A Stitch in Time:

Work Complexity and the Divergent Effects of Employee Monitoring on Productivity

Aruna Ranganathan and Alan Benson*

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While sociologists have long warned that employee monitoring alienates and demotivates workers, early management theorists have argued that monitoring pushes workers to perform better. This paper adjudicates between these rival perspectives by exploring the conditions under which employee monitoring improves or impairs productivity. We argue that the effect of monitoring on productivity depends on the work being monitored. Using quantitative data from an Indian garment manufacturing plant, we examine how a monitoring technology introduced on three of the plant's twelve production lines affected productivity. We find that the effect of monitoring varied by the complexity of the work performed: both across and within production lines, monitoring improved productivity for simple work but decreased productivity for complex work. Our qualitative data suggest that workers performing simple work creatively interpreted the monitoring technology as play while workers engaged in complex work understood monitoring as coercive process control. We contribute to research on monitoring and productivity by demonstrating how key features of work, such as work complexity, can moderate the effect of monitoring on productivity through workers' differential interpretations of monitoring technologies. Our results also suggest that the classic sociological and management theories of monitoring both have merit, but in different work contexts.

* Aruna Ranganathan is an assistant professor at Stanford University. Alan Benson is an assistant professor at the University of Minnesota. For helpful comments, we thank Ethan Bernstein, Hengchen Dai, Amir Goldberg, Tom Kochan, Adam Seth Litwin, Ching Ren, Jesper Sorensen, Ezra Zuckerman, and participants at the Wharton People & Organizations Conference, Wharton People Analytics Conference, Organization Science Winter Conference, Organizational Ecology Conference, ES-OOW Conference, Olin Business School, Stanford GSB, and Carlson School of Management. The usual disclaimer applies. Correspondence: arunar@stanford.edu.
In *The Wealth of Nations*, Adam Smith described how skilled pinmakers were being replaced by unskilled workmen, each performing menial operations such as drawing, straightening, or cutting wire. Over two hundred years, the decomposition of economic production into well-defined, routine tasks has continued unfettered, giving birth to the modern factory, mass production, the managerial class, and a host of practices and technologies designed to standardize work, control workers, and hold them accountable to their assigned tasks. At the heart of this transformation lies the introduction of employee monitoring, defined by scholars as the implementation of “observation system[s] that gather information about [employees’] activity or tasks” (Bernstein 2017, pp. 3). Employee monitoring initially relied on timekeepers and in-person audits in factories (Dalton 1959, Nelson 1975), but recent advances in information technology have facilitated employers’ ability to monitor their workers in a wide variety of workplaces inexpensively and unobtrusively (Chalykoff and Kochan 1989, Litwin 2017). For example, call center workers are monitored through call recording software while truck drivers are monitored through GPS technologies (Batt 2002, Batt and Moynihan 2002, Gray and Silbey 2014).

Early sociologists witnessing the introduction of employee monitoring warned against the dehumanizing and alienating effects of monitoring practices and technologies on workers (Marx 1900, Braverman 1903). More recent empirical work, building on this perspective, has demonstrated the adverse effects of monitoring technologies on employees’ work-life boundaries, sense of self, and their productivity (Attewell 1987, Vallas 1988, Adler 2007, Bernstein 2012, Stanko and Beckman 2015, Anteby and Chan forthcoming). Scholars argue that monitoring shifts the nexus of control from workers to the organization, thereby crowding out workers’ sense of autonomy and intrinsic desire to work (Deci and Ryan 1985, Freeland and Zuckerman 2014). Employee monitoring also deters workers from engaging in the types of experimentation and rule-
breaking that is necessary to foster process innovation (Bernstein 2012). In this way, these studies caution that monitoring could be harmful to workers and their productivity.

In contrast, early management theorists heralded the productivity-enhancing potential of employee monitoring practices (Taylor 1914, Mayo 1933, Herzberg 1959, McGregor 1960). For example, proponents of scientific management proposed that finely tracking workers would allow supervisors to enforce production in the “one best way” and thereby improve productivity (Taylor 1914), while the Hawthorne experiments found that the act of monitoring in itself could improve the productivity of workers simply because of the interest being shown in them (Mayo 1933). A large and growing economics literature on information systems and productivity has echoed this refrain, arguing that monitoring deters opportunistic behaviors like shirking and cheating. Recent studies have largely concluded that the adoption of monitoring technologies in themselves or as part of a system of formal management practices explains much of the variation in productivity across firms, industries, and countries (see, for example, Brynjolfsson and Hitt 2000, Bloom and Van Reenen 2006, Aral et al. 2012).

How can employee monitoring both impair and improve worker productivity at the same time? If monitoring is indeed alienating as sociological theory predicts, we would expect workers to be less engaged and perform worse; however, an alternative literature on monitoring technologies suggests the opposite. Resolving these inconsistent predictions is critical because the extent to which an employer monitors its workers is at the heart of the economic, social, and psychological contract that defines the employment relationship. In this paper, we suggest that instead of debating whether monitoring generally has a net positive or negative effect on worker productivity, which has been the focus of the existing research, a more appropriate question might be: under what conditions does monitoring increase or decrease worker productivity, and why?
We argue that, to understand the effects of employee monitoring on productivity, we must first pay attention to the work being performed. Indeed, several organizational scholars have called for bringing work back into the study of organizational dynamics (Stern and Barley 1996, Barley and Kunda 2001, Bechky 2011, Anteby and Bechky 2016). Answering this call, we build on job characteristics theory (Hackman and Oldham 1976) and demonstrate how one feature of work – work complexity – moderates the impact of monitoring on productivity. We argue that when work is simple, monitoring improves productivity, but when work is complex, monitoring impairs productivity. To explain this pattern, we posit that workers performing simple work experience monitoring as play (Roy 1952, 1959, Burawoy 1979, Mollick 2014) whereas workers engaged in complex work experience monitoring as process control (Marx 1900, Braverman 1903). More broadly, this suggests that the predictions of early sociologists and management theorists both had merit, but in explaining the effects of monitoring on different kinds of work: sociologists were studying complex work, whereas management theorists were investigating simpler work.

To develop this argument, we investigate how employee monitoring affected productivity at a large garment manufacturing plant producing pants and jackets in India. The monitoring intervention was implemented in three of twelve production lines in late 2012. Each production line consists of workers performing specific tasks or operations. The treated lines in this case were chosen for a reason unrelated to their productivity: they were closest to the technical support offices, which aided installation and maintenance of the monitoring technology. The intervention involved tagging work-in-progress garments with radio frequency identification (RFID) tags; workers were instructed to scan these tags on newly installed RFID scanners at their workstation prior to working on the garment, allowing the plant and the workers themselves to monitor individual productivity in real-time. Monitoring was neither directly tied to rewards nor
punishments in this context.

We collected both quantitative and qualitative data in this setting. Our quantitative data allowed us to exploit variation in work complexity both across and within product lines. We collected six years of daily line-level productivity data before and after the intervention for all jacket and pant lines to exploit variation in complexity between pant and jacket lines, where the production of pants is rated as being less complex (taking less time to perform) than the production of jackets. To overcome the concern that pant and jacket lines might differ on dimensions other than complexity, we additionally collected daily operation-level productivity data for a sample of days before and after the intervention for pant lines to exploit variation in work complexity across operations within pant lines. Having such pre- and post-intervention productivity data is rare, since the existence of such data is typically a by-product of monitoring. Similarly, having complete and simultaneous data on treated and nontreated groups is an asset. We supplemented this quantitative data with qualitative field data to allow us to speak to theoretical mechanisms.

This paper makes three important contributions to the study of monitoring and worker productivity. First, we shift the debate from whether monitoring affects worker productivity to the conditions under which monitoring increases or decreases productivity. Second, we bring job characteristics theory to the study of employee monitoring and argue that features of work such as complexity moderate the effect of monitoring on worker productivity. Third, the institutional details of our setting and our fieldwork allow us to rule in one novel mechanism to explain our differential effects, namely that monitoring is experienced differently by workers engaged in simple versus complex tasks.

In what follows, we review the relevant literature before presenting qualitative data to develop two main hypotheses. We then describe how we tested these hypotheses with a quasi-
experimental research design and productivity data, and lastly discuss the implications of this research for theory and practice.

MONITORING AND WORKER PRODUCTIVITY

The relationship between monitoring and productivity has long been a central question in the sociology, economics, and management literatures (Marx 1900, Taylor 1914, Mayo 1933). Research on employee monitoring at work has experienced a resurgence in recent years, as technological advancements have made it significantly easier to monitor workers (Chalykoff and Kochan 1989, Giddens 1991, Lyon 1994). Further, the current interest in monitoring, technology, and productivity extends beyond just the US context to industries around the world (Bloom et al. 2013, Bernstein 2012). Yet, we continue to have conflicting evidence regarding the effects of monitoring on workers and their productivity.

