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Assessing sales contest effectiveness: the role of salesperson and sales district characteristics

Srinath Gopalakrishna · Jason Garrett · Murali K. Mantrala · Shrihari Sridhar

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Abstract Sales contests are widely employed to improve short-term sales performance, but knowledge about their effectiveness at the individual salesperson level remains sparse. Proponents argue that contests increase sales by stimulating salespeople, while critics say that contests merely encourage strategic timing of sales efforts. The authors draw on the strategic sales timing literature and goal theory to hypothesize that in a consultative selling scenario, sales will dip below the baseline before the contest but increase above the baseline during and after the contest. They posit that sales district potential and salesperson ability moderate the pre-contest sales dip, contest sales boost, and post-contest sales. Results from a model based on individual-level data on 1180 salespeople in 78 sales districts are largely supportive of the hypotheses. They highlight the need for researchers to integrate the role of strategic timing, salesperson, and sales district characteristics to assess sales contest outcomes. For practitioners, the findings show that in consultative selling situations, contests can generate a net sales increase despite the occurrence of timing games, and the sales gain is higher in districts with lower sales potential and among salespeople with higher sales ability.

Keywords Sales contests · Sales force management · Marketing strategy · Multilevel models

S. Gopalakrishna (✉) · M. K. Mantrala
Trulaske College of Business, University of Missouri, 434 Cornell Hall, Columbia, MO 65211, USA
e-mail: srinath@missouri.edu

M. K. Mantrala
e-mail: mantralam@missouri.edu

J. Garrett
Foster College of Business, Bradley University, 123 Baker Hall, Peoria, IL 61625, USA
e-mail: kjgarrett@bradley.edu

S. Sridhar
Smeal College of Business, Penn State University, 457 Business Building, University Park, PA 16802, USA
e-mail: sus55@psu.edu

1 Introduction

Sales contests are widely employed to boost salespeople's short-term productivity. US annual spending on sales contests exceeds \$9 billion (Lim, Ahearne, and Ham 2009). Despite their general popularity and the heavy expenditures involved, questions about whether contests effectively stimulate individual salespeople and boost overall sales persist in the academic and practitioner circles (Tosdal 1924; Murphy and Dacin 1998).

A major issue with contests is that they can induce salespeople to engage in *strategic timing games* such as stalling and/or withholding orders (sandbagging) until the contest begins in order to display higher sales within the contest horizon (Dodge 1973; Marchetti 2004). The concern is that timing games may merely redistribute sales over the contest analysis period and imply no net sales gain (e.g., sales declines before and/or after the contest may nullify the sales lift during the contest). While anecdotal evidence supports strategic timing behavior when contests are preannounced, no empirical work explains how factors such as district sales potential and selling ability affect individual salespeople's propensity for timing games and the impact of these behaviors on individual and aggregate contest results. Such an investigation is sorely needed to improve the current understanding of whether and how to run sales contests that can be successful despite the likely occurrence of individual-level timing games.

In this paper, we examine the daily sales of 1180 agents situated in 78 districts of a regional US insurance company over 1 year. Each agent participated in two sales contests, each of 6 weeks' duration, that were announced in advance of the contest start date. The data provided by the company included the daily life insurance sales made by each agent during both contest and non-contest periods of the year, the sales potential in the agent's district, and a measure of the agent's selling ability linked to the agent's performance in past contests. Given these data, we employ a nested ordered probit regression model to investigate the following research questions:

(1) Do contests induce agents to play sales timing games before, during, and after sales contests?
(2) How do the dynamic (strategic timing game) behaviors vary across agents of differing sales ability and across districts of differing sales potentials?
(3) Do cumulative sales aggregated from pre-contest, within-contest, and post-contest phases produce overall net sales gains?

