UNIVERSITY OF CALIFORNIA

Los Angeles

Essays on People's Operations

A dissertation submitted in partial satisfaction

of the requirements for the degree

Doctor of Philosophy in Management

by

Juan Angel Matamala Gonzalez

2021

ABSTRACT OF THE DISSERTATION

Essays on People's Operations

by

Juan Angel Matamala Gonzalez
Doctor of Philosophy in Management
University of California, Los Angeles, 2021
Professor Nico Voigtlaender, Co-Chair
Professor Christian Dippel, Co-Chair

I open my dissertation with a review of the literature on incentives and the effects of automation on workers. This chapter sets the background for the discussion offered in the following two chapters. In the second chapter, I will focus on the study of leisure at work as an incentive for workers. I then close my dissertation with an analysis of the effects of automation on the use of time at work.

People's behavior depends on extrinsic and intrinsic motivations. Extrinsic motivations include financial rewards and promotions (Bandiera, Barankay, and Rasul 2007, Wowak and Hambrick 2010, Friebel et al. 2017, Lazear 2018). Intrinsic motivations include job meaning (Ariely, Kamenica, and Prelec 2008, Grant 2008, Chandler and Kapelner 2013, Cassar 2019), personal goals (Hamilton 2000, Stern 2004, Astebro et al. 2014), autonomous decision-making (Falk and Kosfeld 2006, Benz and Frey 2008, Fehr, Herz, and Wilkening 2013, Chen et al. 2019), or recognitions and awards (Kosfeld and Neckermann 2011, Ashraf, Bandiera, and Jack 2014, Chan et al. 2014, Bradler et al. 2016, Gallus 2017, Gibbs, Neckermann, and Siemroth 2017).

An intrinsic motivation that has received little attention is that of simply resting: If workers value break time, they may be willing to exert additional effort in to order to complete their tasks more quickly and consume leisure at work. This dissertation explores this possibility and studies the role of leisure at work as an implicit incentive to exert effort. I provide a simple conceptual framework and an empirical examination of the effects of leisure at work on effort. My analysis confirms that the opportunity to consume leisure at work motivates people to work harder.

In my conceptual framework, effort is costly but allows workers to increase their consumption of break time. As a result, a worker's optimal effort is such that the marginal utility of leisure at work equals the marginal cost of effort. This implies that situations that increase the marginal utility of leisure at work will also induce workers to exert more effort.

I test the predictions of my conceptual framework using two years of worker-task level data from the distribution center the largest home improvement retailer in Chile. My unique data set contains detailed information about the worker who was assigned each task, the type of task that was assigned, the time at which each task was assigned and completed, and various other task characteristics. In my empirical analysis, I exploit the exogenous variation in the timing of FIFA Soccer Tournaments. During the broadcasting of a soccer match, workers who have completed all their tasks can attend on-site broadcasting events, which in turn increases the implicit benefits to exert effort. My results confirm the predictions of my conceptual framework and have implications for management and the understanding of productivity. My findings also offer insights into the Gig Economy and remote work, where people can manage their work time and breaks autonomously.

The above analysis offers a new look at the implications of the distribution of time use at work. Inspired by this, I investigate a closely related issue: I show that automation affects workers' time use. To provide empirical evidence of this phenomenon, I examine the wholesale division of a large U.S. multinational in Chile. I find that the distribution of time use at work changed after the introduction of an e-commerce software that automated the online order fulfillment process (i.e., the software receives purchase orders and determines when and which workers should process them). Time use is affected because automation changes the relative productivity of workers across tasks. Perhaps one of the most relevant lessons is that automation reduces total effective working time (i.e., the time workers spend completing tasks). This is because increases in productivity resulting from automation are not necessarily accompanied by an increase in the demand for labor services, which may explain why technological innovations are not necessarily accompanied by increases in observed firm-level performance.

The dissertation of Juan Angel Matamala Gonzalez is approved.

Rodrigo Pinto

Paola Giuliano

Christian Dippel, Committee Co-Chair

Nico Voigtlaender, Committee Co-Chair

University of California, Los Angeles

2021

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGMENTS

I am extremely grateful for my family, my academic advisors, and the colleagues and friends I have developed while at UCLA.

VITA

2008–2013	B.A. Economics, Pontificia Universidad Catolica de Chile
2012–2013	M.A. Economics, Pontificia Universidad Catolica de Chile
2016–2021	Teaching and Research Assistant, UCLA Anderson School of Management

CHAPTER 1

Literature

1.1 Effort and Incentives

A worker's effort is a fundamental input in the production process. But since effort is costly, firms must use economic incentives to motivate individuals to exert it.

Economic incentives include extrinsic motivations such as financial rewards or promotions (Bandiera, Barankay, and Rasul 2007, Wowak and Hambrick 2010, Friebel et al. 2017, Lazear 2018) and intrinsic motivations such as job meaning (Ariely, Kamenica, and Prelec 2008, Grant 2008, Chandler and Kapelner 2013, Cassar 2019), personal goals (Hamilton 2000, Stern 2004, Astebro et al. 2014), autonomous decision-making (Falk and Kosfeld 2006, Benz and Frey 2008, Fehr, Herz, and Wilkening 2013, Chen et al. 2019), or recognitions and awards (Kosfeld and Neckermann 2011, Ashraf, Bandiera, and Jack 2014, Chan et al. 2014, Bradler et al. 2016, Gallus 2017, Gibbs, Neckermann, and Siemroth 2017).

In the simplest framework, one can think of workers facing a tradeoff between the benefits and costs of effort. Simply put, if $c(e)$ and $r(e)$ are a worker's cost and benefits of exerting an effort level e, the worker's optimal effort e^* is such that $e^* = \arg\max_e r(e) - c(e)$.

In spite of the apparent simplicity of the previous depiction, it is not easy for an employer to induce workers to exert a desired effort level. First, effort is not directly observable. Second, a worker's output is not perfectly correlated with effort. Third, risk-aversion also affects a worker's effort choices. Consequently, in the early 1970s, a large literature emerged around the problem of designing contracts that drive workers to exert effort. In this section, I review this literature.

Despite the apparent simplicity of the above representation, it is not easy for an employer to induce workers to exert a desired level of effort. First, effort is not directly observable and, on top of that, a worker's output is not perfectly correlated with effort. Second, risk-aversion also affects a worker's choice of effort. These complications and the need to understand the determinants of effort inspired a large literature focused on studying the problem of designing contracts that encourage workers to exert effort. In this section, I review this literature.

1.1.1 Monetary Compensation and Effort

Motivating workers to exert effort is a central issue in management and economics. Commonly, individuals provide effort in exchange for money. It is therefore natural that most of the literature initially studying the determinants of effort focused on how financial rewards affect the provision of effort.

In practice, there are many different ways to provide financial rewards to workers: wages, salaries, piece rates, and tournaments. A useful way to think about these different compensation schemes is the framework presented in Lazear (2018). The author classifies compensation schemes using a two-by-three matrix, in which the columns indicate whether workers are paid based on their input (e.g., number of hours worked) or output (e.g., number of units produced), and the rows indicate whether workers receive an absolute payment that is discrete (e.g., wages), an absolute payment that is continuous (e.g., piece rates), or a payment that is relative (e.g., prizes). This taxonomy is summarized in Table 1.1 and is the framework I will use to organize the following discussion of financial rewards and effort.

1.1.1.1 Payment Based on Input

Payment based on input is probably the most common compensation scheme in place. Most full-time workers belong to this category because they are paid by the hour (i.e., time input)

Table 1.1: Taxonomy of Monetary Compensation

	Payment on input	Payment on output
Discrete	Pay per hour with a specified hours requirement	Fixed payment for completion of a given task or set of tasks
Continuous	Time-based pay that allows the worker to choose how much time to work	Piece rates
Relative	Promotions tournaments based on subjective evaluations	Promotions tournaments based on output

Note: Adapted from "Compensation and Incentives in the Workplace" by E. P. Lazear, 2018, Journal of Economic Perspective, 32(3), 195–214.

in a discrete fashion (i.e., they must work 40 hours per week). Most part-time workers also belong to this category. However, part-time workers are paid in a continuous manner because they have flexibility on the amount of time that they choose to work.

Maybe because of its popularity, payment based on input was among the first compensation schemes that were examined in the literature. In general, payment based on input, such as hourly wages, is a good alternative when firms are risk-neutral and workers are risk-averse. The intuition behind this result is that it is optimal for the risk-neutral party (in this case the firm) to bear the cost of uncertainty.

Unfortunately for employers, an individual who is paid based on input may also have less incentives to provide effort (e.g., a worker may have incentives to show up for work but not to work hard). For this reason, workers are usually required to meet a minimum effort requirement to avoid termination. Broadly speaking, suppose that a firm wants workers to exert a minimum effort level equal to e_{min}. Workers then would receive a wage w whenever they exert an effort level that is at least e_{min} and would be fired otherwise. As described in Lazear (2000b), as long as unemployment is painful for workers (not a very strong assumption), this compensation scheme is high-powered in the sense that it induces workers to exert a given level of effort (i.e. e_{min}) as long as the wage exceeds the cost of effort. One complication, however, is that in most cases effort is not observable. However, this is not really a serious problem. Indeed, the desired level of effort can usually be achieved even if effort is not observable. The only requirement for payment based on input to be successful in motivating workers is to have access to a variable that is partially correlated with effort — e.g., number of hours worked or being at work on time (Lazear 2000b).

1.1.1.2 Payment Based on Output

The most common example of payment based on output is piece rates. This is because a worker who is paid piece rates is compensated according to the units of output that he or she produces. Thus, the implementation of piece rates implicitly requires two conditions: 1) The output has to be observable and 2) The quality of the output can be verified. The first condition is quite obvious, since in order to be able to compensate workers on the basis of their output, production must be counted. The second condition is a bit more subtle and stems from the fact that there is a trade-off between output and quality: A worker could increase his or her output (and thus his or her pay) by being less careful and decreasing the quality of output. This is clearly an undesirable outcome and companies must take steps to avoid it.

Examples of studies that examine the effect of piece rates include Lazear (2000a) and Shearer (2004). Lazear (2000a) shows that the introduction of piece rates at the Safelite Glass Corporation improved worker productivity by 44 percent. The author also shows that profits increased, suggesting that piece rates were superior to wages (this is not always the case). Meanwhile, Shearer (2004) uses a field experiment to estimate that paying piece rates instead of wages increased productivity by 20 percent in a Canadian tree-planting firm.

In spite of the apparent benefits, piece rates are not widely utilized. In practice, a worker's output is not always easy to measure. Moreover, a worker's job may be multidimensional, which makes the implementation of piece rates ever more difficult (Lazear 2018). When workers are responsible for multiple tasks, incentives to perform one of them may negatively affect the incentives to perform the others. Let me illustrate this phenomenon using the example of a manager who needs to take decisions on a wide range of issues: hiring, investment, suppliers, etc. When designing the manager's compensation package, the board needs to take into account how the incentives to hire productive workers affect the incentives to pursue good investment projects. Otherwise, undesirable effects may occur. If the board bases compensation largely on hiring decisions, the manager may not put enough effort into finding the best investment projects or the most efficient suppliers and may jeopardize the future of the company. Similar situations arise in many jobs. In academia, for example, professors need to juggle between research, teaching, and administrative duties. Incentives must be carefully designed so that the different tasks are performed well.

Holmstrom and Milgrom (1991) note that, as described above, workers in many jobs perform multiple tasks and study what is the optimal compensation in the presence of multitasking. They examine linear-contracts and assume that workers exhibit Constant Absolute Risk-Aversion (CARA) preferences. In their model, a worker performs different tasks and each task produces an observable output that is equal to sum of the effort that the worker puts into that task plus a normally distributed random error. One important feature of the model is that workers face an effort-substitution problem: Exerting more effort on one task increases the marginal cost of exerting effort on other tasks. The intuition is simple. Let us get back to the manager example. The more effort the manager puts into overseeing hiring decisions, the more fatigued he or she will become. Thus, after overseeing all the hiring decisions, he or she will find it more difficult to stay focused while comparing investment projects. As a result, Holmstrom and Milgrom (1991) show that workers will tend to work more on those tasks whose output is more informative about effort and, therefore, increase compensation relatively more. This is an important lesson for managers. In principle, it indicates that if the performance of tasks important to the firm cannot be adequately measured, it is better for the firm to limit itself to paying workers a salary.

1.1.1.3 Relative Payment

There are many situations in which workers are compensated on a relative manner. Consider, for example, the case of promotions. Employees are usually evaluated on a number of parameters and the best performing worker is the one who is promoted. In other words, a worker is not compensated according to his or her absolute performance (i.e., marginal product), but according to how his or her performance compares with that of his or her peers.

The situation described in the previous paragraph is reminiscent of a "tournament": Workers compete against each other for the best performance review, and the promotion is the prize for the winner or best performer. However, the idea of tournaments is broader and does not only apply to promotions. In fact, tournaments can also be used as part of a worker's compensation package in the form of bonuses, for example.

The theoretical underpinnings of tournaments were first established by Lazear and Rosen (1981). They examine payment schemes that compensate equally capable workers according to their performance ranking within the organization. Among other interesting results, Lazear and Rosen (1981) show that when workers are risk neutral, tournaments can be equivalent to compensation schemes based on individual performance. However, the problem complicates when workers are risk-averse or when workers have different skill levels. This is because tournaments alter the costs of supervision and thus the amount of risk borne by workers. Nonetheless, Lazear and Rosen (1981) identify situations where tournaments are superior to alternative compensation systems. When workers are risk-averse, for example, tournaments may be preferable to payment systems based on individual performance, depending on workers' utility functions and the degree to which output is influenced by random shocks outside workers' control (i.e., "luck").

Furthermore, Nalebuff and Stiglitz (1983) show that when uncertainty is large, tournaments offer better incentives than compensation schemes based on individual performance.

Nalebuff and Stiglitz (1983) also show that, as the number of contestants increases, tournaments can approximate the outcomes that would be obtained with perfect information.

However, tournaments can also have negative consequences on performance. For example, tournaments can create incentives to sabotage the work of others in order to get a better evaluation. Carpenter, Matthews, and Schirm (2010) analyze this possibility by using real-effort experiments to compare performance under piece rates and tournaments in situations where workers can affect the performance evaluation of their peers. Their results show that tournaments increase effort only in the absence of subjective peer evaluation. This is because when peer evaluation is part of the performance evaluation, workers expect to be sabotaged by their peers (i.e., they expect to receive a lower "grade") and consequently react by exerting relatively less effort. This result means that for a tournament to be successful in motivating workers, workers must have confidence in the evaluation system.

1.1.2 Nonmonetary Compensation and Effort

In the previous section I have reviewed some of the literature that examines the effect of monetary rewards on effort. However, workers' willingness to exert effort also depends on nonmonetary incentives. For example, researchers are willing to sacrifice higher salaries to get jobs where they can pursue and publish their research program (Stern 2004) and entrepreneurs are willing to accept lower incomes than they would in paid employment to remain self-employed (Hamilton 2000).

Thus, evidence suggests that non-monetary incentives can also influence the provision of effort and the design of optimal compensation systems. Accordingly, in this section, I review some of the academic work investigating the effects of nonmonetary incentives on performance.

1.1.2.1 Job Meaning

Job meaning can play an important role in a worker's willingness to exert effort. For instance, Ariely, Kamenica, and Prelec (2008) use a laboratory experiment to demonstrate that individuals are willing to accept lower wages when their work is more meaningful. In their experiment, participants were asked to assemble Bionicle Lego models under two different conditions. In the first group, participants kept the Bionicles they assembled in front of them. In the second group, Bionicles were destroyed immediately after being assembled. Participants could decide to stop building Bionicles at any time. The results show that participants whose Bionicles were destroyed assembled significantly fewer Bionicles. The authors speculate that the reason for their findings is that the destruction of the Bionicles made the participants feel that their work was meaningless. This patterns are important because they suggest that intrinsic motivation can have a significant impact on productivity and labor supply.

Job meaning also motivates workers outside the laboratory. For instance, Grant (2008) finds that job meaning is important to fundraising callers. Through a field experiment, Grant (2008) shows that fundraising callers who read stories about how their work can make a difference in other people's lives get significantly more pledges.

In a natural field experiment, Chandler and Kapelner (2013) ask individuals employed through Amazon's Mechanical Turk to label medical images and find that output was higher among workers who were informed that they were labeling tumor cells to help medical researchers. In other words, workers were more motivated when they knew that their work was helping others.