The Case against Monitoring

Much of the scholarly interest in monitoring at work traces back to the labor process literature. This literature has long studied the factory system and recognized the central role of technologies that reinforce employer control in the workplace (Attewell 1987, Fligstein and Fernandez 1988, Wallace and Kalleberg 1982). Marx (1900) recognized monitoring as one such tool by which managers exert control over workers on behalf of capital. Building on this, Braverman (1903) theorized about a spectrum of practices that management uses to deskill workers and subvert control over the labor process, including the modern bureaucracy, employee monitoring, and automation. More recent scholarship has studied the routines and procedures by which organizations foster the “production of consent” for monitoring (Burawoy 1979).
The labor process literature has especially focused on how monitoring affects the work relationship and has argued that monitoring alienates workers by preventing them from fully expressing their talents. As Marx and Engels put it, it seems more fulfilling to “do one thing today and another tomorrow, to hunt in the morning, fish in the afternoon, rear cattle in the evening” (Marx and Engels 1988, pp. 97). However, monitoring prompts workers to focus narrowly on certain tasks, leading them to neglect other productive, and possibly fulfilling, activities (Adler and Borys 1996, Zuckerman et al. 2003). Monitoring also reduces workers’ sense of autonomy and crowds out workers’ intrinsic motivation for performing a task (Vallas 1988, Freeland and Zuckerman 2014).\(^1\) While the labor process literature is not principally interested in how monitoring affects productivity, some recent empirical studies have linked a narrow focus on certain tasks under monitoring regimes and a reduction in autonomy to reduced job performance (Sewell and Wilkinson 1992, Stanton and Barnes-Farrell 1996).

The more recent literature on transparency, in comparison, has focused more directly on the connection between monitoring (and other information regimes) on worker productivity (Bernstein and Li 2017). This literature investigates how employee monitoring technologies are often implemented contemporaneously with the adoption of transparent management practices in settings as diverse as schools and gas utility companies (Gilliom and Monahan 2012). Studies on transparency suggest that monitoring can backfire if it deters productive rule-breaking. In a field experiment in an electronics factory in China, Bernstein (2012) found that production lines that featured an open floor plan were less productive than randomly selected treated lines that received privacy curtains. He concluded that productivity losses associated with open floor plans and

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\(^1\)This idea has since been developed by the self-determination theory as well (Deci and Ryan 1975). For a conceptual overview with a review of laboratory studies, see Gagné and Deci (2005). In manufacturing settings, see, for example, Kruse et al. (2010) and Benson and Sajjadi (forthcoming).
transparency were largely attributable to the unwillingness of workers on nontreated lines to experiment and improve production routines. Similarly, Campbell et al. (2011) also found that tightly monitored business units learned more slowly than loosely monitored business units in a study of six hotel properties owned by one property group.

The surveillance literature further highlights the productivity-diminishing effects of monitoring. Studies in this literature have investigated how U.S. Transportation Security Administration (TSA) agents and U.S Navy officers, for example, operate under heavy surveillance of their work performance as well as the boundary between their work and non-work life (Stanko and Beckman 2015, Anteby and Chan forthcoming). In particular, the surveillance literature (e.g. Sewell 1998, Marx 2016), tracing back to Foucault (1977) has emphasized the origins and reproduction of surveillance “in the form of a foreman’s gaze” (Anteby and Chan forthcoming, pp. 2). This literature has highlighted that workplace surveillance can be interpreted as either caring or coercive (Lyon et al. 2012). Surveillance is viewed as caring when people believe that the observers have benevolent motivations whereas surveillance is seen as coercive when people believe that the observers have perverse motivations (Anteby and Chan forthcoming). In particular, when surveillance is viewed as coercive, productivity is theorized to suffer (Grant and Higgins 1989, Batt 2002).

In this way, the sociologically-oriented literatures on labor process theory, transparency and surveillance all agree that monitoring will impair productivity, though they each offer different reasons or mechanisms to explain these negative effects of monitoring.

The Case for Monitoring

In contrast, early management theories and more recent research in economics and
information systems has been nearly universal in their praise for the productivity benefits that result from technology-enabled monitoring practices and the broader suite of technologies that facilitate control over workers. For instance, Taylor’s (1914) scientific management movement and McGregor’s (1960) Theory X adopted the premise that monitoring workers to ensure that job duties are performed in the “one best way” would improve worker performance, implicitly rejecting that rule-breaking by rank-and-file workers could be productive. Mayo (1933) and the human relations movement adopted the premise that workers are innately self-motivated but respond positively to monitoring because they enjoy the attention that accompanies being observed.

More recently, single-firm and single-occupation studies in economics have empirically demonstrated the role of technology-enabled monitoring in improving productivity and work organization. Some of these studies emphasize how monitoring encourages good behaviors. For instance, Hubbard (2000) found that the advent of onboard computers improved truckers’ driving, and Staats et al. (2017) found that RFID tracking software improved hand washing compliance among hospital workers. Some other studies demonstrate how monitoring can also discourage bad behaviors. Pierce et al. (2015) found that employee monitoring technology enhanced productivity and reduced theft at a restaurant chain. Outside of the US context, Duflo et al. (2012) found that installing video cameras reduced teacher absenteeism and improved students’ performance in Indian schools, while Olken (2007) found that audit warnings discouraged administrators and contractors in Indonesia from misusing funds. These empirical studies are largely consistent with a core tenet of agency theory, namely, that monitoring (or the threat of monitoring) deters workers from opportunistic behaviors like shirking or cheating, especially when monitoring allows employers to condition rewards or punishment on the wide range of activities that employers are
able to observe (Shapiro and Stiglitz 1984, Holmstrom 1982).

Monitoring has also been heralded as an effective management practice in the information systems literature. Many academic studies have found that monitoring enhances performance either in itself or as part of a system of complementary management practices (see, for example, Aral et al. 2012, Brynjolfsson and Hitt 2000, Basker 2012, Bloom and Van Reenen 2006, Bloom et al. 2013). Using firm-level data from a variety of industries, Brynjolfsson and Hitt (1995) found evidence of supranormal economic returns for investments in computer-based technologies. Subsequent work by Brynjolfsson and Hitt (2000, 2003) and Aral et al. (2012) found evidence from a panel of large firms that returns to computer investments grow over time and appear to complement existing organizational practices. This literature conceptualizes monitoring technologies as part of a broader regime of effective technologies and practices designed to track, standardize, and analyze work.

In this way, early management theories and more recent empirical research in economics and I.T. agree that monitoring improves worker productivity through tracking performance, paying attention to workers and deterring opportunistic behaviors.

To summarize, despite significant scholarly attention to the practice of employee monitoring in organizations, both theoretical and empirical studies have been largely divided as to whether monitoring in itself improves or impairs worker productivity. In his review of the literature, Bernstein (2017, pp. 3, 4) suggests that, “the time is ripe for a synthesis which can offer a coherent frame to our own field’s question of how observation affects employee performance in contemporary workplaces.” Indeed, monitoring technologies such as those in this study are facilitating employers’ ability to monitor workers, and it is therefore crucial to dig deeper into how these monitoring technologies affect worker productivity.
Our field observation revealed that within the same manufacturing plant, in some situations, monitoring seemed to improve worker productivity, but in other situations, monitoring seemed to impair productivity. This observation motivated us to move away from asking whether monitoring affects productivity and toward investigating the conditions under which monitoring might improve or impair productivity. In particular, we looked closely at the work itself and found a job characteristic that has thus far been absent from research on monitoring: the complexity of the work being monitored. Indeed, existing studies on monitoring and productivity have been conducted in diverse settings ranging from restaurants to high-tech manufacturing, such that there is wide variation in the complexity of the work being monitored, which might underlie the divergent results in the literature. Hence, we turn to an alternative literature on work and job characteristics for a way forward.

**Research on Work and Job Characteristics**

Scholars of work have long been investigating how the nature of work performed differs across organizations, occupations and jobs (Barley 1986, Bechky 2003). For example, the work of professionals is typically subject to less supervision (Abbott 1988), work within large, bureaucratic organizations is less subject to change (Jacoby 1985), and in fact, the very same jobs might consist of different “bundles of tasks” in different organizations (Cohen 2013, 2016).

In particular, the job characteristics theory identifies “core” dimensions along which jobs vary (Turner and Lawrence 1965). Examples of these dimensions include the identity and significance of the tasks involved (Hackman and Oldham 1976). This theory posits that job characteristics can directly affect employee attitudes and behavior at work and their responses to

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2 Note that this model has sometimes been critiqued for ignoring context and for its methods (Roberts and Glick 1981).
organizational practices (Hackman and Lawler 1971). For example, jobs that rank highly on “core dimensions” such as autonomy and variety offer employees greater meaningfulness (Bellah et al. 2007, Bunderson and Thompson 2009, Ranganathan forthcoming). Similarly, jobs that require greater skill in a variety of tasks elicit greater commitment and effort from their incumbents (Wrzesniewski et al. 2017, Rosso et al. 2010). Perhaps most relevant for our study is the prediction that job characteristics affect “affective reactions or feelings” of employees to organizational practices and interventions as well (Hackman and Oldham 1975, pp. 162). Scholars therefore advice using a “Job Diagnostic Survey” in diagnosing existing jobs as an input in planning organizational interventions (Hackman and Oldham 1975).

