



THE EFFECT OF PLANNED BREAKS ON WORKER PRODUCTIVITY AND THE MODERATE ROLE OF WORKLOAD IN A MANUFACTURING ENVIRONMENT



Siyuan Yi¹
 Qiguo Gong²
 Feng Dong³
 Hui Wang^{4*}

^{1,2,3}School of Economics and Management, University of Chinese Academy of Sciences, Beijing, China.

¹Email: yisiyuan1s@mailsucas.ac.cn Tel: +86-13389637527

²Email: gonggg@ucas.ac.cn Tel: +86-13520307259

³Email: dongfeng15@mailsucas.ac.cn Tel: +86-15510328323

⁴School of Economics, Chongqing Technology and Business University, Chongqing, China.

⁴Email: wanghui19@ctbu.edu.cn Tel: +86-13051360539



(+ Corresponding author)

ABSTRACT

Article History

Received: 9 April 2020

Revised: 28 October 2020

Accepted: 19 November 2020

Published: 7 December 2020

Keywords

Planned break

Productivity

Manufacturing industry

Empirical analysis

Prais–Winsten regression

Moderate effect

JEL Classification:

L60, M11, M54.

The purpose of this paper is to empirically explore the impact of planned breaks on employee productivity and the moderate role of workload in a manufacturing environment. The dataset for this research, which comprises 3043985 records, was collected from assembly lines in a manufacturing company, and the Prais–Winsten regression model was used to empirically analyze the relationship between productivity and breaks. The results showed that productivity improved during the 30 minutes before the start of a break, which mainly resulted from employees' expectations of the upcoming break and the alleviation of any negative emotions due to their current work. It was also found that productivity declined during the 30 minutes after the end of a break due to the dominating effect of forgetting the recent rest and having a disordered work rhythm in the manufacturing environment. Additionally, it was noticed that a lighter workload mitigated the negative post-break impact on productivity while reinforcing the pre-break positive impact on productivity. The results implicate that managers should schedule breaks for employees and appropriately reduce their workload to improve productivity.

Contribution/Originality: This study contributes to the existing literature on how planned breaks affect employee productivity and is one of very few studies that investigates the moderate effect of workload on breaks and productivity.

1. INTRODUCTION

Behavior management of employees in production and operation processes is crucial and human factors in operations management have garnered much attention from scholars (Greasley & Owen, 2018; KC et al., 2020). KC et al. (2020) summarized the key role that employees play in learning and task selection. In fact, during the operation process, employees react to factors such as breaks and workload and change their operational behavior accordingly. Moreover, since employees are not machines, the continuity of their work cannot be extended infinitely. Generally, companies must arrange for them to take appropriate breaks after a certain period of work to alleviate any negative effects caused by physical and mental exhaustion (Henning et al., 1997), boredom (Fisher, 1993) and burnout (Schaufeli & Bakker, 2004). When returning to their tasks after a break, it is difficult for

employees to maintain consistency in their operational behavior from the break. Previously, scholars only focused on the impact of a break based on post-break performance of employees while ignoring the impact of a break on efficiency before the break. In addition to previous research, this article not only explores the impact that breaks have on post-break performance in a manufacturing environment, but also investigates the impact of upcoming planned breaks on employee productivity, and more specifically, the impact that the planned breaks may induce before it occurs. As described above, the operational level of employees is not exogenous and can be affected by breaks (Pendem et al., 2016; Tucker, 2015). Therefore, it is important to study how planned breaks affect employee behavior and operational performance in operations management.

Essentially speaking, a break is a welcome interruption in a working day. However, empirical research on interruption by utilizing mass data from the production line is relatively scarce, and Cai et al. (2017) pointed out that it may be partially due to the difficulty of identifying interruptions and establishing a causal relationship. In fact, there are expected and unexpected break patterns during production operations (Pendem et al., 2016). Compared to unexpected breaks, the timing and location of planned breaks are easier to determine in empirical studies since the start time, end time and duration of the planned break, which can be inferred from regular rest and meal arrangements between shifts, are relatively fixed. In addition, a large amount of data was gathered from data collection systems (such as MES, ERP, and CPS), which can also be used to identify the location and duration of breaks. The investigation of planned breaks alleviates the interruption identification problem and its related causality problem making it possible to study the impact of breaks on production performance.

Just as every coin has two sides, studies have shown that the effects of breaks on operational performance can be both positive and negative (Froehle & White, 2014; Groenevelt et al., 1992). Until now, most of the research has focused on the impact of breaks on employee performance after a break ends. On the one hand, disordered work rhythm (Hopp et al., 2004; Schultz et al., 2003), distraction (Healey et al., 2006) and reduced proficiency and forgetfulness (Bailey, 1989; Ramdas et al., 2017; Teyarachakul et al., 2016) caused by interruptions can inhibit employee performance for a certain period after they return to work. On the other hand, an interruption can also ease employee fatigue, improve satisfaction (Li et al., 2020), relax the mood (Kim et al., 2018) and boost energy (Kim et al., 2017; Trougakos et al., 2014). The positive effects relieve physical and mental pressure of employees and improve their performance after a break. Since the positive and negative effects coexist, a question that needs further exploration is which effect is more dominant in a manufacturing environment.

Besides the post-break effects, breaks also affect employees' operational behavior before it starts. However, this issue has received little attention from scholars. For a planned break, employees have a clear understanding of the break-related information, such as the start, duration and end time of the break. Once employees have foreknowledge of the when, where, and why the break occurs, they can minimize the negative effects of the break by logically arranging their other activities (McFarlane, 2002). The transparency of planned break information may have an impact on an employee's mood or behavior before the break, which, in turn, leads to changes in productivity. In an actual manufacturing environment, how employees respond before a break is also a topic worth discussing.

In previous studies, the workload moderates various factors that affect employee behavior. When a break is taken, both the psychological workload (Bailey & Iqbal, 2008; Miyata & Norman, 1986) and the cumulative number of continuous work shifts (Pendem et al., 2016) can moderate the relationship between a break and employee performance. Considering the impact of a break, how the workload moderates the impact on employee productivity before and after a break is also worth exploring.

We collected million-level data recorded in an assembly line. We divided a continuous work stage with two adjacent breaks into three parts: 30 minutes before taking a break, 30 minutes after a break ends, and the middle period of a consecutive work stage (see Figure 1). This article explores the impact of planned breaks on employee productivity and the moderate role of workload by adopting the Prais–Winsten regression model for conducting

empirical research. The Prais–Winsten regression model has been widely used in the field of operations management, such as service operation (Lapre & Tsiriktsis, 2006; Staats & Gino, 2012), supply chain (Kleijnen & Van Schaik, 2011; Obermaier, 2012) and marketing (Van Donselaar et al., 2016) and applies to the time-series cross-sectional data of this paper. The results showed that employee productivity increased during the 30 minutes before the start of a break, while productivity reduced during the 30 minutes after the break ended. Furthermore, the empirical results also indicated that a lighter workload can alleviate the negative effects after the end of a break and strengthen the positive impacts before the beginning of a break. This article provides new insights into the theory of taking breaks.

The structure of this paper is as follows: related literature reviews and hypotheses development are presented in Section 2, Section 3 introduces the data collection process, variable selection and analysis methods, empirical analysis results and robustness tests are discussed in Section 4, and conclusions and the discussion of the management implications of our main findings are included in Section 5.