Finally, the degree to which a job contributes to society is also important for job meaning, intrinsic motivation and performance. For instance, Lanfranchi, Narcy, and Larguem (2010) examine workers' preferences over job attributes in the for-profit and nonprofit sectors. They find that workers in the nonprofit are willing to give up a greater percentage of their wages to work an extra hour which, the authors argue, is an indication of greater intrinsic motivation.

1.1.2.2 Autonomy

The data also show that people value autonomous decision making and that workers are willing to make a greater effort for the opportunity to make their own decisions. For instance, Benz and Frey (2008) document the relationship between self-employment and job satisfaction in 23 countries and find that the self-employed are more satisfied with their jobs precisely because they enjoy greater autonomy. Similarly, Falk and Kosfeld (2006) examine the impact of autonomy on worker performance in an experimental principal-agent game. In the game, the principal can control the agent's decisions by imposing certain performance requirements. The results show that worker performance is negatively affected when autonomy is reduced.

These results suggest that individuals derive utility from having the right to make their own decisions. This is confirmed by Fehr, Herz, and Wilkening (2013) who study the motivational effects of authority using an authority-delegation game. In the game, there are a number of potential projects and principal has the right to decide which project to implement, while the agent can only make a project recommendation. Although the principal can delegate the decision to the agent, the results show that the principal tends to retain authority even in situations where delegating would mean a higher expected income.

1.1.2.3 Recognitions and Awards

Recognition and awards are another type of nonmonetary incentives that, according to the literature, have the potential to boost worker performance. For example, Kosfeld and Neckermann (2011) measure the impact of recognitions on effort in a field experiment. Students working on a data-entry job were randomly assigned to a control and a treatment group. In the control group, students received only monetary compensation for their work. In the treatment group, students received both monetary compensation and a congratulatory card honoring the top performing student. The results showed that the performance of the students in the treatment group was at least 12 percent higher than that of the students in the control group.

Bradler et al. (2016) also use a field experiment to examine the effect of public recognition on worker productivity. The authors recruited more than 300 people to work on a three-hour data entry task. They find that receiving unexpected public recognition significantly increases the performance of both individuals whose work was recognized and workers who did not receive recognition. In other words, observing coworkers receiving public recognition also motivates workers to put in extra effort. This probably occurs because workers who did not receive recognition want their work to be recognized as well.

Ashraf, Bandiera, and Jack (2014) conduct a field experiment at a public health organization promoting HIV prevention. They study the performance of individuals recruited to sell condoms when they receive a monetary reward and when they receive recognitions in the form of star stamps. They find that individuals who received star stamps for each pack of condoms sold performed better than individuals rewarded with monetary incentives.

Evidence also indicates that awards and recognitions are effective in increasing researcher performance. For example, Chan et al. (2014) show that receiving academic awards is associated with higher research productivity. In particular, the authors find that receiving the John Bates Clark Medal or Fellowship of the Econometric Society is followed by a significant increase in subsequent publications and citations.

Recognition and awards also have a positive effect on other business performance variables such as employee retention and innovation. For example, Gallus (2017) uses a field experiment to demonstrate that symbolic awards increase retention rates of Wikipedia editors. Similarly, Gibbs, Neckermann, and Siemroth (2017) use a field experiment to examine the effect of symbolic awards on worker creativity at a large technology company. Workers in the treatment group received 2,000 points that could subsequently be redeemed for consumer goods if their ideas were accepted for implementation or for presentation to customers. Offering such rewards significantly increased the quality of ideas.

1.1.2.4 Personal Goals

Personal goals can also be an important motivation for individuals. For example, Loewenstein (1999) tries to elucidate why mountaineers go through the hardships and miseries of climbing mountains so avidly. The author argues that, despite all the suffering involved in climbing, mountaineers derive a pleasurable feeling from climbing. This feeling is not related to the climbing experience itself, but to the thrill of reaching the top of the mountain (i.e., the personal goal). And it is this thrill that keeps climbers going.

This sense of accomplishment is not limited to mountaineers and also motivates workers in a wide variety of jobs and activities. For example, personal goals may explain why researchers are willing to give up income for the opportunity for academic achievement (Stern 2004). Generally speaking, individuals feel good when they apply their skills to achieve a certain goal that matters to them, and this feeling motivates them to work harder than they otherwise would.

The available empirical evidence supports that having personal goals improves performance. For example, Corgnet, Gómez-Miñambres, and Hernán-González (2015) examine the effects of goal setting policies in a laboratory experiment. They find that assigning performance goals that are challenging but achievable increases workers' provision of effort. In addition, they also find that performance goals are more effective when monetary incentives are strong. Goerg and Kube (2012) find similar results. They use a field experiment to explore the relationship between performance goals, monetary incentives, and worker performance. In their experiment, workers receive a bonus conditional on the achievement of a pre-set goal, which can be self-selected or set by the manager. The authors find that goals lead to a significant increase in performance. Furthermore, self-chosen goals do not need to be backed up by monetary incentives to improve performance.

1.1.2.5 Leisure as an Incentive for Effort

As we have seen above, individuals are willing to exert effort in exchange for whatever reward they value, whether monetary or not. One type of motivation for hard work that has so far received very little attention in the literature is simply to be able to enjoy a break. If workers value time off, they may be willing to go the extra mile to (satisfactorily) complete their tasks more quickly and consume leisure at work.

Naturally, the amount of effort that workers will be willing to exchange for time off will depend on how entertaining the activities in which they can engage during break time are. In general, we should see that the more attractive these activities are, the harder workers will work to finish their work faster and increase their consumption of leisure time. This is the possibility I explore in the second chapter of my dissertation.

1.2 The Effects of Automation on Workers

Automation increases firm productivity by reducing costs and increasing product quality (Brynjolfsson and Hitt 2000, Miller and Tucker 2011, Xue, Hitt, and Chen 2011, Aral, Brynjolfsson, and Van Alstyne 2012, Bavafa, Hitt, and Terwiesch 2018, Tan and Netessine 2019). However, in addition to its effects on productivity, research also suggests that automation is able to change the relative demand for capital and labor through changes in the task content of jobs and in the comparative advantages of production factors. (Dewan and Min 1997, Acemoglu and Restrepo 2019).

The situation described above is important, because it means that automation has the capacity to alter the time use of workers, a phenomenon that has so far gone unnoticed: When the distribution of tasks and their relative productivities change, so does the total effective working time and also the time devoted to each task. Consider the case of a worker who performs two different tasks and spends half of the working day on each of them. If a technological innovation automates one of the tasks, making it disappear, and increases the worker's productivity in the other task. When the first task disappears, the worker gets additional time (half of the working day) to dedicate to the task that has not been fully automated. However, this is not the only phenomenon that affects the worker's use of time. Since the increased productivity allows the worker to complete the remaining task more quickly, the effective working time will decrease even further for a constant number of tasks. Thud, if management is not able to increase the number of tasks assigned to the worker or to reassign the worker to other tasks, the increase in individual productivity may not be reflected in the firm's overall performance.

This effect of automation on time use may explain, among other things, the paradox that automation has not translated into increased productivity (Brynjolfsson, Rock, and Syverson 2018). This is because for automation to realize its potential, companies must adjust their organizational design.

Analyzing the effects of automation on productivity and time use requires worker-level data. However, most of the research in on automation has focused on firm-level (e.g., Brynjolfsson and Hitt 2000, Acemoglu, Lelarge, and Restrepo 2020) or country-level (e.g., Dewan and Kraemer 2000) data. Due to a general lack of data availability, little research has been conducted at a level of detail sufficient to reveal the dynamics of how automation specifically affects productivity and time use at the worker level (Tan and Netessine 2019).

Only recently has a growing number of papers started to turn to granular-level data to study the impact of technology on labor productivity. For example, Aral, Brynjolfsson, and Van Alstyne 2012 examine accounting records and e-mail usage data at a recruiting firm and find that access to electronic communication networks helps workers improve the quality of matches between job seekers and vacancies. In related work, Tan and Netessine 2019 measure the impact of a device that facilitates the table service process at restaurants on check size and meal duration. Their results indicate that the tabletop technology increases the total spending of an average check by about 1 percent and reduces meal duration by about 10 percent.

Tan and Netessine 2019 reveal that automation has the ability to increase the productivity of waiters and waitresses by enabling them to reduce the time it takes customers to complete their meals. However, their paper does not analyze whether the time savings are spent on completing more tasks or are allocated to alternative tasks. The first case could occur if, for example, the number of customers regularly exceeds the number of tables available (i.e., when demand exceeds production capacity), so that workers would use the time freed up by automation to meet previously unsatisfied demand. The second case would arise if automation generates time savings greater than the time required to serve additional customers. In the last scenario, the positive effects of automation may be attenuated depending on the value added of the tasks to which workers can devote their extra time (in the most extreme situation all this time becomes idle time). Also, as mentioned before, it is important to mention once again that the effect of automation on time use is also mediated by the way in which automation transforms the task content of jobs (Acemoglu and Restrepo 2019). For instance, in the restaurant example, the tabletop device also means that the waiters and waitresses do not need to process the bill payment anymore, which frees up even more time. But whatever the case may be, this discussion highlights the role of managers in maximizing the gains from self-sufficiency in their role as organizers of the production process and distributors of tasks among workers, and inspires the last chapter of this dissertation.

CHAPTER 2

Leisure at Work as an Incentive for Effort

2.1 Introduction

In 2006, Toquir Choudhri, a former education analyst for the New York Department of Education, was charged with surfing the Internet at work. Mr. Choudhri argued that he was not guilty: he had earned the right to use the Internet by working faster than required and finishing his assignments ahead of schedule. The judge agreed with him and dismissed the case. This example reveals a type of motivation for hard work that has so far received very little attention in the literature: Simply to be able to enjoy a break. If workers value time off, they may be willing to go the extra mile to complete their tasks more quickly and consume leisure at work.

Mr. Choudhri's example shows that in many jobs people face a tradeoff between effort and leisure. This has usually been ignored in the literature, because it is generally assumed that leisure is any time not spent at work (Voss 1967, Dickinson 1999, Aguiar and Hurst 2007). My aim is to fill this gap by introducing a simple framework that explains a worker's trade-off between effort and leisure at work. In my framework, workers maximize their utility by choosing the effort that equals the marginal utility of break time with the marginal cost of effort. With this I infer that workers exert more effort when the attractiveness of the activities in which they may engage during break time increases, which I empirically validate with data from a distribution center (DC) in Chile.

The literature has extensively studied various other extrinsic and intrinsic motivations for exerting effort. Extrinsic motivations include financial rewards and promotions.[1] Intrinsic motivations include job meaning,[2] personal goals,[3] autonomous decision-making,[4] or recognitions and awards.[5] I advance the literature by documenting a new set of facts about the relationship between work leisure and effort. First, I introduce a simple model of effort choice. In the model, an employer assigns tasks to a salaried worker on the condition that all tasks are completed satisfactorily. The worker can gain leisure at work by exerting more than the minimum effort required to cope with his workload. Under these conditions, the optimal effort is such that the marginal utility of leisure at work is equal to the marginal cost of effort. In my analysis, I assume that the employer's decision on when and how many tasks to assign is exogenous to the worker's effort. This assumption is convenient because it reflects the empirical setting I study below and also allows me to illustrate the effect of leisure at work on effort in a straightforward fashion. However, this assumption is not restrictive. For example, many workers are assigned a fixed list of tasks — for example, a letter carrier must deliver a given number of letters and packages each day —, or they are assigned tasks based on aggregate demand conditions — for example, the workload of doctors depends on the number of incoming patients.

My model predicts that workers exert more effort when leisure at work is low. This is because when leisure is scarce, the marginal utility of leisure at work is high. My model also predicts that the provision of amenities at work (e.g., televisions, game rooms, gyms, etc.) may incentivize the provision of effort. This is because work amenities have the potential to increase the marginal utility of leisure at work. Finally, my model warns of employers who

[1]See Bandiera, Barankay, and Rasul (2007), Wowak and Hambrick (2010), Friebel et al. (2017), Lazear (2018)

[2]See Ariely, Kamenica, and Prelec (2008), Grant (2008), Chandler and Kapelner (2013), Cassar (2019)

[3]See Hamilton (2000), Stern (2004), Astebro et al. (2014)

[4]See Falk and Kosfeld (2006), Benz and Frey (2008), Fehr, Herz, and Wilkening (2013), Chen et al. (2019)

[5]See Kosfeld and Neckermann (2011), Ashraf, Bandiera, and Jack (2014), Chan et al. (2014), Bradler et al. (2016), Gallus (2017), Gibbs, Neckermann, and Siemroth (2017)

assign too many tasks (i.e., leisure at work is nonexistent) or employers who do not provide amenities at work (i.e., leisure consumption at work provides no benefit to workers). In these cases, exerting effort beyond the minimum has no additional benefit in terms of leisure and, therefore, workers are better off choosing the minimum possible effort.

In my approach, leisure time at work does not refer to scheduled breaks. Rather, when I say leisure time I refer to all the time in which workers do not have tasks to perform because they have completed their assignments beforehand. In this sense, unscheduled breaks can be seen as part of a worker's compensation.

To identify the effect of changes in the attractiveness of the consumption of break time (i.e. marginal utility of leisure at work) on effort, I rely on the exogenous variation in the timing at which FIFA Soccer Tournaments are broadcast. During the broadcastings, workers who have completed all their tasks can watch the matches in designated areas. Since scheduled breaks do not necessarily overlap with the broadcastings, workers must make an extra effort to finish their tasks ahead of schedule. Under the assumption that the soccer matches increase the marginal utility of on-the-job leisure, workers should exert relatively more effort during them.

Not all soccer matches are equally attractive. Workers prefer watching their own national team and so exert more effort during soccer matches in which Chile is between the playing teams. I also find that the effect of the broadcastings is stronger among men. This pattern is not surprising and is a reflection of the typically lower interest of women in soccer in Chile and, more generally, in competitive sports (Deaner, Balish, and Lombardo 2016).

The spike in effort during the broadcastings leads to an expansion, albeit small, in workers' output. This is important because it means that management could increase productivity by motivating effort through the provision of workplace perks that increase the attractiveness of leisure. This is in line with the results of related research that finds that unscheduled breaks positively affect worker productivity (Gino et al. 2021).

Related literature has found that workers speedup when workload is high. For instance, KC and Terwiesch (2009) document this phenomenon using operational data from patient transport services to show that workers accelerate their speed of work as load increases. Staats and Gino (2012) find that a higher workload boosts short-term productivity at a Japanese bank's home loan application-processing line. Tan and Netessine (2014) examine data from a restaurant chain to show that servers work more promptly when the number of tables or diners increase above a certain threshold. My model is consistent with these observations: the higher the workload, the less break time. Hence the marginal utility of leisure at work is higher, and so effort increases. The empirical analysis also verifies this prediction.

My contribution is to examine a motivation for effort that is being a main driver of the Gig Economy and remote work. According to Chen et al. (2019), Uber drivers' surplus is twice as large as the surplus that they would obtain in less-flexible work arrangements. Moreover, as suggested by Boltz et al. (2020), work arrangements that allow workers to decide when to start and stop working significantly increase productivity. It is quite possible that these results are due to the elements discussed here, i.e., the "pay" derived from rest. If this were the case, traditional jobs could be enriched with better opportunities for rest, thereby simultaneously increasing firms' productivity and workers' welfare, without incurring in higher financial costs.

My paper is complemented by a number of studies that look into the implicit benefits and costs of exerting effort. For instance, Goerg, Kube, and Radbruch (2019) use laboratory experiments to examine the effectiveness of financial rewards in motivating workers to perform a certain task when the opportunity cost of working varies. However, in such study, individuals decide on whether or not to work. In reality, workers are assigned tasks and they must complete them: They can only choose their effort level. Other examples of papers that study the effect of outside options for workers are Corgnet, Gómez-Miñambres, and Hernán-González (2015) and Koch and Nafziger (2016).

The remainder of the paper is organized as follows. Section 2 describes the empirical setting of the study. Section 3 develops the hypotheses to be tested. Section 4 presents the empirical approach. In Section 5, I discuss the results. I conclude in Section 6.

2.2 Background

I study the main DC of the largest home improvement retailer in Chile. Over 600 workers perform tasks such as picking or packing items or loading or unloading trucks. Shipment orders must complete different tasks depending on their characteristics. For instance, the shipping of a few products requires workers to pick and pack those items; while shipping a full pallet of products only requires workers to move it from its storage location to its loading zone.

