6%	76.0%
N_A (Agents)	378	115	83	105	75

Panel A contains answers from the preliminary survey that we administered one week prior to the start of the experiment. The survey was not administered to the *External Control* group. The question wording, as it is displayed in the table, has been adapted from its original form to remove institutionally unique jargon. Agents were provided with a link to the survey and were asked to complete it while at work. Agents were not aware of which treatment they were going to be placed in at the time they took the survey. The question regarding the dollar value of the proposed incentives is the average valuation for the set of prizes offered in the *Pair-Incentives* treatment. Panel B contains answers from a survey given at the end of the treatment period using the same protocol. These questions are meant to assess the overall salience of the treatments.

Table A.2: **Results With Agent Fixed Effects and Other Revenue Measures**

Specification:	Log Revenue Per Call		Log Revenue Per Hour		Total Revenue	
	Treatment	Post	Treatment	Post	Treatment	Post
	(1)	(2)	(3)	(4)	(5)	(6)
Structured-Meetings	0.250***	0.173***	0.220**	0.132*	528.10***	811.730**
	(0.052)	(0.041)	(0.090)	(0.072)	(184.33)	(355.098)
Pair-Incentives	0.145***	0.043	0.115	0.038	496.55***	475.167
	(0.052)	(0.059)	(0.074)	(0.082)	(172.52)	(483.673)
Combined	0.269***	0.207***	0.174**	0.156**	704.25***	812.945**
	(0.049)	(0.068)	(0.074)	(0.083)	(221.04)	(319.715)
Internal Control	0.010	0.78	-0.043	-0.008	-27.78	-23.48
	(0.048)	(0.051)	(0.073)	(0.059)	(239.54)	(176.261)
Individual FE	✓	✓				
Manager FE (θ_g)			✓	✓	✓	✓
Week FE (λ_t)	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓
Adj. R-Square	0.485	0.517	0.476	0.274	0.43	0.280
Observations	3,821	7,334	3,821	7,334	3,821	7,334

This table is similar to the specifications in Tables 2 and 3 Column 5 but changes dependent variables or the specification. Columns 1 and 2 add worker fixed effects. Columns 3 and 4 change the dependent variable to the log of revenue-per-hour, log(RPH). Columns 5 and 6 examine total revenue per week in levels. All specifications include week and manager fixed effects. Standard errors are clustered at the sales manager level and are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively.

Table A.3: **Persistence of Sales Gains From 8 to 24 Weeks After the Intervention**

	8 Weeks	12 Weeks	16 Weeks	20 Weeks	24 Weeks
	(1)	(2)	(3)	(4)	(5)
Structured-Meetings	0.208***	0.182***	0.188***	0.205***	0.189**
	(0.061)	(0.057)	(0.065)	(0.075)	(0.077)
Pair-Incentives	0.030	0.024	0.038	0.057	0.069
	(0.057)	(0.045)	(0.052)	(0.053)	(0.052)
Combined	0.242***	0.256***	0.224***	0.227***	0.210***
	(0.062)	(0.059)	(0.067)	(0.075)	(0.078)
Manager FE (θ_g)	✓	✓	✓	✓	✓
Adj. R-Square	0.418	0.375	0.359	0.356	0.351
Observations	3,252	4,213	4,995	5,658	6,236

Here we compare the persistence of productivity gains across different periods of time after the intervention. Each column includes successively more data, with 8, 12, 16, 20, and 24 weeks after the beginning of treatment. The variables *Structured-Meetings*, *Pair-Incentives*, and *Combined* are set to 1 in the weeks after the treatments for those agents randomly assigned to the treatments, and are zero for the four weeks before the intervention. Each specification contains week and sales manager fixed effects. The *Internal Control* group is the omitted category. Standard errors are clustered at the sales manager level and are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively.

Table A.4: **Agent Turnover at Different Horizons After the Intervention**

	8 Weeks	12 Weeks	16 Weeks	20 Weeks	24 Weeks
	(1)	(2)	(3)	(4)	(5)
Structured-Meetings	0.054	0.072	0.029	0.027	-0.047
	(0.053)	(0.055)	(0.054)	(0.052)	(0.047)
Pair-Incentives	-0.006	0.039	0.030	0.041	0.060
	(0.055)	(0.057)	(0.056)	(0.054)	(0.049)
Combined	0.048	0.078	0.061	0.038	-0.043
	(0.053)	(0.055)	(0.053)	(0.052)	(0.047)
Manager FE (θ_g)	✓	✓	✓	✓	✓
Week FE (λ_t)	✓	✓	✓	✓	✓
Adj. R-Square	0.015	0.058	0.006	0.004	0.013
Observations	653	653	653	653	653

Here we compare the turnover of agents across different horizons; 8, 12, 16, 20, and 24 weeks after treatment begins. The dependent variable is an indicator that the agent is no longer included in the sample. The omitted category is the *Internal Control*. Standard errors are clustered at the sales manager level and are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively.

