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**HETEROGENEOUS EFFECTS OF
PERFORMANCE PAY WITH MARKET
COMPETITION: EVIDENCE FROM A
RANDOMIZED FIELD EXPERIMENT**

Pooyan Khashabi, Matthias Heinz, Nick Zubanov,
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INDUSTRIAL ORGANIZATION



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Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

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Abstract

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JEL Classification: N/A

Keywords: pay for performance (PfP), Management Practices, market competition, business stealing, competitor response

Pooyan Khashabi - p.khashabi@lmu.de
Ludwig-Maximilians University Munich

Matthias Heinz - heinz@wiso.uni-koeln.de
University of Cologne and CEPR and CEPR

Nick Zubanov - nick.zubanov@uni-konstanz.de
University of Konstanz

Tobias Kretschmer - t.kretschmer@lmu.de
Ludwig-Maximilians University Munich and CEPR

Guido Friebel - gfriebel@wiwi.uni-frankfurt.de
Goethe University Frankfurt, IZA and CEPR

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Pooyan Khashabi

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Ludwig-Maximilians University Munich

Guido Friebe

Goethe University Frankfurt

ABSTRACT

It is well established that the effectiveness of pay-for-performance (PfP) schemes depends on employee- and firm-specific factors. Much less is known about the role of factors outside the firm. We investigate the role of market competition on the effectiveness of PfP. Our theory posits that there are two counteracting effects, a *business stealing* and a *competitor response* effect, that jointly generate an inverted U-shape relationship between PfP effectiveness and competition. Weak competition creates low incentives to exert effort because there is little extra market to gain, while strong competition creates low incentives as competitors respond more. PfP hence has the strongest effect for moderate competition. We test this prediction with a field experiment on a retail chain which confirms our theory and refutes alternative explanations.

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INTRODUCTION

Pay-for-performance (PfP) schemes are an integral part of many firms' management practices and HR strategy (Becker and Gerhart, 1996; Bloom and Van Reenen, 2011; Gerhart, Rynes and Fulmer, 2009; Lemieux, MacLeod and Parent, 2009). There is robust evidence that such schemes affect overall employee performance (Lazear, 2000; Friebel *et al.*, 2017), and a large body of work has linked their effectiveness to a number of contextual factors within the firms that use them. But how important is the environment a firm finds itself in determining the effectiveness of PfP practices?

This question is interesting both theoretically as well as empirically. Theoretically, while there is no doubt that competition as well as management practices affect firm performance, the effectiveness of applying specific practices in certain competitive settings has not been studied in much detail. However, the marginal benefit of a management practice is likely to be affected by the competitive environment, which determines the expected profit margin and likely strategic responses by competitors. Hence, a management practice may be more or less effective depending on the competitive environment in which it is applied. Empirically, the implementation of management practices is typically subject to endogenous choices as practices are applied where they are most likely to succeed, and firms applying certain practices often differ from those that do not. Consequently, isolating empirically the effect of a particular management practice (PfP schemes) in heterogeneous competitive environments is challenging, but potentially rewarding. Moreover, there is a consensus that different market structures may convey different incentives to firms to engage in efficiency-enhancing behavior and that oligopolistic markets often fare best. It is thus an empirical question whether this also applies to the implementation of PfP schemes.

We build and subsequently test a simple analytical model that posits that a PfP scheme as a competitive action carries both a *business stealing effect* that increases the marginal benefits of such an action with the degree of competition, and a *competitor response effect* that decreases its marginal benefits with higher competition. These two effects combined imply an inverted U-shaped relationship between competition and the effectiveness of PfP schemes. We test this prediction by looking at performance effects of a given PfP scheme conditional on the intensity of local competition. We run a field experiment with a German bakery retail chain of 193 shops operating in local markets. In 2014, a team PfP scheme was introduced to half of the shops (randomly chosen) upon (over-)fulfilling a pre-defined sales target. In the control group, sales teams received only a fixed wage. This exogenous PfP assignment was combined with detailed, hand-collected data on the competitive structure of local markets. Our setting of randomly assigned treatment to shops within a single firm eliminates the confounding effects of selection and heterogeneity across firms (with and without PfP schemes) and thus allows us identify the causal effect we are interested in fairly precisely.

The findings confirm our theory: the effect of PfP on sales is highest (up to 9%) when local competition is moderate. Sales teams located in low- and high-competition areas respond much less to incentives. This result is robust to possible alternative explanations. Moreover, we take advantage of the heterogeneity in competitor types to empirically disentangle the business stealing from the competitor response effect. We show that in locations where competitors are less likely to respond – i.e. where competitors are large chain supermarkets — the effectiveness of PfP increases with competition, rather than showing an inverted U-shape pattern. This suggests the presence of the business stealing effect when the competitor response effect is likely to be muted.

Our work contributes to ongoing strategy research on the impact of external factors on the effectiveness of management practices in the broader context of strategic human resource management. We identify heterogeneous effects of a commonly used management practice for the incentives to provide discretionary effort. The implications of such heterogeneity go beyond cautioning that the “one-size fits all” approach in the design of management practices might not work. In fact, strategic behavior by incentivized agents, i.e. the expectation of competitor responses, seems to be an important factor influencing the effectiveness of incentives and the likelihood of their adoption in addition to business stealing (Raith, 2003) and bankruptcy risk (Hart, 1983). An additional contribution is to study compensation strategy for a low-technology service task. Most research on PfP schemes has focused on CEOs and top management, while non-executive pay is the largest part of total compensation costs to firms. By studying incentive pay for ordinary service workers – a large and growing job category (Autor, 2015) – we complement the existing strategy literature on PfP schemes. Finally, our work responds the call for more use of field experiments in strategy research (Chatterji *et al.*, 2016), showcasing the potential that field experiments offer for detecting causal relationships in natural settings.

PRIOR WORK

There is a broad consensus that incentives work “on average”, i.e. they improve performance in the outcome variables that is incentivized (Kerr, 1975; Prendergast, 1999). However, some studies have reported inconclusive results (Pfeffer, 1998), suggesting that there is significant heterogeneity in the effectiveness of PfP. Scholars have tried to explain the heterogeneity in PfP effectiveness through differences in employee attitudes towards incentives, including motivation crowding-out (Frey and Jegen, 2001; Gneezy and Rustichini 2000), gaming the compensation system (Harris and Bromiley, 2007; Holmstrom and Milgrom, 1991;

Larkin, 2014; Obloj and Sengul, 2012), comparison costs and peer effects (Chan, Li and Pierce , 2014; Giarratana, Mariani and Weller, 2017; Obloj and Zenger, 2015 and 2017), the communication of PfP schemes (Englmaier, Roider and Sunde, 2016) and demographic characteristics such as gender (Delfgaauw *et al.*, 2013; Manthei, Sliwka and Vogelsang, 2017). At the team level, researchers have considered the tradeoff between individual and team-wide incentives (Bandiera, Barankay and Rasul, 2013; Pierce, 2012; Hamilton, Nickerson and Owan, 2003; Kretschmer and Puranam, 2008), free-riding (Holmstrom, 1982), and unequal treatment within teams (Friebel *et al.*, 2017) as limiting factors for PfP effectiveness. This battery of studies is successful in showing that PfP schemes work only if the circumstances are favorable, and that many internal factors about the nature of the task, the level of incentives and the personal characteristics of employees receiving the incentives may play a role.

An important subset of studies investigating the performance effects of PfP schemes is the literature on top executive incentives, often in the form of stock options. Most strategic management research especially has focused on CEOs and top management almost to the exclusion of non-executives (Chng *et al.*, 2012; Devers *et al.*, 2007; Finkelstein and Hambrick, 1988; Gomez-Mejia and Wiseman, 1997; van Essen, Otten and Carberry, 2015; Wowak and Hambrick, 2010). Indeed, Larkin, Pierce and Gino (2012) report that nearly 75% of recent papers on compensation in top strategy journals study executive pay, in contrast to compensation for non-executive employees, which has been the domain of the HR literature (Gerhart and Fang, 2015; Gerhart and Weller, 2017). A complementary body of work in strategic management has highlighted that PfP works well for simple and ordinary tasks but is less suitable for more knowledge-intensive activities (Ederer and Manso, 2013; Gambardella, Panico and Valentini, 2015).