Upon receipt of a shipping order, a software identifies the set of tasks to be performed and allocates them to workers. The allocation algorithm assumes constant worker productivity, and prioritizes tasks in order to optimize trucks space utilization. Consequently, the total number of tasks that workers perform does not depend on effort, but on the amount and specifications of the shipping orders and the number of workers on duty. Conditional on a worker being available, task assignments are therefore exogenous to workers. For this same reason, an available worker has a greater chance of receiving new assignments. Workers may thus have less incentives to complete tasks more quickly, which means, among other things, that my results could underestimate the motivational effect of break time. However, this is probably not the case: Table A.1 in the Appendix shows that the relationship between throughput and the time a worker takes to complete a task is negligible. In other words, more productive workers do not receive a significantly higher number of assignments.

Mobile devices assist workers to perform their tasks and also track their progress. For instance, when workers are asked to pick products, the mobile devices report the location where the items are stored. Workers also use such devices to verify that they have picked the right items. These features ensure that tasks are performed virtually error-free, as confirmed by the DC manager.[6]

Financial rewards and career incentives are not important drivers of effort in this DC. Workers receive fixed salaries plus 7 CLP (0.01 USD) per task completed, which is less than 0.002 percent of the entry-level salary. Moreover, in absolute terms, the variable salary is only 6 percent of the total compensation. Regarding to promotion opportunities, less than 1.5 percent of workers were internally promoted in 2018. For this reason, I proceed under the simplifying assumption that there is no pay for performance and that there are no promotion opportunities.

In most workplaces in Chile, workers who have completed all their tasks are allowed to watch FIFA Soccer Tournaments being broadcast during working hours while waiting for further assignments. The DC I study is no exception. Since the broadcasting of soccer matches usually takes place outside scheduled breaks, I argue that this mechanism acts as an incentive for workers to exert effort. Figure B.1 in the Appendix shows workers while watching a FIFA soccer match at work.

2.3 Conceptual Framework and Hypotheses Development

Let us consider the following conceptual framework. Workers choose their effort level e^* to maximize their utility u:

$$e^* : \operatorname*{argmax}_{e} u(e) = \bar{w} + \rho(y(e)) + \delta(y(e)) + \varphi(\ell(e)) - c(e), \tag{2.1}$$

where y is output, $\bar{w}$ is a fixed wage, ρ is a performance dependent payment, δ corresponds to incentives other than financial rewards (e.g., the chance to be promoted), φ is the utility

[6] In speaking to the head of the DC, I was assured that virtually all shipments are completed without mistakes.

derived from the consumption of on-the-job leisure ℓ, and c is the cost of exerting effort e.

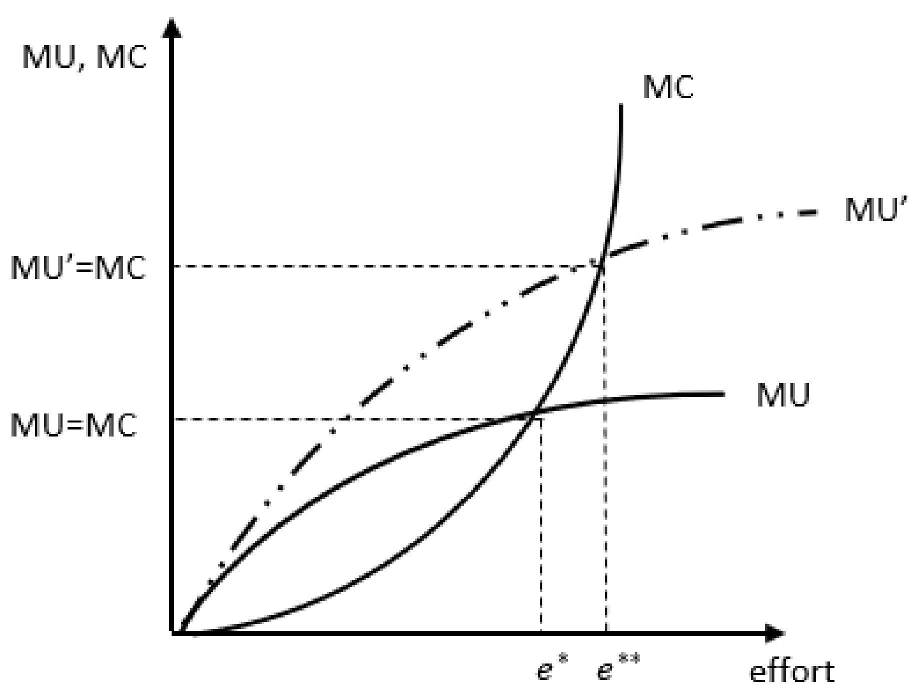
In the DC, there is no pay for performance and there are no opportunities for promotion. Thus, $\rho(y) = \delta(y) = 0$. Considering a concave utility of break time (φ) and a convex cost of effort (c), the optimal effort is given by:

$$\varphi'(\ell(e))\ell'(e) = c'(e). \tag{2.2}$$

In other words, the optimal level of effort is such that the marginal utility of the consumption of leisure at work equals the marginal cost of effort.

The intuition for what happens when the attractiveness of leisure increases is presented in Figure 2.1. In the graph, a greater attractiveness of break time increases the marginal utility of leisure at work from MU to MU'. When this occurs, the worker has a greater motivation to work harder and increases his effort from e^* to e^**.

Figure 2.1: Marginal Utility of Leisure at Work and Effort



In my context, soccer matches increase the marginal utility of leisure at work, so they motivate workers to make a greater effort.

Hypothesis 1: *Workers effort will increase during the broadcasting of a soccer match.*

However,workers' own national team matches are more attractive. Thus, workers' incentives to exert effort are higher when Chile is between the playing teams.

Hypothesis 2: *Workers effort is higher during soccer matches in which Chile is playing.*

Women tend to have less interest in competitive sports than men (Deaner, Balish, and Lombardo 2016). For this reason, during a soccer match, workers' incentives to exert effort are higher among men.

Hypothesis 3: *During the broadcasting of a soccer match, men effort will be higher than women effort.*

Recalling that the utility of leisure at work is concave and that the cost of effort is convex, I derive additional testable implications regarding to the effect of workload on effort. Consider Equation 2.2. Under the assumption that break time is decreasing in the amount of tasks, the marginal utility of leisure at work is increasing in workload.

Hypothesis 4: *Workers effort increases in response to increased workload.*

The above mechanism is important because it implies that the workload acceleration effect identified in the literature (KC and Terwiesch 2009, Staats and Gino 2012, Tan and Netessine 2014, KC et al. 2020) may be due to the existence of leisure at work.

However, a higher workload will not always be related to greater effort. In particular, during a soccer match, assigning too many tasks to a worker may reduce effort because a very high workload makes it impossible for workers to enjoy the soccer match, and therefore the benefits of working harder to get break time disappear.

Hypothesis 5: *During a soccer match, an excessive workload will cause a reduction in effort.*

Implicit in the analysis is the idea that workers can only consume unscheduled break time when all tasks have been completed. This implies that management needs to check that tasks have been completed. This is not a restrictive condition. An employer can monitor how many units of output a worker has produced or whether the worker has submitted his report. However, even in settings in which output is not observable, this condition is not that troublesome. As described in Lazear (2000a), management only needs to observe a variable that is partially correlated with effort — e.g., number of hours worked. In the Appendix C, I describe the model in more detail.

2.4 Data

I test my hypotheses using information from the DC described above. I received worker-task data in real time for the universe of tasks performed in the DC in 2016-2017 on conditions of anonymity and non-disclosure. The data cover all the 104,833,191 tasks processed between January 2016 and December 2017. For each task, I observe the worker who performed the task, the times at which the task was assigned and completed, and various other task characteristics, including the location at which a task begins and ends. I do not have records of the exact shifts performed by workers, so I assume that two consecutive tasks separated by 10 hours or more correspond to different shifts.

Data is captured by the warehouse management software (WMS) used in the DC through handheld mobile devices. At the start of each shift, each worker must log on to their own mobile device using a unique user. From that point on, the WMS assigns tasks to workers and captures the time and user to which each task is assigned together with the task details. In turn, workers must record the time at which a task is completed. This is done through barcode scanning. For example, if a worker must pick up three hammers, the mobile device informs the worker that he needs to pick three hammers and which hammers must be picked up. After the worker finds them, he must scan the barcode on the hammers to confirm that they are the correct products. By doing this, the WMS recognizes that the task has been completed and captures the time at which this event occurred.

The only restriction on workers is to complete tasks in less than a time limit that varies by task type. This is important because it means that a worker can consume leisure time at work if he completes tasks faster than the rate at which the tasks are assigned. When a worker is idle, he has priority to receive a new task. This, in principle, prevents me from using the speed at which tasks are assigned as a measure of abundance of leisure time at work. However, the WMS has a feature that allows me to implement an alternative strategy that I exploit later: each task contains a different number of subtasks that is random from the worker's point of view.

The DC data does not contain information on worker characteristics. Thus, I recover the gender of a worker by merging this database with information from the Electoral Authority. In doing so, I recover gender for 216 workers, which account for a third of the sample. Of these 216 workers, 88 percent turn out to be men.

2.4.1 Dependent variable

I measure a worker's effort as a task time to completion ($TimeToCompletion$), where a greater effort is associated to a drop in the time that workers take to perform a task (i.e., a lower time to completion). Thus, terms such as greater effort, faster work speed, or reduction in time to completion are equivalent.

For each task, I observe the hour, minute and second at which the task was assigned and completed. Thus, if a worker was assigned a task at 8:30:00 a.m. on January 1, 2016 and he completed the task at 8:35:00 a.m. on January 1, 2016, then the worker's time to completion on that task was 5 minutes. On average, a task lasts 0.32 minutes and a worker performs 551 tasks per shift. This means that workers spend about 3 hours per shift working on tasks and always consume a positive amount of leisure at work. In comparison, in the United

States, full-time male workers spend 6 hours per day on work and work-related activities (Hamermesh, Frazis, and Stewart 2005).

A potential problem with my measure of effort, however, is that workers may decrease a task time to completion by sacrificing the quality of execution. For example, a worker could finish a task faster by being less careful and selecting the wrong item or damaging it through mishandling. Unfortunately, these situations are not recorded in the data, but in the opinion of the DC manager, they are very infrequent. It is therefore unlikely that my results are influenced by quality problems.

Table 2.1: Descriptive statistics.

Variable	Observations	Mean	SD	Min	Max
Speed at which tasks are completed (tasks per hour)	89,457,789	941.41	1,145.09	0.12	3,600
Average time between tasks (hours)	89,457,789	0.04	0.13	0	5.50

Note: This Table shows summary statistics for the described variables. The level of observation is worker-task. The data covers over 500 different workers.

Table D.1 in the Appendix also shows the average number of tasks a worker receives depending on the time of day and day of the week. Finally, Figure E.1 shows the distribution of the number of tasks by task type in my sample.

2.5 Empirical Analysis

2.5.1 Identification Strategy

I explore the incentive effect leisure at work by exploiting variations in the timing at which FIFA Soccer Tournaments are broadcast. During the broadcasting of soccer matches, workers who have completed all their tasks can attend on-site broadcasting events, which in turn increases the implicit benefits to exert effort by allowing workers to spend their break time on a more enjoyable activity.

The identification strategy of this paper thus assumes that the timing of when soccer matches are played is exogenous to the DC. The full list and details of the soccer matches considered in the analysis is presented in the Appendix.

Finally, since the broadcasting of FIFA Soccer Tournaments mostly occur outside scheduled breaks, the only way for workers to watch soccer matches at work is to complete their task assignments ahead of time.

2.5.2 Econometric Model

I explore whether workers exert relatively more effort during the broadcasting of a soccer match (Hypothesis 1) by estimating the following equation:

$$TimeToCompletion_{i,t} = \alpha_1 + \gamma_1 FIFA_{i,t} + X_{i,t}\beta_1 + u_{i,t}. \tag{2.3}$$

Here, i and t denote workers and tasks, respectively, and $u_{i,t}$ is a random disturbance term. $FIFA_{i,t}$ is a dummy variable that takes the value 1 if worker i performed task t during the broadcasting of a soccer match and 0 otherwise. $X_{i,t}$ consists of a set of variables that control for the heterogeneity in worker and task characteristics. This set of controls includes shift fixed effects, worker-shift fixed effects, hour fixed effects, and worker-hour fixed effects; which are intended to capture inter-temporal differences in technology and in the number and specifications of shipping orders as well as differences in workers' preferences over when to consume on-the-job leisure. Tasks vary in type and workers may be more or less proficient in certain tasks depending on their unobserved ability. For this reason, I also include worker fixed effects, task fixed effects, and worker-task fixed effects. When picking or packing products workers need to move across different locations. Thus, I also correct for the location in which a task starts and ends (start and end fixed effects) and for the distance between both locations (distance fixed effects). Finally, since the handling of different items may require different degrees of attention, I also control for the type of products involved in a task (product fixed effects).

Recalling that not all soccer matches are a priori equally attractive, and that Chile's matches should motivate workers much more than other matches (Hypothesis 2), I estimate:

$$TimeToCompletion_{i,t} = \alpha_2 + \gamma_2 FIFANonChile_{i,t} + X_{i,t}\beta_2 + u_{i,t}, \tag{2.4}$$

$$TimeToCompletion_{i,t} = \alpha_3 + \gamma_3 FIFAChile_{i,t} + X_{i,t}\beta_3 + u_{i,t}, \tag{2.5}$$

and

$$TimeToCompletion_{i,t} = \alpha_4 + \gamma_4 FIFANonChile_{i,t} + \gamma_5 FIFAChile_{i,t} + X_{i,t}\beta_4 + u_{i,t}, \tag{2.6}$$

where $FIFAChile_{i,t}$ is a dummy variable that takes the value 1 if worker i performed task t during the broadcasting of a soccer match in which Chile was between the playing teams and 0 otherwise, and $FIFANonChile_{i,t}$ is a dummy variable that takes the value 1 if worker i performed task t during the broadcasting of a soccer match in which Chile was not between the playing teams.

In order to validate my results, I propose a different econometric specification. According to my framework, workers should exert more effort during the broadcasting of a soccer match but not before the match starts or ends. For this reason, I also estimate:

$$TimeToCompletion_{i,t} = \alpha_5 + \gamma_6 FIFABefore_{i,t} + \gamma_7 FIFA_{i,t} + \gamma_8 FIFAAfter_{i,t} + X_{i,t}\beta_5 + u_{i,t}, \tag{2.7}$$

$$TimeToCompletion_{i,t} = \alpha_6 + \gamma_9 FIFANonChileBefore_{i,t} + \gamma_{10} FIFANonChile_{i,t} + \gamma_{11} FIFANonChileAfter_{i,t} + X_{i,t}\beta_6 + u_{i,t}, \quad (2.8)$$

$$TimeToCompletion_{i,t} = \alpha_7 + \gamma_{12} FIFAChileBefore_{i,t} + \gamma_{13} FIFAChile_{i,t} + \gamma_{14} FIFAChileAfter_{i,t} + X_{i,t}\beta_7 + u_{i,t}, \quad (2.9)$$

and

$$TimeToCompletion_{i,t} = \alpha_8 + \gamma_{15} FIFAChileBefore_{i,t} + \gamma_{16} FIFAChile_{i,t} + \gamma_{17} FIFAChileAfter_{i,t} + \gamma_{18} FIFANonChileBefore_{i,t} + \gamma_{19} FIFANonChile_{i,t} + \gamma_{20} FIFANonChileAfter_{i,t} + X_{i,t}\beta_8 + u_{i,t}, \quad (2.10)$$

where $FIFABefore_{i,t}$ and $FIFAAfter_{i,t}$ are dummy variables that take the value 1 if worker i performed task t within one hour before the start of a soccer match and within one hour after the end of a soccer match and 0 otherwise. Analogously, $FIFAChileBefore_{i,t}$ and $FIFAChileAfter_{i,t}$ are dummy variables that take the value 1 if worker i performed task t within one hour before the start of a soccer match in which Chile was between the playing teams and within one hour after the end of a soccer match in which Chile was between the playing teams and 0 otherwise. Finally, $FIFANonChileBefore_{i,t}$ and $FIFANonChileAfter_{i,t}$ are dummy variables that take the value 1 if worker i performed task t within one hour before the start of a soccer match in which Chile was not between the playing teams and within one hour after the end of a soccer match in which Chile was not between the playing teams and 0 otherwise.

