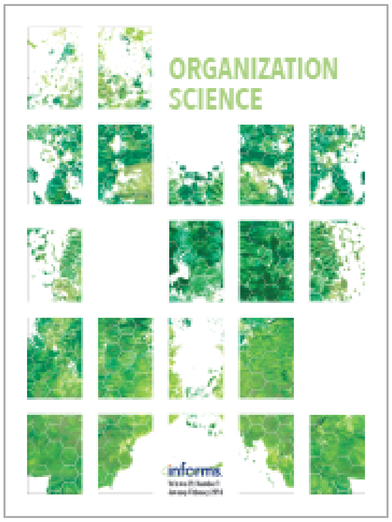

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Market Competition and the Effectiveness of Performance Pay

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Abstract. It is well established that the effectiveness of pay-for-performance (PfP) schemes depends on employee- and organization-specific factors. However, less is known about the moderating role of external forces such as market competition. Our theory posits that competition generates two counteracting effects—the *residual market* and *competitor response* effects—that vary with competition and jointly generate a curvilinear relationship between PfP effectiveness and competition. Weak competition discourages effort response to PfP because there is little residual market to gain from rivals, whereas strong competition weakens incentives because an offsetting response from competitors becomes more likely. PfP hence has the strongest effect under moderate competition. Field data from a bakery chain and its competitive environment confirm our theory and let us refute several alternative interpretations.

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Keywords: pay for performance (PfP) • market competition • incentives • field experiment

Introduction

As one of the most commonly used managerial practices, *pay-for-performance* (PfP) schemes work in motivating employees *on average* (Prendergast 1999, Lazear 2000, Gerhart et al. 2009). That is, firms implementing PfP schemes at different levels of the organization typically perform better in the dimensions incentivized by the scheme (Kerr 1975, Milgrom and Roberts 1992). However, the effectiveness of such schemes depends on several moderating factors. Prior research finds that, beyond the parameters of the incentive scheme itself, factors internal to the organization, such as employee and job characteristics, influence its effectiveness (Garbers and Konradt 2014, Nyberg et al. 2018). Much less is known about the type of external environment, such as the degree of market competition, in which PfP schemes are most likely to work. This is surprising given that competition affects firm behavior to the point that "the best of all monopoly profits is a quiet life" (Hicks 1935, p. 8). For instance, competition affects firms' innovative behavior (Schumpeter 1942) such that too little or too much market competition leads to reduced incentives (and effort) to innovate (Aghion et al. 2005). Furthermore, performance pay is often linked to market or operational performance. If performance is measured in market outcomes as opposed to operational goals such as physical output per unit of input, converting operational performance into market performance becomes relevant for effort choice under a PfP scheme, determining its effectiveness. How this conversion works depends on external factors, including competition. Hence, we ask *if the success of PfP schemes is contingent on the degree of product market competition and, if so, how*.

We identify two forces through which competition can drive the effectiveness of PfP schemes: the extent to which a focal firm could boost payoff (e.g., sales) by winning business from competitors (labeled the *residual market effect*) and the likelihood of competitor reaction to restore the status quo (the *competitor response effect*). To capture these forces, we develop a simple model in which variations in competition, defined as the number of competitors to the focal firm, generate variations in the expected net benefit to the agent from discretionary effort and hence create different responses to a given PfP scheme. Although higher competition stimulates effort by increasing the expected payoff from winning residual market from rivals, more competition also implies a higher likelihood of competitor response, which reduces the expected benefit from effort. Both effects combined generate a curvilinear relationship between market competition and the effectiveness of PfP, such that the incentive scheme works best at moderate competition levels.

We test this relationship by estimating the effectiveness of a PfP scheme conditional on the intensity of local competition using data from a field experiment in a German bakery retail chain of 193 shops, a random half of which was assigned to a PfP scheme (see Friebel et al. (2017)[1]). We complement the field experiment data by collecting extensive data on competing bakeries around the shops belonging to our study firm. Our experimental setting and the richness of our data let us test the implications of our model, perform robustness tests, and rule out plausible alternative explanations to our findings.

To preview our results, a piecewise linear regression estimated on our data shows that the PfP effect on sales is *first increasing* by about 3% per additional competitor until the number of competitors reaches three. Beyond this point, the effect of PfP *decreases* by about 1.5% per additional competitor. This pattern is confirmed if we separate shops into three competition groups (low/moderate/high) and measure PfP effects specific to each group. We also find that the likelihood of *participation in the PfP scheme*, which we define as exerting additional sales effort when exposed to the PfP (i.e., the treated shops), is highest (up to 70%) under moderate competition (three or four local competitors), significantly above than the global average participation rate (23%).

We contribute to research on incentive design in organizations by showing that external factors such as competition can affect the outcomes of management practices generally considered "internal," such as PfP. We go beyond measuring the net effect of PfP at different competition levels, and we propose how competition affects *participation* in these schemes and how much this influences the overall *effectiveness* of PfP schemes. Our results inform research on compensation structures in particular and management practices more generally, suggesting that firms have to consider outside factors in their design. Moreover, research on the interplay of competition and incentives (Vroom and Gimeno 2007) is complemented because not only do incentives shape competitive behavior but also competition shapes the use and effects of incentives. Finally, we contribute to prior work on incentives in organization and strategy. Although most studies in this domain focus on chief executive officer (CEO) and top management compensation (Larkin et al. 2012), we study compensation for retail and service workers—a large and growing job category (Autor 2015).

Related Literature

There is a broad consensus that incentives work *on average*—that is, they improve the average performance in the outcome variable that is incentivized (Kerr 1975, Prendergast 1999, Gerhart et al. 2009). However, the effectiveness of PfP is not homogeneous across and even within firms (Pfeffer 1998, Nyberg et al. 2018). Scholars have tried to explain the heterogeneity in PfP effectiveness through various moderators at the individual, team, task, and organizational levels. For example, incentives produce different performance effects depending on motivation crowding-out (Frey and Jegen 2001, Gubler et al. 2016), gaming the compensation system (Holmstrom and Milgrom 1991, Harris and Bromiley 2007, Obloj and Sengul 2012, Larkin 2014), comparison costs and peer effects (Chan et al. 2014, Gartenberg and Wulf 2017, Giarratana et al. 2017, Obloj and Zenger 2017), and demographics (Delfgaauw et al. 2013, Manthei et al. 2018). At the team and organization levels, scholars have considered the trade-off between individual and teamwide incentives (Hamilton et al. 2003, Kretschmer and Puranam 2008, Pierce 2012, Bandiera et al. 2013), access to incentive schemes (Friebel et al. 2017), task interdependencies (Siegel and Hambrick 2005), and the communication of PfP schemes (Englmaier et al. 2016) as moderators of PfP effectiveness. A number of studies indicate that PfP schemes work only when factors *within* the organization are favorable (Becker and Gerhart 1996, Elvira and Graham 2002, Tosi and Greckhamer 2004, Cobb and Lin 2017, Kang and Han Kim 2017). Factors *outside* the firm that may affect the impact of PfP remain largely unexplored.

Prior work on incentive design in organization and strategy research focuses almost exclusively on CEOs and top management. Indeed, Larkin et al. (2012) report that nearly 75% of recent papers on compensation in top management journals study executives, whereas compensation for nonexecutive employees is more prominent in the human resources (HR) literature (Gerhart and Fang 2015, Gerhart and Weller 2017). This is surprising given that a major part of compensation costs and organizational performance are related to nonexecutives, and that it is the many nonexecutives whose (often unobserved) efforts shape organizational outcomes. Interestingly, complementary work shows that common incentive schemes actually work better for simple and ordinary tasks than for knowledge-intensive activities (Ederer and Manso 2013, Gambardella et al. 2015).

Although the intensity of market competition has been shown to affect organizations in many key dimensions such as the generation or adoption of innovations (Aghion et al. 2005, Vives 2008, Kretschmer et al. 2012), we study market competition as a factor outside the organization potentially impacting the effectiveness of PfP schemes. Hence, our study relates to research on the effects of competition on firm efficiency and profits (Porter 1990, Nickell 1996, Bloom and Van Reenen 2007). This work suggests that firms facing strong competition try to increase their efficiency through beneficial management practices, including PfP schemes. Vroom and Gimeno (2007) show how ownership structure (corporate versus franchised) influences incentives, competitive behavior, and ultimately performance. Relatedly, several studies have linked market competition to the adoption of managerial incentive schemes. Schmidt (1997) shows that the risk of bankruptcy can lead firms to offer managerial incentives in competitive markets. Baggs and De Bettignies (2007) and Raith (2003) highlight several theoretical mechanisms that show how competition may impact firms' propensity to adopt performance-related incentives. Although there is empirical evidence for a higher prevalence of incentive contracts under more competition (Cuñat and Guadalupe 2005, Baggs and De Bettignies 2007), the effect of competition on performance gains from PfP is not yet known.