2 Hypotheses development

The impact of sales contests on customer value and on sales agents has received some attention in the literature (Garrett and Gopalakrishna 2010; Wotruba and Schoel 1983). Sales contests, as in the scenario we report on, are frequently announced ahead of time. The advance notice allows agents to be better prepared and permits the company to generate excitement leading up to the event. Especially in consultative selling situations where the link between sales effort and outcome is *not* instantaneous, agents may try to generate additional sales in the contest period that qualifies for winning a contest prize. They may alter their selling efforts in the pre-contest period in two ways: (i) sandbagging, i.e., delaying sales closure until after the contest start date for those prospects that are very close to buying (Fu and Jones 2005), and (ii) redirecting the time and effort saved by postponing those sales closures toward additional prospects that can be developed and closed within the contest (assuming that the contest duration is sufficiently long relative to the sales cycle, which is about 3 weeks in the case of life insurance). These possible responses to the announcement of an upcoming contest lead us to expect a lower than normal probability of sales before the contest begins and a higher than normal probability of sales once the contest opens. However, we also allow for the likelihood that among the additional prospects pursued by the agent, some may not close until after the contest ends. This leads us to the following hypotheses:

> H_{1a}: The probability of sales in the pre-contest phase will be lower than the probability of sales in the baseline (non-contest) time periods (a "sales dip").
> H_{1b}: The probability of sales in the within-contest phase will be higher than the probability of sales in the baseline time period (a "sales boost").
> H_{1c}: The probability of sales in the post-contest phase will be higher than the probability of sales in the baseline time period (a "sales boost").

Territory potential has a big impact on the sales agent's perceptions of goal difficulty (Sinha and Zoltners 2001). Common sales goals are viewed as more difficult in low-potential than in high-potential territories. Thus, agents in lower sales potential districts should perceive greater within-contest goal difficulty and, consequently, engage in more sandbagging in the pre-contest phase to partly alleviate this difficulty. Furthermore, as argued by Oyer (1998) and Steenburgh (2008), sales compensation with a temporal deadline can induce effort adjustments. Specifically, effort is shifted toward the activity that yields the highest reward. Agents in low sales potential districts might see themselves as underdogs (Chen et al. 2011) and, therefore, are more likely to engage in sandbagging. Blending this view with goal theory supports the notion that agents in lower potential sales districts will also engage in intensified prospecting in the pre-contest phase to improve sales achievement within the contest period. Thus, we propose:

> H_{2a}: The sales dip in the pre-contest phase will be *more* pronounced in low sales potential districts than in high sales potential districts.
> H_{2b}: The sales boost in the contest phase will be *more* pronounced in low sales potential districts than in high sales potential districts.

Next, we address how differing levels of sales ability moderate the strategic timing games. Specifically, agents with higher sales ability will have the confidence to produce higher performance levels in the event (Bandura 1982; Ridlon and Shin 2013). An agent previously successful in a sales contest would possess greater self-assurance that s/he can put in the additional effort, manage the sales cycle, and initiate and complete a sale during the contest period (assuming that the contest duration is sufficiently long). Therefore, this individual has less need to sandbag or prospect *before the contest begins* and might put in more prospecting and closing effort *during the contest*. This produces higher sales during the contest and, in addition, more sales that are not closed before the contest ends implying more spillover into the post-contest phase due to inherent uncertainty in the sales cycle. Thus, we propose:

> H_{3a}: The sales dip in the pre-contest phase will be *less* pronounced for salespeople with high sales ability.
> H_{3b}: The sales boost in the contest phase will be *more* pronounced for salespeople with high sales ability.
> H_{3c}: The sales boost in the post-contest phase will be *more* pronounced for salespeople with high sales ability.

3 Data

3.1 Empirical context

Product Our empirical context involves a regional insurance company in the USA with annual sales over $1 billion. The focal product sold by the agents is life insurance, the company's most profitable product line with a sales cycle of about 3 weeks, requiring a consultative selling approach with much deliberation by a prospective customer before purchase.