To test whether the motivation effect of soccer matches is more prevalent among men than among women (Hypothesis 3), I estimate the following expressions:

$$TimeToCompletion_{i,t} = \alpha_9 + \eta_1 Female_i + \kappa_1 Female_i \times FIFA_{i,t} + \delta_1 Male_i \times FIFA_{i,t} + \tilde{X}_{i,t}\beta_9 + u_{i,t}, \quad (2.11)$$

$$TimeToCompletiont_{i,t} = \alpha_{10} + \eta_2 Female_i + \kappa_2 Female_i \times FIFANonChile_{i,t} + \delta_2 Male_i \times FIFANonChile_{i,t} + \tilde{X}_{i,t}\beta_{10} + u_{i,t}, \quad (2.12)$$

$$TimeToCompletion_{i,t} = \alpha_{11} + \eta_3 Female_i + \kappa_3 Female_i \times FIFAChile_{i,t} + \delta_3 Male_i \times FIFAChile_{i,t} + \tilde{X}_{i,t}\beta_{11} + u_{i,t}, \quad (2.13)$$

and

$$TimeToCompletion_{i,t} = \alpha_{12} + \eta_4 Female_i + \kappa_4 Female_i \times FIFANonChile_{i,t} \kappa_5 Female_i \times FIFAChile_{i,t} + \delta_4 Male_i \times FIFANonChile_{i,t} + \delta_5 Male_i \times FIFAChile_{i,t} + \tilde{X}_{i,t}\beta_{12} + u_{i,t}, \quad (2.14)$$

where $Male_i$ is a dummy variable that takes the value 1 if worker i is male and 0 otherwise. Analogously, $Female_i$ is a dummy variable that takes the value 1 if worker i is female and 0 otherwise. $\tilde{X}$ is defined in the same way as X except that, in order to make the previous estimations possible, $\tilde{X}$ does not include worker fixed effects, worker-shift fixed effects, worker-task fixed effects, nor worker-hour fixed effects.

Finally, I examine what is the effect of workload on effort. As previously mentioned, conditional on the existence of tasks, the task allocation software will assign new tasks to available workers. This means that the number of tasks a worker receives per unit of time is endogenous. To solve this problem, I exploit an additional feature of our data. Depending on the number and specifications of the shipping orders arriving to the DC, different workers can receive different numbers of tasks at once. Thus, I estimate the following equation:

$$TimeToCompletion_{i,t} = \alpha_{13} + \sum_{n}^{6} \xi_n Load(n)_{i,t} + X_{i,t}\beta_{12} + u_{i,t}, \tag{2.15}$$

where $Load(n)_{i,t}$ is a dummy that takes the value 1 if the total number of tasks that worker i received simultaneously at time t is between $[5 \times (n-1), 5 \times n)$ and 0 otherwise.

2.6 Results and Discussion

2.6.1 Stylized Facts

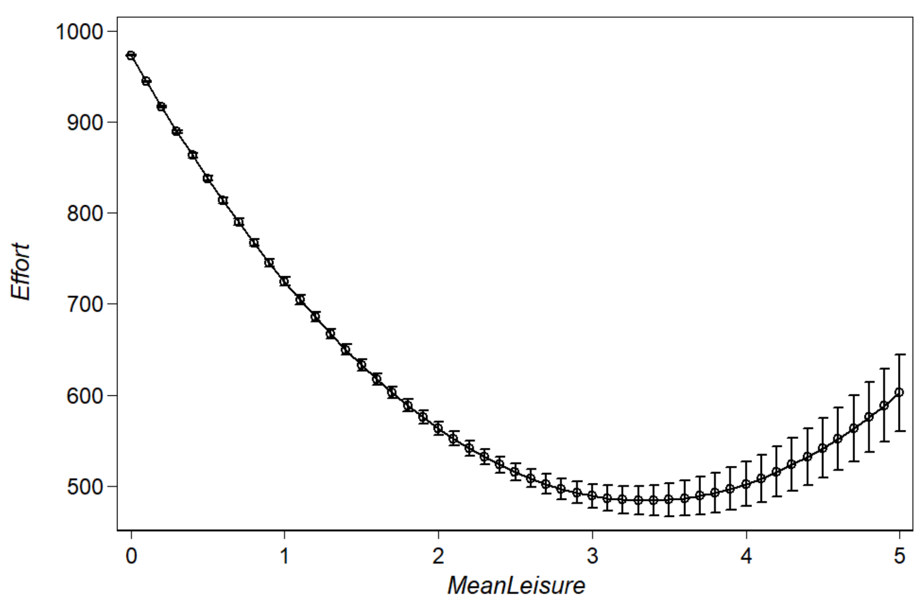
Before presenting the results of the estimations of the equations described in the previous section, I show some of the non-causal patterns observed in the data. In particular, I show that effort and leisure time between tasks are negatively correlated. The intuition is as described in the conceptual framework: when leisure at work is small, the marginal utility of leisure at work is larger. As a result, workers have more incentive to exert more effort and complete their tasks more quickly when the time between tasks is smaller. For this purpose, I estimate the following regression:

$$Effort_{i,t} = \beta_0 + \mathbf{X}_{i,t}\beta_1 + \beta_2 MeanLeisure_{i,t} + \beta_3 MeanLeisure^2_{i,t} + u_{i,t}, \tag{2.16}$$

where i denotes worker and t denotes task, as before. In addition, $u_{i,t}$ is a mean zero error term and $\mathbf{X}_{i,t}$ consists of a set of variables that control for the heterogeneity in worker and task characteristics. This set of variables includes worker fixed effects, task fixed effects, shift fixed effects, hour fixed effects, worker-shift fixed effects, worker-hour fixed effects, worker-task fixed effects, location fixed effects, product fixed effects, and number of items per task. $Effort_{i,t}$ is defined as the inverse of $TimeToCompletion$ (i.e. the smaller $TimeToCompletion$ is, the larger $Effort$ is) for while worker i performed task$t$. Finally, $MeanLeisure_{i,t}$ is the average time between tasks experienced by worker i up to the assignment of task t.

Figure 2.2 plots the adjusted predictions of effort using Equation 2.16. As expected, effort and leisure time between tasks are negatively correlated.

Figure 2.2: Leisure at Work and Effort



Note: This figure plots the adjusted predictions of effort at different levels of leisure time between tasks. The figure shows that effort and leisure time between tasks are negatively correlated.

2.6.2 Results

I now turn to the estimation of the regressions introduced in the last section. I run my regressions using the `reghdfe` package (Correia 2017). One of the things to note is that this package identifies the model by choosing the constant that makes the prediction at the means of the independent variables equal to the mean of the dependent variable. It is for this reason that the estimated constant in most of the regressions is equal to the average time to completion. It is important to note that the package does not modify the value of any other coefficient.

Table 2.2 summarizes the results of estimating the set of regressions that examine effort behavior during the broadcasting of soccer matches. I find that $TimeToCompletion$ is significantly lower during the broadcasting of soccer matches. Column (1) indicates that the average task is completed 3.2 seconds faster. This amounts to approximately 16 percent shorter completion times. This lends support to Hypothesis 1 that the increased attractiveness of leisure at work motivates workers to make an extra effort.

Column (2), (3), and (4) show that most of the effect of the broadcasting of soccer matches is explained by matches in which Chile is between the playing teams. Columns (2), (3), and (4) reveal that only soccer matches in which Chile is between the playing teams have a statistically significant effect. During a Chile's soccer match, the average task is completed 12.8 seconds more quickly (approximately 60 percent faster). These results strongly support Hypothesis 2. The magnitude of my results is comparable to the estimates of Boltz et al. (2020), who use a lab experiment to calculate that flexible work arrangements can increase worker productivity by up to 50 percent.

Table 2.3 summarizes the results of estimating the set of regressions that examine effort behavior before, during, and after the broadcasting of soccer matches. These results are

Table 2.2: Performance Implications of the Broadcasting of Soccer Matches

	(1)	(2)	(3)	(4)
FIFA	-0.0528 ***			
	(0.0070)			
FIFANonChile		-0.0030		-0.0030
		(0.0081)		(0.0081)
FIFAChile			-0.2126 ***	-0.2126 ***
			(0.0145)	(0.0145)
Constant	0.3308 ***	0.3306 ***	0.3308 ***	0.3308 ***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
R^2	0.2934	0.2934	0.2934	0.2934
Observations	89,457,789	89,457,789	89,457,789	89,457,789

Note: The dependent variable is *TimeToCompletion*. All models include fixed effects for worker, task, worker and task, shift, worker and shift, hour of the day, worker and hour of the day, location in which a task starts, location in which a task ends, distance between the locations in which a task starts and ends, and product.
$***\ p < 0.01$; $**\ p < 0.05$; $*\ p < 0.10$.

relevant for two reasons. First, they corroborate that workers only exert more effort during a Chile's soccer match but not before or after the match. This can be seen in Column (2), (3), and (4), where only the coefficient of *FIFAChile* is statistically significant. Together, these patterns offer additional support to both Hypothesis 1 and Hypothesis 2. Second, because effort is stable before and after a soccer match, Table 2.3 also indicates that the increase in effort during soccer matches does not come at the expense of lower effort at other times (e.g., maybe because working at a faster pace during the broadcasting of a soccer match ends up in fatigue).

In addition, the results shown in Table 2.3 also allow us to do back of the envelope calculations of the potential effect of increased effort on individual output. Let us consider Chile's soccer matches. The average effective working time within one hour before the start of a soccer match in which Chile is between the playing teams is 20 minutes. Analogously, the average effective working time during the broadcasting of a soccer match in which Chile is between the playing teams is 26 minutes per hour. Finally, the average effective working time within one hour after the end of a soccer match in which Chile is between the playing teams is also 26 minutes. In other words, the average effective working time is very similar before, during, and after the broadcasting of a soccer match. However, because of the differences in the incentives to exert effort, the maximum output before, during, and after the broadcasting of a soccer match in which Chile is between the playing teams is 62 ($20/(0.3308 - 0.0075)$) tasks, 223 ($26/(0.3308 - 0.2143)$) tasks, and 80 ($26/(0.3308 - 0.0039)$) tasks per hour, respectively. However, the previous calculations need not be reflected in the data. This is because the number of tasks that a worker performs also depends on the number of tasks that the worker is assigned. Because in the DC tasks are assigned following an algorithm that assumes constant worker productivity, I should actually see that workers perform a similar amount of tasks at all times. This is precisely what I observe. During a soccer match, workers perform between 4-10 more tasks only. This result is reassuring for two reasons. First, it is evidence that the task allocation algorithm is constant. Second, it indicates that soccer matches do not act as a distraction. For example, it may be possible that during a soccer match a worker spends less time per unit worked, but works on fewer units. The fact that workers perform a similar amount of tasks at all times suggests that there is no such effect.

The previous results show that increasing the marginal utility of leisure at work can increase both effort and output. This could be achieved by offering workers different activities to engage in during break time (e.g. game rooms). Because these activities would be available to all workers, there is also a scale effect that could make these job amenities more cost effective in motivating effort provision than financial rewards. In the case of soccer matches, it only takes a large screen to motivate workers, whereas pay for performance would involve paying more to all workers. However, it must be noticed that taking advantage of the motivation effect of leisure at work also involves updating task allocation policies. In my particular example, the task allocation algorithm is constant. In order for the DC to increase output, the number of task assignment should also increase.

Table 2.3: Worker Performance Before, During, and After the Broadcasting of a Soccer Match

	(1)		(2)		(3)		(4)	
FIFABefore	-0.0024							
	(0.0074)							
FIFA	-0.0527	***						
	(0.0072)							
FIFAAfter	0.0053							
	(0.0106)							
FIFANonChileBefore			0.0024				0.0023	
			(0.0099)				(0.0099)	
FIFANonChile			-0.0029				-0.0030	
			(0.0083)				(0.0083)	
FIFANonChileAfter			-0.0037				-0.0036	
			(0.0159)				(0.0159)	
FIFAChileBefore					-0.0075		-0.0074	
					(0.0112)		(0.0113)	
FIFAChile					-0.2143	***	-0.2143	***
					(0.0148)		(0.0148)	
FIFAChileAfter					-0.0039		-0.0040	
					(0.0141)		(0.0141)	
Constant	0.3308	***	0.3306	***	0.3308	***	0.3309	***
	(0.0004)		(0.0004)		(0.0004)		(0.0004)	
Controls	Yes		Yes		Yes		Yes	
R^2	0.2934		0.2934		0.2934		0.2934	
Observations	89,457,789		89,457,789		89,457,789		89,457,789	

Note: The dependent variable is *TimeToCompletion*. All models include fixed effects for worker, task, worker and task, shift, worker and shift, hour of the day, worker and hour of the day, location in which a task starts, location in which a task ends, distance between the locations in which a task starts and ends, and product.
$***\ p < 0.01$; $**\ p < 0.05$; $*\ p < 0.10$.

Table 2.4 summarizes the results of estimating the set of regressions that examine effort behavior during the broadcasting of soccer matches by gender. First, notice the reduction in sample size due to data availability. Second, recall that the functional form of this regression is not entirely comparable to the previous estimations. In particular, in order to include gender fixed effects, I have excluded worker fixed effects which means that variables that are constant at the worker level — such as ability — will not be captured in the model. This is in part of the reason for the difference in the magnitude of the estimated coefficients when compared to the rest of the regressions. Regarding the results, the coefficients once again show that Chile's soccer matches cause a significant reduction in a task time to completion. Furthermore, and more importantly, the interaction terms reveal that this effect is only significant among men. Thus, my results support my hypothesis that the increase in effort during the broadcasting of soccer matches is concentrated among men (Hypothesis 3).

The literature has shown that workers speed up when workload is high (KC and Terwiesch 2009, Staats and Gino 2012, Tan and Netessine 2014, KC et al. 2020). Therefore, if workload increases during FIFA Soccer Tournaments, my results could be explained by increased workload and not by the presence of leisure at work. For this reason, I re-estimate my regressions this time controlling for workload. The results are presented in Table G.1 in the Appendix. Several patterns worth highlighting can be observed. First and foremost, my results are robust to controlling for workload.

Second, I corroborate that an increase in workload also causes workers to speedup. This can be observed by looking at the workload dummies in Table G.1 in the Appendix, which are positive, decreasing, and statistically significant. Since the base category is the maximum workload, decreasing dummies mean that time to completion decreases as workload increases (i.e., workers speedup). For example, increasing the number of tasks a worker receives at the same time from $[0, 5)$ ($Load(1)$) to $[5, 10)$ ($Load(2)$), reduces execution time by $0.8644 - 0.3790 = 0.4854$ minutes. This effect is nonlinear and marginally decreasing. My conceptual framework offers an explanation for this phenomenon. Higher workload means less break time, which increases the marginal utility of leisure at work. This in turn motivates workers

Table 2.4: Performance Implications of the Broadcasting of Soccer Matches by Gender

	(1)		(2)		(3)		(4)	
Female	0.0476	***	0.0478	***	0.0476	***	0.0475	***
	(0.0048)		(0.0048)		(0.0048)		(0.0048)	
FemaleFIFA	0.0637							
	(0.0529)							
MaleFIFA	-0.0258	*						
	(0.0152)							
FemaleFIFANonChile			0.0237				0.0241	
			(0.0635)				(0.0635)	
MaleFIFANonChile			-0.0085				-0.0084	
			(0.0173)				(0.0173)	
FemaleFIFAChile					0.1521		0.1521	
					(0.0953)		(0.0953)	
MaleFIFAChile					-0.0798	**	-0.0798	**
					(0.0312)		(0.0312)	
Constant	0.3749	***	0.3749	***	0.3749	***	0.3749	***
	(0.0010)		(0.0010)		(0.0010)		(0.0010)	
Controls	Yes		Yes		Yes		Yes	
R^2	0.1993		0.1993		0.1993		0.1993	
Observations	28,993,132		28,993,132		28,993,132		28,993,132	

Note: The dependent variable is *TimeToCompletion*. All models include fixed effects for task, shift, hour of the day, location in which a task starts, location in which a task ends, distance between the locations in which a task starts and ends, and product.
$***\ p < 0.01$; $**\ p < 0.05$; $*\ p < 0.10$.

to increase their effort. Taken together, these results support Hypothesis 4.

Finally, the interaction terms also reveal an interesting pattern: During Chile matches, increases in workload might decrease effort. Consider $Load(6) \times FIFAChile$. Given that the base category is the maximum workload, the negative coefficients reveal that decreasing workload during a Chile match from the maximum workload to $[25 - 30)$ tasks ($Load(6) \times FIFAChile$) decreases time to completion by -2.78 minutes. This result supports Hypothesis 5 and can be explained by the fact that too many tasks prevent the worker from watching the soccer match and, therefore, make the benefits of exerting more effort disappear.

