Automation, Specialization, and Productivity: Field Evidence

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Abstract

Becker and Murphy (1992) proposed that job specialization would increase productivity but is limited by the costs of coordinating workers. They reasoned that technology facilitates coordination, and so, increases specialization and productivity. Here, we propose a different role for technology. Automation substitutes machines for workers in particular tasks, leaving workers to specialize in the non-automated tasks, hence not requiring coordination. Specialization reduces the marginal cost of effort, and so, workers increase effort and productivity. The proposition is supported by a field experiment. Conventionally, supermarket cashiers perform two tasks – scan purchases and collect payment. Singapore supermarkets divided the job, with humans scanning and machines collecting payment. The new job design increased cashier productivity in scanning by over 10 percent. Productivity rose by increasing effort in scanning, rather than through learning or reducing task-switching.

Keywords: Automation; Job design; Job tasks; Productivity; Cashiers
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1 Introduction

In the *Wealth of Nations*, Adam Smith famously argued that specialization of work (division of labor) would increase productivity through worker learning, reduced task switching, and application of particular equipment (West, 1964; Chandra, 2004). Indeed, the core of the Industrial Revolution was to transform craft work (a skilled craftsman producing the entire item) to factory work (several workers, each specializing in a few tasks, jointly producing the item). If specialization increases productivity, what holds it back? A major reason is the extent of the market (Young, 1928; Chandra, 2004).

Becker and Murphy (1992) offered an alternative explanation. Specialization may be limited by the cost of coordinating between workers. Cashiers must scan items and collect payment; taxi drivers must navigate and drive; researchers must keep up with state of the art and do novel work; and doctors must examine patients, diagnose illnesses, and prescribe treatment. All of these jobs involve separate tasks. In principle, the tasks could be split among separate workers each specializing in one task, but coordination would be very costly, and hence, the tasks are integrated in one job. The costs of coordination may be due to asymmetric information, conflicts in incentives, idle time, or simply the physical cost of communication (Becker and Murphy, 1992; Batt et al., 2019; KC, 2020).

Becker and Murphy (1992) reasoned that technology reduces the cost of communication, and so, increases specialization. (By contrast, Dessein and Santos (2006) emphasized the exploitation of local information, and argued that technology reduces specialization.) Here, we propose a different role for technology. Automation substitutes machines for workers in particular tasks, leaving workers to specialize in the non-automated tasks. Then workers coordinate with machines rather than other workers. Cashiers work with customer self-payment machines, drivers work with navigation systems, researchers work with Google Scholar, and doctors work with UpToDate (a medical decision support system). Humans coordinate with machines at lower cost than with other humans.

Theoretically, we show that such automation increases productivity. Compared to the integrated job design, automation increases efficiency by enabling workers to specialize in the non-automated tasks without incurring costs of coordination. Specialization reduces the worker's total cost of effort and also reduces her marginal cost of effort in the non-automated tasks, and so, increasing effort. Workers whose marginal cost of effort is higher without automation would increase their effort relatively more. Compared to non-automated division of labor, automation increases efficiency by enabling workers to specialize without costs of coordination.

The proposition that automation increases efficiency by increasing workers' efforts in non-automated tasks is consistent with empirical studies of automation in late 19th century U.S. manufacturing (Atack et al., 2017, 2019), airplane cockpits (Roscoe, 1993), and restaurants (Tan and Netessine, 2020). However, these empirical regularities can be explained in other ways. A more precise empirical test of our theory requires a causal experimental design and task-level data by worker. Accordingly, we carried out a field experiment in a Singapore supermarket chain.

Specifically, we examined the empirical effect of automation in a within-subjects design that observed each worker in both non-automated and automated work. Conventionally, the job of a supermarket cashier comprises two tasks – scanning and packing purchases and collecting payment. Collecting payment, especially cash, is cognitively demanding and stressful. It requires mental calculations, resolving short change with customers, and accounting to management for cash shortfalls (Png and Tan, 2021).

East Asian supermarkets have introduced a new "scan-only" checkout format. The scan-only format divides the cashier's job into two, with the human worker performing the scanning and packing, while a machine collects payment from the customer. Technology enabled the job redesign, and interestingly, machines took over the relatively high-skilled task of collecting payment (Acemoglu and Restrepo, 2018b). We carried out a field experiment in four outlets of a Singapore supermarket group that were, for administrative reasons, only partly reconfigured from the conventional to the scan-only checkout format. By arrangement with store managers, cashiers rotated among the checkout counters in a within-subjects experiment.