Contest details The company administered two 6-week sales contests to motivate its agents to sell life insurance. Each contest was announced a few weeks before the event and had multiple winners of prizes of varying value across different sales achievement levels. The hurdle levels were the same for all agents, i.e., there was no handicapping (Ridlon and Shin 2013). More specifically, all agents who crossed predetermined sales hurdles received a prize. There were four such hurdles in each contest. The lowest tier or hurdle was set at 5 policies. In one contest, the prize for crossing that hurdle was 500 gold-embossed business cards. Upon exceeding higher hurdle levels (8, 12, and 15 policies), the prizes of increasing value were awarded. In addition, there was a tournament style award for placing among the top performers. For example, the top agent in each state received a beautiful brass-plated office globe inlaid with semi-precious metals. Thus, the contests had a hybrid prize structure which combined elements of "beat goals" and "beat others." The hybrid nature of the contests provides incentives to *all* agents to remain engaged in the contest, a key objective emphasized by company management. That is, agents with low sales ability could win some prize by beating the hurdle level within their reach with some extra effort, while those with high ability could, in addition, compete for the higher value prize by attaining higher performance levels. The potential for timing games was similar in both contests. Agents were updated at least weekly regarding their contest standing (more frequently toward the end of the contest). Additionally, management felt that a large part of the motivation to participate and win came from the public recognition that award winners received later in the firm. Lastly, agents typically sold within specific geographic districts where district sales managers set goals and reviewed performance against objectives.

Variables Our data involved a *balanced* panel of 1180 agents, whose daily sales were recorded for an entire year, thereby spanning both the contest and non-contest phases. In addition, we obtained details about the sales territory and agents, which we discuss below.

3.2 Dependent variable

We define the dependent variable as the number of life insurance policies sold by an agent on a single day. As shown in Fig. 1a, the modal number of policies sold by an agent on any given day is 0, and sales of 3 or more policies on a single day are rare.

3.3 Independent variables

Contest phase We denote the contest phase using a dummy variable coded as 1 if the date falls within the official contest start and end dates and 0 otherwise. The dates were late January to early March for the first contest and late August to early October for the second.

Pre-contest phase We define the pre-contest phase to be one sales cycle in duration (i.e., 3 weeks) before the official contest start date. Our discussions with company managers suggested that any possibility of strategic timing behavior by the agents (i.e., "sandbagging" of orders until the contest begins) would not be sustainable beyond one sales cycle. In a later section, we demonstrate that our results are robust to the length of the pre-contest window. We coded this variable as 1 for all dates that were within the 3-week window before the official contest start date and 0 otherwise.

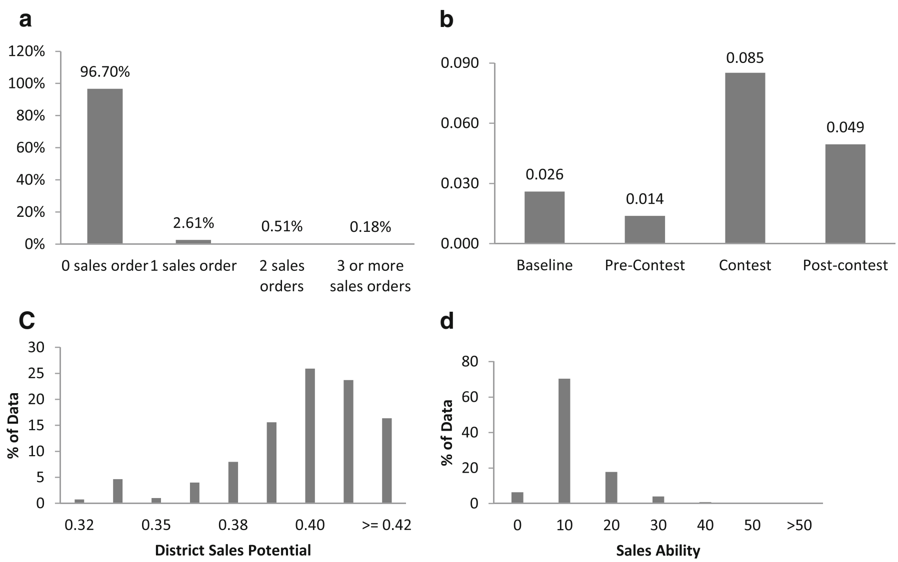

Fig. 1 Histograms. **a** Sales orders per agent per day. **b** Average number of sales orders per agent per day. **c** District sales potential. **d** Agent sales ability