To provide a better idea of the magnitude of my results, in Figure 2.3 I compare my estimates with the productivity changes that would result from various hypothetical scenarios.

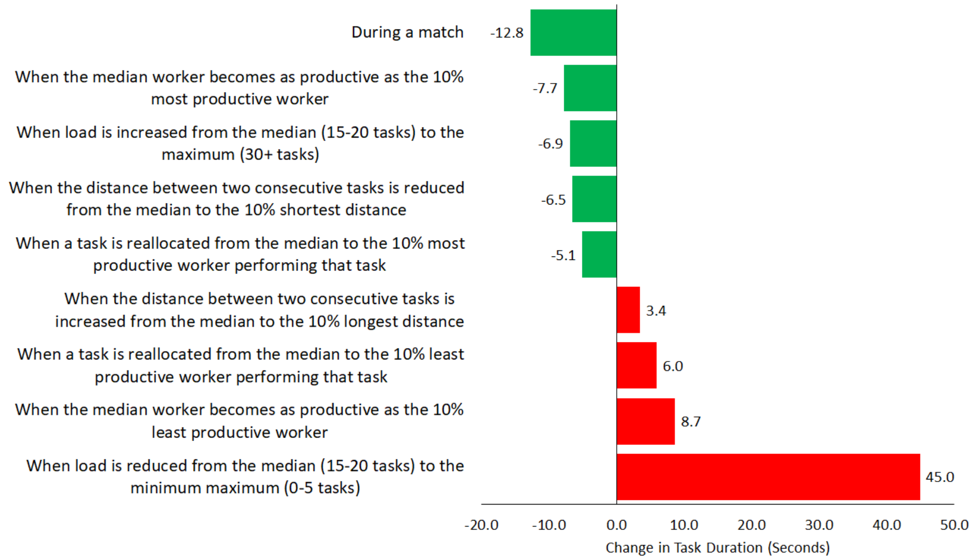
First, I compare the match effect with the productivity changes from making the median worker as productive as the 10 percent most productive worker or the 10 percent least productive worker. I measure worker productivity using the distribution of the worker fixed effects estimated in my regressions. As the figure shows, the productivity gains caused by the motivational effect of soccer matches are noticeably larger than an improvement in worker skills.

I then compare the motivational effect of soccer matches with the productivity gains resulting from a hypothetical reduction in the distance that workers must travel in order to complete their tasks. I measure the effect of distance on productivity using the distribution of the estimated distance fixed effects. The productivity gains caused by the motivational effect of soccer matches are again noticeably larger than the productivity gains that would result from a decrease in distance.

I also explore how the match effects compare to reallocating the tasks to the workers that perform them best. To this end I rely on the distribution of my worker-task fixed effects. The motivational effect of matches on productivity is also significantly more relevant.

Finally, the figure also shows that the workload effect can be important. Giving work-

Figure 2.3: Comparison of the Magnitude of the Effect of Soccer Matches on Time to Completion.



ers too few tasks significantly increases the duration of a task. This occurs because when workload is low, leisure at work is abundant and, therefore, its attractiveness is lower. As a result, workers have less incentives to exert effort.

Putting my results into perspective shows that the effect of leisure at work is significant, especially when compared to other options for increasing productivity. For example, increasing the productivity of the average worker may involve training and the redesign of hiring practices, and improving the allocation of tasks requires a new task allocation system, all of which can be extremely costly. Furthermore, alternatives such as reducing the distance between tasks requires changing the structure of the DC, which may not be even possible.

2.6.3 Managerial Implications: Benefits from "Rewarding" Workers with On-the-Job Leisure

The simple conceptual framework introduced in this paper together with the empirical estimations show that the motivational effect of leisure at work may have important benefits for the operations of an organization.

First, in the DC that I study, motivational effect of leisure at work more than compensates the decrease in effective working time that comes from allowing workers to consume break time. The higher effort, in turn, translates into a marginal increase in output per worker. These results suggest that the elimination of leisure at work could lead to a fall in output per worker. This means that employers who strive to keep workers busy all the time (e.g., by assigning an increasing number of tasks to workers who complete their workload early) may be negatively affecting the productivity of their firms.

Second, my results also point to the important role of workplace perks as an incentive for workers. This is because workplace perks increase the attractiveness and value of leisure at work.

Third, from an operational perspective, it is advantageous that workers complete their tasks more quickly. For example, having available workers (i.e., workers in break time) allows management to increase revenue by fulfilling unexpected orders. In addition, shorter processing times may also help to encourage purchases from impatient customers (Plambeck and Ward 2008).

Finally, leisure at work can slacken workers' participation constraint. Thus, the consumption of leisure at work can reduce the wages needed to induce workers to exert any level of effort. This, in turn, can save labor costs.

2.7 Conclusion

Conditional on work quality, individuals who exert additional effort finish their tasks faster and consume unscheduled break time. In the absence of pay for performance or opportunities for promotion, a worker's optimal effort is such that the marginal utility of leisure at work equals the marginal cost of effort. Consequently, the more attractive the activities in which workers can engage during break time, the higher the effort that they will exert.

I explore two years of worker-task data for the universe of tasks performed in a large DC in Chile. I find that watching soccer at work increases the attractiveness of break time, and workers respond by exerting more effort during soccer matches. The magnitude of my estimates is significant and greater than the productivity gains that would result from matching the productivity of the median worker to that of the 10 percent most productive worker.

My findings suggest that firms could benefit from offering workplace perks that increase the marginal utility of leisure at work. This is important because workplace perks may be more cost-effective than financial rewards such as pay-for-performance or bonuses. My results also suggest the existence of unexplored benefits of working from home or at the Gig Economy: Deciding where and when to work means that workers can decide to consume break time precisely when leisure is most valuable. As previously discussed, the latter creates strong incentives for workers to work harder. Thus, workplace perks and break time may have additional benefits that have not yet been studied. My paper provides evidence in this direction by showing that greater and better opportunities to use leisure time at work have the potential to transform into greater incentives to exert effort.

In addition, my results can be useful for the development of online teaching as well. In fact, with universities teaching online, students can learn when and where they want. Precisely because the freedom to choose when and where to study affects the value of free time, universities must adjust the way courses are taught and the opportunities career services offer students.

However, my results also have limitations that open interesting avenues for further research. For example, soccer is probably the most popular sport in Chile and arouses a lot of interest. My estimates may therefore be capturing the upper bound impact of leisure at work. In addition, FIFA Soccer Tournaments are infrequent and it is unclear what the effect will be if the DC offers breakroom activities on a regular basis.

In any case, whether in a traditional, a remote, or a Gig job, it is clear that people value break time activities, and therefore they drive workers to be more productive. In the post-pandemic world, where many rules of what jobs will look like are being rewritten, it is clear that the quantity and quality of rest during shift work must be integrated into the equation.

CHAPTER 3

Automation, Productivity, and Time Use

The consequences of automation for workers are uncertain are uncertain and controversial. On the one hand, automation increases worker productivity and creates new tasks, which increases the demand for labor. On the other hand, automation also replaces tasks currently performed by workers, which in turn decreases the demand for labor. The final outcome depends on which of these two opposing effects predominates.

The former discussion reveals that a thorough examination of the impact of automation on the demand for labor requires an understanding of how new technologies affect the task content of jobs and the relative productivity of workers across the different tasks that they perform. Acemoglu and Restrepo (2019) move in this direction by developing a task-based framework for thinking about the implications of automation. Their model is simple, but it is effective in capturing some of the main dynamics of automation and their impact on the demand for labor. First, automation increases the productivity of capital and labor at tasks that they currently perform (i.e., productivity effect), which increases the demand for labor. Second, automation reallocates tasks from labor to capital (i.e., displacement effect), which decreases the demand for labor. Finally, automation creates new tasks in which labor has a comparative advantage (i.e., reinstatement effect), which increases the demand for labor.

But although this task-based framework highlights some of the most important mechanisms through which automation affects labor demand, automation does more than just change the task content of jobs and the relative productivity of workers in different tasks. Indeed, there is a phenomenon closely related to changes in the task content of jobs and relative productivity between tasks, but which has often gone unnoticed: automation alters workers' use of time. When the distribution of tasks performed by workers and their relative productivities change, so does the time allocated to each task and the total effective working time. This change in the use of time has the potential to alter the marginal productivity of labor and, therefore, the performance of a firm.

To illustrate the effect of automation on time use, consider the simplest case of a worker who performs only two different types of tasks and spends half of the workday on each of them. Imagine now that the introduction of a new technological innovation automates and completely replaces one of the tasks, making it disappear, but increases the productivity of the worker in the other task. At first glance, perhaps the most obvious consequence is that, since one of the tasks has disappeared, the effective working time will decrease by exactly half of the working day if there were no additional changes. This is because workers no longer need to spend time on this task. However, at the same time in the background a much less obvious phenomenon is occurring: if the workload of the task that has not been automated, but whose productivity has increased, remains constant (or increases by less than the change in productivity), the actual work time will decrease even more. This occurs because the increase in productivity allows the worker to complete the tasks more quickly. Thus, if management is not able to increase the number of tasks assigned to workers or to reassign workers to other tasks with an equal or greater return, the increase in individual productivity may not be reflected in the company's results. Among other things, this may explain the paradox that automation does not always translate into increase in observed productivity (Brynjolfsson, Rock, and Syverson 2018). In other words, for automation to realize its potential, companies must adjust their organizational design and production processes. However, documenting the effect of automation on time use is not straightforward. Probably one of the most important complications in describing this phenomenon is the availability of data at the necessary level of granularity.

Perhaps because of this same data constraints, the empirical literature studying automation has so far been mostly limited to the analysis of firms or plants and has focused almost exclusively on industrial robots (Dinlersoz and Wolf 2018, Koch, Manuylov, and Smolka 2019, Acemoglu, Lelarge, and Restrepo 2020). This is an important limitation because to observe the effect of automation on time use one needs to be able to look at the performance of workers on each of their tasks. It is also worth noting that, although industrial robots are an important example of automation, they are adopted by a small number of companies (Bessen et al. 2020), which also limits the applications of the existing literature.

In this paper, I describe the effects of the introduction of an e-commerce software that automated the online order fulfillment process in the wholesale division of the Chilean branch of an American multinational retail corporation In my analysis, I use extremely detailed data on productivity and time use at the worker-task level from the pickers of two of the six stores of the wholesale division. The software automated the system that assigns the tasks to the pickers, but not the tasks performed by them. On the contrary, the pickers were helped by the software, which, among other things, provides detailed information on the location of the products that the pickers have to pick up, thus increasing their productivity. I focus on pickers due to data limitations. But proceeding in this way also have its advantages. In particular, focusing on pickers is helpful because it helps to narrow down the effects of automation on time use.

Before the introduction of the e-commerce software, the company under analysis processed online sales in an entirely manual fashion. To purchase online, customers had to visit the company's website and choose the products they wanted to buy. However, the online catalog was not synchronized with the company's computer systems and, therefore, after choosing the products, customers had to wait for a call from customer service to confirm the order, the pick-up store and process the payment. Once these details were confirmed, customer service would forward the order details to the relevant store manager who had to decide when and which worker would process the order. When the manager decided it was time to process the order, she or he would print the order details and assign the order to a picker, whose first task was to check that the products ordered were available in the store. If some of the products were out of stock, customers were contacted once again to see if the unavailable products could be substituted with alternatives or if the order had to be cancelled.

Online purchase processing was radically transformed after the introduction of the software. Once the software went live, customers began to be able to place their orders completely online. The software keeps track of the products available in each of the stores and assigns orders to pickers via mobile devices. In this way, customer service managers and store managers no longer have to intervene in the order fulfillment process. Naturally, the latter alters the way in which telephone operators and store managers spend their time, since it frees up all the time previously spent on order fulfillment. However, it's not just phone operators and store managers who are affected. Since the mobile devices through which the software assigns tasks to the pickers provide information such as the list of products ordered and their location, the pickers (i.e., the workers in charge of picking and packing the products purchased by customers) are complemented by the software and should experience an increase in their productivity. Thus, depending on the workload, this increase in productivity also has the potential to alter the use of time.

Although, as mentioned above, customer service agents, store managers, and other jobs were affected by the introduction of the software, my empirical analysis focuses on pickers. The reason for this is simply due to data availability. The data on worker productivity and time use prior to automation, which took place in March 2021, comes from the notes of consultants who followed and analyzed in detail the activities performed by pickers and store managers. Initially, the same measurement would be replicated after the introduction of the software, which would have provided me with comparable data to study the effects of automation on both store managers and pickers. However, movement restrictions introduced in Chile following unexpected increases in Covid-19 infections made this impossible. Fortunately, the e-commerce software tracks when pickers are assigned a task and when they complete it. This allows me to observe how many tasks a picker performs, how long it takes to complete each task (productivity), and also the total time spent on these tasks (time use) before and after automation. The analysis only covers a period of time with similar Covid-19 related mobility restrictions, so that the data are comparable and the results are not affected by regulatory changes.

I find that, as expected, the pickers' productivity increases with the introduction of the software. However, the extra productivity is not accompanied by additional tasks, which means that pickers get extra time to dedicate to other activities. Thus, the effect of the software on the company's performance depends critically on the operational return on these new activities.

One of my contributions is to provide evidence on the effects of automation beyond robotics. In addition, only recently has a growing body of work begun to turn to granular data to study the impact of technology on productivity. For example, Tan and Netessine (2019) examine the impact of a tabletop device that facilitates the table service process at restaurants on check size and meal duration. Thus, my second contribution is to explore the effect of automation at the worker level not only on individual productivity, but also on the use of time, a dimension rarely touched in the literature.

3.1 Background

As mentioned in the introduction, I study the effects of automation on the productivity and time use of pickers in the wholesale division of a large American multinational in Chile. The multinational incorporated the wholesale division into its family of brands in 2012 and, since its launch, the wholesale division has focused exclusively on selling to other companies using a membership system. For this reason, the wholesale division aims to offer a service designed to meet the specific needs of companies such as restaurants and hotels. This is reflected in the fact that most of the products sold in the wholesale division are not available in other chains owned by the multinational in the local market.

The wholesale division currently has six stores distributed throughout the country, three of which are in the Santiago metropolitan region, where the capital city is located. Prior to the outbreak of the Covid-19 pandemic, customers of the wholesale division could only shop in the stores. However, the deepening of the restrictions associated with the pandemic forced the wholesale division to give its customers the ability to shop online. Due to the surprising and sudden expansion of Covid-19, the wholesale division had to react quickly and, in order to achieve the goal of creating an online purchasing system in record time, it was necessary to implement a creative, but essentially manual process. The product catalog was uploaded to the company's website, where customers could review it and choose the items they wanted to purchase. The catalog was not synchronized with the wholesale division's computer systems, so after selecting the desired products, customers were contacted by phone to confirm their orders, payment method and pick-up or delivery location. The call center then sent the order to the relevant store manager, who decided how and when the order would be completed. This step mainly involved choosing the time the order would be processed and selecting the picker responsible for collecting and packaging the products. After the manager assigned the purchase order, the picker's first task was to check that all the requested products were available in stock and, if not, to inform the store manager, who in turn instructed the call center to contact the customer and offer alternative products. If the customer accepted the suggested changes, the order continued to be processed. If the customer refused, the order was cancelled.

Although the online sales system described above served its purpose, it soon proved insufficient for the company's needs. For one thing, the process was too time-consuming and tedious. In addition, the fact that employees had to contact customers when the ordered products were not available led to significant productivity losses and inefficiencies. For these reasons, the wholesale division decided to automate the online sales process with the introduction of an e-commerce software. The software would allow the company to track the stock of available products in real time and complete all stages of an online sale without the need for the call center or store managers to intervene. In this way, customers would be able to check that the products they wanted to buy were available online at the time they placed their order and also process the payment for their purchase. The software would also take care of sales processing, including assigning purchase orders for fulfillment directly to pickers via mobile devices, and would also decide on processing times.

The software was initially scheduled to be launched in early February 2021. But after a series of delays, the software finally went live at the end of March 2021. This event is the subject of this study. As can be anticipated from the previous paragraph, the software significantly changed the task content of jobs. First of all, telephone operators were no longer involved in the processing of online purchases, which means that part of the call center tasks were replaced. Similarly, store managers were also replaced by the technology, as they no longer had to assign orders to pickers among their tasks. All this was done by the software and, therefore, a large number of workers saw how some of their tasks were reduced and how the distribution of the use of their time was altered. Unfortunately, for the reasons mentioned above, I do not have productivity or time use data for managers and telephone operators after the introduction of the software, which prevents me from identifying the activities to which these workers allocated their freed-up time. This may be a particularly important dimension, since the profitability of the software depends in part on the added value of these new activities.

