Incentive and Sorting Effects of Challenging Performance Targets: Evidence from the Field

MARTIN ARTZ
University of Münster

JENS BÖKE
University of Münster

MARTIN HOLZHACKER
Michigan State University

MICHAL MATĚJKA
Arizona State University

February 2025

The paper has benefited from helpful comments of Robert Bowen, Stephen Glaeser, Ranjani Krishnan, Eva Labro, Adrienne Rhodes (discussant), and workshop participants at University of Calgary, Chapman University, Michigan State University, University of North Carolina, and the 2025 American Accounting Association Management Accounting Section Meeting.

Incentive and Sorting Effects of Challenging Performance Targets: Evidence from the Field

ABSTRACT

Prior studies often examine how target difficulty affects effort in laboratory experiments but we still have a limited understanding of the incentive effects of targets in real-world settings where employees carry out complex tasks over a long period of time. We exploit exogenous changes in target difficulty due to abnormal weather to show that challenging but achievable targets increase daily sales of retail store employees evaluated relative to monthly targets. However, we also show that target-based incentives: (i) are inherently weak at the beginning of the month, (ii) get much stronger towards the end of the month but only if targets remain challenging but achievable, and (iii) the likelihood that targets remain challenging but achievable gets much smaller over time. Finally, we find that challenging targets facilitate sorting in that highly productive employees repeatedly meet their targets and earn bonuses while less productive employees with limited success in meeting their targets voluntarily depart.

Keywords: Performance targets, goal setting, incentives, employee sorting.

JEL codes: M12, M21, M41.

1 Introduction

An important insight from a large stream of work on goal setting is that challenging targets increase effort and performance (Locke and Latham [1990], Locke and Latham [2002]). However, the vast majority of studies on the incentive effects of performance targets use data from laboratory experiments where participants carry out relatively simple tasks over a short period of time. Only a few studies use field, survey, or archival data on target difficulty (Webb, Jeffrey, and Schulz [2010], Presslee, Vance, and Webb [2013], Eyring and Narayanan [2018], Aranda, Arellano, and Davila [2019]) and even those studies rarely examine the extent to which the incentive effects of targets persist as the performance evaluation period unfolds.

Our study aims to improve our understanding of the economic effects of challenging targets in real-world settings where performance is evaluated over long time periods. This is important for several reasons. First, economic theory predicts that the incentive effects of targets are driven by the extent to which employee effort changes the likelihood of meeting a target (Hu, Li, and Ray [2021]). However, this economic force is difficult to isolate in experiments where targets are set just before participants exert effort, because the choice of effort may reflect not only a rational assessment of probabilities but also short-lived affective responses to targets such as anxiety, arousal, or disappointment (Locke and Latham [2002], Gneezy and List [2006], Berger, Guo, and Presslee [2023]). Second, prior studies using short experimental tasks do not test an important implication of economic theory, namely that the incentive effects of challenging targets increase as the performance evaluation period unfolds and outcome uncertainty gets resolved. Third, firms may use target-based rewards not only to motivate effort but also to facilitate employee selection and retention and these additional economic benefits are rarely examined in laboratory experiments (Matějka [2018]).

To motivate our empirical analysis, we derive several predictions from the target-setting model of Matějka and Ray [2017] where target difficulty affects both the incentive and participation constraints of a firm employee. The incentive constraint assures that the employee increases effort up to a point where its marginal cost equals the marginal benefit, i.e., the expected increase in incentive compensation. Assuming that incentive compensation consists of a fixed bonus for meeting a predetermined performance target, the marginal benefit of effort is entirely driven by how the likelihood of meeting the target changes with effort. Consistent with goal setting theory, challenging but achievable targets have strong incentive effects because a small increase in effort can greatly increase the likelihood of meeting the target. Conversely, very easy (difficult) targets have weak incentive effects because the employee anticipates that the bonus will (not) be earned regardless of effort.

A key implication of the target-setting model is that the incentive effects of targets are not constant within a performance evaluation period but evolve over time as uncertainty gets resolved. In particular, the model predicts that targets can only have weak incentive effects at the beginning of a period when employees are exposed to a lot of outcome uncertainty. The incentive effects of targets then get stronger over time but only if they remain challenging but achievable. The offsetting effect is that the likelihood of targets remaining to be challenging but achievable decreases over time. In other words, as the period unfolds, target-based incentives get stronger for some employees, but others are no longer motivated by targets that become very easy (difficult) to achieve.

Finally, target difficulty affects not only the incentive constraint but also the participation constraint. In the simplest model with only one employee, target difficulty and the resulting expected bonus can be calibrated so that the participation constraint is always binding. In a more realistic setting with multiple employees, it may not always be possible to adjust targets for differences in employee productivity due to information asymmetry or legal constraints. With uniform salary, bonus, and performance target, the participation constraints are binding only for employees with the lowest productivity while all others earn rents in excess of their reservation utility. In such settings, any increase in target difficulty also increases the likelihood that less productive employees do not earn their bonuses and voluntarily quit the job.

We test these predictions using 2013–2018 data on daily sales of 511 employees (sales representatives) in 43 stores of a clothing retailer in Europe. The employees earn a fixed salary and are eligible for a monthly bonus equal to about 10% of their total compensation if they meet their monthly sales target. The 12 monthly targets for each store are determined by corporate staff once a year and are the same for all employees in the same store, after adjusting for the number of hours in the employment contract. Once set, targets are not revised during the year. Employees can track their daily and cumulative monthly sales and update their beliefs about the likelihood of meeting their monthly target. Actual sales depend not only on their effort in assisting customers but also on random events—weather is a particularly important source of random variation because good weather substantially reduces store traffic and daily sales in our setting.

To measure the incentive effects of targets, we estimate a Logit model of the likelihood of meeting the monthly target as a function of cumulative month-to-date performance after most of the month (60% in our main tests) has passed. The Logit model can estimate target incentive strength as the effect of an incremental increase in performance (through higher effort in the remainder of the month) on the change in the likelihood of achieving the monthly target. High values of this measure represent a challenging but achievable monthly target for a given month-to-date performance. We also use an indicator variable for targets with the probability of being achieved between 10% and 90%, which implies that the bonus can be earned if an employee puts in some effort. The indicator variable is zero if month-to-date performance has been so (un)favorable that additional effort would make little difference. To measure effort, we estimate abnormal sales in the remainder of the month (40% in our main tests), after adjusting for employee, store-month, and day fixed effects.

Our main findings are as follows. First, similar to prior work, we find that challenging but achievable targets significantly increase end-of-month effort. The novel and important feature of our study is that we can use weather as a source of exogenous shocks to monthly target difficulty. We find that the effect of target difficulty on end-of-month effort is significantly stronger when it is driven by weather, particularly when bad weather increases month-to-date performance so that very difficult targets become challenging but achievable. We find similar results when we use bad weather as an instrument for target difficulty.

Second, our study is one of the first to provide empirical evidence that the incentive effects of challenging targets get stronger as the monthly performance evaluation period unfolds. Specifically, we find a significant effect of target incentive strength after 30% of the month has passed on effort in the remaining 70% of the month. This effect almost doubles when estimated after 60% of the month and then doubles again when estimated after 90% of the month. Thus, conditional on the monthly targets remaining challenging but achievable, their incentive effects increase monotonically as the end of the month approaches. That said, we also find a decreasing likelihood that targets remain motivating, e.g., 65% of targets are challenging but achievable after 30% of the month but only 23% remain so after 90% of the month has passed.

Third, we find that performance targets facilitate sorting because monthly target difficulty varies greatly over time and some employees are much more successful in meeting their monthly target than others. During the 2013–2018 sample period, the probability of meeting the monthly target is 43% on average but it varies greatly depending on individual productivity. We predict and find that repeated failure to meet monthly targets significantly increases the likelihood of voluntary turnover. In other words, using the same targets for monthly bonuses of all employees motivates the highly productive ones to stay and the less productive ones to leave.

Combined, our findings contribute to prior literature by highlighting not only the benefits of targets in motivating effort but also their limitations. Although we replicate prior findings that challenging but achievable targets increase effort (Locke and Latham [2002]), we also document that targets are at the "challenging but achievable" level for most employees only at the beginning of a performance evaluation period, which is also when their incentive effects are the weakest. As the period unfolds and uncertainty about random events affecting performance gets resolved, target-based incentives get substantially stronger but only for a decreasing proportion of employees still facing challenging but achievable targets. Thus, our evidence suggests that the benefits of target-based rewards are offset to a large extent by their limitations because even targets that are well calibrated at the beginning of a period often end up having no incentive effects and sometimes possibly even too strong effects.

Our study also extends prior experimental work by shedding some light on why targets motivate effort. In contrast to prior work, employees in our setting make effort choices long after they learn about their targets, which rules out short-lived affective responses to being assigned a performance target (Gneezy and List [2006], Berger et al. [2023]). We find evidence consistent with our theory that employees rationally assess how their effort changes the likelihood of meeting a target and maximize their expected rewards. In particular, we find that targets motivate effort primarily when the target is close to expected performance and the likelihood of meeting it is highly sensitive to effort.

Compared to other non-experimental work on the incentive effects of targets (Webb et al. [2010], Kim, Matějka, and Park [2023]), our research design alleviates concerns about common endogeneity issues (Indjejikian, Matějka, and Schloetzer [2014b]). We use granular daily data on performance relative to pre-determined monthly targets and strict fixed-effect specifications, which reduces susceptibility to reverse causality and other endogeneity issues. We also exploit random variation in target difficulty due to weather and show that exogenous increases in target incentive strength greatly increase end-of-period effort.

Finally, our findings highlight the sorting benefits of target-based rewards, which are often overlooked in prior work (Matějka [2018]). Despite the randomness in monthly performance, some employees are much more successful than others in meeting their targets. As a consequence, the firm can encourage less productive employees to leave voluntarily simply by increasing target difficulty. This may be particularly important in settings with high uncertainty about employee productivity and high costs of non-voluntary employee termination.

2 *Prior Literature*

A large stream of psychology-based literature focuses on the benefits of performance targets in motivating effort. Hundreds of experimental studies on goal setting show that participants increase their effort if they are given specific and challenging targets (Locke and Latham [1990], Locke and Latham [2002]). However, it remains unclear whether the findings based on short and simple tasks in laboratory experiments generalize to real-world settings, where employees perform complex tasks over a long period of time. As discussed below, task complexity and task duration strongly affect the incentive effects of targets.

A meta-analysis of the literature by Wood, Mento, and Locke [1987] shows that the incentive effects of targets are strongest for the simplest tasks and weakest for complex tasks. Gneezy and List [2006] highlight the importance of task duration: “Whereas interaction in the lab is typically abbreviated and usually takes no longer than two hours, interaction in labor markets typically lasts weeks, months, or years. One lesson learned from the psychology literature is that there are important behavioral differences between psychological processes in the short run and in the long run” (p. 1366). The immediate reaction to a performance target may be affective, reflecting feelings about being assigned a target (Hsee and Rottenstreich [2004]). In contrast, the long-term reaction may be calculative, reflecting “a rational assessment of probabilities” of receiving the target-based reward (Berger et al. [2023]). Short laboratory experiments cannot easily disentangle the immediate from the long-term reaction, which limits generalizability of their findings to the extent that the long-term reaction is the main driver of effort in real-world settings with long task durations.