One important dimension of jobs that has received significant academic attention is their level of complexity (Campbell 1988). Broadly, complexity is understood as the degree to which work in its very substance requires thought and imposes cognitive demands on the individual performing the work (Kohn and Schooler 1978). Several scholars have attempted to define complexity purely in terms of objective task qualities such as the number of subtasks (March and Simon 1958), the number of roles that need to be satisfied (Campbell 1984), and the time taken to perform a task (Lopata et al. 1985). Some scholars include intrinsic interest in their definition of complexity to account for the fact that simple tasks may be experienced as boring (Shaw 1976, Campbell 1988). The Department of Labor’s Dictionary of Occupational Titles and O*NET also measure the interpersonal, operational, and problem-solving dimensions of work complexity, which vary widely across jobs (Kohn and Schooler 1973, 1978).

Irrespective of how complexity is measured, however, scholars agree that complexity is a job characteristic that affects how workers perceive organizational practices and interventions. For example, work complexity can affect how employees respond to changes in their goal-setting
process (Latham 2007, Daley 2012) or to changes in the diversity of their team (Horwitz 2005). Therefore, in this paper, we investigate whether and how work complexity might affect workers’ interpretation of monitoring practices and ultimately, their productivity. Before stating our hypotheses (developed through our qualitative data), we describe our setting for this study.

SETTING AND HYPOTHESES DEVELOPMENT

Our setting is a manufacturing plant in India that makes men’s suits. Like most plants that include production lines or arrangements in which a given product being manufactured is passed through a set linear sequence of operations or non-divisible tasks, our plant too features 12 production lines, 147 garment operations within the lines, and 2,212 line workers over the study period, 2009-2014. Each line produces one type of product and consists of a set of operations: the 9 pant lines each consist of 51 pant operations, and the 3 jacket lines each consist of 96 jacket operations. Workers are assigned to a single operation on a single line and rarely move.

In 2012, the plant management introduced a monitoring technology on a trial basis to keep track of their employees’ production and help them meet production deadlines. The CEO of the plant had seen this technology being used in manufacturing facilities on a recent visit to China and was keen to implement the same technology at his plant upon returning to India. The workers were not told anything about the purpose of the intervention. In fact, the scanners were installed overnight at the plant on certain lines and workers were simply instructed on the following day on how to use the technology.

The technology involved tagging unfinished items with RFID tags so that their progress could be tracked down the production line. RFID scanners were installed at each workstation on certain lines, and workers were instructed to scan the RFID garment tags on their scanners prior to
working on the garment. These scanners reported the number of units produced and individual efficiency as a percentage of set targets, which was updated in real time. Although performance data were now tracked at an individual level, pay remained uncommissioned and workers continued to be paid a fixed daily wage rate. In other words, the monitoring intervention in this case should be thought of as an intervention that allowed the plant to track workers’ productivity digitally and allowed workers to track themselves by seeing their “current efficiency.” Figure 1 shows an RFID terminal and how the terminals were installed on the lines.

[Figure 1]

**Qualitative Methods**

In this context, we conducted one year of ethnographic fieldwork as well as 40 interviews with workers and managers between January and June 2015. This qualitative data was collected by one of the authors and a research assistant, producing more than 200 single-spaced pages of fieldnotes and interview transcripts. The fieldwork and interviews were conducted post-intervention after the monitoring technology was installed in the treatment lines. Observation consisted of daily production activities in the pants and jackets sections and how workers were supervised and monitored in both treated and nontreated lines. The focus of the interviews was to understand how workers described, understood and responded to the RFID monitoring system. We analyzed this qualitative data inductively to develop our hypotheses (Glaser and Strauss 1967, Strauss and Corbin 1990). Analysis consisted of multiple readings of field and interview notes, composition of analytical memos, and the tracking of patterned activities and issues over time.

**Hypotheses: Bringing in Work Complexity**
Our observation in this Indian manufacturing plant first revealed that there was significant heterogeneity in the complexity of the work being performed by individual workers on the shop floor, even though they were all engaged in garment production operations. In our setting, we observed that complexity was understood as the time taken to perform a specific garment task: simple operations took less time to execute than complex operations. For example, one worker engaged in a simple “inseam” operation said, “I do a straight stitch along the seam . . . there’s no thinking, I just need to keep the production going.”3 In contrast, a worker engaged in a relatively more complex “sleeve headroll attach” operation said, “I stitch pieces of fabric varying in size onto a curved piece of felt material which supports the sleeve across the shoulder—it’s an accomplishment every single time!” Operationally, we observed management taking great pains to keep track of this variation in complexity between different operations, which they used to allocate work and measure efficiency. In addition to its operational importance, our interview data revealed that work complexity also seemed to be important for the meaning that workers sought from their work as well as their interpretations of the monitoring technology.

In line with the predictions from existing literature, our interviews with workers engaged in simple versus complex operations revealed variation in how meaningful they understood their work as being. For example, interviews with workers engaged in various simple operations revealed that they found their job to be “boring,” “repetitive,” and “monotonous,” whereas in other interviews, workers performing more complex operations described their job as “fulfilling” and “challenging.”

Our observation further revealed that work complexity appeared to govern how workers interpreted the monitoring intervention. In particular, workers performing simple work viewed the

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3 Quotations in this section not explicitly attributed to specific informants are from fieldnotes.
monitoring technology as a game or play. For example, one worker performing a simple “fly blind hem” operation said, “My work was boring before . . . I like pressing the various buttons [on the machine] and this makes the work fun.” Another worker engaged in simple trimming said, “Today if I do 80, then tomorrow I try for 81 . . . in this way, each day is a competition!” Yet another worker attaching labels to the waistband of pants told us “that the last hour was her time to push the maximum number of pieces” and that she “relished seeing her RFID machine at this time.” Other workers doing simple operations similarly described how the machine allowed them to “smash their way” through their task and we noticed that they talked about the machines with “delight on their faces.”

Workers in this plant were, in fact, accustomed to playing games at work. We observed them, for example, playing musical chairs or challenging each other to eat while working, even though food was strictly prohibited in the lines. In our fieldnotes, we document one particular instance where “two workers were staring at their supervisor intently to make sure she was distracted, [after which] one of them surreptitiously pulled out some candy, tore open the wrapper and gleefully shared the candy with her partner.” Such games are in line with those documented by early sociologists of work who observed shopfloor workers playing poker at work or stealing and hiding each other’s bananas (De Man 1928, Roethlisberger and Dickson 1943, Roy 1952). Roy (1959, pp. 158) explains this tendency to play games as a means to relieve the “beast of monotony” that sets in when work is so exceedingly tedious that it would make any worker “go nuts.”

Mollick and Werbach (2015) distinguish between games at work, described above, and games about work, positing that when games at work are popular, workers seek to gamify core work-related tasks too. For example, workers might try to meet a particular self-imposed quota or
follow a self-directed pattern of “stamping one color at a time” Roy (1959, pp. 161). Such games about work are often encouraged by managers because they create “consent” to the work and increase worker productivity (Burawoy 1979). As such, some organizations voluntarily create games to motivate worker productivity (Mollick and Rothbard 2014) whereas in other contexts, including the plant we study, workers voluntarily gamify aspects of their jobs, unbeknownst to their managers (Sallaz 2002, Sherman 2007).

In our context, workers engaged in simple operations found their work to be monotonous and as such, monitoring through its sophisticated technology and feedback mechanism allowed these workers to gamify their work, turning their work into play. Moreover, this lens of seeing monitoring as a game seemed to motivate workers performing simple work to be more productive. A worker engaged in basic “assembly loading” said, “The machine has helped me realize my potential . . . I am delivering better production numbers than I ever thought I could do!” Therefore, based on our qualitative data and supported by the gamification literature, we hypothesize:

**Hypothesis 1.** The effect of monitoring on worker productivity will be positive in the context of simple work.

In contrast, our observation indicated that workers engaged in complex work responded very differently to monitoring. These workers took pride in their work and valued having autonomy in performing their relatively more time-intensive operations. For example, one worker sewing intricate internal pockets said, “Operators like me deliver because of our deep familiarity and interest in our operation.” Another worker working on a complex “arm holes” operation said that “she enjoys her operation so much that she did not take much leave even for her own wedding.”