In contrast to the experience of the telephone operators and store managers, the software did not replace any of the tasks performed by the pickers. On the contrary, the software made the pickers' job easier. Pickers now not only receive orders via mobile devices, but also information about the location of the products to be picked. The latter presumably has a positive impact on pickers' productivity, which, as previously explained, can also affect the distribution of time use. The following analysis will focus exclusively on the effects of the software on picker performance and time use. I proceed in this way mainly due to data limitations: I only have data from pickers on task-level productivity and time use before and after the introduction of the software.

I will describe the effects of the software in two dimensions. The first is on productivity, measured as the time it takes pickers to complete an order. The effect of automation on worker productivity is an aspect that the management literature has already studied (see Tan and Netessine 2019, for example). However, the evidence is still beginning to develop.

Second, I also evaluate the effects of automation on a dimension that has remained unnoticed: time use. As already mentioned, automation changes the productivity of pickers. This increase in productivity is accompanied by a decrease in the time spent assembling orders, which leads pickers to redistribute their time to other activities. This change in the use of time can have important consequences for the overall productivity of the company depending on the added value of the tasks to which the workers reallocate their time.

3.2 Data

My analysis is based on two main sources of information on picker performance, one before the introduction of the software and one after. Data for the period before the introduction of the software were collected in late February 2021 by consultants who followed two randomly selected pickers in two of the company's stores (the total number of pickers on a shift varies between 4 and 6) for the entire workday and took note of the activities they performed and the time they spent on each activity . This level of detail allows me to obtain estimates of worker productivity for each task performed (i.e., the time it took to complete each task), but also to observe how time is distributed among the different activities during the workday.

The data for the period after the introduction of the software is taken directly from the information collected by the software itself, and includes the time stamp at which pickers were assigned to process an order and when they completed it. Initially, the wholesale division planned to use consultants to collect time usage data comparable to that described for the period prior to the introduction of the software as well. However, the significant increase in the number of people infected with Covid-19 in Chile during March 2021 forced the government to introduce further restrictions on people's mobility, which made the consultants' work impossible.

The fact that the consultants were unable to collect data on picker time use does not affect my productivity comparisons, as the information collected by the software is sufficient to measure the time it takes each picker to complete each task (this is because the software records the timestamp at which the pickers were assigned to process an order and when they completed it). However, this does affect the level of detail at which I can analyze the effect of automation on time use. In particular, I will only be able to compare changes in time spent picking and packing (i.e. time spent on tasks) versus time spent on other activities.

The information used in this study comes from stores located in Cerrillos and Pudahuel. Pickers work from 8 a.m. to 4 p.m. in the first store, and from 8:30 a.m. to 3 p.m. in the second store. The time that pickers must spend on activities that are not directly related to order processing according to company estimates is detailed is as follows. Pickers have 5 minutes to get ready for work (e.g., change clothes), 15 minutes for breakfast, and 60 minutes for lunch. The analysis corrects for these activities.Finally, it is also important to note that the time period under analysis is characterized by the same movement restrictions related to Covid-19. Therefore, the comparison is not influenced by any regulatory changes.

3.3 Results and Discussion

3.3.1 Pre-Automation

In this section, I look at productivity at the worker-task level, measured as the time it takes workers to complete their tasks, and the time use of workers prior to the introduction of the e-commerce software. Since there is a natural flow between time allocation and productivity, I begin the analysis by discussing the use of time.

Table 3.1 shows the average time (in minutes) that pickers spent on different activities during the workday before automation. One thing that stands out is that unproductive time and time spent on other activities (i.e. breakfast, lunch, and putting on the work uniform) varies between 2.5 hours and 4 hours. These numbers mean that workers spend only about 4 hours performing tasks. This figure is very similar to that of the distribution center analyzed in the previous chapter.

Regarding how time is distributed among the different activities, workers in Cerrillos and Pudahuel seem to use their time at work in a similar way. Probably the only and most notable difference between the two stores is the unproductive time, which is 3 times higher in Cerrillos. This is very interesting because the difference in unproductive time between Cerrillos and Pudahuel is one and a half hours, precisely the difference between the length of the working day between the two stores. In other words, this information suggests that Cerrillos could decrease the length of the workday without affecting total production. Clearly, this may raise the question of why the working day is not reduced. This may be due to operational reasons, but the discussion of why the workday is not reduced is beyond the scope of this paper.

Given the significant difference between the unproductive time in the two stores, the table 3.2 presents the breakdown of unproductive time by store. The first thing that jumps out is that most of the unproductive time in both stores is due to workers arriving late or leaving early. This is interesting because if it is assumed that to arrive late or leave early workers need the approval of their supervisor, and that the supervisor only gives these approvals when they do not affect the productive process (i.e., when the number of tasks is low enough that they can be completed even if the worker arrives late or leaves early), this means that both stores face a low workload. Now, if this is the case and the workload is low, e-commerce software may not be profitable in the short term. This is because, as discussed above, automation will free up time that will not necessarily be spent on high return activities.

Table 3.1: Time Use Prior to the Software Introduction (Minutes)

Time spent...	Cerrillos	Pudahuel
Preparing for work (e.g., change clothes)	8	0
Team meetings	8	5.5
Gathering working tools	9	3.5
Picking products	76.5	78.5
Checking product availability	23	14
Filling order forms	0.5	0
Packing and storing products	57	59
Filling invoices	22.5	54
Processing payments	1.5	0
Checking shipments	12.5	0
Filling waybills	5	5
Loading trucks	0	18.5
Waiting for customers to arrive to pick up orders	0	4
Others	106	99
Unproductive time	155	51

Note: This table presents the average time (in minutes) that pickers spent on each activity prior to the introduction of the e-commerce software. Others include the time spent on breakfast, lunch, and putting on a work uniform.

Table 3.2: Time Use Prior to the Software Introduction (Minutes)

Unproductive Time	Cerrillos	Pudahuel
Worker does not have the necessary work materials	2.5	0
Worker works at a slow pace	5	1
Worker needs to redo previously completed work	34	2.5
Worker arrives late/leaves earlier	41.5	43.5
Worker does not know how to perform the task	0	0
Worker has no tasks to perform	26	0
Worker needs to move to other areas within the store	1	5.5

Note: This table presents the average time (in minutes) that pickers spent on unproductive activities (i.e., not working) prior to the introduction of the e-commerce software.

Thus, to understand the consequences of automation on workers in the wholesale division, it is necessary to understand how the software affects the time workers spend on each of their tasks. Thus, after the above discussion, I now turn to describe worker productivity at the task level. In the context of this study, a task corresponds to the preparation of a purchase order (i.e., each task is a separate purchase order). For example, if a customer buys 50 pounds of flour, 50 pounds of salt, and 50 pounds of butter, the worker's task corresponds to picking and packing these products and having them ready for the customer to pick up later.

On average, pickers in Cerrillos worked on 6 tasks during their workday and took 3.5 hours to complete them. In Pudahuel, pickers worked on an average of 3.5 tasks and took 1.6 hours to complete. These figures translate into an average worker taking 0.58 hours to complete a task in Cerrillos and 0.45 in Pudahuel. The details of the time workers used to complete each of their tasks are presented in Table 3.3. Note that, since I am studying a wholesale division that only serves businesses, the size of the orders tends to be quite large. This is the reason for the perhaps seemingly low number of tasks that workers have to complete.

Note that Table 3.3 also shows that there is a large variation in productivity. This is because different tasks involve picking and packing different types and quantities of products. Later, when I compare the changes in productivity and time usage, I will take this into account by checking the order details.

3.3.2 Post-Automation and Comparison

The data collection from the e-commerce software was far from perfect and required several adjustments and validations. The first problem is that pickers did not necessarily logged in on their mobile devices using their unique username. The software assigns tasks and collects performance information based on user names. If a worker does not log off at the end of his shift and the next worker continues to use the same user, it will appear as if only one worker

Table 3.3: Detail of the Time Spent by Pickers on Tasks (Pre-Software)

A. Cerrillos

Worker 1

Task	Time (Minutes)	Time (Hours)
Task 1	19	0.32
Task 2	16	0.27
Task 3	34	0.57
Task 4	31	0.52
Task 5	63	1.05
Task 6	1	0.02
Task 7	9	0.15
Total Time	173	2.88

Worker 2

Task	Time (Minutes)	Time (Hours)
Task 1	3	0.05
Task 2	6	0.10
Task 3	6	0.10
Task 4	223	3.72
Task 5	8	0.13
Total Time	246	4.10

B. Pudahuel

Worker 1

Task	Time (Minutes)	Time (Hours)
Task 1	24	0.40
Task 2	64	1.07
Task 3	33	0.55
Task 4	1	0.02
Total Time	122	2.03

Worker 2

Task	Time (Minutes)	Time (Hours)
Task 1	12	0.20
Task 2	49	0.82
Task 3	4	0.07
Total Time	65	1.08

Note: A task corresponds to the preparation of a purchase order (i.e., each task is a separate purchase order). For example, if a customer buys 50 pounds of flour, 50 pounds of salt, and 50 pounds of butter, the worker's task corresponds to collecting and packing these products and have them ready for the customer to pick them up later.

performed all the tasks, which is clearly an error.

The second problem, and related to the previous one, is that if a worker forgets to disconnect from his device at the end of his shift, the software will continue to assign tasks to him. Thus, if a worker does not log off, and even if another worker does not use the device, the software will register that the picker was assigned a task. Naturally, the task will not be completed until the worker returns on his next shift. If this is not taken into consideration, it will appear that the worker took much longer to complete his task than he actually did. It should be noted that the same thing will happen if a worker forgets to log off during a lunch break, for example.

A third problem is that the software can assign several tasks simultaneously. This implies that when a worker is assigned two or more tasks at the same time, it is not possible to identify the amount of time the workers spent on each task separately.

The last problem to consider is that, although in principle a picker should work and complete a task as soon as possible after the task has been assigned, occasionally workers must interrupt a picking task to work on other assignments that a store manager deems appropriate.

The correction of the issues described above required careful coordination with the company's team and a thorough review of the data. First, the analysis rules out any observations in which pickers were assigned two or more tasks simultaneously. Since the implementation of the software to date, only a few of the tasks were assigned in groups of two or more, so this approach is not really restrictive.

To solve problems related to the misuse of mobile devices by employees (i.e. not logging off during a break or at the end of a shift or not using their own user), the company carried out an intervention in which the importance of using the devices in the correct way was highlighted. This intervention was successful and significantly reduced the problems. The data used in this part of the analysis correspond to the post-intervention period. During this same time, store managers were stressed to not interfere with order processing, which also solves the last problem with the data collected in the weeks immediately following the software introduction.

The study of the variables that determine the correct and successful adoption of technological tools is, in any case, an interesting topic. For example, the incorrect use of mobile devices or the overruling of software decisions by store managers may be due to negative views on automation and a detailed analysis could measure the consequences on productivity as well as potential ways to solve the difficulties. However, it should also be noted that the intrusion of store managers is not necessarily negative for the company's performance. In fact, it is possible to think of scenarios where the opposite is true and where store managers can improve software assignments by incorporating information that the software does not have. These are areas for future research.

Table 3.4 presents the comparison in the average time a picker took to complete a task before the introduction of the software and the time a collector takes to complete a task after the introduction of the software. Two things should be mentioned at this point. The first is that, for the time being, I only have the ability to disclose aggregate data. This is due to company concerns that further disaggregation might reveal relevant operational information. Second, the comparisons for the average time that pickers take to complete a task presented in the table control for worker and task characteristics (number of products, total price of products, and types of products). The information contained in the Table corresponds to the second half of April 2021. Thus, data availability is limited and it is maybe too early to assess the significance of the results. Nevertheless, the data still reveal suggestive patterns.

Table 3.4 reveals some interesting details. First, the time that workers take to complete a task decreased, on average, by 0.1338 hours or 8.028 minutes. Second, the number of task assignments per shift increased only marginally by 0.45. Thus, the software appears to have effectively increased picker productivity. Second, given the average number of tasks, the decrease in time it takes to complete a task is relatively greater than the increase in the number of tasks assigned per shift. This means that, after the implementation of the software, the time spent on tasks fell.

From conversations with store managers, the former is what actually happened. Probably given the economic conditions that have resulted from the Covid-19 pandemic, I was also told that most of this extra time appears to have been spent on non-productive activities (i.e. leisure). This is interesting because it highlights the importance of the role of demand and labor flexibility. If the number of workers cannot be easily modified and if the demand for labor services does not increase, then automation or new technologies may not be improve a company's performance, as is the case in this study. This is simply because, when the level of demand is not a constraint on production, the additional time generated by automation (i.e. productivity gains) does not translate into output increases. However, the company could still benefit if labor costs could be saved, which can only occur if there is sufficiently flexible legislation.

Table 3.4: Pre/Post-Software Comparison

A. Cerrillos

Pre/Post-Software Change Change	Average Time per Task (Hours)	Average Number of Tasks per Shift
Worker 1	-0.2453	-1.4
Worker 2	-0.1287	0.7

B. Pudahuel

Pre/Post-Software Change Change	Average Time per Task (Hours)	Average Number of Tasks per Shift
Worker 1	-0.0579	0.6
Worker 2	-0.1033	1.9

Note: This table presents the change in the average time it took a picker to prepare a task before the software and the time it takes a picker to finish a task after the software. The table also shows the average number of tasks assigned to a worker on each shift before and after the software. The comparisons for the average time control for worker and task characteristics (number of products, total price of products, and types of products).

3.4 Conclusion

In this paper, I use extremely detailed data on task-level productivity and worker-level time use of pickers in two of the six stores of the wholesale division of the Chilean branch of a U.S. multinational retailer to describe the effects of the introduction of software that automated the online order fulfillment process on worker performance. Focusing on pickers is useful because it helps to measure the effects of automation on productivity and time use in a clean and easy way.

Automation increased picker productivity because the implementation of the software involved, among other things, the introduction of mobile devices that facilitated the pickers' work (but did not replaced the tasks performed by the pickers). The pickers were helped by the software because it provides, through the mobile devices, detailed information on the location of the products that the pickers have to pick, thus increasing their productivity.

One of the main distinguishing features of my study is the consideration of the effects of automation not only on productivity, but also on time use, a dimension usually ignored. Generally speaking, a higher productivity should translate into a higher demand for labor. However, this is not necessarily the case if automation alters workers' time use.

In the context of this paper, pickers did indeed become more productive, which allowed them to complete their tasks more quickly. However, the time that pickers saved was not spent on other productive activities. Thus, in this particular case, if the workload does not expand or if the company is unable to find other tasks of value to the pickers, automation will actually decrease the need for workers, even though it has increased productivity. This highlights the importance of understanding automation as a process of organizational transformation and considering its consequences in a holistic manner.

APPENDIX A

Performance and Throughput

Table A.1: Performance and Throughput

	(1)		(2)		(3)	
$FIFAChile$			-0.3186	***	-0.3186	***
			(0.0184)		(0.0184)	
$FIFANonChile$	-0.0030				-0.0030	
	(0.0081)				(0.0081)	
$Throughput$	0.0000		0.0000		0.0000	
	(0.0000)		(0.0000)		(0.0000)	
$ThroughputxFIFAChile$			0.0003	***	0.0003	***
			(0.0000)		(0.0000)	
$ThroughputxFIFANonChile$	0.0000				0.0000	
	(0.0000)				(0.0000)	
$Constant$	0.3306	***	0.3308	***	0.3308	***
	(0.0004)		(0.0004)		(0.0004)	
R^2	0.2934		0.2934		0.2934	
Observations	89,457,672		89,457,672		89,457,672	

Note: The dependent variable is $TimeToCompletion$. All models include fixed effects for worker, task, worker and task, shift, worker and shift, hour of the day, worker and hour of the day, location in which a task starts, location in which a task ends, distance between the locations in which a task starts and ends, and product. $Throughput_{i,t}$ is worker i's average throughput (in tasks per hour) between the beginning of a shift and the start of task t.
$***\ p < 0.01$; $**\ p < 0.05$; $*\ p < 0.10$.

