# Individualizing Management Practices

Inauguraldissertation
zur
Erlangung des Doktorgrades
der

Wirtschafts-und Sozialwissenschaftlichen Fakultät
der
Universität zu Köln

2025

vorgelegt
von

Saskia Alina Opitz, M.Sc.

aus

Heidelberg

Referent: Professor Dr. Dirk Sliwka
Korreferent: Professor Dr. Matthias Heinz
Tag der Promotion: 17.02.2025

# Acknowledgements

There is a long list of people I want to thank with all my heart at this point, as they not only made it possible for me to complete my PhD but also turned the journey into one of the best times of my life—despite the emotional highs and lows along the way. If I were to list everyone who made this time special, this dissertation would be significantly longer. Therefore, I am limiting myself to a shorter list. If you are not mentioned by name, it does not mean that I have forgotten you.

I am deeply grateful to:

... my main advisor, Dirk Sliwka, without whose invaluable support over the past years and belief in my abilities, this PhD would not have been possible.

... my second advisor, Matthias Heinz, for his open door, for listening to all my questions, and for his valuable strategic advice.

... Timo Vogelsang and Tom Zimmermann for always being there with advice and support, even though you were not officially my advisors. It has been an additional great pleasure to have you as co-authors.

... Axel Ockenfels for believing in me and bringing me to the MPI.

... my former colleague Sidney, who took me under his wing during my early days and helped me through all crises.

... my colleagues in the Department of Corporate Development, especially Paula, Leo, Marina, and Simon. Without you, this time would not have been as enjoyable. And of course, Claudia, for everything she does for us every day.

... my colleagues at the MPI for Research on Collective Goods, especially Yero, Aenne, Melisa, and Simon. I will surely miss our shared office.

... the Joachim Herz Stiftung and the ECONtribute Excellence Cluster (Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy – EXC 2126/1–390838866) for the financial support.

... all the people I love, my family, and my friends for their emotional support.

# Contents

# Introduction

Firm performance depends heavily on the motivation of people. However, people differ in what motivates them. A large literature in economics, management and management accounting investigates the effect of management practices on performance as well as other outcomes such as turnover or employee perceptions (See for example Bloom and Van Reenen (2011) for an overview), also showing heterogeneity in the responses of employees to management practices based on individual characteristics, e.g. based on gender (Delfgaauw et al., 2013; Gneezy et al., 2003; Niederle and Vesterlund, 2007), social preferences (Bandiera et al., 2005) or personality (Donato et al., 2017).

To motivate their employees more effectively, firms could thus individualize their management practices. There are primarily two approaches: 1) A company can assign management practices to employees based on individual characteristics e.g. by using AI methods (centralized approach), 2) a company can provide more discretion to their managers/employees such that they can use their local knowledge (decentralized approach). This dissertation sheds light on both approaches making use of various empirical methods and data sources. One of the three chapters is based on an extensive proprietary firm dataset. This data is combined with self-collected survey data as well as a field experiment. Another chapter is based on two large-scale online experiments on Amazon MTurk. The third chapter uses data from a field experiment in collaboration with a company.

Chapter 1[1] investigates the centralized approach in individualizing a management practice. We investigate the merit of using recently advanced methods combining machine learning algorithms and causal inference for targeted assignment of incentives. Running two large-scale experiments with gig workers, we could show that a machine learning algorithm can detect heterogeneity in worker reactions to different incentive schemes. In a second step, we show that targeted algorithmic assignment of incentive schemes based on observable worker characteristics increases performance significantly in comparison to assigning all workers to the single best incentive scheme. In a third step, we show that the quality of the algorithmic assignment depends on how reliably the characteristics are measured. Thus, we demonstrate that using a centralized approach to individualize monetary incentives can be beneficial for companies by increasing employee motivation. However, it is important to consider issues such as data privacy preferences, fairness concerns and potential for manipulation.

[1]This chapter is based on Opitz et al. (2024). Please find the description of my contribution to this co-authored paper at the beginning of the chapter.

In Chapter 2[2], I examine the decentralized approach in the context of a specific monetary incentive system. In this study, my coauthors and I explore how managers make use of discretion in management practices. We focus on bonus assignments and employee outcomes within a bonus system where managers have discretion over the timing of bonuses, rather than making annual or biannual bonus decisions. A key assumption of these so-called spot bonus systems is that timely bonuses provide employees with more recognition for their work compared to delayed bonuses. We investigate the use of this widespread tool by analyzing extensive personnel records and linked survey data from a large multinational company. Our results reveal that managers award most bonuses at the end of the budget year, despite the system's intention to reward employees promptly. Analyses using the historical firm data, a field experiment, and an additional expert survey indicate that this practice aligns with the predictions of a Bayesian learning model, which suggests that managers need time to gather information to accurately assess performance signals. Thus, the postponement of bonus assignments may be rational from the managers' perspective. However, we find that employees report significantly higher levels of perceived recognition when they receive a bonus earlier in the year, suggesting that this rational behavior might be suboptimal for the company. We propose several strategies for companies that wish to retain a discretionary approach while still promoting timely bonuses.

Chapter 3[3] presents evidence on the individualization of a management practice that differs from monetary incentives. In this single-authored project, I investigate how highlighting flexibility options—such as working from home or flexible work hours—in job ads posted on social media platforms influences the number of applicants for various jobs. By conducting a field experiment in collaboration with a recruiting service provider, using 176 job ads from over 40 different companies, I examine the average treatment effect across industries and other job characteristics, as well as how the effect size depends on specific job characteristics. My results show that highlighting either working from home or flexible work hours significantly increases the number of applications compared to not highlighting any job characteristics. Additionally, I provide initial evidence of heterogeneity in the impact of highlighting working from home, depending on job characteristics. However, I find no evidence that emphasizing flexible work options is detrimental for jobs with any specific characteristics. Therefore, while highlighting existing flexible work options appears beneficial for all companies aiming to increase the number of applicants, the effectiveness may vary depending on certain aspects of the job.

[2]This chapter is based on Block et al. (2024). Please find the description of my contribution to this co-authored paper at the beginning of the chapter.

[3]This chapter is based on Opitz (2024). The paper is single-authored.

Taken together, the studies presented in this dissertation provide insights in the effectiveness of two approaches firms can use to individualize management practices: centrally targeting management practices or providing managers with discretion. As more and more data as well as advanced methods become available, firms become less dependent on the latter approach. However, to investigate and compare the relative merits of both approaches in other contexts will be a task for future research.

## References


Bandiera, O., Barankay, I., & Rasul, I. (2005). Social preferences and the response to incentives: Evidence from personnel data. *The Quarterly Journal of Economics*, *120*(3), 917–962.

Block, S., Opitz, S., Sliwka, D., & Vogelsang, T. (2024). Discretion over bonus timing. *Available at SSRN 4322361*.

Bloom, N., & Van Reenen, J. Human resource management and productivity. In: In *Handbook of labor economics*. Vol. 4. Elsevier, 2011, pp. 1697–1767.

Delfgaauw, J., Dur, R., Sol, J., & Verbeke, W. (2013). Tournament incentives in the field: Gender differences in the workplace. *Journal of Labor Economics*, *31*(2), 305–326.

Donato, K., Miller, G., Mohanan, M., Truskinovsky, Y., & Vera-Hernández, M. (2017). Personality traits and performance contracts: Evidence from a field experiment among maternity care providers in india. *American Economic Review*, *107*(5), 506–10.

Gneezy, U., Niederle, M., & Rustichini, A. (2003). Performance in competitive environments: Gender differences. *The Quarterly Journal of Economics*, *118*(3), 1049–1074.

Niederle, M., & Vesterlund, L. (2007). Do women shy away from competition? do men compete too much? *The Quarterly Journal of Economics*, *122*(3), 1067–1101.

Opitz, S. (2024). *Highlighting benefits in job ads: A field experiment* [Mimeo].

Opitz, S., Sliwka, D., Vogelsang, T., & Zimmermann, T. (2024). The algorithmic assignment of incentive schemes. *Management Science*, *71*(2), 1546–1563.

# 1 The Algorithmic Assignment of Incentive Schemes

**Abstract**

The assignment of individuals with different observable characteristics to different treatments is a central question in designing optimal policies. We study this question in the context of increasing workers' performance via targeted incentives, using machine learning algorithms with worker demographics, personality traits, and preferences as input. Running two large-scale experiments we show that (i) performance can be predicted by accurately measured worker characteristics, (ii) a machine learning algorithm can detect heterogeneity in responses to different schemes, (iii) a targeted assignment of schemes to individuals increases performance significantly above the level of the single best scheme, and (iv) algorithmic assignment is more effective for workers who have a high likelihood to repeatedly interact with the employer, or who provide more consistent survey answers.

This chapter is published as: Opitz, S., Sliwka, D., Vogelsang, T., & Zimmermann, T. (2024). The algorithmic assignment of incentive schemes. *Management Science*, *71*(2),1546–1563. ISSN: 1526-5501 (Online); ISSN: 0025-1909 (Print)

The paper is coauthored with Prof. Dr. Dirk Sliwka, Prof. Dr. Timo Vogelsang and Prof. Tom Zimmermann, PhD. In this paper, I contributed significantly to various stages of the research process. Together with my co-authors, I was involved in the development of the core ideas, which were initially based on the notion proposed by Prof. Dr. Dirk Sliwka. I was responsible for programming, testing, and conducting the experiment on MTurk. Additionally, I programmed and implemented the algorithm in collaboration with my co-authors, particularly Prof. Tom Zimmermann, PhD. Additionally, I took primary responsibility for the data analysis and the preparation of the tables. While the writing of the paper was a joint effort, my main contributions were in the design, experimental procedure, and the method part. Furthermore, I played a leading role in revising the paper following the reviewers' feedback, once again focusing on the data analysis.

# 2 Discretion over Bonus Timing

**Abstract**

We study bonus assignments by managers who have discretion over bonus timing, analyzing extensive personnel records and linked survey data from a multinational firm. We find that – even though the bonus system is intended to provide timely rewards – managers award most bonuses at the end of a year. As predicted by a rational Bayesian learning model, we find supportive evidence for an information acquisition channel according to which managers delay bonuses because they want to gather more information to assess performance signals correctly. However, our survey results also reveal that employees who receive bonuses earlier in the year perceive a stronger recognition compared to those receiving late bonuses. Thus, the bonus delay – while potentially rational for the managers aiming at allocating bonuses to the most deserving employees – may therefore not be optimal from a company's perspective.

This chapter is based on the working paper published as Block et al. (2024)[4]. Minor revisions have been made to fit the format of this thesis. The paper is coauthored with Dr. Sidney Block, Prof. Dr. Dirk Sliwka and Prof. Dr. Timo Vogelsang. For this paper, my contributions were primarily focused on data preparation, analysis, the planning and conducting of the field experiment, and restructuring the paper. While the initial contact with the company was established and the survey with employees and supervisors in 2020 was planned and conducted by my co-authors, and the theoretical model was developed by Prof. Dr. Dirk Sliwka, I was primarily responsible for processing the administrative data provided by the partner company. The initial data analysis was done mainly in collaboration with Dr. Sidney Block, while the planning and conducting of the field experiment was a joint effort. Following feedback from a journal, we undertook a complete revision of the paper, which involved a new focus, the integration of new data, and additional analyses, without further involvement from Dr. Sidney Block. I also programmed the expert survey and planned and conducted the expert interview. I led the data analysis and prepared the tables. Finally, I worked closely with Prof. Dr. Timo Vogelsang and Prof. Dr. Dirk Sliwka in rewriting the paper.

[4]The company survey and the field experiment were approved by the study firm's works council and an IRB board. The expert survey was also approved by an IRB board. We pre-registered the field experiment on socialscienceregistry.org with the ID AEARCTR-0007891.

## 2.1 Introduction

We study the role of time in the assignment of discretionary bonuses. In recent years, many firms have granted managers autonomy to determine the timing of bonus payments, thereby adding a new layer of discretion to traditional discretionary bonus systems studied in prior literature (e.g., Abernethy et al., 2020; Baiman and Rajan, 1995; Bol et al., 2015; Cai et al., 2023; Gibbs et al., 2004; Höppe and Moers, 2011). In these so-called spot bonus systems, managers have to decide, within a given period and budget, not only who should receive a bonus and the respective bonus amount but also on when to award a bonus to an employee. In this paper, we conceptualize managers' choice of timing of such bonuses by developing an analytical model of bonus assignments and we provide empirical evidence from archival data, employee- and expert surveys, and a field experiment[5].

Spot bonuses are monetary payments that can be paid to an employee at any point in time to reward outstanding performance outcomes in a timely manner. Frequently, firms setting up a spot bonus system assign a budget[6] that can be used for the bonuses in a given year. Spot bonuses can then be awarded at any point in time throughout the year typically based on the respective supervisor's suggestion. Managers are then explicitly asked to reward excellent contributions at the point in time when they have been provided.[7] These systems have become quite common in many countries (Das, 2020; PayScale, 2021; WorldAtWork, 2014). Analyzing a representative survey on German companies, we, for instance, document that about 56% of firms with more than 500 employees state to have such a bonus system in place.

Managers deciding on bonus timing face an intertemporal decision problem. To study their bonus timing, we develop a rational Bayesian learning model where managers aim at tying bonuses to the most deserving performance outcomes. As they receive noisy performance information, managers have to rationally update their beliefs on actual performance and allocate bonuses accordingly being aware of a limited budget. The model illustrates a rational *information acquisition* mechanism that leads to a tendency to delay bonus payments whenever two conditions are met: (i) performance assessments are noisy and (ii) employees differ in their underlying abilities. We show that even

[5]The survey and the field experiment were approved by the study firm's works council and an IRB board.

[6]Alternatively, firms provide certain guidelines on how many employees should receive a bonus within a year, e.g. top 30%.

[7]UC-Berkeley (2024), for instance, states on its website: "Spot Awards are designed to recognize special contributions, as they occur, for a specific project or task". In some firms, spot bonuses can also be based on coworker nominations or can be awarded to teams. PayPal (2024) states: "Recognition Awards (Spot Awards): A Spot Award is a one-time award that managers may give to individuals (or teams) for outstanding work. [...] If you want to nominate someone on your team or another, talk to your manager or another manager [...]".

when performance is distributed evenly over the year, more bonuses are awarded later in time in this case. The reason is that rational managers' ability to discern truly high performance from mere noise is increasing with the accumulated evidence from earlier periods.

Drawing on an extensive proprietary data set of personnel records from a large multinational firm with more than 10,000 employees and 2,000 managers, we find that the share of employees receiving a bonus is indeed increasing over time within each budget period. In fact, managers award the majority of bonuses at the very end of the budget period.

We also discuss potential alternative mechanisms beyond the *information acquisition* motive. For instance, managers may engage in *precautionary savings* early in the budget period because they are uncertain about the necessity of future bonuses, thereby accumulating funds early in the budget period to be spent later (Balakrishnan et al., 2007; Liebman and Mahoney, 2017; Zimmerman, 1976). Or, managers may simply pay too little attention (e.g., Birnberg and Shields, 1984; Bordalo et al., 2022) to bonus assignments during the budget period, which makes bonus assignment an urgent matter only when the budget is about to expire (*inattention*).

By further testing the predictions of our model, running a survey among 23 compensation experts from larger companies, and implementing a field experiment within our study firm, we provide evidence for *information acquisition* as a key motive to delay bonus payments. For instance, when being asked to rate 10 different mechanisms potentially driving bonus delay, the surveyed experts rate *information acquisition* as the most prominent motive. Moreover, we show that spot bonus sizes are larger earlier in the year which appears hard to reconcile with a predominant *precautionary savings* motive. Finally, in our field experiment, randomly selected managers were explicitly reminded about the firm's goal to allocate early bonuses and the anticipated advantages of doing so. We find no evidence that managers adjust their awarding behavior, suggesting that *inattention* is not a key driver of delayed bonus payments.

While we show that managers may rationally want to delay bonuses when aiming at rewarding the most deserving performance, it is, however, unclear whether this is also an optimal policy from the firm's perspective if the aim is to provide employee recognition in a timely manner. After all, this provision of timely recognition is often a key motive for introducing discretion over bonus timing and prior research in organizational behavior indeed documents benefits of immediate as opposed to delayed feedback (e.g., Berger and Ludwig, 2007; Dihoff et al., 2004; Mason and Redmon, 1993; Northcraft et al., 2011; Reid and Parsons, 1996).

To investigate this tension, we study whether and how the timing of bonus assignments is associated with employee attitudes. Specifically, we combine personnel records with large-scale survey data to investigate whether early (and thus, on average, more timely) rewards are linked to employees' perceived recognition, job satisfaction, and engagement.[8] Our key observation here is that employees report a significantly higher level of recognition if they receive bonuses during rather than at the end of the year. This finding appears well in line with findings in organizational behavior research, which has rather consistently shown beneficial effects of immediate as opposed to delayed feedback (Berger and Ludwig, 2007; Dihoff et al., 2004; Mason and Redmon, 1993; Northcraft et al., 2011; Reid and Parsons, 1996). However, it shows a tension between managers' rational motives to delay bonuses when they want to reward the most deserving performance events and the (valuable) aim to provide recognition in a timely manner. We discuss potential implications of this tension.

Our paper contributes to the nascent literature investigating how time matters in employee compensation and performance management. We develop a formal theoretical model that illustrates how the aim to rationally use collected information affects bonus timing and tests its propositions. We thereby broaden the existing literature by examining how managers use their discretion over bonus timing, and give first insights into the relationship between bonus timing and employee attitudes. Existing literature on time and bonuses, for instance, studied bonuses paid as time-off rather than in money (Vogelsang, 2024), and the role of deterministic bonus timing (Boosey and Goerg, 2020). Moreover, as spot bonuses are explicitly used to combine positive performance feedback with tangible rewards in order to provide recognition the paper is also related to the recent accounting literature on the optimal frequency and timing of feedback (e.g., Casas-Arce et al., 2017; Hecht et al., 2020; Holderness Jr et al., 2020; Waddoups, 2022).[9]

In addition, our work relates to the literature on the dynamics of spending patterns when there are fixed budgets (Pollack and Zeckhauser, 1996; Siemroth, 2022; Zimmerman, 1976). In the context of government organizations, this work, for instance, documents spending spikes at the end of the budget period (e.g., Balakrishnan et al., 2007; Baumann, 2019; Eichenauer, 2020; Fitzenberger et al., 2016; Liebman and Mahoney, 2017). We show that similar patterns occur when managers have discretion over timing in spending bonus budgets. Moreover, while this literature typically stresses a *precautionary savings* motive as key reason for delayed payouts (i.e. decision makers postpone payments due to the uncertainty about potentially more deserving later cases), we formalize and

[8]Previous research documents a positive relationship between receiving rewards and various employee attitudes (e.g., Green and Heywood, 2008; Kulikowski, 2018; Pouliakas, 2010) as well as positive effects of recognition on performance (e.g., Burke et al., 2017; Lourenço, 2016).

[9]This literature rather consistently documents drawbacks of too frequent feedback. Together with the above cited findings on the benefits of immediate as opposed to delayed feedback these findings thus appear to support the use of spot bonuses to provide both infrequent but immediate positive feedback for outstanding performance.

test an *information acquisition* mechanism, which appears particularly important in the context of spot bonuses: The more time has elapsed in a given budget period, the more information can be collected on a specific employee's performance, which makes it easier to build a case warranting a bonus payout later in the budget period. To understand the key difference, note that the budgeting literature typically considers settings where *different and independent* cases come up sequentially and the decision maker has to decide whether to spend money on the case at hand or wait. In our context a decision maker continuously tracks a given set of employees and thus the performance of an employee in earlier periods is informative for the assessment of later periods. As we show in our formal model this leads to a motive to delay even when future payouts are perfectly predictable and decision makers are risk neutral.

We also contribute to a rich literature in accounting, psychology, and economics which has studied the role of managerial discretion in subjective performance evaluations (e.g., Bol, 2011; Bol and Smith, 2011; Grabner et al., 2020; Kusterer and Sliwka, 2024; Maas et al., 2012; Manthei and Sliwka, 2019; Moers, 2005; Woods, 2012) and the allocation of bonuses (e.g., Abernethy et al., 2020; Baiman and Rajan, 1995; Bol et al., 2015; Cai et al., 2023; Gibbs et al., 2004; Höppe and Moers, 2011; Kampkötter and Sliwka, 2018). While this literature has shown that discretionary evaluations tend to be "biased" as the distribution of manager's assessments systematically deviates from the distribution of actual employee performance[10], our results indicate that there may also be a discrepancy between the timing of employee performance and the timing of bonuses supposed to reward performance.

Finally, the evidence we provide in the context of our field experiment also contributes to the literature on attention in accounting and economics (see, e.g., Birnberg and Shields, 1984; Bordalo et al., 2022; Manthei et al., 2023a). Our findings suggest that bonus delay is not the result of a managerial attention problem but rather appears to be an intentional decision by managers.

The remainder is structured as follows. Section 2.2 details the theoretical model. Section 2.3 describes the data and the setting. Section 2.4 provides results on bonus timing and the information acquisition channel. Section 2.5 presents results on alternative mechanisms. Section 2.6 presents exploratory findings on the question whether the behavior we find is optimal. Section 2.7 provides a concluding discussion of our findings and potential avenues for future research.

[10] In particular, ratings and bonus payments are more compressed and more lenient than reflected in the underlying performance distributions.

## 2.2 Information Acquisition and the Timing of Bonuses

Traditional discretionary bonus schemes, such as bonus pool arrangements[11], grant managers autonomy to distribute a fixed bonus budget to their subordinates at a given point in time (typically once a year). In spot bonus systems, which are the focus of this study, managers additionally have to decide on the timing of the bonus payments. The key idea of such schemes is to provide rewards for performance outcomes realized at any point during a year when employees have demonstrated high performance.

Managers deciding on bonus timing then face an intertemporal decision problem. Importantly, as managers track a given set of employees over the budget period, signals about the performance in earlier periods are informative about an employee's performance later. In turn, managers sequentially acquire performance signals which help them to discern truly high performance from mere noise. We provide a formalization of this *information acquisition* mechanism in the following.

### 2.2.1 Analytical Model

Consider a firm employing a continuum of agents on $S = [0, 1]$ indexed by $i$. The agents work for $T \geq 2$ periods $t = 1, .., T$ in a given year. The actual performance of an agent $i$ in period $t$ is given by

$$y_{it} = \eta_{it} + a_i$$

where the $\eta_{it} \sim N\left(0, \sigma_\eta^2\right)$ capture time varying elements of performance and $a_i$ is agent $i$'s ability and thus constant over time.

The organization now awards bonuses for high performance throughout the year. As we focus here on bonus timing, assume that the bonus size for each payout is fixed[12] and it has to be determined which agents $i$ receive a bonus $b_{it} \in \{0, 1\}$ in period $t$. As laid out in the above, spot bonus systems typically entail a budget or a guideline on the number of bonuses that can be awarded. Hence, we assume that over the whole year a mass $p < 1$ of bonus payouts can be made, for instance, because the firm sets a fixed budget for the bonuses or because it uses a guideline specifying that bonuses should be awarded for the $p \cdot 100\%$ best performance outcomes. This implies the following budget constraint

$$\sum_{t=1}^{T} \left( \int_S b_{it} di \right) = p. \tag{1}$$

[11] Bonus pools have, for instance, been studied by Baiman and Rajan (1995), Rajan and Reichelstein (2006), Rajan and Reichelstein (2009), or Kampkötter and Sliwka (2018).

[12] Companies might also have clear guidelines on the spot bonus size. For example, in the company we study, the size of the spot bonus depends mainly on the hierarchical level.

There is a set of supervisors who each observe a subset of the employees such that each employee has exactly one supervisor. We allow for the possibility that supervisors have prior information on their subordinates: An agent $i$'s supervisor expects his ability to be $a_i \sim N\left(m_i, \sigma_r^2\right)$ where $m_i$ is thus the expected value of an agent's performance and $\sigma_r^2$ is the residual uncertainty on the agent's ability at the beginning of the year. Across the workforce these ex-ante expectations are normally distributed with $m_i \sim N\left(m, \sigma_m^2\right)$. Hence, $\sigma_m^2$ measures the heterogeneity in prior performance assessments: When $\sigma_m^2 = 0$ then teams are homogeneous and supervisors have the same beliefs about the expected performance of all agents at the beginning of the year and only then start to learn about ability differences. When, however, $\sigma_m^2 > 0$ they have further information on ability differences.[13] An alternative interpretation is that when $\sigma_m^2 = 0$ supervisors ignore prior knowledge about performance differences and use only information collected during the budget period, whereas they use prior information when $\sigma_m^2 > 0$.

Throughout the year these supervisors collect information on their assigned agent's performance and each period $t$ they observe noisy performance signals

$$s_{it} = y_{it} + \varepsilon_{it}$$

for each agent where $\varepsilon_{it} \sim N\left(0, \sigma_\varepsilon^2\right)$ are independent noise terms. Each supervisor observes a set of employees and presents performance assessments $\hat{y}_{it}$ to the firm. Each assessment $\hat{y}_{it}$ of agent $i$ in period $t$ is based on the pieces of information collected by the respective supervisor in the considered budget year up to point $t$ and are determined by Bayes' rule. Assessments are thus equal to the conditional expectation about true performance $y_{it}$ given the prior expectations on agent $i$'s performance and the collected signals up to the current period:[14]

$$\hat{y}_{it} = E_i\left[y_{it} \,|\, s_{i1}, ...s_{it}\right].$$

[13]Hence, the overall variance in abilities $\sigma_a^2 = \sigma_m^2 + \sigma_r^2$ can be decomposed in variance in prior beliefs $\sigma_m^2$ and residual uncertainty $\sigma_r^2$. This is equivalent to a setting where supervisors have a common prior $a_i \sim N\left(m, \sigma_a^2\right)$, but the receive signals $\omega_i = a_i + \gamma_i$ about an agent's performance where $\gamma_i \sim N\left(0, \sigma_\gamma^2\right)$. Then $m_i = E\left[a_i \,|\, \omega_i\right] = m + \frac{\sigma_a^2}{\sigma_a^2+\sigma_\gamma^2}\left(\omega_i - m\right)$ and $\sigma_r^2 = V\left[a_i \,|\, \omega_i\right] = \frac{\sigma_a^2\sigma_\gamma^2}{\sigma_a^2+\sigma_\gamma^2}$. In turn $\sigma_m^2 = \frac{\sigma_a^4}{\sigma_a^2+\sigma_\gamma^2}$ and thus $\sigma_r^2 + \sigma_m^2 = \sigma_a^2$.

[14]Note that a selfish supervisor will have an interest to report this if the firm checks the performance assessments with a certain probability and then inspects the collected signals up to this point in time. When the supervisor's utility is a decreasing function of the deviation between her report and the a rational assessment of performance based on these signals, it is optimal to report the conditional expectation.