Theory

We think of PfP schemes as a management practice whereby employees' pay is linked to some predefined performance measure (sales in our case). We are interested in the forces of market competition that shape the *effectiveness* of PfP schemes in generating extra sales through encouraging employee *participation* in the PfP scheme[2]—that is, exerting additional sales effort in pursuit of a PfP reward. Consistent with expectancy theory (Vroom 1964, Campbell and Pritchard 1976), employees will participate in the PfP scheme by exerting effort only if their expected reward exceeds the effort costs.[3] We posit that market competition generates two counteracting effects on the outcome of sales effort and hence the expected reward from PfP, labelled the *residual market* and *competitor response* effects, whose relative strengths vary with competition. These effects determine employees' decision to participate in a PfP scheme and its effect on sales. We first introduce them in turn, discuss their combined effect, and finally represent them in a formal model.

The Residual Market Effect

The effectiveness of employees' extra effort triggered by PfP (e.g., working faster or providing better customer service) depends on how much sales and market they can capture from rivals. We discuss that the intensity of competition can have a positive effect on the effectiveness of PfP as a result of facilitating bigger market gains from rivals.[4]

For a given market size, the strength of this effect depends on the firms' ex ante market share. Firms in more competitive environments face more rivals and thus tend to have a lower share of the overall market. Hence, the potential share of business that can be captured through extra sales effort is large. On the contrary, in low-competition environments, few firms dominate the market and already enjoy larger market shares on average. Therefore, additional sales effort would capture only a limited residual market. In the extreme case of no competition—a monopolist serving the whole market—no business gain is possible (without market expansion, which we rule out in our model). Because a larger residual market increases the expected payoff from PfP for employees, it makes a PfP scheme more attractive to them, increasing their likelihood of participating and the resulting sales gain (panel A in Figure 1). This mechanism, in essence, is similar to the argument that the extent of *business stealing* through competitive action increases with competition (Hermalin 1992, Raith 2003, Baggs and De Bettignies 2007, Vives 2008).

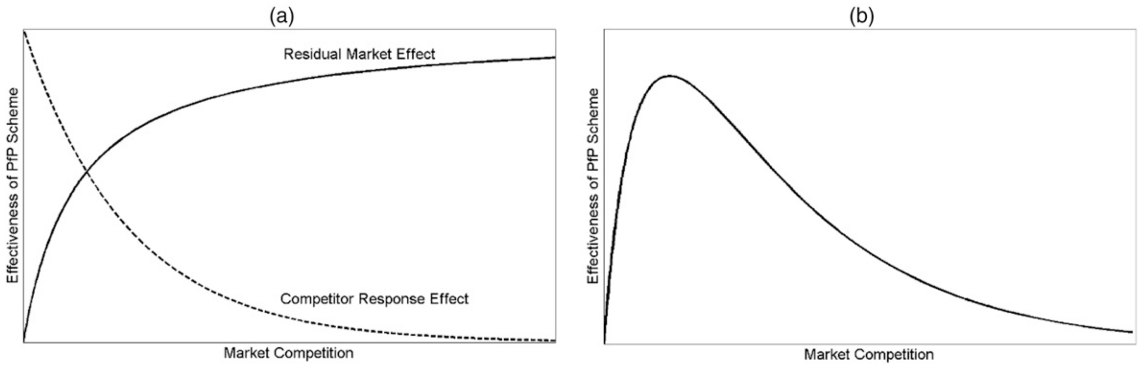
The Competitor Response Effect

The gains from extra sales effort also depend on whether competitors will react to it. In fact, any gains from sales effort may be offset completely by competitors' responses. Competitors respond because they witness a decline in sales and attribute them to the focal firm's competitive actions (D'Aveni 1994, Ferrier et al. 1999, Zucchini et al. 2018). Competitor responses need not mirror the initial competitive action and can include a range of reactions, such as a shop facelift or a marketing campaign to restore or even improve their competitiveness. This mechanism also depends on the level of market competition: with more competitors, a response by one or more of them becomes more likely, reducing the expected gain from sales effort and hence the expected payoff from PfP to employees (panel A in Figure 1).[5] Anticipating this, employees are less willing to participate in the PfP scheme.

The Residual Market and Competitor Response Effects Combined

The overall effect of competition on PfP effectiveness in generating extra sales is the combination of the two above-mentioned effects, their strength varying with the extent of market competition. As competition increases from a low level, the positive residual market effect tends to dominate the negative competitor response effect because, given that competitors are not too many, the chance the firm can increase sales without facing competitor response is relatively

Figure 1. Residual Market and Competitors' Response Effects, with Respect to Market Competition (Panel A) and the Combined Effect (Panel B)



high. As a result, the overall effect of PfP increases with competition when competition is low (panel B in Figure 1).

As the number of competitors continues to increase, however, competitor response becomes ever more likely, and the balance between the two effects reverses. The combination of the residual market and competitor response effects generates a nonmonotonic, inverted U-shaped pattern of PfP effectiveness with competition (panel B in Figure 1). The intuition behind this pattern is simple: when competition is low, PfP does not effectively motivate employee participation because there is not enough business to capture from competitors. At high competition levels, PfP is ineffective because competitor responses reduce expected gains from it and discourage participation in the scheme. PfP schemes therefore have the highest impact at moderate competition levels.

The Formal Model

The potential gain through the residual market effect and the hazard of competitor response create counteracting mechanisms on the effectiveness of PfP with market competition. To support our verbal arguments and illustrate the combined effect more precisely, we formally describe the balance between the two in a simple model based on the following assumptions: (i) the focal firm's ex ante market share (i.e., $s(n)$) is a function of the number of competitors n, with $0 < s(n) \leq 1$, $s'(n) < 0$, and $s''(n) > 0$; (ii) the probability of each individual competitor responding is a constant P; (iii) market size is fixed to 1 (i.e., discretionary effort cannot expand market size); (iv) the goods produced by competitors are perfectly substitutable; and (v) PfP is linear in sales. Table 1 lists our modeling assumptions, their effect, and their correspondence to real life. Assumption (i) is fairly general and simply says that firms with many competitors tend to have a smaller share of the market.[6] We relax assumption (ii) as an extension (see Online Appendix A.2). Assumption (iii) lets us focus on the "pure" residual market and competitor response effects, abstracting from other incentives coming from changing market size. Assumptions (iv) and (v) simplify our algebra; relaxing them introduces greater complexity without producing new insights.[7]

We begin by capturing employees' incentives to participate in a given PfP scheme and then derive the expressions for participation rate and the sales gain from PfP. Both participation rate and sales gain vary with local competition and will be estimated empirically later on.

Given the participating focal firm's ex ante market share $s(n)$ and total market size normalized to 1 (assumption (iii)), if no competitor responds, it will capture the whole market (assumption (iv)), gaining $1 - s(n)$ above its ex ante sales (i.e., the entire residual market). If k competitors respond, they will share the market equally with the focal firm, so the focal firm will gain $\frac{1}{k+1} - s(n)$. Multiplying all possible values of the gain with the respective probabilities of competitor response and summing up, we obtain the following expression for the expected sales gains from participating in the PfP scheme:

$$\begin{aligned} G(n) &= \sum_{k=0}^{n} C_k^n \cdot P^k \cdot (1-P)^{n-k} \cdot \left(\frac{1}{k+1} - s(n)\right) \\ &= 1 - s(n) + \frac{1-(1-P)^n - (n+1-(1-P)^n) \cdot P}{(n+1) \cdot P}. \end{aligned}$$