Post-contest phase We define the post-contest phase to be one sales cycle in duration (3 weeks) following the official contest end date. Company executives affirmed that it was unlikely that effort initiated during the contest led to a sales closure beyond 3 weeks after the contest end date, i.e., length of one sales cycle. In a later section, we demonstrate the robustness of our results to the length of the post-contest window. As before, we coded this variable as 1 for post-contest dates that were within 3 weeks of the official contest end date and 0 otherwise. In Fig. 1b, we plot the mean daily sales in the baseline, pre-contest, contest, and post-contest periods. Compared to the baseline period (average daily sales=.026), there is a drop in the average daily sales in the pre-contest period (.014), a sales boost during the contest (.085), and continued sales above the baseline during the post-contest phase (.049).

District sales potential Prospecting typically begins with an agent looking for customers (households) that have not previously purchased life insurance. Based on market penetration data from *Claritas*, we derived a district's sales potential as one minus the life insurance penetration for that sales district, where penetration is defined as the percentage of households within a district that have purchased any brand of life insurance.

Sales ability We measure sales ability as the number of life insurance policies sold by the agent in the previous year during similar contests.

The histograms in Fig. 1c, d depict considerable variation in both district sales potential and sales ability across agents.

3.4 Control variables

We control for gender differences across agents and account for time-related factors (unobserved to the researchers) that may produce idiosyncratic dips and bumps in sales with month dummies. Table 1 displays the descriptive statistics and correlations for all variables.

Table 1 Descriptive statistics

Variables	*M*	SD	1	2	3	4	5	6	7
1. Sales	.041	.253	1	–	–	–	–	–	–
2. Contest	.236	.424	.096****	1	–	–	–	–	–
3. Pre-contest	.115	.319	−.039****	−.200****	1	–	–	–	–
4. Post-contest	.115	.319	.012****	−.200****	−.130****	1	–	–	–
5. District potential	.398	.021	−.004***	.000	.000	.000	1	–	–
6. Sales ability	7.446	7.064	.088****	.000	.000	.000	−.028****	1	–
7. Gender	1.206	.404	.006****	.000	.000	.000	.005***	.008****	1

*p<.10; ** p<.05; *** p<.01; ****p<.001, significance

4 Method

4.1 Model specification

Our model specification is driven by two key factors. First, it must account for unobserved heterogeneity in agent performance as well as reflect the aspect of multilevel data with a hierarchically nested structure (i.e., each agent is nested within a particular district and observed each day in the year). Second, our measure of sales data is an ordered variable that is not distributed normally. Hence, least squares estimation will have shortcomings such as heteroscedasticity and predicted outcomes falling outside the data interval range. Thus, we employ a multilevel ordered probit model, suitable for ordered categorical variables such as the number of sales observed on any given day (cf. Duncan, Khattak, and Council 2000). We observe the sales $y_{ijt}=\{0, 1, 2, 3,\ldots\}$ by agent i in district j on day t. Let $y^*_{ijt}=(-\infty<y^*_{ijt}<\infty)$ be the underlying latent variable that captures the sales likelihood intensity. At the first level of analysis, the nested ordered probit model is stated as follows:

$$\begin{aligned}y^*_{ijt} = {} & \beta_{0i} + \beta_1\text{PRE-CONTEST}_{ijt} + \beta_2\text{CONTEST}_{ijt} + \beta_3\text{POST-CONTEST}_{ijt} \\ & +\beta_4\text{PRE} - \text{CONTEST}_{ijt} \times \text{DIST}_{\text{POTENTIAL}_{ijt}} + \beta_5\text{CONTEST}_{ijt} \times \text{DIST}_{\text{POTENTIAL}_{ijt}} \\ & +\beta_6\text{POST-CONTEST}_{ijt} \times \text{DIST}_{\text{POTENTIAL}_{ijt}} + \beta_7\text{PRE-CONTEST}_{ijt} \times \text{SALES}_{\text{ABILITY}_{ijt}} \\ & +\beta_8\text{CONTEST}_{ijt} \times \text{SALES}_{\text{ABILITY}_{ijt}} + \beta_9\text{POST-CONTEST}_{ijt} \times \text{SALES}_{\text{ABILITY}_{ijt}} \\ & +\beta_{10}\text{DIST}_{\text{POTENTIAL}_{ijt}} + \beta_{11}\text{SALES}_{\text{ABILITY}_{ijt}} + \beta_{12}\text{LAGGED}_{\text{SALES}_{ijt}} + \theta'\mathbf{Z_{ijt}} + \varepsilon_{ijt}.\end{aligned} \tag{1}$$

In Eq. 1, β_1, β_2, and β_3 denote the main effect of the pre-contest, contest, and post-contest phases, respectively (relative to the baseline). Also, β_4, β_5, and β_6 denote the interaction effect between district sales potential and the pre-contest, contest, and post-contest phases. The parameters β_7, β_8, and β_9 denote the interaction effect between salesperson sales ability and the pre-contest, contest, and post-contest phases, while β_{10} and β_{11} are the main effects of district sales potential and sales ability, respectively.

We include lagged sales (β_{12}, defined as the number of sales orders generated by the agent in the past week) in the model to parsimoniously capture state dependence in sales outcomes and long-term effects of salesperson effort reflected in sales outcomes (we thank an anonymous reviewer for this suggestion). Z_{ijt} refers to the vector of control variables and their effects on sales captured through the vector θ. Finally, β_{0i} is the random intercept that captures the unobserved heterogeneity in an agent's propensity to generate sales on any given day. At the second level of analysis, the intercept β_{0i} is modeled as

$$\beta_{0i} = \lambda_{00} + \xi_{0i}, \xi_{0i} \sim N\left(0, {\sigma_\xi}^2\right) \tag{2}$$

where λ_{00} is interpreted as the grand mean of the data, with its own random between-agent residual, ξ_{0j}. Given the specification for y^*_{ijt} and denoting the cumulative distribution of y^*_{ijt} to be $\Phi(.)$, the probability of $y^*_{ijt}=\{0,1,2,3,\ldots N\}$ is

$$p\left(y = y_{ijt}\right) = \begin{cases} \Phi\left(\lambda_K - y^*_{ijt}\right) - \Phi\left(\lambda_{K-1} - y^*_{ijt}\right), y = N \\ \cdots\cdot \\ \Phi\left(\lambda_3 - y^*_{ijt}\right) - \Phi\left(\lambda_2 - y^*_{ijt}\right), y = 3 \\ \Phi\left(\lambda_2 - y^*_{ijt}\right) - \Phi\left(\lambda_1 - y^*_{ijt}\right), y = 2 \\ 1 - \Phi\left(\lambda_1 - y^*_{ijt}\right), y = 1. \end{cases} \tag{3}$$

The threshold parameters λ_k (k=1 to K) help shape the distribution of the response variable y_{ijt}. We estimate Eqs. 1–2 simultaneously using a maximum likelihood–expectation maximization algorithm (Singer and Willett 2003). We use asymptotic White standard errors to help guard against misspecification of the error variance-covariance matrix (White 1982; Naik et al. 2008) and verify that the estimated model does not suffer from serially correlated errors.

5 Results

Model selection In Table 2, we present model 1 with only the control variables and the main effects of the key independent variables. In model 2, we add the interaction effects of the pre-contest, contest, and post-contest phases with district sales potential and agent sales ability, respectively (i.e., $2\times3=6$ interactions). Compared to model 1 that has only main effects, the inclusion of interaction effects (model 2) significantly improves the model fit (Δ_{deviance}=1458.2, p<.01). Therefore, we use model 2 to discuss our findings.