Several accounting studies examine the incentive effect of targets using field, survey, or archival data. Webb et al. [2010] use data on performance of call center employees in two consecutive months. The employees could select their own targets from a menu of three performance levels in the second month of the study. Good past performance was associated with the choice of a more difficult target and both past performance and target difficulty were in turn positively associated with current performance. Aranda et al. [2019] use data on annual targets from the branches of a travel retailer over a four-year period. They find that higher target difficulty is associated with greater performance when the acceptance of more difficult targets (relative to peers) is rewarded with subjective bonuses. Kim et al. [2023] use executive compensation data from S&P 1500 firms to show that annual target difficulty is positively associated with performance.

The advantage of these studies relative to prior experimental work is that performance is measured over realistically long evaluation periods, which improves external validity. The disadvantage is the susceptibility to biases when target difficulty is not assigned randomly but measured with noise. Persistent shocks to past performance or differences in individual productivity may introduce biases because they increase both current performance and archival measures of target difficulty (Indjejikian et al. [2014b], Matějka, Mahlendorf, and Schäffer [2024]). Similar trade-offs between external and internal validity are encountered in survey studies on the association between target difficulty and performance (Simons [1988], Hirst and Lowy [1990], Ioannou, Li, and Serafeim [2016]). Survey measures of perceived target difficulty may be less susceptible to biases due to persistent performance shocks, but common method biases or reverse causality may still be a threat to internal validity.

Some accounting studies also highlight the costs of challenging performance targets such as managerial short-term orientation (Van der Stede [2000]), dysfunctional behavior (Holzhacker, Kramer, Matějka, and Hoffmeister [2019], Shang, Wang, and Zu [2023]), and end-of-period gaming (Bouwens and Kroos [2011], Bol and Lill [2015], Casas-Arce, Holzhacker, Mahlendorf, and Matějka [2018], Bouwens, Hofmann, and Schweiger [2024]). Thus, challenging but achievable targets motivate not only productive effort but also gaming and the latter can undermine long-term performance. In addition, challenging but achievable targets may not be well suited to motivate creativity, which can benefit from slack in the form of highly achievable targets (Webb, Williamson, and Zhang [2013], Brüggen, Feichter, and Williamson [2018]) and sometimes even from very difficult targets (Pfister and Lukka [2019]). More generally, slack targets can alleviate multi-tasking issues (Davila and Wouters [2005], Huang, Balakrishnan, and Pan [2016], Balakrishnan, Huang, and Wu [2022]) and increase perceived fairness and trust between managers and employees (Bol, Keune, Matsumura, and Shin [2010], Bol and Lill [2015]). Conversely, challenging targets could undermine motivation in settings where creativity, multi-tasking, and trust are important.

Finally, economic theory holds that firms can increase their productivity not only by motivating employees but also by recruiting, retaining, and promoting highly productive employees (Campbell [2008], Bender et al. [2018], Deller [2023]). Several accounting studies show that retention concerns are an important determinant of target difficulty. Matějka, Merchant, and Van der Stede [2009] find that loss-making firms concerned about managerial retention increase the relative emphasis on easier-to-achieve nonfinancial targets and reduce the emphasis on difficult-to-achieve earnings targets. There is also evidence that earnings target difficulty is negatively associated with retention concerns (Indjejikian, Matějka, Merchant, and Van der Stede [2014a]) and that earnings targets are much more difficult to achieve during recessions when alternative employment opportunities are limited (Casas-Arce, Indjejikian, and Matějka [2020]). Firms primarily concerned about employee retention may therefore avoid the use of challenging targets despite their motivational benefits.

In summary, specific challenging targets can enhance performance on short and simple tasks. Nevertheless, the increase in short-term performance can be driven by gaming rather than productive effort and come at the cost of long-term performance. Whether the benefits of challenging targets dominate their costs likely depends on task complexity, duration, retention concerns, and other contextual factors. Several recent accounting studies provide evidence suggesting that the motivating effects of challenging targets generalize from laboratory experiments to more complex tasks in real-world settings. However, there is still relatively little evidence on how task duration affects the incentive and sorting effects of targets, particularly when the performance evaluation period is long enough for performance targets to get outdated (Arnold and Artz [2015], Hyun, Matějka, Oh, and Ahn [2022], Arnold, Artz, and Grasser [2023]).

3 *Theory and Hypotheses*

3.1 THE ECONOMICS OF TARGET-BASED INCENTIVES

We rely on the target-setting model from Matějka and Ray [2017] and Hu et al. [2021] to motivate our hypotheses. In the simplest version of the model, summarized in Appendix B, a firm contracts with an employee to supply productive effort in exchange for a fixed salary and bonus conditional on meeting a predetermined performance target. Performance is a function of the unobservable effort as well as random noise with cumulative distribution function G and density g. If both parties are risk-neutral, the first-best effort can be implemented with an incentive contract that balances performance target difficulty as follows.

First, the employee's incentive constraint implies that the marginal cost of effort equals its marginal benefit. The benefit of effort is that it increases performance and therefore also G, the probability of meeting the target (and earning the bonus). For example, a very high effort or a very low target all but guarantee that the target will be met, which means that G will be close to its maximum of one. Given a fixed bonus, the marginal benefit of effort is entirely driven by g, the change in the probability of meeting the target. It follows that g measures incentive strength of the target because it is proportional (up to a constant) to the change in expected bonus as a result of a change in effort.

As illustrated in Figure 1, assuming that the noise term has a unimodal symmetric density with zero mean, a target equal to expected performance has the strongest incentive effect because noise realizations around zero have the most probability mass. More generally, in any region with a high probability mass, a slight increase in effort results in a large change in the likelihood of meeting a target and therefore also in a large change in expected compensation and strong incentives. Setting the target further away from expected performance reduces incentive strength. For example, a very difficult target, set in the right-tail region of the density function g with very little probability mass, can only be met in the unlikely event of a highly favorable noise realization. Putting in more effort to meet this target does not change G and expected compensation by much, so incentives are very weak in this region. The same applies to a very easy target in the left-tail region of the density function. The employee will almost certainly meet the target, except when the noise realization is highly unfavorable. Putting in more effort to guard against such an unlikely event does not change G by much, so incentives are also very weak.

Second, the firm's profit maximization implies that the marginal cost of effort must equal the marginal benefit to the firm, where the latter is a constant representing the marginal product of effort. Combining the firm's and the employee's optimization problems yields the equilibrium condition that g (as a function of the performance target choice) equals a constant optimal level. Figure 1 describes the optimal level of incentives with the horizontal dashed line for a given marginal product of effort and bonus.[1] In general, the performance target will not equal expected performance because it could result in overly strong incentives and effort higher than the first-

[1] In its simplest form, the target-setting model is overparameterized in that there are many different combinations of bonus and target levels that implement the first-best effort. However, the qualitative insights about incentive effects of performance targets discussed here remain the same regardless of the bonus level.

best level. The optimal level of incentives will typically be below the highest possible level, which can be implemented with two different targets, marked by the two vertical dashed lines. One target is lower than expected performance, the other is higher, but they both yield the same incentive strength, *g*, because the likelihood of earning the bonus is equally sensitive to effort at both target levels. In other words, what matters for incentives is not the target level per se but how far it is from expected performance.

Finally, besides determining effort through the employee's incentive constraint, the firm's choice of a performance target also affects the participation constraint. Expected compensation, which is decreasing in the target level, must reimburse the employee for the cost of effort plus reservation utility from the next-best employment opportunity. In the simplest version of the target-setting model, this does not affect the target choice, because the firm can always adjust the salary to make the participation constraint binding. However, the reservation utility affects the choice of a performance target when there are additional contracting frictions such as limited liability (or minimum wage), information asymmetry about the reservation utility, or multiple employees that for legal reasons must have the same salary, bonus, and target levels. For example, if the salary cannot be lower than some minimum level, the firm will prefer to set the target above expected performance because it reduces expected compensation and rents, while implementing the same effort as the target below expected performance with the same *g*.

3.2 HYPOTHESES

The above discussion of the target-based incentives motivates several testable predictions. As in prior work (Locke and Latham [2002]), our baseline prediction is that challenging but achievable targets motivate greater effort. Nevertheless, our theoretical motivation is different from prior work in two aspects. First, we assume that employees are rational expected utility maximizers and, consequently, incentives are driven by how effort changes the likelihood of meeting a target. Second, we can precisely define the extent to which a target is "challenging but achievable," as (the absolute value of) the distance between the target and expected performance. This is illustrated in Figure 1. The closer a target is to expected performance, the higher its incentive effects and employee effort. Conversely, very easy (difficult) targets in the tails of function *g* with low probability mass have little or no incentive effects.

The same assumptions and the resulting incentive constraint in our target-setting model motivate two hypotheses that have not been tested in prior work. The key theoretical insight is that the incentive effects of targets depend on the amount of uncertainty about the random noise component in employee performance. This is particularly important in settings with long performance evaluation periods, where targets are set at the beginning of a period and remain unchanged even as much of the uncertainty about end-of-month performance gets resolved. For example, if performance is evaluated over a monthly period of 20 working days, then employees experience random shocks to performance and choose effort many times during a month. At the beginning of the first week of the month, an employee knows that cumulative monthly performance will be affected by 20 daily random shocks, which amounts to a lot of uncertainty about meeting the target. After three weeks, the employee has observed 75% of the random noise realizations and can estimate the likelihood of meeting the target with much greater accuracy, which affects the choice of effort.

Although the simplest target-setting model assumes that the choice of effort happens only once during a performance evaluation period, the model can motivate predictions about the choice of effort with high versus low uncertainty about the random noise component of performance. Figure 2 illustrates the effect on incentive strength. High uncertainty at the beginning of a period can be represented with a density function *g* that has a low peak and heavy tails. This implies that many different target levels have largely the same, weak incentive effects because cumulative performance is determined primarily by random noise rather than employee effort. As the performance period unfolds, the mean of the updated distribution *g'* may or may not shift to reflect past noise realizations but the variance must decrease and the probability mass around expected performance must increase because there are fewer random shocks still to be realized.[2] It follows that a target close to expected performance will have much stronger incentive effects towards the end of a period than at the beginning.

H1a: *Challenging but achievable targets motivate more effort at the end of a performance evaluation period than at the beginning of the period.*

A flip side of the same argument is that, on average, targets are increasingly likely to get outdated as the performance evaluation period unfolds. Both *g* and *g'* in Figure 2 are probability density functions, which means that more probability mass around expected performance for *g'* is offset by less mass in the tails of the distribution. In other words, the range of performance outcomes that seem plausible at the beginning of a period (represented by *g*) must be much wider than the range of outcomes plausible after much of performance uncertainty is realized (*g'*). Some of the targets initially set to be challenging but achievable will become very easy (difficult) to achieve and lose their incentive effects as the period unfolds.

H1b: *The likelihood that targets are challenging but achievable at the end of a performance evaluation period is lower than at the beginning of the period.*

[2] By the law of large numbers, if the individual random noise components within a performance evaluation period are identically and independently distributed, then the average of all the random realizations converges to the mean of the distribution. This implies that the longer the performance evaluation period, the smaller the shift in the mean and the larger the decrease in variance between the beginning and the end of a period.