As such, workers engaged in complex work viewed the same monitoring intervention as
process control rather than as a game. They interpreted the RFID technology as unnecessarily controlling and interfering with their rhythm and their preexisting relationship with their work. One worker performing a complex “lapel seam” operation said, “My work is critical and difficult to do . . . having industrial engineers observing while work is being done would make even a normally fast operator slow down.” Another such worker said, “Before the machine was introduced, I was able to allocate my time on my own, but now the countdown has added additional work pressure . . . and made it not fun.” Further, this interpretation of monitoring as process control seemed to result in lower performance. One worker performing the “under collar zig zag stitch” said, “I do not like having the watchman machine . . . I used to really like my operation, now I’m not so sure . . . [I] think that it has not positively impacted my production levels.”

In fact, the labor process literature has argued that when workers see labor process technologies at work as unnecessarily controlling or coercive, they often engage in conscious or unconscious acts of rebellion against management, a form of “goldbricking” that detracts from productivity (Roy 1952, Burawoy 1979) For example, Roy (1959, pp. 437) documents that “resentment against piecework prices that were considered too low to offer possibilities of quota earnings often resulted in deliberate attempts to produce at lower rates.” At other times, the reactions are not as deliberate but are “little, subconscious” reactions to being controlled or being stifled by pressure that negatively impact productivity (Roth 1966, Gardner 2012). Therefore, based on predictions from these studies alongside our qualitative data, we hypothesize:

**Hypothesis 2.** The effect of monitoring on worker productivity will be negative in the context of complex work.

In this way, our qualitative data allows us to rule in one novel mechanism to explain the differential effects of monitoring on productivity. Our qualitative data suggest that the same
monitoring intervention is perceived differently by workers performing simple versus complex work giving us two testable hypotheses about the conditions under which monitoring will improve or impair productivity. In the next section, we describe the quantitative methods and data that we use to test these hypotheses.

**QUANTITATIVE METHODS, DATA AND MEASURES**

We test our hypotheses by exploiting a natural experiment at the plant. On October 1, 2012, plant management installed RFID monitoring technology on two of the nine lines producing men’s pants, and on December 1, 2012, management installed the technology on one of the three lines producing men’s jackets.\(^4\) Notably, when the technology was installed on a line, all operations within that line became monitored. We have data on daily line-level and operation-level productivity both before and after the monitoring intervention. This gives us the opportunity to investigate the effect of monitoring on productivity in the treated lines and operations, with the nontreated lines and operations as a comparison group to control for time-varying trends in productivity, and further explore heterogeneity by work complexity. The empirical strategy will first exploit variation in complexity across pant and jacket lines. Figure 2 visually depicts this empirical strategy. We then additionally exploit variation in work complexity across operations within pant lines.

![Figure 2]

**Complexity Across Product Lines**

In the garment manufacturing industry, complexity often varies by the type of product. In

\(^4\) While the plan was for the plant to roll out the technology across the rest of the plant over time, because of the high cost of this technology, this roll out did not happen.
interviews with both managers and workers, we learned that jackets are considered to be a more complex product than pants. One industrial engineering manager said, “Jackets are a more complex product and they have greater SMVs.” A supervisor on the shop floor added, “Because jackets are more complex overall, the individual operations being performed by workers are also more complex.” As is common among garment manufacturers, our plant rates the complexity of products according to their standard minute values (SMVs). Specifically, an SMV represents the number of minutes allowed for qualified workers working at a standard performance level to complete a given product from start to finish, with higher values corresponding to more complex products requiring greater time.

In our plant, we were able to collect data on SMVs of different pants and jackets being produced. In particular, the mean SMV of pants was 28.99 with a standard deviation of 3.65. In contrast, the mean SMV of jackets was 88.44 with a standard deviation of 9.76. What this indicates is that substantively, producing a jacket takes almost thrice the amount of time as producing a pant, on average. A simple t-test also reveals that this difference in mean SMVs of pants and jackets is statistically significant at the 0.01 level.

Therefore, we first exploit this variation in complexity across pants and jackets by comparing how monitoring affects productivity in the relatively more complex jackets lines as compared to the simpler pant lines. Our dependent variable for this analysis is daily line-level productivity. Line-level productivity is measured in the factory by “percent efficiency,” a measure of productivity that accounts for the complexity of the product being produced. For example, if the manufacturer rates a product as having an SMV of 30, then it expects a line to complete one

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5 SMVs are also referred to as standard allowed minutes, or SAMs.
6 If we divide the mean SMV of pants by the number of pant operations (51) and the mean SMV of jackets by the number of jacket operations (96), we see that the mean SMV of pant operations ÷ 0.56 – is still about half that of jacket operations ÷ 0.92.
unit of the product in 30 minutes. If the line takes 50 minutes to complete the product on average, then the percent efficiency for that line is 60% (30 / 50). We have daily line-level percent efficiency data for each of the twelve lines (9 pant lines and 3 jacket lines) from 2009 to 2014. This data was collected manually, pre- and post-treatment, by comparing the number of fully finished garments produced by a line to the daily target for that line at the end of each day.

**Complexity across Operations within Pant Lines**

To overcome the concern that pant and jacket lines might differ on dimensions other than complexity, we additionally exploit variation in complexity across operations within pant lines. Just like the plant rates the complexity of garments using SMVs, our plant rates the complexity of specific operations too, according to their standard minute values (SMVs). Here, an SMV represents the number of minutes allowed for a qualified worker working at a standard performance level to complete a given operation, with higher values corresponding to more complex operations requiring greater time. Operations rated with higher SMVs typically require a greater number of subtasks, greater dexterity, and greater skill to complete.

In an interview, an industrial engineering manager in the plant explained, “each worker is assigned to an operation which should be thought of as a task that cannot be broken down any further . . . and so, even in the relatively easy pant production, some tasks naturally take longer to do, have greater SMV (standard minute values) and are considered to be more complex.” For example, attaching pant waistbands is a relatively complex operation with an SMV of 0.95, meaning an operator must execute an operation every 57 seconds (including rework and rest) to achieve 100% efficiency. In contrast, attaching wash care labels is a relatively simple operation with an SMV of 0.19, corresponding to performing the operation in 11.4 seconds. While there are
relatively few complex operations within pant lines, we exploit variation in complexity across pant-line operations to investigate the effect of monitoring on different operations. To conduct this analysis, we obtained daily operation-level productivity data within pant lines for a subset of dates in 2012. We exclude jacket lines in the operation-level analysis because we do not have pretreatment productivity data for jacket production. Fortunately, for the pant lines, we have some operation-level data both before and after the treatment.

Similar to line-level productivity, operation-level productivity is measured by “percent efficiency,” a measure depending on both the speed of the operator and the complexity of the operation. For example, if the manufacturer rates an operation as having an SMV of 0.75, then it expects a skilled operator to complete one operation in 0.75 minutes. If a particular worker takes an average of 0.50 minutes to complete an operation over a shift, then the percent efficiency for that worker is 150% (0.75 / 0.50). At the end of the production line, inspectors check all products and return any products with deficient quality to the responsible worker. This rework reduces a worker’s measured efficiency, in that rework takes time but does not count toward items produced. The SMV benchmark also includes expected rework time, along with rest and other allowances. Because the percent efficiency includes both initial production and rework, plant management treats efficiency as a measure of both quantity and quality.

Manual records provided the pre- and post-treatment operation-level productivity data for the pant lines. In the pretreatment period, systematic monitoring at the individual level within lines was done at random intervals with the aid of a manual system in which a data entry clerk (who had no formal authority) counted how many items workers performing specific operations had produced. Importantly, in the treated lines post-treatment, the plant supervisors continued to use the manual system despite the new RFID technology and data, for three main reasons. First,
supervisors split their time across lines, and the new monitoring technology was only available for treated lines. Second, supervisors simply did not have easy access to the data; they spent their time on the shop floor, but the RFID data were only accessible through a computer on a separate floor. Third, there was inertia to move away from the old monitoring system.

In this way, to conduct both our line-level and operation-level analyses, we use manually-collected productivity data to exclude the possibility that our estimated treatment effect is biased by changes in the data collection regime.

**Empirical Strategy: Difference-in-Differences**

The analysis thus consists of three parts: (1) the unconditional analysis, where we examine overall changes in productivity at treated lines posttreatment; (2) the analysis that conditions on the complexity of the product line; and (3) the analysis that conditions on the complexity of operations within the pant lines.

First, we estimate the effect of the monitoring intervention on productivity, before conditioning on complexity:

\[
Y_{it} = \beta_0 + \beta_1 \text{post}_{it} + \beta_2 \text{treated}_i + \beta_3 \text{posttreated}_{it} + \phi_i + \tau_t + \epsilon_{it} \quad (1)
\]

In equation (1), \(Y_{it}\) is the productivity (the percent efficiency) of line \(i\) on day \(t\). \(\text{treated}_i\) is an indicator that takes a value of 1 if line \(i\) is ever a treated line; and \(\text{post}_{it}\) is an indicator for whether line \(i\) was in the posttreatment period on day \(t\), regardless of whether that line was actually treated. Because of the technology’s staggered introduction, this variable takes a value of 1 for lines producing pants after October 1, 2012, or for lines producing jackets after December 1, 2012. Then, \(\text{posttreated}_{it}\) is an indicator that takes a value of 1 if treated line \(i\) is in the treatment period at time \(t\), which is functionally equivalent to the interaction between the “post” and “treated”
indicators. We run our regressions with and without line effects, denoted by $\phi$, and similarly, with and without month and day of week fixed effects, denoted by $\tau$. We cluster standard errors by line to allow for errors to be correlated within lines.