APPENDIX B

Workers During the Broadcasting of a FIFA Soccer Game

Figure B.1: Workers During the Broadcasting of a FIFA Soccer Game

APPENDIX C

Model of Effort and Leisure at Work

In this appendix, I develop my conceptual framework, which explains how leisure at work can act as an incentive to exert effort, in detail. In my analysis, I assume that the employer's decision on when and how many tasks to assign is exogenous to effort. This assumption is convenient and practical, as it allows me to illustrate the influence of leisure at work on effort in a straightforward manner and also reflects the empirical setting I study.

My model is continuous in the sense that workers only care about total leisure consumption at work. This means that individuals are indifferent between consuming a 2-hour break in the morning or consuming a 1-hour break in the morning and a 1-hour break in the afternoon. This is clearly a simplifying assumption. In reality, the timing and duration of rest breaks are likely to affect the relationship between work leisure and effort. For example, workers might prefer breaks that take place during a specific period of the day, or they might value only those breaks that are long enough to perform a desired activity. However, abstracting from this dimension is neither a crucial nor a restrictive assumption for my model. In principle, it can be assumed that workers cannot decide when to consume leisure at work: individuals must work whenever they are assigned a task. This means, in practice, that workers can increase the duration of their breaks by putting in extra effort, but they cannot choose the timing of those breaks. Therefore, assuming that workers only care about the total consumption of leisure at work does not jeopardize the ability of my model to capture the working conditions of most individuals.

C.0.1 Preliminaries

Let us imagine a full-time salaried worker with no promotion possibilities. The worker is endowed with T units of time and receives a wage $\bar{w}$ for the time spent at the workplace t, which is divided between actual working time h and leisure at work ℓ. Due to labor regulations or contractual obligations, the worker must remain at his workstation for the entire working day.

The assignment of tasks is exogenous to the worker's effort. This assumption can be interpreted in several ways. In particular, one can think of an employer who assumes in his decisions that workers perform at a constant level of effort at all times. Since task assignments are exogenous to effort, the employer's decision on when and how many tasks to assign is equivalent to choosing time between two consecutive sets of task assignments. For simplicity, I assume that the time between tasks is observed by the worker. This would be the case if workers were given a complete list of their tasks at the start of the workday. However, this is not always the case. For example, workers might receive tasks randomly (e.g., the exact number of customers arriving at a register at any given time is unknown to a cashier). In these cases, the model could be extended to allow for, say, a Poisson process in the arrival of tasks.

The worker decides how much effort to exert — defined as the speed of work —, in order to maximize his surplus, which is equal to the sum of the wage $\bar{w}$ plus a concave utility of leisure at work $\phi(\ell)$ minus a convex cost of effort $c(e)$. Perhaps because the worker always consumes some amount of leisure outside of work, the utility of leisure at work is assumed to be such that $\phi(0) = 0$.

The worker must exert a minimum effort $e_{\min}$. This is the level of effort such that the worker completes all tasks but does not consume leisure at work. If the effort is less than this minimum level, the worker is fired. There is also a maximum effort level $e^{\max}$ that can be interpreted as the highest possible work speed given the production technology.

The worker can gain leisure at work by exerting more effort than the minimum required:

$$\ell = 1/e_{\min} - 1/e, \tag{C.1}$$

where, without loss of generality, the number of tasks has been normalized to one. This is the worker's tradeoff: although effort is costly, the higher the effort, the more leisure at work that is consumed.

In the model, the minimum and maximum effort are assumed to be constant. I proceed in this way for simplicity but the model could be extended to accommodate situations in which $e_{\min}$ and $e^{\max}$ may vary. For example, the minimum effort requirement could be increased when the overall workload is relatively higher.

C.0.2 Leisure at Work as an Incentive for Effort

The worker's problem is given by:

$$\max_{e \in [e_{\min}, e^{\max}]} u = \bar{w} + \phi\left(\ell = 1/e_{\min} - 1/e\right) - c(e), \tag{C.2}$$

and the first order condition is:

$$\phi'(\ell(e))\ell'(e) = c'(e). \tag{C.3}$$

Equation C.3 says that a worker's optimal effort is such that the marginal utility of leisure at work equals the marginal cost of effort.

The above result is useful for several reasons. First, it makes it clear that when the marginal utility of leisure at work increases, workers are willing to exert more effort. This is extremely important because it means that the provision of amenities that increase the marginal utility of leisure at work should also increase effort.

So far, I have assumed that there is an interior solution. In other words, I have assumed that the worker consumes some positive amount of leisure at work. However, there is a corner solution in which the worker cannot consume leisure at work (e.g., when all tasks are completed, new tasks are immediately assigned). When an individual cannot consume leisure at work regardless of how hard he or she works, the additional effort is costly but brings no benefit, since leisure at work does not increase. When this happens, the worker is better off exerting as little effort as possible, i.e. choosing $e = e_{\min}$. This is what explains the fact that during a soccer game, workers exert significantly less effort when the number of tasks is extremely high.

APPENDIX D

Average Number of Task Assignments

Table D.1: Average Number of Tasks Received by a Worker per Day of the Way and Hour of the Day

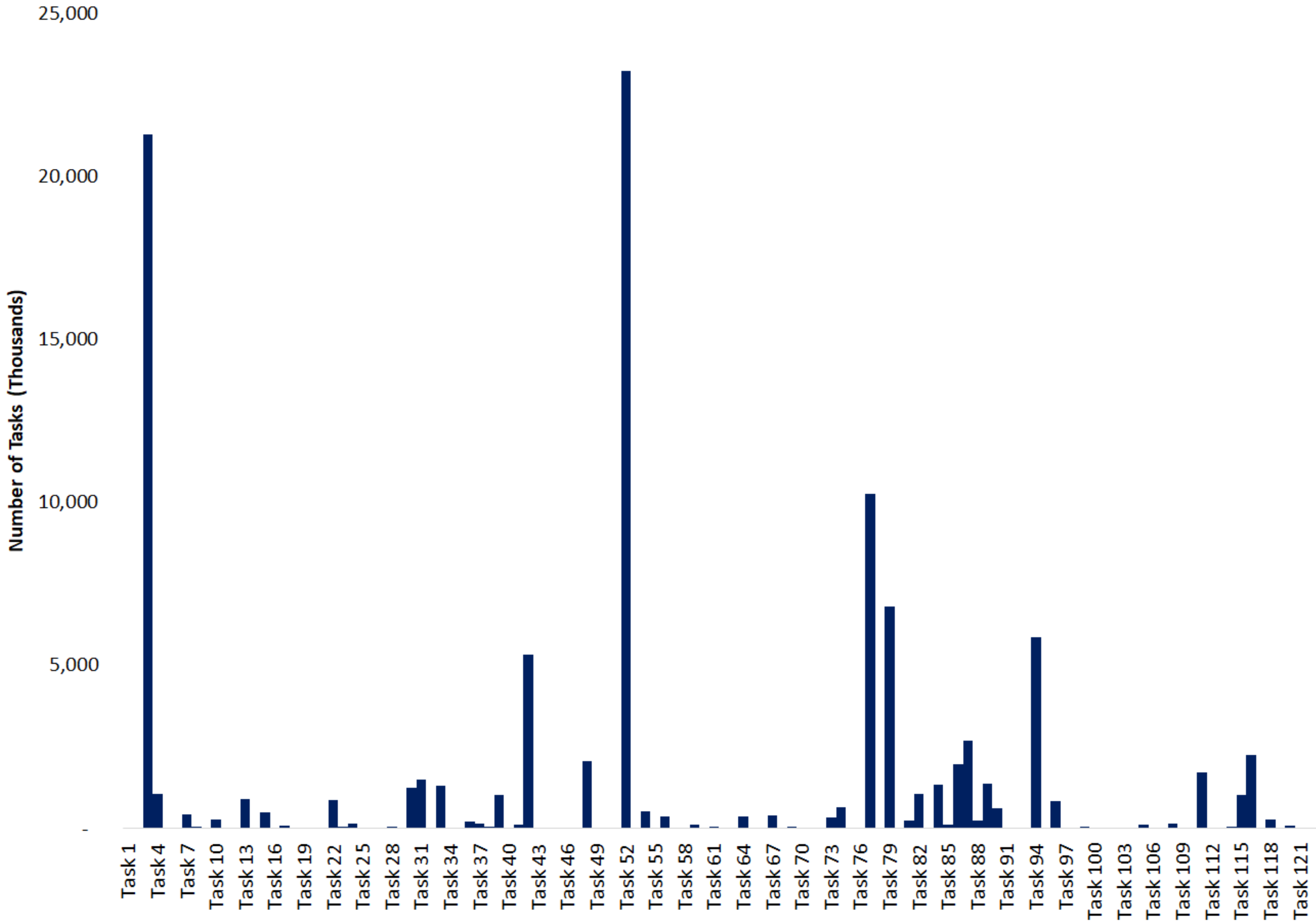
Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
12AM	152.5206	131.233	136.54167	154.693	121.4122	139.3187	6.5
1AM	136.1915	44.40741	45.538462	66.01754	45.93103	48.68182	
2AM	113.6818	109.1013	151.88095	144.4091	141.9239	161.6667	3
3AM	183.0984	133.1905	150.775	139.35	151.3936	150.093	2
4AM	53.85714	127.95	134.29474	133.2019	112.6337	89.34694	
5AM	153.8462	120.8111	139.22353	138.8046	134.3077	135.5263	
6AM	118.55	113.1917	119.33333	139.3966	108.7963	110.6195	
7AM	102.2649	110.8966	104.79427	110.4283	108.6587	75.74783	14.42857
8AM	120.1952	123.0951	113.91788	119.2345	114.8986	100.2416	29.3871
9AM	119.0422	119.0912	120.19355	115.1105	121.6718	116.4853	64.15517
10AM	110.7813	124.0752	116.24343	115.8021	114.7983	119.1815	88.16901
11AM	118.9384	124.0543	115.64909	117.6367	124.0384	122.5127	101.7558
12PM	116.6208	109.4927	112.73613	111.3689	117.5626	115.2393	113.1548
1PM	122.3806	120.7838	121.0209	114.6142	129.979	110.0644	79.54762
2PM	130.3752	124.0897	123.11823	126.1222	123.056	101.642	113.1342
3PM	122.3681	122.6705	118.1874	121.5756	125.6479	115.4462	105.0122
4PM	129.03	121.7069	123.48197	127.752	130.5039	112.2083	106.939
5PM	112.5307	114.236	113.40439	108.6396	109.8978	78.96476	80.91026
6PM	107.0256	108.393	108.4936	112.3165	99.37269	89.28302	82.89041
7PM	131.4637	128.7705	126.48097	124.3771	128.7723	89.12766	95.61404
8PM	130.3536	131.7119	123.53169	123.6841	119.8626	91.7971	79.59575
9PM	107.2146	108.3372	106.21626	109.2105	98.82401	82.36066	107
10PM	81.45622	95.66802	75.8659	76.74684	74.06522	4.5	58.87931
11PM	89.27273	95.79518	92.707031	74.23828	104.4198		70.24138

Note: This table presents the average number of tasks received by a worker during each day of the week and time of day. The table excludes observations in which the average number of tasks received by a worker is above 500. These observations correspond to tasks associated with a worker but which are performed automatically. For example, label printing tasks are performed automatically but are associated with the worker responsible for the printing station.

APPENDIX E

Total Number of Tasks by Type of Task

Figure E.1: Total Number of Tasks by Type of Task



APPENDIX F

List of FIFA Soccer Matches Considered in the Empirical Analysis

Table F.1: **Soccer Matches Considered in the Empirical Analysis.**

Playing Teams	Tournament	Time in Chile
Chile vs. Argentina	FIFA World Cup Qualifiers	3/24/2016 20:30
Venezuela vs. Chile	FIFA World Cup Qualifiers	3/29/2016 20:30
Chile vs. Jamaica	Friendly	5/27/2016 19:30
Mexico vs. Chile	Friendly	6/1/2016 22:00
United States vs. Colombia	Centennial Cup America Group Stage	6/3/2016 21:30
Costa Rica vs. Paraguay	Centennial Cup America Group Stage	6/4/2016 17:00
Haiti vs. Peru	Centennial Cup America Group Stage	6/4/2016 19:30
Brazil vs. Ecuador	Centennial Cup America Group Stage	6/4/2016 22:00
Jamaica vs. Venezuela	Centennial Cup America Group Stage	6/5/2016 17:00
Mexico vs. Uruguay	Centennial Cup America Group Stage	6/5/2016 20:00
Panama vs. Bolivia	Centennial Cup America Group Stage	6/6/2016 19:00
Argentina vs. Chile	Centennial Cup America Group Stage	6/6/2016 22:00
United States vs. Costa Rica	Centennial Cup America Group Stage	6/7/2016 20:00
Colombia vs. Paraguay	Centennial Cup America Group Stage	6/7/2016 22:30
Brazil vs. Haiti	Centennial Cup America Group Stage	6/8/2016 19:30
Ecuador vs. Peru	Centennial Cup America Group Stage	6/8/2016 22:00
Uruguay vs. Venezuela	Centennial Cup America Group Stage	6/9/2016 19:30
Mexico vs. Jamaica	Centennial Cup America Group Stage	6/9/2016 22:00
Chile vs. Bolivia	Centennial Cup America Group Stage	6/10/2016 19:00
Argentina vs. Panama	Centennial Cup America Group Stage	6/10/2016 21:30
United States vs. Paraguay	Centennial Cup America Group Stage	6/11/2016 19:00
Colombia vs. Costa Rica	Centennial Cup America Group Stage	6/11/2016 21:00
Ecuador vs. Haiti	Centennial Cup America Group Stage	6/12/2016 18:30
Brazil vs. Peru	Centennial Cup America Group Stage	6/12/2016 20:30
Mexico vs. Venezuela	Centennial Cup America Group Stage	6/13/2016 20:00
Uruguay vs. Jamaica	Centennial Cup America Group Stage	6/13/2016 22:00
Chile vs. Panama	Centennial Cup America Group Stage	6/14/2016 20:00
Argentina vs. Bolivia	Centennial Cup America Group Stage	6/14/2016 22:00
United States vs. Ecuador	Centennial Cup America Quarterfinal	6/16/2016 21:30
Peru vs. Colombia	Centennial Cup America Quarterfinal	6/17/2016 20:00
Argentina vs. Venezuela	Centennial Cup America Quarterfinal	6/18/2016 19:00
Mexico vs. Chile	Centennial Cup America Quarterfinal	6/18/2016 22:00
United States vs. Argentina	Centennial Cup America Semifinal	6/21/2016 20:00
Colombia vs. Chile	Centennial Cup America Semifinal	6/22/2016 21:00
United States vs. Colombia	Centennial Cup America Third Place Playoff	6/25/2016 20:00
Argentina vs. Chile	Centennial Cup America Final	6/26/2016 20:00
Paraguay vs. Chile	FIFA World Cup Qualifiers	9/1/2016 21:00
Chile vs. Bolivia	FIFA World Cup Qualifiers	9/6/2016 20:30

Continued on next page

Table F.1 – **continued from previous page**

Playing Teams	Tournament	Time in Chile
Ecuador vs. Chile	FIFA World Cup Qualifiers	10/6/2016 18:00
Chile vs. Peru	FIFA World Cup Qualifiers	10/11/2016 20:30
Colombia vs. Chile	FIFA World Cup Qualifiers	11/10/2016 17:30
Chile vs. Uruguay	FIFA World Cup Qualifiers	11/15/2016 20:30
Chile vs. Croatia	Friendly	1/11/2017 8:35
Iceland vs. Chile	Friendly	1/14/2017 4:35
Argentina vs. Chile	FIFA World Cup Qualifiers	3/23/2017 20:30
Chile vs. Venezuela	FIFA World Cup Qualifiers	3/28/2017 19:00
Chile vs. Burkina Faso	Friendly	6/2/2017 20:30
Russia vs. Chile	Friendly	6/9/2017 14:30
Romania vs. Chile	Friendly	6/13/2017 14:00
Russia vs. New Zealand	FIFA Confederations Cup Group Stage	6/17/2017 11:00
Portugal vs. Mexico	FIFA Confederations Cup Group Stage	6/18/2017 11:00
Cameroon vs. Chile	FIFA Confederations Cup Group Stage	6/18/2017 14:00
Australia vs. Germany	FIFA Confederations Cup Group Stage	6/19/2017 11:00
Russia vs. Portugal	FIFA Confederations Cup Group Stage	6/21/2017 11:00
Mexico vs. New Zealand	FIFA Confederations Cup Group Stage	6/21/2017 14:00
Cameroon vs. Australia	FIFA Confederations Cup Group Stage	6/22/2017 11:00
Germany vs. Chile	FIFA Confederations Cup Group Stage	6/22/2017 14:00
Mexico vs. Russia	FIFA Confederations Cup Group Stage	6/24/2017 11:00
New Zealand vs. Portugal	FIFA Confederations Cup Group Stage	6/24/2017 11:00
Germany vs. Cameroon	FIFA Confederations Cup Group Stage	6/25/2017 11:00
Chile vs. Australia	FIFA Confederations Cup Group Stage	6/25/2017 11:00
Portugal vs. Chile	FIFA Confederations Cup Semifinal	6/28/2017 14:00
Germany vs. Mexico	FIFA Confederations Cup Semifinal	6/29/2017 14:00
Chile vs. Germany	FIFA Confederations Cup Final	7/2/2017 14:00
Chile vs. Paraguay	FIFA World Cup Qualifiers	8/31/2017 19:30
Bolivia vs. Chile	FIFA World Cup Qualifiers	9/5/2017 17:00
Chile vs. Ecuador	FIFA World Cup Qualifiers	10/5/2017 18:00
Brazil vs. Chile	FIFA World Cup Qualifiers	10/10/2017 20:30