H1a and H1b follow directly from the incentive constraint in the target-setting model. Next, we focus on the participation constraint and argue that challenging targets can also increase firm profits by facilitating the retention of highly productive employees and/or encouraging voluntary turnover of less productive employees. Although the simplest target-setting model with just one employee does not speak to this issue directly, it can easily be extended to motivate additional hypotheses. Specifically, we assume that the firm contracts with multiple employees and cannot discriminate through any of the compensation choices. If the salary, bonus, and target level are the same for all employees, then the participation constraint of the least productive employee must be binding and all other employees earn rents above their reservation utility. This implies that targets are not adjusted for individual productivity and that highly productive employees are more likely to meet their targets (Indjejikian and Nanda [2002]).

Differences in the likelihood of meeting performance targets and the resulting differences in expected compensation must then also have consequences for the willingness to stay employed. If the salary, bonus, and target level are the same for all, then the least productive employees rarely meet targets, earn expected compensation close to their reservation utility, and are therefore more likely to leave for an alternative employment opportunity or altogether stop working. Conversely, highly productive employees regularly earn bonuses, which increases their expected compensation and reduces the likelihood of voluntary turnover.

H2a: *The likelihood of voluntary turnover is negatively associated with individual productivity*.

In addition, we expect that an increase in target difficulty and a recent failure to earn bonuses increases voluntary turnover even after controlling for employee productivity. This may be a consequence of the firm's choice of a higher target difficulty for all employees or it could reflect recent changes in individual productivity that render targets more difficult to achieve only for some employees.

H2b: *The likelihood of voluntary turnover is positively associated with recent failure to meet a target*.

4 Research Design

4.1 FIELD SETTING

We use 2013–2018 data on daily sales of 511 sales representatives in 43 stores of a retailer in one of the largest European countries. The retailer sells everyday clothing, shoes, and accessories such as belts, socks, and watches, targeting the middle-price segment of the mass market with intense competition. In order to clearly differentiate itself from the competition, the retailer puts a focus on providing high-quality and personalized fashion advice and effective customer service.

Corporate headquarters is responsible for product selection, pricing, advertising, as well as store location and design. Each store has a manager responsible for hiring, training, shift scheduling, visual merchandising, and stock management. Nevertheless, managers also spend much of their time assisting customers. A typical store has at least three additional employees, many of them part-timers. Each shift typically has two employees even though store traffic can vary greatly, being particularly high on Friday evenings, Saturdays, and occasional Sundays.

The primary responsibility of employees is to greet customers, answer questions, draw attention to new products or special promotions, provide fashion advice, check out merchandise, and process returns. Other key responsibilities include product presentation, inventory management, as well as cleaning and improving the store's visual appearance. Employees vary in their sales skills, willingness to work with the customer, and overall job attitude. Some high performers generate several times more revenue than the lowest performers, which implies that free riding of some employees may be an issue. Nevertheless, given legal constraints and local culture, the retailer does not dismiss employees for low performance. Voluntary turnover is relatively high and many employees stay for less than a year.

Employee compensation consists of a fixed salary plus a performance bonus of about 10% of the salary dependent on meeting monthly sales targets. The targets are set by corporate headquarters in a top-down process that does not involve store managers. Specifically, corporate management first set the annual target for the whole organization based on past actual sales and a growth component. Next, the annual target is converted into monthly targets based on seasonality, holidays, and other predictable drivers of sales. The total monthly target is then broken down into store-level targets, which are further disaggregated into monthly targets for each employee based on the ratio of their contract hours to total store hours. According to corporate management, the intention is to set ambitious targets that should be achievable by high performers.

4.2 VARIABLE MEASUREMENT

Our empirical analysis uses the following variables. *DailySales* is the total amount of sales booked by an employee on a given day (in €, adjusted for returns). *HoursWorked* is the number of productive hours on that day, measured as the number of hours between the first and last daily sale. *Target* is the monthly sales target for the employee. *%TargetAchieved* is calculated as actual monthly sales divided by the *Target*. *TargetMet* is an indicator variable for meeting the *Target* at the end of the month, i.e., *%TargetAchieved* ≥ 1. *%SalesToDate* is month-to-date performance as a percentage of *Target*. In our main tests, we measure it as cumulative sales after

60% of the month has passed divided by *Target*. We use 30% and 90% cut-off points in alternative specifications.

We control for employee heterogeneity using four indicator variables for different employment categories. *Manager* is an indicator for employees with job title "Manager" or "Assistant Manager." *SalesRep1* is an indicator for full-time employees without managerial responsibilities. *SalesRep2* is an indicator for part-time employees working less than 1.0 but more than 0.5 of the full-time equivalent and *SalesRep3* for part-timers working 0.5 of the full-time equivalent or less. *StoreTarget* is the monthly store sales target, i.e., the sum of *Target* for all employees in a store.

We use three variables to measure the effects of weather. *AbnRain* is abnormal daily rainfall (in hours), calculated as the deviation from the average rainfall on the same day in prior ten years. *AbnSun* is abnormal sunshine (in hours), calculated as the deviation from the average sunshine on the same day in prior ten years. *AbnTemp* is abnormal temperature (in °C), calculated as the deviation from the average temperature on the same day in prior ten years.

Finally, we measure voluntary turnover with an indicator variable for the last month of employment, *Turnover*. We winsorize all continuous variables at the one percent level, except for variables measured as percentages.

4.3 CHALLENGING BUT ACHIEVABLE TARGETS

A key insight from our theoretical model, summarized in Figure 1, is that challenging but achievable targets are close to expected performance. We rely on the theory to empirically measure this theoretical construct as follows. First, we estimate ex ante target difficulty, denoted in our model by *G*, which is the probability of achieving the monthly target conditional on all information available before an employee decides how much effort to exert on any given day.

Although the monthly target is fixed, target difficulty varies daily as cumulative month-to-date performance changes due to recent random shocks to performance and effort. The following Logit model estimates the probability of achieving the monthly target as a function of month-to-date performance:

$$\begin{aligned}TargetMet_{i,m} = {} & \beta_1 + \beta_2\,\%SalesToDate_{i,m} + \beta_3\,SalesRep1_{i,m} + \beta_4\,\%SalesToDate_{i,m} \cdot SalesRep1_{i,m} + \\ & + \beta_5\,SalesRep2_{i,m} + \beta_6\,\%SalesToDate_{i,m} \cdot SalesRep2_{i,m} + \\ & + \beta_7\,SalesRep3_{i,m} + \beta_8\,\%SalesToDate_{i,m} \cdot SalesRep3_{i,m} + Month\ FE,\end{aligned} \tag{1}$$

where *i* represents employees and *m* represents months. *TargetMet* is the indicator for meeting the monthly sales target. *%SalesToDate* is the percentage of the monthly sales target met at different points within the month. We allow the effect of past performance on the likelihood of meeting the target to vary across the four different employee categories by including all nonredundant main effects and interactions of the three *SalesRep* indicators and *%SalesToDate.* We also control for seasonality and time trends by including 72 month fixed effects (FE). We cluster standard errors by employee.

Panel A of Figure 3 presents the fitted values from (1), i.e., the predicted likelihood of achieving the monthly target as a function of *%SalesToDate.* To measure challenging but achievable targets, we use an indicator variable *TargetEffectOn* equal to one if the predicted likelihood of meeting the target is in the 10–90% range.[3] *TargetEffectOn* equals zero for very difficult targets (with less than 10% probability of being achieved) and for very easy targets (with more than 90% probability of being achieved).

Second, we obtain an approximation of the probability density function *g* by using the coefficient estimates from (1) to calculate the marginal effects of *%SalesToDate* on the

[3] Alternative definitions of *TargetEffectOn* using 20–80 and 30–70 percent ranges yield qualitatively similar results.

likelihood of achieving the monthly target (see Panel B of Figure 3). This yields a continuous measure of challenging but achievable targets, *TargetEffect*, that does not require any arbitrary ranges or cut-off points. High values of *TargetEffect* imply that a slight increase in effort greatly increases the likelihood of achieving the target because month-to-date performance is close to expected performance. Low values imply either highly favorable or unfavorable month-to-date performance and consequently very easy (difficult) targets.

4.4 SALES EFFORT

To test our predictions about the effect of challenging but achievable targets on sales effort, we estimate the following model:

$$DailySales_{i,m,d} = \gamma_1 + \gamma_2\, TargetEffect(On)_{i,m} + Controls + Rep\ FE + Day\ FE + Store\&Month\ FE, \qquad (2)$$

where *i* represents employees, *m* months, and *d* days. The estimation sample includes all days *after* the cut-off point used to calculate the continuous or binary measure of challenging but achievable targets. In our main tests, the *TargetEffect*(*On*) variables are calculated after 60% of the month has passed, which means that we can use the remaining 40% of days of the month to estimate (2). We control for the number of hours an employee worked on each day (*HoursWorked*) and for abnormal weather (*AbnRain*, *AbnSun*, and *AbnTemp*). We also use a granular fixed effect structure controlling for: (i) employee characteristics (*Rep FE*) that are largely time-invariant such as skill, productivity, education, or age, (ii) day effects such as company-wide sales events, proximity to major holidays, seasonality, or macroeconomic drivers of sales, and (iii) store-month effects such as local special events, store-specific advertising, new employee training, or understaffing. Standard errors are two-way clustered by employee and day.

5 *Results*

5.1 DESCRIPTIVE EVIDENCE

5.1.1 Sample Descriptives

Table 1 presents descriptive statistics for the two different samples in our empirical analysis. Panel A describes the monthly sample of 8,632 employee-month observations, which we use to estimate model (1). On average, the monthly sales target of €9,302 is 8% higher than actual sales, as reflected in the 92% average of *%TargetAchieved*. Nevertheless, *%TargetAchieved* varies widely with the top quartile being 11% over target and the bottom quartile being 33% below target. Similarly, the average of *TargetMet* suggests that the monthly targets are challenging because only 43% of employees meet their targets.

The average of *%SalesToDate* implies that 52% of the monthly target is met after 60% of the month. The wide variation in *%SalesToDate* explains why only 41% of the targets remain motivating (*TargetEffectOn* = 1) after most of the month has passed. The remaining 59% of targets are very easy (difficult) to achieve at that point. *TargetEffect* is the continuous measure of the extent to which targets remain challenging but achievable, based on estimating model (1). Its average implies that greater effort results into a marginal increase in the likelihood of achieving the target by 1.7%, although there is considerable variation in this measure as well.

Store managers or assistant managers comprise 34% of the sample (*Manager*) and full-time employees 19% (*SalesRep1*). Part-time employees working more than 0.5 of the full-time equivalent comprise 32% (*SalesRep2*) and the remaining 15% are part-timers with full-time equivalent of 0.5 or less (*SalesRep3*). The typical store has three or four employees and the monthly sales target of the whole store is €32,535 on average.

Panel B of Table 1 describes the sample of 145,398 daily observations, which we use to test H1a and H1b. *DailySales* are highly volatile with an average of €502. The volatility is largely due to differences in the number of hours worked. The average of *HoursWorked* is 5.1 with a standard deviation of 2.3. Another contributing factor is weather, as summarized in abnormal daily rainfall (*AbnRain*), sunshine (*AbnSun*), and temperature (*AbnTemp*). All three variables are measured as deviations from their respective 10 year averages, which explains why their averages are close to zero.

5.1.2 Discontinuity in the Distribution of Performance Relative to Target

Figure 4 provides descriptive evidence on the incentive effects of monthly sales targets. It presents the histogram of performance relative to target and shows the highest frequency of performance just above target, i.e., slightly above *%TargetAchieved* = 1, offset by relatively low frequency of performance just below the target. This is consistent with prior findings of a discontinuity in performance distributions when managers have incentives to meet various benchmarks (Burgstahler and Dichev [1997]). In our setting, this means that employees who are close to meeting the monthly target increase their effort just enough to earn their bonus. We interpret it as ex post evidence that targets motivate effort. In what follows, we describe how we estimate the ex ante incentive effects of targets, which depend on how close month-to-date sales are to expected performance.