The firm's objective function is to maximize the predicted performance $\hat{y}_{it}$ of bonus recipients at the time of receiving the bonus

$$\sum_{t=1}^{T}\left(\int_{S} b_{it}\hat{y}_{it}di\right) \tag{2}$$

under the budget constraint (1). The firm thus aims at allocating the bonus budget to those agent-month combinations where the case for a high performance is best supported by the supervisor's assessment based on available at the respective point in time.

#### 2.2.2 Optimal Bonus Assignment

First, we determine the individual performance assessments $\hat{y}_{it}$ obtaining the following result:

**Lemma 1** *The optimal assessment of period $t$ performance of an agent $i$ is*

$$\begin{aligned}\hat{y}_{it} &= E_i\left[a_i + \eta_{it}\,|s_{i1}, ...s_{it}\right] \\ &= m_i + \frac{\sigma_\eta^2\left(s_{it} - m_i\right)}{\sigma_\eta^2 + \sigma_\varepsilon^2} + \frac{\sigma_r^2\sigma_\varepsilon^2\sum_{\tau=1}^{t}\left(s_{i\tau} - m_i\right)}{\left(\sigma_\eta^2 + \sigma_\varepsilon^2 + \sigma_r^2 t\right)\left(\sigma_\eta^2 + \sigma_\varepsilon^2\right)}.\end{aligned}$$

**Proof:** See Appendix 2.9.

This assessment in a period $t$ is thus a function of (i) the prior expectation $m_i$ at the beginning of the year, (ii) the information $s_{it}$ collected in the period under consideration, but also (iii) the performance in earlier periods of the year ($s_{i\tau}$ for $\tau = 1, ..., t-1$). The reason for the latter is that earlier signals also help to filter out noise and to provide a more accurate representation of the agent's true performance.

Note that $\hat{y}_{it}$ evolves over time according to the observed signals and is also normally distributed. Importantly, this implies that – while the variance of actual performance $V\left[y_{it}\right]$ is stable over time – the variance of performance assessments $\sigma_{\hat{y}_t}^2 = V\left[\hat{y}_{it}\right]$ is strictly increasing in $t$ as the following result shows:

**Lemma 2** *When $\sigma_r^2 > 0$ and $\sigma_\varepsilon^2 > 0$, the variance of optimal performance assessments $\hat{y}_{it}$ is increasing over time, i.e. $\sigma_{\hat{y}_1}^2 < \sigma_{\hat{y}_2}^2 < ... < \sigma_{\hat{y}_T}^2$.*

**Proof:** See Appendix 2.9.

The intuition is the following: As only few signals are observed in early periods, rational assessments do not vary strongly with observed signals when information is noisy. But as more information is gathered, individual performance assessments become more precise and, in turn, performance assessments become more differentiated. Hence, the variance of assessments between agents increases.[15] In other words, it becomes easier over time to disentangle truly high performance from mere luck.

In a next step, we can determine the optimal assignment of bonuses based on these performance evaluations. Note that optimal assignment policy is a threshold policy such that bonuses will be assigned to agents where $\hat{y}_{it} > \theta_t$ for some positive constants $\theta_t$.[16] As the assessments $\hat{y}_{it}$ are normally distributed with ex-ante mean $E\left[\hat{y}_{it}\right] = E\left[m_i\right] = m$ and variance $\sigma^2_{\hat{y}_t}$, we thus have that the share of bonuses awarded in period $t$ is equal to

$$p_t = \Pr\left(\hat{y}_{it} > \theta_t\right) = 1 - \Phi\left(\frac{\theta_t - m}{\sigma_{\hat{y}_t}}\right)$$

where $\Phi(x)$ is the cumulative distribution function of a standard normal distribution. We can use this to derive the following result:

**Proposition 1** *The share $p_t$ of employees receiving a bonus is increasing over time, i.e. $p_1 < p_2 < ... < p_T$ if and only if performance is imperfectly observable (i.e. $\sigma^2_r > 0$ and $\sigma^2_\varepsilon > 0$), .*

**Proof:** See Appendix 2.9.

Hence, the result shows that whenever performance is imperfectly observable, more bonuses are awarded at the end of the budget period – even though average performance is stable over time. This result is due to the following mechanism: As laid out in the above, performance assessments based on signals collected within the given year become more precise when more information is gathered over time. In turn, these assessments become more differentiated in later months. Early in the year, it is more difficult to make a case for outstanding performance only based on this information. Over time, it becomes easier to identify truly high performance. In other words, the more information is gathered, the easier it is to build a case showing superior performance worth receiving a bonus.

[15] See e.g. Kusterer and Sliwka (2024) for recent experimental evidence showing how access to a larger number of performance signals leads to more differentiated performance evaluations.

[16] Suppose that $\theta_{0t}$ is the lowest value of $\hat{y}_{it}$ leading to a bonus in $t$. If there is a set of performance levels $S$ with $inf\ Y > \theta_{0t}$ that do not lead to a bonus, then (2) can be increased by raising $\theta_{0t}$ and instead awarding bonuses for performance levels in $S$ instead.

It is important to note that this effect is entirely driven by the motive to acquire more precise information. If either abilities[17] – and thus all underlying components of performance that are stable over time – were perfectly known ex-ante ($\sigma_r^2 = 0$) or performance throughout the year perfectly observable without any noise ($\sigma_\varepsilon^2 = 0$) then bonuses would be uniformly distributed over time.

It is instructive to consider a two period version of the model to derive one further testable comparative statics prediction on the timing of bonuses. Namely, we can show the following:

**Proposition 2** *The larger the heterogeneity in ability assessments $\sigma_m^2$ the higher the fraction of bonuses that are awarded early on.*

**Proof:** See Appendix 2.9.

The intuition for the result is the following: As laid out in the above $\sigma_m^2$ measures heterogeneity in prior performance assessments. That is, when $\sigma_m^2$ is larger, supervisors have information – for instance from having worked with them in the past – that some agents are better than others. In that case it is easier for them to identify true high performance without having to wait for more signals throughout the year. In turn, they should rationally award more bonuses early on. In other words, if a supervisor receives a signal indicating high performance from a person that has consistently performed very highly in the past (thus having a high prior ability expectation $m_i$), she can be more certain that this was not merely a "lucky shot"(driven just by a high realization of $\epsilon_{it}$). In contrast, when $\sigma_m^2 = 0$ supervisors have no prior information and only learn about the agents relative performance by observing their performance during the considered time frame. In turn, they have a rational motive to postpone bonus payments to acquire sufficient information.

We will test this result later on in two ways: First, we can assess a supervisor's tenure and expect supervisors of longer tenure (and thus more past information that allow differentiated priors) to award bonuses earlier on. Second, we use data on employees' annual performance evaluations and expect that more bonuses are awarded earlier on when performance evaluations have a larger variance.

[17]Note that if this is not the case an agent's performance outcomes are independent over time, i.e. prior performance is not predictive for future performance.

## 2.3 The Environment

### 2.3.1 Use of Spot Bonus Systems

Before describing the institutional details of the specifics of the bonus scheme in our study firm, we report here some evidence on the use of spot bonuses in general. As outlined in the introduction, spot bonuses appear to be widely utilized (Das, 2020; PayScale, 2021; WorldAtWork, 2014). To collect further representative evidence on their prevalence, we draw on an item that one of the authors had included in the German Linked Personnel Panel survey, a representative survey among German companies conducted on behalf of the federal ministry of labor. This particular item asks: "Does your company offer financial recognition for outstanding performance, which can be awarded during the year and independently of the regular bonus and for which there is usually a separate budget available?"[18]. Overall, 44.73% of all 769 companies that answered have such a spot bonus system in place. Notably, the prevalence of this system varies slightly across different company sizes, with 41.16% implementation in smaller companies (up to 99 employees) and 56.14 % in larger corporations (exceeding 500 employees), as illustrated in Figure 2.3 in Appendix 2.10).

Additionally, we supplemented our investigation by conducting a survey in cooperation with the German Association for Human Resource Management (DGFP). This gave us the opportunity to survey German compensation and benefit experts in large companies. Of the 23 experts who fully completed the survey, 17 stated that they have a spot bonus system in place, with bonuses proposed by the supervisor. On average, 7.3% of employees receive a spot bonus in a given year in these companies.

### 2.3.2 The Firm

We collaborate with a large multinational industrial firm employing more than 10,000 employees in more than 30 countries around the world. Approximately half of the workforce works in production, while the other half belongs to other functions such as R&D, sales, marketing, HR, IT, or finance. Though the firm's business is dependent on the business cycle, it is not seasonal such that the firm's output is relatively stable over the financial year (which coincides with the calendar year and the budget period). Almost all jobs in the firm have in common that employees work interactively with others and that individual performance is hard to quantify objectively. Every permanently employed worker's compensation consists of three components: A fixed salary, a bonus for firm-wide performance paid out to nearly all employees as a function of the overall firm profitability, and an individual discretionary spot bonus.

[18]Please note that this is a translation of the original German item.

### 2.3.3 The Spot Bonus

The key purpose of the spot bonus is to reward excellent individual performance. In internal documents, the firm summarizes the purpose of the spot bonus as follows: "It [the spot bonus] *recognizes* outstanding performance in a *timely manner*."[19] Managers award spot bonuses based on their own discretion. Managers receive discretion because individual performance is hard to quantify objectively in a timely manner[20] and managers are close to their direct reports and should be able to identify outstanding performance more quickly, which would be hard to identify for top management, or accounting, and HR department. Importantly, spot bonuses are not based on predefined targets as in classical management-by-objectives (e.g., Bol et al., 2010) but payments are determined by managers ex-post. Specifically, within the limits of their yearly spot bonus budget[21] and a time frame from February to November, awarding managers have discretion over i) who receives a bonus, ii) what size a bonus should have, and iii) when a bonus is awarded.

If a spot bonus is paid, its size mostly depends on the hierarchical level and base salary of the receiving employee. Hence, the core issue is not so much the decision about the magnitude of the payout, but its timing. We conducted an interview with the manager responsible for setting up the system more that 15 years ago (at the time global head of HR in the firm). He continuously stressed the purpose of the system is to reward excellent performance most immediately.[22]

We can actually see in the data that higher performance ratings by the direct supervisor are strongly associated with a higher likelihood of receiving a spot bonus. It is also weakly associated with receiving spot bonuses earlier in the year (see Table 2.6 in Appendix 2.10). Thus, supervisors in our company do actually seem to reward what they perceive as higher performance.

[19] A formal agreement with the firm's works council in Germany, for instance, lists as criteria the "fulfillment of main tasks", "complexity, and scope of the extra task", as well as "time expenditure for the task" should be considered.

[20] Even where objective performance measures are available many such (in particular financial) metrics are lagging indicators of performance.

[21] The spot bonus budget is determined by the following formula: For each employee $i$ in the team, the planner receives $\textit{Annual Salary}_i \times \textit{Spot Bonus Percentage}_i$, where the spot bonus percentage varies between 1% and 4% depending on the managerial level of the employee.

[22] In particular, he stressed that while in his view "money never provides sustainable motivation" but "[..] if money is used wisely and at the right time, it can still trigger something positive. Whether it's gratitude and appreciation or more commitment". He continued to explain the importance of timeliness as appreciation "is more likely to be triggered by this timely element" rather than by traditional annual evaluations, i.e. "talking now in April of the following year about something that you did in the summer of last year" which he claimed to have much weaker effects.

There are two important roles in the assignment process: supervisors and spot bonus planners. The supervisor, at any time of the awarding period, has the right to propose that an employee should receive a spot bonus (and its size). The planner is legally responsible for awarding the spot bonus, and she thus has to approve the proposed spot bonus. For around 50% of the employees, the roles of supervisor and planner coincide. In the remaining cases, the planner is one or more levels above the supervisor in the firm hierarchy (see Table 2.7 in Appendix 2.10).[23]

Once a spot bonus is awarded, the firm's HR system automatically generates a letter, stating the bonus size and expressing the firm's gratitude for the employee's great performance. The supervisor and the receiving employee then have a private meeting, in which the supervisor explains why the spot bonus was awarded, thanks the employee for the performance, and hands over the letter. Due to the private nature of this process, spot bonuses are generally not discussed with colleagues in the firm.[24]

In the subsequent sections of this paper, we mainly focus on supervisors as they initiate the awarding process and maintaining direct communication with the spot bonus recipients. However, we also ensure the robustness of our findings by focusing on the planner as the formally responsible manager.

### 2.3.4 Data

We draw on the firm's personnel records and matched survey data. We have access to employees' socio-demographic characteristics and organizational positions. This data spans the years 2016 through 2019 and covers more than 10,000 employees, of which around 2,000 are supervisors, and 700 also have the role of bonus planners. In particular, our data set includes an employee's age, gender, tenure, region, organizational unit[25], salary, promotions, performance ratings for 2019 until 2021, team size, and hierarchical level. All variables vary at the employee-year level.

Table 2.7 in Appendix 2.10 provides summary statistics on the firm's workforce. On average, employees are 45.57 years old, work in production, and have 14.98 years of tenure at the firm. 82% of the employees are men. Supervisors and planners do not differ much from employees along these four dimensions, except that the share of planners

[23]Additionally, each spot bonus award has to be approved by a manager higher up the hierarchy. They are also responsible for the final decision in case supervisors and planners do not agree. It is important to note that disagreements between planners and supervisor are extremely rare.

[24]Of the 17 firms that have a spot bonus system in our expert survey sample, 15 answered "no" to the question: "Do employees know whether their colleagues have received a bonus?". The remaining two stated "I do not know".

[25]For the years 2016-2019, we have a unique identifier for each employee indicating the business unit and/or function of an employee. Moreover, for the year 2020, we know the name of an employee's function.

is substantially smaller in production as span of controls are larger, and the roles of planner and supervisor coincide less often there. Moreover, supervisors have an average span of control of 6 employees, and planners are responsible for awarding spot bonuses to about 14 employees on average.

In addition to the above-mentioned variables, the personnel records feature data on all spot bonuses paid by the firm in the years 2016 through 2019. For each bonus, we know the recipient, the bonus size, the supervisor of the recipient, the responsible planner, and the payout date. Because the payout of the spot bonus takes place with the payout of the next paycheck, there is some lag between the actual awarding of a spot bonus and the payout date.[26]

Table 2.8 in Appendix 2.10 documents summary statistics on the spot bonus. Around 35 to 40 percent of employees receive a spot bonus in a given year. Only four percent of employees receive more than one spot bonus in a year. The size of the average spot bonus in a given year varies between 2.4 and 2.5 percent of an employee's annual salary.

In addition to the firm's personnel records, we use data from large-scale surveys we designed in collaboration with the study firm and can link to the personnel data on the level of individual employees. The aim of the surveys was to study employees' perceptions about their work situation and different management practices. With the help of local HR staff, we ran the surveys in all operating countries of the firm in May 2020 and July 2020.[27] Of the global 2019 workforce, 41% of all employees responded to at least one of the surveys.[28]

## 2.4 Results

### 2.4.1 Timing of Spot Bonuses

We first analyze the distribution of spot bonuses over time. Given that the firm's business operations exhibit no seasonal variations and outstanding employee performance should occur during the entire year, a logical benchmark for the observed distribution of spot bonus timing is a uniform distribution over time. However, as outlined in Section 2.2 Proposition 1, our model suggests that managers delay the payment of bonuses even when actual performance is evenly distributed over time.

[26] For this reason, we observe spot bonuses in month 12, although supervisors cannot award spot bonuses in December. Moreover, there are very few exceptions of spot bonuses paid out in January (12 out of more than 20,000 spot bonuses). We drop these exceptional bonuses paid out in January from our sample.

[27] The two consecutive surveys were run in this short time frame because the firm, among others, wanted to use them to assess changes in overall working conditions during the COVID pandemic. See Appendix 2.11 for screenshots of all survey items.

[28] Employees who received a spot bonus in 2019 are statistically more likely to participate in at least one of the surveys than those employees who did not receive a spot bonus in 2019 (55% of bonus recipients participated). However, the participation rate of spot bonus recipients does not vary with the month in which they received a spot bonus in 2019.

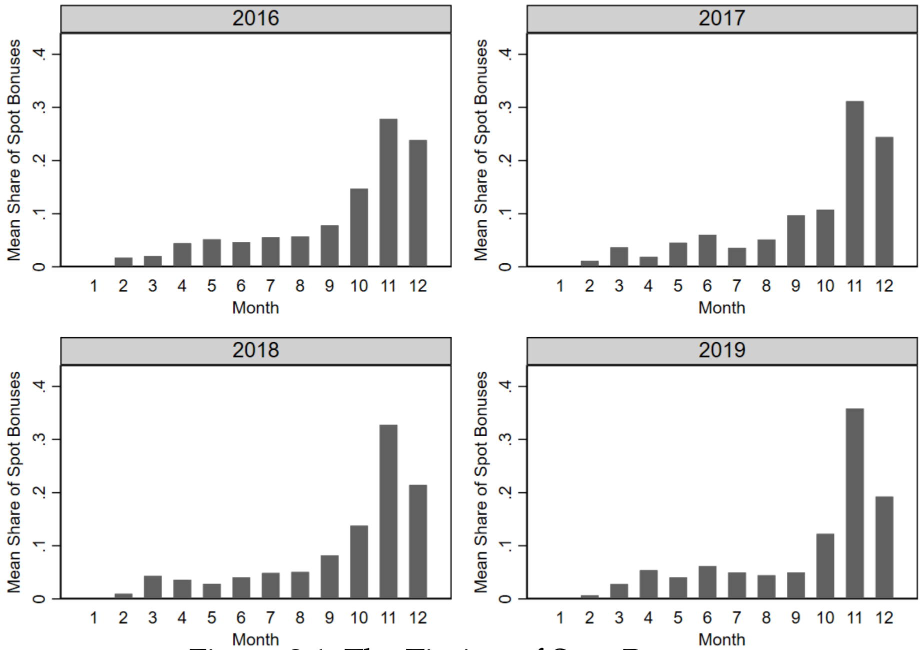


Figure 2.1: The Timing of Spot Bonuses

**Note:** This graph plots the mean share of spot bonuses paid out by the supervisors in each month of a year. We present one graph per year of our observation period (2016-2019).

When plotting the distribution of spot bonuses over the months of a year in Figure 2.1, we indeed observe substantial deviations from a uniform distribution over time. Three empirical patterns emerge. First, relatively few spot bonuses are awarded in the early months of a year as the first quarter accounts for only 4%, and the second quarter for only 14% of all spot bonus awards. Second, there is a spike in spot bonuses in November and December. It is important to recall that November is the last month in which supervisors can nominate employees for a bonus. As there is some delay in bonus payouts, a substantial share of these is then paid out in December. Third, the timing pattern is similar in all years of the observation period. We also tested whether the share of bonuses awarded is uncorrelated with the month using the Spearman rank correlation. The null hypothesis that there is no correlation was clearly rejected (Spearman's rho: 0.304, p-value: < 0.001).[29]

[29] Regressions of spot bonus incidence on time are reported in Table 2.9 in Appendix 2.10.

Recall that the model of information acquisition implies a gradual increase in bonus payouts.[30] It is therefore interesting to note that there is a particular spike towards the end of the budget period. A broader interpretation would be that many supervisors rather aim at waiting until the very end to determine which employees are the most deserving.[31]

To validate the bonus delay finding further and to ensure that the observed patterns are not company-specific, we further managed to receive similar data on the timing of spot bonuses by another multinational company with more than 15,000 employees in a related industry which operates a spot bonus system similar to the one described above.[32] Indeed, we also observe that more bonuses are assigned later in the year (see Figure 2.4 in Appendix 2.10). Also here we can clearly reject the null hypothesis that there is no correlation between share of bonuses awarded and month (Spearman's rho: 0.856, p-value: $< 0.001$).

### 2.4.2 Information and Bonus Timing

As shown in Proposition 2 the information acquisition mechanism implies that a higher degree of prior information should lead to earlier bonus assignments as it is easier then for manager to discern high performance from mere luck earlier in the budget period. The result shows that a higher variance in prior performance assessments should be associated with earlier bonus timing. This has two implications, which we test in turn.

First of all, the result implies that stronger heterogeneity in team performance should result in a higher fraction of early bonuses. The key reason is that in heterogeneous teams relative performance differences become obvious earlier on.

First, we thus test whether a spread in performance is indeed associated with awarding earlier spot bonuses. To test this, we use data from individual annual performance ratings. These ratings vary on a scale from 1 (worst) to 5 (best) and most employees receive a 3. We can access the 2019 ratings to construct three measures for performance differences, i.e. whether there is any spread in the performance ratings[33], the performance spread (maximum rating in the team - minimum rating in the team), and the standard deviation of performance ratings within the team. Subsequently, we regress the mean month in which a supervisor awards spot bonuses on these measures of dispersion. Table 2.1

[30]The model does not make a specific prediction on the shape of the distribution over time. Numerical simulations for instance show that depending on the parameters the shape can be concave or convex where convex shapes occur when signals are very noisy as there is more reason to delay in this case.

[31]Indeed, a model where supervisors do not aim to match bonuses to the most deserving performance events but rather to the most deserving employees (i.e. these with the highest total performance over the whole year) would predict that all bonuses are awarded at the last moment.

[32]For this other company we do not have access to further personnel and survey data. Hence, in our subsequent analysis of mechanisms we focus on our main study firm.

[33]50% of supervisors do not have any rating spread in 2019. Of these 78% gave all their employees the rating 3 on the scale from 1 to 5.

Table 2.1: Performance Rating Spread

| | *Mean Month of Spot Bonuses Awarded$_i$* | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| *Any Spread Dummy$_i$* | -0.360** | | |
| | (0.166) | | |
| *Rating Spread$_i$* | | -0.242** | |
| | | (0.111) | |
| *Standard Deviation$_i$* | | | -0.443* |
| | | | (0.252) |
| *Mean Rating 2019$_i$* | 0.041 | 0.010 | -0.073 |
| | (0.215) | (0.214) | (0.258) |
| Controls | Yes | Yes | Yes |
| Clustered at | Planner | Planner | Planner |
| Number of Clusters | 436 | 436 | 339 |
| Observations | 632 | 632 | 477 |
| Adjusted R-squared | 0.016 | 0.015 | 0.016 |

**Note:** This table reports results on how the mean month in which supervisors award spot bonuses varies depending on the performance spread. The independent variable is a dummy for whether there was any difference in performance rating 2019 for the employees in the team (column (1)), the performance rating spread in the team, i.e. the difference between maximum and minimum rating (column (2)), or the standard deviation in performance ratings in the team. Performance ratings are on a scale from 1 to 5. We control for supervisor age, gender and level. The observations are at the supervisor level where *i* refers to a supervisor. Standard errors are clustered at the planner level, and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

shows the results. Notably, all three measures of performance differences are negatively correlated with the mean month in which supervisors award spot bonuses. Hence, in line with the model's prediction supervisors award spot bonuses earlier when confronted with greater disparities in performance among their team members.

A second implication of the formal result is that supervisors with a better prior knowledge should award spot bonuses earlier. When managers know more about the expected performance of individual agents they need less time to acquire sufficient information to assign a bonus.

To test this, we use three different measures. First, we examine the respective manager's tenure, reasoning that supervisors with more organizational experience are likely to better know their subordinate employees and to possess a more comprehensive understanding of what constitutes outstanding performance. Second, we use cases where new supervisors join the organization. Those new supervisors likely have very little prior knowledge on their subordinates' strengths and weaknesses. Thirdly, we use the cases in which new team members joined. While the latter measure may not directly influence the supervisor's understanding of organizational performance standards,

Table 2.2: Tenure and Spot Bonus Timing

| | *Mean Month of Spot Bonuses Awarded$_{it}$* | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| *Tenure$_{it}$* | -0.018*** | | |
| | (0.006) | | |
| *New Manager$_{it}$* | | 0.297* | |
| | | (0.162) | |
| *New Employees$_{it}$* | | | 0.219 |
| | | | (0.199) |
| Controls | Yes | Yes | Yes |
| Clustered at | Planner | Planner | Planner |
| Number of Clusters | 709 | 381 | 709 |
| Observations | 3,505 | 1,698 | 3,505 |
| Adjusted R-squared | 0.049 | 0.058 | 0.044 |

**Note:** This table reports results on how the mean month in which supervisors award spot bonuses varies depending on the supervisor's tenure and whether there are new members in the team. The independent variable is supervisor tenure in months (measured in December of the year)(column (1)), a dummy whether the supervisor joined the company the year before the one in which we observe the spot bonuses or in January of the same year, i.e. before the spot bonus system opens, excluding all supervisors that joined in the current year after January (column (2)) or a dummy whether newly hired team members joined in the year or not (column (3)). We control for team size, supervisor age, gender, level, function (production or not) and region. The observations are at the supervisor-year level where $i$ refers to a supervisor and $t$ refers to a year. Standard errors are clustered at the planner level, and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

supervisors need to get to know the new team members in order to assess who are the best performers within the team. Table 2.2 shows the results for regressions of the mean month in which supervisors award spot bonuses on these three measures. We include all years from 2016 to 2019. Consistent with the predictions of our model, we see a significant negative relation between tenure and the average spot bonus award month. Thus, the longer a supervisor is in the organization, the earlier he or she awards spot bonuses (column (1)). As column (2) shows, managers who had joined the company in the year before or prior to the opening of the spot bonus system in the same year award bonuses later (column (2)). We see the same albeit weaker and not statistically significant pattern for newly hired team members joining (column (3)).[34] This suggests a tendency for supervisors to award spot bonuses earlier when having a better prior knowledge on employee performance.

In summary, our findings provide empirical support for the model's prediction that supervisors with better prior knowledge on performance of their teams award earlier spot bonuses.

[34]The results are qualitatively the same if we use new team members, i.e. also defining team members as new if they changed teams within the company.

## 2.5 Alternative Mechanisms

### 2.5.1 Expert Survey

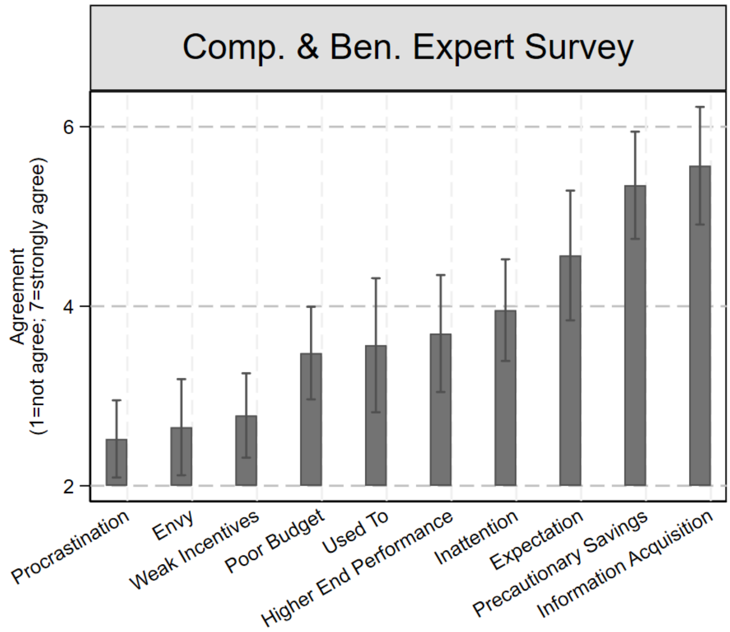



Figure 2.2: Mechanism Relevance Evaluation by Comp. & Ben. Experts

**Note:** This graph plots the mean perceived applicability of the different proposed mechanisms for the timing pattern we find for the spot bonus awards of a sample of compensation and benefit experts in Germany (n=23).