Hypothesis tests As expected, we find a negative main effect of the pre-contest phase on sales performance (β_1=−.880, p<.01). Also, as expected, we find a positive main effect of the contest phase on sales performance (β_2=.970, p<.001). Thus, in support of H_1, we find evidence for a sales dip in the pre-contest phase (H_{1a}) and a sales boost in the contest phase (H_{1b}). The sales boost in the post-contest phase is not significant, even though the sign indicates that the impact might continue in the post-contest phase (β_3=.259, ns). We find that the main effect of district sales potential is not significant (β_{10}=.411, ns). However, as hypothesized in H_{2a}, the sales dip in the pre-contest phase is less pronounced when the district potential is higher (β_4=1.796, p<.05). Also, in support of H_{2b}, the sales boost in the contest phase is less pronounced when the district sales potential is higher (β_5=−1.154, p<.01).

With regard to ability, we find a positive main effect of agent ability (β_{11}=.025, p<.001). While directionally correct, we do not find support for H_{3a} where we hypothesized the sales dip in the pre-contest phase being less pronounced for agents with higher ability (β_7=.002, ns). This suggests that even agents who performed well in previous contests withhold sales before the contest begins, i.e., high past performers remain motivated by the present contest as they continue to seek more recognition (Murphy and Sohi 1995). We find support for H_{3b} and H_{3c}, i.e., the sales boost is more pronounced for agents with higher ability in the contest phase (β_8=.008, p<.001) and the post-contest phase (β_9=.002, p<.05).

In Table 3, we provide robustness checks. Specifically, defining the length of the pre-contest and post-contest phases to be 2 weeks (model 3) or 4 weeks (model 4) instead of 3 weeks (chosen in model 2) did not substantially alter the results. Similarly, treating the dependent variable as a continuous variable instead of an ordered variable (model 5) also yields similar results.

5.1 Sales contest effectiveness

Based on the estimates from model 2, we (a) predict the number of policies sold on a given day in any of the three contest phases and (b) assess the change in the predicted

Table 2 Estimation results

Variables	Model 1: main effects	Model 2: interaction effects
Pre-contest	−.148****	−.880***
	(.031)	(.361)
Contest	.601****	.970****
	(.028)	(.201)
Post-contest	.214****	.259
	(.030)	(.239)
District potential	−.149	.411
	(.390)	(.551)
Pre-contest*district potential		1.796**
		(.898)
Contest*district potential		−1.154***
		(.500)
Post-contest*district potential		−.196
		(.593)
Sales ability	.028****	.025****
	(.001)	(.001)
Pre-contest*sales ability	–	.002
	–	(.002)
Contest*sales ability	–	.008****
	–	(.001)
Post-contest*sales ability	–	.002**
	–	(.001)
Gender	.050***	−.007
	(.020)	(.033)
Lagged sales	.132****	.137****
	(.011)	(.011)
Month fixed effects	Included	Included
Intercepts	Included	Included
Akaike's information criterion (AICC)	131,727.1	130,268.9
Number of agents	1180	1180
Number of days	365	365

Standard errors in parentheses

*p<.10; ** p<.05; *** p<.01; ****p<.001, significance

probability of selling a specified number of policies due to changes in the independent variables. From Table 4, panel A, holding all other covariates at their mean value, the predicted probability of selling one policy on a given day in the baseline period is 1.65 %. In the pre-contest phase, this probability drops to 1.11 %. By contrast, the probability of a sale in the contest phase rises to 5.71 %, while in the post-contest phase, it remains higher than the baseline period at 2.62 %.