5.1.3 The Effect of Month-To-Date Performance on Target Achievement

Table 2 presents coefficient estimates of Logit model (1), which we use to calculate our measures of challenging but achievable targets. Figure 3 plots the fitted values based on the Logit estimates. Before estimating the full model, the first column of Table 2 shows a simplified model using only month-to-date performance, as measured by *%SalesToDate*, which is highly predictive of ex post success with meeting the monthly target (*TargetMet*). Besides the significant coefficient estimate ($p < 0.001$), we find that the point biserial correlation between the dependent variable and the fitted values from the simplified model is 0.773 (untabulated). This is only slightly lower than the 0.797 correlation based on the full Logit model (1).

The second column of Table 2 estimates model (1) and shows slight differences in how month-to-date performance predicts *TargetMet* across the four employee groups. For example, part-timers working less than 20 hours a week are more likely to meet their monthly targets than other employees but the effect of month-date performance is less strongly associated with *TargetMet*.

5.1.4 The Effect of Weather on Daily Sales

Table 3 estimates the following model to examine how weather fluctuations affect daily sales:

$$DailySales_{i,m,d} = \theta_1 + \theta_2\, AbnRain_{s,m,d} + \theta_3\, AbnSun_{s,m,d} + \theta_4\, AbnTemp_{s,m,d} + \theta_5\, HoursWorked_{i,m,d} \\ \theta_6\, StoreTarget_{s,m} + Rep\ FE + Day\ FE + Calendar\ Month\ FE + Year\ FE, \quad (3)$$

where *i* represents employees, *s* stores, *m* months, and *d* days. Standard errors are two-way clustered by store and day. Besides the three abnormal weather variables defined earlier, we also include *StoreTarget* to at least partly control for store-month effects. In contrast to model (2), we do not include store-month fixed effects, which could filter out much of the weather effects.[4] We do include fixed effects for sales reps, days, calendar months, and years.

Model (3) allows us to estimate the cumulative effect of weather on month-to-date sales just before a given day. Specifically, we calculate cumulative abnormal sales, $AbnSales_{i,m,d}$, as the sum of the predicted values ($\theta_2\, AbnRain_{s,m,d} + \theta_3\, AbnSun_{s,m,d} + \theta_4\, AbnTemp_{s,m,d}$) from the beginning of the month to day $d-1$. To illustrate the economic magnitude of common weather

[4] For the same reason, we do not include fixed effects for each of the 2,190 days in the sample. Instead, we use 31 effects for days in a month, 12 effects for month in a year, and 6 year effects.

fluctuations, we calculate the interquartile range, i.e., the difference between the third and the first quartile of abnormal daily sales (untabulated). The interquartile range is €35, as compared to average daily sales of €502. The interquartile range of cumulative abnormal sales on the last day of the month is €274, which represents the total monthly effect of common weather fluctuations. The total monthly effect of large fluctuations is €533, calculated as the difference between the top and bottom decile of cumulative abnormal sales on the last day of the month.

By combining the estimates in Tables 3 and 4, we can also calculate the effect of weather on the incentive effects of targets. First, we obtain adjusted month-to-date performance, i.e., cumulative sales without the effect of abnormal weather, as *%SalesToDateAdj = %SalesToDate – AbnSales / Target*. Second, the estimates in Table 2 allow us to calculate *TargetEffect* for any value of *%SalesToDate*. We use *%SalesToDateAdj* from the first step to calculate *TargetEffectAdj*, a measure of how challenging the target would have been, had there been no abnormal weather. Third, we disaggregate *TargetEffect* into its five components: (i) the incentive effect of the target without any weather effects (*TargetEffectAdj*), (ii) an increase in the incentive effect because bad weather increased store traffic and shifted a very difficult target closer to expected performance (*dTargetEffect1*), (iii) an increase in the incentive effect because good weather reduced store traffic and shifted a very easy target closer to expected performance (*dTargetEffect2*), (iv) a decrease in the incentive effect because bad weather increased store traffic and made the target very easy to achieve (*dTargetEffect3*), (v) a decrease in the incentive effect because good weather reduced store traffic and made the target very difficult to achieve (*dTargetEffect4*).

5.2 INCENTIVE EFFECTS OF TARGETS

The baseline prediction is that challenging but achievable targets motivate more effort than very easy (difficult) targets. We estimate model (2) to test for the association between abnormal daily sales and challenging but achievable targets. We measure the latter with the indicator variable *TargetEffectOn*, which equals one for targets with at least some incentive effects and zero for very easy (difficult) targets with more than 90% (less than 10%) likelihood of being achieved after 60% of the month has passed. We also use a continuous measure of challenging but achievable targets, *TargetEffect*, calculated as the marginal effect of month-to-date sales on the likelihood of achieving the target.

Table 4 presents the estimates of model (2). Both measures of challenging but achievable targets, *TargetEffectOn* ($p < 0.001$) and *TargetEffect* ($p < 0.001$), are positively associated with abnormal daily sales. When *TargetEffectOn* equals one, average daily sales in the remaining 40% of the month are €41.1 higher than when the monthly target is very easy (difficult). This amounts to an 11.3% increase in an employee's daily sales when *TargetEffectOn* equals to one (based on the predicted values from model (2), holding all other variables constant at their averages).

As discussed earlier, month-to-date sales can vary greatly due to weather. Although Table 4 controls for weather effects in the remaining 40% of the month, it does not exploit the random variation in month-to-date sales in the first 60% of the month, which is an important determinant of the incentive effect of targets, *TargetEffect*. Table 5 disaggregates *TargetEffect* into its five components reflecting different effects of abnormal weather (as defined above).

Column (1) of Table 5 shows that the effect of *TargetEffectAdj* on abnormal effort in the last 40% of the month is highly significant ($p < 0.001$) and only slightly lower than the effect of

TargetEffect in the last column of Table 4 (reproduced in the first column of Table 5). Interestingly, an even stronger effect comes from large values of *dTargetEffect1*, which we refer to as exogenous increases in target incentive strength, because they represent targets getting closer to expected performance due to bad weather increasing cumulative abnormal sales in the first 60% of the month. The difference between the coefficient estimates, *dTargetEffect1* versus *TargetEffectAdj*, is significant ($p = 0.010$), which we interpret as evidence that exogenous, weather-driven increases in target incentive strength have an even greater effect on effort than challenging but achievable targets in months with no abnormal weather.

An alternative way to alleviate endogeneity concerns about the estimation in Table 4 is to use the exogenous increase in target incentive strength, *dTargetEffect1*, as an instrument for *TargetEffect* in model (2). It is a valid instrument because it is highly correlated with *TargetEffect* by construction and because past abnormal weather driving *dTargetEffect1* has no direct effect on daily sales in model (2).[5] Column (2) of Table 5 presents 2SLS estimates of model (2). The coefficient of *TargetEffect* is slightly higher than in Table 4 and remains highly significant ($p < 0.001$), even though the standard error is much larger because we only exploit the variation in *TargetEffect* due to weather-driven increases in sales.

5.3 TESTS OF H1a AND H1b

Combined, the findings in Tables 5 and 6 provide strong support for the baseline prediction that challenging but achievable targets increase effort and performance. However, even though these findings are entirely consistent with the evidence in prior work, they provide only limited insights about the incentive effects of targets. The theory also predicts that the incentive effects

[5] Although abnormal weather is serially correlated for two adjacent days, the serial correlation becomes negligible after a few days. Also, note that model (2) controls for contemporaneous abnormal weather. When we include one or more lags of abnormal sales due to weather, we find that none of them have a significant effect on daily sales.

change over time as uncertainty about the random component of monthly performance gets resolved. Conditional on targets remaining challenging but achievable, H1a predicts that target-based incentives are initially weak but get stronger as the end of a performance evaluation period approaches. The offsetting effect predicted by H1b is that the likelihood of targets remaining challenging but achievable decreases as the performance evaluation period unfolds.

Before testing H1a and H1b, we illustrate the extent to which uncertainty about end-of-period performance gets smaller over time. Specifically, we compare the predictive power of the Logit model (1) after 30%, 60%, and 90% of the month passed, by calculating the point biserial correlation between *TargetMet* and the predictive values from each of the three Logit estimations. As expected, the correlation is lowest at the beginning and highest at the end of the month—0.663 after 30%, 0.797 after 60%, and 0.885 after 90% of the month passed.

Panel A of Table 6 presents the test of H1a. It shows the estimates of model (2) after 30% and 90% of the month passed and compares them to the estimates from Table 4 based on the 60% cut-off point (in the middle column). As expected, column (1) shows that the effect of *TargetEffectOn* is smallest after 30% of the month (26.688, $p < 0.001$). The effect gets more than three times larger (87.463, $p < 0.001$) when estimated after 90% of the month in column (3). The difference between the two coefficients is highly significant ($p < 0.001$), and so is the difference between any other pair of the *TargetEffectOn* coefficients in Table 6, which provides strong support for H1a. In other words, the incentive effects of monthly targets get stronger over time if they remaining challenging but achievable.

Panel B of Table 6 shows that the incentive effect of monthly targets conditional on *TargetEffectOn* = 1 is not the only thing that changes over time. Consistent with H1b, we find that the likelihood of *TargetEffectOn* = 1 is decreasing as the end of the month approaches. After

30% of the month, the likelihood that targets remain challenging but achievable is 0.645. After 60% of the month, this likelihood decreases significantly to 0.407 ($p < 0.001$). After 90% of the month, there is another significant decrease to 0.233 ($p < 0.001$).

We conclude that there are two opposing forces that determine the overall incentive effect of targets. As the month progresses, some employees have increasingly strong incentives to meet their challenging but achievable targets. However, there is also a growing proportion of employees for whom the monthly target is no longer motivating, either because past performance or random events rendered the target very easy (difficult) to achieve. Thus, it can be misleading to make inferences about the incentive effect of targets solely based on the effect conditional on targets remaining challenging but achievable. The overall effect, adjusting for the likelihood of outdated targets, may be much smaller than the conditional effect.

5.4 TESTS OF H2a AND H2b

Our next set of predictions focuses on the sorting effects of targets. We use past success in meeting targets as a proxy for individual productivity. Given the limited or no updating of performance targets in our setting, we expect a positive serial correlation in performance relative to target reflecting that highly productive employees repeatedly meet their monthly targets and others repeatedly fail. Specifically, we estimate the following Logit model:

$$\begin{aligned} TargetMet_{i,m} = {} & \delta_1 + \delta_2\, \%MetBefore_{i,m-1} + \delta_3\, SalesRep1_{i,m} + \delta_4\, SalesRep2_{i,m} + \delta_5\, SalesRep3_{i,m} + \\ & + Store\ FE + Month\ FE, \end{aligned} \tag{4}$$

where $TargetMet_{i,m}$ is the indicator for employee i meeting target of month m. $\%MetBefore_{i,m-1}$ is the percentage of all monthly targets achieved from the beginning of the sample until the prior month, which reflects persistent components of productivity (such as skill, education, or age). In our main tests, we require six months of non-missing data so that $\%MetBefore_{i,m-1}$ measures average performance in at least the five preceding months. We use the three *SalesRep* indicators to control for the different employee categories and also include store and month fixed effects in our estimation. Standard errors are clustered at the store level.[6]

Column (1) of Table 7 presents the estimates of model (4) and validates our assumption that individual productivity increases the likelihood of meeting monthly targets. As in Table 2, full-time employees (*SalesRep1*) are the least likely to meet their targets and those with a full-time equivalent of 0.5 or less (*SalesRep3*) are the most likely to meet them. As expected, high past productivity as measured by $\%MetBefore_{i,m-1}$ is strongly positively associated with the likelihood of meeting the current target (2.341, $p < 0.001$). To assess the economic magnitude of this effect, we compare highly productive employees with $\%MetBefore_{i,m-1}$ one standard deviation above its mean to unproductive employees one standard deviation below the mean. The likelihood of meeting the target is 0.533 for the former group and 0.311 for the latter, which implies that highly productive employees earn on average almost twice as much in bonuses as unproductive employees.