So far, the analysis has shown that more bonuses are awarded later in a year and we also provided evidence for more specific implications of the proposed *information acquisition* mechanism. Nonetheless, it is reasonable to assume that alternative mechanisms also contribute to the observed delay in bonus payments. To get a first idea about the potential relative importance of these alternative mechanisms we first ran an online survey among German compensation and benefits experts directly asking them for their opinion on reasons for the observed time pattern in bonus assignments. In cooperation with the German Association for Human Resource Management (DGFP), we distributed the link to the survey to a mailing list of 200 compensation and benefits professionals in large German companies. We obtained 23 complete responses.

To elicit these expert opinions, we depicted the observed time pattern and asked the respondents to rate the relative importance of ten different reasons for the higher likelihood of late bonus awards. We compiled this list by collecting ideas in the research team as well as based on in depth conversations with practitioners from our study firm as well as other firms on the issue. Table 2.3 shows the exact wording of the question and listed reasons. Participants were asked to what extent they perceived the reason to be applicable on a scale from 1 (does not apply at all) to 7 (fully applicable). Figure 2.2 shows the mean level of agreement of the experts.

Table 2.3: Wording Mechanisms

| Mechanism | Description "Supervisors rather award bonuses at the end of the year, because..." |
|---|---|
| Information Acquisition | ...they first want to wait for the entire budget period to determine which services deserve a spot bonus |
| Inattention | ...they do not think about awarding spot bonuses during the year |
| Procrastination | ...they shy away from the effort of awarding spot bonuses and therefore postpone them |
| Envy | ...they want to reduce envy within the team |
| Precautionary Savings | ...they save during the year in order to retain flexibility when awarding spot bonuses in case of unforeseen events (e.g. very good performance) |
| Poor Budget | ...the budget calculation is inaccurate and there is too much money left over at the end of the year |
| Weak Incentives | ...early bonuses reduce the incentive to perform well later in the year. |
| Higher End Performance | ...employee performance is higher at the end of the budget period |
| Expectation | ...employees expect a bonus at the end of the budget period |
| Used To | ...they are used to awarding a bonus at the end of the budget period |

On average, the experts displayed the highest agreement with the *information acquisition* channel. Nearly as much agreement, on average, received the *precautionary savings* mechanism whereby supervisors engage in saving throughout the year to have enough budget left at the end of the year for unforeseen events (e.g. very good performance). The mechanisms with the third highest agreement is *expectation*, positing that supervisors delay spot bonus allocation as employees expect to receive spot bonuses at the end of the year. *inattention* received the fourth highest agreement suggesting that supervisors do not pay sufficient attention to spot bonus allocation during the year. The experts exhibited lower levels of agreement with mechanisms proposing that there is actually more high performance at the end of the year (*higher end performance*), supervisors are used to awarding spot bonuses late (*used to*) or an unfitting budget allocation leading to excess budget at the end of the year (*poor budget*). The mechanisms receiving the least agreement were (*procrastination*) during the year, worries that early bonuses would weaken the incentives for employees to perform well (*weak incentives*) and (*envy*) in the team.

We further offered an open text field for further mechanisms that they think might be playing a role for this finding. This let to one additional suggestion of using a spot bonus as a consolation price if there was no salary increase in the year. However, as our study firm carries out its annual salary increase process in spring, this cannot explain our findings.

### 2.5.2 Discussion of Mechanisms

In the following, we discuss several of the alternative mechanisms, which the experts also perceived as applicable apart from the *information acquisition* mechanism.

**Precautionary savings:** We note that our formal model entails also elements of a precautionary savings motive: Supervisors anticipate that they will have more precise information later on and thus reserve larger parts of the budgets for later bonus payments. However, in contrast to typical models of precautionary savings in the budgeting literature, in our model, supervisors are not risk averse and future expenditure needs can be accurately predicted. But of course, risk aversion and imperfect predictability are important behavioral drivers and thus it appears worthwhile to discuss their implications. Such a *precautionary savings* mechanism suggests that supervisors allocate relatively smaller spot bonuses at the beginning of the budget period in order to save budget. To test this implication, we regress the mean spot bonus size the supervisor awards in a month on the month in which they award it. Column (1) in Table 2.4 shows the results. Contrary to what this mechanism suggests, we find that bonuses allocated later in the year tend to be smaller than those allocated earlier. Using a binary split between early (February to October) and late (November-December) spot bonuses, we observe the same trend. Thus, – while we do not want to claim that the precautionary savings motive plays no role in our setting – it appears unlikely that it is the key driver of bonus delay.[35]

[35]Recall that in our formal model of information acquisition, we assumed that bonuses are constant in size. However, within the model, the required size of the observed signal leading to a bonus is larger in earlier periods. This suggests that a pattern where earlier bonuses are less frequent but larger when awarded can be consistent with a model where bonus size is a function of the observed signals.

Table 2.4: Spot Bonus Size

| | *Mean Spot Bonus Size$_{it}$* | |
|---|---|---|
| | (1) | (2) |
| *Month$_t$* | -0.034$^{***}$ | |
| | (0.008) | |
| *End Year$_t$* | | -0.209$^{**}$ |
| | | (0.082) |
| Constant | 2.986$^{***}$ | 2.835$^{***}$ |
| | (0.074) | (0.042) |
| Clustered at | Planner | Planner |
| Number of Clusters | 682 | 541 |
| Observations | 3,893 | 1,660 |
| Adjusted R-squared | 0.791 | 0.561 |

**Note:** This table reports results on how the mean size of spot bonuses supervisors award varies between the months they are awarded and during the year vs end of year respectively. The dependent variable is mean spot bonus size, which is defined as the mean bonus amount in percent of a supervisor's employees' annual salaries. The independent variable is the month the spot bonus is awarded (column (1)) or an indicator for whether the spot bonus was awarded during the year (i.e., February-October) (column (2)). Employees who do not receive a spot bonus are not included in this table. The observations are at the supervisor where $i$ refers to a supervisor and $t$ refers to the time, i.e. month or during vs late. Standard errors are clustered at the planner level, and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

**Expectations:** To investigate the *expectations* mechanism, we revisited the timing of the company's regular annual bonus. It is important to note that the company-wide bonus is paid out in spring each year based on overall financial success. Consequently, there is no tradition to pay out bonuses in November/December where most spot bonus payments are paid out. It thus appears very unlikely that the year-end spike has developed due to timing expectations shaped by regular bonus payments. To provide complementary evidence, we can further look again at column (3) in Table 2.2 to consider the timing of spot bonuses to newly hired employees. If past expectations was the main driver of bonus delay, we should observe a lower number of bonuses for this group at the end of the year as these new hires should not have expectations regarding bonus timing. However, if anything, new employees tend to receive more rather than less spot bonuses at the end of the year .

**Inattention:** To investigate the *inattention* mechanism as a potential driver of spot bonus delay, we conducted a field experiment during the summer of 2021. The study firm sent a reminder email to a randomly chosen subset of around half of the supervisors. The reminder email served the key purpose to draw attention to the spot bonus system and its intended benefits (Barron et al., 2022). The reminder was sent just after the second quarter of 2021 ended (July 1, 2021).[36] See Figure 2.6 in Appendix 2.10 for the exact wording of the reminder email. To avoid spillovers arising from conversations between supervisors, we assigned all supervisors in the same function and location to the same treatment. Furthermore, we used a stratified randomization procedure based on region, whether the function is production or not, as well as dummies for very large organizational units. Table 2.11 in Appendix 2.10 presents the experimental results. In column (1), we regress the share of bonuses that a supervisor awards in the third quarter, i.e. in the quarter immediately following the reminder, on a dummy indicating whether the supervisor is part of the treatment group. Column (2) additionally controls for the share of spot bonuses the supervisor awarded in the second quarter, a dummy for the managerial level as well as strata dummies. We find no evidence that the reminder intervention had a discernible effect on the assignment of bonus payments. Even though we acknowledge, that the email reminder may not have generated full attention for the importance to assign timely bonuses as these emails may have been overlooked by some recipients, it should at least have raised this attention on average. The fact that the point estimate is not only insignificant but also very close to zero indicates that it is unlikely that delayed bonus payments are due to a lack of attention for the topic during the year.

**Higher end year performance:** As already laid out in section 2.4.1, the firm's business operations exhibit no seasonal variations. While the industry in which the firm is operating is subject to cyclical variations due to fluctuations in both customer demand and supply by competitors over time, these cyclical variations appear to be uncorrelated to the month of the year. Hence, while indeed in some industries revenues may by seasonal which could explain specific annually recurring time patterns in realized performance outcomes, there is no indication that this is the case in our study firm.

## 2.6 Is the Timing also Optimal from the Firm's Perspective?

The empirical results described above support the predictions from our analytical Bayesian learning model. Hence, manager's spot bonus assignment appears to be consistent with rational behavior on their side. But a key question is whether this behavior is also optimal from the firm's perspective. After all, the firm uses the system to provide timely recognition to its employees and prior research in organizational behavior indeed documents benefits of immediate as opposed to delayed feedback (e.g., Berger and Ludwig, 2007; Dihoff et al., 2004; Mason and Redmon, 1993; Northcraft et al., 2011; Reid and Parsons, 1996). Thus, the delayed timing may generate a tension between this aim and the managers' rational motive to postpone bonus awards to collect more information.

[36]Due to a change in the process of administering spot bonuses, bonuses in 2021 could only be awarded starting from April 2021.

To asses this question, we examine the association between bonus timing and employee attitudes measured with the surveys described in section 2.3.4 , specifically focusing on perceived employee recognition, job satisfaction, and engagement.

Perceived employee recognition is measured as the average of the two items: "My supervisor personally compliments me when I do outstanding work", and "If I improve my performance, my supervisor is going to notice it".[37] Job satisfaction is measured by three items taken from Hackman and Oldham (1975) ("Generally speaking, I am very satisfied with this job", "I am generally satisfied with the kind of work I do in this job", and the reverse coded "I frequently think about leaving this job"). We measure engagement as the average of three items taken from Rich et al. (2010) ("I try my hardest to perform well on my job", "I feel energetic at my job", and "At work, I focus a great deal of attention on my job"). If an employee participated in both surveys, we average the responses in both surveys.[38] Cronbach's Alpha for the respective scales is $\alpha = .89$ for recognition, $\alpha = .87$ for job satisfaction, and $\alpha = .83$ for engagement.

We regress the standardized (z-scored) recognition, job satisfaction, and engagement that employees report in the 2020 surveys on spot bonus data from 2019.[39] Our key independent variables include whether an employee received a spot bonus in 2019 as well as the interaction with the month since the beginning of the spot bonus period in which the employee received the spot bonus, i.e. month 0 for February, month 1 for March, etc. We drop employees who receive more than one spot bonus in 2019 (less than 5% of employees, see Table 2.8 in Appendix 2.10). Accordingly, the comparison group is the group of employees who responded to our 2020 surveys but did not receive a spot bonus in 2019. In the regressions, we include as additional control variables function, tenure, and managerial level, spot bonus size (0 for non-recipients).

As bonus timing is of course not endogenously determined, it is of course important to consider potential causes for omitted variable bias. Our data allows us to address two key potential sources of such a bias. First, it is conceivable that more capable managers award earlier bonuses and at the same time provide stronger recognition through other means beyond the spot bonus. To eliminate this concern we only use the within-supervisor variation in bonus timing by including supervisor fixed effects in all regressions.

[37]Item i) is taken from Podsakoff et al. (1984) and item ii) was developed together with the firm when the survey was set up.

[38]We included all job satisfaction items and engagement items in both surveys. The same is true for recognition item ii), i.e., "If I improve my performance, my supervisor is going to notice it". In contrast, recognition item i) was measured only in the second survey. However, we asked respondents to answer question i) twice, once regarding the current situation, and once regarding the time when the first survey was conducted (backward-looking). To improve measurement reliability, we averaged these four variables to calculate the final recognition variable. Our results are robust to using only three of the four variables, i.e., excluding the backward-looking measure of item i).

[39]The spot bonus system was paused in 2020 due to the Covid pandemic, and reinstated in 2021. Hence, our results cannot be driven by employees receiving a spot bonus shortly before our surveys in 2020.

Another key concern is that higher performing employees receive bonuses earlier and at the same time experience higher levels of recognition independent of the spot bonus award, which would lead to a correlation between early bonuses and recognition. To address this concern we include the mean performance rating over the years 2019-2021 as a control variable. We cluster standard errors at the planner level in all specifications.

Table 2.5: The Relationship between Spot Bonus Timing and Employee Attitudes

| | *Recognition$_i$* | | *Job Satisfaction$_i$* | | *Engagement$_i$* | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Spot Bonus$_i$* | 0.160 | 0.540*** | 0.402*** | 0.512*** | 0.263** | 0.247 |
| | (0.110) | (0.186) | (0.106) | (0.185) | (0.124) | (0.225) |
| *Spot Bonus$_i$ $\times$ Month$_i$* | | -0.047** | | -0.014 | | 0.002 |
| | | (0.021) | | (0.021) | | (0.023) |
| *Mean Performance Rating$_i$* | 0.186** | 0.186** | 0.234*** | 0.234*** | 0.135 | 0.135 |
| | (0.073) | (0.073) | (0.076) | (0.077) | (0.083) | (0.083) |
| *Spot Bonus Size$_i$* | 0.013 | 0.009 | -0.039* | -0.040* | -0.020 | -0.020 |
| | (0.024) | (0.024) | (0.022) | (0.022) | (0.029) | (0.029) |
| Additional Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Supervisor Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Clustered at | Planner | Planner | Planner | Planner | Planner | Planner |
| Number of Clusters | 249 | 249 | 249 | 249 | 249 | 249 |
| Observations | 1,076 | 1,076 | 1,076 | 1,076 | 1,076 | 1,076 |
| Adjusted R-squared | 0.124 | 0.129 | 0.122 | 0.121 | 0.122 | 0.121 |

**Note:** This table reports results of regressions where we regress an employee's self-reported standardized (using Z-scores) recognition, job satisfaction, and engagement in 2020 on spot bonus timing in 2019. Specifically, we use an indicator whether an employee received a spot bonus in 2019 as well as the interaction with the spot bonus period month (i.e. February being month 0, March month 1, etc.) in which the employee received the spot bonus. The independent variables are based on HR data as of December 2019. Next to spot bonus size, we control for an employee's age, gender, region, function (indicator if in production), level, company tenure, team size (headcount managed by the same supervisor), and the underlying performance measured as mean of the performance ratings from 2019 to 2021. We furthermore include supervisor fixed effects in all columns. Standard errors are clustered at the planner level, and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.5 provides the respective regression results. First, note that when we disregard the timing (i.e. in columns (1), (3) and (5), job satisfaction, and engagement are significantly higher for employees who receive a spot bonus in comparison to those who do not receive a spot bonus but this is not the case for recognition.

Employees perceive significantly higher recognition (only) when they receive a bonus early on. Also, recognition among employees who receive a spot bonus early is significantly higher than recognition among employees who do so at the end of the year. Employees who receive a spot bonus throughout the year 2019 thus report a significantly higher perceived recognition in spring 2020 than those having received a bonus at the end of 2019 – even though less time elapsed between the bonus payout and the date at which the survey was run for the latter. This pattern is in line with the view that timely spot bonuses indeed serve their intended role to provide more effective employee recognition. Thus, while the late awarding of spot bonuses is rational according to our information acquisition model, it does not seem to be necessarily optimal given the firm's stated objective of increasing recognition.

The delayed timing appears to be less of an issue when considering job satisfaction and engagement where we find little evidence for drawbacks due to delay. Controlling for performance assessments employees are more satisfied and exhibit higher engagement if they receive a bonus rather independently from when this is the case.

Finally, note that there is no systematic association between the size of the spot bonus and either recognition or engagement and only a weak association with job satisfaction. Hence, it is the incidence and – for employee recognition – the timing rather than the actual size of the bonus that appear to affect employee attitudes.

In conclusion, while the behavior of managers in the timing of spot bonus assignment is well in line with rational information acquisition, it may not necessarily represent the optimal approach from the firm's perspective when the key aim is to provide employee recognition. In that case the delayed bonus payouts may undermine this objective as employees potentially see less of a connection between their actions and awarded bonuses.

## 2.7 Conclusion

We study the timing of discretionary bonus payments. Consistent with our analytical model of information acquisition, we find that managers award bonuses more often late rather than early in the bonus period. Furthermore, in line with the model, we find that managers award bonuses earlier when there are greater disparities in performance among their team members and when managers are more experienced.

When consulting compensation experts about the timing pattern of spot bonuses, these experts also assess information acquisition as the most prominent motive behind bonus delay.

While the predicted behavior of managers is thus well in line with rational information acquisition, it may not be optimal from the firm's perspective when the aim is to provide timely recognition: Using employee survey data, we indeed provide evidence that employees report higher levels of recognition if they receive a spot bonus early rather than at the end of the budget period.[40]

[40] Future research, beyond the scope of this paper, should aim at investigating specific behavioral drivers behind this effect. It is important to determine whether the effect arises, for instance, from employees being surprised or because the recognition was timely (e.g., Lurie and Swaminathan, 2009).

The fact that simple nudges did not reduce bonus delay at all, support the view that delay is indeed a deliberate choice by managers. This, in turn, suggests that firms must change accompanying budgeting procedures or find other ways to more actively manage the assignment of spot bonuses if they indeed want to use spot bonuses to promote more timely recognition. One approach could be to provide quarterly or half-year budgets. While this might still lead to spending spikes at the end of the respective budget period, it would force managers to distribute bonuses more evenly and thus to provide more timely rewards.[41]

Our formal model also suggests a complementary approach: As we have shown, managers rationally award bonuses earlier when they can make use of prior information on their employees' performance, as it becomes easier to justify outstanding performance early in the budget period. Conversely, managers tend to delay bonus payments more when they rely solely information acquired during the budget period.[42] Hence, it appears worthwhile for firms to emphasize that the process of information acquisition should not be limited to the information collected within the budget period, but should also incorporate prior information. In other words, while budgets or guidelines on who should receive a bonus (e.g. the top 30% performers in a year) might be necessary to cap bonus spending, the process of information acquisition should ideally be decoupled from the budget period. Of course, it is again an empirical question to test (i) whether such decoupling works and (ii) how it can be achieved most effectively. The design of processes to achieve this goal will be an interesting endeavor for future research on managerial discretion over bonus timing.

[41]More timely recognition may increase the frequency of feedback provided to employees. While recognition in general can be beneficial for the organization (e.g., Burke et al., 2017; Lourenço, 2016) it has to be noted that providing feedback too frequently can be problematic (e.g., Casas-Arce et al., 2017; Hecht et al., 2020; Holderness Jr et al., 2020; Lurie and Swaminathan, 2009; Waddoups, 2022). Hence, it is interesting question for future research to determine the optimal granularity of such processes.

[42]To see this, note that limiting managers to use only information in the budget period corresponds to forcing them to use a symmetric prior, i.e. having $\sigma_m^2 = 0$ which by Proposition 2 leads to late bonus assignments. By the same token, if managers learn worker's abilities $a$ perfectly over time and make use of this information the model predicts no delay, i.e. a uniform distribution of bonuses over time when $\sigma_r^2 = 0$ by Proposition 1.

## 2.8 References


Abernethy, M. A., Hung, C.-Y., & van Lent, L. (2020). Expertise and discretionary bonus decisions. *Management Science*, *66*(1), 415–432.

Baiman, S., & Rajan, M. V. (1995). The informational advantages of discretionary bonus schemes. *The Accounting Review*, 557–579.

Balakrishnan, R., Soderstrom, N. S., & West, T. D. (2007). Spending patterns with lapsing budgets: Evidence from us army hospitals. *Journal of Management Accounting Research*, *19*(1), 1–23.

Barron, K., Damgaard, M., & Gravert, C. A. (2022). *When do reminders work? memory constraints and medical adherence* (tech. rep.). CESifo Working Paper No. 9996.

Baumann, S. (2019). Putting it off for later: Procrastination and end of fiscal year spending spikes. *The Scandinavian Journal of Economics*, *121*(2), 706–735.

Berger, S. M., & Ludwig, T. D. (2007). Reducing warehouse employee errors using voice-assisted technology that provided immediate feedback. *Journal of Organizational Behavior Management*, *27*(1), 1–31.

Birnberg, J. G., & Shields, M. D. (1984). The role of attention and memory in accounting decisions. *Accounting, Organizations and Society*, *9*(3-4), 365–382.

Block, S., Opitz, S., Sliwka, D., & Vogelsang, T. (2024). Discretion over bonus timing. *Available at SSRN 4322361*.

Bol, J. C. (2011). The determinants and performance effects of managers' performance evaluation biases. *The Accounting Review*, *86*(5), 1549–1575.

Bol, J. C., Hecht, G., & Smith, S. D. (2015). Managers' discretionary adjustments: The influence of uncontrollable events and compensation interdependence. *Contemporary Accounting Research*, *32*(1), 139–159.

Bol, J. C., Keune, T. M., Matsumura, E. M., & Shin, J. Y. (2010). Supervisor discretion in target setting: An empirical investigation. *The Accounting Review*, *85*(6), 1861–1886.

Bol, J. C., & Smith, S. D. (2011). Spillover effects in subjective performance evaluation: Bias and the asymmetric influence of controllability. *The Accounting Review*, *86*(4), 1213–1230.

Boosey, L., & Goerg, S. (2020). The timing of discretionary bonuses–effort, signals, and reciprocity. *Games and Economic Behavior*, *124*, 254–280.

Bordalo, P., Gennaioli, N., & Shleifer, A. (2022). Salience. *Annual Review of Economics*, *14*, 521–544.

Burke, J., Hecht, G., & Stern, M. (2017). *The effects of anticipation and recognition source in employee recognition programs* (tech. rep.). Available at SSRN 2823837.

Cai, W., Gallani, S., & Shin, J.-E. (2023). Incentive effects of subjective allocations of rewards and penalties. *Management Science*, *69*(5), 3121–3139.

Casas-Arce, P., Lourenço, S. M., & Martínez-Jerez, F. A. (2017). The performance effect of feedback frequency and detail: Evidence from a field experiment in customer satisfaction. *Journal of Accounting Research*, *55*(5), 1051–1088.

Das, S. (2020). Reward your employees — without breaking the bank [*Harvard Business Review*. Available at: https://hbr.org/2020/08/reward-your-employees-without-breaking-the-bank. Accessed January 26th, 2022].

Dihoff, R. E., Brosvic, G. M., Epstein, M. L., & Cook, M. J. (2004). Provision of feedback during preparation for academic testing: Learning is enhanced by immediate but not delayed feedback. *The Psychological Record*, *54*(2), 207–231.

Eichenauer, V. (2020). *December fever in public finance* (tech. rep.). KOF Working Papers No. 470. KOF Swiss Economic Institute, ETH Zurich.

Fitzenberger, B., Furdas, M. D., & Sajons, C. (2016). *End-of-year spending and the long-run employment effects of training programs for the unemployed* (tech. rep.). IZA Discussion Paper No. 10441.

Gibbs, M., Merchant, K. A., Stede, W. A. V. d., & Vargus, M. E. (2004). Determinants and effects of subjectivity in incentives. *The Accounting Review*, *79*(2), 409–436.

Grabner, I., Künneke, J., & Moers, F. (2020). How calibration committees can mitigate performance evaluation bias: An analysis of implicit incentives. *The Accounting Review*, *95*(6), 213–233.

Green, C., & Heywood, J. S. (2008). Does performance pay increase job satisfaction? *Economica*, *75*(300), 710–728.

Hackman, J. R., & Oldham, G. R. (1975). Development of the job diagnostic survey. *Journal of Applied Psychology*, *60*(2), 159–170.

Hecht, G., Hobson, J. L., & Wang, L. W. (2020). The effect of performance reporting frequency on employee performance. *The Accounting Review*, *95*(4), 199–218.

Holderness Jr, D. K., Olsen, K. J., & Thornock, T. A. (2020). Assigned versus chosen relative performance information: The effect of feedback frequency on performance. *Journal of Management Accounting Research*, *32*(1), 137–158.

Höppe, F., & Moers, F. (2011). The choice of different types of subjectivity in ceo annual bonus contracts. *The Accounting Review*, *86*(6), 2023–2046.

Kampkötter, P., & Sliwka, D. (2018). More dispersion, higher bonuses? on differentiation in subjective performance evaluations. *Journal of Labor Economics*, *36*(2), 511–549.

Kulikowski, K. (2018). The model of relationships between pay for individual performance and work engagement. *Career Development International*, *23*(4), 427–443.

Kusterer, D., & Sliwka, D. (2024). Social preferences and rating biases in subjective performance evaluations. *Management Science*, *forthcoming*.

Liebman, J. B., & Mahoney, N. (2017). Do expiring budgets lead to wasteful year-end spending? evidence from federal procurement. *American Economic Review*, *107*(11), 3510–3549.

Lourenço, S. M. (2016). Monetary incentives, feedback, and recognition—complements or substitutes? evidence from a field experiment in a retail services company. *The Accounting Review*, *91*(1), 279–297.

Lurie, N. H., & Swaminathan, J. M. (2009). Is timely information always better? the effect of feedback frequency on decision making. *Organizational Behavior and Human Decision Processes*, *108*(2), 315–329.

Maas, V. S., Van Rinsum, M., & Towry, K. L. (2012). In search of informed discretion: An experimental investigation of fairness and trust reciprocity. *The Accounting Review*, *87*(2), 617–644.

Manthei, K., & Sliwka, D. (2019). Multitasking and subjective performance evaluations: Theory and evidence from a field experiment in a bank. *Management Science*, *65*(12), 5861–5883.

Manthei, K., Sliwka, D., & Vogelsang, T. (2023a). Information, incentives, and attention: A field experiment on the interaction of management controls. *The Accounting Review*, *98*(5), 455–479.

Mason, M. A., & Redmon, W. K. (1993). Effects of immediate versus delayed feedback on error detection accuracy in a quality control simulation. *Journal of Organizational Behavior Management*, *13*(1), 49–83.

Moers, F. (2005). Discretion and bias in performance evaluation: The impact of diversity and subjectivity. *Accounting, Organizations and Society*, *30*(1), 67–80.

Northcraft, G. B., Schmidt, A. M., & Ashford, S. J. (2011). Feedback and the rationing of time and effort among competing tasks. *Journal of Applied Psychology*, *96*(5), 1076–1086.