As in a standard experimental difference-in-differences framework, the causal identification comes from the difference between treated and nontreated lines before and after the treatment. This yields estimates for the causal effect of the treatment as long as, whatever the ex ante differences between the lines, the treatment is not correlated with other factors also affecting productivity. Although the treated lines in this case were not explicitly chosen at random, management chose these treated lines to be closest to the offices of the engineers responsible for maintaining the technology and in this way, the choice of treatment lines was quasi-random. As shown in Table 1, the treated lines were not systematically different with regard to observable worker characteristics prior to the installation of the monitoring technology.

[Table 1]

**Complexity across Product Lines**

Next, we examine how the effect of monitoring varies by product-level complexity. For this, we rerun equation (1) separately for lines producing jackets and pants:

\[
Y_{pt} = \beta_0 + \beta_1 \text{post}_{pt} + \beta_2 \text{treated}_{pt} + \beta_3 \text{posttreated}_{pt} + \phi_p + \tau_t + \varepsilon_{pt} \quad (2a)
\]

\[
Y_{jt} = \beta_0 + \beta_1 \text{post}_{jt} + \beta_2 \text{treated}_{jt} + \beta_3 \text{posttreated}_{jt} + \phi_j + \tau_t + \varepsilon_{jt} \quad (2b)
\]

where $p$ denotes the nine simple pant lines, $j$ denotes the three complex jackets lines, and all other variables remain the same. Hypothesis 1 concerns the direction of the coefficient on $\beta_3$ in the first equation (2a), and Hypothesis 2 concerns the direction of the coefficient on $\beta_3$ in the second equation (2b).
Equations (2a) and (2b) are convenient for comparing the productivity growth of treated lines versus nontreated lines, separately for the simple and complex product lines. However, we may also wish to test whether the effect of the monitoring technology is different between these simple and complex product lines. For this, we fully interact equation (1) with an indicator that the line is producing complex jackets:

\[ Y_{it} = \beta_0 + \beta_1 \text{post}_{it} + \beta_2 \text{treated}_{it} + \beta_3 \text{posttreated}_{it} + \beta_4 \text{complex}_i + \beta_5 \text{post}_{it} \times \text{complex}_i + \beta_6 \text{treated}_{it} \times \text{complex}_i + \beta_7 \text{posttreated}_{it} \times \text{complex}_i + \phi_i + \tau_t + \epsilon_{it} \]  

(2c)

where \( \text{complex}_i \) denotes that line \( i \) is producing the more complex product (jackets), and all other variables remain as before. As a three-way interaction, remember that \( \beta_0 \) through \( \beta_3 \) are estimated with the simple (pant) lines. Then, \( \text{posttreated}_{it} \times \text{complex}_i \) is our coefficient of interest, estimating the difference in the effect of monitoring on productivity between simple and complex product lines. As before, we run these three regressions with and without line, month, and day of week fixed effects. We cluster standard errors by line.

This line-level analysis allows us to examine how monitoring affected productivity depending on product-level complexity. As in any difference-in-difference test, our chief concern is a failure of the parallel trends assumption: treated lines should have the same trend in productivity as nontreated lines in the absence of the treatment. To address this concern, we first plotted the weekly difference in efficiency between treated and nontreated lines both pre- and post-treatment and found that the parallel trends assumption was met in the pre-treatment period, where the difference in productivity between the treated and nontreated lines was flat. Additionally, we differentially estimated our main regressions with only the pre-treatment data and found no effect of monitoring. Finally, we also added a linear time term to our regression specifications, restricting the sample to the pre-treatment period, and found that the coefficient on the time term was not
significant.

**Complexity across Operations Within Pant Lines**

Lastly, we exploit variation in complexity across operations within pant lines. This operation-level analysis has three distinct advantages over the line-level analysis. First, pant and jacket lines could be correlated with some factor other than average complexity that yields productivity gains or losses from monitoring; switching to the operation-level analysis allows us to evaluate complexity more directly. Second, there are a large number of operations, and therefore a relatively larger number of clusters in the operation as compared to line analysis, which affords much greater statistical power. Third, since our measure of complexity is a continuous variable, the operation-level analysis allows us to estimate the effect of monitoring at discrete intervals of complexity as well.

For these tests, our empirical strategy mirrors what we use for line complexity. Specifically, we begin by splitting pant operations into simple operations and complex operations, depending on whether they are respectively below or above the 75th percentile SMV among pant operations. We run the regression using the 75th percentile cutoff (corresponding to an SMV of 0.75) because pants operations are already relatively simple, so we denote complex pant operations to be the most complex among them.\(^7\) The regressions take the form:

\[
Y_{ist} = \beta_0 + \beta_1 \text{post}_t + \beta_2 \text{treated}_i + \beta_3 \text{posttreated}_{it} + \phi_i + \tau_t + \varepsilon_{ist} \quad (3a)
\]

\[
Y_{ict} = \beta_0 + \beta_1 \text{post}_t + \beta_2 \text{treated}_i + \beta_3 \text{posttreated}_{it} + \phi_i + \tau_t + \varepsilon_{ict} \quad (3b)
\]

where \(Y_{ist}\) and \(Y_{ict}\) represents the efficiency for line \(i\)’s simple operation \(s\) or complex operation \(c\) at day \(t\), and all other variables are as they were before. We run these regressions with and without

\(^7\) Our results are robust to variations in this cutoff point.
line, month, and day of week fixed effects and standard errors clustered by operation.

Likewise, we perform a fully interacted regression:

$$Y_{iot} = \beta_0 + \beta_1 \text{post}_t + \beta_2 \text{treated}_i + \beta_3 \text{posttreated}_it + \beta_4 \text{complex}_o + \beta_5 \text{post}_t \times \text{complex}_o + \beta_6 \text{treated}_i \times \text{complex}_o + \beta_7 \text{posttreated}_it \times \text{complex}_o + \phi_i + \tau_t + \epsilon_{iot} \quad (3c)$$

where $Y_{iot}$ is the percent efficiency for line $i$’s operation $o$ at month $t$. For consistency and completeness, we show results where complex$_o$ is treated as a discrete variable indicating whether the SMV rating of the operation is above the 75th percentile SMV among pant jobs, and additionally, where complex$_o$ is a continuous variable representing the SMV rating of the operation. Having described our quantitative methods, data and measures, we now present our results.

RESULTS

We begin by showing, in Table 2, summary statistics of the mean and standard error of percent efficiency (our measure of productivity) at treated and nontreated lines before and after the monitoring technology was implemented. We present this for all lines, by product line, and by operational complexity within pant lines. We also present estimates for the first-differences and difference-in-differences.

[Table 2]

Panel 1 of Table 2 shows that overall productivity improved at both treated and nontreated lines, although the overall improvement was slightly greater at treated lines. Note that the mean percent efficiency is not 100% but rather around 60%. As such, a gain of 4% points in efficiency generally corresponds to about a 7% gain in productivity ($64\% / 60\% = 107\%$). Also note that the
overall differences reported in this first panel include both the direct effect of monitoring on pant and jacket lines and also the compositional effect that places greater weight on pants, which compose nine of the twelve lines.

The second panel (2a) shows changes in productivity among the simple product lines (two treated pant lines and seven nontreated pant lines). Productivity remained relatively flat at the nontreated lines and substantially rose at the two treated lines after the introduction of the monitoring technology. The next panel (2b) shows changes in productivity among the complex product lines (one treated jacket line and two nontreated jacket lines). In contrast to the pant lines, productivity at the treated jacket lines declined even as productivity at the nontreated lines improved. These summary statistics offer preliminary support for our hypotheses by demonstrating that, when comparing the difference in productivity between treated and control lines before and after the intervention, the effect of monitoring on simple lines was positive, while the effect of monitoring on complex lines was negative.

The third panel shows changes in productivity within the pant operations. Efficiency for operations with complexity below the 75th percentile complexity (in 3a) remained approximately constant within the nontreated lines. However, efficiency at treated lines rose by 5.1% points posttreatment. For complex operations (in 3b), efficiency slightly declined at nontreated lines and declined by a larger amount at treated lines. These summary statistics offer additional support for our hypotheses by demonstrating that, similar to the line-level results, the effect of monitoring on simple operations was positive, while the effect of monitoring on complex operations was negative. We next turn to our regression results, where we have the ability to add controls and cluster our standard errors.