Contrary to the scores of studies on factors internal to the firm and their impact on PfP effectiveness, factors *outside* the organization that may hamper or facilitate the effect of PfP are still largely unexplored. Given that the intensity of competition has been shown to affect firm behavior in many other dimensions like the generation or adoption of innovations (Aghion *et al.* 2005; Kretschmer, Miravete and Pernías, 2012), we focus on competition as a context variable outside the firm as a potential moderator for the effectiveness of PfP schemes. It has been shown that competition affects firm efficiency and profits directly (Bloom and Van Reenen, 2007; Porter, 1990; Nickell, 1996), which suggests that firms facing strong competition seek out ways of increasing their efficiency, e.g. through beneficial management practices. Related to this, a stream of theoretical studies has linked the intensity of market competition to the likelihood of adoption of incentives (Baggs and De Bettignies, 2007; Hart, 1983; Raith, 2003; Schmidt, 1997; Vives, 2008). Specifically, Raith (2003) and Schmidt (1997) theorize that there are counteracting forces determining the relation between managerial incentive adoption and competition. Through different theoretical mechanisms, Baggs and De Bettignies (2007) posit that competition increases firms' propensity to adopt steep (i.e. performance-related) incentives. These predictions are tested by several empirical studies, which broadly confirm that adoption and sensitivity of incentive contracts increase with competition (Baggs and De Bettignies, 2007; Cuñat and Guadalupe, 2005).

THEORY

PfP contracts are designed to motivate employees to voluntarily exert discretionary (non-contractible) effort (Prendergast, 1999). Team PfP schemes aim to boost joint effort and performance at the team level. When referring to effort throughout our theory, we imply costly actions of the team taken to increase the performance. Extra effort in this framework may mean

working faster, improving service quality or reducing operational costs. With a PfP contract, the team decides whether to exert discretionary effort to increase expected output and the resulting expected bonus, or keep the previously chosen effort level unchanged despite the potential bonus. As we show below, by affecting the outcomes of this decision, market competition affects the optimal effort choice and consequently the effectiveness of the PfP contract. Our setup is a sales team within a shop, where PfP bonus is paid to them conditional on shop sales. We assume:

A1) Teams independently (from other shops) choose effort to maximize net expected payoff from the PfP.

A2) Teams operate in a homogenous product market with $n \geq 0$ locally based competitors producing goods that are close substitutes.

A3) Team efforts change their market *share*, while their possible effects on market *size*, for instance, by stimulating customers to spend more, are second-order. Moreover, prices and margins remain the same.¹

The first assumption made for simplicity and is inconsequential given our focus on the factors outside the firm that influence the effectiveness of PfP. The second and third assumptions are reasonable given our context in which there is a standard production technology, the nature of demand for baked bread, is local and demand for bread is stable.²

The expected increase in sales after exerting effort under PfP is by definition proportional to the product of the extra market share to be gained, denoted by $f(n)$, and the probability of gaining it, denoted by $p(n)$. Both components depend on the number of locally operating

¹ The inflation-adjusted growth rate of the German market for bread and related products is less than 0.5% per year. Source: www.baeckereihandwerk.de.

² Relaxing these assumptions would make the model messier, but the basic forces at play would remain the same.

competitors (n)— which is our proxy of market competition (Kalnins, 2003). With sales being the performance measure, we specify a sales team’s expected payoff as follows:

$$(1) \quad E(\text{Payoff}) = \alpha[p(n) \cdot f(n)] - \bar{e},$$

where $0 < \alpha < 1$ is the share of additional sales that is distributed to agents and \bar{e} is the cost of effort.³ The team will exert effort if the expected bonus net of effort costs is nonnegative, and will not react to the PfP otherwise. Thus, with a constant cost of effort, the incentive to exert discretionary effort under PfP depends on the market share gain the effort could potentially generate, and on the probability of gaining it — i.e. $[p(n) \cdot f(n)]$. We now explain how these two factors determine the effectiveness of PfP, and how their effect depends on local competition.

The “business stealing” effect. We assume that competitive actions enabled by additional effort can lead to winning more business. Given constant market size, this means business is taken away from competitors – a phenomenon often referred to as the *business stealing effect* (Raith, 2003). The market gain through business stealing increases with competition (Baggs and De Bettignies; 2007; Hermalin, 1992; Raith, 2003; Vives, 2008). Indeed, when competition is high, a sales team has a small ex-ante market share so that a large portion of the market remains to be “stolen” through competitive action. In contrast, with low competition, the team is likely to enjoy a large market share already, with less to be gained than when competition is high. In the extreme case of no competition, the monopolist already serves the whole market, so extra effort cannot increase market share. As the market share gained through business stealing translates into extra bonus for the sales team, more competition increases the marginal product of effort and thus the

³ The linearity assumption is made for analytical convenience but is actually more restrictive than needed as there is a wider class of monotonic functions $\alpha[\cdot]$ that may generate our results, including the piecewise one that was actually implemented by our study firm. Also note that in our formulation, there is no penalty for a possible market loss that may occur as a result of competitor response. While this is a restrictive assumption, it is not unrealistic since PfP contracts, including that practiced in our study firm, are typically limited-liability ones.

likelihood of exerting discretionary effort and the effectiveness of PfP in terms of the additional sales it generates.

To demonstrate this effect in our formal setting, consider a simple case of a focal shop with n identical competitors and perfectly substitutable goods. In this case, the focal shop and competitors initially share the market equally. Normalizing market size to one, each competitor's ex-ante share equals $\frac{1}{n+1}$. In this example, any competitive action by the focal sales team – if not countered by competitors— would generate a monopoly by winning the rest of the market. Thus, the ex-post market share gain will be $f(n) = 1 - \frac{1}{n+1}$, which increases with n . Hence, higher competition increases the expected payoff through the business stealing effect – see (1). Figure 1 shows the relation between competition and the expected payoff of effort through business stealing.

FIGURE 1 ABOUT HERE

The “competitor response” effect. The likelihood of market share gain generated through discretionary effort by an incentivized sales team depends on the (re-)actions of competitors, who may respond to remain in the market (D'Aveni, 1994; Ferrier, Smith and Grimm, 1999; Porter, 1980). These responses need not be identical to the competitive action of the focal firm – i.e. introduction of a PfP scheme. There can be a range of competitive responses, which would offset the payoff of effort for the focal team. As the focal team anticipates this response, the PfP scheme may result in lower, or even no extra effort if the chances of competitor response are high.

Suppose each competitor reacts to the competitive action of the focal shop with a constant probability P .⁴ Consider first the simple case of no competitor reaction, which happens with probability $p(n) = (1 - P)^n$. In this case, assuming, as above, perfect substitutability, the market share gain through business stealing is $1 - \frac{1}{n+1}$, and the expected net benefit from extra effort is $E(\text{Payoff}) = \alpha \cdot (1 - \frac{1}{n+1})(1 - P)^n - \bar{e}$. Clearly, while the market share to be won through a competitive action increases with n , the chances of winning it decrease with n due to the competitor response effect – see Figure (1). The product of these effects has an inverted-U pattern.