PayPal. (2024). Recognition awards (spot awards) [Accessed March 21st, 2024]. https://www.paypalbenefits.com/chi/family-support/recognition

PayScale. (2021). 2021 compensation best practices report [Accessed January 26th, 2022]. https://www.payscale.com/research-and-insights/cbpr/

Podsakoff, P. M., Todor, W. D., Grover, R. A., & Huber, V. L. (1984). Situational moderators of leader reward and punishment behaviors: Fact or fiction? *Organizational Behavior and Human Performance*, *34*(1), 21–63.

Pollack, H., & Zeckhauser, R. (1996). Budgets as dynamic gatekeepers. *Management Science*, *42*(5), 642–658.

Pouliakas, K. (2010). Pay enough, don't pay too much or don't pay at all? the impact of bonus intensity on job satisfaction. *Kyklos*, *63*(4), 597–626.

Rajan, M. V., & Reichelstein, S. (2006). Subjective performance indicators and discretionary bonus pools. *Journal of Accounting Research*, *44*(3), 585–618.

Rajan, M. V., & Reichelstein, S. (2009). Objective versus subjective indicators of managerial performance. *The Accounting Review*, *84*(1), 209–237.

Reid, D. H., & Parsons, M. B. (1996). A comparison of staff acceptability of immediate versus delayed verbal feedback in staff training. *Journal of Organizational Behavior Management*, *16*(2), 35–47.

Rich, B. L., Lepine, J. A., & Crawford, E. R. (2010). Job engagement: Antecedents and effects on job performance. *Academy of Management Journal*, *53*(3), 617–635.

Siemroth, C. (2022). Ending wasteful year-end spending: On optiomal budget rules in organizations. *International Economic Review*, *forthcoming*.

UC-Berkeley. (2024). Spot awards [Accessed March 21st, 2024]. https://hr.berkeley.edu/compensation-benefits/compensation/recognition/spot-awards

Vogelsang, T. (2024). Time is (not) money: Incentive effects of granting leisure time. *European Accounting Review*, *33*(2), 435–459.

Waddoups, N. (2022). Feedback-driven time segmenting: The effect of feedback frequency on employee behavior. *Contemporary Accounting Research*, *39*(3), 1516–1541.

Woods, A. (2012). Subjective adjustments to objective performance measures: The influence of prior performance. *Accounting, Organizations and Society*, *37*(6), 403–425.

WorldAtWork. (2014). Bonus programs and practices [Accessed January 26th, 2022]. https://www.worldatwork.org/resources/research/surveys/bonus-programs-and-practices

Zimmerman, J. L. (1976). Budget uncertainty and the allocation decision in a nonprofit organization. *Journal of Accounting Research*, *14*(2), 301–319.

## 2.9 Appendix: A Formal Model

**Proof of Lemma 1:**
Note that by a standard result on sampling from a normal distribution (see e.g. DeGroot (1970, pp. 166) and Holmström, 1999) before period $t$ the conditional distribution of $a_i$ given the signals $s_{i1}, ..s_{it-1}$ is a normal distribution with expected value

$$m_{it-1} = m_i + \frac{\sigma_r^2 \sum_{\tau=1}^{t-1} (s_{i\tau} - m)}{\sigma_\eta^2 + \sigma_\varepsilon^2 + \sigma_r^2 (t-1)}$$

and variance

$$\sigma_{it-1}^2 = \frac{\left(\sigma_\varepsilon^2 + \sigma_\eta^2\right) \sigma_r^2}{\sigma_\varepsilon^2 + \sigma_\eta^2 + (t-1) \sigma_r^2}.$$

To determine $E_{it} \left[a_i + \eta_{it} \left| a_i + \eta_{it} + \varepsilon_{it} \right.\right]$ we can now apply the result that if two random variables $X$ and $Y$ are jointly normal then $E[Y\ X|] = E[Y] + \frac{Cov[X,Y]}{V[X]} (X - E[X])$ to obtain

$$\begin{aligned} E_{it} \left[a_i + \eta_{it} \left| a_i + \eta_{it} + \varepsilon_{it} \right.\right] &= m_{it-1} + \frac{\sigma_{it-1}^2 + \sigma_\eta^2}{\sigma_{it-1}^2 + \sigma_\eta^2 + \sigma_\varepsilon^2} (s_{it} - m_{it-1}) \\ &= \frac{\sigma_\varepsilon^2}{\sigma_{it-1}^2 + \sigma_\eta^2 + \sigma_\varepsilon^2} m_{it-1} + \frac{\sigma_{it-1}^2 + \sigma_\eta^2}{\sigma_{it-1}^2 + \sigma_\eta^2 + \sigma_\varepsilon^2} s_{it}. \end{aligned}$$

By substituting $m_{it-1}$ and $\sigma_{it-1}^2$ this becomes

$$\begin{aligned} & \frac{\sigma_\varepsilon^2}{\frac{\left(\sigma_\varepsilon^2+\sigma_\eta^2\right)\sigma_r^2}{\sigma_\varepsilon^2+\sigma_\eta^2+(t-1)\sigma_r^2}+\sigma_\eta^2+\sigma_\varepsilon^2} \left(m_i + \frac{\sigma_r^2 \sum_{\tau=1}^{t-1}(s_{i\tau}-m_i)}{\sigma_\eta^2+\sigma_\varepsilon^2+\sigma_r^2(t-1)}\right) + \frac{\frac{\left(\sigma_\varepsilon^2+\sigma_\eta^2\right)\sigma_r^2}{\sigma_\varepsilon^2+\sigma_\eta^2+(t-1)\sigma_r^2}+\sigma_\eta^2}{\frac{\left(\sigma_\varepsilon^2+\sigma_\eta^2\right)\sigma_r^2}{\sigma_\varepsilon^2+\sigma_\eta^2+(t-1)\sigma_r^2}+\sigma_\eta^2+\sigma_\varepsilon^2} s_{it} \\ = \ & m_i + \frac{\sigma_r^2\sigma_\varepsilon^2}{\left(\sigma_\varepsilon^2+\sigma_\eta^2\right)\left(\sigma_\varepsilon^2+\sigma_\eta^2+t\sigma_r^2\right)} \sum_{\tau=1}^{t-1} (s_{i\tau} - m_i) + \frac{\sigma_\eta^2\left(\sigma_\varepsilon^2+\sigma_\eta^2+t\sigma_r^2\right)+\sigma_r^2\sigma_\varepsilon^2}{\left(\sigma_\varepsilon^2+\sigma_\eta^2\right)\left(\sigma_\varepsilon^2+\sigma_\eta^2+t\sigma_r^2\right)} (s_{it} - m_i) \end{aligned}$$

which is equal to

$$= m_i + \frac{\sigma_\eta^2}{\sigma_\varepsilon^2 + \sigma_\eta^2} (s_{it} - m_i) + \frac{\sigma_r^2 \sigma_\varepsilon^2}{\left(\sigma_\varepsilon^2 + \sigma_\eta^2\right)\left(\sigma_\varepsilon^2 + \sigma_\eta^2 + t\sigma_r^2\right)} \sum_{\tau=1}^{t} (s_{i\tau} - m_i). \tag{3}$$

■

**Proof of Lemma 2:**
To compute the variance of (3), first apply the law of total variance to obtain (using that $E\left[\hat{y}_{it} | m_i\right] = m_i$)

$$\begin{aligned} \sigma_{\hat{y}_t}^2 &= V\left[E\left[\hat{y}_{it} | m_i\right]\right] + E\left[V\left[\hat{y}_{it} | m_i\right]\right] \\ &= V[m_i] + V\left[\hat{y}_{it} | m_i\right]. \end{aligned}$$

Hence

$$\sigma_{\hat{y}_t}^2 = \sigma_m^2 + V_i \left[ \frac{\sigma_\eta^2}{\sigma_\eta^2 + \sigma_\varepsilon^2} s_{it} + \frac{\sigma_r^2 \sigma_\varepsilon^2}{\left(\sigma_\eta^2 + \sigma_\varepsilon^2 + \sigma_r^2 t\right)\left(\sigma_\eta^2 + \sigma_\varepsilon^2\right)} \sum_{\tau=1}^{t} s_{i\tau} \right].$$

Using that (for random variables $X$ and $Y$ and constants $a$,$b$) $V[aX + bY] = a^2 V[X] + b^2 V[Y] + 2abCov[X, Y]$ we have

$$\begin{aligned}\sigma_{\hat{y}_t}^2 &= \sigma_m^2 + \left(\frac{\sigma_\eta^2}{\sigma_\eta^2+\sigma_\varepsilon^2}\right)^2 V_i[s_{it}] + \left(\frac{\sigma_r^2\sigma_\varepsilon^2}{(\sigma_\eta^2+\sigma_\varepsilon^2+\sigma_r^2 t)(\sigma_\eta^2+\sigma_\varepsilon^2)}\right)^2 V_i\left[\sum_{\tau=1}^{t}\left(a_i + \eta_{i\tau} + \varepsilon_{i\tau}\right)\right] \\ &\quad + \frac{2\sigma_r^2\sigma_\varepsilon^2\sigma_\eta^2}{(\sigma_\eta^2+\sigma_\varepsilon^2+\sigma_r^2 t)(\sigma_\eta^2+\sigma_\varepsilon^2)^2} Cov_i\left[s_{it}, \sum_{\tau=1}^{t} s_{i\tau}\right]\end{aligned}$$

$$\sigma_{\hat{y}_t}^2 = \sigma_m^2 + \frac{1}{\left(\sigma_\eta^2 + \sigma_\varepsilon^2\right)^2}\left[\sigma_\eta^4\left(\sigma_\eta^2 + \sigma_\varepsilon^2 + \sigma_r^2\right) + 2\sigma_r^2\sigma_\varepsilon^2\sigma_\eta^2 + \frac{\sigma_r^4\sigma_\varepsilon^4}{\frac{\sigma_\eta^2+\sigma_\varepsilon^2}{t} + \sigma_r^2}\right] \tag{4}$$

which is strictly increasing in $t$ if and only if $\sigma_r$ and $\sigma_\varepsilon > 0$. ■

**Proof of Proposition 1:**
As a first step we show that these thresholds $\theta_t$ do not vary over time: As the optimal assignment policy is a threhold policy the objective function is

$$\sum_{t=1}^{T}\left(\int_S I_{\{\hat{y}_{it}>\theta_t\}} \hat{y}_{it} di\right).$$

Suppose that there are two periods $t, t'$ with $\theta_t < \theta_{t'}$. Then $\theta_t$ can be increased and $\theta_{t'}$ lowered while keeping

$$p = \sum_{t=1}^{T}\left(\int_S I_{\{\hat{y}_{it}>\theta_t\}} di\right) = \sum_{t=1}^{T} \Pr\left(\hat{y}_{it} > \theta_t\right)$$

constant which will stricly increase the objective function. Hence, we have that

$$\theta_t = \theta \quad \forall t = 1, ..T.$$

In a next step, note that $\theta - m > 0$. To see this, suppose that $\theta < m$ then $p_t = 1 - \Phi\left(\frac{\theta-m}{\sigma_{\hat{y}_t}}\right) > \frac{1}{2}$ for all periods $t$ and $\sum_{t=1}^{T} p_t > \frac{T}{2} > 1$ which leads to a contradiction. Now note that as $\sigma_{\hat{y}_t}$ is increasing in $t$ we have that

$$p_t = \Pr\left(\hat{y}_{it} > \theta\right) = 1 - \Phi\left(\frac{\theta - m}{\sigma_{\hat{y}_t}}\right)$$

is also increasing in $t$. ■

**Proof of Proposition 2:**

Let $v\left(\sigma_m^2, t\right)$ be the variance of ratings as a function of $\sigma_m^2$ and $t$ as given by (4) and note that $\frac{\partial v\left(\sigma_m^2, t\right)}{\partial \sigma_m^2} = 1$. The share of bonuses awarded in period $t$ is

$$p\left(v\left(\sigma_m^2, t\right), \theta\right) = 1 - \Phi\left((\theta - m)\left(v\left(\sigma_m^2, t\right)\right)^{-\frac{1}{2}}\right)$$

where is $\theta$ implicitly defined by the budget constraint

$$p\left(v\left(\sigma_m^2, 1\right), \theta\right) + p\left(v\left(\sigma_m^2, 2\right), \theta\right) = p.$$

We want to characterize

$$\begin{aligned}
\frac{dp\left(v\left(\sigma_m^2,1\right),\theta\left(\sigma_m^2\right)\right)}{d\sigma_m^2} &= \frac{\partial p\left(v\left(\sigma_m^2,1\right),\theta\right)}{\partial v}\frac{\partial v\left(\sigma_m^2,1\right)}{\partial \sigma_m^2} + \frac{\partial p\left(v\left(\sigma_m^2,1\right),\theta\right)}{\partial \theta}\frac{\partial \theta\left(\sigma_m^2\right)}{\partial \sigma_m^2} \\
&= \frac{\partial p\left(v\left(\sigma_m^2,1\right),\theta\right)}{\partial v} + \frac{\partial p\left(v\left(\sigma_m^2,1\right),\theta\right)}{\partial \theta}\frac{\partial \theta\left(\sigma_m^2\right)}{\partial \sigma_m^2}. \qquad (5)
\end{aligned}$$

where by the implicit function theorem

$$\frac{\partial \theta\left(\sigma_m^2\right)}{\partial \sigma_m^2} = -\frac{\frac{\partial p\left(v\left(\sigma_m^2,1\right),\theta\right)}{\partial v} + \frac{\partial p\left(v\left(\sigma_m^2,2\right),\theta\right)}{\partial v}}{\frac{\partial p\left(v\left(\sigma_m^2,1\right),\theta\right)}{\partial \theta} + \frac{\partial p\left(v\left(\sigma_m^2,2\right),\theta\right)}{\partial \theta}}$$

such that (5) is equal to

$$\frac{\partial p\left(v\left(\sigma_m^2,1\right),\theta\right)}{\partial v} - \frac{\frac{\partial p\left(v\left(\sigma_m^2,1\right),\theta\right)}{\partial v} + \frac{\partial p\left(v\left(\sigma_m^2,2\right),\theta\right)}{\partial v}}{\frac{\partial p\left(v\left(\sigma_m^2,1\right),\theta\right)}{\partial \theta} + \frac{\partial p\left(v\left(\sigma_m^2,2\right),\theta\right)}{\partial \theta}}\frac{\partial p\left(v\left(\sigma_m^2,1\right),\theta\right)}{\partial \theta}.$$

As

$$\frac{\partial p(v, \theta)}{\partial \theta} = -\phi\left((\theta - m)v^{-\frac{1}{2}}\right)v^{-\frac{1}{2}} < 0$$

we have $\frac{dp\left(v\left(\sigma_m^2,1\right),\theta\left(\sigma_m^2\right)\right)}{d\sigma_m^2} > 0$ is equivalent to

$$\begin{aligned}
\frac{\partial p\left(v\left(\sigma_m^2, 1\right), \theta\right)}{\partial v} - \frac{\frac{\partial p\left(v\left(\sigma_m^2,1\right),\theta\right)}{\partial v} + \frac{\partial p\left(v\left(\sigma_m^2,2\right),\theta\right)}{\partial v}}{\frac{\partial p\left(v\left(\sigma_m^2,1\right),\theta\right)}{\partial \theta} + \frac{\partial p\left(v\left(\sigma_m^2,2\right),\theta\right)}{\partial \theta}}\frac{\partial p\left(v\left(\sigma_m^2, 1\right), \theta\right)}{\partial \theta} &> 0 \\
\Leftrightarrow \frac{\frac{\partial p\left(v\left(\sigma_m^2,1\right),\theta\right)}{\partial v}}{\frac{\partial p\left(v\left(\sigma_m^2,1\right),\theta\right)}{\partial \theta}} < \frac{\frac{\partial p\left(v\left(\sigma_m^2,2\right),\theta\right)}{\partial v}}{\frac{\partial p\left(v\left(\sigma_m^2,2\right),\theta\right)}{\partial \theta}}&. \qquad (6)
\end{aligned}$$

Now we can use

$$\frac{\partial p(v, \theta)}{\partial v} = \frac{1}{2}\phi\left((\theta - m)v^{-\frac{1}{2}}\right)(\theta - m)v^{-\frac{3}{2}}$$

and, in turn

$$\frac{\frac{\partial p(v,\theta)}{\partial v}}{\frac{\partial p(v,\theta)}{\partial \theta}} = \frac{\frac{1}{2}\phi\left((\theta-m)v^{-\frac{1}{2}}\right)(\theta-m)v^{-\frac{3}{2}}}{-\phi\left((\theta-m)v^{-\frac{1}{2}}\right)v^{-\frac{1}{2}}} = -\frac{\theta - m}{2v}$$

such that

$$\frac{\frac{\partial p\left(v\left(\sigma_m^2, t\right), \theta\right)}{\partial v}}{\frac{\partial p\left(v\left(\sigma_m^2, t\right), \theta\right)}{\partial \theta}} = -\frac{\theta - m}{2v\left(\sigma_m^2, t\right)}.$$

which is strictly increasing in $t$ as $v\left(\sigma_m^2, t\right)$ is strictly increasing in $t$ by Lemma 2, such that (6) always holds. ■

## 2.10 Appendix: Further Evidence

Table 2.6: Performance Rating and Spot Bonuses

| | *Received Spot Bonus$_i$* | *Received Late$_i$* |
|---|---|---|
| | (1) | (2) |
| *Performance Rating 2019$_i$* | 0.179*** | -0.045* |
| | (0.021) | (0.026) |
| Controls | Yes | Yes |
| Supervisor Fixed Effects | Yes | Yes |
| Clustered at | Planner | Planner |
| Number of Clusters | 388 | 278 |
| Observations | 2,314 | 1,292 |
| Adjusted R-squared | 0.428 | 0.556 |

**Note:** This table reports results of an OLS regression where the dependent variables are whether an employee received a spot bonus in 2019 (column (1)) or whether an employee received a spot bonus late in the year, i.e. in the peak months November or December(column (2)). The data are on the employee level. The number of observations is relatively small in comparison to other regressions as only a subset of employees receive performance ratings. In column (2), we further restrict the sample to employees who received a performance rating as well as a spot bonus in 2019. We include age, gender, managerial level, a dummy whether the employee works in production or not, as well as supervisor fixed effects as controls. Standard errors are clustered at the planner level, and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.7: Summary Statistics - Workforce

| | *Employees* | | *Supervisors* | | *Planners* | |
|---|---|---|---|---|---|---|
| | Mean | S.D. | Mean | S.D. | Mean | S.D. |
| Age | 45.566 | 10.931 | 47.729 | 8.850 | 49.417 | 7.860 |
| Female | 0.185 | 0.389 | 0.160 | 0.366 | 0.197 | 0.398 |
| Tenure | 14.976 | 13.317 | 13.862 | 11.761 | 13.870 | 10.965 |
| Performance Rating | 3.227 | 0.584 | - | - | - | - |
| Team Size | - | - | 5.980 | 7.913 | 14.015 | 26.277 |
| Production | 0.546 | 0.498 | 0.417 | 0.493 | 0.179 | 0.384 |
| Managerial Level 1 | 0.073 | 0.260 | 0.149 | 0.356 | 0.064 | 0.244 |
| Managerial Level 2 | 0.063 | 0.242 | 0.209 | 0.406 | 0.264 | 0.441 |
| Managerial Level 3 | 0.040 | 0.196 | 0.225 | 0.418 | 0.491 | 0.500 |
| Managerial Level 4 | 0.005 | 0.072 | 0.039 | 0.193 | 0.111 | 0.315 |
| Managerial Level 5 | 0.000 | 0.000 | 0.018 | 0.133 | 0.052 | 0.223 |
| Headquarter Country | 0.502 | 0.500 | 0.390 | 0.488 | 0.529 | 0.500 |
| Observations | 13,286 | | 2,001 | | 690 | |

**Note:** This table reports summary statistics (mean and standard deviation) for employees, supervisors and planners. We report the summary statistics for the workforce of 2019. Age and tenure are reported in years. The performance rating is on a scale from 1 to 5, a higher rating meaning a better performance. Female, production (function in 2020), headquarter country (if working in the country of the headquarter) are indicator variables. Moreover, we include an indicator variable for whether an employee is on a specific managerial level (the remainder are non-managerial employees). For supervisors, team size is defined as the mean number of employees they supervise in 2019. For planners, team size is defined as the mean number of employees for whom they decide about awarding spot bonuses.

Table 2.8: Summary Statistics - Spot Bonuses

| | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|
| Received Spot Bonus | 0.389 | 0.353 | 0.378 | 0.399 |
| | (0.488) | (0.478) | (0.485) | (0.490) |
| Received > 1 Spot Bonus | 0.043 | 0.038 | 0.040 | 0.037 |
| | (0.202) | (0.191) | (0.197) | (0.188) |
| Spot Bonus Size (%) | 2.502 | 2.430 | 2.433 | 2.484 |
| | (1.801) | (1.600) | (1.644) | (1.671) |
| Award Month | 9.260 | 9.496 | 9.564 | 9.410 |
| | (2.704) | (2.623) | (2.520) | (2.657) |

**Note:** This table reports summary statistics (mean and standard deviations) on the spot bonuses paid in the observation period. Received spot bonus and received more than one spot bonus are indicator variables. Spot bonus size is measured in percent of an employee's annual salary. If an employee did not receive a spot bonus, this employee is not included in this variable. Award month can take the values two to 12, indicating the respective month of the year in which a spot bonus was awarded. Standard deviations are reported in parenthesis.

Table 2.9: Share of Spot Bonuses Awarded in a Given Month

| | *Share of Spot Bonuses Awarded*$_{it}$ | |
|---|---|---|
| | (1) | (2) |
| *Month*$_t$ | 0.024*** | |
| | (0.001) | |
| *March*$_t$ | | 0.020*** |
| | | (0.003) |
| *April*$_t$ | | 0.017*** |
| | | (0.004) |
| *May*$_t$ | | 0.030*** |
| | | (0.005) |
| *June*$_t$ | | 0.041*** |
| | | (0.006) |
| *July*$_t$ | | 0.038*** |
| | | (0.005) |
| *August*$_t$ | | 0.038*** |
| | | (0.005) |
| *September*$_t$ | | 0.068*** |
| | | (0.007) |
| *October*$_t$ | | 0.124*** |
| | | (0.008) |
| *November*$_t$ | | 0.311*** |
| | | (0.015) |
| *December*$_t$ | | 0.215*** |
| | | (0.013) |
| Year Fixed Effects | Yes | Yes |
| Supervisor Fixed Effects | Yes | Yes |
| Clustered at | Planner | Planner |
| Number of Clusters | 855 | 855 |
| Observations | 45,579 | 45,579 |
| Adjusted R-squared | 0.055 | 0.102 |

**Note:** This table reports results of an OLS regression where the dependent variable is the share of spot bonuses awarded by a supervisor in a year month, and the independent variable is spot bonus year month and spot bonus year month dummies with February as reference month (in column (2)). The data are on the supervisor-month level, $t$ referring to a month and $i$ referring to a supervisor. We include year and supervisor fixed effects as controls. Standard errors are clustered at the planner level, and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.10: Balance Table

| | *Reminder Group* | | *Control Group* | | |
|---|---|---|---|---|---|
| | Mean | S.D. | Mean | S.D. | $p$-value |
| *Panel A: Randomization Unit* | | | | | |
| Share Spot Bonuses in Q2 | 0.088 | 0.191 | 0.066 | 0.183 | 0.174 |
| Tenure | 15.530 | 9.048 | 16.189 | 9.225 | 0.392 |
| Female | 0.199 | 0.355 | 0.238 | 0.384 | 0.210 |
| Managerial Level 1 | 0.156 | 0.317 | 0.198 | 0.355 | 0.137 |
| Managerial Level 2 | 0.356 | 0.426 | 0.318 | 0.410 | 0.275 |
| Managerial Level 3 | 0.259 | 0.371 | 0.244 | 0.371 | 0.629 |
| Managerial Level 4 | 0.098 | 0.270 | 0.090 | 0.263 | 0.739 |
| Production | 0.131 | 0.338 | 0.130 | 0.337 | 0.983 |
| Large No. of Supervisors | 0.014 | 0.118 | 0.014 | 0.116 | 0.964 |
| Large Avg. Team Size | 0.007 | 0.084 | 0.007 | 0.083 | 0.975 |
| Region 1 (Headquarter Region) | 0.339 | 0.474 | 0.339 | 0.474 | 0.996 |
| Region 2 | 0.095 | 0.294 | 0.099 | 0.300 | 0.874 |
| Region 3 | 0.074 | 0.263 | 0.075 | 0.264 | 0.959 |
| Region 4 | 0.099 | 0.299 | 0.113 | 0.317 | 0.584 |
| Region 5 | 0.095 | 0.294 | 0.079 | 0.270 | 0.479 |
| Region 6 | 0.113 | 0.317 | 0.120 | 0.325 | 0.800 |
| Region 7 | 0.184 | 0.388 | 0.175 | 0.380 | 0.776 |
| Observations | 283 | | 292 | | 575 |
| *Panel B: Supervisor* | | | | | |
| Share Spot Bonuses in Q2 | 0.156 | 0.298 | 0.082 | 0.226 | 0.000 |
| Tenure | 17.967 | 11.915 | 17.966 | 11.873 | 0.999 |
| Team Size | 6.837 | 6.807 | 7.137 | 10.212 | 0.499 |
| Female | 0.157 | 0.364 | 0.178 | 0.383 | 0.269 |
| Managerial Level 1 | 0.129 | 0.336 | 0.153 | 0.361 | 0.182 |
| Managerial Level 2 | 0.260 | 0.439 | 0.255 | 0.436 | 0.813 |
| Managerial Level 3 | 0.328 | 0.470 | 0.279 | 0.449 | 0.037 |
| Managerial Level 4 | 0.075 | 0.264 | 0.071 | 0.257 | 0.758 |
| Production | 0.216 | 0.412 | 0.242 | 0.428 | 0.227 |
| Region 1 (Headquarter Region) | 0.590 | 0.492 | 0.544 | 0.498 | 0.076 |
| Region 2 | 0.051 | 0.221 | 0.058 | 0.234 | 0.565 |
| Region 3 | 0.056 | 0.229 | 0.077 | 0.267 | 0.094 |
| Region 4 | 0.071 | 0.257 | 0.073 | 0.261 | 0.852 |
| Region 5 | 0.046 | 0.209 | 0.038 | 0.191 | 0.442 |
| Region 6 | 0.065 | 0.247 | 0.071 | 0.257 | 0.671 |
| Region 7 | 0.121 | 0.326 | 0.138 | 0.345 | 0.327 |
| Observations | 719 | | 790 | | 1509 |

**Note:** This table reports summary statistics (mean and standard deviations) on the characteristics in the reminder and control group before the start of the field experiment. Panel A reports result on the level of the randomization unit, i.e. groups of supervisors based on the combination on function, business unit and location code. Panel B reports results on the supervisor level. If a supervisor did not award any spot bonus in 2021 or if no spot bonus was awarded in the randomization unit, then these observations are missing. Large number of supervisors is a dummy indicating whether the randomization unit consists of more than 20 supervisors. Large average team size is a dummy indicating whether the average number of employees of a supervisor in the randomization unit is larger than 40. We further report, in the last column, the $p$-values of a two-sided t-test for continuous variables for the null hypothesis that the mean of the two groups of supervisors is the same. For indicator variables, we report the results of a proportion test. The number of observations relates to the number of randomization units or supervisors for which we have information for at least one of the characteristics.