Table A.5: **Does Ability to Answer Calls Change with Treatments?**

	(1)	(2)	(3)
Structured-Meetings	-0.041	-0.040	-0.041
	(0.031)	(0.031)	(0.031)
Pair-Incentives	-0.036	-0.036	-0.036
	(0.030)	(0.030)	(0.030)
Combined	-0.019	-0.019	-0.020
	(0.047)	(0.046)	(0.047)
Demographics		✓	✓
Partner Demo.			✓
Manager FE (θ_g)	✓	✓	✓
Week FE (λ_t)	✓	✓	✓
Adj. R-Square	0.114	0.114	0.116
Observations	2,550	2,550	2,550

Here we compare the change in workers' ability to take calls, defined as adherence, across the three different active treatment groups and the *Internal-Control* using data from the 4 weeks before and 4 weeks during the study. The variables *Structured-Meetings*, *Pair-Incentives*, and *Combined* are set to 1 in the study weeks for those randomly assigned to those treatments, and zero otherwise. Each specification contains week and sales manager fixed effects. The *Internal-Control* group is the omitted category, as we do not have data on adherence for the *External-Control* group. Standard errors are clustered at the sales manager level and are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively.

Table A.6: **Do Agents Give-up After Winning or Losing a Prize**

	Pair-Incentives	Combined	Both
	(1)	(2)	(3)
Won Last Week	-0.035**	-0.027*	-0.033***
	(0.014)	(0.014)	(0.010)
Demographic Controls	✓	✓	✓
Manager FE (θ_g)	✓	✓	✓
Week FE (λ_t)	✓	✓	✓
R-Square	0.114	0.159	0.136
Observations	673	770	1,446

This table reports regressions of log RPC on an indicator that the agent received a prize in the prior week. The estimate is relative to a baseline of agents who did not win in the previous week. The sample contains only those agents in either the *Pair Incentives* or *Combined* treatments during the experimental period.

A Appendix

A.1 Theory Development

We provide a parsimonious model to specify costs that hinder agent knowledge transfer and to illustrate how treatments potentially allow agents to overcome these costs. It is important to note that we do not attempt to characterize an optimal contract; instead, we consider comparative statics based on features of observed contracts. For simplicity, we focus on two agents, L and H. Suppose each agent has a commonly-known body of knowledge, $Z_i \subset \Omega$ for $i \in \{L, H\}$, where $z \in \Omega$ is knowledge required to complete an individual sale. The random variable z can be thought of as the issue (or collection of issues) that arise in a transaction, and $f(z)$ is the probability that issue z arises on any given call. Thus, $\theta_i = \int_{z \in Z_i} f(z)dz \leq 1$ is a measure of agent i's knowledge, capturing the probability that the agent has the necessary knowledge required to successfully close a transaction. To simplify what follows, we further assume that agents' knowledge is ordered, such that $\theta_L < \theta_H \Rightarrow Z_L \subset Z_H$.[46] Put simply, agents with a higher probability of closing sales possess a broader body of knowledge.

Agents may connect with other agents to transfer knowledge, but establishing a connection is potentially costly and requires one or both agents to invest in the relationship ex-ante. We analyze a two stage model where the agents choose how much to invest towards establishing a relationship, $k_i \geq 0$, simultaneously in the first stage. If the sum of the relationship-specific investments exceed a commonly-known threshold, $K > 0$, then we say that a connection is forged between the two agents. When a connection is forged, the lesser informed agent, L absorbs his better informed colleague's knowledge, such that $\theta_L' = \theta_H > \theta_L$. On the other hand, agent H's knowledge, θ_H, is unaffected by the connection with her less informed colleague. Finally, if no connection is made, then both agents' knowledge remains constant.