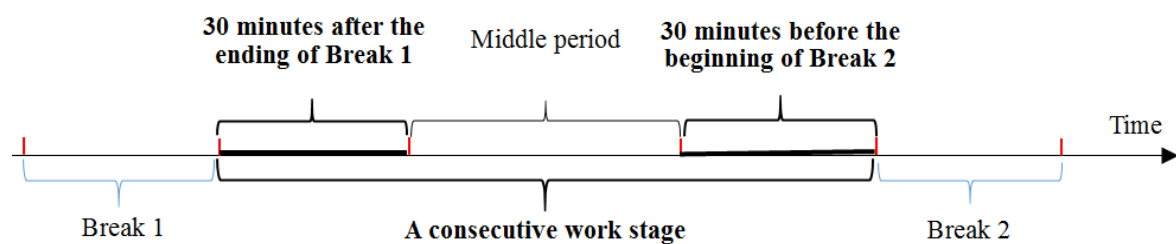


Figure 1. Division of a consecutive working stage between two adjacent breaks.

2. LITERATURE AND HYPOTHESES

Manufacturing systems are often affected by a variety of factors that may lead to process variability, such as maintenance, rework, machine failure, breaks and meals. Interruption research can be traced back to Zeigarnik (1938) and current research focuses on human factors, cognitive psychology and human–computer interaction (Andreasson et al., 2017; Kolbeinsson, 2016). This article explores one of the important types of interruptions described by Jett and George (2003) – breaks. McFarlane (2002) proposed three different interruption coordination modes that the author termed as immediate interruptions (random interruptions for which no prior notification is given), negotiated interruptions (employees are notified of intended interruptions and they can choose when to accept the interruptions) and scheduled interruptions (interruptions that happen according to a predetermined schedule). Among these interruption modes, scheduled interruptions, or planned breaks, are what we examine this research.

In recent years, research has been conducted on rests and meals during work shifts (Di Pasquale et al., 2017). Tucker et al., (2003) showed that even in a short period, a break has an impact on the physical and psychological health of employees. Therefore, understanding whether planned breaks affect employee performance can provide useful guidance for a company's production schedule.

We believe that different working environments can affect the behavior of employees during their breaks and thus affect their performance after taking a break. In a knowledge-based working environment where the work process is generally more complicated, knowledge workers are required to be highly focused on their work. Through experimental research on the standing rest of knowledge workers, Thorp et al., (2014) found that regular standing breaks not only relieved employees' fatigue, but also improved their attention, alertness and motivation at work, thereby enhancing their performance. For knowledge workers, a break is also conducive to physical recovery and mood relaxation. Epstein et al., (2016) pointed out that ten minutes after a break, a positive effect induced by the mental refreshment and relaxation of knowledge workers on productivity emerges. Moreover, due to the easing of physical discomfort, reduction of psychological stress and effective communication during the break, Lu et al., (2014) demonstrated that employee efficiency increased significantly within half an hour after a break in the IT

service industry. They also indicated that effective communication can help knowledge workers think deeply and solve problems encountered at work. Hence, in a knowledge-based working environment, there is evidence that breaks promote employee productivity for some time afterwards.

However, in the manufacturing industry where employees conduct simple, highly repetitive and short-duration operations they do not need to spend much time thinking, which is necessary for knowledge-based tasks. Though taking a break can help them to relax, it may lead to other situations, such as reduced proficiency, forgetfulness (Bailey, 1989; Teyarachakul et al., 2016; Teyarachakul et al., 2011), time pressure (Leroy & Glomb, 2018), disordered work rhythm (Hopp et al., 2004; Schultz et al., 2003) and procrastination caused by tedious work (Jett & George, 2003). These factors, separately or combined, may lead to a reduction in employee productivity causing negative effects to dominate in a manufacturing environment. Froehle and White (2014) believed that the existence of interruptions is inappropriate in a manufacturing process and that companies should try to reduce the frequency of interruptions by working overtime and adjusting batches, etc. Compared with a knowledge-based working environment, the performance of employees in a manufacturing environment will decrease over time after a break ends. Based on the above analysis, we propose the following hypothesis:

Hypothesis 1. *In a manufacturing environment with simple and highly repetitive tasks, planned breaks reduce employee productivity after a break has ended.*

How planned breaks impact employee productivity before they happen is rarely supported by empirical research. Through implementing interruption experiments, Schultz et al. (2003) found that employees performed better before they are interrupted than they do after they take a break. However, their finding has not yet been supported empirically.

Generally, employees are aware of upcoming breaks and transparent information plays an important role in their physical and psychological responses. In a manufacturing environment, it is important to provide the right people with the right information at the right time (Caldarola et al., 2018). If people know when, where, why and how to take a break in advance, they can minimize any negative effects of taking a break by logically arranging rest, meals and other activities (McFarlane, 2002). Lee et al., (2018) proposed that there is an interruption lag between a primary task and a peripheral task (interruption). The classification of interruption delivery modes by McFarlane (2002) indicate that the total task completion time is longer in the immediate interruption mode than in the scheduled interruption mode, and this can be explained by the longer interruption lag in the immediate interruption mode as employees may not be ready to switch to another task when an interruption occurs compared with being fully aware of the start time of a scheduled interruption. Moreover, a higher error rate was noticed in the immediate interruption mode. Therefore, providing employees with interruption-related information in advance may affect their operational performance. Research by Lindbeck and Snower (2000) showed that when employees got the opportunity to switch tasks, their negative emotions would reduce to a certain extent and more effort would be made to maintain a high level of enthusiasm in the final stage of their current task. Therefore, we believe that when employees switch from working to taking a break, their negative emotions may be relieved, thereby improving their operational performance, especially in a repetitive and tedious manufacturing assembly line. Once assembly line workers realize the urgency of time, they consolidate or complete their main tasks or goals before the break (McFarlane, 2002) and they will put more effort in to compensate for any potential losses caused by the imminent break (Mark et al., 2008). Therefore, Hypothesis 2 is proposed as follows:

Hypothesis 2. *In a manufacturing environment with simple and highly repetitive tasks, planned breaks improve employee productivity before their breaks begin.*

Workload management, which may profoundly impact worker behavior, has been widely studied (KC et al., 2020; Saghafian et al., 2018; Tan & Netessine, 2014). Previous research supports the non-linear effect of workload on operational productivity (Adler & Clark, 1991; Lapre & Tsikriktsis, 2006). The interest of this article is to understand how workloads affect the impact of planned breaks on productivity before and after, which has received

little attention from scholars to date. As an important factor, some studies have explored the direct impact of workload on operational performance. However, few studies have focused on how breaks affect employee performance under different workloads. An influential article on this issue was written by Miyata and Norman (1986), who found that, under lighter emotional stresses, the delivery of a notification results in lower interruption costs. Similarly, based on experimental studies of three tasks, route planning, document editing and message classification, Bailey and Iqbal (2008) explored the cost of interruptions under different workloads. Their experimental results showed that in a lighter workload environment more attention and resources can be used for interrupted tasks, so the cost of interruptions is lower. During the potato harvesting process, when the harvesters face unexpected breaks that lead to diversion, Pendem et al. (2016) found that the workload magnified the negative impacts after a break ended. The above research indicated that a lighter workload is more beneficial to operational performance when interruptions occur. Since rest is a common type of break, workload may have a similar moderate effect on the impact of breaks on operational performance. Based on the above analysis, and Hypotheses 1 and 2, we assume that workload plays a positive role in the relationship between planned breaks and employee productivity. Therefore, we propose the following as Hypothesis 3:

Hypothesis 3. *Lighter workload levels magnify the effects of planned breaks on worker productivity, such that the negative post-break effects are weaker and the positive pre-break effects are stronger.*

3. DATA AND EMPIRICAL STRATEGY

3.1. Manufacturing Setting

Data from two assembly lines was used to validate the hypotheses presented above. We chose data from these assembly lines for the following reasons, first, the company has two identical assembly lines with every step on each line operated manually, which helped us to measure and study the productivity of employees. Second, the quantity of products completed in one shift per assembly line reached nearly 4,000 pieces, which provided us with a large amount of sample data for the research. Third, the times for rest and meals were specified by the company, meaning that breaks were already scheduled. Once the employees left the assembly line for a rest or meal, the assembly line stopped working immediately, and therefore, we could accurately identify the times for rests and meals for employees during the production process. Finally, the MES enterprise records had relatively complete data on the processing times for main procedures and employee information, thus providing strong data to support our research objectives.