Table 2.11: The Effect of the Reminder on the Share of Spot Bonuses in the Next Quarter

| | *Fraction of Spot Bonuses Awarded in the Third Quarter$_i$* | |
|---|---|---|
| | (1) | (2) |
| *Reminder$_i$* | -0.027 | 0.000 |
| | (0.027) | (0.022) |
| Controls | No | Yes |
| Clustered at | Randomization Unit | Randomization Unit |
| Number of Clusters | 569 | 569 |
| Observations | 1,491 | 1,491 |
| Adjusted R-squared | 0.001 | 0.122 |

**Note:** This table reports results of regressions where we regress the share of spot bonuses awarded in the third quarter in 2021, i.e. in the quarter after the reminder, on a dummy for whether supervisors received a reminder. The data are on the (functional) supervisor level, *i* referring to a (functional) supervisor. We drop (functional) supervisors who have not yet been (functional) supervisors when the reminder was sent out as well as (functional) supervisors whose subordinates do not receive any spot bonus in 2021. In column (2), we include as controls the share of spot bonuses awarded in the second quarter, a dummy for management level 3, as well as strata dummies (strata are constructed based on the (functional) supervisor's function, the (functional) supervisor's region, a dummy for whether the mean team size in the randomization unit is large as well as a dummy for whether the randomization unit consists of many (functional) supervisors). Note that randomization units are build based on function and location of the (functional) supervisors. Standard errors are clustered at the randomization unit level, and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

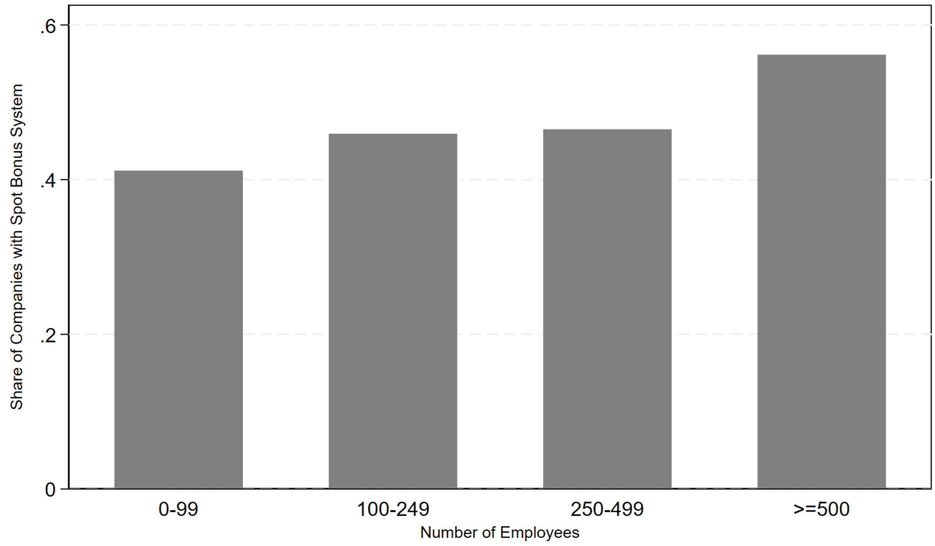



Figure 2.3: Share of Companies with Spot Bonus System

**Note:** This bar chart shows the share of companies in the Linked Personnel Panel (LPP) dataset with spot bonus systems in place by the number of employees employed at the companies.

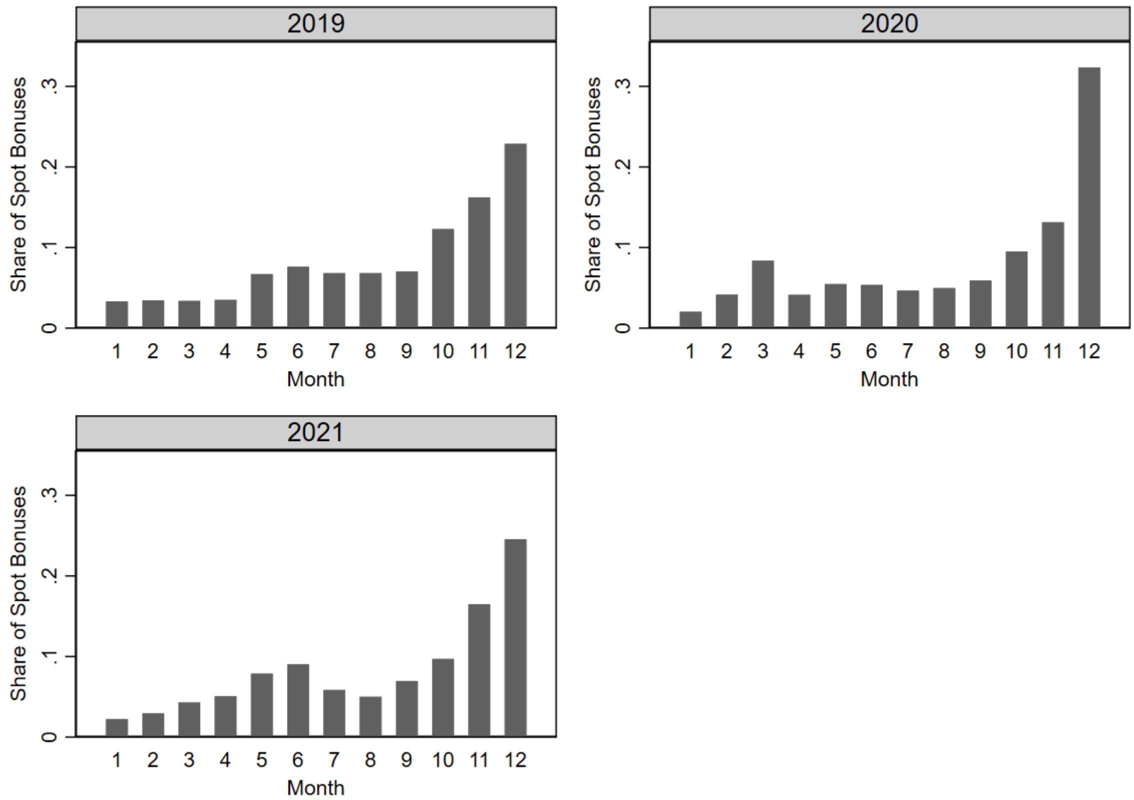



Figure 2.4: The Timing of Spot Bonuses - Second Company

**Note:** This graph plots the mean share of spot bonuses paid out for our second company in each month of a year. We present one graph per year of the observation period (2019-2021). In June 2021 a restructuring project was finalized which explains the slight spike in the second quarter of 2021.

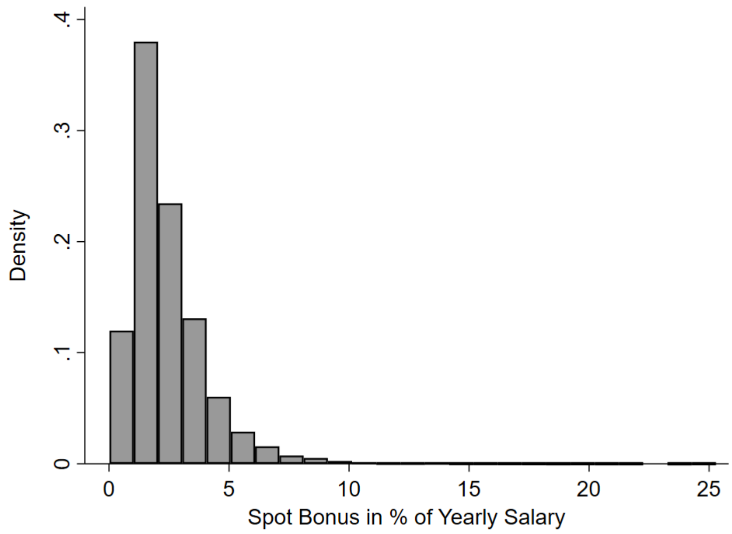



Figure 2.5: Distribution of Spot Rewards in Percent of Annual Salary

**Note:** This histogram plots the distribution of spot bonus sizes in percent of the receiving employee's annual salary.

Dear NAME,

The spot bonus allows you to reward employees for their good performance throughout the entire year, providing immediate feedback and recognition. However, we have seen in past years that the majority of spot bonuses were granted in the fourth quarter.

We believe that a timely performance recognition is directly linked to employees' commitment and satisfaction. Therefore, we would like to encourage you to take a moment to think about employees in your team who have shown very good performance and deserve a spot bonus.

Please take the time to award good performance right away!

Figure 2.6: Email Reminder Wording

**Note:** This figure shows the wording of the email reminder. For NAME, the names of the addressed managers were inserted. Please note that in the original email the company also used a specific name for spot bonuses existing in the company. For better understanding and for reasons of anonymity, we replace it with the term spot bonus.

## 2.11 Appendix: Research Instrument

**This set of questions concerns your work and personal situation. Please indicate your level of agreement on a scale of 1 (disagree strongly) to 7 (agree strongly). Note that you can answer question 10 by writing a text.**

**When you answer the questions, please share your assessment based on how you felt <u>during the last 2 weeks</u>.**

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| 1. Generally speaking, I am very satisfied with this job. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 2. I am generally satisfied with the kind of work I do in this job. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 3. I frequently think about leaving this job. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 4. I try my hardest to perform well on my job. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 5. I feel energetic at my job. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 6. At work, I focus a great deal of attention on my job. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 7. I feel like a part of the "family" at [redacted] | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 8. [redacted] has a great deal of personal meaning for me. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 9. I am very productive. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

10. Please comment on your previous answer.

Figure 2.7: First Page

**This set of questions concerns your work and personal situation. Please provide your answer in the corresponding field.**

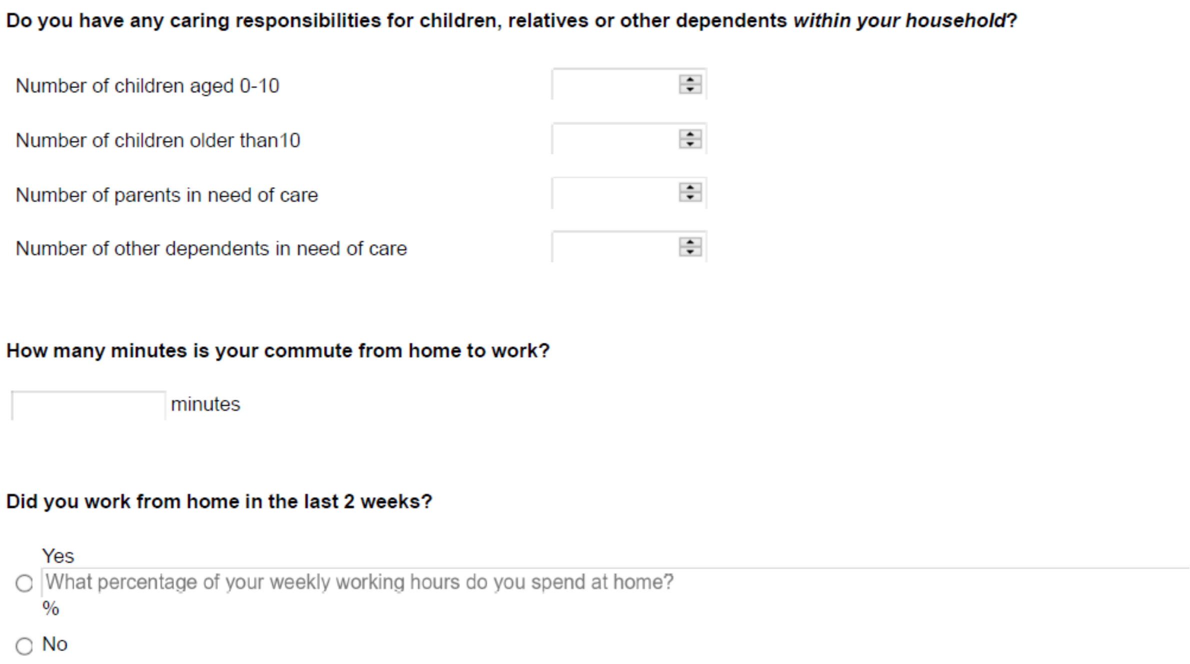
**Gender**

- ○ Female
- ○ Male
- ○ Diverse

**Education**

- ○ School leaving certificate (not highest)
- ○ Highest school leaving certificate
- ○ Bachelor (or equivalent)
- ○ Master (or equivalent)
- ○ Doctorate

Figure 2.8: Demographics



**Do you have any caring responsibilities for children, relatives or other dependents *within your household*?**

Number of children aged 0-10

Number of children older than10

Number of parents in need of care

Number of other dependents in need of care

**How many minutes is your commute from home to work?**

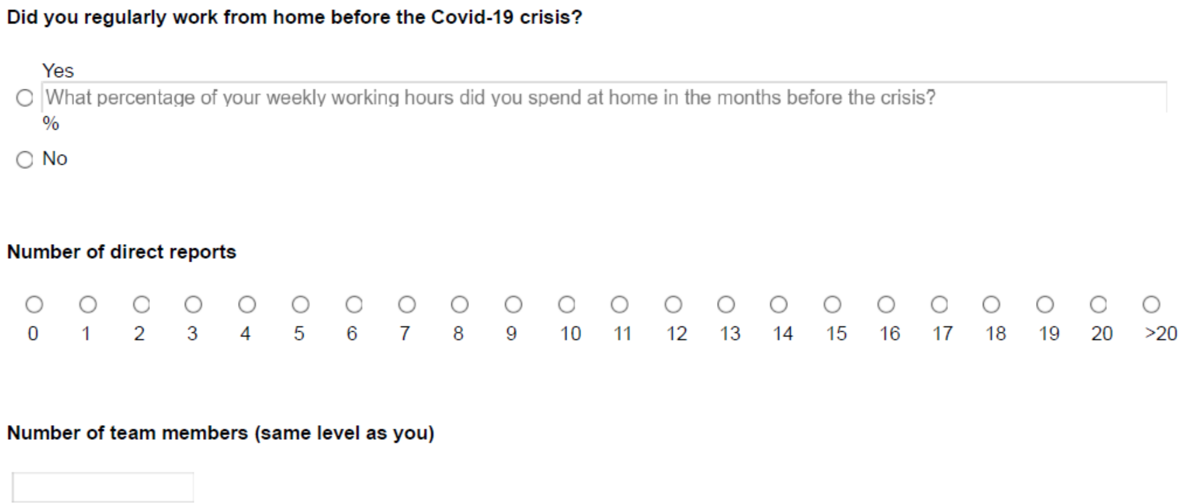
minutes

**Did you work from home in the last 2 weeks?**

Yes
What percentage of your weekly working hours do you spend at home?
%

No

Figure 2.9: General Information (Part 1)



**Did you regularly work from home before the Covid-19 crisis?**

Yes
What percentage of your weekly working hours did you spend at home in the months before the crisis?
%

No

**Number of direct reports**

0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 >20

**Number of team members (same level as you)**

Figure 2.10: General Information (Part 2)

**On the previous page you stated that you did not work from home in the last 2 weeks.**
**Why did you not work from home?**

- ○ My work cannot be done from home
- ○ I do not favor working from home
- ○ Working from home is not favored by my supervisor
- ○ Working from home is not favored by my team members

Figure 2.11: Reasons for Not Working From Home (Only if Not in Last 2 Weeks)

**This set of questions concerns your work and personal situation. Please indicate your level of agreement on a scale of 1 (disagree strongly) to 7 (agree strongly). Note that you can answer question 10 by writing a text.**

**When you answer the questions, please share your assessment based on how you felt __during the last 2 weeks__.**

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| 1. Generally speaking, I am very satisfied with this job. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 2. I am generally satisfied with the kind of work I do in this job. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 3. I frequently think about leaving this job. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 4. I try my hardest to perform well on my job. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 5. I feel energetic at my job. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 6. At work, I focus a great deal of attention on my job. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 7. I feel like a part of the "family" at [redacted] | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 8. [redacted] has a great deal of personal meaning for me. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 9. I am very productive. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

10. Please comment on your previous answer.

Figure 2.12: Work and Personal Situation (Part 1)

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| 11. My workload is too heavy. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 12. My workload is too small. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 13. During working hours, I feel stressed. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 14. I make a clear distinction between working hours and free time. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 15. I think is OK to occasionally take additional breaks (apart from lunch break) during working hours. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 16. Occasionally, I work more than my contracted hours in the working day. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 17. Apart from work: The current situation is stressing me out. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

Figure 2.13: Work and Personal Situation (Part 2)

**This set of questions concerns your team members and supervisors. Please indicate your level of agreement on a scale of 1 (disagree strongly) to 7 (agree strongly). Note that answers to questions 8 and 9 ask you to provide a number.**

**When you answer the questions, please share your assessment based on how you felt <u>during the last 2 weeks</u>.**

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| 1. My boss trusts that I do my job conscientiously. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 2. I work closely with team members in doing my work. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 3. There is a high level of cooperation between team members. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 4. In general, my work can be done very well from home. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 5. If I improve my performance, my supervisor is going to notice it. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 6. My supervisor gives me very regular and timely feedback. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 7. My supervisor always seems to be around checking my work. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 8. On average, how many times a week does your supervisor talk to *you individually*? | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 9. On average, how many times a week does your supervisor talk to *you as a team*? | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

Figure 2.14: Team Members and Supervisors

**Seite 06**

**This set of questions concerns your supervisors. Please indicate your level of agreement on a scale of 1 (disagree strongly) to 7 (agree strongly).**

**When answering the following questions, please share your assessment based on the <u>last 2 weeks</u>.**

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| 1. My supervisor gives personal attention to his direct reports. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 2. My supervisor transmits a sense of mission to his direct reports. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 3. My supervisor increases my level of enthusiasm. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 4. My supervisor emphasizes the use of my intelligence. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 5. My supervisor personally compliments me when I do outstanding work. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 6. My supervisor has a very good set of objective performance measures to evaluate the performance of his direct reports. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 7. My supervisor uses objective performance measures to evaluate the performance of his direct reports. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

Figure 2.15: Supervisors (Only for Employees in the Second Survey) (Part 1)

**This set of questions concerns your supervisors. Please indicate your level of agreement on a scale of 1 (disagree strongly) to 7 (agree strongly).**

**When answering the following questions, please share your assessment based on the <u>first 2 weeks of May</u>.**

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| 1. My supervisor gives personal attention to his direct reports. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 2. My supervisor transmits a sense of mission to his direct reports. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 3. My supervisor increases my level of enthusiasm. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 4. My supervisor emphasizes the use of my intelligence. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 5. My supervisor personally compliments me when I do outstanding work. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 6. My supervisor has a very good set of objective performance measures to evaluate the performance of his direct reports. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 7. My supervisor uses objective performance measures to evaluate the performance of his direct reports. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

Figure 2.16: Supervisors (Only for Employees in the Second Survey) (Part 2)

**This set of questions concerns your direct reports. Please indicate your level of agreement on a scale of 1 (disagree strongly) to 7 (agree strongly). Note that answers to questions 2, 9, 13 and 14 have a different format.**

**When you answer the questions, please share your assessment based on how you felt <u>during the last 2 weeks</u>.**

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| 1. My direct reports are very productive. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

2. Please comment on your previous answer.

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| 3. The productivity of individual direct reports varies widely. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 4. I am in constant contact with my direct reports. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 5. I give my direct reports regular and timely feedback. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 6. It is very easy for me to assess the productivity of my direct reports. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 7. It is very easy for me to motivate my direct reports. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 8. It is very easy for me to delegate tasks to my direct reports and to explain them. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

Figure 2.17: Direct Reports (Only for Supervisors) (Part 1)

9. On average, what percentage of their weekly working hours do your direct reports work from home?

%

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | not applicable |
|---|---|---|---|---|---|---|---|---|
| 10. My direct reports are much more productive when they work from home compared to when they work in the office. | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 11. My direct reports are much less productive when they work from home compared to when they work in the office. | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 12. When individual direct reports work from home, the productivity of the entire team of my direct reports suffers greatly. | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

Figure 2.18: Direct Reports (Only for Supervisors) (Part 2)

13. For my direct reports, the ideal ratio between working from home and working in the office is:

- 5:0 (100% from home)
- 4:1 (80% from home, 20% from the office)
- 3:2 (60% from home, 40% from the office)
- 2:3 (40% from home, 60% from the office)
- 1:4 (20% from home, 80% from the office)
- 0:5 (100% from the office)

14. Which measures have proven to be particularly helpful in managing direct reports who work from home?

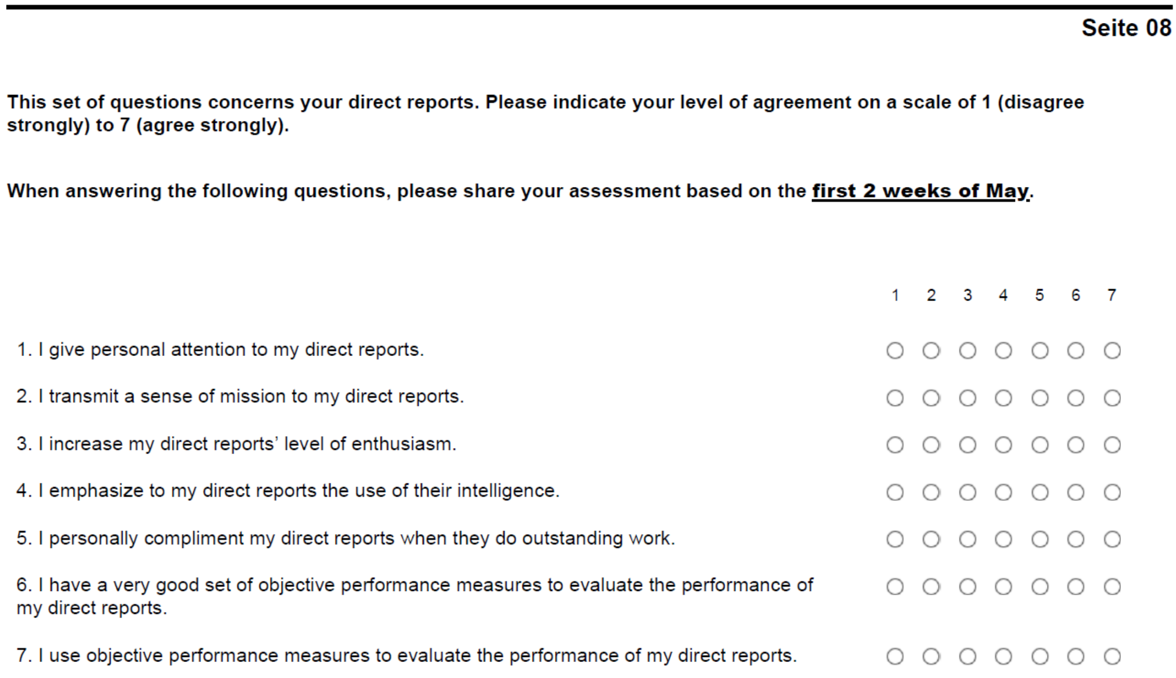
Figure 2.19: Direct Reports (Only for Supervisors) (Part 3)

**This set of questions concerns your direct reports. Please indicate your level of agreement on a scale of 1 (disagree strongly) to 7 (agree strongly).**

**When answering the following questions, please share your assessment based on the last 2 weeks.**

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| 1. I give personal attention to my direct reports. | | | | | | | |
| 2. I transmit a sense of mission to my direct reports. | | | | | | | |
| 3. I increase my direct reports' level of enthusiasm. | | | | | | | |
| 4. I emphasize to my direct reports the use of their intelligence. | | | | | | | |
| 5. I personally compliment my direct reports when they do outstanding work. | | | | | | | |
| 6. I have a very good set of objective performance measures to evaluate the performance of my direct reports. | | | | | | | |
| 7. I use objective performance measures to evaluate the performance of my direct reports. | | | | | | | |

Figure 2.20: Direct Reports (Only for Supervisors in the Second Survey) (Part 1)



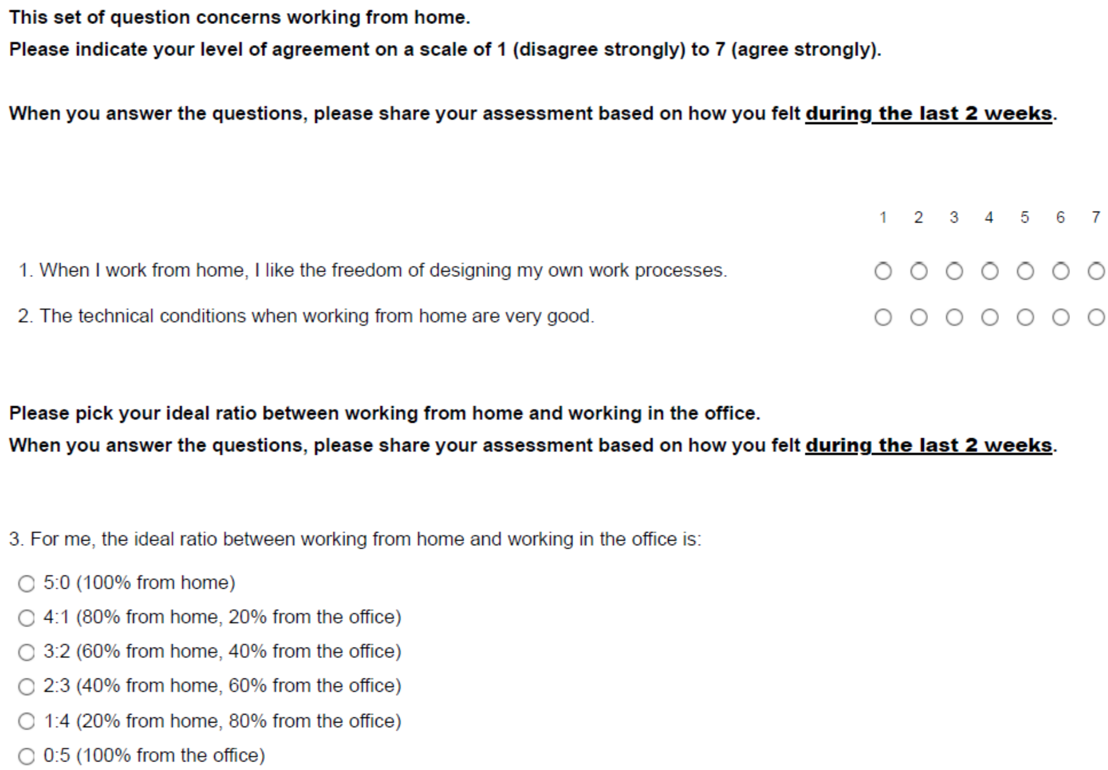
Seite 08

**This set of questions concerns your direct reports. Please indicate your level of agreement on a scale of 1 (disagree strongly) to 7 (agree strongly).**

**When answering the following questions, please share your assessment based on the first 2 weeks of May.**

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| 1. I give personal attention to my direct reports. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 2. I transmit a sense of mission to my direct reports. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 3. I increase my direct reports' level of enthusiasm. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 4. I emphasize to my direct reports the use of their intelligence. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 5. I personally compliment my direct reports when they do outstanding work. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 6. I have a very good set of objective performance measures to evaluate the performance of my direct reports. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 7. I use objective performance measures to evaluate the performance of my direct reports. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

Figure 2.21: Direct Reports (Only for Supervisors in the Second Survey) (Part 2)



**This set of question concerns working from home.**
**Please indicate your level of agreement on a scale of 1 (disagree strongly) to 7 (agree strongly).**

**When you answer the questions, please share your assessment based on how you felt during the last 2 weeks.**

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| 1. When I work from home, I like the freedom of designing my own work processes. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 2. The technical conditions when working from home are very good. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

**Please pick your ideal ratio between working from home and working in the office.**
**When you answer the questions, please share your assessment based on how you felt during the last 2 weeks.**

3. For me, the ideal ratio between working from home and working in the office is:

- ○ 5:0 (100% from home)
- ○ 4:1 (80% from home, 20% from the office)
- ○ 3:2 (60% from home, 40% from the office)
- ○ 2:3 (40% from home, 60% from the office)
- ○ 1:4 (20% from home, 80% from the office)
- ○ 0:5 (100% from the office)

Figure 2.22: Working From Home (Only if Worked From Home in Last 2 Weeks) (Part 1)

**This set of questions is about differences between working at the office and working from home. Please indicate your opinion on a scale of 1 (better at the office) to 5 (better when working from home).**

**When you answer the questions, please share your assessment based on how you felt during the last 2 weeks.**

| | Much better at the office 1 | 2 | Equally good 3 | 4 | Much better when working from home 5 | not applicable |
|---|---|---|---|---|---|---|
| 4. Communication in my team | ○ | ○ | ○ | ○ | ○ | ○ |
| 5. Experienced support by my team members | ○ | ○ | ○ | ○ | ○ | ○ |
| 6. Interaction with customers | ○ | ○ | ○ | ○ | ○ | ○ |
| 7. Interaction with other teams in the company | ○ | ○ | ○ | ○ | ○ | ○ |
| 8. Clarity of my work objectives | ○ | ○ | ○ | ○ | ○ | ○ |
| 9. Working independently | ○ | ○ | ○ | ○ | ○ | ○ |
| 10. Feedback from my manager | ○ | ○ | ○ | ○ | ○ | ○ |
| 11. Feedback from my team members | ○ | ○ | ○ | ○ | ○ | ○ |
| 12. Focus on the work | ○ | ○ | ○ | ○ | ○ | ○ |
| 13. Compatibility of work and private life | ○ | ○ | ○ | ○ | ○ | ○ |
| 14. My own productivity | ○ | ○ | ○ | ○ | ○ | ○ |
| 15. General job satisfaction | ○ | ○ | ○ | ○ | ○ | ○ |

Figure 2.23: Working From Home (Only if Worked From Home in Last 2 Weeks) (Part 2)

**This set of question concerns working from home. You can answer these questions by writing a text in the designated text boxes.**

**When you answer the questions, please share your assessment based on how you felt <u>during the last 2 weeks</u>.**

1. What were the positives when working from home?

2. In your view, what were the biggest challenges when working from home?

3. What measures should [redacted] take to improve working from home?

4. What measures should your supervisor take to improve working from home?

5. What should your team members do to improve working from home?

Figure 2.24: Working From Home (Only if Worked From Home in Last 2 Weeks) (Part 3)

## Thank you for completing this questionnaire!

Your answers were transmitted, you may close the browser window or tab now.