First, we look at the unconditional regression results investigating the effect of monitoring
on productivity across all lines. Note that regression estimates depart from the means presented in Table 2 because the regressions further control for line, month, and day of week effects, and the regression results cluster standard errors at the line level to allow for correlated observations within lines. These regressions correspond to equation (1) in the empirical strategy section. Table 3 presents the results.

[Table 3]

Table 3, column 1, shows the classic difference-in-differences without line or month controls. Treated lines had slightly higher productivity prior to the implementation of the monitoring technology, but no statistically significant growth after the technology was introduced. Column 2 introduces month and day of week fixed effects (note that the Post term cannot be estimated here) while Column 3 introduces line fixed effects (note that the Treated term cannot be estimated here). Column 4 includes line, month and day of week fixed effects (note that the Post and Treated terms are absorbed by the fixed effects). Given that we have a balanced sample and the treatment is largely uncorrelated with the controls, it is not surprising that the main coefficient of interest, the difference-in-differences estimate, changes little as we introduce finer controls. This estimate is small and not statistically different from zero.

Stopping here, we might conclude that the monitoring technology had no effect on productivity. However, the following sections examine the heterogeneity of the treatment effect by product and operational complexity.

**Complexity across Product Lines**

We next examine the effect of monitoring on the simple product (pants) and the more complex product (jackets). These correspond to equations 2a - 2c in the empirical strategy section.
Table 4 presents results.

Table 4, columns 1 and 2 correspond to Equation 2a in the empirical strategy section and show the results of the difference-in-differences analysis on the pant lines. Efficiency at treated pant lines rose an estimated 8.06% points relative to the nontreated lines. Given that these lines were operating at 64.2% efficiency before the treatment, relative productivity improved by about 12.5%. The improvement is also statistically significant. The results are substantively similar after including line, month, and day of week fixed effects.

Table 4, columns 3 and 4 correspond to equation 2b in the empirical strategy section, and show results restricting analysis to the jacket lines. Note that we now have one-third of the full sample observations because only one-third of the lines produce jackets. Compared to nontreated jacket lines, productivity at the treated jacket line dropped by 9.4% points. Again, results are similar if we include line, month, and day of week effects. Taken together, columns 1 through 4 suggest that the effect of the monitoring treatment was positive for the simple lines but negative for the complex lines.

Table 4, columns 5 and 6, correspond to equation 2c in the empirical strategy section and use triple-differences to test whether the treatment effect was significantly different depending on whether the line produced pants or jackets. Before we interpret the main result, a few characteristics deserve note. First, mechanically, the triple-difference coefficient will be approximately equal to the difference between the two-way interactions in the prior columns. Second, we can estimate Post × Treated and Post × Complex in the final column because of the staggered treatment. Third, in even numbered columns, the Treated and Post terms are respectively absorbed by the line and month fixed effects. In column 6, we cannot estimate the Complex term
and the $Treated \times Complex$ term. Now turning to the coefficient of interest, the triple-differences model estimates that the difference in the effect of monitoring between simple and complex lines is 17.5% points in the reduced model and 15.7% points after including the fixed effects. Both are statistically different from zero. Importantly, what this reveals is that the difference in the effect of monitoring on simple versus complex work is statistically significantly different. In this way, Table 4 offers support for our hypotheses using our first measure of complexity at the product-level. Also see Appendix A where we show that these results are robust to a placebo analysis.

**Complexity Across Operations Within Pant Lines**

Next, using operation-level data from the pant lines, we advance our analysis by examining how the effect of the monitoring technology varies by operational complexity. These correspond to Equations 3a-3c in the empirical strategy section. Table 5 presents results in a setup that is very similar to Table 4.

[Table 5]

Table 5, columns 1 and 2, restrict analysis to the relatively simple pant operations: operations with SMV values less than or equal to 0.75, which correspond to the 75th percentile among pant operations. Once again, the post and treatment terms drop out in Column 2 because they are absorbed by line, month, and day of week fixed effects. Compared to nontreated pant operations, efficiency rose at treated operations posttreatment. The coefficients in columns 1 and 2 are significant ($p < 0.1$) and substantively large (the estimated increase in efficiency of 4.97% points and 5.36% points is about an 8.2% and 8.9% gain relative to the prior efficiency among simple operations).

Table 5, columns 3 and 4, restrict analysis to pant operations with SMV values above the
75th percentile among operations in the pant lines (SMV > 0.75). Compared to nontreated pant operations, efficiency declined by 4.15% points and 3.58% points in the treated operations, before and after including fixed effects. These differences are respectively significant with $p < 0.05$ and $p < 0.01$, and are substantive, representing declines in efficiency of 6.2% and 5.4% relative to the prior efficiency among complex operations.

Table 5, columns 5 and 6, include all operations and test whether the effect of monitoring is different between simple and complex operations. The resulting coefficients are substantial (respectively representing differences of more than 15% and 10% of mean productivity at pant lines) and statistically significant at 1% in the reduced model and 10% in the full model.

Whereas the product-level analysis features only two products, the operation-level analysis features a greater number of pant operations with varying levels of SMV ratings. This allows us to further estimate the effect of the monitoring technology at different intervals of complexity. We estimate the difference in percent efficiency at treated operations posttreatment at eight discrete SMV values, rounding the SMV values of each operation to the nearest tenth. Functionally, this is equivalent to running the regression in Table 5, column 6, except with interaction terms for each discrete bin of complexity at 0.1 SMV interval. We present coefficient estimates and standard errors in Figure 3.

[Figure 3]

As shown in Figure 3, the error bars are relatively large within any one category of SMV values. Nonetheless, results suggest that there is a negative relationship between complexity and the effect of the monitoring technology on productivity. Consistent with the earlier regression results, this is driven by gains in productivity among the most simple operations and losses in productivity among the most complex operations.
In sum, these results show that the effect of the monitoring treatment was positive for the simple operations but negative for the complex operations, and that this difference in the effect of monitoring was also statistically significant. We further show that the results are robust to estimating the effect of monitoring at discrete intervals of complexity. In this way, this set of results supplements our analysis using product-level variation in complexity and offers further support for our hypotheses, using our second measure of complexity at the operation-level.

DISCUSSION

In this paper, we sought to ask the question: under what conditions does employee monitoring increase or decrease worker productivity, and why? We study a garment manufacturing plant in India where an RFID monitoring intervention was introduced in a subset of production lines in late 2012. We do fieldwork in this setting, which informed our hypotheses regarding the differential effect of monitoring depending on the complexity of work performed. We observe that workers engaged in simple work seemed to interpret monitoring as a game or play in contrast to workers engaged in complex work, who interpreted monitoring as process control. Consistent with our hypotheses, we found that productivity improved among lines and operations performing simple work and declined among lines and operations performing complex work. We conclude that our results provide evidence that the effect of employee monitoring depends on key features of work such as complexity, which affects how workers interpret monitoring technologies. In doing so, we bring a renewed focus on the work being performed to the study of monitoring and productivity.

Alternative Mechanisms
We suggest that an important mechanism underlying the effect of monitoring on productivity is workers’ differential interpretations of monitoring technologies depending on the work being performed by them. We observe that workers engaged in simple work found their work to be monotonous and as such they reinterpreted the monitoring technology to enable play, creatively reappropriating who the technology serves. In contrast, workers engaged in complex work took pride in their work and interpreted the same monitoring technology as a coercive means of managerial process control. We argue that these differential worker interpretations of monitoring resulted in divergent effects of monitoring on productivity.

While our fieldwork allows us to rule in this novel mechanism, we fully acknowledge that there could be other psychological mechanisms underlying our results as well. For instance, social facilitation theory (Zajonc et al. 1965) proposes that workers have low levels of arousal when performing routine work, and therefore the presence of an audience (e.g. a supervisor) raises arousal, and there is an inverted-U relationship between arousal and performance. As such, productivity is locally increasing with respect to stimulation (and monitoring) for routine work, until the point at which it begins to decline. Unfortunately, testing this specific theory (and related theories, such as cognitive overload) would require measures of stress and arousal, which we do not have. Nonetheless, our study offers new and unique evidence in relation to the extant laboratory studies in social facilitation theory. In particular, prior studies have spanned relatively little time, for example, testing the effect of monitoring over the span of an hour. It is less clear whether test subjects or workers would remain aroused over a long period of time or would alternatively become acclimated to a monitor. Our study features a monitor over a long time in the field and can therefore speak to the long-term consequences of electronically monitoring workers, thus advancing the existing literature. Further, as a field rather than a lab study, external validity of our
findings is also less of a concern.