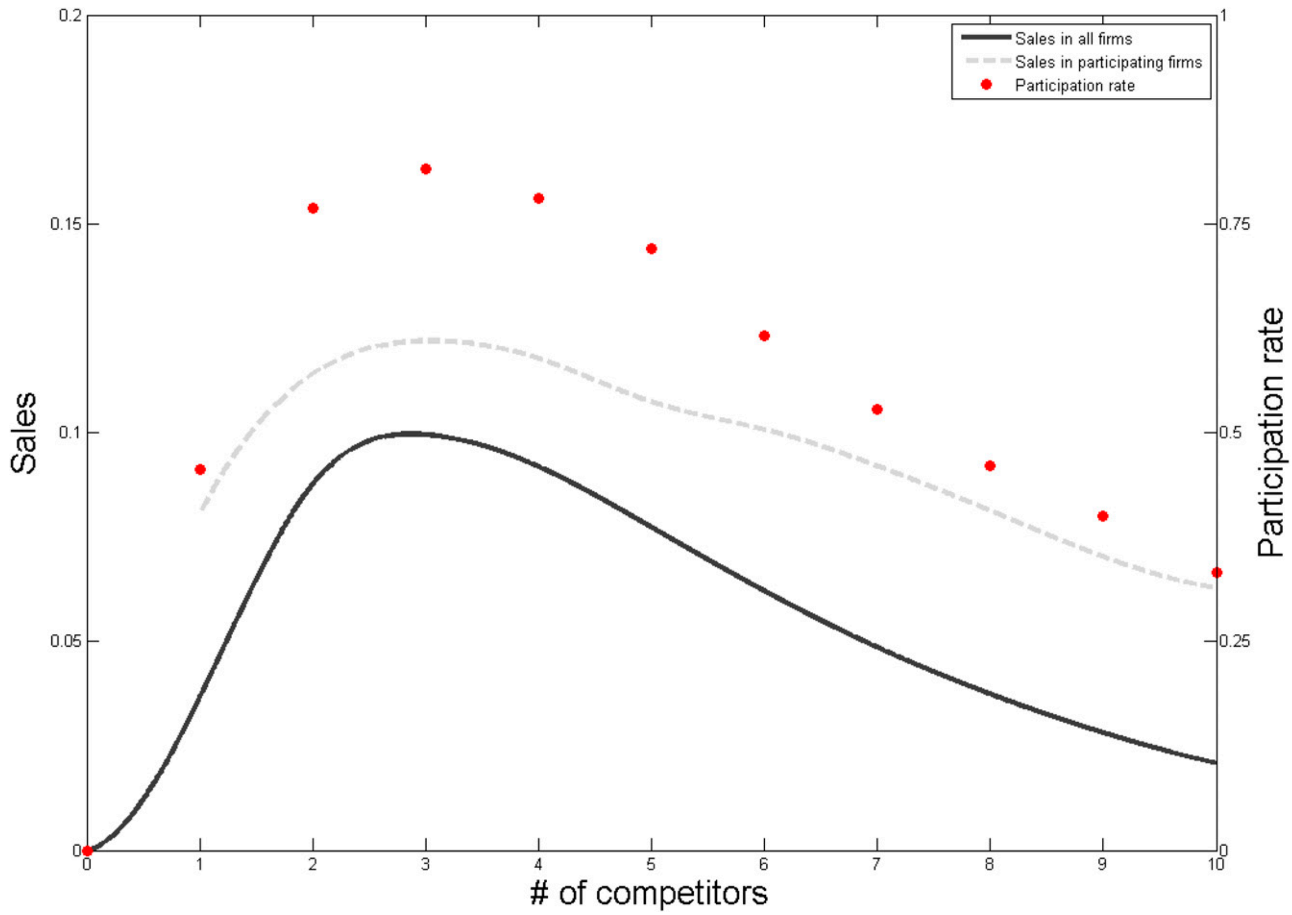
This equation captures the *residual market effect* through term $1 - s(n) \geq 0$, which monotonically increases with competition ($s'(n) < 0$ by assumption (i)), and the *competitor response effect* through term $\frac{1-(1-P)^n-(n+1-(1-P)^n) \cdot P}{(n+1) \cdot P} \leq 0$, whose magnitude also monotonically increases with n. Their sum is a curvilinear function of the number of competitors peaking at some moderate level of competition, as illustrated in Figure 2.

Given the expected sales gain from participation in the PfP scheme, employees will participate if

Table 1. Overview of the Theoretical Model Assumptions

Assumption/property	Formal correspondence	Impact on result(s)	Real-life correspondence	Consequences of relaxing
Exogenous incentives assignment	N/A	Causal identification of the average PfP effect across competition regimes	There is random assignment into the treatment group or control group (field experiment).	PfP schemes are implemented in shops most likely to benefit from them.
Exogenous competition	n is given (exogenous)	Clean identification of the differential effect of treatment with respect to competition	Shops are not systematically different in areas with more or less local competitors.	The treatment effect conflates with systematic differences across competition groups (we tested for systematic shop differences across different competition levels, based on observables. (See Table 7.)
(Weak) diminishing market share	$s'(n) < 0$	Residual market effect (i.e., in markets with a higher number of competitors, more residual business is available to be gained from rivals)	Shops operating in the areas with more rivals tend to have a lower share of the overall market.	There is a weaker treatment effect because shops with many competitors may not have stronger incentives to exert effort. The treatment effect would peak at lower competition levels (see Online Appendix A1).
Constant competitor response	P = constant	Increasing likelihood of any competitor response with more competitors	Competing shops' retaliation is the same across different competition levels.	*Random* probability of response generates very similar results (see Online Appendix A2). Alternative assumption: If the probability of response is higher for some competitor types than others, or with higher competition, the treatment effect will peak at lower competition levels (see Online Appendix C4).
Fixed market size	Sum of gross payoffs (market shares) = 1	Competition is only in market shares (clean estimation of effects based on market share change, abstracting from other incentives coming from changing market size)	Consumers have a fixed demand for the good and decide only where to buy it from.	If discretionary effort increases market size, the treatment effect will peak at higher levels of competition because there is an added payoff to exert discretionary effort.
Perfect substitution of products	Infinite elasticity of market share with respect to effort	Firms conducting a competitive action (i.e., discretionary effort) take the entire market from competitors that do not	Consumers consider bakeries close substitutes and react strongly to their competitive action (e.g., working faster or providing better customer experience), conditional on shops locations being fixed.	If discretionary effort leads to smaller market share increases, the treatment effect will be weaker and peak at lower levels of competition because the incentive to exert effort is smaller. Alternative assumption: If elasticity of substitution increases with competition, a positive mechanism (similar to the residual market share effect) will be generated.
Linear PfP reward	Employee payoff = $\alpha \cdot G(n)$	Continuous payoff function for employees	Employees adjust efforts smoothly, irrespective of how close they are to receiving the bonus.	If employees work "towards the threshold," expect a stronger difference in outcome variable (sales) between successful (above-threshold) and unsuccessful (below-threshold) shops. (See Table 7.)

Figure 2. (Color online) Expected Payoff (Sales) and Participation Rates with Respect to Market Competition



Notes. The figure shows the expected payoff sales (*Y* axis, left) and participation rate (*Y* axis, right) versus the number of competitors (*X* axis). The participation rate is calculated from Equation (1), and the expected sales is calculated using Equation (2). For the special case of the above-mentioned plots, α is set to 1, P is set to 20%, $e \sim$ N(0.35,0.1), and s($n = \frac{1}{0.8n+1}$) to match our empirical setting.

their expected payoff, a linear function of sales (assumption (v)), $\alpha \cdot G(n)$, exceeds the costs of effort (i.e., $E[\alpha \cdot G(n) - e] \geq 0$). To reflect the uncertainty in the actual costs of effort for a given agent, and the variation in costs between agents, we specify the cost of effort e as a random variable following a probability distribution with cumulative distribution function $F(e)$. The *participation rate* is then

$$\text{Prob}(\alpha \cdot G(n) - e \geq 0) = F(\alpha \cdot G(n)), \tag{1}$$

and the expected sales gain from PfP is

$$\Pi(n) = F(\alpha \cdot G(n)) \cdot G(n). \tag{2}$$

Both the participation rate and expected sales gain from PfP vary with the number of competitors in a curvilinear fashion (Figure 2). Note that the average treatment effect of all firms (solid line) always lies below the treatment effect of the participating firms (dashed line), as it is the product of participation (dotted line) and treatment effect of participating firms.

Our formal model relies on simplifying assumptions such as fixed market size and perfect elasticity of substitution, which, though plausible in our specific study setting (see the next section), may not hold universally. However, they let us focus on studying the theoretical mechanisms of our interest in a parsimonious framework that generates a straightforward empirical counterpart.