Figure 2 depicts the schematic of an assembly line. There are six employees on each line and all procedures are in tandem. First, the mainboard is loaded into the machine by the first employee to retain its relevant information. The loading procedure includes the detection of the mainboard information and the laser coding process. In the process of shell covering, the second employee puts the mainboard in the box and passes it to the next workstation. To test the locking screws, a third employee places the assembled product on the machine to install the screws for reinforcing. Next, the fourth employee utilizes the laser to name and paste the barcode. Then, the fifth employee puts the footpads on the corners of each product. Finally, the sixth employee packs the finished product for the transporter for storage. After this point, the entire assembly process is over.

The usual production time is Monday to Friday, but when a production task is urgent, people will work overtime on the weekends. Two shifts are arranged for each workday—day shift and night shift. The working hours for the day shift and night shift are 8:00 am - 18:00 pm and 20:00 pm - 6:00 am, respectively. The company arranges rests and meals for each work shift with a break time of 15 minutes and a mealtime of 30 minutes (night shift) or one hour (day shift). Before the start of each shift, staff is assigned to their corresponding positions within the two assembly lines where the positions are non-fixed. Generally, employees will work in the position to which they are assigned until the end of the shift.

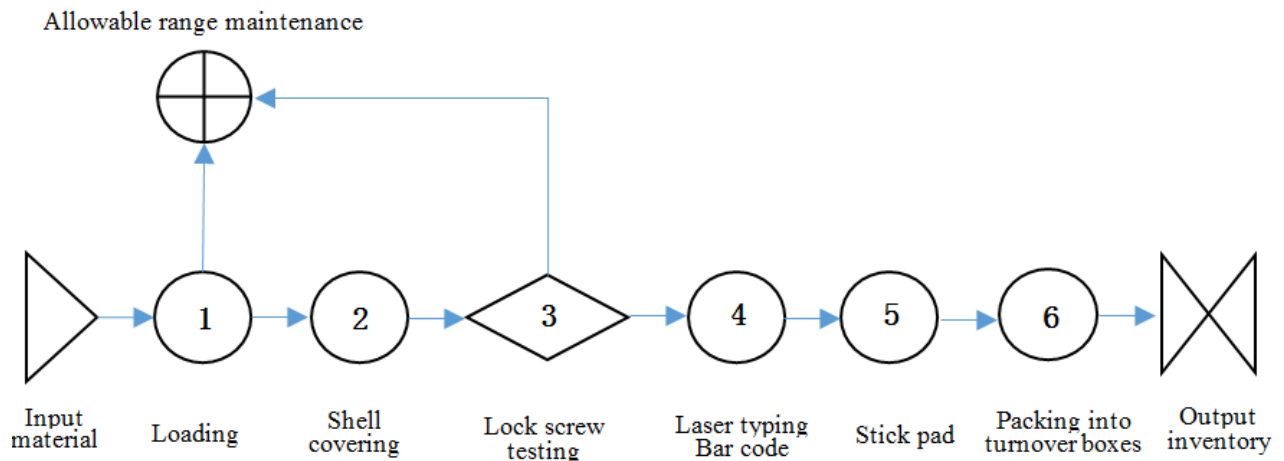


Figure 2. Procedures of the production assembly line.

Source: Developed by authors according to data sources from the selected manufacturing company.

3.2. Data

For the purpose of our research, we selected the production data of two assembly lines from a manufacturing enterprise from August 28, 2018 to December 8, 2018. There are six procedures for each assembly line, but relatively complete data was only recorded for three key procedures; Procedure 1 (loading), Procedure 3 (locking screw testing) and Procedure 6 (packing into turnover boxes) (see Figure 1). The raw dataset obtained from the MES system comprises the ID of each product and its entry time for Procedures 1, 3 and 6. These test procedures are characterized by constant repetition, simple operation, a single product and short duration. As shown in Table 1, we divided a workday into nine work stages and seven breaks according to the company's shift and break schedule. Some pre-processing steps were used for data processing. First, since the company's MES did not record data from August 29 to September 3, 2019, to maintain data continuity, we excluded data from August 28, 2019. The deleted data only accounted for 0.48% of the total data, and when included the empirical results remained consistent. Therefore, the deleted part did not affect our empirical results. Second, our analysis also excluded a small number of errors and missing data.

Table 1. Arrangement of planned breaks and work stages.

Day shift: 08:00-18:00		Night shift: 20:00-06:00	
Working time/break	Time	Working time/break	Time
Stage 1	08:00-10:00	Stage 6	20:00-22:00
Rest	10:00-10:15	Rest	22:00-22:15
Stage 2	10:15-11:50	Stage 7	22:15-23:30
Lunch	11:50-12:50	Late-night snack	23:30-00:00
Stage 3	12:50-15:00	Stage 8	00:00-03:00
Rest	15:00-15:15	Rest	03:00-03:15
Stage 4	15:15-17:00	Stage 9	03:15-06:00
Dinner	17:00-18:00		
Stage 5	18:00-20:00		

Source: Developed by authors according to data sources from the selected manufacturing company.

In this paper, the data for three key procedures (Procedures 1, 3 and 6) on the assembly line were selected for our empirical analysis. The assembly data obtained in each stage was intercepted in 10-minute time intervals for subsequent analysis. Taking the first procedure in Stage 1 as an example, since production may not strictly start at 8:00 am and end at 10:00 am, we recorded the time when the first mainboard reached Procedure 1 as the starting time of this stage, and the time when the last mainboard (after which there is no further mainboard inflow and a rest subsequently begins) reached Procedure 1 as the end time of this stage. From the arrival time of the first mainboard, when the n th (n indicates the sequence number of the mainboard) mainboard reached Procedure 1 is no

more than 10 minutes and the time when the $(n+1)$ th ($n+1$ indicates the sequence number of the mainboard) product reached Procedure 1 is more than 10 minutes, the arrival time of the n th product is the end time point of the first 10-minute time interval of this stage. The arrival time of the $(n+1)$ th product was taken as the start time of the second 10-minute interval of this stage, and so on. We recorded all subsequent 10-minute time intervals according to the above logic. The details are shown in Figure 2 and the same processing method was also used for Procedures 3 and 6. Finally, we obtained a panel dataset with 69 employees, 75 days, 680 shifts, 3043985 product records and 35868 10-minute time intervals.

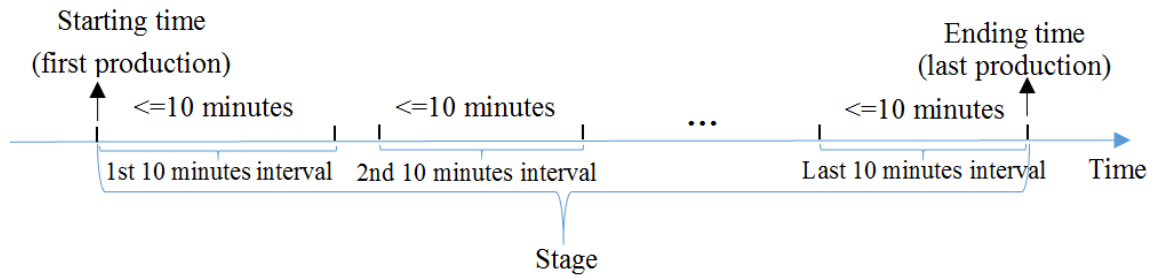


Figure 3. 10-minute time intervals of Procedure 1 (loading process).