Generalizing on the above result, suppose i out of n competitors choose to react by responding to the competitive action taken by the focal team, while the remaining $n - i$ do not react and lose their market share. The probability of this event is $C_i^n \cdot P^i \cdot (1 - P)^{n-i}$, where C_i^n is the number of i -combinations out of n . The corresponding market share gain per competitor is $\frac{1}{i+1} \cdot (1 - \frac{i+1}{n+1})$ – that is, each of the i responding competitors plus the focal shop gets an extra $\frac{1}{i+1}$ th of the difference between the whole market of size 1, and their total previous market share, $\frac{i+1}{n+1}$. Aggregating over all possible cases of competitor reactions, from none to all reacting, the expected net benefit from extra effort to the focal sales team is

$$(2) \quad E(\text{Payoff}) = \alpha \cdot \sum_{i=0}^n C_i^n \cdot P^i \cdot (1 - P)^{n-i} \cdot \frac{1}{i+1} \cdot (1 - \frac{i+1}{n+1}) - \bar{e}.$$

Equation (2) shows that the response by one or more competitors reduces the focal firm's gains from moving to a monopoly (if no competitor responds) to competing with a number of other firms (that have responded). Given that exerting discretionary effort is costly for the team,

⁴ Representing P as a function of contextual factors, such as market density, is straightforward, but tangential to our core logic.

with the market share shrinkage caused by competitor response, the amount of bonus may not be worth the cost of effort. Thus, although more competition increases the potential gain from a competitive action, it may reduce the expected realized gain by increasing the probability of competitor response – also plotted in Figure (1).

Combining the effects: an inverse U-shape relationship. To predict the effectiveness of PfP schemes at different competition levels, we check how the expected payoff changes with respect to competition. To do this, we plot the simulated values of equation (2) against the number of competitors n and for different values of the competitor response probability P . Figure (2) shows an inverted U-shape between the number of competitors and the expected payoff from a competitive action. This implies that PfP schemes would be most effective when competition is moderate: not too low for the business stealing effect to emerge, and not too high for the competitor response effect not to cancel the business stealing effect.

FIGURE 2 ABOUT HERE

We can also identify an interesting implication regarding the response probability in Figure (2). As expected, when the probability of competitors’ response decreases, the expected payoff of a competitive action grows. In the extreme case where there is no risk of retaliation by competitors – i.e. $P = 0$ – the competitors’ response effect is totally muted. Therefore, the plot in this case shows a pure business stealing effect – an increasing function similar to Figure (1). As discussed above, some contextual factors may affect the response probability. For instance, large chain retailers are less likely to respond to a competitive action of a local bakery, and thus, P in

their case is likely to be smaller compared to local independent bakeries. In the empirical section, we use these factors to disentangle the two mechanisms in our estimations.

The analytical model above serves as simple framework to illustrate the two theoretical mechanisms and their composite effect. Clearly, the model relies on simplifying assumptions made for analytical convenience— e.g. perfect elasticity of substitution between firm products. The real world is of course more complicated and measurement is noisy. The simplifications made, however, allow us to focus on the mechanisms of interest for our study, and illustrate their dynamics with respect to competition.

STUDY BACKGROUND

The study firm and its competitive environment. Our study firm operates a network of bakery shops. We use data from 193 shops during the observation period, January 2013 until June 2014. We merge the data Friebel et al. (2017) used to study the internal determinants of sales-related effort with hand-collected data on the competitive structure of local markets. In contrast to their study, our timeframe is shorter because competition unfolded over time, as we explain in footnote 5. The average shop sells around 27,000 Euros worth of fresh bread products monthly, receives 10,000 customer visits, and employs 7 shop assistants, mostly women with only basic work qualifications working part-time and earning €9 – €11 per hour, depending on tenure (Table 1 reports these and other descriptive statistics; Table 2 reports basic correlations). The firm is active in a metropolitan area with several million inhabitants consisting of several cities (see Figure 3).

FIGURE 3 AND TABLES 1-2 ABOUT HERE

The study firm had enjoyed sound performance fueled by attractive locations of its bakeries and economies of scale owing to centralized production. The situation changed from 2011, when supermarket chains ALDI and LIDL started opening up in-store fresh bread departments on their premises, a process that involved installation of automated ovens, continued throughout 2011-2012 and was finalized by 2013⁵. According to the firm's management, the increase in competition by ALDI and LIDL (henceforth *large retailers*)⁶ led to a swift erosion of profits, because the fresh bread they sold was of comparable quality and yet much cheaper. The effect of the market entry of the large retailers on local competition was large indeed: of the average of 3.5 bakeries within a 1 km radius from our firm's shops, 0.9 are large retailers. Hence, the entry of large retailers means an increase in the number of local competitors by one fourth. This is a large effect, especially given the relatively high (firm-level) price elasticity of demand for fresh bread, the relatively large scale of the discounters' operations, and little customer loyalty.

Intensified product market competition prompted the firm to fundamentally rethink its business strategy and management practices along several dimensions. First, it reengineered its production and logistics to broaden the assortment of products to include items traditionally sold in cafés, such as snacks, cakes, sandwiches and beverages, in addition to bread. Second, shops were redesigned to look more like cafés. Third, new marketing instruments were employed to strengthen its brand by underlining its regional heritage and adherence to good causes. None of these initiatives were successful in offsetting the effects of increased competition. Consequently, the firm introduced additional HR practices to motivate employees to show more sales-oriented

⁵ Since we do not know when each large retailer installed a bakery in which store, we do not use the data before 2013.

⁶ There are other large retailers in the German market who did not install automated ovens for a number of reasons, in particular, because on their premises, bakery shops of different chains were operating.

behavior. In particular, the firm introduced a bonus paid to the sales teams in shops that reached their monthly sales target. It is this practice that we helped design and test, and which we explore in this study.

The firm and its shops. The firm is managed by the board of directors who appoint regional managers to oversee up to 15 shops in their geographical regions and liaise with the shop supervisors who report to them. Supervisors manage their shops on a daily basis, together with the team. Their task is to ensure that all technological and accounting procedures are adhered to, and that the shop is adequately staffed at all times. Other tasks, such as pricing, marketing campaigns and hiring are centralized. However, there is large scope for exerting discretionary effort in providing higher quality service, dealing with customers more efficiently, preparing the food (for instance, sandwiches) to higher standards, etc.

Historically, performance-based incentives were given to top managers, regional managers and shop supervisors. In contrast, shop assistants had not received any PfP before our experiment started. The *no-PfP* policy for shop assistants reflected the management belief that supervisors controlled the assistants well enough to make the most of their efforts. However, the strategic shift to more service orientation, triggered by intensified competition, challenged this belief as customer experience delivered by shop assistants became a more important part of the firm's business model. Consequently, top management decided to introduce a new PfP scheme for shop assistants as well.

In the new PfP scheme, the bonus for the shop assistants was to be paid to the entire shop team (including the supervisor) upon reaching the sales target. 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 sales, especially at

peak times. Second, with a variety of interconnected and often simultaneously occurring 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, Gupta and Delery, 2002; Kretschmer and Puranam, 2008).

The rules of the PfP scheme for shop sales teams were as follows. 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 team bonus was shared between shop assistants and supervisors in proportion to their working hours in the month in question.⁷ The attraction of this PfP scheme, illustrated in Figure (4), is its simplicity – an important consideration for the workers it was designed for (Englmaier *et al.*, 2016).

FIGURE 4 ABOUT HERE

Introducing the new PfP scheme. The PfP scheme was first introduced on April 1st 2014 as a pilot in 97 shops randomly selected by us. The randomness of the treatment assignment helped achieve the balancedness of the control (no PfP) and treatment (PfP) groups in terms of average sales and other characteristics (Table 1) in particular, the competition on the market. The balancedness is important for an unbiased estimation of the impact of the treatment. The scheme was piloted until June 30th 2014, after which it was rolled out to all shops.

⁷ An exception of the bonus rules was made for the “mini-jobbers”, a special category of workers recognized by the German tax code. Mini-jobbers, who make up 12% of the firm workforce (FTE-adjusted), can earn up to €450 per month and are exempt from all wage taxes. However, if a mini-jobber earns more than €450 per month, they will become liable for taxes on the full amount of their earnings. Therefore, mini-jobbers were excluded from the scheme.

In agreement with the worker council and to support the implementation of the PfP scheme in the chosen shops, we prepared information leaflets to be placed in the back office of the treatment shops, and letters to be sent to the treatment group employees. We informed the shop assistants about the PfP rules and provided simple examples of bonus calculations. We did not mention the control group and the involvement of the researcher to avoid potential Hawthorne-type effects.