Study Background

The Study Firm and Its Shops

Our study firm is active in one of the large metropolitan areas in Germany with more than four million inhabitants residing in several cities and dozens of smaller towns (we provide a map of the market in the online appendix). Our sample runs from January 2013 until June 2014 and combines the data from Friebel et al. (2017)[8] with detailed observations of local competitors (next section) collected for this study. The firm operates a network of 193 bakery shops, a random half of which were offered an opportunity to participate in a PfP scheme (details in the following subsections). In terms of our theoretical model, the shops selected into the PfP scheme may be regarded as "firms" with a PfP scheme and the rest as firms without a PfP scheme. Beneficial to our setup, all shops belonging to the same firm rules out many of the contextual differences between shops.

Table 2 reports basic descriptive statistics for the "treatment" (PfP scheme) and "control" (no PfP scheme) shops in our sample. The average shop sells around 27,000 euros worth of fresh bread products and receives just under 10,000 customer visits monthly, employing seven (mostly part-time) shop assistants who earn €9–€11 per hour, depending on tenure. Each shop has a supervisor whose task is to ensure compliance with all the technological, HR, and accounting procedures. Other tasks, such as pricing, marketing, and hiring, are centralized. However, discretionary effort by the shop team may still affect sales through better service, quality of food, or cleanliness.

Local Competition

To measure local competition, we identified every bakery within a 1 km radius from each focal shop. The 193 bakeries from our study firm have 684 competitors in a 1 km radius. Our main competition measure is based on the count of local competitors (Kalnins 2003, Schmidt et al. 2017). Yet to test the validity of this competition measure and the robustness of our results, we collected further information on a subset of competitors: for all bakeries in big towns (71 bakeries from our study firm; 264 competitors in a 1 km radius), we collected additional data by visiting *every* shop and taking measurements of its physical size, typically by using an ultrasound-measuring device (see Online Appendix B for details). We use these data to compute an alternative competition measure for this subsample of shops.

We identified two competitor types. First, conventional bakeries (such as our study firm) make up three-quarters of the total number of competitors: of the 3.54 competitors within a 1 km radius from a focal shop, on average, 2.65 are conventional bakeries (Table 2, panel B). The second type, which accounts for the remaining quarter, are discount supermarkets Aldi and Lidl (henceforth *large retailers*) that operate in-store unmanned fresh bread facilities.[9] Although selling fresh bread is the conventional bakeries' main business, it is only a small fraction of large retailers' total sales. Accordingly, the probability of competitor response (P in our model) by conventional bakeries is likely to be higher than that by large retailers—a feature we use in further analysis (Online Appendix C4).

Table 2. Pretreatment Shop Characteristics

	All shops (n = 193)	Control (n = 96)	Treatment (n = 97)	t-Test p-value
	Panel A: Characteristics of the shops			
Monthly sales	27,108.453 (13,055.102)	26,640.202 (11,303.489)	27,582.349 (14,604.501)	0.615
Monthly sales (in logs)	10.120 (0.410)	10.110 (0.397)	10.131 (0.422)	0.725
Monthly sales target	28,797.697 (13,583.071)	28,321.908 (11,512.960)	29,278.316 (15,383.534)	0.628
Sales growth (year-on-year)	0.007 (0.098)	0.006 (0.093)	0.007 (0.103)	0.481
Monthly no. of customer visits	9,681.377 (3,843.335)	9,590.301 (3,812.740)	9,773.843 (3,873.412)	0.740
Number of employees	7.190 (3.018)	7.200 (3.037)	7.179 (3.000)	0.959
Monthly total hours worked	721.162 (332.860)	718.545 (335.387)	723.762 (330.426)	0.910
Employee age	40.516 (6.416)	40.168 (6.484)	40.861 (6.331)	0.438
	Panel B: Characteristics of the shop location			
Mean no. of competitors in 1 km radius	3.544 (3.028)	3.698 (3.169)	3.392 (2.889)	0.484
Mean no. of large retailers in 1 km radius	0.891 (0.898)	0.885 (0.916)	0.897 (0.884)	0.929
Share of large retailers in total	0.284 (0.327)	0.282 (0.323)	0.287 (0.332)	0.917

Notes. Standard deviations are in parentheses. Last column reports the p-values of the two-sided t-test of equality of the means. Panel A: The data are from January 2013 to March 2014. Panel B: The data are as of the beginning of the treatment and remained unchanged throughout the treatment period (April–June 2014).

The PfP Scheme

Large retailers began entering the retail bakery market in late 2011, completing the installation of fresh bread facilities in all their stores by 2013, the start of our study period. This shook up the entire bakery market, including our study firm. In addition to increasing the number of competitors, it led to an erosion of profits because the fresh bread large retailers sold was of similar quality but cheaper. This prompted our study firm to rethink its management practices. After several initiatives (logistic changes, shop refurbishments, marketing campaigns, etc.) with limited success, it introduced a PfP scheme that paid a bonus to the sales teams in shops that reached their monthly sales target to motivate more sales-oriented behavior. It is this practice that we helped the study firm to design and which we test and explore.

The bonus was paid to the entire shop team upon reaching a predefined sales target, except for the "mini-job" employees who had to be excluded for tax reasons. The decision to reward the team rather than individuals was made for two reasons. First, a small amount per transaction and only one cash register in a shop would make it impractical to record individual contribution to sales, especially at peak times. Second, with interconnected and often parallel jobs, such as handling goods, operating the oven, serving customers, etc., running a shop requires cooperation and team effort, which would be discouraged by individual incentives (Shaw et al. 2002, Kretschmer and Puranam 2008). Teams that reached their monthly sales target received a bonus of €100. The bonus increased by €50 for each percentage point above the target and was capped at €300 for exceeding the sales target by 4% or more.

The PfP scheme was introduced on April 1, 2014, as a pilot in 97 randomly selected shops. The pilot lasted until June 30, 2014, after which it was rolled out to all shops. The treatment was randomly assigned to the study firm's shops to ensure that treatment and control groups are balanced so that an unbiased estimate of the treatment effect can be obtained from a difference-in-difference regression. As shown in Table 2, the treatment and control shops are indeed balanced in observable characteristics, including pretreatment sales (the outcome variable), sales growth (an indication that the "parallel trends" assumption holds), and the number and structure of local competitors (the moderator). In the treated shops, all team members received leaflets and explanations about the PfP; only the worker council, top management, and regional managers were informed about the experiment. We trained regional managers in how to react to potential inquiries. Only three employees in the control group asked about the PfP.

Empirical Strategy and Main Results

Our theory predicts a curvilinear relationship between local competition and two outcome variables, the participation in the PfP scheme (see Equation (1)) and the effectiveness of the scheme on sales gain (see Equation (2)). To test these relationships, we first use an approach that lets us identify the heterogeneity of the overall effect by competition group and then extend it to account for both participation and effectiveness conditional on participation.

Sales Gains from PfP by Level of Competition

We estimate the expected sales gain from PfP, modelled in the theory section (Equation (2)), contingent on local competition from the following difference-in-difference equation:

$$\ln(y_{it}) = treatment_i \times after_t \times D(competition_i) + month_t + shop_i + controls_{it} + error_{it}, \quad (3)$$

where y_{it} measures the performance outcome in shop i in month t (sales in most of our analysis), the $treatment_i$ dummy is 1 if shop i was randomly assigned into the PfP scheme[10] and 0 otherwise, $after_t$ is a dummy variable equal 1 for all months in the treatment and 0 in the pretreatment period, $competition_i$ is a measure of local competition and $D(competition_i)$ is a mapping that links it with the treatment effect, the *month* and *shop* fixed effects control for seasonality and shop-specific unobservables that affect sales, $controls_{it}$ are additional shop-specific controls such as log hours worked per month, and $error_{it}$ is the idiosyncratic error term clustered at the shop level.