Table 3 Robustness checks

Variables	Model 2: 3 weeks	Model 3: 2 weeks	Model 4: 4 weeks	Model 5: continuous
Pre-contest	−.880***	−.625*	−.695**	−.022
	(.361)	(.426)	(.344)	(.024)
Contest	.970****	.964****	1.031****	.115****
	(.201)	(.170)	(.029)	(.018)
Post-contest	.259	.268	.361**	−.002
	(.239)	(.266)	(.209)	(.023)
District potential	.411	.519****	.457	.022
	(.551)	(.420)	(1.487)	(.040)
Pre-contest*district potential	1.796**	1.000	1.527**	−.056
	(.898)	(1.064)	(.863)	(.060)
Contest*district potential	−1.154***	−1.264***	−1.120****	−.207****
	(.500)	(.426)	(.437)	(.046)
Post-contest*district potential	−.196	−.310	−.386	−.002
	(.593)	(.666)	(.526)	(.060)
Sales ability	.025****	.025****	.023****	.002****
	(.001)	(.002)	(.004)	(.000)
Pre-contest*sales ability	.002	.001	.002*	.001****
	(.002)	(.002)	(.002)	(.000)
Contest*sales Ability	.008****	.008****	.009****	.005****
	(.001)	(.001)	(.001)	(.000)
Post-contest*sales ability	.002**	.003*	.004***	.002****
	(.001)	(.002)	(.001)	(.000)
Gender	−.007	−.004	−.007****	.004**
	(.033)	(.026)	(.001)	(.002)
Lagged sales	.137****	.139****	.137****	.029****
	(.011)	(.010)	(.011)	(.002)
Month fixed effects	Included	Included	Included	Included
Intercepts	Included	Included	Included	Included
Akaike's information criterion (AICC)	130,268.9	130,263.4	130,205.2	25,319.2
Number of agents	1180	1180	1180	1180
Number of days	365	365	365	365

Standard errors in parentheses

*p<.10; ** p<.05; *** p<.01; ****p<.001, significance

Company data suggests that the average dollar value of a life insurance sale is $300. Since the sales probability drops from 1.65 % in the baseline period to 1.11 % in the pre-contest phase, the average loss in revenue in the pre-contest phase lasting 3 weeks (21 days) relative to the baseline is (1.65–1.11)%*21*300=$34 per agent. Similarly, the revenue gain in the contest phase (42 days) is $512 per agent. Finally, the sales probability in the post-contest phase stays above the baseline, and the gain in revenue

Table 4 Decomposing sales contest effectiveness

	Panel A			Panel B					
	All agents			Low potential sales districts			High potential sales districts		
	Probability of sale	Probability change	Revenue change	Probability of sale	Probability change	Revenue change	Probability of sale	Probability change	Revenue change
Baseline (no contest)	1.65	–	–	1.5	–	–	1.97	–	–
Pre-contest period	1.11	−0.54	(−$34)	0.62	−0.88	($55)	1.85	−0.12	($8)
Contest period	5.71	4.06	$512	6.59	5.09	$641	4.89	2.92	$368
Post-contest	2.62	0.97	$61	2.49	0.99	$62	2.76	0.79	$50
Net change	–	–	$539	–	–	$648	–	–	$410

	Panel C					
	Low ability agents			High ability agents		
	Probability of sale	Probability change	Revenue change	Probability of sale	Probability change	Revenue change
Baseline (no contest)	1.54	–	–	2.1	–	–
Pre-contest period	0.99	−0.55	($35)	1.41	−0.69	($43)
Contest period	5.4	3.86	$486	7.46	5.36	$675
Post-contest	2.45	0.91	$57	3.34	1.24	$78
Net change	–	–	$509	–	–	$710

Panel A is the change in sales probability and revenue—all agents, panel B is the change in sales probability and revenue—low vs. high sales potential districts, and panel C is the change in sales probability and revenue—low vs. high sales ability agents (relative to the baseline) is \$61 per agent. Combining all three phases, we find that the net gain is \$539 per agent from the sales contest. Interestingly, the drop in the pre-contest phase is less than 10 % of the net gain from the contest.