Besides the worker council and top management, the only group of workers with whom we communicated regarding the PfP scheme were the regional managers. Unlike shop assistants and supervisors, the regional managers knew that we were running a pilot and that control shops existed. In a meeting at the end of March 2014, top management and us informed all regional managers about the PfP experiment and handed every manager the list of the control and treatment shops in their region. In the same meeting, we trained regional managers in how to explain the team bonus to shop supervisors and assistants in the treatment group. We also instructed regional managers on the standard response to questions about the PfP from employees in control shops: “This is a pilot. Every shop had the same chance to be drawn into the PfP scheme. The worker council agreed to this procedure.” We find no evidence for information spillovers between treatment and control group shops in the post-intervention survey.

Random assignment of shops in treatment and control group. The treatment was randomly assigned to the shops of the study firm to ensure unbiased estimation of the treatment effect. Panel A of Table 1 reports the characteristics of shops in the control vs. treatment group. Panel B compares our measures of local market competition. The treatment and control shops are balanced in terms of observable characteristics, including market competition. Table 3 shows the number of treatment shops by competition category for the period before treatment began

(January 2013– March 2014). Each category has similar numbers of treatment and control shops.

TABLE 3 ABOUT HERE

ESTIMATION PROCEDURES AND RESULTS

Average treatment effect. The random assignment of the PfP treatment to shops and the balancedness of the control and treatment samples with respect to sales and local competition enable a straightforward estimation of the average treatment effect on sales, as well as its variation with competition. Moreover, we can interpret the estimation results in a causal way. We estimate the average treatment effects of the PfP by a difference-in-difference estimator:

$$(3) \quad \ln(y_{it}) = \beta * treatment_i * after_t + month_t + shop_i + \gamma * controls_{it} + error_{it},$$

where y_{it} measures performance (sales, number of customer visits, sales per customer) of shop i in month t , $controls_{it}$ are shop-specific control variables such as log hours worked per month; $after_t$ is a dummy variable, equal 1 for all months from April to June 2014, and 0 for all months in the rest of our observations (from January 2013 to March 2014); the $treatment_i$ dummy takes value 1 if the PfP scheme was implemented in shop i , and $error_{it}$ is the idiosyncratic error term clustered at the shop level. We include $month$ and $shop$ fixed effects to control for seasonality and shop-specific unobservables that affect sales, such as local market size. In equation (3), coefficient β is the difference-in-differences estimate of the average treatment effect of the PfP on shop sales.

TABLE 4 ABOUT HERE

Table 4, column 1 reports the estimates from equation (3) of the treatment effects on sales (Panel A), customer visits (Panel B) and sales per customer (Panel C) for all shops. We find an average treatment effect on sales of 2.6%, on customer visits of 2.2% and on sales per customer visit of 0.2%. Hence, most of the sales resulting from PfP was generated through serving more customers. Table 4 also presents separately the results for big towns (>50,000 inhabitants). We do so to account for differences in local market sizes and hence larger scope to affect sales in urban compared to rural locations. Therefore, the average treatment effect and its variation with local competition should be larger in big towns than elsewhere, which is confirmed by the estimates of all effect sizes being larger in the big towns.

Is there an inverse U-shaped relationship between PfP and competition? We adapt the estimator in equation (3) to allow for treatment effects specific to each competition intensity level, as formulated in equation (4):

$$(4) \quad \ln(y_{it}) = \sum_{g=1}^G \beta_g * treatment_i * after_t * competition\ intensity_{ig} + month_t + shop_i \\ + \sum_{g=1}^G \gamma_g * controls_{it} * competition\ intensity_{ig} + error_{it}$$

where $g = \{low, moderate, high\}$ is the indicator for each competition category, and $competition\ intensity_g$ is a dummy with value 1 if shop i belongs to competition category g . Hence, the coefficient β_g for each value of g measures the treatment effect specific for the respective competition intensity group. A less computationally efficient alternative to equation (4) producing the same estimates, is to run (3) on the subsamples for each competition category.

We measure market competition as the total number of competitors (Kalnins, 2003) – including independent, bakery chains like our study firm, and large retails – in a 1 km radius from

the focal shop, which is within walking distance.⁸ Using this measure, we build three competition categories: low for fewer than 3 competitors, moderate for 3 or 4 competitors, and high for more than 4 competitors in a 1 km radius from the focal study shop. The rationale for choosing this categorization is as follows. First, we need at least three competition categories to identify the non-linear effect we hypothesize. Second, increasing the number of categories would increase the number of parameters to estimate, reducing statistical power. Third, the thresholds chosen were the best to balance the share of the control and treatment shops in each category.⁹

TABLE 5 ABOUT HERE

Table 5 reports the estimates from equation (4) of the treatment effects on sales (Panel A), customer visits (Panel B) and sales per customer (Panel C) for the three competition categories we have specified, as well as separately for the whole sample and big towns.

The treatment effect on sales is at its maximum (5.2% on the whole sample, 8.9% in big towns, both p-values < 0.01) in the moderate competition category, drastically going down in size in both the high and low competition categories (all p-values > 0.40). The inverted U-shape they form is in line with our theoretical predictions on the impact of the two opposing forces – business stealing and competitor reaction – affecting optimal effort choice under PfP.

Panel B of Table 5 reports the treatment effects on the log number of customer visits by competition category. Under moderate competition, the effects are 3.5% (p-value = 0.06) on the whole sample, and 7.9% (p-value < 0.01) for big towns. The effects under low and high

⁸ Customers in the fast food industry rarely travel for long distances, even in areas where travel is relatively fast (Salvaneschi, 1996). However, our results are robust to more generous definitions (3 km) of the relevant market.

⁹ While the estimates change slightly, our key findings are robust to alternative competition categorizations.

competition are small, in the region of 1-2% (p-values > 0.11). Again, the pattern of the effect on customer visits is consistent with the predicted relationship between competition and PFP effectiveness.

While much of the average increase in sales resulting from PFP was generated through serving more customers, the increase in sales was not entirely and everywhere due to extra customer visits. Panel C presents the treatment effect estimates for log sales per customer visit. The estimates by competition category follow a very similar pattern: around zero for the high and low, and going up to 1.5% for the moderate competition areas. This small but still significant effect (p-values = 0.01 on the whole sample and 0.11 for big towns) suggests that the discretionary effort by the incentivized sales teams impacted both the extensive (more customer visits) and intensive (more sales per customer visit) margins, with a much bigger effect on the former.¹⁰

All in all, the inverse U-shape pattern in the performance effect of the same incentive scheme under different levels of competition consistently shows up in our results.

Disentangling the business stealing from the competitor response effect. Our results presented so far are the net effect of the business stealing and competitor response effects, which jointly have created the inverse U in the treatment effect. While we cannot observe competitor response directly, we can identify characteristics that affect the likelihood of responding to a competitive action, and look at how these characteristics affect the dynamics of the treatment effect with competition.

¹⁰ We have used another diff-in-diff estimator that controls for shop-specific seasonality, by regressing the year-on-year change in sales on the same changes in labor input and the treatment dummy and its interactions with the competition measure. The results are qualitatively similar and have larger significance levels.

The characteristic we will use is the distinction between large retailers and the other bakeries. “Judo economics” (Gelman and Salop, 1983) suggests that when deciding whether to respond to a competitive action, firms compare the costs of responding with the costs of accommodating. Such comparison is more likely to favor accommodating over responding when the firm is large, since then the global revenue losses from responding will likely outweigh the local revenue gains. Therefore, the competitor response effect should be smaller in areas where competitors are large firms compared to areas where the number of competitors is the same but they are smaller in size.

Large retailers are global businesses and therefore unlikely to be moved by local competitive actions. The sale of fresh bread makes up only a small percentage of the total sales of large retailers. Therefore, business stealing should be more pronounced compared to the competitor response effect in areas where local competition is dominated by large retailers. Consequently, we expect the treatment effect to increase monotonically with competition in those areas (as shown in Figure (2) for the case of $P = 0$). However, the competitor response effect should be strong in markets where small bakeries and pure bakery chains are the main competitors because these shops have stronger incentives to react and are small enough to adjust to the local conditions.