The estimated sales gain from PfP is the difference-in-difference treatment effect specific to a given level of competition, $D(competition_i)$, which requires specifying the measure of competition and the mapping $D(\cdot)$.[11] Our main measure of competition is the number of local competitors within a 1 km radius from each focal shop, as customers in everyday food markets baked goods rarely travel long distances (Salvaneschi 1996). Using the competitor count as a measure of competition is common in the literature; see, for example, Kalnins (2003) and Schmidt et al. (2017). Our main specification for the mapping $D(\cdot)$, labelled *S-I* in what follows, is a piecewise connected linear function in the number of local competitors, n:

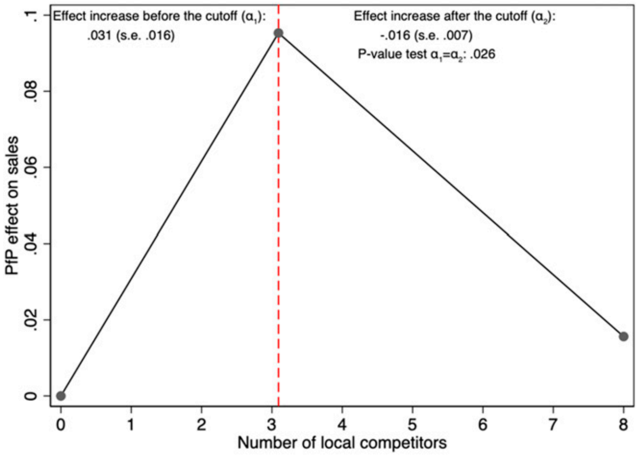
$$D(n) = \alpha_1 \cdot n \times I(n \le \gamma) + (\alpha_1 \cdot \gamma + \alpha_2 \cdot [n - \gamma]) \times I(n > \gamma), \quad (4)$$

where $I(x) = 1$ if condition x is satisfied and 0 otherwise, and the parameters α_1 and α_2 (the changes in the treatment effect with competition below and above the cutoff γ) and the cutoff point γ are estimated from the data. Piecewise regression has been used extensively in management research to detect nonmonotonic relationships (see, e.g., Lungeanu et al. (2016) and Stuart (2017)).[12] The term $D(n)$ approximates the predicted nonmonotonic relationship between PfP effect and local competition by two straight lines with different slopes, α_1 and α_2, connecting with each other at the cutoff point (see Figure 3)—hence the "piecewise connected." A significant positive estimate of α_1, and a significant negative one of α_2, would support our theory.

Column (1) of Table 3 reports the average sales gain from PfP and the parameter estimates of S-I. The average sales gain from PfP, 2.5% on the whole sample, hides heterogeneity with local competition. Our parameter estimates from S-I imply that the sales gain from PfP increases by about 0.031 (coefficient α_1; p-value = 0.05) with every additional competitor until the number of competitors reaches 3.09 (= γ; p-value = 0.00), at which point it peaks at 0.095 (= $\alpha_1 \cdot \gamma$; p-value = 0.05) and then decreases by 0.016 (= α_2; p-value = 0.02) per additional competitor above γ. The heterogeneity in the sales gain from PfP with competition implied by these estimates and shown in Figure 3 is sizeable and statistically significant: the equality test of the slopes α_1 and α_2 before and after the cutoff gives a p-value of 0.026.

Columns (2) and (3) of Table 3 report the same results for the (log) number of customer visits and (log) sales per customer visit. As with sales, PfP effects peak at moderate competition levels (about 3 for customer visits and about 4 for sales per visit). Comparing PfP effects for different performance outcomes suggests that most of the sales gain from PfP came from more customers. Finally, Table 4 presents the robustness of S-I to alternative estimations of the piecewise regression (see the Online Appendix C1 for the details).

Figure 3. (Color online) Graphical Illustration of the Piecewise Regression Results (S-I)



Note. The plot corresponds to the estimates in column (1) of Table 3.

Participation in the PfP Scheme by Level of Competition

We now estimate the participation rate as specified in our theoretical model (Equation (1)). Absent observable information on participation, we infer participation from the available data via a *finite mixture regression model* (FMM). FMMs are used in the management literature for identification of distinct subgroups within a study sample and for estimating subgroup-specific relationships when subgroup identifiers are unobserved (Brown and Kim 2013, Hsu and Lim 2013, Sakhartov and Folta 2013, Ebbes et al. 2014, Mani and Nandkumar 2016, Goes et al. 2017). From a technical standpoint, FMM models the distribution of the dependent variable, conditional on the regressors, as a mixture of distributions belonging to each subgroup. This procedure has the advantage over standard regression models of having more degrees of freedom to model the outcome variable (i.e., the distributional parameters of each subgroup, the share of each subgroup in the data, and the likelihood of each observation belonging to each subgroup), allowing for a more accurate fit.[13] This approach is especially useful if the distribution of outcomes is likely to take on different characteristics across groups.

In our case, our theoretical model predicts two subgroups, participants and nonparticipants in the PfP scheme, with an expected zero sales gain from PfP for nonparticipants and a positive, but heterogeneous, sales gain for participants. Panel A of Table 5 reports the results of an FMM with two subgroups. As illustrated in Figure 4, the estimated subgroup-specific average sales gains from PfP are 0.163 (p-value = 0.02) in the first subgroup (23% of shops) and −0.019 (p-value = 0.58) in the second (77% of shops), a large and statistically significant difference (p-value = 0.015). The weighted-average PfP effect across subgroups is 0.023, close to the average effect of 0.025 on the entire sample (Table 3). Given our estimates, we interpret the first subgroup as the participating shops and the second as nonparticipants in the PfP scheme. Studying the properties of shops most likely to belong to the first subgroup (participants) gives interesting insights that further support our intuition. It is useful to link these results back to Figure 2. Our results suggest that participation is highest under moderate competition (resembling the dotted line in Figure 2), and the participating treatment effect (dashed line) lies above the average treatment effect (solid line).

Panel B of Table 5, visualized in Figure 5, reports the coefficients from a linear regression of the estimated

Table 3. Treatment Effect by Competition, Estimated by Piecewise Model (S-I)

	(1)	(2)	(3)
Outcome variable:	*Log sales*	*Log customer visits*	*Log sales per customer visit*
Average effect of PfP	0.025	0.022	0.002
	(0.012)	(0.010)	(0.007)
α_1: Increase in PfP effect before the cutoff	0.031	0.020	0.007
	(0.016)	(0.016)	(0.003)
α_2: Increase in PfP effect after the cutoff	−0.016	−0.014	−0.003
	(0.007)	(0.007)	(0.002)
γ: The cutoff (no. of competitors at which PfP effect peaks)	3.093	3.000	4.202
	(0.864)	(2.777)	(1.093)
The implied maximum effect of PfP (at the cutoff)	0.095	0.061	0.028
	(0.049)	(0.049)	(0.012)
p-value of the PfP effect heterogeneity test ($\alpha_1 = \alpha_2$)	0.026	0.118	0.031

Notes. The table shows the average outcome gain from PfP and the parameter estimates of S-I (piecewise regression—see Equations (3) and (4)). Controls include shop and month fixed effects and log total hours worked. The number of shop-month observations is 3,409; the total number of shops is 193. Standard errors clustered by shop are in parentheses (two-sided tests).

probability of belonging to the first subgroup (interpreted as participating shops) on a number of shop and area characteristics, standardized, where appropriate, to aid comparisons. Strikingly, local competition is the most important predictor: PfP-eligible shops facing moderate competition, with three or four local competitors, are about 70% likely to participate (i.e., fall into the first subgroup), far higher than the participation rates in the low- or high-competition environments, or the global average (23%). The estimates for three and four competitors are significantly different from the estimates for fewer ($n = 1, 2$) or more ($n = 4, 5, 6, 7+$) competitors (p-value < 0.01). This is consistent with our theoretical arguments that predict the participation rate to peak at moderate levels of competition. The empirical results presented earlier are also consistent, estimating this level at about three local competitors. The observation that participation increases with the share of large retailers among local competitors supports our theoretical prediction that a shop is more likely to participate if the probability of competitor response is low (Online Appendix C4). The other significant predictors of participation rate are urban location and the share of incentivized workers, which suggests that shops are more likely to participate in the PfP scheme under favorable demand (urban location) and supply (percent incentivized workers) conditions.

Additional Results

We perform multiple robustness tests on the piecewise specification S-I, probing the sensitivity of its results to variations in the choice of controls and method to compute regression coefficient standard errors as well as the measure of competition (Herfindahl-Hirschman Index of concentration (HHI) versus a simple competitor count). The results presented in Table 4 and explained in more detail in Online Appendix C1 show that none of these modifications changes the magnitude or pattern of our main results.

In Online Appendix C2 we consider an alternative regression specification, labelled S-II, in which the mapping $D(\cdot)$ that links sales gains from PfP to competition level is the assignment of a shop into one of three competition groups—*low*, *moderate*, or *high*—defined in terms of the number of local competitors. The grouping that best fits the data is determined by using a simple search procedure. This independently obtained grouping is consistent with our main results and shows in particular that the sales gain from PfP peaks in shops facing three local competitors (see Table 6), its magnitude similar to that computed from specification S-I (see the Online Appendix C2). We apply this simpler linear specification S-II to examine the parallel trends assumption underlying the difference-in-difference treatment effect estimators. We find that a more flexible specification, robust to possible failure of this assumption, produces very similar results (Online Appendix C3). Finally, in Online Appendix C4 we perform a mechanism check using plausible variation in the probability of competitor response P by competitor type (large discount retailers versus small bakeries) and find indicative support for our theorized residual market and competitor response effects, albeit not statistically significant at conventional levels.