**Contributions to the Study of Monitoring and Productivity**

Our paper makes three important contributions to the study of monitoring and productivity. First, we shift the debate away from the question of whether monitoring affects worker productivity and toward determining the conditions under which monitoring increases or decreases productivity. Early sociological theories and more recent empirical studies suggest that monitoring could be detrimental to productivity (e.g. Braverman 1903, Bernstein 2012). In contrast, early management theories and recent empirical work in economics suggests the opposite - that monitoring improves worker productivity (Taylor 1914, Bloom et al. 2013). Our paper helps bridge the two perspectives by demonstrating that depending on key characteristics of the job being performed, the same monitoring technology can sometimes be effective in increasing worker productivity but at other times, be counterproductive. In this way, our paper calls for the study of employee monitoring to move into investigating the conditions moderating the effect of monitoring on productivity.

Second, we bring job characteristics theory to the study of employee monitoring and argue that features of work such as complexity moderate the effect of monitoring on worker productivity. Scholars of work have long posited that jobs vary along “core” dimensions (Hackman and Oldham 1980) and that these core job features influence the motivation levels and behaviors of their incumbents. Exploiting variation in work complexity within garment production, we find that monitoring improves productivity for simple work, but hinders productivity for complex work. We thus suggest that considering features of the work being monitored is critical to the study of monitoring. In fact, the moderating effect of work complexity may be even more salient in other
contexts because both the simple and complex garment operations in our study are arguably less complex than typical jobs from the universe of settings in which we may wish to study the effect of monitoring on productivity. In this way, our paper follows the tradition of recent organizational scholars (Stern and Barley 1996, Barley and Kunda 2001, Bechky 2011, Anteby and Bechky 2016) in bringing work back into the study of organizational dynamics.

Third, this study contributes to the monitoring literature by ruling in a novel mechanism to explain the differential effects of employee monitoring on productivity by work complexity, namely that monitoring is experienced differently by workers engaged in simple versus complex tasks. The sociological literatures propose three mechanisms to explain the negative effects of monitoring, namely that monitoring alienates workers (Marx and Engels 1988), it deters experimentation (Bernstein 2012) and it is coercive (Anteby and Chan forthcoming). On the flip side, the early management and economics literatures suggest three different mechanisms to explain the positive effects of monitoring, namely that monitoring improves worker productivity by tracking performance (Taylor 1914), paying attention to workers (Mayo 1933) and deterring opportunistic behaviors (Shapiro and Stiglitz 1984). However, none of these mechanisms can explain how the same monitoring technology might influence productivity differently based on the work being performed, in a context where monitoring is not directly linked to rewards or punishment. We bring ideas from gamification (Burawoy 1979) and goldbricking (Roy 1952) to the study of monitoring by arguing that monitoring is seen as play by workers performing simple work but is seen as process control by other workers performing complex work.

This paper also contributes to the research on games and gamification at work (Roy 1952, Burawoy 1979, Mollick and Rothbard 2014). While this literature has documented that workers often engage in games at work, and that such games can improve productivity (Mollick and
Werbach (2015), the literature has paid less attention to the conditions under which workers are likely to voluntarily engage in gamification. We contribute to this literature by arguing that when work is simple and routine, it is easier for workers to gamify their work, and additionally, gamification is attractive for its potential to increase work satisfaction given that the work intrinsically provides little meaning. Similarly, we also contribute to the literature on goldbricking (Roy 1952, 1959) by positing that workers are more likely to engage in conscious or unconscious acts of rebellion that detract from productivity when their work is complex and organizational interventions impinge on workers’ pre-existing pride in their work.

**Resolving the Long-Standing Theoretical Debate**

Early sociological scholarship (Marx 1900, Braverman 1903) and management theorists (Taylor 1914, Mayo 1933, Herzberg 1959) offered opposing accounts of how workers interpret and respond to monitoring. Sociologists construed monitoring as the device by which managers exert control over workers and predicted that monitoring would alienate workers from their work product. Management scholars, in contrast, argued that workers would respond positively to the attention that monitoring bestowed on them. Our paper suggests that more focus on the work being monitored might help explain the divergent accounts in the literature.

In particular, Marx (1900) and Braverman (1903) were studying the transformation of work from complex, craft work within craft guilds to routine jobs within mass-manufacturing facilities. These scholars observed the sharp loss of autonomy experienced by workers and theorized about the negative effects of monitoring. In contrast, early management theories were narrowly focused on investigating simple, routine jobs within factories. These jobs, which were devoid of autonomy from the start, may have been less prone to monitoring’s demotivating effects, thus leading to
theories of the positive effect of monitoring. This suggests that the predictions of early sociologists and management theorists both had merit, but in explaining the effects of monitoring on different kinds of work: sociologists were perhaps studying complex work, whereas management theorists were perhaps investigating simpler work.

Our review of the more recent empirical studies similarly reveals that across different studies, there is wide variation in the complexity of the work being monitored. Indeed, existing studies on monitoring and productivity have been conducted in diverse settings performing very different kinds of work, ranging from restaurants (Pierce et al. 2015) to high-tech manufacturing (Bernstein 2012). Further the negative effect of monitoring on productivity has been emphasized in studies investigating relatively more complex work (e.g. Bernstein 2012). Thus, focusing on job characteristics and the work context might help explain the divergent effects of monitoring on productivity documented in the literature while also advancing our theoretical understanding of how workers interpret and respond to the increasingly prevalent monitoring technologies in workplaces.

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Zajonc, R. B.

Zuckerman, E. W., T. Kim, K. Ukanwa, and J. von Rittmann
FIGURES AND TABLES

Figure 1: Technology to Monitor Workers: RFID Scanners Installed on Treated Lines
Figure 2: Study Design
The figure presents difference-in-differences coefficient estimates and standard errors for the effect of treatment on efficiency, by operational complexity (rounded to the nearest 0.1 SMV).
Table 1: Descriptive Statistics of Workers in Treated and Nontreated Lines

<table>
<thead>
<tr>
<th></th>
<th>Treated Lines</th>
<th>Nontreated Lines</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Count of workers on same line</td>
<td>245.9</td>
<td>242.1</td>
<td>3.770</td>
</tr>
<tr>
<td></td>
<td>(159.5)</td>
<td>(155.8)</td>
<td></td>
</tr>
<tr>
<td>Share high skilled</td>
<td>0.0121</td>
<td>0.0131</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(0.109)</td>
<td>(0.114)</td>
<td></td>
</tr>
<tr>
<td>Share female</td>
<td>0.933</td>
<td>0.908</td>
<td>0.024*</td>
</tr>
<tr>
<td></td>
<td>(0.251)</td>
<td>(0.289)</td>
<td></td>
</tr>
<tr>
<td>Share from Karnataka</td>
<td>0.858</td>
<td>0.837</td>
<td>0.021</td>
</tr>
<tr>
<td></td>
<td>(0.349)</td>
<td>(0.369)</td>
<td></td>
</tr>
<tr>
<td>Age (in years)</td>
<td>28.43</td>
<td>28.40</td>
<td>0.029</td>
</tr>
<tr>
<td></td>
<td>(6.808)</td>
<td>(6.484)</td>
<td></td>
</tr>
<tr>
<td>Tenure in plant (in years)</td>
<td>1.117</td>
<td>1.013</td>
<td>0.104</td>
</tr>
<tr>
<td></td>
<td>(2.005)</td>
<td>(1.670)</td>
<td></td>
</tr>
<tr>
<td>Number of Workers</td>
<td>579</td>
<td>1068</td>
<td></td>
</tr>
</tbody>
</table>

*Note. Standard deviations in parentheses

* p<0.1, ** p<0.05, *** p<0.01
Table 2: Summary Statistics: Effect of Monitoring on Productivity

<table>
<thead>
<tr>
<th></th>
<th>Before RFID Implemented</th>
<th>After RFID Implemented</th>
<th>Difference: After–Before</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SE</td>
<td>Mean</td>
</tr>
<tr>
<td>Panel 1: Unconditional Analysis</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Across All Lines</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treated</td>
<td>65.9%</td>
<td>(0.2)</td>
<td>70.0%</td>
</tr>
<tr>
<td>Control</td>
<td>59.0%</td>
<td>(0.2)</td>
<td>60.6%</td>
</tr>
<tr>
<td>Treated–Control</td>
<td>6.8%</td>
<td>(0.3)</td>
<td>9.4%</td>
</tr>
<tr>
<td>Panel 2: Analysis by Product</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2a. Simple Product Lines (Pants)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treated</td>
<td>64.2%</td>
<td>(0.2)</td>
<td>73.0%</td>
</tr>
<tr>
<td>Control</td>
<td>59.4%</td>
<td>(0.2)</td>
<td>60.1%</td>
</tr>
<tr>
<td>Treated–Control</td>
<td>4.8%</td>
<td>(0.3)</td>
<td>12.9%</td>
</tr>
<tr>
<td>2b. Complex Product Lines (Jackets)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treated</td>
<td>68.8%</td>
<td>(0.4)</td>
<td>63.9%</td>
</tr>
<tr>
<td>Control</td>
<td>57.5%</td>
<td>(0.4)</td>
<td>62.1%</td>
</tr>
<tr>
<td>Treated–Control</td>
<td>11.2%</td>
<td>(0.5)</td>
<td>1.8%</td>
</tr>
<tr>
<td>Panel 3: Analysis by Operation</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3a. Simple Operations</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treated</td>
<td>60.0%</td>
<td>(1.2)</td>
<td>65.1%</td>
</tr>
<tr>
<td>Control</td>
<td>57.1%</td>
<td>(1.2)</td>
<td>57.2%</td>
</tr>
<tr>
<td>Treated–Control</td>
<td>2.9%</td>
<td>(1.8)</td>
<td>7.9%</td>
</tr>
<tr>
<td>3b. Complex Operations</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treated</td>
<td>71.6%</td>
<td>(1.4)</td>
<td>66.4%</td>
</tr>
<tr>
<td>Control</td>
<td>65.4%</td>
<td>(1.0)</td>
<td>64.4%</td>
</tr>
<tr>
<td>Treated–Control</td>
<td>6.2%</td>
<td>(1.7)</td>
<td>2.0%</td>
</tr>
</tbody>
</table>