Figure 2.25: Last Page

# 3 Highlighting Benefits in Job Ads: A Field Experiment

**Abstract**

In this study, I investigate the impact of highlighting specific information in job advertisements on the number of applicants and the composition of the applicant pool. In collaboration with a recruiting service provider, I conducted a field experiment with job ads from over 40 firms on social media platforms where potential candidates see job ads that highlight either work-from-home, flexible work hours, or no job characteristic. Using the results from 3,348 applications for 176 job ads, I find that highlighting either of these flexible work options, compared to not highlighting any job characteristic, significantly increases the number of applicants. Additionally, an analysis of the applicant pool shows that the share of female applicants is higher when flexible work hours are highlighted. Finally, by leveraging the diversity of job types included in the experiment, I further show evidence on heterogeneity.

This chapter is based on the working paper Opitz (2024).[43] The paper is single-authored.

[43]The field experiment was approved by the IRB board of the WiSo faculty of the University of Cologne and pre-registered on socialscienceregistry.org with the AEARCTR-0012474.

## 3.1 Introduction

Finding the right applicants for a job is crucial for organizational success. Research indicates that employees who fit well tend to perform better and have lower turnover rates (e.g., Cai, 2023; Campbell, 2012; Friebel et al., 2023). Therefore, personnel selection is recognized as a key management control for organizations (Merchant and Van der Stede, 2017). However, companies can only select from applicants who have self-selected into the applicant pool. Job advertisements, serving as the initial point of contact between potential applicants and the organization, provide an opportunity to influence this self-selection process. In this study, I investigate through a field experiment with job ads from over 40 companies how highlighting specific employee benefits, particularly flexibility benefits, in job ads affects application behavior.

Highlighting flexibility benefits in job ads could attract more applicants for two main reasons. First, research shows that employees value these benefits (e.g., He et al., 2021; Mas and Pallais, 2017), and emphasizing them might make the job more appealing. Second, highlighting flexibility might signal a positive corporate culture. For example, emphasizing work-from-home options can indicate a company's level of trust in its employees, as monitoring becomes much more difficult (Spence, 1978). As a result, showcasing flexibility benefits may encourage more applicants to apply for the job.

However, there are factors that might counteract this effect. Post-pandemic, many firms already offer some form of flexibility (e.g., Aksoy et al., 2022; Brenscheidt et al., 2023; Ham et al., 2024), which could mean that employees now expect these options and may not be influenced by them being highlighted.[44] Additionally, the effectiveness of highlighting flexibility benefits might vary depending on the specific job characteristics, such as location or field of activity.

To investigate the effect of highlighting flexibility benefits on the number of applications, I ran a field experiment in cooperation with a recruiting service provider. For the experiment we focus on one of the services the clients can choose, namely posting the job ads on Meta's social media platforms (Facebook and Instagram). Over a six-month period, we posted different versions of job ads offering flexible work hours and/or working from home on Meta's platforms. For all job ads that offered only flexible working hours, we created a version that highlighted flexible working hours and one version that did not highlight any job characteristic. For all job ads that offered only working from home, we similarly created a version that highlighted working from home and a version that did not highlight any job characteristic. For all job ads offering both

[44] Most studies showing that employees value flexibility benefits are pre-pandemic, so results might differ now. The only exception, to my knowledge, is Fuchs et al. (2024). While they also show a positive effect of providing workplace flexibility for entry-level jobs, they do not find an effect for experienced employees. Additionally, their flexibility options are not standard (e.g., offering work-from-home or flexible work hours) but rather individual solutions, which are not necessarily common post-pandemic.

there were three versions, one each highlighting the respective flexibility benefit and one not highlighting any job characteristic. Using Meta's developer API, we randomized which version individual users could see, ensuring each user viewed only one version of the job ad.

Using this random variation in exposure to different versions, I can cleanly identify the causal effect of highlighting flexible working hours or working from home in job ads on application behavior. I find that both flexibility options substantially increase the number of applications—by 20.09% for flexible working hours and even by 31.30% for working from home. Highlighting the option to work from home also significantly reduces the average cost per application (by 10.11% and 25.06% respectively). Using my data, I can also provide insights into whether these treatments affect the composition of the applicant pool in terms of gender, which might influence how attractive highlighting these benefits is for companies aiming to attract specific groups, such as female applicants. My results show that the share of female applicants is higher when flexible working hours are highlighted, compared to when no job characteristics are highlighted. However, this effect is not observed for working from home. This may be because the share of female applicants in the control group is already high for these jobs (75%), compared to 44.4% for jobs with flexible work hours.

Leveraging that my cooperation company has clients from many different industries that try to fill different kinds of positions, I further exploratively investigate for which kinds of jobs highlighting flexibility benefits is beneficial. Using a data-driven approach (post-Lasso OLS, Belloni and Chernozhukov, 2013) to select a subset of the available job characteristics for investigation, I find evidence that highlighting remote work has a greater impact on customer support roles, while being less effective for positions in public administration. I do not find evidence that the available job characteristics explain variations in the effect size when highlighting flexible work hours. Additionally, I do not find evidence that emphasizing time or location flexibility benefits is detrimental for jobs with certain characteristics.

My study makes several contributions to the literature. First, using experiments with job ads from over 40 companies in different industries, I can show that there is a generalizable positive effect for highlighting flexibility options (at least across industries). I thus contribute to the literature on employees' valuation of flexibility benefits (e.g., Aksoy et al., 2022; Bloom et al., 2022; Mas and Pallais, 2017) and the effects of workplace flexibility (e.g., Baek, 2023; Bloom et al., 2022, 2015; Brueggen et al., 2024; Kelliher and Anderson, 2010; Leslie et al., 2012; Mas and Pallais, 2017) by providing clear field experimental evidence that the impact of highlighting flexibility benefits in job ads is not limited to specific industries like tech (Fuchs et al., 2024; He et al., 2021). Additionally, I show that there is still a positive effect of highlighting flexibility benefits in job ads even post-pandemic. The studies most similar to mine are He et al. (2021), who varied flexibility benefits and pay in job ads from a single tech company on a Chinese job board pre-pandemic, and Fuchs et al. (2024), who varied information on flexibility and career opportunities in job ads from a single tech firm in Europe. Both studies are set in very specific contexts, whereas my research adds to the literature by providing evidence across various firms and industries.

Second, running a field experiment with job ads of a broad range of companies allowed me to investigate heterogeneity in the effects. This is an advantage in comparison to other job ad studies (e.g., Del Carpio and Fujiwara, 2023; Flory et al., 2015; Hurst et al., 2024), which often vary ads from only one company. It is especially distinct from studies investigating flexibility benefits in job ads (Fuchs et al., 2024; He et al., 2021), which use job ads from just one tech company each. An exception among job ad studies is Choi et al. (2023), who collaborate with a career advice agency and randomize whether job seekers receive additional diversity information in job recommendation emails. However, to the best of my knowledge, no studies have investigated flexibility benefits in job ads in this way.

Third, a notable difference from other job ad studies is that I vary only whether and which job characteristic is highlighted, not whether it is offered to applicants. In my study, neither the actual job characteristics nor the job ad texts differ. This allows me to provide evidence on a less invasive form of intervention that companies can easily adjust and tailor to different job profiles. Thus, I contribute to the literature on attention in accounting and economics (e.g., Birnberg and Shields, 1984; Bordalo et al., 2022; Hirshleifer and Teoh, 2003; Manthei et al., 2023b) by demonstrating that merely highlighting a characteristic in an ad can make a difference.

The remainder of the paper is structured as follows: Section 3.2 reviews the related literature and outlines the hypothesis development. Section 3.3 provides details on the experimental design. In Section 3.4, I present the results on the average treatment effect, heterogeneity analyses as well as the gender composition in the applicant pool. Section 3.5 concludes.

## 3.2 Theoretical Background

Personnel controls, i.e. selecting employees and providing them with the skills and resources needed to motivate and control themselves, is considered one of the key management control mechanisms for companies (Merchant and Van der Stede, 2017). A central aspect is hiring employees whose abilities and preferences are a good fit for the company (Campbell, 2012; Feichter and Grabner, 2020). This can be achieved if i) the company has an effective system for selecting applicants who are well-suited for the job and ii) if there is a pool of suitable applicants for the company to choose from.[45]

While attracting candidates is therefore a crucial part of the process, it has been understudied until now. In times when many companies struggle to find candidates for their positions ("War for Talent," Binvel et al., 2018; Michaels et al., 2001), the question of how to attract the right candidates becomes increasingly important. Since attracting applicants means that they self-select into the applicant pool, it is essential to understand how this self-selection process works. Some studies show that the existence and form of variable pay can influence employee self-selection into companies (Hales et al., 2015; Kachelmeier and Williamson, 2010; Lazear, 2000). Furthermore, Cardinaels et al. (2018) show self-selection based on pay-level differences. Baruah et al. (2021) study how the choice of recruiting channel is aligned with output contractibility in firms to facilitate effective self-selection into the applicant pool. However, there are many other tools companies could use to facilitate self-selection that deserve attention, such as job ads.

To attract candidates, they need to be informed about the company, the position, and its offerings. Typically, information is disseminated through job ads on channels such as the company website or job boards. However, social media is also being increasingly utilized, particularly to reach 'passive' candidates (e.g., Cappelli, 2001; Doherty, 2010), who are potential candidates not actively seeking a new job and who do not actively seek information through job portals or similar channels.

Potential candidates, whether active or passive, are exposed to a lot of information at once. This information partly comes from the company's job ads and partly from other posts and ads they are viewing. Candidates actively searching for a job typically browse through multiple job ads in a short period. Similarly, passive candidates on social media encounter numerous posts from friends and acquaintances, alongside advertisements for products, services, and job opportunities.

[45] A still relatively small but growing body of literature investigates how companies can select applicants with a good fit. Studies show that employee referral programs are effective in hiring suitable employees (Campbell, 2012; Friebel et al., 2023). Other research examines how the decentralization or centralization of hiring decisions can affect employee fit (Deller and Sandino, 2020; Lill et al., 2024). Cai (2023) demonstrates that a culture-fit measurement system can be beneficial. Additionally, Abernethy et al. (2015) explore how companies combine employee selection with incentive contracting.

While the amount of information available is vast, attention— including that of potential applicants— is limited (see, for example, Kahneman, 1973). The focus of attention is influenced by both controlled and uncontrolled processes. It is partly driven by the goals a person wants to achieve but can also be automatically drawn towards prominent (i.e., salient) stimuli (e.g., Bordalo et al., 2022; Hirshleifer and Teoh, 2003; Treisman and Gelade, 1980). Therefore, by making specific job characteristics more salient, a company might be able to direct candidates' attention in that direction.

As salient stimuli receive more weight in decision-making (Bordalo et al., 2022), which job characteristic is made salient can influence two decisions when screening multiple posts and ads: i) whether to pay significant attention to this ad among all others, and ii) whether to take action on the ad, i.e. whether to apply. Therefore, it may be advantageous to highlight a job characteristic that is valued by candidates. One such characteristic is flexibility. Studies have consistently shown that employees highly value workplace flexibility and are even willing to accept lower compensation in exchange for it (Aksoy et al., 2022; Bloom et al., 2022; He et al., 2021; Mas and Pallais, 2017). Two common types of workplace flexibility are flexible work hours and working from home options (see, for example, Mas and Pallais, 2020).

While flexible work hours offer employees the freedom to determine their work schedule, work-from-home grants them the flexibility to choose their work location. Therefore, these options differ in several respects: while work-from-home saves time by eliminating commuting, flexible work hours do not reduce time spent but allow employees to decide when to allocate their work hours. Additionally, both options typically pose challenges for employers in monitoring employees, such as tracking their work hours. As a result, flexibility benefits often necessitate a degree of trust from the employer (Allen et al., 2015).

Thus, potential candidates who notice a highlighted flexibility option in a job ad can perceive value from two different aspects: i) the value of being able to utilize the flexibility option, and ii) the perceived signal about the company culture, including the level of trust.[46]

Considering that highlighting flexibility benefits increases their salience and can thus weigh more heavily in the decision-making process for job applicants, and given that employees value flexibility benefits, I propose the following hypothesis:

H1: Highlighting a flexibility benefit (flextime or WFH) increases the number of applications

[46] According to Spence (1978), information can serve as a signal when the costs for low-quality companies (in this context, those perceived as low trusting) are too high to falsely send the signal. For companies that highlight flexibility benefits, there is an expectation that new hires will want to utilize these benefits; otherwise, they may become highly dissatisfied. This situation could be seen as imposing an unreasonably high cost for companies perceived as lacking in trust.

Whether highlighting a flexibility benefit in a job ad increases the number of applications and how strong this effect is, is potentially strongly dependent on the characteristics of the job itself. It might for example be the case that highlighting the possibility of working from home increases the number of applicants more strongly for jobs in rural areas as it might be seen as more valuable not having to move there than to a large city. It might also be that highlighting flexibility options have a stronger effect for fields of activity or industries where it is not as common since it might be more salient then. As there are many different job characteristics to consider, I do not form hypotheses but explore these heterogeneities using a data-driven approach in Section 3.4.2.

## 3.3 Experimental Design

### 3.3.1 The Environment

I collaborate with a recruiting service provider that offers services to a wide range of clients, spanning from small firms to multinational corporations with several thousand employees across diverse industries such as construction, logistics, banking, and consulting. Clients are mainly located in Germany.

The recruiting service provider offers services throughout the whole recruiting process. This includes posting job ads across various channels, providing application management tools, and offering a metric to assess candidate-position fit, thereby supporting personnel selection. One of their primary services involves posting job ads on social media platforms. These platforms then distribute the ads to their user base. To utilize this service, clients submit a job description along with additional details such as employee benefits. Using this information, the company creates a job ad.

This study specifically examines the job ads posted by the company on Meta's social media platforms (Facebook and Instagram). For these platforms the company creates an ad that consists of the job title, the hiring firm logo and the hiring firm location as well as an illustration. Figure 3.2 in the Appendix shows a fictitious sample job ad. In the description text belonging to the ad, applicants find the job ad text. Thus, they already see the full text together with the ad.

Potential applicants view the job ads on their Facebook or Instagram feeds. Job ads are only shown to users that fit the profile of the advertised job opening. Whether a user fits depends on their locations as well as their interests.[47] The interests are linked to specific business activities, e.g. IT/software or food/hospitality. When users click on the job ad, they can apply directly using a pre-filled short form with their Meta data. The form requests only their name and email address, with an optional field for phone number.

Following this initial contact, the recruiting service provider manages the application process. They email applicants a link to a comprehensive application form that includes all necessary information requested by the client. This may include a current CV, educational background details, or specific skills.

### 3.3.2 Treatments

During the experimental period, my partner company posted job ads on Meta's social media platforms (Facebook and Instagram) in three different versions. Each user could only view one version of the ad. One version highlighted work-from-home opportunities (*Working from Home* treatment), another highlighted flexible working hours (*Flextime* treatment), and the third did not emphasize any specific job characteristic. For jobs that offered only one of these benefits (such as work-from-home), the company posted two versions: one without any highlighted characteristics and one emphasizing the offered benefit (e.g., work-from-home). Jobs that did not offer either of these benefits were excluded from the experiment.

The flexibility benefits were highlighted by including the respective benefit on the job ad and making it more prominent with the addition of an icon (see Figure 3.2 in the Appendix). Importantly, the text of the job ad remained unchanged, ensuring all potential candidates received the same information about the company, the job tasks as well as the list of benefits offered.

### 3.3.3 Experimental Procedure and Data

The experiment started on December 6, 2023, and ran for six months. The last new short job ads were posted on June 6, 2024. During this period, 176 job ads met the criteria of offering at least one of the flexibility benefits, i.e. flexible working hours or work-from-home, and were posted on Facebook/Instagram as part of the experiment.

[47]Only users within a certain radius of the company's location can see the ad if the job does not offer work from home. The size of the radius around the company's location depends on how easy it is to commute there. If the job offers work from home, the ad can be seen anywhere in Germany.

Of these, 84 job ads offered working from home, 126 offered flexible work hours, and 34 offered both working from home and flexible work hours. The job ads originated from 42 different clients. The number of job ads from individual clients varied greatly during the experimental period, ranging from 1 to around 51 (median: 2).

Using the Meta developer API, the recruiting service provider could randomly split the population of Facebook users into several groups, with each group able to see only one of the job ad versions. The split was performed independently for each job ad. Thus, whether an individual saw the work-from-home version of one of the job ads was independent of the version the individual saw of another job ad. The advantage of using this developer API was the ability to post different job ad versions simultaneously. Thus, in contrast to other job ad studies (e.g., Flory et al., 2015; Fuchs et al., 2024; He et al., 2021), I avoided the issue of time discrepancies in version posting, which could potentially introduce confounding factors.[48]

The three versions of each ad are displayed for a maximum of two months. If an ad remains online beyond two months, only the version that achieved the lowest cost per application during this period is displayed, for budgetary reasons. However, due to technical issues, I only utilize data from the first month for the primary analyses. This limitation arises because the treatment assignment needed to be re-randomized for all job ads after the first month. Since I lack information on individuals who did not apply, I cannot track which ad version they might have seen in the first month if they applied in the second month. Therefore, I exclude data from the second month. In the first month, each job ad version was seen on average by 3,693 unique viewers. Of these on average 9 applied.

In addition to receiving data on the number of individual views, costs, and applications for each version of the job ads, I also obtained information from the recruiting service provider on the job characteristics. For each job, I received data on working time (full-time or part-time), employment type (e.g., permanent or freelance), career level (entry, experienced, or other), field of activity (e.g., sales, administration, customer support, engineering, etc.) and location[49].

[48]Because I do not have information on viewers of the ads who did not apply, I cannot check for balance between the treatment and control groups. However, since each job ad version was seen by an average of 3,693 unique viewers, an imbalance is unlikely due to the large sample size.

[49]Location information was missing in parts of the job ads. For these, I added the information either by using details provided in the job ad title or by looking up the respective company.

To investigate the heterogeneities later on, I added two potentially important job characteristics. First, I categorized all jobs into industry sectors based on the Global Industry Classification Standard (S&P Global Market Intelligence, 2018). Sectors included in my sample are Materials (e.g chemical companies), Industrials (e.g. consultancies or machinery manufacturers), Consumer Discretionary (e.g. producers of household durables), Consumer Stables (e.g. food producers), Financials (e.g. banks or insurance brokers), IT (e.g. IT service providers) and Health Care.

Second, I merged the data with additional data on the population size at the job location. For population size, I used data from the German Statistical Office (Statistisches Bundesamt, 2023) and manually added the data for locations not included. [50] See Table 3.5 in the Appendix for summary statistics.

In total, the job ads generated 3,348 applications. For a subset of applicants, I received gender data (male or female).[51] Of the applicants for whom gender was recorded, 60.6% are female.

## 3.4 Results

### 3.4.1 Effect on Applications

To investigate the effect of highlighting a flexibility option in job ads on applications, I use two different outcome measures. The first is the number of applications per 1,000 individuals who view the job ad, and the second is the cost per application. These two measures complement each other, as they differ in two important ways. First, the number of applications per 1,000 views is defined even when no one applies, whereas the cost per application cannot be calculated in such cases. Second, cost per application takes into account how much the company paid to show the ad to these applicants and is thus an important performance indicator for my collaboration company. However, since Meta uses auctions to determine which ads are shown to individual users, the cost of displaying an ad varies between users based on factors beyond the company's control. As ads compete for limited ad spots, the cost for 1,000 viewers of one version may differ from the cost for 1,000 viewers of another version, even when everything except the highlighting of the flexibility benefits is the same. This creates more variance in cost per application that cannot be explained by the job ad characteristics or treatments in comparison to applications per 1,000 viewers.

[50] Locations not included were either outside of Germany or were municipalities rather than towns or cities. I looked these up and added the respective number of inhabitants.

[51] Due to technical issues, I only received data on approximately 25% of the applicants, specifically those who applied after mid-April. As a result, the analyses using applicant data differ from the pre-registered version due to insufficient statistical power.

Table 3.1: Effect on Applications

| | *Application per 1000 Unique Viewers$_i$* (1) | *Cost Per Application$_i$* (2) |
|---|---|---|
| *Flextime Treatment$_i$* | 0.460*** | -2.174* |
| | (0.139) | (1.166) |
| *WFH Treatment$_i$* | 0.820*** | -6.078*** |
| | (0.189) | (1.998) |
| $p$-value Flextime=WFH | 0.085 | 0.058 |
| Job Ad Fixed Effects | Yes | Yes |
| Clustered at | Job Ad | Job Ad |
| Number of Clusters | 176 | 164 |
| Observations | 386 | 361 |
| Adjusted R-squared | 0.845 | 0.373 |

**Note:** This table reports results of regressions where I regress the number of applications per 1,000 unique viewers (column (1)) and the cost per applications (columns(2)) on treatment indicators for the *Flextime* treatment and the *Working from Home* treatment. The data is at the job ad-version level. The number of observations varies, as the cost per application can only be computed if there is at least one application for that job ad version. Job ad fixed effects are included as controls. Standard errors are clustered at the job ad level, and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Column (1) in Table 3.1 presents the results of the regression of the number of applications per 1,000 individuals viewing the job ad on highlighting flexible work hours or working from home. I include job ad fixed effects to control for differences between jobs. The results show that both highlighting flexible work hours and offering the option to work from home significantly increase the number of applicants. Highlighting flexible work hours increases the number of applications by on average 0.46 per 1,000 viewers, which represents a 20.09% increase compared to the control group for the same ads (mean: 2.29). The effect of highlighting working from home is even more pronounced, with an increase of 0.82 applications per 1,000 unique viewers, corresponding to a 31.30% increase compared to the control group (mean: 2.62). The difference between the effects of highlighting flexible work hours and working from home is marginally statistically significant (Wald test $p$-value: 0.085).

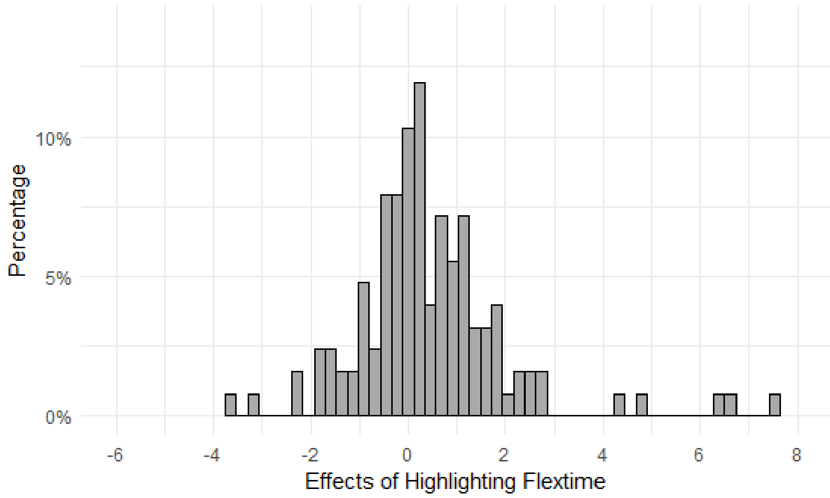
Column (2) presents the results for cost per application. Both highlighting flexible work hours and offering a working from home option reduce the cost per application. However, the effect of flexible work hours is only marginally statistically significant. Despite this, both coefficients are sizable. Highlighting flexible work hours reduces the cost per application by €2.17, which corresponds to a 10.11% decrease compared to the average cost per application in the control group for these ads (€21.47). Highlighting working from home leads to an even larger reduction of €6.08, representing a 25.08% decrease compared to the average cost of €24.24 per application in the control group for these ads. The difference in effect sizes between flexible work hours and working from home is also marginally statistically significant (Wald test $p$-value: 0.058).