5.1.1 Moderator effects

In Table 4, panel B, we present the probability of a sale for high sales potential districts (holding other covariates at their mean value). The probability of selling one policy on a given day in the baseline period is 1.97 %. Consistent with H_{2a}, we find that the pre-contest sales probability is 1.85 %; hence, the drop in probability is 0.12 % which is less than 0.54 % (average across all districts; see Table 4, panel A). Consistent with H_{2b}, the contest sales probability is 4.89 %; hence, the gain is 2.92 % which is less than 4.06 %, the average gain across all districts (see Table 4, panel A). Finally, the sales probability in the post-contest phase is 2.76 %.

Accordingly, the loss in revenue in the pre-contest phase (relative to the baseline) for high sales potential districts is \$8 per agent, the revenue gain in the contest phase is \$368 per agent, and the revenue gain in the post-contest phase is \$50 per agent. Combining all three phases, the net gain is \$410 per agent in high sales potential districts. This gain is about 24 % less than the gain of \$539 per agent across all districts. However, as noted in Table 4, panel B, a similar analysis for low potential districts shows a net gain of \$648 per agent, i.e., 20 % more than the gain across all districts.

In Table 4, panel C, we depict the probability of a sale for a *high-ability agent* (holding other covariates at their mean value). The probability of selling one policy on a given day in the baseline period is 2.1 %. In line with H_{3a}, we find that the pre-contest sales probability is 1.41 %; hence, the drop in probability is 0.69 % which is more than 0.54 % (average across all districts; see Table 4 panel A). Also, consistent with H_{3b}, we find that the contest sales probability is 7.46 %; hence, the gain in probability is 5.36 % which is more than 4.06 %, the average across all districts (see Table 4, panel A). Finally, the sales probability in the post-contest period is 3.34 %.

The revenue loss in the pre-contest phase is \$43 per agent, the revenue gain in the contest phase is \$675 per agent, and the revenue gain in the post-contest phase is \$78 per agent. Combining, we find that the net gain is \$710 per agent among high-ability agents which is 32 % higher than the gain of \$539 per agent across all districts. In Table 4, panel C, a similar analysis for low-ability agents shows a gain of \$509 which is 5 % less than the gain across all districts.

6 Summary and conclusion

There has been a long-standing debate on whether sales contests, especially those that are preannounced, motivate additional effort or end up inducing strategic timing games that produce no net sales gain. In this research, we investigate this issue in a consultative selling (life insurance sales) scenario, focusing on the likely pattern of individual-level sales timing games and how this pattern is moderated by district sales potential and agent ability. We find evidence supporting our hypothesized pattern of a pre-contest sales dip, followed by a within-contest and post-contest boost in the sales probability. The pattern occurs not just due to sandbagging but also because agents shift their effort from closing toward prospecting in the pre-contest phase to boost their chances of winning a prize. This led to our hypotheses about how district sales potential and sales ability might affect this basic response pattern that were largely supported by the data. Also, the empirical model permits quantitative assessments of the probability of sales by agents of varying ability in districts of varying sales potentials. We find that the sales boost in the contest ($512 per agent) and post-contest ($61 per agent) phases more than makes up for the revenue lost due to the sales dip in the pre-contest phase ($34 per agent). Also, the sales gain is higher in districts with lower sales potential and among agents with higher sales ability. Thus, we add to the sparse empirical research on sales contest effectiveness showing that situational variables (e.g., sales potential) and individual agent characteristics must be combined with hard data to assess if sales contests do produce net overall sales gains.

Two areas merit consideration for future research. First, in this setting, management ran the sales contests in all territories for fairness reasons. Future research should include a control group, i.e., territories where agents are not exposed to the sales contest, to better benchmark the effects while accounting for other possible confounding factors (for example, the impact of a competitor withdrawing from the market during the same period). Second, we examined the overall effectiveness of contests in stimulating sales of *one product* (life insurance), across all phases. Future research may investigate the impact on the entire product portfolio, to potentially identify any negative sales effects on other products.

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