Indeed, we observed in the preparation of our study in January 2014 that within a few days, relatively small competitors reacted to marketing innovations of our firm. For instance, they copied promotions like “Bread of the week”, or charitable activities providing donations to local NGOs, sports clubs etc. for each bread sold. The top management of our study firm told us that it is common that small competitors copy marketing campaigns. Hence, we expect the same inverted-U pattern we identified before, however, with weaker treatment effects.

To test this, we run an extended version of the difference-in-difference estimator in which we interact the treatment effect with the intensity of competition and the share of large retailers in the total number of competitors within 1 km from the focal shop – equation (5).

$$(5) \quad \ln(y_{it}) = \sum_{g=1}^G \beta_g \cdot treatment_i \cdot after_t \cdot share\ large\ retailers_i \cdot competition\ intensity_{ig} + month_t + shop_i + \sum_{g=1}^G \gamma_g \cdot controls_{it} \cdot competition\ intensity_{ig} + error_{it}$$

We then estimate the treatment effects in the areas with *share large retailers* = 0 (all competitors are non-large retailers), *share large retailers* = 1/4 (the average share of large retailers in the total competition, see Panel B of Table 1), and *share large retailers* = 1 (all competitors are large retailers). The results in Table 6 show that the coefficient of the treatment effect monotonically increases with competition in the areas where all competitors are large retailers. In these areas, the treatment is likely to reflect the pure business stealing effect that would have been observed globally if competitors had not responded to the discretionary effort action of the incentivized sales teams in our study firm. The pattern for the average shop (*share large retailers* = 1/4) is an inverted U, similar to the one observed before (recall Table 5), reflecting a mixture of the business stealing and competitor response effects. In the areas where all competitors are non-large retailers (*share large retailers* = 0) there is also an inverted U, but the maximum treatment effect, 4.3%, is lower than that reported for the average shop under moderate competition (5.2% in Table 5), reflecting the higher likelihood of the competitor response in those areas. Seeing the business stealing and competitor response effects “in motion” this way lends further support to our theory as well as uncovers heterogeneity in PFP effects in different competitive environments. While the overall significance of the treatment

effect heterogeneity with respect to the structure of local competition is inevitably weakened by four-way interactions (p-value=0.186), we are nevertheless encouraged by the directional support for our conjecture.

TABLE 6 ABOUT HERE

Competition and efficiency. The decrease in the size of the PfP effect as competition intensity changes from moderate to high may also be driven by an additional factor on top of the competitor response effect identified in Table 6. The Pfp scheme may have failed to generate a significant effect on sales in high-competition areas because shops in those areas may already have been operating close to their maximum production efficiency before team incentives were introduced. Indeed, as competition increases average efficiency by eliminating underperforming firms (Bloom, Sadun and Van Reenen, 2016) and by stimulating managers and employees in existing firms to work harder to avoid bankruptcy (Schmidt, 1997), shops in more competitive areas could be more efficient than comparable shops in less competitive areas, and the treatment effect would decrease with pre-treatment production efficiency because there is less unrealized efficiency potential. These two effects combined would weaken the treatment effect similar to the competitor response effect.

TABLE 7 ABOUT HERE

To examine whether and how production efficiency shapes our results, we estimate a stochastic frontier regression with shop fixed effects (Jondrow *et al.*, 1982; Belotti and Ilardi, 2014). This model is essentially equation (3) with all variables, except that its error term ($error_{it}$)

is 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 components lets us identify them separately). Higher values of the efficiency component mean sales are closer to the maximum achievable for given factor inputs (hours worked and shop characteristics, such as size and location, captured in the fixed effect) and “technology” that transforms these inputs into sales. We use this efficiency component, normalized to have mean zero and unit standard deviation for convenience, as a measure of production efficiency.

Table 7 reports descriptive statistics of the efficiency measure by competition group and its interactions with the treatment effect. As predicted, the treatment effect is lower in more efficient shops, especially in the moderate competition group. However, as shops located in more competitive areas are no more efficient,¹¹ production efficiency cannot explain the inverted U-shape in the PfP effect we found previously. Moreover, as the estimates in Table 7 show, the treatment effect and its pattern survive controlling for production efficiency.

Competition and performance targets. One important feature of the PfP scheme is the existence of shop-specific sales targets. Sales targets are mainly derived from past sales adjusted by the common sales trend. Importantly, sales targets for the upcoming year are set at the end of the previous year, i.e. months before the PfP scheme was conceived and the randomization was conducted (indeed, as Table 1 shows, sales targets do not differ between treatment and control shops). However, the perceived likelihood of reaching the target may have affected the shop team’s effort choice and thereby co-shaped the treatment effect pattern we observe.

¹¹ No significant differences in production efficiency by competition group is a curious finding whose fuller exploration is beyond the scope of this paper. Suffice to say that the predicted positive link between efficiency and competition intensity is more likely to appear at the corporate level rather than workplace, which is the level of analysis in our paper. Also, observing firm dynamics with competition requires a longer period than ours.

TABLE 8 ABOUT HERE

To examine this, we let the treatment effect interact with both the competition group and the pre-treatment frequency of reaching the sales target. The results in Table 8 show that this frequency is about a third in the low and moderate competition groups, and is slightly (but not significantly, both p-values > 0.6) higher in the high-competition group. This small difference is inconsequential for our earlier results because the treatment effect does not interact significantly with pre-treatment success. We thus rule out another additional explanation of our findings.

DISCUSSION AND CONCLUSION

The strategic management literature has traditionally emphasized the notion of fit between firm strategy and other organizational factors including firms' environment (Balkin and Gomez-Mejia, 1987 & 1990; Miller, 1986; Miller and Friesen, 1983; Prescott, 1986). Compensation strategy as one of the key drivers of firm performance and growth should also be viewed in this framework. Studies in this stream have mostly focused on the congruence between compensation strategy and firms' other strategic decisions including diversification (Kerr, 1985; Napier and Smith, 1987), governance (Werner, Tosi and Gomez-Mejia , 2005), R&D (Galbraith and Merrill, 1991; Yanadori and Marler, 2006), product-market strategy (Balkin and Gomez-Mejia, 1990; Gupta and Govindarajan, 1984) and orientation towards change (Boyd and Salamin, 2001). Nevertheless, the congruence between a widespread compensation strategy – namely PfP— and firm environment is still understudied. PfP schemes commonly link the bonus provision to explicit or implicit market performance. Thus, market competition can influence their effectiveness, and should accordingly be considered in their design. However, this logic is

surprisingly absent in the literature and compensation handbooks (see e.g. Newman, Gerhart and Milkovich, 2017).

We study the role of the competitive environment in shaping the effectiveness of firms' performance pay. Our study has important implications for both scholars and practitioners. By theorizing on and testing the mechanisms by which competition impacts P_fP, we ask which markets are most suited to offering these contracts. We show that P_fP is most effective when competition is moderate: too little competition leads to low incentives because there is little extra market to gain, while too much competition increases the likelihood of competitor response. By showing that external market factors should be considered in the design of incentive schemes, our study also talks to executive pay research, and more generally to research on managerial practices.

Our findings also contribute to ongoing research on P_fP schemes. Our controlled experimental setup enables let us minimize potential contamination effects and answer the research question precisely. For instance, besides the incentive effect, the literature reports sorting as one of the channels that affects firm productivity through P_fP (Bandiera, Barankay and Rasul, 2007; Cadsby, Song and Tapon, 2007; Lazear, 1986). Moreover, technology, product and market differences across firms are reported to impact their decision to adopt P_fP (Boning, Ichniowski and Shaw, 2007). By conducting a randomized field experiment in a single firm, we minimize the empirical challenges arising from across-firm heterogeneity and generate valid results.