In the second stage, each agent takes their knowledge, θ_i, as given and chooses their sales effort, $e_i \geq 0$ with a personal cost of effort $e_i^2/2$. Sales effort and knowledge combine to produce expected sales: $E[Y_i] = \theta_i e_i$, upon which agents earn a commission of $B \in (0, 1)$. Taking agent $-i$'s investment strategy as given, agent i solves:

$$\max_{e_i} \left(\max_{k_i} U(e_i, k_i; \theta_i, \theta_{-i}) \right) = B\theta_i(k_i; k_{-i}, \theta_{-i})e_i - e_i^2/2 - k_i. \tag{A.1}$$

Working backwards from the second stage, the first-order condition yields $e_i^* = B\theta_i$, allowing us to write agent i's equilibrium utility as: $(B\theta_i)^2/2 - k_i$. In the first stage, each agent chooses their relationship-specific investment as a function of the potential gains from connecting with their peer; specifically, the amount of knowledge that they can glean from the relationship. Because the better informed agent has nothing to gain from connecting with the less informed agents, the former will be unwilling to make relationship investments absent additional incentives. Accordingly, the knowledge seeker (agent L), optimally invests:

$$k_L^* = \begin{cases} 0, & \text{if } B^2(\theta_H^2 - \theta_L^2)/2 \leq K \\ K, & \text{if } B^2(\theta_H^2 - \theta_L^2)/2 > K. \end{cases}$$

Our model highlights two types of frictions to knowledge exchange, *initiation costs* and *contracting costs*. *Initiation costs* capture the knowledge seeker's costs, including overcoming social

[46] This assumption is justified if agents endogenously choose which knowledge to invest in acquiring. Knowledge about the most frequent problems has the highest payoff for sales, which gives rise to this ordering.

stigmas and search costs. The magnitude of these costs are incorporated in the connection threshold, K. Because we model the relationship-specific investment as a threshold, *initiation costs* may also include transfers between the agents required to compensate knowledge providers for help. *Contracting costs* limit the knowledge provider's ability to benefit from improving her partner's performance. In our model, the firm collects a tax of $(1 - B)$ on sales, which limits the knowledge seeker's willingness to shoulder all of the upfront relationship development costs. Other considerations include the inability of knowledge seekers to borrow from future human capital (Garicano and Rayo, 2017), which could be incorporated in richer models that limit the transfer of resources between knowledge seekers and providers more generally.

A.1.1 Structured-Meetings Treatment

The *Structured-Meetings* treatment targeted initiation costs by decreasing the investment threshold needed to forge a connection from K to $K' < K$, via a series of worksheets and partner-lunches. Relative to the *Internal-Control* benchmark, only the cost of connecting changes, as the benefit to the less informed agent remains at $\frac{B^2(\theta_H^2 - \theta_L^2)}{2}$ whereas the benefit to the better informed agent remains at zero. Consequently the *Structured-Meetings* treatment:

- Induces more connections due to the decreased connection investment threshold, K'.
- Induces the (ex-ante) less knowledgeable agent to increase sales if and only if a connection is made due to his increased sales productivity.
- Will have the largest effect when agents are paired with star performers (above median productivity), as highlighted in Figure A.1.

A.1.2 Pair-Incentives Treatment

The *Pair-Incentives* treatment targeted contracting costs by providing partnered agents with additional incentives to increase their joint sales. In particular, the treatment provided agent H with an explicit incentive to transfer knowledge to her less informed partner to increase his sales. We model this incentive with an expected bonus commission $b > 0$ paid to each agent on their joint sales. Accordingly, when agent i and $-i$ are formally paired together, agent i expects to collect $(B + b)Y_i + bY_{-i}$.[47] Relative to the benchmark, *Internal-Control* treatment, *both* agents in the *Pair-Incentives* treatment explicitly gain from the less-informed agent increasing his knowledge. In particular, the benefit to agent L of connecting with agent H is given by $\frac{(B+b)^2(\theta_H^2 - \theta_L^2)}{2}$, whereas the direct benefit to agent H is given by: $\frac{b^2(\theta_H^2 - \theta_L^2)}{2}$. In the *Internal-Control* treatment, the equivalent benefits are given by $\frac{B^2(\theta_H^2 - \theta_L^2)}{2}$ and 0, respectively. Consequently, relative to the *Internal-Control* treatment, the *Pair-Incentives* treatment:

- Induces both agents to exert more sales effort due to the increased commission, b, on their own output, Y.
- Induces more connections by raising both agents' returns to first-stage, relationship-specific investments.

[47]The actual treatment compensated sales gains relative to the pre-treatment period and awarded prizes to agent-pairs who managed to outperform two other, randomly selected agent-pairs. We follow Bandiera et al. (2013) in modeling this with linear profit sharing rules.