Since most jobs in my sample offer either working from home or flexible work hours, but not both, the difference in effect size may be driven by other characteristics rather than the treatment itself. It might for example be the case that highlighting any job characteristic would have a smaller effect for the kind of jobs that only offer flexible work hours and not working from home. To overcome this problem, I can investigate the jobs ads in my sample that offer both working from home and flexible work hours and compare the treatments thus within the same ad. However, as there are only 34 job ads that offer both options, this sub-sample is relatively small. Using this sub-sample, the difference in effect sizes remains sizable (20% larger effect size for applications per 1,000 viewers and 71% larger effect size for cost per application), although not statistically significant—likely due to the smaller sample size (see Table 3.4 in the Appendix).

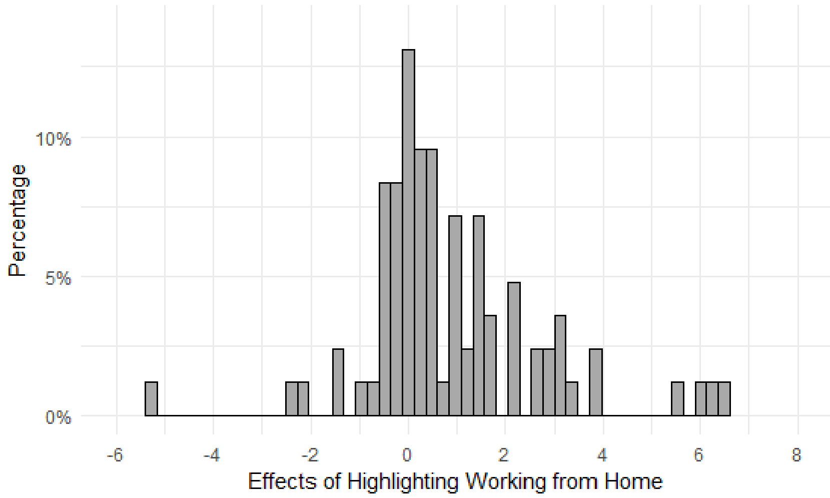
Overall, my results demonstrate that the positive effect of flexibility options on the number of applications, as found by He et al. (2021) and Fuchs et al. (2024) for individual tech companies, can be generalized to other industries and to posting job ads on social media platforms instead of job boards. Thus, I find support for Hypothesis 1. While I show that highlighting flexibility options has sizable effects on both applications per view and cost per application, an alternative explanation could be that any additional information about job characteristics, or increased attention from the additional icon on the job ad, drives these results. Although I cannot completely rule out this possibility with my data, the large difference in effect sizes between working from home and flexible work hours, even in the subsample of jobs offering both, suggests that this is not the full explanation.

### 3.4.2 Assessing Heterogeneity Based on Job Characteristics

Since I conducted experiments with 176 different job ads from 42 companies, I can investigate whether and how the effects of highlighting flexibility options vary based on job characteristics. Because I randomized within each job ad, I can compute the treatment effect for each one individually. Figure 3.1 presents a histogram of the treatment effects for flexible work hours (Panel (a)) and for working from home (Panel (b)) on applications per 1,000 viewers. I chose to use applications per 1,000 viewers as the outcome variable for two reasons: (i) I have more observations for this variable, as it includes cases with zero applications, and (ii) the adjusted R-squared for the regression in Table 3.1 on the treatment variables and job ad fixed effects is much higher for applications per 1,000 views (0.845) compared to cost per application (0.373), indicating that fewer external factors influence this outcome.[52]




(a) Flextime




(b) Working from Home

Figure 3.1: Treatment Effect Distribution

**Note:** This figure shows the distribution of the treatment effects for highlighting flexible work hours or working from home on the number of applications per 1,000 unique viewers across individual job ads. Each observation represents the difference in the number of applications per 1,000 unique viewers for a job ad when highlighting flexible work hours compared to not highlighting any job characteristic (Panel (a)), and the difference when highlighting working from home compared to not highlighting any job characteristic (Panel (b)), for the same job ad.

As Figure 3.1 shows, the treatment effects for the different job ads vary, ranging from negative to positive. However, this may simply result from random variation around the average treatment effect and not necessarily indicate actual differences in treatment effects between job ads with different characteristics. To test this, I use a

[52] Figure 3.3 in the Appendix displays the histogram for cost per application.

Kolmogorov-Smirnov test to compare the empirical distribution of the individual effects (as shown in Figure 3.1) with the distribution we would expect if there were no systematic differences in treatment effects—specifically, a normal distribution with the average treatment effect as the mean[53]. I find that for both flexible work hours and working from home, the empirical distribution is only marginally significantly different from the normal distribution around the mean ($p$-value Flextime = 0.074; $p$-value Working from Home = 0.099). Therefore, based on this test, I cannot conclusively say that the effects for jobs with certain characteristics differ from the average treatment effect on the number of applications per 1,000 viewers.[54]

To investigate this further, I examine whether the job characteristics in my sample can explain variation in the effects for individual job ads. A naive approach would be to regress the treatment effects of the job ads on their characteristics. However, given the large number of job characteristics - using all job characteristics would create 44 regressors - compared to the number of observations, this approach could be problematic. To address this, I use the post-Lasso procedure proposed by Belloni and Chernozhukov (2013). This procedure involves two steps. First, I use a Lasso model to select the job characteristics most relevant for predicting the conditional average treatment effect.[55] Second, I perform an OLS regression using only those job characteristics that were not shrunk to zero by the Lasso model, as suggested by Belloni and Chernozhukov, 2013. This second step is necessary because Lasso can introduce bias into the model by shrinking coefficients.

As there are, however, also job characteristics that only exist for one or two jobs overall, like some fields of activity or employment type models (e.g. working student), I pre-processed the variables for the Lasso model to improve the interpretability of the findings. I combined these rare characteristics to categories that appear more often. Overall, I thus reduced the number of job characteristics looked at to 25 (see Table 3.6 in the Appendix for the characteristics kept in the model). Afterwards, I fitted two lasso models, one for the *Flextime* treatment and one for the *Working from Home* treatment using as outcome the observed treatment effects for each for the different job ads. Interestingly, the Lasso model does not provide any coefficient that differs from zero for the *Flextime* treatment. Thus, I do not find evidence that any of the

[53]Note that the formula for the standard deviation is SD = Standard Error $\times \sqrt{n}$

[54]For the effect on cost per application, I find that the empirical distribution for flexible work hours is not statistically significantly different from the normal distribution around the mean (Kolmogorov-Smirnov test $p$-value = 0.436), while it is statistically significantly different for working from home (Kolmogorov-Smirnov test $p$-value = 0.002).

[55]I use the R package hdm (Chernozhukov et al., 2016), which includes the data-driven penalty theoretically derived by Belloni and Chernozhukov, 2013.

characteristics I use here, i.e. field of activity, industry sector, working time (full-time or part-time/negotiable), employment type (permanent, freelance or other), career level (entry, experience or other) or population size of the town or city where the job is located, can meaningfully predict the effect on the number of applications for the position.

For *Working from Home* the Lasso model shrinks all but two coefficients to zero. Table 3.2 shows the result of the post-Lasso OLS regression including these two job characteristics, i.e. the job being in customer service or not as well as being in an uncategorized sector, i.e. public administration[56]. The results show that while the positive effect on the number of applications is larger for customer service jobs, it is smaller for jobs in the public administration. However, I do not find evidence that highlighting working from home in a job ad is detrimental for a jobs with any specific characteristics.

Table 3.2: Post-Lasso OLS Results for *Working from Home*

| | *Job Ad Treatment Effects*$_i$ (1) |
|---|---|
| *Customer Service*$_i$ | 3.918*** |
| | (0.793) |
| *Public Administration*$_i$ | -0.542*** |
| | (0.188) |
| *Constant* | 0.691*** |
| | (0.188) |
| Observations | 84 |
| Adjusted R-squared | 0.191 |

**Note:** This table reports results of a regression where I regress the treatment effect for each job ad offering working from home on the job characteristics for which the lasso model did not set the coefficients to zero. The job ad treatment effect is defined as the difference between the number of applications per 1,000 viewers for the version highlighting working from home and the number of applications per 1,000 viewers for the version that does not highlight any job characteristic. 'Customer Service' as well as 'Public Administration' are dummy variables. Robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Taken together, my results show first evidence that there is heterogeneity in how well the highlighting of flexibility options in job ads work for different jobs. However, it is important to note that due to the limited sample size, some heterogeneities might remain undiscovered. Additionally, while my findings suggest that highlighting working from home can influence the number of applications, varying depending on whether the job

[56]Public administration is not part of any sector in the Global Industry Classification Standard (S&P Global Market Intelligence, 2018). As a result, these jobs were not assigned to any sector and remain uncategorized. However, since all uncategorized jobs are in public administration, I can clearly make the connection.

is in customer service or public administration, these results should be interpreted with caution. The small sample size means there are only a few jobs with these characteristics in my sample. Therefore, other unmeasured characteristics common to these jobs might also drive the observed relationship.

### 3.4.3 Additional Analyses: Composition of the Applicant Pool

Highlighting flexibility options in job ads might not only have different effects based on job characteristics but might also differently affect applicants leading to a change in the composition of the applicant pool. An often discussed aspect of flexibility benefits in that regard is their impact on whether women apply for a particular job. Some evidence suggests that women, especially those with more responsibilities at home, value flexibility more than men (e.g., Aksoy et al., 2022; Mas and Pallais, 2017). However, recent field experiments on job ads have not found that flexibility options increase the number of applications more for women than for men in the tech sector (Fuchs et al., 2024; He et al., 2021). However, given the strong male dominance in tech jobs (Capgemini, 2021), the tech sector may be a unique context for diversity, and results might differ across other industries.

To explore this question, I analyze the differences in gender composition in the applicant pools for the various job ad versions, focusing on the subset of applicants for whom gender data is available.[57] The results are presented in Table 3.3.

Column (1) shows that it is, on average, 16.3 percentage points more likely for an applicant to be female if flexible work hours are highlighted compared to when they are not. However, highlighting working from home does not seem to influence the gender of applicants. A logit model (column(2)) results in the same coefficient signs and significance levels. One reason for the lack of impact of highlighting working from home might be that the share of female applicants in job ads offering working from home is already 75% for the control group in which no job characteristic is highlighted. In contrast, the share of female applicants for job ads offering flexible work hours is only 44.4% for the control group. Therefore, female applicants who highly value working from home might already be actively seeking out these options, resulting in a high share of female applicants even without the explicit highlight of the working-from-home option.

Thus, while the increase in the number of applicants for working from home does not seem to lead to a larger share of female applicants—consistent with the findings of Fuchs et al. (2024) and He et al. (2021)—there is a notable increase in the share of female applicants for job ads highlighting flexible work hours.

[57]These are applicants for positions after mid-April, for whom I received individual data despite technical issues, and who completed the comprehensive application form.

Table 3.3: Highlighting of Flexibility Options and Share of Female Applicants

| | $Female_i$ | |
|---|---|---|
| | OLS | Logit |
| | (1) | (2) |
| *Flextime Treatment*$_i$ | 0.163** | 1.037** |
| | (0.074) | (0.504) |
| *WFH Treatment*$_i$ | -0.046 | -0.285 |
| | (0.132) | (1.014) |
| $p$-value Flextime=WFH | 0.159 | 0.198 |
| Job Ad Fixed Effects | Yes | Yes |
| Clustered at | Job Ad | Job Ad |
| Number of Clusters | 32 | 20 |
| Observations | 201 | 166 |
| Adjusted R-squared | 0.358 | - |
| Pseudo R-squared | - | 0.036 |

**Note:** This table shows the results of regressions of an indicator whether the applicant is female on treatment indicators. The sample includes the subset of applications for which gender is available. Non-binary is not included. Thus, the reference group here are male applicants. Column (1) presents the results using a linear probability, while column (2) presents the results using a logit model. Both models include job ad fixed effects as controls. The sample sizes differ between the linear probability model and the logit model because the logit model only includes observations with varying outcomes within job ads. Thus, job ads with all male or all female applicants are excluded from the logit model.

## 3.5 Conclusion

In this study, I investigate how highlighting flexible work hours or working from home in job ads affects both the number of applications and the composition of the applicant pool, using a field experiment with job ads from 42 firms across various industries. I find that both flexibility options substantially increase the number of applications per unique viewer with working from home having a larger effect size, though this difference is not statistically significant. Heterogeneity analyses reveal that highlighting working from home in job ads can be more or less beneficial depending on specific job characteristics. However, I do not find evidence that highlighting flexibility options is detrimental for jobs with any specific characteristic, indicating that, based on the characteristics present in my data, highlighting flexibility options does not have a negative impact. Furthermore, highlighting flexible work hours is associated with a larger share of female applicants in the applicant pool.

These findings have several implications for companies offering flexibility options to their employees. First, companies across industries that already offer flexibility options can attract more applications by highlighting these options in their job ads. Second, highlighting working from home appears to have a larger effect, though not significantly larger, and might therefore be the preferred choice for companies offering both types of flexibility if a choice has to be made. Third, emphasizing flexible work hours may be especially beneficial for companies that want to attract a higher number of female applicants.

While studying the effect of highlighting flexibility options in job ads using real job ads and actual applicants has many advantages, the study has some limitations due to these features. First, I cannot observe characteristics of non-applicants. Second, the number of job ads and job ad versions is limited by the real need of the clients. Due to these limitations, I cannot completely rule out all alternative explanations for my results that may be unrelated to flexibility, such as the impact of highlighting any benefit. However, I can clearly demonstrate that highlighting flexibility benefits has the described effects within a sample of jobs with diverse characteristics. Future studies could explore whether these effects are specific to flexibility benefits or can be generalized to the highlighting of other employee benefits.

Future research should also investigate whether the increase in the number of applications translates into an increase in suitable applications. While increasing the pool of applicants may potentially increase the number of suitable candidates, this is not clear a priori. Those who additionally apply are likely to be individuals who highly value the highlighted job characteristic, such as flexibility benefits. For example, these candidates may have responsibilities at home or long commutes. A survey conducted across 27 countries indicates that women, parents, and individuals with longer commutes place a high value on work-from-home options (Aksoy et al., 2022). Since these candidates should be equally suitable for the positions, offering flexibility benefits is expected to increase the overall pool of suitable applicants.

However, additional applications may come from candidates who highly value flexibility benefits to the extent that they apply even if they are not a good fit. These applications could originate from candidates who realize the mismatch after some time and do not proceed further in the process, or from candidates who either do not recognize the poor fit or prioritize flexibility so much that they neglect it. There is also the possibility that some applicants view flexibility options as an opportunity to avoid responsibilities, given the increased distance in monitoring (see Lill, 2020). Regarding working from home, experiments conducted by Brueggen et al. (2024) suggest that individuals prone to dishonesty are more likely to choose remote work. Consequently, if the effort expended on a task is not easily observable, employees working from home might engage in more shirking behavior.

As an additional potential downside, emphasizing flexibility could deter some suitable applicants from applying. While flexibility benefits are generally advantageous for potential candidates, who also have the option not to utilize them, highlighting these benefits might raise concerns about potential drawbacks when these options are extensively utilized in the company, such as reduced interaction with colleagues or limited feedback from supervisors (Allen et al., 2015; Bloom et al., 2022, 2015).

Taken together, while there is a larger pool of potential suitable applicants available, highlighting flexibility benefits might also attract additional applicants who are not suitable for the position or even deter suitable applicants in some cases. Therefore, more research is needed to determine whether highlighting flexibility options is genuinely beneficial for all companies.

## 3.6 References


Abernethy, M. A., Dekker, H. C., & Schulz, A. K.-D. (2015). Are employee selection and incentive contracts complements or substitutes? *Journal of Accounting Research*, *53*(4), 633–668.

Aksoy, C. G., Barrero, J. M., Bloom, N., Davis, S. J., Dolls, M., & Zarate, P. (2022). *Working from home around the world* (tech. rep.). National Bureau of Economic Research, Working Paper No. 30446.

Allen, T. D., Golden, T. D., & Shockley, K. M. (2015). How effective is telecommuting? assessing the status of our scientific findings. *Psychological Science in the Public Interest*, *16*(2), 40–68.

Baek, I. G. (2023). The effect of telecommuting on information acquisition: Evidence from the us patent office. *The Accounting Review*, *98*(3), 21–46.

Baruah, R., Grabner, I., & Moers, F. (2021). *In search of intrinsic motivation: The complementarity between recruitment strategy and compensation contract design* (tech. rep.). mimeo.

Belloni, A., & Chernozhukov, V. (2013). Least squares after model selection in high-dimensional sparse models. *Bernoulli*, *19*(2), 521 –547.

Binvel, Y., Franzino, M., Laouchez, J.-M., & Penk, W. (2018). Future of work: The global talent crunch [Accessed: September 16, 2024. https://www.kornferry.com/content/dam/kornferry/docs/pdfs/KF-Future-of-Work-Talent-Crunch-Report.pdf].

Birnberg, J. G., & Shields, M. D. (1984). The role of attention and memory in accounting decisions. *Accounting, Organizations and Society*, *9*(3-4), 365–382.

Bloom, N., Han, R., & Liang, J. (2022). *How hybrid working from home works out* (tech. rep.). National Bureau of Economic Research, Working Paper No. 30292.

Bloom, N., Liang, J., Roberts, J., & Ying, Z. J. (2015). Does working from home work? evidence from a chinese experiment. *The Quarterly Journal of Economics*, *130*(1), 165–218.

Bordalo, P., Gennaioli, N., & Shleifer, A. (2022). Salience. *Annual Review of Economics*, *14*, 521–544.

Brenscheidt, S., Siefer, A., Hünefeld, L., Backhaus, N., Halke, T., Lück, M., Kaboth, A., Möller, H., & Teborg, S. (2023). Arbeitswelt im wandel: Zahlen - daten - fakten (2023) [Avaiable at: https://www.baua.de/DE/Angebote/Publikationen/Praxis/A109. Accessed June 28th, 2024].

Brueggen, A., Feichter, C., & Haesebrouck, K. (2024). Home office: Causal evidence on selection and location effects from telecommuting. *Journal of Management Accounting Research*, 1–19.

Cai, W. (2023). Formalizing the informal: Adopting a formal culture-fit measurement system in the employee-selection process. *The Accounting Review*, *98*(3), 47–70.

Campbell, D. (2012). Employee selection as a control system. *Journal of Accounting Research*, *50*(4), 931–966.

Capgemini. (2021). Female representation in technology organizations in 2021, by selected countries [Accessed: September 05, 2024. https://www.statista.com/statistics/1256204/representation-of-gender-tech-by-country/].

Cappelli, P. (2001). Making the most of on-line recruiting. *Harvard Business Review*, *79*(3), 139–148.

Cardinaels, E., Chen, C. X., & Yin, H. (2018). Leveling the playing field: The selection and motivation effects of tournament prize spread information. *The Accounting Review*, *93*(4), 127–149.

Chernozhukov, V., Hansen, C., & Spindler, M. (2016). High-dimensional metrics in r. https://arxiv.org/abs/1603.01700

Choi, J. H., Pacelli, J., Rennekamp, K. M., & Tomar, S. (2023). Do jobseekers value diversity information? evidence from a field experiment and human capital disclosures. *Journal of Accounting Research*, *61*(3), 695–735.

Del Carpio, L., & Fujiwara, T. (2023). *Do gender-neutral job ads promote diversity? experimental evidence from latin america's tech sector* (tech. rep.). National Bureau of Economic Research, Working Paper No. 31314.

Deller, C., & Sandino, T. (2020). Who should select new employees, headquarters or the unit manager? consequences of centralizing hiring at a retail chain. *The Accounting Review*, *95*(4), 173–198.

Doherty, R. (2010). Getting social with recruitment. *Strategic HR Review*, *9*(6), 11–15.

Feichter, C., & Grabner, I. (2020). Empirical management control reserach—an overview and future directions. *Schmalenbachs Zeitschrift für betriebswirtschaftliche Forschung*, *72*, 149–181.

Flory, J. A., Leibbrandt, A., & List, J. A. (2015). Do competitive workplaces deter female workers? a large-scale natural field experiment on job entry decisions. *The Review of Economic Studies*, *82*(1), 122–155.

Friebel, G., Heinz, M., Hoffman, M., & Zubanov, N. (2023). What do employee referral programs do? measuring the direct and overall effects of a management practice. *Journal of Political Economy*, *131*(3), 633–686.

Fuchs, L., Heinz, M., Pinger, P., & Thon, M. (2024). *How to attract talents? field-experimental evidence on emphasizing flexibility and career opportunities in job advertisements* (tech. rep.). ECONtribute Discussion Paper No. 332.

Hales, J., Wang, L. W., & Williamson, M. G. (2015). Selection benefits of stock-based compensation for the rank-and-file. *The Accounting Review*, *90*(4), 1497–1516.

Ham, C. C., Hann, R. N., Wang, W., & Yang, J. (2024). *Disclosing work-from-home flexibility to compete for talent? evidence from job postings* (tech. rep.). SSRN, Working Paper No. 4201819.

He, H., Neumark, D., & Weng, Q. (2021). Do workers value flexible jobs? a field experiment. *Journal of Labor Economics*, *39*(3), 709–738.

Hirshleifer, D., & Teoh, S. H. (2003). Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics*, *36*(1-3), 337–386.

Hurst, R., Lee, S., & Frake, J. (2024). The effect of flatter hierarchy on applicant pool gender diversity: Evidence from experiments. *Strategic Management Journal*.

Kachelmeier, S. J., & Williamson, M. G. (2010). Attracting creativity: The initial and aggregate effects of contract selection on creativity-weighted productivity. *The Accounting Review*, *85*(5), 1669–1691.

Kahneman, D. (1973). *Attention and effort*. Prentice Hall.

Kelliher, C., & Anderson, D. (2010). Doing more with less? flexible working practices and the intensification of work. *Human Relations*, *63*(1), 83–106.

Lazear, E. P. (2000). Performance pay and productivity. *American Economic Review*, *90*(5), 1346–1361.

Leslie, L. M., Manchester, C. F., Park, T.-Y., & Mehng, S. A. (2012). Flexible work practices: A source of career premiums or penalties? *Academy of Management Journal*, *55*(6), 1407–1428.

Lill, J. B. (2020). When the boss is far away and there is shared pay: The effect of monitoring distance and compensation interdependence on performance misreporting. *Accounting, Organizations and Society*, *86*, 101143.

Lill, J. B., Majerczyk, M. J., & Tafkov, I. D. (2024). Candidate selection in teams: Be the best or surround yourself with the best? *Journal of Management Accounting Research*, 1–20.

Manthei, K., Sliwka, D., & Vogelsang, T. (2023b). Information, incentives, and attention: A field experiment on the interaction of management controls. *The Accounting Review*, *98*(5), 455–479.

Mas, A., & Pallais, A. (2017). Valuing alternative work arrangements. *American Economic Review*, *107*(12), 3722–3759.

Mas, A., & Pallais, A. (2020). Alternative work arrangements. *Annual Review of Economics*, *12*, 631–658.

Merchant, K., & Van der Stede, W. (2017). *Management Control Systems*. Pearson Deutschland. https://elibrary.pearson.de/book/99.150005/9781292110585

Michaels, E., Handfield-Jones, H., & Axelrod, B. (2001). *The war for talent*. Harvard Business Press.

Opitz, S. (2024). *Highlighting benefits in job ads: A field experiment* [Mimeo].

S&P Global Market Intelligence. (2018). The global industry classification standard (gics) [Accessed: September 11, 2024. https://www.spglobal.com/marketintelligence/en/documents/112727-gics-mapbook_2018_v3_letter_digitalspreads.pdf]. https://www.spglobal.com/marketintelligence/en/documents/112727-gics-mapbook_2018_v3_letter_digitalspreads.pdf

Spence, M. Job market signaling. In: In *Uncertainty in economics*. Elsevier, 1978, pp. 281–306.

Statistisches Bundesamt. (2023). Städte (alle gemeinden mit stadtrecht) nach fläche, bevölkerung und bevölkerungsdichte am 31.12.2022 [Accessed: September 11, 2024. https://www.destatis.de/DE/Themen/Laender-Regionen/Regionales/Gemeindeverzeichnis/Administrativ/05-staedte.html]. https://www.destatis.de/DE/Themen/Laender-Regionen/Regionales/Gemeindeverzeichnis/Administrativ/05-staedte.html

Treisman, A. M., & Gelade, G. (1980). A feature-integration theory of attention. *Cognitive Psychology*, *12*(1), 97–136.

## 3.7 Appendix

Table 3.4: Effect on Applications (Jobs offering Flextime and WFH)

| | *Application per 1000 Unique Viewers$_i$* (1) | *Cost Per Application$_i$* (2) |
|---|---|---|
| *Flextime Treatment$_i$* | 0.606$^{*}$ | -5.928$^{*}$ |
| | (0.301) | (3.244) |
| *WFH Treatment$_i$* | 0.732$^{**}$ | -10.174$^{**}$ |
| | (0.332) | (4.214) |
| $p$-value Flextime=WFH | 0.667 | 0.188 |
| Job Ad Fixed Effects | Yes | Yes |
| Clustered at | Job Ad | Job Ad |
| Number of Clusters | 34 | 33 |
| Observations | 102 | 99 |
| Adjusted R-squared | 0.909 | 0.363 |

**Note:** This table reports results of regressions where I regress the number of applications per 1,000 unique viewers (column (1)) and the cost per applications (columns(2)) on treatment indicators for the *Flextime* treatment and the *Working from Home* treatment. The data is at the job ad-version level, and the dataset is restricted to jobs that offer both flexible work hours and working from home. The number of observations varies because the cost per application can only be computed if there is at least one application for the job ad version. Job ad fixed effects are included as controls. Standard errors are clustered at the job ad level, and reported in parentheses. * $p$ < 0.1, ** $p$ < 0.05, *** $p$ < 0.01.