Further, we contribute to the literature on the effect of market competition on the strength and likelihood of adoption of incentives (Baggs and De Bettignies, 2007; Hart, 1983; Raith 2003; Vives 2008; Cuñat and Guadalupe, 2005). The existing literature finds that P_fP is more likely to

be used in more competitive environments (Bloom and Van Reenen, 2007). Our model predicts that the effectiveness of a PfP scheme goes down when the intensity of competition exceeds some optimal level. These two results are not necessarily contradictory, since 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 beyond the scope of this study that incentivize firms facing high competition to implement PfP, such as the risk of bankruptcy (Schmidt, 1997) or the need to compete for talent (Bénabou and Tirole, 2016). Finally, implementing PfP is a firm-wide decision and is therefore affected by the level of competition that the firm as a whole is facing, rather than the local variations that we study.

Our paper, as any study, is not free of limitations. First, our empirical setup does not directly measure discretionary effort and even what teams do when exerting it. Thus, we cannot directly test whether the ineffectiveness of PfP for extreme low/high competition is due to low effort exerted by the sales team (i.e. due to little expected payoff), or due to market forces offsetting the efforts of the sales team. While investigating this is interesting from an academic perspective, it does not alter the managerial implications of our study. Moreover, as the special study context of this paper – i.e. the fresh bread market – enables empirical robust analysis, it may (or may not) come at the cost of lowering external validity. We have leveraged assumptions such as substitutability of products, thanks to our study context. However, some of these assumptions may not hold for other markets, which may influence the findings. Specifically, our model and findings are applicable to describe standard retail contexts, where transaction costs depend on geographical proximity between customers and service providers. Therefore, these findings may not be applicable to retail contexts with different characteristics, e.g. e-commerce. 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 vs. flat pay

based on its shops' competition environment – needs to consider potential confounding factors such as social comparison costs (Obloj and Zengers, 2015 and 2017). We believe that these present a fertile ground for future work in this area.

We believe our results on the role of market competition in PfP effectiveness offer insights for strategy scholars and managers designing compensation strategy. We hope this will stimulate theoretical and empirical work on the interaction of external factors and management practices.

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Tables and Figures

Table 1: Pre-treatment shop characteristics

Panel A: Characteristics of the shops				
	<i>All shops</i> (<i>n=193</i>)	<i>Control</i> (<i>n=96</i>)	<i>Treatment</i> (<i>n=97</i>)	<i>t-test</i> <i>p-value</i>
Mean sales	27,211 (13,149)	26,730 (11,341)	27,701 (14,750)	0.608
Mean sales (in logs)	10.12 (0.41)	10.11 (0.40)	10.13 (0.42)	0.710
Mean sales targets	28,798 (13,583)	28,322 (11,513)	29,278 (15,384)	0.628
Mean # of customer visits	9,681 (3,843)	9,590 (3,813)	9,774 (3,873)	0.740
Mean number of employees	7.19 (3.02)	7.20 (3.04)	7.18 (3.00)	0.959
Mean total working time	721 (333)	719 (335)	724 (330)	0.910
Mean age	40.52 (6.42)	40.17 (6.49)	40,86 (6.33)	0.438
Panel B: Characteristics of the shop location				
Mean market competition (= # of competitors, 1 km radius)	3.54 (3.03)	3.70 (3.17)	3.39 (2.89)	0.484
Mean market competition from large retailers (= # of large retailers, 1 km radius)	0.89 (0.90)	0.89 (0.92)	0.90 (0.88)	0.929
Share of large retailers (in total) (= # large retailers / total # of competitors, 1 km radius)	0.28 (0.33)	0.28 (0.32)	0.29 (0.33)	0.917
Big town	36.3%	38.5%	34.0%	0.516

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. “Big town” refers to municipalities with more than 50,000 inhabitants.

Table 2: Pairwise correlations

	Mean sales	Mean # of customer visits	Mean # of employees	Mean total working time	Mean age	Mean market competition	Mean % of large competitors
Mean # of customer visits	0.920						
Mean number of employees	0.748	0.689					
Mean total working time	0.792	0.738	0.934				
Mean age	-0.202	-0.239	-0.202	-0.182			
Mean market competition	-0.034	-0.008	0.009	0.034	-0.060		
Mean % of large competitors	0.129	0.180	0.079	0.104	-0.096	-0.117	
Big town	0.223	0.294	0.215	0.267	-0.269	0.046	0.342

Notes: The data are from January 2013 to March 2014. “Big town” refers to municipalities with more than 50,000 inhabitants.

Table 3: Summary statistics per competition category (pre-treatment)

<i>Sample</i>	<i>All shops (n=193)</i>			<i>Shops in big towns (n=70)</i>		
	<i>Low</i>	<i>Moderate</i>	<i>High</i>	<i>Low</i>	<i>Moderate</i>	<i>High</i>
<i>Level of competition</i>						
# of competitors in 1 km radius	0, 1, 2	3, 4	> 4	0, 1, 2	3, 4	> 4
# of shops	81	53	59	30	21	19
Treatment shops (in %)	51.9%	50.8%	47.5%	53.3%	38.3%	47.4%
Mean sales	27,527 (11,559)	28,179 (18,379)	25,937 (8,954)	30,397 (13,230)	33,018 (24,575)	30,151 (8,321)
Mean # of customer visits	9,862 (3,950)	9,695 (4,271)	9,423 (3,248)	11,253 (4,877)	10,941 (4,947)	11,320 (3,331)

Notes: Standard deviations are in parentheses. The data are from January 2013 to March 2014. “Big town” refers to municipalities with more than 50,000 inhabitants³

Table 4: Average treatment effect on sales, number of customer visits and sales per customer

Panel A: Log (sales)		
<i>Sample</i>	<i>All shops (n=193)</i>	<i>Shops in big towns (n=70)</i>
Treatment effect	0.026 (0.012)	0.037 (0.025)
Panel B: Log (number of customer visits)		
Treatment effect	0.022 (0.010)	0.032 (0.018)
Panel C: Log (sales per customer visit)		
Treatment effect	0.002 (0.007)	0.004 (0.018)

Notes: The table shows estimated average treatment effects (diff-in-diff, see equation 3), for all shops, and for the subsample of shops in big towns. The dependent variable in Panel A is log (sales), in Panel B log (number of customer visits) and in Panel C log (sales per customer visit). “Big town” refers to municipalities with more than 50,000 inhabitants. I Controls include shop and month fixed effects, log total hours worked, and the share of large retailers in the total competition. Number of shop-month observations: 3,148. Number of shops: 193. Standard errors clustered by shop are in parentheses.

Table 5: Average treatment effect on sales, number of customer visits and sales per customer visit, by level of competition

Panel A: Log (sales)						
<i>Sample</i>	<i>All shops (n=193)</i>			<i>Shops in big towns (n=70)</i>		
	<i>Low</i>	<i>Moderate</i>	<i>High</i>	<i>Low</i>	<i>Moderate</i>	<i>High</i>
Treatment effect	0.019 (0.022)	0.052 (0.019)	0.009 (0.019)	0.018 (0.053)	0.089 (0.022)	0.021 (0.038)
Panel B: Log (number of customer visits)						
Treatment effect	0.023 (0.014)	0.035 (0.018)	0.007 (0.018)	0.019 (0.028)	0.079 (0.021)	0.010 (0.036)
Panel C: Log (sales per customer visit)						
Treatment effect	-0.007 (0.017)	0.015 (0.006)	0.003 (0.005)	-0.001 (0.047)	0.015 (0.009)	0.004 (0.006)

Notes: The table shows estimated average treatment effects (diff-in-diff, see equation 4) per category of competition, for all shops, and for the subsample of shops in big towns. The dependent variable in Panel A is log (sales), in Panel B log (number of customer visits) and in Panel C log (sales per customer visit). “Big town” refers to municipalities with more than 50,000 inhabitants. Controls include shop and month fixed effects, and log total hours worked. Standard errors clustered by shop are in parentheses.