A.1.3 Combined Treatment

The *Combined* treatment included both the *Pair-Incentives* and *Structured-meeting* interventions. Relative to the *Internal Control* treatment, agents in the *Combined* treatment faced both a reduced connection threshold, K', and an additional commission, b, on joint output. The treatment thus:

- Provides a test of whether both initiation costs and contracting costs were independently restricting knowledge transfers.
- Provides a test of whether the interventions are themselves complements or substitutes (Athey and Stern, 1998).

A.1.4 Graphical Representation of Comparative Statics

We plot the potential effects of each treatment in Figure A.1. In particular, the figure shows that knowledge transfers occur in equilibrium whenever the knowledge gap between paired agents is sufficiently large. The solid black line demarks the minimum spread in knowledge between two agents in the *Internal Control* group needed to overcome the first-stage, relationship-specific, investment threshold. The long-dashed blue line plots the minimum knowledge spread amongst agents in the *Pair-Incentives* treatment, the short-dashed red line plots the same threshold for the *Structured-Meetings* treatment, and the dashed and dotted green line represents the minimum spread for agents in the *Combined* treatment. We note that the knowledge transfer region, shaded in the figure in gray, expands profoundly with the interventions. However, the ordering of the treatments (which expands the knowledge transfer region most) and the sub- or super-modularity of the *Combined* treatment are only illustrated for arbitrary parameter values of K, K', B and b. The relative cost and benefit of relaxing initiation and contracting costs are empirical questions.

Figure A.1 highlights the empirical prediction that knowledge transfers are most likely to occur between agents with vastly different levels of knowledge. Agents are more likely to connect with significantly better or worse informed peers, because the value to doing so increases with the provider's relative knowledge advantage. The same logic suggests that if knowledge transfers are at the root of any observed productivity gains, then the greatest gains should occur between agent pairs with highly differentiated knowledge levels; for example, between below- and above-median agent pairs.

A.2 Implementing the Experiment

To communicate both the disclosures and the intervention guidelines, we did the following: (1) we solicited the help of senior executives who shared the details with division and sales managers; (2) we had a designer create and print posters which we placed in the firm's common areas and on their internal TV monitors during the experiment; (3) we set up an e-mail and phone hot-line to answer questions; (4) we set up a website that explained all aspects of the initiative including daily scores and frequently emailed questions;[48] and (5) a subset of the authors were physically on-site at least three days a week at both locations to answer questions, distribute worksheets, and administer the catered lunches. Table A.1 in the Appendix reports agents' answers to several survey questions that suggest participants (1) knew about the treatments, (2) completed the worksheets meant to

[48] The posters pointed employees to the website but the site itself did not explain the treatments until they were live. In particular, agents did not know their treatment cell, nor the details of any treatment until the treatment period began, and within the treatment period, the website *only* surfaced details of an agent's own treatment.

facilitate knowledge transfer, (3) interacted with their partners in a meaningful way, and (4) valued the rewards.

A.3 Survey Responses and Robustness Tables

Several survey results are compiled in Table A.1. All surveys were administers through Qualtrics and distributed via email and links on the experiment website. Over 300 agents completed the preliminary survey, answering questions about their social and work-related conversations with coworkers. These results are contained in Panel A of Table A.1. Post-experiment survey results are in Panel B. These questions allow us to get an approximate measure of the effectiveness and salience of the experiment as a whole and of the *Structured-Meetings* treatment specifically.

A.4 The Study Firm's Return on Investment

This section details the procedure used to estimate the return on investment of each intervention and the total extra-ordinary sales revenue generated by the experiment. The *Internal Control* group revenue-per-call (RPC) during the four week experiment was, on average, \$64.20. If we multiply these by the resultant treatment effects, we get the additional revenue-per-call generated by each intervention.

- *Structured-Meetings*: \$64.20 $\times$ 24.1% $\approx$ \$15.50 extra per call.
- *Pair-Incentives*: \$64.20 $\times$ 13.1% $\approx$ \$8.40 extra per call.
- *Combined*: \$64.20 $\times$ 25.5% $\approx$ \$16.40 extra per call.

We then multiply these numbers by the average number of calls per agent per week within each intervention during the four weeks of the study—58, 64, and 66 calls per week for the *Structured-Meetings*, *Pair-Incentives*, and *Combined* treatment, respectively.

- *Structured-Meetings*: \$15.50 $\times$ 58 = \$899 extra per agent per week.
- *Pair-Incentives*: \$8.40 $\times$ 64 = \$538 extra per agent per week.
- *Combined*: \$16.40 $\times$ 66 = \$1,082 extra per agent per week.