H2a predicts that less productive employees are more likely to leave their jobs than their more productive colleagues who earn higher expected compensation. We test the effect of productivity on voluntary turnover using the same specification as in model (4), except that the dependent variable is an indicator for the last month of employment, *Turnover*. This reduces the power of our tests because turnover is a low probability event—untabulated tests show that the average likelihood of voluntary departure is only 0.031 in any given month.

Column (2) of Table 7 estimates the Logit model of voluntary turnover. Compared to store managers, all other types of employees are significantly more likely to leave. Not surprisingly,

---

[6] Dropping the requirement and including all employees with at least one prior month of data to measure $\%MetBefore_{i,m-1}$ yields qualitatively similar results.

voluntary turnover is highest among employees with a full-time equivalent of 0.5 or less (*SalesRep3*). Controlling for employee types as well as store and month fixed effects, we find that past productivity as measured by $\%MetBefore_{i,m-1}$ is strongly negatively associated with the likelihood of voluntary turnover (–1.620, $p < 0.001$), as predicted by H2a. To illustrate the economic significance of this effect, we compare highly productive employees with $\%MetBefore_{i,m-1}$ one standard deviation above its mean to unproductive employees one standard deviation below the mean. The likelihood of voluntary departure in any given month is 0.032 for the former group and 0.060 for the latter.

H2b predicts that recent failure to meet a target increases the likelihood of voluntary turnover even after controlling for individual productivity. To separate the effect of recent failure to meet a target from persistent components of productivity, we extend the Logit model in column (2) of Table 7 with indicator variables for meeting targets in prior three months and use $\%MetBefore_{i,m-4}$ as a measure of individual productivity.[7] Column (3) of Table 7 shows that the coefficient estimates for all three lags of *TargetMet* are negative (–0.349, $p = 0.001$; –0.314, $p = 0.087$; –0.259, $p = 0.076$; respectively). To test H2b, we use an F-test for the joint significance of all three coefficients and find that it is highly significant ($p < 0.001$), which implies that voluntary turnover is positively associated with recent failure to meet monthly targets. The persistent component of productivity, $\%MetBefore_{i,m-4}$, also has a significantly negative effect on voluntary turnover (–0.739, $p = 0.015$). To illustrate the economic significance of these coefficient estimates, we compare the effect of meeting all three recent targets to meeting none of them for employees with average productivity ($\%MetBefore_{i,m-4}$). The likelihood

[7] To maintain consistency with the other estimations in Table 7, we require at least six months of non-missing data, which means that $\%MetBefore_{i,m-4}$ is the average success with meeting targets in at least two months. We find qualitatively similar results if we require at least nine months of non-missing data so that $\%MetBefore_{i,m-4}$ averages performance relative to target over at least five months.

of voluntary departure is 0.027 when all three recent targets are met and 0.062 when none of them is met, which suggests that failure to meet recent targets affects voluntary turnover as much as the persistent component of productivity. These findings provide strong support for our theory that target-based rewards have important sorting effects, particularly when performance targets are the same for all employees.

6 *Discussion and Conclusions*

We use daily sales data from a large retailer to measure employee effort choices in response to random shocks to monthly target difficulty. We find evidence consistent with the theory that target difficulty has a non-monotonic effect on effort and that employees work harder if and only if it substantially increases the likelihood of earning their monthly bonus. When poor weather increases store traffic and overly difficult targets suddenly become achievable, employees greatly increase their effort. However, when the likelihood of meeting a target is so high or low that an incremental improvement in performance would make little difference employees put in much less effort.

Besides exploiting exogenous shock to target difficulty, another novel aspect of our study is that we can examine effort choices over a relatively long performance evaluation period, which allows us to minimize the potentially confounding effects of short-lived affective responses to targets (Gneezy and List [2006]). This also yields the following new insights about the use of targets for incentive purposes.

First, a key implication of our economic model is that the effect of targets on effort changes over time (Hyun et al. [2022], Arnold et al. [2023]). Consistent with the theory, we provide new evidence that even challenging but achievable targets only have weak incentive effects at the beginning of a long performance evaluation period. Their incentive effects increase greatly as much of the uncertainty about random shocks to performance gets resolved, provided that they remain challenging but achievable. This suggests that target-based incentives may become too strong towards the end of a performance evaluation period. Although we do not directly examine this issue in our analysis, some prior studies show that target-based rewards are associated with end-of-period performance gaming and other counterproductive window-dressing activities (Merchant [1990], Burgstahler and Dichev [1997], Van der Stede [2000]). Our theory and evidence suggest that this may be an inherent limitation of using targets for incentive purposes—they may motivate too little effort at the beginning of a period and too much effort at the end.

Second, our economic model implies that a small target change can make a big difference to effort. This may be a serious obstacle to using targets in practice, because it is often unclear how to calibrate performance target levels, particularly if they must be the same for all employees (Anderson, Dekker, Sedatole, and Wiersma [2020]). Even if a firm succeeds in setting an initially challenging but achievable target, the target may easily get outdated during the performance evaluation period. In our study, targets motivate higher effort for only 23 percent of employees in the last few days of the month, other employees put in less effort at that point and many of them earn their monthly bonus anyway.

Combined, our findings support a more nuanced view of the incentive effects of targets than the common conclusion from the experimental work showing that targets increase effort. Although we replicate prior findings that challenging but achievable targets increase effort, our results also suggest that this does not necessarily imply an increase in overall performance, which is a combination of different incentive effects in different states of the world triggered by random events. High uncertainty may render target-based incentives too weak at the beginning of a period. Targets may get outdated and have no incentive effects at all at the end of a period.

Target-based incentives may also get too strong in the final days of a performance evaluation period and result in too much effort or the wrong type of effort in multi-tasking settings (Matějka and Ray [2017], Balakrishnan et al. [2022]).

We also depart from most of prior work by emphasizing that the incentive effects of targets may not be the only or even the main reason for using them in performance evaluation. We provide new evidence that limited updating of performance targets can have important sorting effects (Indjejikian and Nanda [2002], Indjejikian et al. [2014b]). Specifically, we show that some employees are much more successful than others in meeting their fixed monthly targets. Thus, firms can use target-based bonuses to reward more productive employees with higher expected compensation even in settings where all major provisions of employment contracts must be the same for all employees. As expected, we find that this induces higher voluntary turnover among the less productive employees. We conclude that the overall welfare implications of targets go beyond increasing employee effort. Targets can increase firm profitability also by encouraging highly productive employees to stay and unproductive employees to leave.

We acknowledge some limits to the generalizability of our findings. First, they are based on data from a single company in an industry with high employee turnover and in a European country with strong labor protection legislation and culture. An important feature of our data, that monthly targets are set for all employees at the same predetermined level, may not apply in other settings. Also, we examine the use of performance targets for lower-level employees, which may entail different trade-offs than the use of targets for higher-level executives. Nevertheless, the findings are entirely consistent with the predictions of an economics-based model of target setting and its theoretical insights likely generalize well beyond the specific setting of our study. Second, although our research design alleviates concerns about endogeneity issues, we cannot rule them out completely because we cannot assign target difficulty at random as in prior experimental work. That said, our analysis does take advantage of detailed daily data, a granular fixed effect structure, and random weather-driven shocks to performance, all of which should help minimize reverse causality and unobserved heterogeneity biases.

References

ANDERSON, S., H. DEKKER, K. SEDATOLE, AND E. WIERSMA. "When one size does not fit all: Using ex post subjective ratings to provide parity in risk-adjusted compensation." *Management Accounting Research* 49 (2020): 1–12.

ARANDA, C., J. ARELLANO, AND A. DAVILA. "Subjective bonuses and target setting in budget-based incentive contracts." *Management Accounting Research* 43 (2019): 45–60.

ARNOLD, M., AND M. ARTZ. "Target difficulty, target flexibility, and firm performance: Evidence from business units' targets." *Accounting, Organizations and Society* 40 (2015): 61–77.

ARNOLD, M., M. ARTZ, AND R. A. GRASSER. "When do firms adjust bonus targets intrayear? Evidence from sales executives' targets." *Contemporary Accounting Research* 40 (2023): 324–355.

BALAKRISHNAN, R., J. HUANG, AND A. WU. "Target setting in a multi-task environment: An empirical investigation." *Journal of Management Accounting Research* 34 (2022): 11–28.

BENDER, S., N. BLOOM, D. CARD, J. V. REENEN, AND S. WOLTER. "Management practices, workforce selection, and productivity." *Journal of Labor Economics* 36 (2018): S371–S409.

BERGER, L., L. GUO, AND A. PRESSLEE. "Motivating employees with goal-based prosocial rewards." *Contemporary Accounting Research* 40 (2023): 231–256.

BOL, J. C., T. M. KEUNE, E. M. MATSUMURA, AND J. Y. SHIN. "Supervisor discretion in target setting: An empirical investigation." *The Accounting Review* 85 (2010): 1861–1886.

BOL, J. C., AND J. LILL. "Performance target revisions in incentive contracts: Do information and trust reduce ratcheting and the ratchet effect?" *The Accounting Review* 90 (2015): 1755–1778.

BOUWENS, J., C. HOFMANN, AND N. SCHWEIGER. "Target setting in hierarchies: The role of middle managers." *Journal of Accounting Research* 62 (2024): 375–410.

BOUWENS, J., AND P. KROOS. "Target ratcheting and effort reduction." *Journal of Accounting and Economics* 51 (2011): 171–185.

BRÜGGEN, A., C. FEICHTER, AND M. G. WILLIAMSON. "The effect of input and output targets for routine tasks on creative task performance." *The Accounting Review* 93 (2018): 29–43.

BURGSTAHLER, D., AND I. DICHEV. "Earnings management to avoid earnings decreases and losses." *Journal of Accounting and Economics* 24 (1997): 99–126.

CAMPBELL, D. "Nonfinancial performance measures and promotion-based incentives." *Journal of Accounting Research* 46 (2008): 297–332.

CASAS-ARCE, P., M. HOLZHACKER, M. D. MAHLENDORF, AND M. MATĚJKA. "Relative performance evaluation and the ratchet effect." *Contemporary Accounting Research* 35 (2018): 1702–1731.

CASAS-ARCE, P., R. INDJEJIKIAN, AND M. MATĚJKA. "Bonus plan choices during an economic downturn." *Journal of Management Accounting Research* 32 (2020): 85–105.

DAVILA, T., AND M. WOUTERS. "Managing budget emphasis through the explicit design of conditional budgetary slack." *Accounting Organizations and Society* 30 (2005): 587–608.