Table 6: Average treatment effect on sales, for category of competition

Panel A: Share of large retailers in the total competition = 0			
<i>Level of competition</i>	<i>Low</i>	<i>Moderate</i>	<i>High</i>
Treatment effect	0.036 (0.019)	0.043 (0.035)	-0.014 (0.030)
Panel B: Share of large retailers in the total competition = 1/4			
Treatment effect	0.045 (0.024)	0.054 (0.043)	-0.018 (0.037)
Panel C: Share of large retailers in the total competition = 1			
Treatment effect	-0.013 (0.063)	0.075 (0.047)	0.111 (0.089)

Notes: The table shows the estimated average treatment effects (diff-in-diff, see equation 5) per category of competition. The dependent variable in all the models is log (sales). Panel A estimates the average treatment effect for the shops with no large retailers (ALDI and LIDL) within a 1 km radius. Panel B estimates the same for the average shop for which $\frac{1}{4}$ of its local competitors are large retailers. Panel C reports the same for the shops for which all the local competitors are large retailers. Controls include shop and month fixed effects, log total hours worked, and the share of large retailers in the total competition. Number of shop-month observations: 3,148. Number of shops: 193. Standard errors clustered by shop are in parentheses.

Table 7: The effect of shop efficiency on average treatment effect on sales

Panel A: Summary of statistics for shop efficiency						
<i>Sample</i>	<i>All shops (n=187)</i>			<i>Shops in big towns (n=68)</i>		
<i>Level of competition</i>	<i>Low</i>	<i>Moderate</i>	<i>High</i>	<i>Low</i>	<i>Moderate</i>	<i>High</i>
Average shop-level efficiency measure	0.067 (1.035)	-0.095 (1.161)	-0.007 (0.767)	0.090 (0.647)	-0.244 (1.045)	-0.111 (0.959)
Panel B: Average treatment effect on Log (sales)						
Treatment effect	0.014 (0.023)	0.048 (0.018)	0.007 (0.018)	0.039 (0.061)	0.092 (0.019)	0.020 (0.025)
Treatment effect * efficiency	-0.013 (0.025)	-0.077 (0.020)	-0.048 (0.030)	-0.080 (0.083)	-0.073 (0.022)	-0.028 (0.030)

Notes: Panel A shows mean and standard deviation (in parentheses) of shop-level efficiency measure (standardized). Owing to technical difficulties of estimating the efficiency term from the stochastic frontier regression, it could not be estimated for all shops. Hence, six shops were dropped from the analysis (two from big towns). Panel B reports estimated average treatment effects (diff-in-diff) per category of competition, for all shops, and for the subsample of shops in big towns. The dependent variable is log (sales). “Big town” refers to municipalities with more than 50,000 inhabitants. Controls include shop and month fixed effects, log total hours worked, and shop-level efficiency. Number of shop-month observations: 3,085 in the sample of all shops, and 1,125 in the subsample of shops in big towns. Standard errors clustered by shop are in parentheses.

Table 8: Average treatment effect on sales, controlling for frequency of reaching the sales target

Panel A: Summary of statistics for frequency of achieving the sales target						
<i>Sample</i>	<i>All shops (n=193)</i>			<i>Shops in big towns (n=70)</i>		
<i>Level of competition</i>	<i>Low</i>	<i>Moderate</i>	<i>High</i>	<i>Low</i>	<i>Moderate</i>	<i>High</i>
Frequency of reaching sales target	0.338 (0.264)	0.334 (0.245)	0.376 (0.271)	0.339 (0.276)	0.409 (0.284)	0.334 (0.244)
Panel B: Average treatment effect on Log (sales)						
Treatment effect	0.021 (0.022)	0.050 (0.018)	0.010 (0.020)	0.021 (0.063)	0.084 (0.020)	0.027 (0.038)
Treatment effect * frequency	-0.007 (0.023)	-0.006 (0.022)	-0.021 (0.013)	0.020 (0.067)	-0.010 (0.016)	-0.022 (0.023)

Notes: Panel A shows mean and standard deviation (in parentheses) of pre-treatment frequency of reaching the sales target. Panel B reports estimated average treatment effects (diff-in-diff) per category of competition, for all shops, and for the subsample of shops in big towns. The dependent variable is log (sales). “Big town” refers to municipalities with more than 50,000 inhabitants. Controls include shop and month fixed effects, log total hours worked, and pre-treatment average frequency of reaching the sales target. Number of shop-month observations: 3,148 in the sample of all shops, and 1,258 in the subsample of shops in big towns. Standard errors clustered by shop are in parentheses.

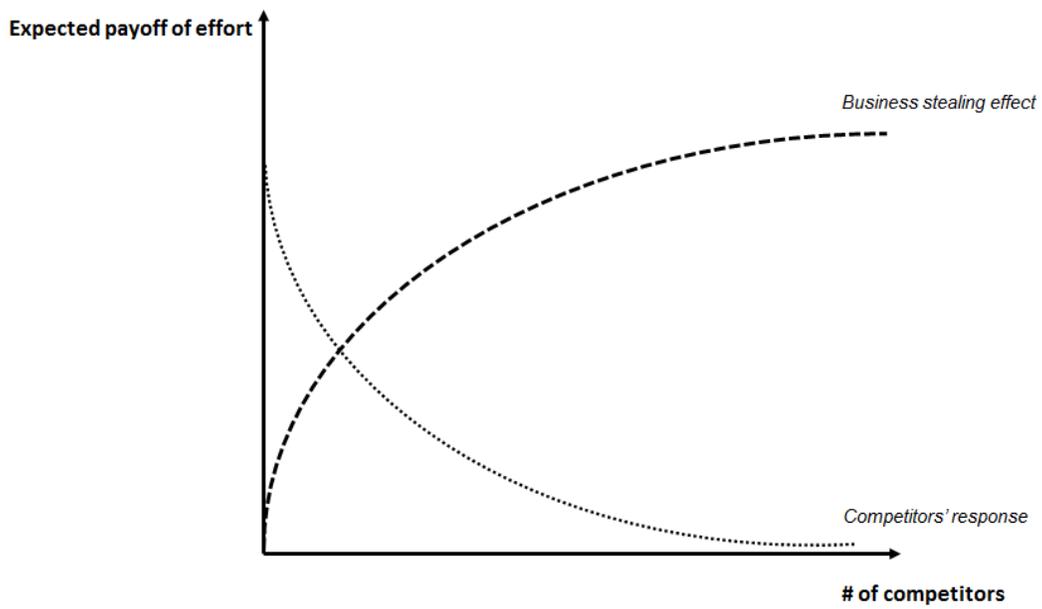


Figure 1: Business stealing and competitors' response effect, with respect to market competition