Alternative Explanations: Ex Ante Production Efficiency and Performance Targets

The fact that sales gains from PfP decrease as we move from moderate to high competition could also be driven by differences in pretreatment characteristics of the focal shops—namely, their operational efficiency and the likelihood of reaching the performance target. If shops are already at the limit of their

Table 4. Treatment Effect by Competition in Alternative Estimations of Piecewise Model (S-I)

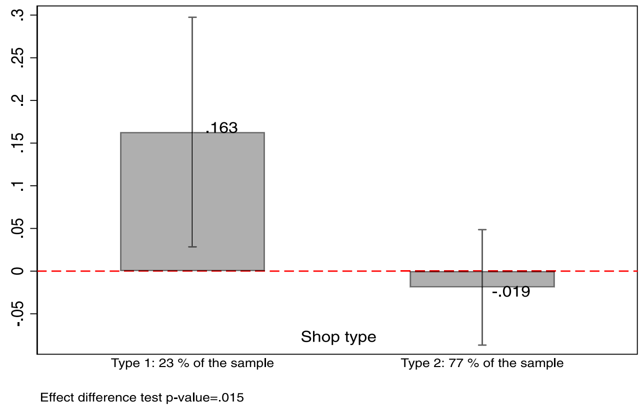
α_1: Increase in PfP effect before the cutoff	α_2: Increase in PfP effect after the cutoff	The implied maximum effect of PfP	p-value test ($\alpha_1 = \alpha_2$)	Fixed effects/ Controls/ Clustered errors
Panel A: PfP effects by competition, various modifications of S-I				
0.023 (0.015)	–0.013 (0.020)	0.071 (0.047)	0.250	No/No/No
0.031 (0.012)	–0.016 (0.005)	0.097 (0.038)	0.003	Yes/No/No
0.031 (0.012)	–0.016 (0.005)	0.095 (0.038)	0.003	Yes/Yes/No
0.031 (0.016)	–0.016 (0.007)	0.095 (0.049)	0.026	Yes/Yes/Yes
Panel B: Collapsing observations into pre- and posttreatment averages				
0.016 (0.010)	–0.020 (0.009)	0.060 (0.038)	0.034	Yes/Yes/Yes
Panel C: Bootstrapping residuals by shop				
0.031 (0.016)	–0.016 (0.007)	0.095 (0.050)	0.030	Yes/Yes/Yes
Panel D: Using the (1/HHI) measure of competition				
0.014 (0.009)	–0.008 (0.003)	0.042 (0.027)	0.040	Yes/Yes/Yes

Notes. Panel A shows alternative specifications to estimate model parameters of S-I (piecewise regression). The dependent variable is *log sales*. The first specification does not include fixed effects and controls, and it does not cluster standard errors. In the following specifications of panel A, we include the fixed effects, controls, and cluster standard errors, which eventually leads to the last specification, which is our main (and preferred) model, as shown in column (1) of Table 3. In panel B we collapse observations within each shop into pre- and posttreatment averages. In panel C we block-bootstrap residuals by shop. In panel D we use an alternative measure of competition based on the inverse HHI index. Standard errors are in parentheses (two-sided tests). See the Online Appendix C1 for further details.

efficiency even without explicit incentives, or if employees think reaching the target is unlikely, a PfP scheme with a target bonus may be ineffective in those shops. Competition eliminates underperforming firms so that shops in more competitive areas could be more efficient than comparable shops in less competitive areas.

To assess this, we retrieve a store-specific production efficiency measure in the pretreatment period from a stochastic frontier regression with shop fixed effects (Jondrow et al. 1982, Belotti and Ilardi 2018). This is essentially specification S-II from the previous section with the error term specified as the sum of the half-normal distributed efficiency component and a normally distributed idiosyncratic error (the assumed difference in the distributions of these two error

Figure 4. (Color online) Illustration of the FMM Results Suggesting Two Types of *Participating* Shops (Type 1) and *Nonparticipating* Shops (Type 2)



Note. The plot corresponds to the estimates in panel A of Table 5.

components allows for their separate identification). Higher efficiency values mean sales are closer to the maximum achievable given factor inputs (hours worked and shop characteristics, such as size and location, captured in the fixed effect) and the technology that converts inputs into sales.

Table 7 reports descriptive statistics of pretreatment efficiency by treatment condition and competition group (panel A) and its interactions with the treatment effect (panel B). Shops located in more competitive areas are not more efficient on average: there are no significant differences in efficiency by either treatment condition (p-value = 0.37) or competition group (p-value = 0.56), or their combination (p-value = 0.91). Hence, production efficiency cannot explain the pattern in the sales gain from PfP we have found. Moreover, as panel B of Table 7 shows, the pattern of PfP gains with competition survives controlling for focal shops' production efficiency.

The perceived attainability of performance targets may also shape discretionary effort under target-based PfP schemes. Targets in our firm are derived from past sales adjusted by the firmwide sales trend.[14] Sales targets for 2014 were set at the end of the previous year—that is, long before the PfP scheme was conceived and the randomization was conducted. The balancedness of control and treatment groups in their sales targets allows for unbiased estimation of the average treatment effect. However, if shops in competitive markets reach their target less frequently, the differential treatment effects by competition groups could no longer be fully attributed to competition.

Panel C of Table 7 reports pre- and posttreatment average frequencies of achieving sales targets by treatment condition and competition group. The pretreatment frequency is about a third overall, with no significant variation by either competition group (p-value = 0.69), treatment condition (p-value = 0.87),

Table 5. Participation Effect by Competition, Based on FMM Model

	Subgroup 1: Participants	Subgroup 2: Nonparticipants
Panel A: Identified subgroups and their characteristics		
PfP effect on sales	0.163	–0.019
	(0.069)	(0.035)
Share in total	0.230	0.770
	(0.046)	(0.046)
Panel B: Correlates of the likelihood of participation (standardized regression coefficients)		
Log hours worked		–0.037
		(0.033)
Log pretreatment sales		0.027
		(0.044)
Workforce average tenure		–0.020
		(0.016)
Workforce average age		0.012
		(0.018)
Share of female workers		–0.005
		(0.014)
Share of non-mini-job (incentive-eligible) workers		0.037
		(0.014)
Location in big town		0.057
		(0.035)
1 local competitor		0.004
		(0.023)
2 local competitors		0.013
		(0.024)
3 local competitors		0.670
		(0.066)
4 local competitors		0.749
		(0.040)
5 local competitors		0.273
		(0.075)
6 local competitors		0.178
		(0.064)
7+ local competitors		–0.023
		(0.028)
Share large retailers, low competition group		0.004
		(0.011)
Share large retailers, moderate competition group		0.069
		(0.039)
Share large retailers, high competition group		0.116
		(0.056)

Notes. Panel A reports the results of an FMM with two subgroups: subgroup 1 (participants) and subgroup 2 (nonparticipants). Panel B reports the coefficients from a linear regression of the estimated probability of belonging to the first subgroup. The number of shop-month observations is 3,409; the total number of shops is 193. Standard errors clustered by shop are in parentheses (two-sided tests).

or their combinations (p-value = 0.33). The frequency increases after treatment, especially in the moderate competition group, where the difference-in-difference effect of PfP on the likelihood of reaching the target is 26 percentage points (p-value = 0.10), roughly doubling target achievement from its baseline and reflecting the sales gains from PfP in that group.

Letting the PfP effect interact with both the competition group and the pretreatment frequency of reaching the target (Table 7, panel D), we find that moderate competition group shops that were more successful in meeting performance targets pretreatment tend to report larger gains from PfP. However, the overall pattern remaining the same suggests that differences in the success in meeting performance targets is not responsible for our main results.