Table 3.5: Summary Statistics

| | *Flextime* | | *Working from Home* | |
|---|---|---|---|---|
| | Mean | S.D. | Mean | S.D. |
| Entry Level | 0.579 | 0.496 | 0.357 | 0.482 |
| Experienced | 0.405 | 0.493 | 0.631 | 0.485 |
| Full-time | 0.579 | 0.496 | 0.714 | 0.454 |
| Part-time/Negotiable | 0.421 | 0.496 | 0.286 | 0.454 |
| Permanent | 0.548 | 0.500 | 0.798 | 0.404 |
| Freelance | 0.405 | 0.493 | 0.190 | 0.395 |
| Sales | 0.524 | 0.501 | 0.310 | 0.465 |
| Administration | 0.119 | 0.325 | 0.107 | 0.311 |
| Finance/Accounting | 0.087 | 0.283 | 0.071 | 0.259 |
| HR | 0.056 | 0.230 | 0.071 | 0.259 |
| IT | 0.056 | 0.230 | 0.131 | 0.339 |
| Customer Service | 0.032 | 0.176 | 0.048 | 0.214 |
| Engineering | 0.016 | 0.125 | 0.155 | 0.364 |
| Other Fields of Activity | 0.111 | 0.316 | 0.107 | 0.311 |
| Industrials | 0.639 | 0.482 | 0.627 | 0.487 |
| Financials | 0.148 | 0.356 | 0.108 | 0.313 |
| Consumer Discretionary | 0.066 | 0.249 | 0.036 | 0.188 |
| Consumer Staples | 0.049 | 0.217 | 0.036 | 0.188 |
| IT | 0.041 | 0.199 | 0.145 | 0.354 |
| Materials | 0.033 | 0.179 | 0.048 | 0.215 |
| Health Care | 0.025 | 0.156 | 0.000 | 0.000 |
| < 50,000 Population Size | 0.278 | 0.450 | 0.250 | 0.436 |
| 50,000 - 100,000 Population Size | 0.143 | 0.351 | 0.095 | 0.295 |
| >100,000 Population Size | 0.579 | 0.496 | 0.655 | 0.478 |
| Share Female Applicants | 0.679 | 0.396 | 0.660 | 0.412 |
| Observations | 126 | | 84 | |

**Note:** This table presents summary statistics for the job ads, separated by those offering flexible work hours and those offering working from home. The sector categorization is based on the Global Industry Classification Standard by S&P Global and MSCI as described in S&P Global Market Intelligence, 2018. 'Materials' includes for example chemical companies, 'Industrials' includes for example consultancies or machinery manufacturers, 'Consumer Discretionary' includes for example producers of household durables, 'Consumer Stables' includes for example food producers, 'Financials' includes for example banks or insurance brokers.

Table 3.6: List of Job Characteristic Used for the Lasso Model

| Job Characteristic | Type |
|---|---|
| **Career Level** | |
| Entry Level | Binary |
| Experienced | Binary |
| Other | Binary |
| **Working Time** | |
| Full-time | Binary |
| Part-time/Negotiable | Binary |
| **Employment Type** | |
| Permanent | Binary |
| Freelance | Binary |
| Other | Binary |
| **Field of Activity** | |
| Sales | Binary |
| Administration | Binary |
| Finance/Accounting | Binary |
| HR | Binary |
| IT | Binary |
| Customer Service | Binary |
| Engineering | Binary |
| Other | Binary |
| **Section** | |
| Industrials | Binary |
| Financials | Binary |
| Consumer Discretionary | Binary |
| Consumer Staples | Binary |
| IT | Binary |
| Materials | Binary |
| Health Care | Binary |
| Uncategorized (Public Administration) | Binary |
| **Location** | |
| Population Size | Continuous (standardized) |

**Note:** This table shows the job characteristics used as features for the lasso model. Except for 'Population Size' all variables are dummy variables. As continuous variable, I z-scored 'Population Size'. The categories 'other' include all manifestations of this characteristic that are only present once or twice in the whole dataset.

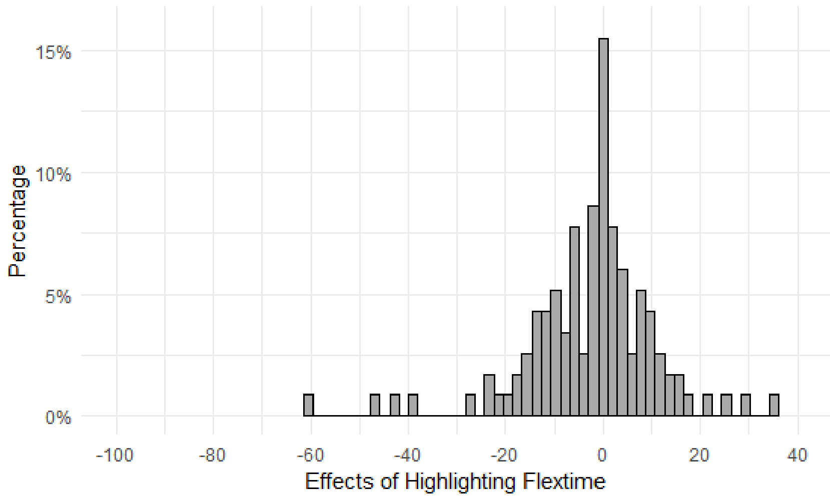

(a) Control


(b) Flexible Work Hours

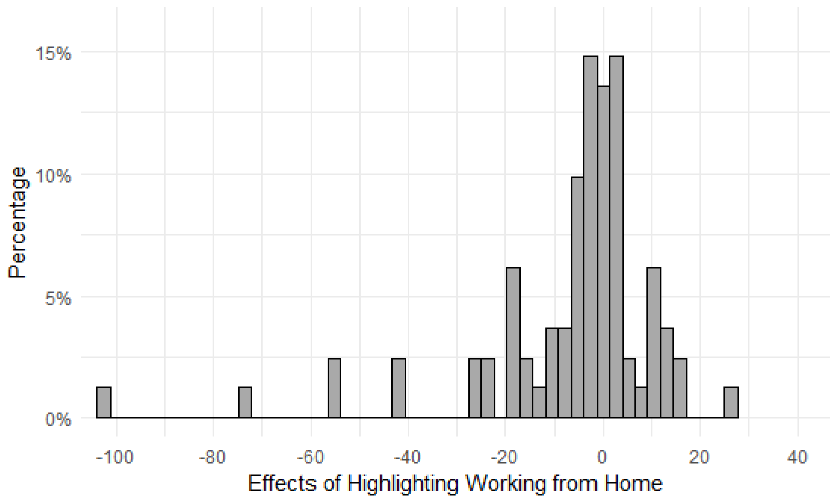

(c) Working From Home

Figure 3.2: Fictitious Sample Job Ad

**Note:** This figure shows the three versions of a fictitious sample job ad, designed in the same format as the real job ads.




(a) Flextime




(b) Working from Home

Figure 3.3: Treatment Effect Distribution (Cost)

**Note:** This figure illustrates the distribution of treatment effects for highlighting flexible work hours or working from home on the cost per application across individual job ads. Each observation represents the difference in cost per application for a job ad when highlighting flexible work hours compared to not highlighting any job characteristic (Panel (a)), and the difference when highlighting working from home compared to not highlighting any job characteristic (Panel (b)), for the same job ad.

# Complete References


Abernethy, M. A., Dekker, H. C., & Schulz, A. K.-D. (2015). Are employee selection and incentive contracts complements or substitutes? *Journal of Accounting Research*, *53*(4), 633–668.

Abernethy, M. A., Hung, C.-Y., & van Lent, L. (2020). Expertise and discretionary bonus decisions. *Management Science*, *66*(1), 415–432.

Aksoy, C. G., Barrero, J. M., Bloom, N., Davis, S. J., Dolls, M., & Zarate, P. (2022). *Working from home around the world* (tech. rep.). National Bureau of Economic Research, Working Paper No. 30446.

Allen, T. D., Golden, T. D., & Shockley, K. M. (2015). How effective is telecommuting? assessing the status of our scientific findings. *Psychological Science in the Public Interest*, *16*(2), 40–68.

Baek, I. G. (2023). The effect of telecommuting on information acquisition: Evidence from the us patent office. *The Accounting Review*, *98*(3), 21–46.

Baiman, S., & Rajan, M. V. (1995). The informational advantages of discretionary bonus schemes. *The Accounting Review*, 557–579.

Balakrishnan, R., Soderstrom, N. S., & West, T. D. (2007). Spending patterns with lapsing budgets: Evidence from us army hospitals. *Journal of Management Accounting Research*, *19*(1), 1–23.

Bandiera, O., Barankay, I., & Rasul, I. (2005). Social preferences and the response to incentives: Evidence from personnel data. *The Quarterly Journal of Economics*, *120*(3), 917–962.

Barron, K., Damgaard, M., & Gravert, C. A. (2022). *When do reminders work? memory constraints and medical adherence* (tech. rep.). CESifo Working Paper No. 9996.

Baruah, R., Grabner, I., & Moers, F. (2021). *In search of intrinsic motivation: The complementarity between recruitment strategy and compensation contract design* (tech. rep.). mimeo.

Baumann, S. (2019). Putting it off for later: Procrastination and end of fiscal year spending spikes. *The Scandinavian Journal of Economics*, *121*(2), 706–735.

Belloni, A., & Chernozhukov, V. (2013). Least squares after model selection in high-dimensional sparse models. *Bernoulli*, *19*(2), 521 –547.

Berger, S. M., & Ludwig, T. D. (2007). Reducing warehouse employee errors using voice-assisted technology that provided immediate feedback. *Journal of Organizational Behavior Management*, *27*(1), 1–31.

Binvel, Y., Franzino, M., Laouchez, J.-M., & Penk, W. (2018). Future of work: The global talent crunch [Accessed: September 16, 2024. https://www.kornferry.com/content/dam/kornferry/docs/pdfs/KF-Future-of-Work-Talent-Crunch-Report.pdf].

Birnberg, J. G., & Shields, M. D. (1984). The role of attention and memory in accounting decisions. *Accounting, Organizations and Society*, *9*(3-4), 365–382.

Block, S., Opitz, S., Sliwka, D., & Vogelsang, T. (2024). Discretion over bonus timing. *Available at SSRN 4322361*.

Bloom, N., Han, R., & Liang, J. (2022). *How hybrid working from home works out* (tech. rep.). National Bureau of Economic Research, Working Paper No. 30292.

Bloom, N., Liang, J., Roberts, J., & Ying, Z. J. (2015). Does working from home work? evidence from a chinese experiment. *The Quarterly Journal of Economics*, *130*(1), 165–218.

Bloom, N., & Van Reenen, J. Human resource management and productivity. In: In *Handbook of labor economics*. Vol. 4. Elsevier, 2011, pp. 1697–1767.
Bol, J. C. (2011). The determinants and performance effects of managers' performance evaluation biases. *The Accounting Review*, *86*(5), 1549–1575.
Bol, J. C., Hecht, G., & Smith, S. D. (2015). Managers' discretionary adjustments: The influence of uncontrollable events and compensation interdependence. *Contemporary Accounting Research*, *32*(1), 139–159.
Bol, J. C., Keune, T. M., Matsumura, E. M., & Shin, J. Y. (2010). Supervisor discretion in target setting: An empirical investigation. *The Accounting Review*, *85*(6), 1861–1886.
Bol, J. C., & Smith, S. D. (2011). Spillover effects in subjective performance evaluation: Bias and the asymmetric influence of controllability. *The Accounting Review*, *86*(4), 1213–1230.
Boosey, L., & Goerg, S. (2020). The timing of discretionary bonuses–effort, signals, and reciprocity. *Games and Economic Behavior*, *124*, 254–280.
Bordalo, P., Gennaioli, N., & Shleifer, A. (2022). Salience. *Annual Review of Economics*, *14*, 521–544.
Brenscheidt, S., Siefer, A., Hünefeld, L., Backhaus, N., Halke, T., Lück, M., Kaboth, A., Möller, H., & Teborg, S. (2023). Arbeitswelt im wandel: Zahlen - daten - fakten (2023) [Avaiable at: https://www.baua.de/DE/Angebote/Publikationen/Praxis/A109. Accessed June 28th, 2024].
Brueggen, A., Feichter, C., & Haesebrouck, K. (2024). Home office: Causal evidence on selection and location effects from telecommuting. *Journal of Management Accounting Research*, 1–19.
Burke, J., Hecht, G., & Stern, M. (2017). *The effects of anticipation and recognition source in employee recognition programs* (tech. rep.). Available at SSRN 2823837.
Cai, W. (2023). Formalizing the informal: Adopting a formal culture-fit measurement system in the employee-selection process. *The Accounting Review*, *98*(3), 47–70.
Cai, W., Gallani, S., & Shin, J.-E. (2023). Incentive effects of subjective allocations of rewards and penalties. *Management Science*, *69*(5), 3121–3139.
Campbell, D. (2012). Employee selection as a control system. *Journal of Accounting Research*, *50*(4), 931–966.
Capgemini. (2021). Female representation in technology organizations in 2021, by selected countries [Accessed: September 05, 2024. https://www.statista.com/statistics/1256204/representation-of-gender-tech-by-country/].
Cappelli, P. (2001). Making the most of on-line recruiting. *Harvard Business Review*, *79*(3), 139–148.
Cardinaels, E., Chen, C. X., & Yin, H. (2018). Leveling the playing field: The selection and motivation effects of tournament prize spread information. *The Accounting Review*, *93*(4), 127–149.
Casas-Arce, P., Lourenço, S. M., & Martínez-Jerez, F. A. (2017). The performance effect of feedback frequency and detail: Evidence from a field experiment in customer satisfaction. *Journal of Accounting Research*, *55*(5), 1051–1088.
Chernozhukov, V., Hansen, C., & Spindler, M. (2016). High-dimensional metrics in r. https://arxiv.org/abs/1603.01700
Choi, J. H., Pacelli, J., Rennekamp, K. M., & Tomar, S. (2023). Do jobseekers value diversity information? evidence from a field experiment and human capital disclosures. *Journal of Accounting Research*, *61*(3), 695–735.

Das, S. (2020). Reward your employees — without breaking the bank [*Harvard Business Review*. Available at: https://hbr.org/2020/08/reward-your-employees-without-breaking-the-bank. Accessed January 26th, 2022].
DeGroot, M. H. (1970). *Optimal statistical decisions*. McGraw-Hill.
Del Carpio, L., & Fujiwara, T. (2023). *Do gender-neutral job ads promote diversity? experimental evidence from latin america's tech sector* (tech. rep.). National Bureau of Economic Research, Working Paper No. 31314.
Delfgaauw, J., Dur, R., Sol, J., & Verbeke, W. (2013). Tournament incentives in the field: Gender differences in the workplace. *Journal of Labor Economics*, *31*(2), 305–326.
Deller, C., & Sandino, T. (2020). Who should select new employees, headquarters or the unit manager? consequences of centralizing hiring at a retail chain. *The Accounting Review*, *95*(4), 173–198.
Dihoff, R. E., Brosvic, G. M., Epstein, M. L., & Cook, M. J. (2004). Provision of feedback during preparation for academic testing: Learning is enhanced by immediate but not delayed feedback. *The Psychological Record*, *54*(2), 207–231.
Doherty, R. (2010). Getting social with recruitment. *Strategic HR Review*, *9*(6), 11–15.
Donato, K., Miller, G., Mohanan, M., Truskinovsky, Y., & Vera-Hernández, M. (2017). Personality traits and performance contracts: Evidence from a field experiment among maternity care providers in india. *American Economic Review*, *107*(5), 506–10.
Eichenauer, V. (2020). *December fever in public finance* (tech. rep.). KOF Working Papers No. 470. KOF Swiss Economic Institute, ETH Zurich.
Feichter, C., & Grabner, I. (2020). Empirical management control reserach—an overview and future directions. *Schmalenbachs Zeitschrift für betriebswirtschaftliche Forschung*, *72*, 149–181.
Fitzenberger, B., Furdas, M. D., & Sajons, C. (2016). *End-of-year spending and the long-run employment effects of training programs for the unemployed* (tech. rep.). IZA Discussion Paper No. 10441.
Flory, J. A., Leibbrandt, A., & List, J. A. (2015). Do competitive workplaces deter female workers? a large-scale natural field experiment on job entry decisions. *The Review of Economic Studies*, *82*(1), 122–155.
Friebel, G., Heinz, M., Hoffman, M., & Zubanov, N. (2023). What do employee referral programs do? measuring the direct and overall effects of a management practice. *Journal of Political Economy*, *131*(3), 633–686.
Fuchs, L., Heinz, M., Pinger, P., & Thon, M. (2024). *How to attract talents? field-experimental evidence on emphasizing flexibility and career opportunities in job advertisements* (tech. rep.). ECONtribute Discussion Paper No. 332.
Gibbs, M., Merchant, K. A., Stede, W. A. V. d., & Vargus, M. E. (2004). Determinants and effects of subjectivity in incentives. *The Accounting Review*, *79*(2), 409–436.
Gneezy, U., Niederle, M., & Rustichini, A. (2003). Performance in competitive environments: Gender differences. *The Quarterly Journal of Economics*, *118*(3), 1049–1074.
Grabner, I., Künneke, J., & Moers, F. (2020). How calibration committees can mitigate performance evaluation bias: An analysis of implicit incentives. *The Accounting Review*, *95*(6), 213–233.
Green, C., & Heywood, J. S. (2008). Does performance pay increase job satisfaction? *Economica*, *75*(300), 710–728.

Hackman, J. R., & Oldham, G. R. (1975). Development of the job diagnostic survey. *Journal of Applied Psychology*, *60*(2), 159–170.

Hales, J., Wang, L. W., & Williamson, M. G. (2015). Selection benefits of stock-based compensation for the rank-and-file. *The Accounting Review*, *90*(4), 1497–1516.

Ham, C. C., Hann, R. N., Wang, W., & Yang, J. (2024). *Disclosing work-from-home flexibility to compete for talent? evidence from job postings* (tech. rep.). SSRN, Working Paper No. 4201819.

He, H., Neumark, D., & Weng, Q. (2021). Do workers value flexible jobs? a field experiment. *Journal of Labor Economics*, *39*(3), 709–738.

Hecht, G., Hobson, J. L., & Wang, L. W. (2020). The effect of performance reporting frequency on employee performance. *The Accounting Review*, *95*(4), 199–218.

Hirshleifer, D., & Teoh, S. H. (2003). Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics*, *36*(1-3), 337–386.

Holderness Jr, D. K., Olsen, K. J., & Thornock, T. A. (2020). Assigned versus chosen relative performance information: The effect of feedback frequency on performance. *Journal of Management Accounting Research*, *32*(1), 137–158.

Holmström, B. (1999). Managerial incentive problems: A dynamic perspective. *The Review of Economic Studies*, *66*(1), 169–182.

Höppe, F., & Moers, F. (2011). The choice of different types of subjectivity in ceo annual bonus contracts. *The Accounting Review*, *86*(6), 2023–2046.

Hurst, R., Lee, S., & Frake, J. (2024). The effect of flatter hierarchy on applicant pool gender diversity: Evidence from experiments. *Strategic Management Journal*.

Kachelmeier, S. J., & Williamson, M. G. (2010). Attracting creativity: The initial and aggregate effects of contract selection on creativity-weighted productivity. *The Accounting Review*, *85*(5), 1669–1691.

Kahneman, D. (1973). *Attention and effort*. Prentice Hall.

Kampkötter, P., & Sliwka, D. (2018). More dispersion, higher bonuses? on differentiation in subjective performance evaluations. *Journal of Labor Economics*, *36*(2), 511–549.

Kelliher, C., & Anderson, D. (2010). Doing more with less? flexible working practices and the intensification of work. *Human Relations*, *63*(1), 83–106.

Kulikowski, K. (2018). The model of relationships between pay for individual performance and work engagement. *Career Development International*, *23*(4), 427–443.

Kusterer, D., & Sliwka, D. (2024). Social preferences and rating biases in subjective performance evaluations. *Management Science*, *forthcoming*.

Lazear, E. P. (2000). Performance pay and productivity. *American Economic Review*, *90*(5), 1346–1361.

Leslie, L. M., Manchester, C. F., Park, T.-Y., & Mehng, S. A. (2012). Flexible work practices: A source of career premiums or penalties? *Academy of Management Journal*, *55*(6), 1407–1428.

Liebman, J. B., & Mahoney, N. (2017). Do expiring budgets lead to wasteful year-end spending? evidence from federal procurement. *American Economic Review*, *107*(11), 3510–3549.

Lill, J. B. (2020). When the boss is far away and there is shared pay: The effect of monitoring distance and compensation interdependence on performance misreporting. *Accounting, Organizations and Society*, *86*, 101143.

Lill, J. B., Majerczyk, M. J., & Tafkov, I. D. (2024). Candidate selection in teams: Be the best or surround yourself with the best? *Journal of Management Accounting Research*, 1–20.
Lourenço, S. M. (2016). Monetary incentives, feedback, and recognition—complements or substitutes? evidence from a field experiment in a retail services company. *The Accounting Review*, *91*(1), 279–297.
Lurie, N. H., & Swaminathan, J. M. (2009). Is timely information always better? the effect of feedback frequency on decision making. *Organizational Behavior and Human Decision Processes*, *108*(2), 315–329.
Maas, V. S., Van Rinsum, M., & Towry, K. L. (2012). In search of informed discretion: An experimental investigation of fairness and trust reciprocity. *The Accounting Review*, *87*(2), 617–644.
Manthei, K., & Sliwka, D. (2019). Multitasking and subjective performance evaluations: Theory and evidence from a field experiment in a bank. *Management Science*, *65*(12), 5861–5883.
Manthei, K., Sliwka, D., & Vogelsang, T. (2023a). Information, incentives, and attention: A field experiment on the interaction of management controls. *The Accounting Review*, *98*(5), 455–479.
Manthei, K., Sliwka, D., & Vogelsang, T. (2023b). Information, incentives, and attention: A field experiment on the interaction of management controls. *The Accounting Review*, *98*(5), 455–479.
Mas, A., & Pallais, A. (2017). Valuing alternative work arrangements. *American Economic Review*, *107*(12), 3722–3759.
Mas, A., & Pallais, A. (2020). Alternative work arrangements. *Annual Review of Economics*, *12*, 631–658.
Mason, M. A., & Redmon, W. K. (1993). Effects of immediate versus delayed feedback on error detection accuracy in a quality control simulation. *Journal of Organizational Behavior Management*, *13*(1), 49–83.
Merchant, K., & Van der Stede, W. (2017). *Management Control Systems*. Pearson Deutschland. https://elibrary.pearson.de/book/99.150005/9781292110585
Michaels, E., Handfield-Jones, H., & Axelrod, B. (2001). *The war for talent*. Harvard Business Press.
Moers, F. (2005). Discretion and bias in performance evaluation: The impact of diversity and subjectivity. *Accounting, Organizations and Society*, *30*(1), 67–80.
Niederle, M., & Vesterlund, L. (2007). Do women shy away from competition? do men compete too much? *The Quarterly Journal of Economics*, *122*(3), 1067–1101.
Northcraft, G. B., Schmidt, A. M., & Ashford, S. J. (2011). Feedback and the rationing of time and effort among competing tasks. *Journal of Applied Psychology*, *96*(5), 1076–1086.
Opitz, S. (2024). *Highlighting benefits in job ads: A field experiment* [Mimeo].
Opitz, S., Sliwka, D., Vogelsang, T., & Zimmermann, T. (2024). The algorithmic assignment of incentive schemes. *Management Science*, *71*(2), 1546–1563.
PayPal. (2024). Recognition awards (spot awards) [Accessed March 21st, 2024]. https://www.paypalbenefits.com/chi/family-support/recognition
PayScale. (2021). 2021 compensation best practices report [Accessed January 26th, 2022]. https://www.payscale.com/research-and-insights/cbpr/

Podsakoff, P. M., Todor, W. D., Grover, R. A., & Huber, V. L. (1984). Situational moderators of leader reward and punishment behaviors: Fact or fiction? *Organizational Behavior and Human Performance*, *34*(1), 21–63.

Pollack, H., & Zeckhauser, R. (1996). Budgets as dynamic gatekeepers. *Management Science*, *42*(5), 642–658.

Pouliakas, K. (2010). Pay enough, don't pay too much or don't pay at all? the impact of bonus intensity on job satisfaction. *Kyklos*, *63*(4), 597–626.

Rajan, M. V., & Reichelstein, S. (2006). Subjective performance indicators and discretionary bonus pools. *Journal of Accounting Research*, *44*(3), 585–618.

Rajan, M. V., & Reichelstein, S. (2009). Objective versus subjective indicators of managerial performance. *The Accounting Review*, *84*(1), 209–237.

Reid, D. H., & Parsons, M. B. (1996). A comparison of staff acceptability of immediate versus delayed verbal feedback in staff training. *Journal of Organizational Behavior Management*, *16*(2), 35–47.

Rich, B. L., Lepine, J. A., & Crawford, E. R. (2010). Job engagement: Antecedents and effects on job performance. *Academy of Management Journal*, *53*(3), 617–635.

Siemroth, C. (2022). Ending wasteful year-end spending: On optiomal budget rules in organizations. *International Economic Review*, *forthcoming*.

S&P Global Market Intelligence. (2018). The global industry classification standard (gics) [Accessed: September 11, 2024. https://www.spglobal.com/marketintelligence/en/documents/112727-gics-mapbook_2018_v3_letter_digitalspreads.pdf]. https://www.spglobal.com/marketintelligence/en/documents/112727-gics-mapbook_2018_v3_letter_digitalspreads.pdf

Spence, M. Job market signaling. In: In *Uncertainty in economics*. Elsevier, 1978, pp. 281–306.

Statistisches Bundesamt. (2023). Städte (alle gemeinden mit stadtrecht) nach fläche, bevölkerung und bevölkerungsdichte am 31.12.2022 [Accessed: September 11, 2024. https://www.destatis.de/DE/Themen/Laender-Regionen/Regionales/Gemeindeverzeichnis/Administrativ/05-staedte.html]. https://www.destatis.de/DE/Themen/Laender-Regionen/Regionales/Gemeindeverzeichnis/Administrativ/05-staedte.html

Treisman, A. M., & Gelade, G. (1980). A feature-integration theory of attention. *Cognitive Psychology*, *12*(1), 97–136.

UC-Berkeley. (2024). Spot awards [Accessed March 21st, 2024]. https://hr.berkeley.edu/compensation-benefits/compensation/recognition/spot-awards

Vogelsang, T. (2024). Time is (not) money: Incentive effects of granting leisure time. *European Accounting Review*, *33*(2), 435–459.

Waddoups, N. (2022). Feedback-driven time segmenting: The effect of feedback frequency on employee behavior. *Contemporary Accounting Research*, *39*(3), 1516–1541.

Woods, A. (2012). Subjective adjustments to objective performance measures: The influence of prior performance. *Accounting, Organizations and Society*, *37*(6), 403–425.

WorldAtWork. (2014). Bonus programs and practices [Accessed January 26th, 2022]. https://www.worldatwork.org/resources/research/surveys/bonus-programs-and-practices

Zimmerman, J. L. (1976). Budget uncertainty and the allocation decision in a nonprofit organization. *Journal of Accounting Research*, *14*(2), 301–319.