The new job design relieved cashiers of the task of collecting payment, and so, mechanically increased overall cashier productivity as measured by customer flow. Here, we focus on cashier productivity in the *non-automated task*, as measured by the rate at which they scanned customer purchases. Based on the preferred estimate, which controls for cashier, date, and hour fixed effects, cashiers scanned items 10.9 percent faster at scan-only than conventional counters.

The challenge to the interpretation of this estimate is that, while the assignment of checkout counter was experimentally manipulated, the flows of customers and items were not. Hence, the relation between cashier productivity and scan-only job design might be due to differences in customers, such as those who were slower in bringing goods to the counter also preferring the conventional checkout. Alternatively, work at scan-only counters suffered fewer interruptions or was less tiring. These alternative explanations were investigated and ruled out.

Apparently, the new job design, which specialized cashiers in the task of scanning, induced them to become more productive. How did the specialization in one task increase cashier productivity? The data rule out learning and reduction of task-switching (Staats and Gino, 2012; Coviello et al., 2015, 2019; Friebel and Yilmaz, 2016; Duan et al., 2021) as explanations. In a related study, Ong and Png (2020) found that, with no difference in wages, most cashiers preferred the scan-only job design, which rules out the increase in productivity as being due to work in the conventional job design being easier.

Rather, the increase in productivity is consistent with the automation of collecting payment reducing the cashier's marginal cost of effort in scanning. Using data from conventional checkout counters, we investigated the relation between the costs of effort in scanning and collecting payment. To account for possible endogeneity, the cashier's scanning speed was instrumented by the quantities of alcoholic beverages, floral items, prepaid cards, and (pre-packed) vegetables purchased. Cashiers scanned alcoholic beverages (need to check customer age) and floral items (fragile) relatively slowly, and prepaid cards and vegetables relatively more quickly. Yet, the quantities of these items would not affect the time needed to collect payment. When cashiers at conventional counters scanned 1 percent faster, they took about 0.4 percent longer to collect payment.

Our interpretation of the empirical relation between the scanning speed and time to collect payment is that the tasks of scanning and collecting payment both drew on cashiers' mental and physical resources. Hence, the marginal cost of effort in one task increased in the effort in the other task (equivalently, the cost of effort exhibited increasing differences in the two tasks). The scan-only job design specialized the cashier in the task of scanning, which reduced her marginal cost of effort, inducing her to work faster, and so, raised productivity. Importantly, consistent with the theory, the increase in scanning speed was more pronounced among cashiers who were relatively slower in the conventional job design.

The present research contributes to a better understanding of the effect of automation on productivity. The proposition that automation of a task reduces the marginal cost of the non-automated tasks flows directly from the premise that conventionally designed jobs comprise multiple tasks in which the worker's cost of effort exhibits increasing differences. First elucidated by Holmstrom and Milgrom (1991), this premise underlies empirical studies of multi-tasking among factory workers, farm managers, physicians, and lawyers (Hong et al., 2018; Englmaier et al., 2017; Dumont et al., 2008; Bartel et al., 2017).[1]

Automation splits the job into separate tasks, with a machine performing one task and the human performing the other. Unlike splitting the job among two humans, splitting the job between human and machine avoids any cost of coordination. So, automation raises productivity in the remaining, non-automated tasks and the job as a whole.

The research here also contributes to a more nuanced appreciation of the effect of automation on labor markets. Prior research shows that automation directly displaces workers by substituting machines for workers in particular tasks, while indirectly raising the demand for labor by increasing overall productivity (Autor and Salomons, 2018; Acemoglu and Restrepo, 2018b). Yet, most prior research implicitly assumed that task-level productivity (whether undertaken by machines or humans) is additively separable. By contrast, in our study, the substitution of machines for workers in one task raised labor productivity in the non-automated task. From a macroeconomic perspective, this would also increase the demand for labor, countervailing the depressing effect of displacement on the demand for labor.