3.3 Variable

3.3.1 Dependent Variable

In our study, the dependent variable is employee productivity. Processing time is generally regarded as the indicator for performance (Reagans et al., 2005; Staats & Gino, 2012). Our data provides the processing time of each product in Procedures 1, 3 and 6, respectively. However, to express the operational performance intuitively, we selected the reciprocal of the average test time as employee productivity, $Efficiency_{ijk}$. This variable measures the productivity of an employee i in the t th 10-minute time interval of the stage k on the day j , which means that the number of tested products per time unit is utilized as the dependent variable. As with prior research conducted by Narayanan et al., (2009) and Staats and Gino (2012), the dependent variable is presented in the natural log form $Efficiency_{ijk}$. There are two main reasons for taking the natural logarithm of the dependent variable; first, the reciprocal of the average test time of the product in 10-minute intervals shows a skewed distribution, and second, the natural logarithmic form can alleviate the impact of other heterogeneous factors on the model to some extent (Wooldridge, 2012).

3.3.2. Explanatory Variable

A complete work stage between two adjacent breaks was divided into three parts: pre-break period, middle period and post-break period. We referred to previous studies to determine a reasonable length for each of these three parts. Lu et al. (2014) empirically studied the impact of interruptions on employee productivity one hour after its occurrence, and they found that the effects only lasted for 30 minutes. The research of DeJarnette (2015) provided evidence that employees spent 15 minutes returning to 90% of their prior work effort after experiencing a complete interruption in productivity. This showed that the impact of interruptions may not last for more than 30 minutes. Hence, 30 minutes is enough to enable employees to return to their normal work level. Reasonably, we took the first 30 minutes of each work stage as the post-break period, the last 30 minutes as the pre-break period and the remaining was treated as the middle period. Considering our research target, categorical variables that indicate pre-break and post-break periods were utilized as the explanatory variables. Therefore, our explanatory

variable is a three-category dummy variable ($Period_Int_{ijkt}$): $Before_Int_{ijkt}$, Mid_Int_{ijkt} and $After_Int_{ijkt}$. $Before_Int_{ijkt} = 1$ represents that the employee i 's t th 10-minute time interval of the stage k on the day j belongs to the 30 minutes before the break (meal or rest) starts and $Before_Int_{ijkt} = 0$ otherwise. Mid_Int_{ijkt} and $After_Int_{ijkt}$ have a similar explanation. To avoid multicollinearity, we only included $Before_Int_{ijkt}$ and $After_Int_{ijkt}$ in our model.

3.3.3. Moderator and Control Variables

In this paper, several factors were used as control variables, and a detailed description for each variable is shown below.

$Workload_{ij}$ is defined as the accumulated quantity of products, specifically, the number of products completed by the employee i on day j from the beginning of a shift to the current moment. Though some research supports a linear effect of workload on operational performance (KC & Terwiesch, 2009; Schultz et al., 2003), the empirical findings of Adler and Clark (1991) and Lapre and Tsiriktsis (2006) also provided evidence for their non-linear relationship. Hence, the square term of the workload variable $Workload_{ij}^2$ was considered in this analysis. In the study of the relationship between an experience (the cumulative number of products) and productivity, Staats and Gino (2012) argued that the exponential form of the experience term is derived from theory and supported empirically, while the powder form (log-log) comes simply from empirical observation. Therefore, if there is only empirical observation but a lack of theoretical support, it would be appropriate to use a log-log form. However, when both empirical observation and theoretical support coexist, the exponential form would be a better choice. In this research, the impact of workload on employee productivity is supported by both theoretical and empirical observations. Moreover, most of the employees on the assembly line had gained some work experience before our data collection, and under such circumstances, the utilization of an exponential form between workload and employee productivity can reduce the bias of prior experience acquisition (Lapre & Tsiriktsis, 2006). Hence, instead of the log-log form, the exponential form was adopted. Additionally, the variable of workload levels was also taken as a moderator. Interaction terms between workload and explanatory variables were also used to explore the moderating effect of workload.

$Shift_{ijkt}$: Indicator variable that makes a distinction between the day shift and night shift. $Shift_{ijkt}$ equals 1 when the shift of employee i arranged in the t th 10-minute time interval of the stage k on the day j is the night shift, otherwise $Shift_{ijkt} = 0$.

$Procedure_{ij}$: Virtual variables that capture three different procedures in the assembly line. $Procedure1_{ij} = 1$, $Procedure2_{ij} = 1$ and $Procedure3_{ij} = 1$ demonstrate that the employee i has a role in Procedures 1, 3 and 6 on the day j , respectively.

P_Number_{ijkt} : The number of finished products by the employee i in the t th 10-minute time interval of the stage k on the day j . Generally, the larger P_Number_{ijkt} , the higher the employee productivity. To some extent, the P_Number_{ijkt} can be regarded as a relatively short-term workload that measures the accumulated number of products tested during each selected 10-minute interval. This variable was used later on in the robustness test to validate the moderating role of workload levels.

$LineStyle_{ij}$: The indicator variable represents the different assembly lines. The employee i does his/her work in Assembly Line 1 on the day j when $LineStyle_{ij} = 1$. Otherwise, he/she works in Assembly Line 2 when $LineStyle_{ij} = 0$.

In addition, some of the employee characteristics needed to be controlled. Employee i 's age (Age_i), gender ($Gender_i$) and length of service ($WorkMonths_i$) were included in our analysis. $WorkMonths_i$ was calculated in the months from the time that the employee i entered the company to the present time.

3.4. Empirical Method

Model 1 is our basic model. The left side of Model 1 is the dependent variable, which captured employee productivity by the number of tested products per time unit. The independent variables of this model include the long-term workload $Workload_{ij}$ and its quadratic term $Workload_{ij}^2$, the short-term workload $Procedure_{ij}$, the virtual variables $Procedure_{ij}$ that indicates the procedure of the focal employee, the virtual variable $LineStyle_{ij}$ that indicates the assembly line that employees work on, and the control variables related to employee characteristics. Without loss of generality, the virtual variable of $Procedure6$ ($Procedure3_{ij}$) was excluded to avoid multicollinearity.

$$\begin{aligned} \ln(Efficiency_{ijkt}) &= \beta_0 + \beta_1 WorkMonths_i + \beta_2 Gender_i + \beta_3 Age_i + \beta_4 Shift_{ijkt} \\ &+ \beta_5 Procedure1_{ij} + \beta_6 Procedure2_{ij} + \beta_7 LineStyle_{ij} \\ &+ \beta_8 P_Number_{ijkt} + \beta_9 Workload_{ij} + \beta_{10} Workload_{ij}^2 + \mu_{ijkt} \end{aligned} \quad (1)$$

Based on Model 1, dummy variables $Before_Int_{ijkt}$ and $After_Int_{ijkt}$ were included in Model 2, while Mid_Int_{ijkt} was not included to avoid a multicollinearity problem. Compared with the middle period of a work stage, Hypotheses 1 and 2 assumed that employees had higher productivity levels within the 30 minutes before a break started and lower productivity levels during the 30 minutes after a break ended. In other words, coefficients β_{11} and β_{12} are positive and negative, respectively, once Hypotheses 1 and 2 are both supported.