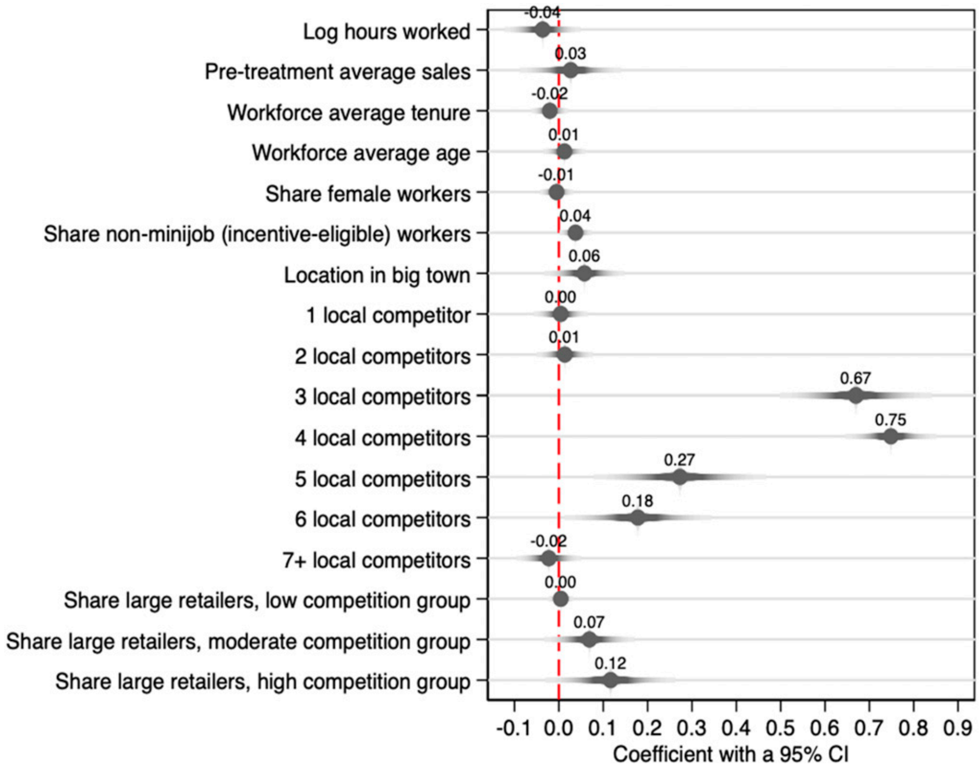
Discussion and Conclusion

We show that firms' competitive environment moderates the performance effects of PfP. We argue theoretically that moderate competition is most conducive for PfP and provide empirical evidence that PfP increases performance by encouraging agents to participate in a PfP scheme by exerting discretionary effort to reach a specified target. Insufficient competition weakens incentives because there is little extra market to capture, whereas excessive competition makes agents wary of competitor responses that could offset their efforts, with both extremes resulting in low participation.

The broader implications of our study first relate to the strategy and organization literatures that have long emphasized the notion of fit between firm strategic decisions and other organizational factors including the environment (Miller and Friesen 1983; Miller 1986; Prescott 1986; Balkin and Gomez-Mejia 1987, 1990). Accordingly, compensation structure "is not an isolated choice for the firm" and "it is important to understand what factors managers should consider when designing their firms' compensation systems and what elements should be in place for compensation systems to produce desirable worker behavior" (Larkin et al. 2012, p. 1210). Nevertheless, the congruence between a widespread compensation strategy—PfP schemes—and the competitive environment firms face is empirically underexplored. If market competition can influence the effectiveness of such schemes, it should be considered in their design. This logic is surprisingly absent in the literature (Newman et al. 2017).

We address this gap by studying the role of the competitive environment in shaping the effectiveness of firms' performance pay. Our study has important scholarly and practical implications. By theorizing on and testing the mechanisms by which competition matters for PfP, we ask which markets are most suited to offering these contracts and find that PfP is most effective under moderate competition. By showing that external factors affect the design of incentive schemes, we also add to research on compensation and more generally managerial practices.

Figure 5. (Color online) Illustration of the Results for the Correlates of Belonging to the Subgroups of the Participating Shops



Note. The plots correspond to the estimates in panel B of Table 5.

Table 6. Treatment Effect by Competition in Alternative Estimations of S-II, and Alternative Competition Definition Based on S-II

Low	Moderate (n = 3)	High	p-value test of effects equality
Panel A: PfP effect by competition group, specification S-II			
0.020 (0.022)	0.063 (0.019)	0.014 (0.017)	0.147
Panel B: PfP effect by competition group, specification S-I (implied estimates given the grouping in S-II)			
0.032 (0.017)	0.097 (0.049)	0.043 (0.038)	0.054
Panel C: PfP effect by competition group, fully flexible group-specific pretreatment trends (based on specification S-II)			
0.021 (0.021)	0.073 (0.024)	0.001 (0.018)	0.057

Notes. Panel A shows the average treatment effect per competition groups for specifications S-II (Equation C1 in the Online Appendix). Panel B shows the average treatment effect, implied by the results of S-II computed for the average number of competitors grouping in S-I. In panel C we use a specification with a fully flexible specification robust to possible failures of the parallel trends assumption (see Equation C2 in the Online Appendix). The number of shop-month observations is 3,409; the total number of shops is 193. Standard errors clustered by shop are in parentheses (two-sided tests).

We also contribute to ongoing work on PfP schemes. Our controlled experimental setup minimizes some potential contamination effects (Chatterji et al. 2016). For instance, besides the incentive effect, the literature reports sorting as one of the channels that affects firm productivity through PfP (Bandiera et al. 2007, Cadsby et al. 2007). Moreover, technology, product, and market differences across firms affect their decision to adopt PfP (Boning et al. 2007). Our field experiment in a single firm minimizes the empirical challenges from across-firm heterogeneity.

Furthermore, we contribute to earlier work on the effect of market competition on the strength and likelihood of adoption of incentives (Hart 1983, Raith 2003, Cuñat and Guadalupe 2005, Baggs and De Bettignies 2007, Vives 2008), which finds that PfP is more likely to be used in highly competitive environments (Bloom and Van Reenen 2007). Our model predicts that the effectiveness of a PfP scheme declines when the intensity of competition exceeds some optimal level. These two results are not necessarily contradictory because the number of relevant competitors does not have to exceed the optimal—after all, most markets are oligopolistic rather than perfectly competitive. Besides, there may be other reasons

Table 7. Shop Efficiency, Frequency of Achieving the Sales Target, and the Treatment Effects by Competition Group

	Low		Moderate		High	
	Control	Treatment	Control	Treatment	Control	Treatment
Panel A: Average pretreatment shop efficiency by competition group and treatment condition						
	0.110 (1.051)	–0.095 (0.944)	–0.102 (0.941)	–0.227 (0.844)	0.203 (1.083)	–0.093 (0.946)
Panel B: PfP effects by competition group and shop efficiency						
PfP treatment	0.020 (0.022)		0.057 (0.020)		0.013 (0.017)	
PfP treatment × Efficiency	0.026 (0.020)		–0.019 (0.021)		–0.031 (0.016)	
Panel C: Frequency of achieving sales target by competition group and treatment condition						
Pretreatment	0.332 (0.471)	0.293 (0.455)	0.252 (0.435)	0.242 (0.429)	0.351 (0.478)	0.398 (0.490)
Posttreatment	0.470 (0.501)	0.484 (0.502)	0.370 (0.487)	0.619 (0.492)	0.462 (0.501)	0.455 (0.500)
Panel D: PfP effects by competition group and frequency of target achievement						
PfP treatment	0.022 (0.021)		0.079 (0.016)		0.016 (0.018)	
PfP treatment × Frequency of achieving target	–0.004 (0.024)		0.045 (0.025)		–0.016 (0.012)	

Notes. Panel A shows mean and standard deviation (in parentheses) of the shop-level efficiency measure (standardized to have zero mean and unit variance) for the treatment and control groups. Six shops were dropped when determining the efficiency term from the stochastic frontier regression. Panel C shows mean and standard deviation (in parentheses) of the pretreatment frequency of reaching the sales target for the treatment and control groups. panels B and D report estimated average treatment effects (difference-in-difference) per category of competition. The dependent variable is *log sales*. Controls include shop and month fixed effects, log total hours worked, and shop-level efficiency. The numbers of shop-month observations are 3,344 (panel B) and 3,409 (panel D) in the sample of all shops. Standard errors clustered by shop are in parentheses (two-sided tests).

beyond the scope of this study that incentivize firms facing high competition to implement PfP, such as the need to compete for talent (Bénabou and Tirole 2016). Finally, implementing PfP is a firmwide decision and is contingent on the level of competition that the firm as a whole is facing, rather than the local variations that we study.

At a broader level, our results mirror the established empirical regularity on competition and innovation (Aghion et al. 2005): there is an optimal level of competition for innovation outcomes, which lies between highly competitive markets and a monopoly. This is perhaps not surprising given that both innovative effort and responses to pay-for-performance schemes are noncontractible and, as such, discretionary effort by employees. Put simply, if process and outcomes were known ex ante, they could simply be included in the contracted activities, and there would be no need to incentivize them. That both noncontractible activities are at their most effective when there is a moderate number of competitors may hint at a balance of fundamental effects at play. Although the mechanisms we identify hold up to close scrutiny in our setting, exploring whether they reflect deeper forces (e.g., a business building effect and a competitive effect), in different settings and involving different discretionary outcomes, would be a promising continuation of our work.