The present research also contributes to understanding the division of labor between firm and customer, a dimension of the vertical organization of production which has gained interest (Xue et al., 2007; Buell et al., 2010; Xue et al., 2011; Field et al., 2012; Hui and Png, 2015; Basker et al., 2017; Tan and Netessine, 2020). Most previous scholarship on the effect of automation on vertical organization emphasized the upstream boundary of the firm (Baker and Hubbard, 2003; Rawley and Simcoe, 2013). The research here considers the downstream boundary between the firm and customer. By requiring the consumer to make payment to a machine instead of a human cashier, the supermarket is

[1] The multi-tasking here is the performance of *different* tasks at the same time or in close succession. By contrast, Lerner and Malmendier (2010), KC (2014), and Coviello et al. (2015, 2019) analyze a different type of multi-tasking – performance of multiple instances of the *same* task at the same time or in close succession, where automation of the task would amount to automation of the entire job.

outsourcing a part of the payment task to its customer. The gain from self-service is not merely the difference in productivity between employee and customer (with machine) in the automated task. Customer self-service may also induce the redesign of jobs, which possibly raises labor productivity in the remaining tasks. Recognizing this additional factor might influence the priority in which tasks should be switched to self-service.

The remainder of this paper is organized as follows. Section 2 presents a simple theoretical analysis of automation where the worker's cost of effort exhibits increasing differences in the separate tasks. Sections 3 and 4 introduce the context and describe the experimental design. Sections 5 and 6 present the data and estimates of the effect of the scan-only job design. Section 7 discusses the mechanism by which automation increased productivity. Section 8 concludes with policy and managerial implications, and directions for future research.

2 Theory

To fix ideas, we present a simple model, following Becker and Murphy (1992), of the organization of work. Specialization increases productivity but division of labor requires costly coordination. Our model abstracts from issues of exploiting local information (Dessein and Santos, 2006).

Consider a job that comprises tasks 1 and 2. As a baseline, suppose that the job design is integrated with generalist workers performing both tasks. Efforts, e_1 and e_2, in tasks 1 and 2 yield output,

$$q(e_1, e_2), \tag{1}$$

where $\partial^2 q/\partial e_1^2 \geq 0$ and $\partial^2 q/\partial e_2^2 \geq 0$ represent the returns to specialization in tasks. The worker incurs cost of effort

$$C(e_1, e_2), \tag{2}$$

where $\partial^2 C/\partial e_1 \partial e_2 > 0$ due to increasing differences in the cost of effort. One possible reason for such increasing differences is costs of switching tasks.[2]

[2]Jobs which satisfy the condition of increasing differences include those of factory workers (Hong et al., 2018), farm managers (Englmaier et al., 2017), physicians (Dumont et al., 2008), and lawyers (Bartel et al., 2017).

Let efforts, e_1^G and e_2^G, maximize net product,

$$q(e_1, e_2) - C(e_1, e_2). \tag{3}$$

Division of Labour

Next, suppose that the job is divided among two workers, with workers 1 and 2 performing tasks 1 and 2. Each worker independently chooses effort in their task. The cost of effort to worker 1 is $C(\kappa e_1, 0)$, while that of worker 2 is $C(0, \kappa e_2)$, where the parameter, $\kappa \geq 1$, characterizes the increase in cost due to coordination with another worker. The workers jointly produce $q(e_1, e_2)$.

Let efforts, e_1^D and e_2^D, maximize net product,

$$q(e_1, e_2) - C(\kappa e_1, 0) - C(0, \kappa e_2). \tag{4}$$

Which is more efficient: the integrated job design or division of labor? The following proposition generalizes the main result of Becker and Murphy (1992) to account for the increasing differences in the cost of effort.

Proposition 1 *The integrated job design is more efficient than division of labor if the increasing differences in the cost of effort are sufficiently large relative to the cost of coordination.*

Proof. Consider the integrated job design with efforts, e_1^G and e_2^G. This would produce output $q(e_1^G, e_2^G)$ at cost $C(e_1^G, e_2^G)$. Suppose that, with division of labor, the two workers exert efforts, e_1^G and e_2^G, respectively. This would produce the same output, $q(e_1^G, e_2^G)$ at cost $C(\kappa e_1^G, 0) + C(0, \kappa e_2^G)$.