DELLER, C. "Beyond performance: Does assessed potential matter to employees' voluntary departure decisions?" *Journal of Accounting Research* 61 (2023): 981–1024.

EYRING, H., AND V. G. NARAYANAN. "Performance effects of setting a high reference point for peer-performance comparison." *Journal of Accounting Research* 56 (2018): 581–615.

GNEEZY, U., AND J. A. LIST. "Putting behavioral economics to work: Testing for gift exchange in labor markets using field experiments." *Econometrica* 74 (2006): 1365–1384.

HIRST, M. K., AND S. M. LOWY. "The linear additive and interactive effects of budgetary goal difficulty and feedback on performance." *Accounting, Organizations and Society* 15 (1990): 425–436.

HOLZHACKER, M., S. KRAMER, M. MATĚJKA, AND N. HOFFMEISTER. "Relative target setting and cooperation." *Journal of Accounting Research* 57 (2019): 211–239.

HSEE, C. K., AND Y. ROTTENSTREICH. "Music, pandas, and muggers: On the affective psychology of value." *J Exp Psychol Gen* 133 (2004): 23–30.

HU, K., Y. LI, AND K. RAY. "Optimal performance targets." *Journal of Management Accounting Research* 33 (2021): 129–149.

HUANG, J., R. BALAKRISHNAN, AND F. PAN. "On the association between current period budget target achievability and the properties of nonfinancial measures." *Journal of Management Accounting Research* 29 (2016): 47–62.

HYUN, J. H., M. MATĚJKA, P. OH, AND T. S. AHN. "Performance targets and ex post incentive plan adjustments." *Contemporary Accounting Research* 39 (2022): 863–892.

INDJEJIKIAN, R. J., M. MATĚJKA, K. A. MERCHANT, AND W. A. VAN DER STEDE. "Earnings targets and annual bonus incentives." *The Accounting Review* 89 (2014a): 1227–1258.

INDJEJIKIAN, R. J., M. MATĚJKA, AND J. SCHLOETZER. "Target ratcheting and incentives: Theory, evidence, and new opportunities." *The Accounting Review* 89 (2014b): 1259–1267.

INDJEJIKIAN, R. J., AND D. NANDA. "Executive target bonuses and what they imply about performance standards." *The Accounting Review* 77 (2002): 793–819.

IOANNOU, I., S. X. LI, AND G. SERAFEIM. "The effect of target difficulty on target completion: The case of reducing carbon emissions." *The Accounting Review* 91 (2016): 1467–1492.

KIM, S., M. MATĚJKA, AND J. PARK. "Economic determinants and consequences of performance target difficulty." *The Accounting Review* 98 (2023): 361–387.

LOCKE, E. A., AND G. P. LATHAM. *A theory of goal setting and task performance*. Englewood Cliffs, NJ: Prentice-Hall, 1990.

LOCKE, E. A., AND G. P. LATHAM. "Building a practically useful theory of goal setting and task motivation: A 35-year odyssey." *American Psychologist* 57 (2002): 705–717.

MATĚJKA, M. "Target setting in multi-divisional organizations." *Journal of Management Accounting Research* 30 (2018): 13–27.

MATĚJKA, M., M. MAHLENDORF, AND U. SCHÄFFER. "The ratchet effect: Theory and empirical evidence." *Management Science* 70 (2024): 128–142.

MATĚJKA, M., K. A. MERCHANT, AND W. A. VAN DER STEDE. "Employment horizon and the choice of performance measures: Empirical evidence from annual bonus plans of loss-making entities." *Management Science* 55 (2009): 890–905.

MATĚJKA, M., AND K. RAY. "Balancing difficulty of performance targets: Theory and evidence." *Review of Accounting Studies* 22 (2017): 1666–1697.

MERCHANT, K. A. "The effects of financial controls on data manipulation and management myopia." *Accounting Organizations and Society* 15 (1990): 297–313.

PFISTER, J. A., AND K. LUKKA. "Interrelation of controls for autonomous motivation: A field study of productivity gains through pressure-induced process innovation." *The Accounting Review* 94 (2019): 345–371.

PRESSLEE, A., T. W. VANCE, AND R. A. WEBB. "The effects of reward type on employee goal setting, goal commitment, and performance." *The Accounting Review* 88 (2013): 1805–1831.

SHANG, R., Z. WANG, AND Y. ZU. "Manager narcissism, target difficulty, and employee dysfunctional behavior." *Contemporary Accounting Research* 40 (2023): 1795–1822.

SIMONS, R. "Analysis of the organizational characteristics related to tight budget goals." *Contemporary Accounting Research* 5 (1988): 267–283.

VAN DER STEDE, W. A. "The relationship between two consequences of budgetary controls: Budgetary slack creation and managerial short-term orientation." *Accounting Organizations and Society* 25 (2000): 609–622.

WEBB, A., S. A. JEFFREY, AND A. SCHULZ. "Factors affecting goal difficulty and performance when employees select their own performance goals: Evidence from the field." *Journal of Management Accounting Research* 22 (2010): 209–232.

WEBB, R. A., M. G. WILLIAMSON, AND Y. ZHANG. "Productivity-target difficulty, target-based pay, and outside-the-box thinking." *The Accounting Review* 88 (2013): 1433–1457.

WOOD, R. E., A. J. MENTO, AND E. A. LOCKE. "Task complexity as a moderator of goal effects: A meta-analysis." *Journal of Applied Psychology* 72 (1987): 416–425.

Figure 1—Firm's Choice of a Performance Target

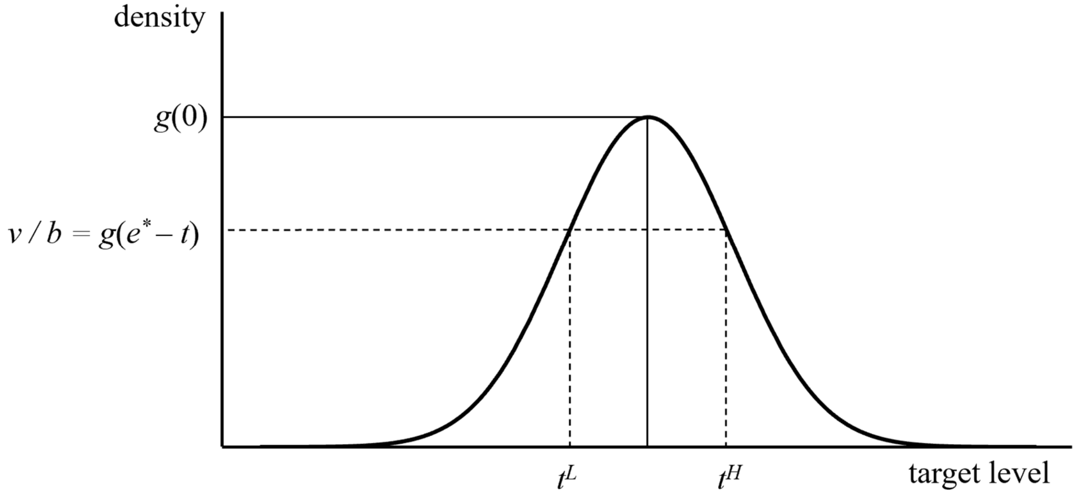


Figure 1 plots the probability density function of the logistic distribution of the random noise ε. Density g (multiplied by bonus b) represents the change in expected bonus as a result of a change in effort e and measures incentive strength of the target. Holding effort constant at some expected level, g is a function of the target level t. When the target is equal to expected performance, it has the highest possible incentive strength (for a given bonus b), as measured by $g(0)$. Appendix B shows that the firm can implement the first-best effort e^* by setting a target so that $g(e^* - t)$ equals to v / b, the marginal product of effort scaled by the bonus. There are two target levels (t^L and t^H) that equivalently implement the first-best effort.

Figure 2—Incentive Effects of Targets at the Beginning versus at the End of a Period

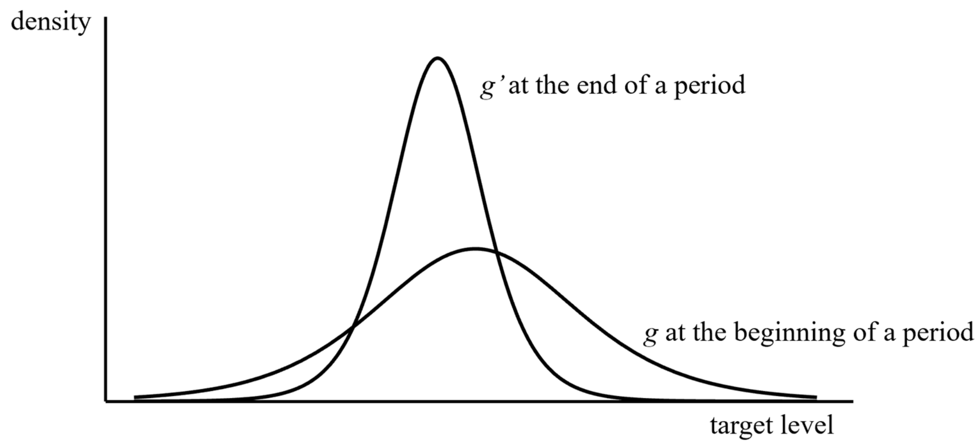
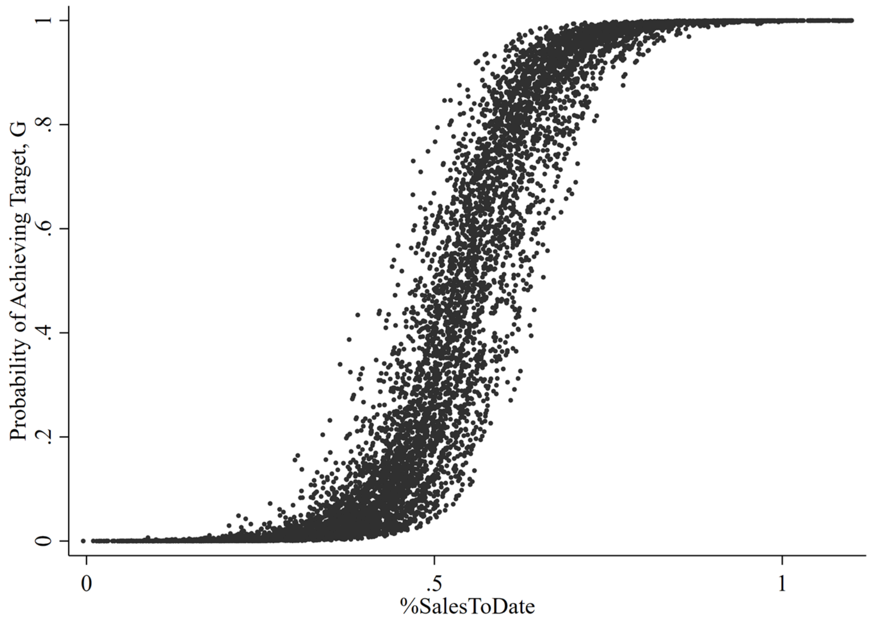