$$\begin{aligned}
& \ln(\text{Efficiency}_{ijkt}) \\
&= \beta_0 + \beta_1 \text{WorkMonths}_i + \beta_2 \text{Gender}_i + \beta_3 \text{Age}_i + \beta_4 \text{Shift}_{ijkt} \\
&+ \beta_5 \text{Pr ocedure1}_{ij} + \beta_6 \text{Pr ocedure2}_{ij} + \beta_7 \text{LineStyle}_{ij} \quad (2) \\
&+ \beta_8 P_Number_{ijkt} + \beta_9 \text{Workload}_{ij} + \beta_{10} \text{Workload}_{ij}^2 \\
&+ \beta_{11} \text{Before_Int}_{ijkt} + \beta_{12} \text{After_Int}_{ijkt} + \mu_{ijkt}
\end{aligned}$$

Model 3 is shown as follows. The interaction terms of the current workload levels from the beginning of this shift and the first (last) 30 minutes of each stage as the period after (before) the last (next) break are included. As expected, the moderated role of workload in Hypothesis 3 indicated that the coefficients of β_{13} and β_{14} are negative and positive, respectively.

$$\begin{aligned}
& \ln(\text{Efficiency}_{ijkt}) \\
&= \beta_0 + \beta_1 \text{WorkMonths}_i + \beta_2 \text{Gender}_i + \beta_3 \text{Age}_i + \beta_4 \text{Shift}_{ijkt} \\
&+ \beta_5 \text{Pr ocedure1}_{ij} + \beta_6 \text{Pr ocedure2}_{ij} + \beta_7 \text{LineStyle}_{ij} \quad (3) \\
&+ \beta_8 P_Number_{ijkt} + \beta_9 \text{Workload}_{ij} + \beta_{10} \text{Workload}_{ij}^2 \\
&+ \beta_{11} \text{Before_Int}_{ijkt} + \beta_{12} \text{After_Int}_{ijkt} \\
&+ \beta_{13} \text{Workload}_{ij} \times \text{Before_Int}_{ijkt} + \beta_{14} \text{Workload}_{ij} \times \text{After_Int}_{ijkt} + \mu_{ijkt}
\end{aligned}$$

Since the dataset comprised a complete history of each employee's work efficiency within one year, it is natural to consider the possible autocorrelation and heteroskedasticity, which have been proven to exist in this panel data, by conducting additional tests (Stata commands "xtgls" and "xtserial"). We selected the Prais–Winsten model to account for the autocorrelation, contemporaneous correlation and heteroskedasticity of our panel data (Lapre & Tsiriktsis, 2006; Staats & Gino, 2012). This method replaced the ordinary least square with panel-corrected standard errors for heteroskedasticity and panel-wide, first-order autocorrelation (Beck & Katz, 1995). The Stata command "xtpcse" was also implemented in our models.

4. RESULT

4.1. Empirical Findings

Columns 1–3 in Table 2 report the regression results from Models 1, 2 and 3, respectively. In Model 1, only three of the variables related to employee traits and environmental factors were significant at a 90% confidence level. Worker age, gender and length of service had no significant impact on productivity. This phenomenon may be due to the simple assembly procedure and short processing time, therefore, the difference among employees cannot be reflected. Similarly, environmental factors, such as shift arrangement, test procedure and assembly line type had no significant impact on productivity. This finding may be explained by features of the selected manufacturing environment. First, the factory has adopted a job allocation system in which the position for each worker is non-fixed. Since the tasks on this assembly line are simple and easy to learn, the employees are capable of conducting every task, but with different levels of familiarity. Under these circumstances, the difference in productivity was not significant for different assembly lines and procedures. Second, because the actual output in each shift differed very little from the targeted tasks of the enterprise, worker productivity had no significant difference among work shifts.

However, the variables P_Number , $Workload$ and $Workload^2$ had a significant effect on employee productivity. The positive coefficient (0.010***) P_Number reflects the ubiquitous viewpoint that the larger the number of products tested during a 10-minute time interval, the higher the employee productivity. The coefficient

of *Workload* is positive while the coefficient of *Workload*² is negative, and they are both significant at a 99% confidence level. That is to say, employee productivity will first increase with the workload, which mainly results from the learning curve and accumulation of experience. After employees' experience accumulates to a certain extent and reaches the threshold, their productivity drops with an increase in workload. Our empirical conclusion is consistent with the findings of Lapre and Tsikriktsis (2006), Staats and Gino (2012) and Tan and Netessine (2014) who stated that employee productivity follows an inverted U-shaped relationship for the accumulated product number.

Explanatory variables *Before_Int* and *After_Int* were added into Model 2 to test Hypotheses 1 and 2. Coefficients of these two dummy variables were significantly positive (0.148***) and negative (-0.022***), respectively. This conclusion manifests that compared with the middle period of a work stage, employee productivity improved during the 30 minutes before a break started and reduced during the 30 minutes after a break ended. Hence, Hypothesis 1 and Hypothesis 2 are both supported. For the post-break period, the break can mitigate the fatigue which has been proven to be negatively correlated with a degree of autonomy during a lunch break (Troughakos et al., 2014), specifically, a higher level of lunch break autonomy resulted in lower of end-of-day fatigue. In this study, employees only enjoyed a certain degree of autonomy, thus their fatigue may be partially relieved after regular rests and meal breaks. Moreover, unlike a knowledge-based working environment where rest can provide relaxation and refreshment both mentally and physically and improve productivity after a break, in a manufacturing environment, however, relaxation brought by rests mainly mitigates physical fatigue while other negative effects such as forgetfulness and a disordered work rhythm dominate over positive relaxation. The forgetfulness of employees during a break may lead to a longer processing time of a single product and it takes a period of learning to reestablish the original level. At the same time, the concept of rhythm points out that in repetitive work, employees form a work rhythm, and when an interruption occurs this rhythm is disrupted, so it takes a while to recover after the interruption (Schultz et al., 2003). Regarding which mechanism dominates the other, the relationship between production efficiency and interruption time needs to be studied. In production, there was a lot of research done on forgetting and learning, and the results of the research showed that forgetting is a result of interruption time (Bailey, 1989), while there was no obvious correlation between the disturbance of production rhythm and the length of interruptions. However, due to the limitation of data, we cannot distinguish between these two mechanisms in the current environment. This finding not only provides evidence of negative effects after a break on worker productivity (Froehle & White, 2014; Leroy & Glomb, 2018), but empirically complements the experiment conclusion of Schultz et al. (2003) that processing the last item in a batch is significantly faster than the first item of the next batch following a short work interruption. As discussed in Section 2, the improvement of productivity in the pre-break period may mainly be generated from time pressure or time constraints of the current task, the relief of negative emotions and the expectation of an upcoming rest, which may urge employees to manage their time and plan activities during the break (Fenner & Renn, 2010). Epstein et al. (2016) showed that if employees feel unproductive before starting a break, it may be hard for them to relax during the break because of the potential stress of work after a break. If the employee feels productive before a break starts, then the work pressure after the break is reduced, so that they can gain enough relaxation during the break. Thus, to better enjoy a rest without concerning themselves with post-break work burdens, employees may urge themselves to be more productive before a break starts. Additionally, the regression results of other control variables are consistent with Model 1.

In a real production process, evidence has begun to accumulate indicating that production workers may adjust their work rates to respond to the system workload, which is called state-dependent behavior. In this research, when working in a serial production line, the products in the process at the buffer may provide feedback for

employees about the work rates of their adjacent coworkers, and in this way employees can adjust their work speed, which is a result of both goal-oriented and norm-oriented behavior (Powell & Schultz, 2004; Schultz et al., 1999). Since employees tend to achieve their goals with a faster speed before a planned break starts, when an employee speeds up, the quantity of work in process at the downstream buffer increases and may stimulate the worker at the downstream workstation to enhance their work speed. Thus, productivity improvement in the pre-break period may partially relate to the enhancement of the overall productivity of coworkers, while productivity decline in the post-break period may partially relate to the decrease in overall productivity of coworkers. However, constrained by data, we were not able to accurately estimate the extent of productivity changes caused by the state-dependent factor, which is one of the limitations of our research.