APPENDIX G

Performance and Workload

Table G.1: Performance and Workload

	(1)		(2)		(3)		(4)	
$FIFA$	-0.0108							
	(0.0133)							
$FIFANonChile$			0.0089				0.0091	
			(0.0143)				(0.0143)	
$FIFAChile$					-0.0644	*	-0.0644	*
					(0.0375)		(0.0375)	
$Load(1)$	0.8645	***	0.8645	***	0.8643	***	0.8644	***
	(0.0025)		(0.0025)		(0.0025)		(0.0025)	
$Load(2)$	0.3792	***	0.3790	***	0.3789	***	0.3790	***
	(0.0024)		(0.0024)		(0.0024)		(0.0024)	
$Load(3)$	0.2029	***	0.2029	***	0.2027	***	0.2027	***
	(0.0022)		(0.0022)		(0.0022)		(0.0022)	
$Load(4)$	0.1148	***	0.1148	***	0.1146	***	0.1145	***
	(0.0022)		(0.0022)		(0.0022)		(0.0022)	
$Load(5)$	0.0571	***	0.0568	***	0.0569	***	0.0569	***
	(0.0021)		(0.0021)		(0.0021)		(0.0021)	
$Load(6)$	0.0538	***	0.0500	***	0.0535	***	0.0536	***
	(0.0023)		(0.0023)		(0.0023)		(0.0023)	
$Load(1)xFIFA$	-0.0092							
	(0.0168)							
$Load(2)xFIFA$	-0.0451							
	(0.0272)							
$Load(3)xFIFA$	0.0131							
	(0.0239)							
$Load(4)xFIFA$	0.0127							
	(0.0263)							
$Load(5)xFIFA$	-0.0651							
	(0.0290)							
$Load(6)xFIFA$	-0.8149	***						
	(0.0311)							
$Load(1)xFIFANonChile$			-0.0257				-0.0258	
			(0.0185)				(0.0185)	
$Load(2)xFIFANonChile$			-0.0229				-0.0231	
			(0.0309)				(0.0309)	
$Load(3)xFIFANonChile$			0.0178				0.0178	
			(0.0274)				(0.0274)	
$Load(4)xFIFANonChile$			0.0125				0.0126	
			(0.0311)				(0.0311)	

Continued on next page

Table G.1 – **continued from previous page**

	(1)		(2)		(3)		(4)	
$Load(5)xFIFANonChile$			-0.0034				-0.0036	
			(0.0339)				(0.0339)	
$Load(6)xFIFANonChile$			-0.0047				-0.0083	
			(0.0363)				(0.0363)	
$Load(1)xFIFAChile$					0.0394		0.0394	
					(0.0426)		(0.0426)	
$Load(2)xFIFAChile$					-0.1118	*	-0.1118	*
					(0.0602)		(0.0602)	
$Load(3)xFIFAChile$					0.0103		0.0104	
					(0.0523)		(0.0523)	
$Load(4)xFIFAChile$					0.0265		0.0266	
					(0.0538)		(0.0538)	
$Load(5)xFIFAChile$					-0.2085	***	-0.2085	***
					(0.0599)		(0.0599)	
$Load(6)xFIFAChile$					-2.7773	***	-2.7774	***
					(0.0633)		(0.0633)	
Constant	-0.1045	***	-0.1045	***	-0.1043	***	-0.1044	***
	(0.0015)		(0.0015)		(0.0015)		(0.0015)	
Controls	Yes		Yes		Yes		Yes	
R^2	0.2945		0.2945		0.2945		0.2945	
Observations	89,457,789		89,457,789		89,457,789		89,457,789	

Notes: The dependent variable is $TimeToCompletion$. All models include fixed effects for worker, task, worker and task, shift, worker and shift, hour of the day, worker and hour of the day, location in which a task starts, location in which a task ends, distance between the locations in which a task starts and ends, and product. $Load(n)$ is a dummy that takes the value 1 if the total number of tasks that a worker received simultaneously is between $[5 \times (n-1), 5 \times n)$ for $n \in [1, 6]$ and 0 otherwise.
$*** \ p < 0.01$; $** \ p < 0.05$; $* \ p < 0.10$.

Bibliography

Acemoglu, Daron, Claire Lelarge, and Pascua Restrepo (2020), “Competing with robots: firm-level evidence from France,” *AEA Papers and Proceedings*, 110, 383–388.

Acemoglu, Daron and Pascual Restrepo (2019), “Automation and new tasks: how technology displaces and reinstates labor,” *Journal of Economic Perspectives*, 33 (2), 3–30.

Aguiar, Mark and Erik Hurst (2007), “Measuring trends in leisure: the allocation of time over five decades,” *Quarterly Journal of Economics*, 122 (3), 969–1006.

Aral, Sinan, Erik Brynjolfsson, and Marshall Van Alstyne (2012), “Information, technology, and information worker productivity,” *Information Systems Research*, 23 (3), 849–867, URL `http://www.jstor.org/stable/23274649`.

Ariely, Dan, Emir Kamenica, and Dražen Prelec (2008), “Man’s search for meaning: the case of Legos,” *Journal of Economic Behavior & Organization*, 67 (3), 671–677.

Ashraf, Nava, Oriana Bandiera, and B. Kelsey Jack (2014), “No margin, no mission? A field experiment on incentives for public service delivery,” *Journal of Public Economics*, 120, 1–17.

Astebro, Thomas, Holger Herz, Raman Nanda, and Roberto A. Weber (2014), “Seeking the roots of entrepreneurship: insights from behavioral economics,” *Journal of Economic Perspectives*, 28 (3), 49–70.

Bandiera, Oriana, Iwan Barankay, and Imran Rasul (2007), “Incentives for managers and inequality among workers: evidence from a firm-level experiment,” *Quarterly Journal of Economics*, 122 (2), 729–773.

Bavafa, Hessam, Lorin M. Hitt, and Christian Terwiesch (2018), “The impact of e-visits on visit frequencies and patient health: evidence from primary care,” *Management Science*, 64 (12), 5461–5480, URL `https://doi.org/10.1287/mnsc.2017.2900`.

Benz, M. and B. S. Frey (2008), "The value of doing what you like: evidence from the self-employed in 23 countries," *Journal of Economic Behavior & Organization*, 68 (3–4), 445—-455.

Bessen, James, Maarten Goos, Anna Salomons, and Wiljan van den Berge (2020), "Firm-level automation: evidence from the Netherlands," *AEA Papers and Proceedings*, 110, 389–393.

Boltz, Marie, Bart Cockx, Ana Maria Diaz, and Luz Magdalena Salas (2020), "How does working-time flexibility affect workers' productivity in a routine job? Evidence from a field experiment," Working paper, Center for Economic Studies & Ifo Institute.

Bradler, Christiane, Robert Dur, Susanne Neckermann, and Arjan Non (2016), "Employee recognition and performance: a field experiment," *Management Science*, 62 (11), 3085–3099.

Brynjolfsson, Erik and Lorin M. Hitt (2000), "Beyond Computation: Information Technology, Organizational Transformation and Business Performance," *Journal of Economic Perspectives*, 14 (4), 23–48, URL `https://www.aeaweb.org/articles?id=10.1257/jep.14.4.23`.

Brynjolfsson, Erik, Daniel Rock, and Chad Syverson (2018), *Artificial intelligence and the modern productivity paradox: a clash of expectations and statistics*, University of Chicago Press, 23–57, URL `http://www.nber.org/chapters/c14007`.

Carpenter, Jeffrey, Peter Hans Matthews, and John Schirm (2010), "Tournaments and office politics: evidence from a real effort experiment," *American Economic Review*, 100 (1), 504–517.

Cassar, Lea (2019), "Job mission as a substitute for monetary incentives: benefits and limits," *Management Science*, 65 (2), 896–912.

Chan, Ho Fai, Bruno S. Frey, Jana Gallus, and Benno Torgler (2014), "Academic honors and performance," *Labour Economics*, 31, 188–204.

Chandler, Dana and Adam Kapelner (2013), "Breaking monotony with meaning: motivation in crowdsourcing markets," *Journal of Economic Behavior & Organization*, 90, 123–133.

Chen, M. Keith, Judith A. Chevalier, Peter E. Rossi, and Emily Oehlsen (2019), "The value of flexible work: evidence from Uber drivers," *Journal of Political Economy*, 127 (6), 2735–2794.

Corgnet, Brice, Joaquín Gómez-Miñambres, and Roberto Hernán-González (2015), "Goal setting and monetary incentives: when large stakes are not enough," *Management Science*, 61 (12), 2926–2944.

Correia, S. (2017), "Linear models with high-dimensional fixed effects: an efficient and feasible estimator," Working paper.

Deaner, R. O., S. M. Balish, and M. P. Lombardo (2016), "Sex differences in sports interest and motivation: an evolutionary perspective," *Evolutionary Behavioral Sciences*, 10 (2), 73–97.

Dewan, Sanjeev and Kenneth L. Kraemer (2000), "Information technology and productivity: evidence from country-level data," *Management Science*, 46 (4), 548–562, URL `https://doi.org/10.1287/mnsc.46.4.548.12057`.

Dewan, Sanjeev and Chung-ki Min (1997), "The Substitution of Information Technology for Other Factors of Production: A Firm Level Analysis," *Management Science*, 43 (12), 1660–1675, URL `https://doi.org/10.1287/mnsc.43.12.1660`.

Dickinson, David L. (1999), "An experimental examination of labor supply and work intensities," *Journal of Labor Economics*, 17 (4), 638–670.

Dinlersoz, Emin and Zoltan Wolf (2018), "Automation, labor share, and productivity: plant-level evidence from US manufacturing," Working paper, Center for Economic Studies, U.S. Census Bureau.

Falk, Armin and Michael Kosfeld (2006), "The hidden costs of control," *American Economic Review*, 96 (5), 1611–1630.

Fehr, Ernst, Holger Herz, and Tom Wilkening (2013), "The lure of authority: motivation and incentive effects of power," *American Economic Review*, 103 (4), 1325–1359.

Friebel, Guido, Matthias Heinz, Miriam Krueger, and Nikolay Zubanov (2017), "Team incentives and performance: evidence from a retail chain," *American Economic Review*, 107 (8), 2168–2203.

Gallus, Jana (2017), "Fostering public good contributions with symbolic awards: a large-scale natural field experiment at Wikipedia," *Management Science*, 63 (12), 3999–4015.

Gibbs, Michael, Susanne Neckermann, and Christoph Siemroth (2017), "A field experiment in motivating employee ideas," *The Review of Economics and Statistics*, 99 (4), 577–590.

Gino, Francesca, Paul Green, Pradeep Pendem, and Bradley R. Staats (2021), "The microstructure of work: understanding productivity benefits and costs of interruptions," Working paper.

Goerg, Sebastian and Sebastian Kube (2012), "Goals (th)at work – goals, monetary incentives, and workers' performance," Discussion Paper Series of the Max Planck Institute for Research on Collective Goods 2012/19, Max Planck Institute for Research on Collective Goods.

Goerg, Sebastian J., Sebastian Kube, and Jonas Radbruch (2019), "The effectiveness of incentive schemes in the presence of implicit effort costs," *Management Science*, 65 (9), 4063–4078.

Grant, Adam M. (2008), "The significance of task significance: job performance effects, relational mechanisms, and boundary conditions," *Journal Applied Psychology*, 93 (1), 108–124.

Hamermesh, Daniel S., Harley Frazis, and Jay Stewart (2005), "Data Watch: The American Time Use Survey," *Journal of Economic Perspectives*, 19 (1), 221–232, URL `https://www.aeaweb.org/articles?id=10.1257/0895330053148029`.

Hamilton, Barton H. (2000), "Does entrepreneurship pay? An empirical analysis of the returns to self-employment," *Journal of Political Economy*, 108 (3), 604–631.

Holmstrom, Bengt and Paul Milgrom (1991), "Multitask principal-agent analyses: incentive contracts, asset ownership, and job design," *Journal of Law, Economics, Organization*, 7, 24–52.

KC, Diwas S., Bradley R. Staats, Maryam Kouchaki, and Francesca Gino (2020), "Task selection and workload: a focus on completing easy tasks hurts performance," *Management Science*, 66 (10), 4359–4919.

KC, Diwas S. and Christian Terwiesch (2009), "Impact of workload on service time and patient safety: an econometric analysis of hospital operations," *Management Science*, 55 (9), 1486–1498.

Koch, A. K. and J. Nafziger (2016), "Gift exchange, control, and cyberloafing: a real-effort experiment," *Journal of Economic Behavior & Organization*, 131, Part A, 409–426.

Koch, Michael, Ilya Manuylov, and Marcel Smolka (2019), "Robots and firms," Working paper, Center for Economic Studies & Ifo Institute.

Kosfeld, Michael and Susanne Neckermann (2011), "Getting more work for nothing? Symbolic awards and worker performance," *American Economic Journal: Microeconomics*, 3 (3), 86–99.

Lanfranchi, Joseph, Mathieu Narcy, and Makram Larguem (2010), “Shedding new light on intrinsic motivation to work: evidence from a discrete choice experiment,” *Kyklos*, 63 (1), 75–93.

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

— (2000b), “The power of incentives,” *American Economic Review*, 90 (2), 410–414.

— (2018), “Compensation and incentives in the workplace,” *Journal of Economic Perspectives*, 32 (3), 195–214.

Lazear, Edward P. and Sherwin Rosen (1981), “Rank-order tournaments as optimum labor contracts,” *Journal of Political Economy*, 89 (5), 841–864.

Loewenstein, George (1999), “Because it is there: the challenge of mountaineering... for utility theory,” *Kyklos*, 52 (3), 315–343.

Miller, Amalia R. and Catherine E. Tucker (2011), “Can health care information technology save babies?” *Journal of Political Economy*, 119 (2), 289–324, URL `https://doi.org/10.1086/660083`.

Nalebuff, Barry J. and Joseph E. Stiglitz (1983), “Prizes and incentives: towards a general theory of compensation and competition,” *The Bell Journal of Economics*, 14 (1), 21–43.

Plambeck, Erica L. and Amy R. Ward (2008), “Optimal control of a high-volume assemble-to-order system with maximum leadtime quotation and expediting,” *Queing Systems*, 60 (1), 1–69.

Shearer, Bruce (2004), “Piece rates, fixed wages and incentives: evidence from a field experiment,” *The Review of Economic Studies*, 71 (2), 513–534.

Staats, Bradley R. and Francesca Gino (2012), “Specialization and variety in repetitive tasks: evidence from a Japanese bank,” *Management Science*, 58 (6), 1141–1159.

Stern, Scott (2004), "Do scientists pay to be scientists?" *Management Science*, 50 (6), 835–853.

Tan, Tom F. and Serguei Netessine (2014), "When does the devil make work? An empirical study of the impact of workload on worker productivity," *Management Science*, 60 (6), 1351–1616.

— (2019), "At your service on the table: impact of tabletop technology on restaurant performance," *Management Science*, 66 (10), 4359–4919.

Voss, Justin (1967), "The definition of leisure," *Journal of Economic Issues*, 1 (1–2), 91–106.

Wowak, Adam J. and Donald C. Hambrick (2010), "A model of person-pay interaction: how executives vary in their responses to compensation arrangements," *Strategic Management Journal*, 31 (8), 803–821.

Xue, Mei, Lorin M. Hitt, and Pei-yu Chen (2011), "Determinants and outcomes of internet banking adoption," *Management Science*, 57 (2), 291–307, URL `https://doi.org/10.1287/mnsc.1100.1187`.