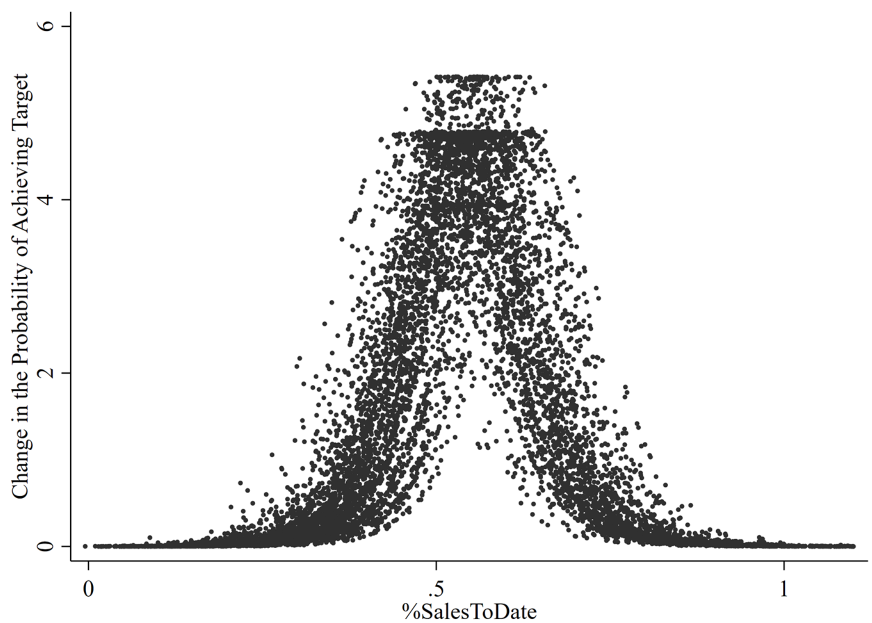
Figure 2 plots two logistic distributions describing uncertainty about performance, holding employee effort constant. The probability density function *g* has a much higher variance due to random noise than the function *g'*. The function *g* therefore represents incentive strength of a target at the beginning of a performance evaluation period, when there is a lot of uncertainty about future noise realization. The function *g'* represents incentive strength of the same target towards the end of the performance evaluation period when much of the noise has been realized and the remaining randomness in performance is much smaller.

Figure 3—Estimating Challenging but Achievable Targets

Panel A. Fitted Logistic Cumulative Distribution Function



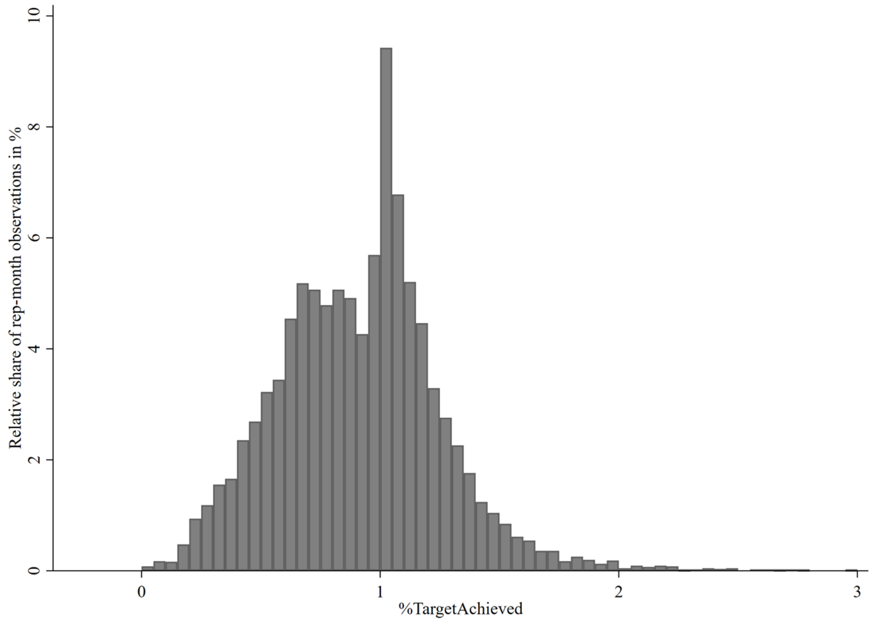
Panel B. Fitted Logistic Probability Density Function



Panel A presents an empirical approximation of the cumulative distribution function *G* in our theoretical model. It is the predicted likelihood of achieving the monthly sales target as a function of month-to-date performance. The predicted likelihood is based on Logit estimation of the *TargetMet* model (1). Month-to-date performance is the percentage of target met after 60% of the month has passed, *%SalesToDate*.

Panel B presents an empirical approximation of the probability density function *g*. Density is the change in *G* estimated with the Logit model, i.e., the marginal effect of *%SalesToDate* on the likelihood of achieving the target. We use *g* as a continuous measure of challenging but achievable targets.

Figure 4—Discontinuity in the Distribution of Performance Relative to Target



The histogram of performance relative to target, *%TargetAchieved*, in the sample of 8,632 employee-month observations. For example, 813 observations (9.4% of the sample) are in the bin with performance at or just above target, i.e., on the [1, 1.05) interval. 491 observations (5.7% of the sample) are in the bin with performance just below target, i.e., on the [0.95, 1) interval.

Table 1—Descriptive Statistics

Panel A. Monthly Sample

	Obs.	Mean	SD	Q1	Median	Q3
Target	8,632	9,302	3,564	6,833	9,013	11,268
StoreTarget	8,632	32,535	11,534	24,375	30,410	38,192
%TargetAchievement	8,632	0.915	0.349	0.673	0.930	1.112
TargetMet	8,632	0.426	0.495	0.000	0.000	1.000
%SalesToDate	8,632	0.522	0.223	0.370	0.505	0.650
TargetEffectOn	8,632	0.407	0.491	0.000	0.000	1.000
TargetEffect	8,632	1.694	1.686	0.154	1.022	3.172
Manager	8,632	0.335	0.472	0.000	0.000	1.000
SalesRep1	8,632	0.193	0.394	0.000	0.000	0.000
SalesRep2	8,632	0.323	0.468	0.000	0.000	1.000
SalesRep3	8,632	0.149	0.356	0.000	0.000	0.000

Panel B. Daily Sample

	Obs.	Mean	SD	Q1	Median	Q3
DailySales	145,398	502	393	216	402	677
HoursWorked	145,398	5.051	2.270	3.000	5.000	7.000
AbnRain	145,398	-0.033	1.149	-0.600	-0.300	0.000
AbnSun	145,398	-0.018	3.900	-2.710	-0.745	3.000
AbnTemp	145,398	0.538	4.314	-2.393	0.445	3.465

See Appendix A for variable definitions. Panel A presents descriptive statistics for the sample of 8,632 employee-month observations from 43 retail stores during 2013–2018. This sample is further disaggregated into 145,398 daily observations with descriptive statistics in Panel B.

Table 2—The Effect of Month-To-Date Performance on the Likelihood of Meeting a Target

	(1) $TargetMet_{i,m}$	(2) $TargetMet_{i,m}$
$\%SalesToDate_{i,m}$	17.072 ***	19.149 ***
	(43.019)	(22.881)
$SalesRep1_{i,m}$		-1.273 *
		(1.813)
$SalesRep1_{i,m} \cdot \%SalesToDate_{i,m}$		2.527 **
		(1.966)
$SalesRep2_{i,m}$		0.594
		(1.008)
$SalesRep2_{i,m} \cdot \%SalesToDate_{i,m}$		-0.098
		(0.094)
$SalesRep3_{i,m}$		2.428 ***
		(3.396)
$SalesRep3_{i,m} \cdot \%SalesToDate_{i,m}$		-3.347 ***
		(2.664)
Percentage of Month Passed	60%	60%
Month FE	No	Yes
Pseudo - R^2	0.544	0.585
Observations	8,632	8,632

***, **, * represent significance at the 0.01, 0.05, and 0.10 levels, respectively. Presented are Logit estimates of model (1), which allow us to measure the incentive effect of targets as a function of month-to-date performance (see Figure 3). *t*-statistics in parentheses are based on standard errors clustered at the employee level. The dependent variable, *TargetMet* is an indicator variable for meeting a monthly target. *%SalesToDate* is month-to-date performance estimated after 60% of the month has passed. See Appendix A for other variable definitions.

Table 3—The Effect of Weather on Daily Sales

	(1)
	DailySales $_{i,m,d}$
AbnRain $_{s,m,d}$	4.392 ***
	(3.243)
AbnSun $_{s,m,d}$	-3.475 ***
	(6.325)
AbnTemp $_{s,m,d}$	-3.599 ***
	(6.773)
HoursWorked $_{i,m,d}$	75.628 ***
	(33.768)
StoreTarget $_{s,m}$	0.002 ***
	(5.630)
Rep FE	Yes
Day FE	Yes
Calendar Month FE	Yes
Year FE	Yes
R^2	0.549
Within - R^2	0.271
Observations	145,398

*** represent significance at the 0.01 level. Presented are OLS estimates of model (3). *t*-statistics in parentheses are based on standard errors clustered at the employee and day levels. See Appendix A for variable definitions.

Table 4—The Effect of Target Difficulty on Daily Sales

	(1) $DailySales_{i,m,d}$	(2) $DailySales_{i,m,d}$
$TargetEffectOn_{i,m}$	41.094 ***	
	(14.042)	
$TargetEffect_{i,m}$		13.236 ***
		(14.118)
$AbnRain_{s,m,d}$	3.882 ***	3.889 ***
	(3.001)	(3.001)
$AbnSun_{s,m,d}$	-2.525 ***	-2.524 ***
	(4.537)	(4.535)
$AbnTemp_{s,m,d}$	-4.533 ***	-4.541 ***
	(5.117)	(5.127)
$HoursWorked_{i,m,d}$	72.402 ***	72.321 ***
	(46.673)	(46.713)
Percentage of Month Passed	60%	60%
Rep FE	Yes	Yes
Store & Month FE	Yes	Yes
Day FE	Yes	Yes
R^2	0.640	0.640
Within - R^2	0.263	0.264
Observations	61,435	61,435

*** represent significance at the 0.01 level. Presented are OLS estimates of model (2). *t*-statistics in parentheses are based on standard errors clustered at the employee and day levels. *TargetEffectOn* is an indicator variable for challenging but achievable targets (with the probability of being achieved between 10% and 90%). *TargetEffect* is a continuous measure of the extent to which targets are challenging but achievable. See Appendix A for other variable definitions.

Table 5—The Effect of Random Variation in Target Difficulty on Daily Sales

	(as in Table 4)	(1)	(2)
	$DailySales_{i,m,d}$	$DailySales_{i,m,d}$	$DailySales_{i,m,d}$
$TargetEffect_{i,m}$	13.236 ***		20.448 ***
	(14.118)		(5.732)
$TargetEffectAdj_{i,m}$		12.427 ***	
		(12.179)	
$dTargetEffect1_{i,m}$		44.701 ***	
		(3.654)	
$dTargetEffect2_{i,m}$		11.969	
		(1.619)	
$dTargetEffect3_{i,m}$		-5.916	
		(0.532)	
$dTargetEffect4_{i,m}$		-10.129	
		(1.228)	
$AbnRain_{s,m,d}$	3.889 ***	3.910 ***	3.880 ***
	(3.001)	(3.017)	(3.004)
$AbnSun_{s,m,d}$	-2.524 ***	-2.524 ***	-2.527 ***
	(4.535)	(4.532)	(4.542)
$AbnTemp_{s,m,d}$	-4.541 ***	-4.555 ***	-4.567 ***
	(5.127)	(5.148)	(5.171)
$HoursWorked_{i,m,d}$	72.321 ***	72.301 ***	72.080 ***
	(46.713)	(46.704)	(46.708)
Percentage of Month Passed	60%	60%	60%
Rep FE	Yes	Yes	Yes
Store & Month FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
R^2	0.640	0.640	0.639
Within - R^2	0.264	0.264	0.263
Observations	61,435	61,435	61,435

*** represent significance at the 0.01 level. *t*-statistics in parentheses are based on standard errors clustered at the employee and day levels. Column (1) presents OLS estimates of model (2) after disaggregating *TargetEffect* into its components reflecting different effects of abnormal weather. Column (2) presents 2SLS estimates of model (2) using *dTargetEffect1*, a weather-driven increase in store traffic that shifted a very difficult target closer to expected performance, as an instrument for *TargetEffect*. See Appendix A for other variable definitions.