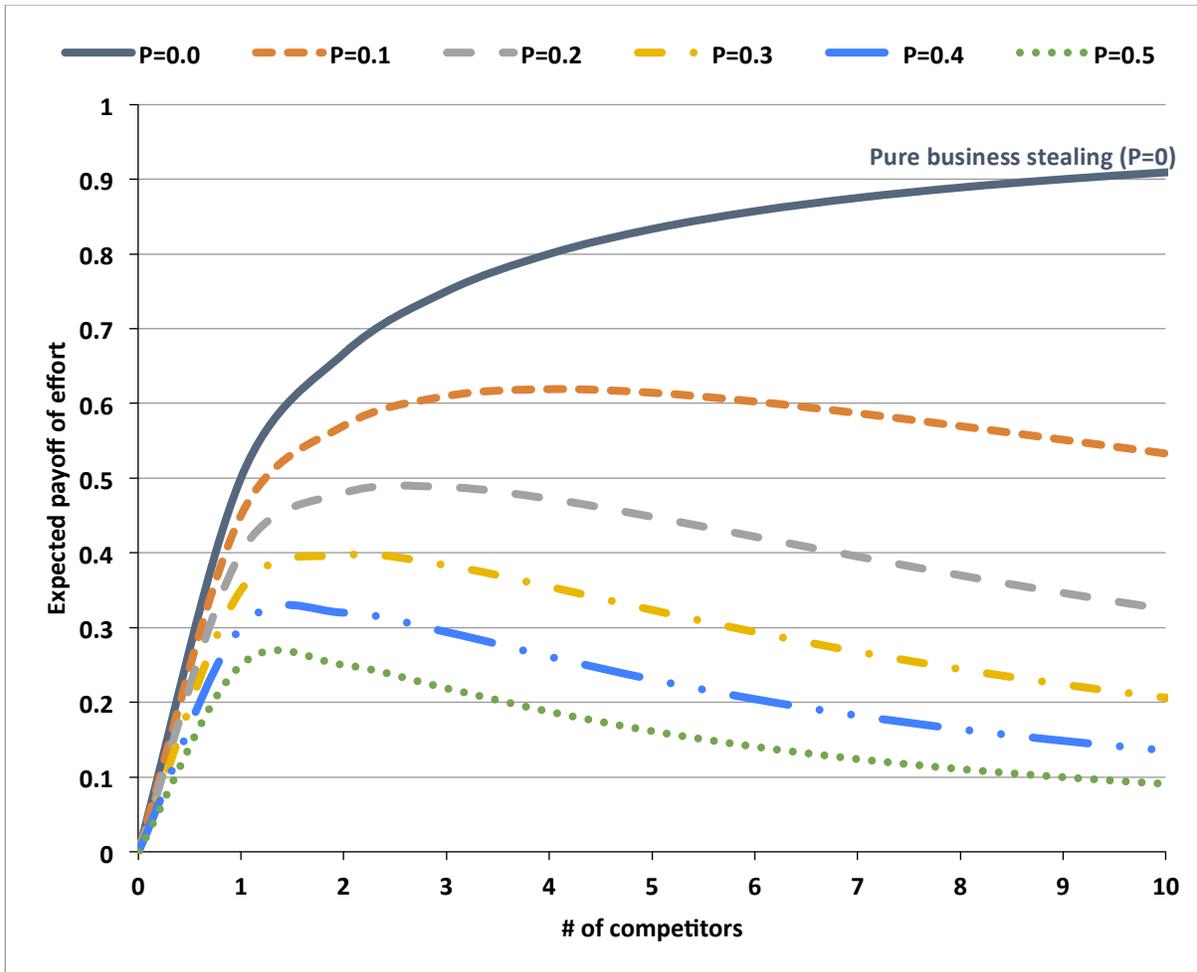


Figure 2: Simulated relation of the expected payoff and market competition – equation (2)

Notes: The figure shows the simulated pattern of expected payoff (Y axis) with respect to number of market competitors (X axis). The payoff function is plotted for different values of P (probability of competitors' response). The payoff function is the equation (2); $E(\text{bonus}) = \alpha \cdot \sum_{i=0}^n C_i^n \cdot P^i \cdot (1 - P)^{n-i} \cdot \frac{1}{i+1} \cdot \left(1 - \frac{i+1}{n+1}\right) - \bar{e}$. In the above figure, α is set to one and \bar{e} is set to zero.

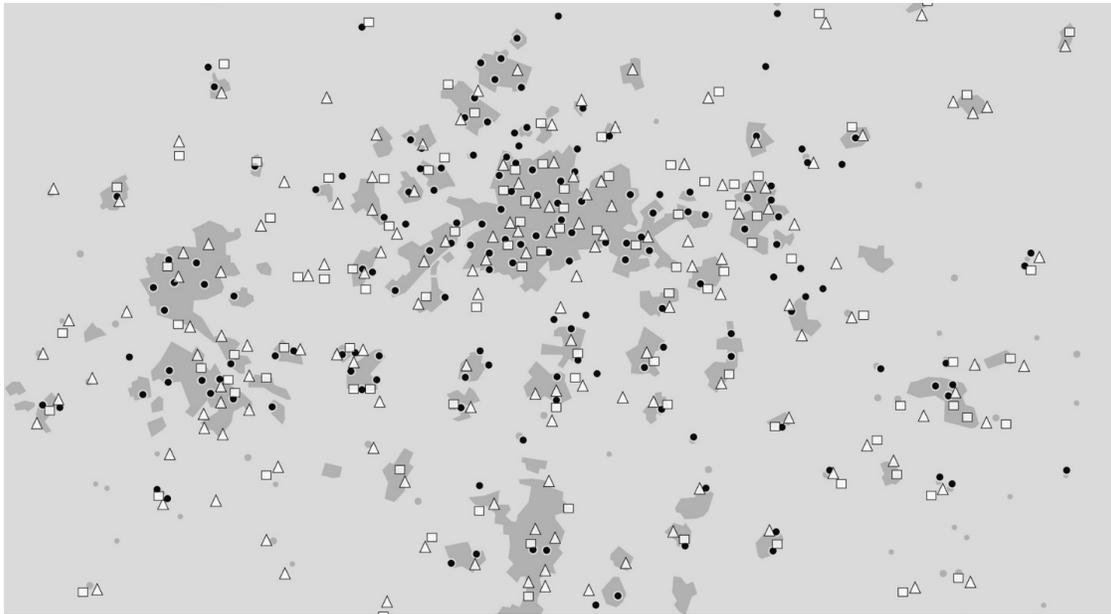


Figure 3: The locations of the shops for our study firm (•), ALDI (◻) and LIDL (Δ)

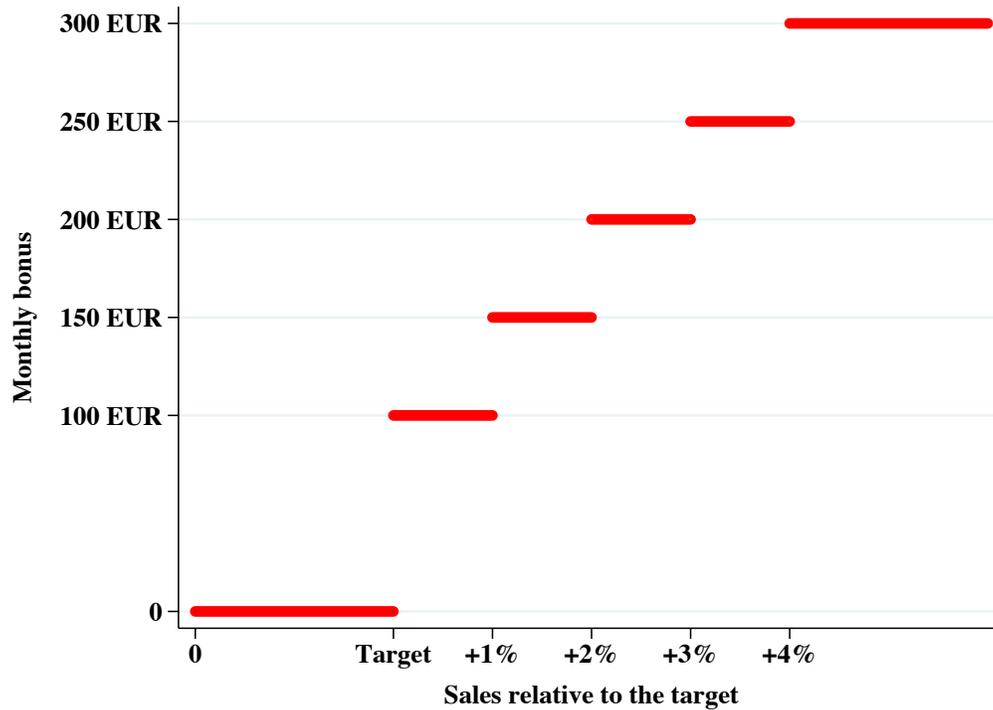


Figure 4: The PfP scheme for the treatment shops

Notes: This figure illustrates the amount of bonus a shop sales team would receive depending on reaching and exceeding its sales target in a given month. Not reaching the target brings no bonus. Reaching or exceeding the target by up to 1% awards a bonus of 100 EUR. Every percentage point on top of 1% above the target brings an additional 50 EUR of bonus. The bonus is capped at 300 EUR paid when the target is exceeded by 4% or more. The bonus is shared between the part-time and full-time employees in the shop in proportion to their working hours during that month.