Note. Cells represent mean percent efficiency at the line-day level (1, 2a, and 2b) and operation-day level (3a and 3b). Analysis 2a is for simple product lines producing pants, 2b is for complex product lines producing jackets, 3a is for relatively simple operations on the pant lines, and 3b is for relatively complex operations on the pant lines.
Table 3: Difference in Differences Regression for Effect of Monitoring Treatment on Productivity across All Lines

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Post</td>
<td>1.60</td>
<td></td>
<td>1.32</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.08)</td>
<td></td>
<td>(1.90)</td>
<td></td>
</tr>
<tr>
<td>Treated</td>
<td>6.82**</td>
<td>6.85**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.37)</td>
<td>(2.31)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post × Treated</td>
<td>2.57</td>
<td>2.65</td>
<td>2.83</td>
<td>3.00</td>
</tr>
<tr>
<td></td>
<td>(4.46)</td>
<td>(4.30)</td>
<td>(4.40)</td>
<td>(4.21)</td>
</tr>
<tr>
<td>Line FE</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Month-Year FE</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Day of Week FE</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>N</td>
<td>16,436</td>
<td>16,436</td>
<td>16,436</td>
<td>16,436</td>
</tr>
</tbody>
</table>

*Note.* Observations are at the line-date level. All estimates are from OLS models. DV: One point is one percent efficiency. Post=1 after RFID implemented. Treated=1 for lines that received RFID. Standard errors clustered by line are in parentheses. *p<0.1, **p<0.05, ***p<0.01
Table 4: Difference-in-Differences Regression for Effect of Monitoring Treatment on Productivity by Product Complexity

<table>
<thead>
<tr>
<th></th>
<th>Simple Lines (Pants)</th>
<th>Complex Lines (Jackets)</th>
<th>All Lines (Pants &amp; Jackets)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Post</td>
<td>0.73</td>
<td>4.52</td>
<td>0.73</td>
</tr>
<tr>
<td></td>
<td>(2.50)</td>
<td>(2.86)</td>
<td>(2.46)</td>
</tr>
<tr>
<td>Treated</td>
<td>4.80*</td>
<td>11.2***</td>
<td>4.80*</td>
</tr>
<tr>
<td></td>
<td>(2.52)</td>
<td>(0.31)</td>
<td>(2.48)</td>
</tr>
<tr>
<td>Post × Treated</td>
<td>8.06**</td>
<td>7.76**</td>
<td>-9.42* -7.79**</td>
</tr>
<tr>
<td></td>
<td>(2.68)</td>
<td>(2.60)</td>
<td>(2.86) (1.38)</td>
</tr>
<tr>
<td>Complex</td>
<td>-1.86</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.11)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post × Complex</td>
<td></td>
<td>3.80</td>
<td>2.27</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(3.46)</td>
<td>(2.96)</td>
</tr>
<tr>
<td>Treated × Complex</td>
<td>6.42**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.50)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post × Treated × Complex</td>
<td></td>
<td>-17.5***</td>
<td>-15.7***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(3.59)</td>
<td>(2.90)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Line FE</th>
<th>No</th>
<th>Yes</th>
<th>No</th>
<th>Yes</th>
<th>No</th>
<th>Yes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Month-Year FE</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Day of Week FE</td>
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<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
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<td>4,299</td>
<td>4,299</td>
<td>16,436</td>
<td>16,436</td>
</tr>
</tbody>
</table>

Note. Observations are at the line-date level. All estimates are from OLS models. DV: One point is one percent efficiency. Post=1 after RFID implemented. Treated=1 for lines that received RFID. Complex=1 for jacket lines. Standard errors clustered by line are in parentheses. * p<0.1, ** p<0.05, *** p<0.01
Table 5: Difference in Differences Regression for Effect of Monitoring Treatment on Productivity, by Operational Complexity in Pant Lines in 2012

<table>
<thead>
<tr>
<th></th>
<th>Simple Operations (Within Pants)</th>
<th>Complex Operations (Within Pants)</th>
<th>All Operations (Within Pants)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Post</td>
<td>0.10</td>
<td>-1.04</td>
<td>0.10</td>
</tr>
<tr>
<td></td>
<td>(0.87)</td>
<td>(1.66)</td>
<td>(0.87)</td>
</tr>
<tr>
<td>Treated</td>
<td>2.93</td>
<td>6.21*</td>
<td>2.93</td>
</tr>
<tr>
<td></td>
<td>(2.63)</td>
<td>(3.17)</td>
<td>(2.62)</td>
</tr>
<tr>
<td>Post × Treated</td>
<td>4.97*</td>
<td>5.36*</td>
<td>4.97*</td>
</tr>
<tr>
<td></td>
<td>(2.77)</td>
<td>(3.07)</td>
<td>(2.76)</td>
</tr>
<tr>
<td>Complex</td>
<td></td>
<td></td>
<td>8.32</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(7.33)</td>
</tr>
<tr>
<td>Post × Complex</td>
<td>-1.14</td>
<td>-1.12</td>
<td>-1.14</td>
</tr>
<tr>
<td></td>
<td>(1.80)</td>
<td>(1.77)</td>
<td>(1.77)</td>
</tr>
<tr>
<td>Treated × Complex</td>
<td>3.29</td>
<td>1.82</td>
<td>3.29</td>
</tr>
<tr>
<td></td>
<td>(3.98)</td>
<td>(3.84)</td>
<td>(3.98)</td>
</tr>
<tr>
<td>Post × Treated × Complex</td>
<td></td>
<td></td>
<td>-9.13***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(3.11)</td>
</tr>
<tr>
<td>Line FE</td>
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<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Yes</td>
</tr>
<tr>
<td>Month FE</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Yes</td>
</tr>
<tr>
<td>Day of the Week FE</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
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<tr>
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<td>3,745</td>
<td>3,745</td>
<td>1,618</td>
</tr>
<tr>
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<td></td>
<td>1,618</td>
<td>5,363</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>5,363</td>
</tr>
</tbody>
</table>

Note. Observations are at the operation-date level. All estimates are from OLS models. DV: One point is one percent efficiency. Post=1 after RFID implemented. Treated=1 for lines that received RFID. Complex=1 for SMV greater than 0.75. Standard errors clustered by operation are in parentheses. * p<0.1, ** p<0.05, *** p<0.01
Our procedure for conducting the placebo analysis is as follows: There are nine pant lines, two of which are truly treated; we first indicate these two truly treated lines as being untreated. Then, from the remaining truly untreated seven lines, we sequentially indicate every combination of two lines as treated lines, giving us a total of 21 placebo treatments (7 choose 2). Lastly, we see how often this procedure reproduces the results observed when we properly indicate the truly treated lines. We do the same for the jacket lines. Note that there are 3 jacket lines, one of which is treated; so the same procedure yields 2 placebo treatments for the jacket lines. Since the placebo interventions are uncorrelated with the true intervention, we should find our same result no more than we would expect by statistical chance. Alternatively, idiosyncratic line-specific time trends, coupled with a finite sample of treated lines, would generate a large number of false positives among the placebos. We rank order the placebo and nonplacebo coefficients for the Post Treated term and present these with their 95% confidence intervals.

Note that the solid markets denote the nonplacebo tests. For the pant lines, none of the 21 placebo treatments generates a positive and statistically significant result with \( p < 0.05 \), although one placebo comes close (\( p = 0.053 \)). This placebo treatment features the two nontreated lines that exhibited the largest growth in productivity during the treatment period, not counting the two treatment lines. Two of the 21 combinations of placebo treatments yield a statistically significant decline relative to the other lines. For the jacket lines, the effects of the placebo treatments are not significantly different from zero. Overall, we conclude that the line placebos do not yield false positives at a greater rate than we would expect by statistical chance.