Model 3 involves the interaction terms of workload and the categorical variables for the pre-break and post-break periods. The coefficients of *Workload* × *Before_Int* and *Workload* × *After_Int* were both significant at a 90% confidence level and are negative and positive, respectively. This conclusion demonstrates that the positive effect of a break on worker productivity during the 30 minutes before a break starts is stronger under lighter workload levels. Similarly, the negative effects of a break on worker productivity for the 30 minutes after a break ends are weaker under lighter workload levels. Regardless of the periods before a break starts or after a break ends, a lighter workload leads to a break having a positive impact on productivity. Hence, Hypothesis 3 is supported.

The regression results of Models 1, 2 and 3 indicate that there are different decision mechanisms for choosing a reasonable workload. On the one hand, based on the direct impact of workload on production efficiency, the inverted U-shaped relationship between workload and employee productivity indicates that, theoretically, there is an optimal workload, which would maximize employee productivity when other factors remain unchanged. On the other hand, according to the indirect moderated effect of the workload on the relationship between breaks and employee productivity, a lighter workload is more conducive to the improvement of employee productivity. In a simple and highly repetitive manufacturing environment, our research found a trade-off between the direct impact of workload on productivity and the indirect effect of a break.

4.2. Robustness Tests

To test the robustness of the regression results, further tests were conducted and the results are listed in columns 4 and 5 in Table 2. First, based on Model 3, we reduced the random factors that may affect the robustness of the results as much as possible, such as non-break interruptions and shutdown. The quantity of tested products within each 10-minute time interval was adopted as a measure of the appearance of abnormal factors. Generally, fewer products were tested if larger non-break interruptions happened. Therefore, to exclude abnormal observations, 3σ the principle was applied for the variable *P_Number*. According to 3σ principle, observations falling outside the range of [21, 148] were deleted and the regression was repeated with a new processed dataset. Column 4 shows that only the interaction term *Workload* × *After_Int* was not significant at a 90% level, however, this coefficient was positive and had a consistent effect direction with Model 3. Hence, the main conclusions of Column 4 are consistent with Model 3 and our empirical findings are robust.

Second, to validate the moderated role of workload, we considered the short-term workload levels and explored whether it had a similar function on the relationship between breaks and employee productivity. Compared with *Workload*, the accumulated number of products from the beginning of this shift, we know that the variable *P_Number* measured the accumulated number of products tested during each 10-minute interval. We utilized

the short-term workload levels P_Number to replace the relatively long-term workload levels $Workload$, and as shown in column 5, the sign of the main coefficients is consistent with that in Model 3. This means that, regardless of the interval length of accumulated workload, our empirical findings still have high robustness.

Table 2. Empirical regression conclusions.

	Model				
	1	2	3	4	5
Constant	-2.823***	-2.917***	-2.913***	-2.873***	-3.366***
	(0.011)	(0.010)	(0.011)	(0.007)	(0.012)
WorkMonths	2.821E-05	1.807E-05	1.759E-05	3.867E-05	-2.844E-05
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gender	8.722E-04	8.267E-04	1.042E-03	-1.441E-03	5.342e-03*
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Age	3.124E-04	2.890E-04	2.38 -04	5.637E-05	4.955e-04*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Shift	-1.847E-03	1.857E-03	1.883E-03	1.688E-03	-3.691E-03
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Procedure1	5.328E-03	4.626E-03	4.524E-03	3.251E-03	-2.232E-04
	(0.004)	(0.004)	(0.004)	(0.002)	(0.003)
Procedure2	3.279E-03	4.365E-03	4.298E-03	3.308E-03	7.355e-03**
	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)
LineStyle	-3.412E-03	-3.737E-03	-3.801E-03	-2.005E-03	-7.025e-03**
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
P_Number	0.009***	0.01***	0.01***	0.01***	0.016***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Workload	6.541e-05***	5.275e-05***	4.792e-05***	3.198e-05***	3.613e-05***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Workload²	-1.3e-08***	-1.15e-08***	-1.03e-08***	-7e-09***	-8.9e-09***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Before_Int		0.148***	0.167***	0.135***	1.066***
		(0.003)	(0.007)	(0.005)	(0.011)
After_Int		-0.022***	-0.03***	-0.013***	-0.172***
		(0.003)	(0.006)	(0.004)	(0.015)
Workload × Before_Int			-7.208e-06***	-1.1e-05***	
			(0.000)	(0.000)	
Workload × After_Int			4.798e-06*	2.25E-06	
			(0.000)	(0.000)	
P_Number × Before_Int					-0.011***
					(0.000)
P_Number × After_Int					0.002***
					(0.000)
Observations	35,868	35,868	35,868	34,939	35,868
R²	0.598	0.629	0.63	0.793	0.759

Note: Significant at 0.1*, 0.05** and 0.01***.

5. DISCUSSIONS AND CONCLUSIONS

Through theoretical research, this paper investigated the hypotheses of expected breaks on the productivity of employees before and after breaks in a manufacturing environment involving simple but highly repetitive tasks. We utilized the Prais–Winsten model to validate our assumptions using assembly line data intercepted at 10-minute intervals. The results of the empirical analysis support both Hypothesis 1 and Hypothesis 2; in the 30 minutes before the start of a break, employee productivity improves due to the approaching break, and in the 30 minutes after the end of a break, employee productivity is reduced compared to the middle period of the work stage. Second, we explored the moderate role of workload by measuring the cumulative quantity of products. The results showed that a lighter workload can improve the impact of breaks on employee productivity. This indicates that a lighter workload mitigates negative effects after a break ends and reinforces positive effects before a break begins. Our empirical results have important theoretical and practical implications; in a simple and highly repetitive task manufacturing environment, setting a reasonable break plan and choosing a reasonable workload level is important to improve employee productivity.

5.1. Implications for Theory

In theory, why does employee productivity fluctuate when they experience a planned break in our manufacturing environment? This question could be explained by combining employee behavior and the conditions of a selected manufacturing environment. Planned breaks provide accurate interruption information for employees to adjust their production activities effectively. Employees utilize the information they have been given in advance to minimize the negative effects of a break before it starts (McFarlane, 2002). To complete the prescribed tasks, employees put in more effort to compensate for time lost during a break (Mark et al., 2008). Simultaneously, an upcoming break provides a positive message to psychologically stressed employees and relaxes their mood. Hence, a planned break improves employee performance before the interruption starts. Furthermore, the work conditions make it necessary for employees to spend some time regaining proficiency after a break. Inconsistent coordination among workers on the same assembly line can also cause a disordered work rhythm and reduced productivity. Therefore, decreased work proficiency (DeMarco & Lister, 2013; Teyarachakul et al., 2016) and distribution of work rhythms (Schultz et al., 2003) reduce employee performance over a short period after a break ends. By analyzing different work and break environments, this paper theoretically complements scholars' research on the impact of breaks on employee productivity.

5.2. Implications for Practice

In practice, our conclusions can be used to improve the operations management of the enterprise. Past research generally assumed that employee productivity remained consistent. At present, the academic community has begun to extensively explore the variability caused by human behavioral factors. Employee behavior is a key factor in determining a company's operational performance. In a manufacturing environment with simple and highly repetitive tasks, our conclusions provide a reference for breaks and workload arrangements for employees. Since imminent breaks can promote employee productivity, developing a reasonable break plan is important to improve productivity. For example, increasing the number of breaks may be a good choice while keeping the total break time constant. However, this is only a suggestion and the specific effects require further study. Additionally, it is important to choose a reasonable workload level. Workload directly affects production efficiency and indirectly moderates the impact of breaks on productivity. Reasonable workload arrangements depend on trade-offs between the two aforementioned effects of workload. The research in this paper does not give an optimal workload level and this issue can be a topic for future studies.