Table 6—Incentive Effects of Targets at Different Times of the Month

Panel A. The Effect of Challenging but Achievable Targets on Daily Sales

	(1)	(as in Table 4)	(3)
	$DailySales_{i,m,d}$	$DailySales_{i,m,d}$	$DailySales_{i,m,d}$
$TargetEffectOn_{i,m}$	26.688 ***	41.094 ***	87.463 ***
	(12.951)	(14.042)	(10.393)
$AbnRain_{s,m,d}$	4.039 ***	3.882 ***	3.009
	(4.058)	(3.001)	(1.470)
$AbnSun_{s,m,d}$	-2.654 ***	-2.525 ***	-1.715
	(6.338)	(4.537)	(1.502)
$AbnTemp_{s,m,d}$	-4.114 ***	-4.533 ***	-4.226 **
	(6.378)	(5.117)	(2.457)
$HoursWorked_{i,m,d}$	69.661 ***	72.402 ***	82.707 ***
	(53.417)	(46.673)	(32.048)
Percentage of Month Passed	30%	60%	90%
Rep FE	Yes	Yes	Yes
Store & Month FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
R^2	0.631	0.640	0.695
Within - R^2	0.254	0.263	0.299
Observations	105,501	61,435	18,164

Panel B. The Likelihood of Targets Remaining Challenging but Achievable

Variable	Obs.	Mean
TargetEffectOn (after 30% of the month passed)	8,632	0.645
TargetEffectOn (after 60% of the month passed)	8,632	0.407 ***
		(9.408)
TargetEffectOn (after 90% of the month passed)	8,632	0.233 ***
		(7.413)

***, ** represent significance at the 0.01 and 0.05 levels, respectively. Panel A presents OLS estimates of model (2). *t*-statistics in parentheses are based on standard errors clustered at the employee and day levels. *TargetEffectOn* is an indicator variable for challenging but achievable targets based on estimates of model (1) after 30%, 60%, and 90% of the month, respectively. The estimates in the middle column (using the 60% of the month cut-off point) are the same as in column (1) of Table 4. Panel B presents the percentages of employee-month observations for which *TargetEffectOn* = 1 after 30%, 60%, and 90% of the month, respectively. *z*-statistic in parentheses are adjusted for clustering at the store level and compare the percentages at one point within the month to the previous point. For example, the likelihood of *TargetEffectOn* = 1 is 0.407 after 60% of the month, which is significantly lower than 0.645 after 30% of the month (as reflected in the 9.408 *z*-statistic). See Appendix A for other variable definitions.

Table 7—Performance Targets and Voluntary Turnover

	(1)	(2)	(3)
	$TargetMet_{i,m}$	$Turnover_{i,m}$	$Turnover_{i,m}$
$\%MetBefore_{i,m-1}$	2.341 ***	-1.620 ***	
	(11.765)	(4.475)	
$TargetMet_{i,m-1}$			-0.349 ***
			(2.995)
$TargetMet_{i,m-2}$			-0.314 *
			(1.713)
$TargetMet_{i,m-3}$			-0.259 *
			(1.775)
$\%MetBefore_{i,m-4}$			-0.739 **
			(2.423)
$SalesRep1_{i,m}$	-0.239 **	0.679 ***	0.692 ***
	(2.056)	(4.222)	(4.156)
$SalesRep2_{i,m}$	0.084	0.568 ***	0.609 ***
	(0.981)	(2.628)	(2.681)
$SalesRep3_{i,m}$	0.278 **	1.452 ***	1.443 ***
	(2.465)	(6.031)	(5.599)
Store FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Pseudo - R^2	0.123	0.129	0.130
Observations	6,376	6,029	5,880

***, * represent significance at the 0.01 and 0.10 levels, respectively. Column (1) presents Logit estimates of model (4) to validate our assumption that individual productivity increases the likelihood of meeting monthly targets. Column (2) presents Logit estimates of model (5) to test for the effect of individual productivity on voluntary turnover. Column (3) estimates the same model as column (2) but separates the effect of individual productivity from the effects of recently (not) meeting targets. *t*-statistics in parentheses are based on standard errors clustered at the store level. See Appendix A for variable definitions.

Appendix A

Variable	Definition
DailySales	daily sales adjusted for returns (in €).
HoursWorked	the number of hours between the first and last daily sale.
Target	the monthly sales target (in €).
%TargetAchieved	the percentage of *Target* met at the end of the month.
TargetMet	an indicator variable for meeting the *Target*, i.e., *%TargetAchieved* ≥ 1.
%SalesToDate	cumulative daily sales as a percentage of *Target* met after 60% of the month (Table 6 also uses 30% and 90% of the month as alternative cut-off points).
Manager	an indicator variable for employees with job title "Manager" or "Assistant Manager."
SalesRep1	an indicator variable for other full-time employees.
SalesRep2	an indicator variable for employees working less than 1.0 but more than 0.5 of the full-time equivalent.
SalesRep3	an indicator variable for employees working 0.5 of the full-time equivalent or less.
StoreTarget	the monthly sales target of the whole store (in €).
AbnRain	abnormal daily rainfall (in hours), calculated as the deviation from the average rainfall on the same day in prior ten years.
AbnSun	abnormal sunshine (in hours), calculated as the deviation from the average sunshine on the same day in prior ten years.
AbnTemp	abnormal temperature (in °C), calculated as the deviation from the average temperature on the same day in prior ten years.
Additional variables used in the tests of H1a and H1b	
TargetEffectOn	an indicator variable equal to 1 if the predicted likelihood of meeting the *Target* is between 10% and 90% based on estimates from model (1) after 60% of the month has passed.

TargetEffect	the marginal effect of *%SalesToDate* on the predicted likelihood of meeting the *Target* based on estimates from model (1) after 60% of the month (Table 6 also uses 30% and 90% of the month as alternative cut-off points).
TargetEffectAdj	*TargetEffect* adjusted for abnormal weather, i.e., an estimate of what *TargetEffect* would have been without abnormal weather, so that *TargetEffect = TargetEffectAdj + dTargetEffect1 + dTargetEffect2 + dTargetEffect3 + dTargetEffect4*.
dTargetEffect1	the increase in *TargetEffect* due to a weather-driven increase in *%SalesToDate*.
dTargetEffect2	the increase in *TargetEffect* due to a weather-driven decrease in *%SalesToDate*.
dTargetEffect3	the decrease in *TargetEffect* due to a weather-driven increase in *%SalesToDate*.
dTargetEffect4	the decrease in *TargetEffect* due to a weather-driven decrease in *%SalesToDate*.
Additional variables used in the tests of H2a and H2b	
Turnover	an indicator variable for the last month of employment.
%MetBefore	individual productivity as reflected in the percentage of all monthly targets achieved from the beginning of the sample until the current month.

Appendix B

Our hypotheses are motivated by the target-setting model of Matějka and Ray [2017], which we describe in more detail below. We assume that both the firm and the employee are risk neutral. Hu et al. [2021] consider a version of the model with a risk-averse employee, which leaves the main insights discussed here qualitatively unchanged.

The employee exerts unobservable effort e that increases contractible performance $q = e + \varepsilon$, where ε is a zero-mean noise term with a unimodal symmetric density g and cumulative distribution function G (e.g., normal or logistic). The employee's cost of effort is $\frac{1}{2} e^2$ and the firm's profit is $V = v\,q$, where v is the marginal product of effort. The timeline is as follows.

First, the firm offers the employee a compensation contract with a fixed salary s and a target-based bonus b paid if and only if q is weakly greater than a predetermined target t. Both the firm and the employee know that the probability of meeting the target equals $G(e - t)$, because the distribution is symmetric and $q \geq t$ implies $\varepsilon \geq t - e$. The firm makes its compensation choices to maximize expected profit net of the employee's compensation, $v\,q - s - b\,G(e - t)$.

Second, the employee accepts the contract if it yields expected utility weakly greater than the reservation utility normalized to zero. Given that the firm can freely adjust the salary, the participation constraint is binding and expected compensation equals cost of effort, $s + b\,G(e - t) = \frac{1}{2} e^2$.

Third, the employee chooses effort to maximize expected utility $s + b\,G(e - t) - \frac{1}{2} e^2$. The resulting incentive constraint implies that the marginal cost of effort equals its marginal benefit, $e = b\,g(e - t)$. The marginal benefit is the change in the expected bonus, which is entirely driven by g, the change in the probability of meeting the target, because the bonus b is constant.

Finally, after the employee chooses his effort, a random shock to performance is realized and q is observed (but not effort e or the noise term ε separately). The employee gets paid $s + b$ if the target was met and s otherwise.

The optimal choice of target follows from the firm's maximization problem. Given the binding participation constraint, the firm's expected profit $v\,q - s - b\;G(e - t)$ equals $v\,q - \frac{1}{2}e^2$. In equilibrium, the marginal cost of effort must equal the marginal benefit to the firm, $e^* = v$. From the employee's incentive constraint, it follows that $e^* = b\;g(e^* - t) = v$. Figure 1 illustrates the resulting equilibrium condition $g(e^* - t) = v / b$, which yields several insights.

There is no unique solution to the contracting problem because there are many combinations of bonus b and target t that satisfy the equilibrium condition. A unique solution could be obtained by imposing additional constraints on the salary or bonus (e.g., keeping them the same as in prior years or the same as for other employees). However, even without additional constraints or forces added to the simple model, the following economic trade-offs apply for any given bonus level.

Increasing target difficulty has a non-monotonic effect on performance reflected in the shape of the probability density function g in Figure 1. Specifically, g is increasing when targets are easy to achieve, i.e., set below expected performance, $t < e^*$. This means that making an easy target more difficult to achieve unambiguously increases effort and performance. Conversely, making a challenging target (set above expected performance) even more difficult to achieve decreases effort because g is decreasing for $t > e^*$. The highest implementable effort for a given bonus b is at a point where the target equals expected performance so that $g(e - t) = g(0)$.

In other words, the function g measures target-based incentive strength in the model. The strongest possible incentives and the highest implementable effort are rarely optimal because the employee's cost of effort is quadratic but its benefit is linear—more effort incurs marginal costs greater than its benefits at some point. The optimal level of effort e^* (and thus the optimal incentive strength for a given bonus b) is given by the dashed horizontal line in Figure 1, for which the equilibrium condition $g(e^* - t) = v / b$ holds and the marginal benefits of effort to the employee equal the benefits of effort to the firm. There are two optimal target levels that satisfy the equilibrium condition. The first target that can implement the optimal effort e^* is t^L , set below expected performance. The same incentive strength and e^* can also be implemented with a target t^H, set above expected performance, as shown by the two vertical dashed lines. Given that g is symmetric, t^L and t^H are equidistant from expected performance because incentive strength decreases in the distance between the target and expected performance.