Our study has some limitations. First, we do not observe exogenous changes in market competition. As such, our estimates report heterogeneous effects of a difference-in-difference model with respect to competition, rather than a triple difference manipulating both incentives and competition. Manipulating market-level variables in the field is impractical. However, treatment and control groups in our study are similar in competition structures and other potential sources of heterogeneity. For instance, ex ante efficiency or the frequency of reaching the sales target does not differ across competition structures, suggesting that the treated and control firms face similar external environments. Studying our research question in a setup with exogenous variations in market competition is promising; however, we do believe that our study is a first and an important step in this research. Second, although we provide suggestive evidence in support of the theorized underlying mechanisms (Online Appendix C4), our empirical setup cannot confidently test these mechanisms. This is largely because of the lack of sample size necessary to precisely estimate four-way interactions and because we do not directly measure discretionary effort. This limitation does not necessarily alter the managerial implications of our results. However, a more rigorous test of underlying mechanisms would certainly be a fruitful avenue for future research. Moreover, although the special study context of this paper—the fresh bread market—enables empirical robust analysis, it may (or may not) come at the cost of lowering external validity. Theoretically, we have leveraged simplifying assumptions such as the substitutability of products, constant market size, and diminishing market share with competition. These assumptions are prevalent in the literature and consistent with our setting. Our model and findings thus apply most readily to standard retail contexts where transaction costs depend on geographical proximity between customers and service providers, and stores are roughly equal sized. Relaxing these assumptions may not generate significant additional insight at the cost of increased complexity. For example, in our model, the effect of competition (n) on the residual market operates via lowering firms' market shares (i.e., $s'(n) < 0$). Although this is a very common assumption, a more general framework could model the residual market as $f(s, n)$ to allow for independent channels by which s and n affect the strength of the residual market effect. Because we study a steady-state market with a set of sufficiently comparable rivals, the market share and number of competitors are closely correlated, which does not leave enough statistical power to discriminate between their individual effects. Our findings thus may not extend to (less common) settings for which the correlation between the number of competitors (n) and the focal firm's market share (s) is low. Yet future work could study these settings, such as, for example, markets with many small entrants that increase n but do not affect the focal firm's market share or industries with clearly defined niches (e.g., different quality layers that have low rates of substitutability across them). Follow-up research could also look for natural experiments such as competitors merging (reducing n but leaving s unchanged) or adjacent markets opening (keeping n constant but reducing the focal firm's share s of the (now bigger) relevant market) to identify both channels.

We also do not control for demand-side heterogeneity in PfP responses. For example, if some markets have high unmet demand that could be tapped through discretionary effort, PfP schemes might be effective over a wider range of competition levels because the incentive to exert effort is amplified by market expansion (in addition to the residual market effect). Finally, our study and its implications are based on rational agents' analysis of PfP schemes. Therefore, the implementation of our results (e.g., a corporation offering a bonus versus flat pay based on its shops' competitive environment) needs to consider factors rooted in behavioral reactions to PfP, such as social comparison (Gartenberg and Wulf 2017, Obloj and Zenger 2017) or attempts to "game" the compensation scheme (Holmstrom and Milgrom 1991, Harris and Bromiley 2007, Obloj and Sengul 2012, Larkin 2014). Including these would make for promising future work.

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Endnotes

[1] Friebel et al. (2017) study the performance effect of team incentives and *within-organization* moderators of this effect, such as the share of unincentivized team members. By contrast, we study the complementary question of how market competition, a factor beyond organizational boundaries, shapes the performance of a PfP scheme.

[2] Consider a team in the shop that was randomly selected into the PfP scheme (i.e., treated). The team will participate if it chooses to take to the opportunity presented by the scheme by working harder to generate extra sales. However, the team may choose not to participate in the PfP scheme it is eligible for, which we refer to as nonparticipation.

[3] In our context, "effort" may be thought of in terms of many dimensions such as speed of work, product/service quality, or operational efficiency, or any combination of these. We are agnostic as to the exact manifestation of effort.

[4] The positive effect of competition on the payoff of a competitive action through business gains is established in the literature and often referred to as the *business stealing effect*. For instance, business stealing in Baggs and De Bettignies (2007) operates via increasing the elasticity of substitution as the number of competitors on the market increases.

As a result, competitive action of the focal firm leads to higher gains from the rivals' market, as in our model. Our theory assumes constant market size and perfect substitutability between rivals' products. We therefore model the positive effect of competition on the PfP effectiveness through market shares. Although these modelling choices are made for the sake of simplicity and consistency with our empirical setting, the adoption of alternative approaches generates very similar intuitions and does not alter the key implication of our model.

[5] Higher competition may also increase the intensity of response by competitors, for example, because of increased risk of bankruptcy (Schmidt 1997).

[6] This nests the special case of firms having equal ex ante market shares ($s(n) = \frac{1}{n+1}$). We relax assumption (i) by considering the case when the focal firm's market share is independent of the number of competitors in Online Appendix A.1, obtaining qualitatively similar theoretical predictions. Our predictions are robust to a still more general specification, $s(n, \theta)$, where θ contains additional characteristics that also affect the ex ante market share of the focal firm, as long as assumption (i) holds—that is, firms facing more competitors do not systematically capture a *larger* market share.

[7] Payoffs being linear in market share gain is analytically convenient, but we would get the same qualitative results with a wider class of PfP schemes, including the one with a capped target bonus used by our study firm. There is also no penalty for market losses as a result of competitor response. This is realistic because most PfP contracts are limited liability.

[8] The time frame of data used is shorter than in Friebel et al. (2017), because both ALDI and LIDL had only concluded the roll out of their automated bakery ovens in late 2013.

[9] We do not consider other large retailers in Germany that did not install in-house fresh bread facilities because bakeries were already operating on their premises. On-premise bakeries are included in our sample.

[10] Note that the treatment dummy refers to the experimental assignment into the PfP group rather than actually participating in the scheme. We address the issue of participation later in the analysis.

[11] Ignoring differential treatment effects is equivalent to restricting $D(competition_i)$ to be constant and equal to the average treatment effect β, which we report as well.

[12] An alternative would be a quadratic function of competition. However, this approach produces large errors if the true relationship is not quadratic (Simonsohn 2018). In our case, the relationship between the sales gain from PfP and competition is clearly not quadratic because it is not symmetric around its peak (recall Figure 2). Note also that one could estimate a more general version of specification (4) with an additive parameter β_0 measuring the implied effect under no competition ($n = 0$). Assuming $\beta_0 = 0$ in specification (4) is consistent with our theoretical model and supported by our data (p-value = 0.37). Relaxing this assumption does not materially affect our results.

[13] Formally, for a sample consisting of two subgroups with sample shares p and $1-p$ and regression equations $y = x\beta_1 + u_1$ and $y = x\beta_2 + u_2$, where the error terms u_1, u_2 follow normal distributions with zero means and standard deviations σ_1, σ_2, the marginal probability density function is $f(y;\beta_1,\beta_2,\sigma_1,\sigma_2,p) = p \times \frac{1}{\sigma_1}\phi(\frac{y-x\beta_1}{\sigma_1}) + (1-p) \times \frac{1}{\sigma_2}\phi(\frac{y-x\beta_2}{\sigma_2})$. Its parameters, including the subgroup-specific regression coefficients β_1, β_2 and sample shares p, are estimated with maximum likelihood given $f(y;\beta_1,\beta_2,\sigma_1,\sigma_2,p)$. The method cannot precisely identify the group to which an observation belongs. Instead, it estimates the likelihood of an observation i belonging to subgroup 1 using Bayes' rule:

$$P(subgroup1|y_i, x_i) = \frac{p \times \frac{1}{\sigma_1}\phi\left(\frac{y_i - x_i\beta_1}{\sigma_1}\right)}{p \times \frac{1}{\sigma_1}\phi\left(\frac{y_i - x_i\beta_1}{\sigma_1}\right) + (1-p) \times \frac{1}{\sigma_2}\phi\left(\frac{y_i - x_i\beta_2}{\sigma_2}\right)}$$

(Moffatt 2016, pp. 184–186).

[14] The sales targets in 2014 average 98%.

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