5.3. Limitations and Future Research

Though the dataset utilized for this analysis was of the best quality that could be obtained, the authors admit that there are some shortcomings in this research. First, the research only selected the assembly process of one manufacturing company and does not include the influence of different factors in other manufacturing environments and production processes. Second, the behavior of employees during the break period was not included in the analysis. Behavior during a break is likely to have an important impact on employee productivity after a break. Finally, the empirical model of this paper does not consider teamwork or interaction among employees, therefore, the factors of competition and collaboration were ignored. Moreover, potential state-dependent behavior cannot be empirically verified. Hopefully, these factors can be considered in future research to achieve a more comprehensive and in-depth study.

Funding: The authors contributed equally to the conception and design of the study. Moreover, this research was conducted under author H. Wang's project: Research on Inventory Information and Sales Relationship Considering Consumer Behavior - Taking Clothing Sales as An Example (project approval number: 2053027; fund account number: 950320027). We gratefully acknowledge this support.

Competing Interests: The authors declare that they have no competing interests.

Acknowledgement: All authors contributed equally to the conception and design of the study.

REFERENCES

- Adler, P. S., & Clark, K. B. (1991). Behind the learning curve: A sketch of the learning process. *Management Science*, 37(3), 267-281. Available at: <https://doi.org/10.1287/mnsc.37.3.267>.
- Andreasson, R., Lindblom, J., & Thorvald, P. (2017). Interruptions in the wild: Portraying the handling of interruptions in manufacturing from a distributed cognition lens. *Cognition, Technology and Work*, 19(1), 85-108. Available at: <https://doi.org/10.1007/s10111-016-0399-6>.
- Bailey, C. D. (1989). Forgetting and the learning curve: A laboratory study. *Management Science*, 35(3), 340-352. Available at: <https://doi.org/10.1287/mnsc.35.3.340>.
- Bailey, B. P., & Iqbal, S. T. (2008). Understanding changes in mental workload during the execution of goal-directed tasks and its application for interruption management. *ACM Transactions on Computer-Human Interaction (TOCHI)*, 14(1), 21. Available at: <https://doi.org/10.1145/1314683.1314689>.
- Beck, N., & Katz, J. N. (1995). What to do (and not to do) with time-series cross-section data. *American Political Science Review*, 89(3), 634-647. Available at: <https://doi.org/10.2307/2082979>.
- Cai, X., Gong, J., Lu, Y., & Zhong, S. (2017). Recover overnight? Work interruption and worker productivity. *Management Science*, 64(8), 3489-3500. Available at: <https://doi.org/10.1287/mnsc.2017.2792>.
- Caldarola, E. G., Modoni, G. E., & Sacco, M. (2018). *ManuLearning: A knowledge-based system to enable the continuous training of workers in the manufacturing field*.
- DeJarnette, P. (2015). Effort momentum. Technical Report, Citeseer.
- DeMarco, T., & Lister, T. (2013). *Peopleware: Productive projects and teams*: Addison-Wesley.
- Di Pasquale, V., Fruggiero, F., Iannone, R., & Miranda, S. (2017). A model for break scheduling assessment in manufacturing systems. *Computers and Industrial Engineering*, 111, 563-580. Available at: <https://doi.org/10.1016/j.cie.2017.05.017>.
- Epstein, D. A., Avrahami, D., & Biehl, J. T. (2016). *Taking 5: Work-breaks, productivity, and opportunities for personal informatics for knowledge workers*. Paper presented at the Proceedings of the 2016 CHI Conference 29 on Human Factors in Computing Systems.
- Fenner, G. H., & Renn, R. W. (2010). Technology-assisted supplemental work and work-to-family conflict: The role of instrumentality beliefs, organizational expectations and time management. *Human Relations*, 63(1), 63-82. Available at: <https://doi.org/10.1177/0018726709351064>.
- Fisher, C. D. (1993). Boredom at work: A neglected concept. *Human Relations*, 46(3), 395-417. Available at: <https://doi.org/10.1177/001872679304600305>.

- Froehle, C. M., & White, D. L. (2014). Interruption and forgetting in knowledge-intensive service environments. *Production and Operations Management*, 23(4), 704-722. Available at: <https://doi.org/10.1111/poms.12089>.
- Greasley, A., & Owen, C. (2018). Modelling people's behavior using discrete-event simulation: A review. *International Journal of Operations and Production Management*, 38(5), 1228-1244. Available at: <https://doi.org/10.1108/IJOPM-10-2016-0604>.
- Groenevelt, H., Pintelon, L., & Seidmann, A. (1992). Production lot sizing with machine breakdowns. *Management Science*, 38(1), 104-123. Available at: <https://doi.org/10.1287/mnsc.38.1.104>.
- Healey, A., Sevdalis, N., & Vincent, C. (2006). Measuring intra-operative interference from distraction and interruption observed in the operating theatre. *Ergonomics*, 49(5), 589-604. Available at: <https://doi.org/10.1080/00140130600568899>.
- Henning, R. A., Jacques, P., Kissel, G. V., Sullivan, A. B., & Alteras-Webb, S. M. (1997). Frequent short rest breaks from computer work: Effects on productivity and well-being at two field sites. *Ergonomics*, 40(1), 78-91. Available at: <https://doi.org/10.1080/001401397188396>.
- Hopp, W. J., Tekin, E., & Van Oyen, M. P. (2004). Benefits of skill chaining in serial production lines with cross-trained workers. *Management Science*, 50(1), 83-98. Available at: <https://doi.org/10.1287/mnsc.1030.0166>.
- Jett, Q. R., & George, J. M. (2003). Work interrupted: A closer look at the role of interruptions in organizational life. *Academy of Management Review*, 28(3), 494-507. Available at: <https://doi.org/10.5465/amr.2003.10196791>.
- KC, D. S., Staats, B. R., Kouchaki, M., & Gino, F. (2020). Task selection and workload: A focus on completing easy tasks hurts performance (pp. 18-16). Harvard Business School NOM Unit Working Paper, No. (17-112).
- KC, D. S., & Terwiesch, C. (2009). Impact of workload on service time and patient safety: An econometric analysis of hospital operations. *Management Science*, 55(9), 1486-1498. Available at: <https://doi.org/10.1287/mnsc.1090.1037>.
- Kim, S., Park, Y., & Headrick, L. (2018). Daily micro-breaks and job performance: General work engagement as a cross-level moderator. *Journal of Applied Psychology*, 103(7), 772-786. Available at: <https://doi.org/10.1037/apl0000308>.
- Kim, S., Park, Y., & Niu, Q. (2017). Micro-break activities at work to recover from daily work demands. *Journal of Organizational Behavior*, 38(1), 28-44. Available at: <https://doi.org/10.1002/job.2109>.
- Kleijnen, J. P., & Van Schaik, F. D. (2011). Sealed-bid auction of Netherlands mussels: Statistical analysis. *International Journal of Production Economics*, 132(1), 154-161. Available at: <https://doi.org/10.1016/j.ijpe.2011.03.026>.
- Kolbeinsson, A. (2016). *Managing interruptions in manufacturing: Towards a theoretical framework for interruptions in manufacturing assembly*. PhD Thesis.
- Lapre, M. A., & Tsikriktsis, N. (2006). Organizational learning curves for customer dissatisfaction: 30 heterogeneity across airlines. *Management Science*, 52(3), 352-366. Available at: <https://doi.org/10.1287/mnsc.1050.0462>.
- Lee, B., Chung, K., & Kim, S. H. (2018). Interruption cost evaluation by cognitive workload and task performance in interruption coordination modes for human-computer interaction tasks. *Applied Sciences*, 8(10), 1780. Available at: <https://doi.org/10.3390/app8101780>.
- Leroy, S., & Glomb, T. M. (2018). Tasks interrupted: How anticipating time pressure on resumption of an interrupted task causes attention residue and low performance on interrupting tasks and how a "ready-to-resume" plan mitigates the effects. *Organization Science*, 29(3), 380-397. Available at: <https://doi.org/10.1287/orsc.2017.1184>.
- Li, K., Xu, S., & Fu, H. (2020). Work-break scheduling with real-time fatigue effect and recovery. *International Journal of Production Research*, 58(3), 689-702. Available at: <https://doi.org/10.1080/00207543.2019.1598600>.
- Lindbeck, A., & Snower, D. J. (2000). Multitask learning and the reorganization of work: From tayloristic to holistic organization. *Journal of Labor Economics*, 18(3), 353-376. Available at: <https://doi.org/10.1086/209962>.
- Lu, Y., Heching, A., & Olivares, M. (2014). *Productivity analysis in services using timing studies*. New York: Working Paper, Columbia University.
- Mark, G., Gudith, D., & Klocke, U. (2008). *The cost of interrupted work: more speed and stress*. Paper presented at the Proceedings of the SIGCHI Conference on Human Factors in Computing Systems.
- McFarlane, D. C. (2002). Comparison of four primary methods for coordinating the interruption of people in human-computer