Next we multiply these amounts by the number of agent-weeks in each intervention to get to total amount of extra revenue generated by the four-week intervention.

- *Structured-Meetings*: \$899 $\times$ 379 = \$340,721 extra revenue earned across all four weeks.
- *Pair-Incentives*: \$538 $\times$ 396 = \$213,048 extra revenue earned across all four weeks.
- *Combined*: \$1,082 $\times$ 353 = \$381,946 extra revenue earned across all four weeks.

Now we consider the costs of implementing each intervention.

- *Structured-Meetings*: \$7 was spent on all agents for lunch each week: \$7 $\times$ 379 = \$2,700 in treatment costs (rounded up).
- *Pair-Incentives*: 1/3 of the agents won a prized valued at \$50: \$50 $\times$ 1/3 $\times$ 396 $\approx$ \$6,600 in treatment costs (rounded up)

- *Combined*: Consider both of these two cost structures for the 353 agent-weeks in this intervention: (\$7 × 353) + (\$50 × 1/3 × 353) ≈ \$8,400 in treatment costs (rounded up)

Finally, we calculate the return on investment of a individual intervention as

$$\text{ROI} = \frac{(\text{Extra Revenue} \times \text{Profit Fraction}) - \text{Treatment Cost}}{\text{Treatment Cost}} \tag{A.2}$$

where *Extra Revenue* equals the extra revenue earned from the given intervention across all four weeks of the experiment, *Profit Fraction* equals 5%,[49] and *Treatment Cost* equals the treatment cost calculated above. Performing computations leads to ROIs of 531%, 61%, and 127% for the *Structured-Meetings*, *Pair-Incentives*, and *Combined* treatments, respectively. Summing up the three extra revenue earned numbers results in a total extra revenue earned of (\$340,721 + \$213,048 + \$381,946) = \$935,715.

B Documentation

The following are materials that were provided to participating sales agents and their supervisors in an effort to streamline the communication, increase the salience of the competition, and gather self-reported data. The first two sheets show the front and back sides of the collaboration worksheets completed by agents in the *Structured-Meetings* and *Combined* treatments. The next sheet contains the lunchtime talking points that we encouraged partners to discuss as they ate their free lunch (those in the *Structured-Meetings* and *Combined* treatments only).

[49]This is a conservative estimate that is motivated by conversations had with firm executives.

[redacted] Sales Representative Collaboration Worksheet
PLEASE PRINT LEGIBLY

Your Full Name: ____________________ [redacted]: ________________________

Think about the **most successful** sales call **you** had in the last week. What did you do that made it successful?

Think about the **least successful** sales call **you've** had in the last week. How could you have done better?

Describe the most difficult deal-breaker that **you've** come across **in the last week**; for example: *upgrading callers to a specific new bundle*.

Please write down two goals for **you** to work on for the **rest of this week**; for example: *be braver in suggesting products*.

Goal 1:

Goal 2:

If you did the same exercise **last week**: were you successful in executing your goals? If no, why not?

Goal 1:

Goal 2:

Your Partner's Full name and [redacted]ID: ______________________________________

Please TALK to your partner about the questions below and write down their responses.

Ask **your partner** about their **most successful** sales call **last week,** what did they do right?

Ask **your partner** about their **least successful** sales call from the **last week**. What advice did **you** offer your partner?

Was **your partner** successful in accomplishing their goals **last week**? If no, why not?

Goal 1:

Goal 2:

What are **your partner's** two goals for **rest of this week**?

Goal 1:

Goal 2:

Please write down one thing **your partner recommended you** to try:

What day would you and our partner like to pick-up lunch from 12-2? (must hand in with 24 hour notice!): ☐ Thursday ☐ Friday

RXd by Adviser: date/time:

Lunch Talking Points

[redacted] 3 & 4

You do not need to turn this sheet in, put please read through it: is designed to help you make the most of the time with your partner.

1) *Bon Appetit!*

2) Have either of you had an awesome sale since you last met? What made it great?

3) Have either of you had a call go completely sideways? What happened? Does your partner have any advice?

4) Your partner gave you some advice on how to handle difficult stations earlier this week. Did it help?

5) You and your partner each made goals earlier this week, what progress have you each made on those goals?

6) If you have suggestions on how this lunch program could be more productive, please let your adviser know—we greatly appreciate your feedback.

Thank you!