- interaction. *Human-Computer Interaction*, 17(1), 63-139. Available at: https://doi.org/10.1207/S15327051HCI1701_2.
- Miyata, Y., & Norman, D. A. (1986). Psychological issues in support of multiple activities. In *User Centered System Design: New Perspectives on Human-Computer Interaction*. D. A. Norman and S. W. Draper, Eds (pp. 265-284). Hillsdale, N.J: Lawrence Erlbaum Associates.
- Narayanan, S., Balasubramanian, S., & Swaminathan, J. M. (2009). A matter of balance: Specialization, task variety, and individual learning in a software maintenance environment. *Management Science*, 55(11), 1861-1876. Available at: <https://doi.org/10.1287/mnsc.1090.1057>.
- Obermaier, R. (2012). German inventory to sales ratios 1971-2005 an empirical analysis of business practice. *International Journal of Production Economics*, 135(2), 964-976. Available at: <https://doi.org/10.1016/j.ijpe.2011.11.013>.
- Pendem, P., Green, P., Staats, B. R., & Gino, F. (2016). The microstructure of work: How unexpected breaks let you rest, but not lose focus. Harvard Business School NOM Unit Working Paper, (17-058), Cambridge.
- Powell, S. G., & Schultz, K. L. (2004). Throughput in serial lines with state-dependent behavior. *Management Science*, 50(8), 1095-1105. Available at: <https://doi.org/10.1287/mnsc.1040.0233>.
- Ramdas, K., Saleh, K., Stern, S., & Liu, H. (2017). Variety and experience: Learning and forgetting in the use of surgical devices. *Management Science*, 64(6), 2590-2608. Available at: <https://doi.org/10.1287/mnsc.2016.2721>.
- Reagans, R., Argote, L., & Brooks, D. (2005). Individual experience and experience working together: Predicting learning rates from knowing who knows what and knowing how to work together. *Management Science*, 51(6), 869-881. Available at: <https://doi.org/10.1287/mnsc.1050.0366>.
- Saghafian, S., Hopp, W. J., Iravani, S. M., Cheng, Y., & Diermeier, D. (2018). Workload management in telemedical physician triage and other knowledge-based service systems. *Management Science*, 64(11), 5180-5197. Available at: <https://doi.org/10.1287/mnsc.2017.2905>.
- Schaufeli, W. B., & Bakker, A. B. (2004). Job demands, job resources, and their relationship with burnout and engagement: A multi-sample study. *Journal of Organizational Behavior: The International Journal of Industrial, Occupational and Organizational Psychology and Behavior*, 25(3), 293-315. Available at: <https://doi.org/10.1002/job.248>.
- Schultz, K. L., McClain, J. O., & Thomas, L. J. (2003). Overcoming the dark side of worker flexibility. *Journal of Operations Management*, 21(1), 81-92. Available at: [https://doi.org/10.1016/S0272-6963\(02\)00040-2](https://doi.org/10.1016/S0272-6963(02)00040-2).
- Schultz, K. L., Juran, D. C., & Boudreau, J. W. (1999). The effects of low inventory on the development of productivity norms. *Management Science*, 45(12), 1664-1678. Available at: <https://doi.org/10.1287/mnsc.45.12.1664>.
- Staats, B. R., & Gino, F. (2012). Specialization and variety in repetitive tasks: Evidence from a Japanese bank. *Management Science*, 58(6), 1141-1159. Available at: <https://doi.org/10.1287/mnsc.1110.1482>.
- Tan, T. F., & Netessine, S. (2014). When does the devil make work? An empirical study of the impact of workload on worker productivity. *Management Science*, 60(6), 1574-1593. Available at: <https://doi.org/10.1287/mnsc.2014.1950>.
- Teyarachakul, S., Chand, S., & Tzur, M. (2016). Lot sizing with learning and forgetting in setups: Analytical results and insights. *Naval Research Logistics*, 63(2), 93-108. Available at: <https://doi.org/10.1002/nav.21681>.
- Teyarachakul, S., Chand, S., & Ward, J. (2011). Effect of learning and forgetting on batch sizes. *Production and Operations Management*, 20(1), 116-128. Available at: <https://doi.org/10.1111/j.1937-5956.2010.01140.x>.
- Thorp, A. A., Kingwell, B. A., Owen, N., & Dunstan, D. W. (2014). Breaking up workplace sitting time with intermittent standing bouts improves fatigue and musculoskeletal discomfort in overweight/obese office workers. *Occupational and Environmental Medicine*, 71(11), 765-771. Available at: <http://dx.doi.org/10.1136/oemed-2014-102348>.
- Trougakos, J. P., Hideg, I., Cheng, B. H., & Beal, D. J. (2014). Lunch breaks unpacked: The role of autonomy as a moderator of recovery during lunch. *Academy of Management Journal*, 57(2), 405-421. Available at: <https://doi.org/10.5465/amj.2011.1072>.
- Tucker, A. L. (2015). The impact of workaround difficulty on frontline employees response to operational failures: A laboratory experiment on medication administration. *Management Science*, 62(4), 1124-1144. Available at: <https://doi.org/10.1287/mnsc.2015.2170>.

- Tucker, P., Folkard, S., & Macdonald, I. (2003). Rest breaks and accident risk. *The Lancet*, 361(9358), 680. Available at: [https://doi.org/10.1016/S0140-6736\(03\)12566-4](https://doi.org/10.1016/S0140-6736(03)12566-4).
- Van Donselaar, K. H., Peters, J., De Jong, A., & Broekmeulen, R. A. (2016). Analysis and forecasting of demand during promotions for perishable items. *International Journal of Production Economics*, 172, 65-75. Available at: <https://doi.org/10.1016/j.ijpe.2015.10.022>.
- Wooldridge, J. M. (2012). *Introductory econometrics: A modern approach*. Natorp Boulevard: South Western Cengage Learning.
- Zeigarnik, B. (1938). On finished and unfinished tasks. In W. D. Ellis (Ed.), *A source book of gestalt psychology* (pp. 300-314). New York: Harcourt. Brace & World.

Views and opinions expressed in this article are the views and opinions of the author(s), Asian Economic and Financial Review shall not be responsible or answerable for any loss, damage or liability etc. caused in relation to/arising out of the use of the content.