The difference in cost between the integrated job design and division of labor would be

$$\begin{aligned}\Delta_C &= C(e_1^G, e_2^G) - C(\kappa e_1^G, 0) - C(0, \kappa e_2^G) \\ &= \Big[C(e_1^G, e_2^G) - C(e_1^G, 0) - C(0, e_2^G)\Big] - \Big[C(\kappa e_1^G, 0) + C(0, \kappa e_2^G) - C(e_1^G, 0) - C(0, e_2^G)\Big].\end{aligned} \tag{5}$$

If $C(\cdot,\cdot)$ does not exhibit increasing differences and $\kappa = 1$, then $\Delta_C = 0$. Consider the two terms in brackets on the right-hand side of (5). Since $C(\cdot,\cdot)$ exhibits increasing differences, the first term, $C(e_1^G, e_2^G) - C(e_1^G, 0) - C(0, e_2^G) > 0$, and increases in the extent of the increasing differences. Since $\kappa \geq 1$, the second term on the right-hand side, $C(\kappa e_1^G, 0) + C(0, \kappa e_2^G) - C(e_1^G, 0) - C(0, e_2^G) \geq 0$, and increases in κ.

Thus, if the increasing differences are sufficiently large relative to the cost of coordination, κ, then $\Delta_C > 0$. This implies that the integrated job design produces the same output at lower cost, and so, is more efficient. QED.

Automation

Now suppose that task 2 is automated such that a machine generates effort, e_2, at fixed cost, F, and variable cost, $m(e_2) = me_2$. The automated variable cost is (weakly) less than the human variable cost, i.e., $me_2 \leq C(0, e_2)$. In the automated job design, workers specialize in task 1 at cost $C(e_1, 0)$, and together with the machine, produce $q(e_1, e_2)$.

Let efforts, e_1^A and e_2^A, maximize net product,

$$q(e_1, e_2) - C(e_1, 0) - me_2 - F. \qquad (6)$$

The next two results present our main theoretical insights.

Proposition 2 *Compared to the integrated job design, automation is more efficient and it would be optimal to increase the worker's effort to an extent increasing in the degree of increasing differences in the cost of effort.*

Proof. Consider the integrated job design with efforts, e_1^G and e_2^G. This would produce output $q(e_1^G, e_2^G)$ at cost $C(e_1^G, e_2^G)$. Suppose that, with automation, the worker exerts effort, e_1^G, and the machine generates e_2^G. This would produce the same output, $q(e_1^G, e_2^G)$, at cost, $C(e_1^G, 0) + me_2^G - F$.

The difference in cost between the integrated job design and automation would be

$$\Delta_{GA} = C(e_1^G, e_2^G) - C(e_1^G, 0) - me_2^G - F > C(e_1^G, e_2^G) - C(e_1^G, 0) - C(0, e_2^G) - F. \qquad (7)$$

$C(\cdot,\cdot)$ exhibits increasing differences, and so, $\Delta_{GA} > 0$ if the increasing differences are sufficiently large and F is sufficiently small.

Under the integrated job design, the worker's marginal cost of effort in task 1 would be $\frac{\partial C(e_1^G, e_2^G)}{\partial e_1}$. With automation, the marginal cost would be $\frac{\partial C(e_1^G, 0)}{\partial e_1}$. The difference in marginal cost

$$\Delta_c = \frac{\partial C(e_1^G, e_2^G)}{\partial e_1} - \frac{\partial C(e_1^G, 0)}{\partial e_1} > 0, \tag{8}$$

since $C(\cdot,\cdot)$ exhibits increasing differences. QED.

Automation increases efficiency by allowing the worker to specialize in task 1, which reduces the cost of effort because the cost of effort increases in effort in task 2. The proof takes the worker's efforts as given and shows that automation reduces the cost of effort. Of course, automation can do even better. In particular, automation reduces the worker's marginal cost of effort in task 1, and so, it would be optimal to increase the worker's effort in task 1. Indeed, the larger is the degree of increasing differences in the cost of effort, the more should the worker increase her effort. Further, automation reduces the number of tasks that the worker performs and increases job specialization.

Proposition 3 *Compared to division of labor, automation is more efficient and it would be optimal to increase the worker's effort to an extent increasing in coordination costs.*

Proof. Consider division of labor with efforts, e_1^D and e_2^D. This would produce output $q(e_1^D, e_2^D)$ at cost $C(e_1^D, 0) + C(0, e_2^D)$. Suppose that, with automation, the worker exerts effort, e_1^D, and the machine generates e_2^D. This would produce the same output, $q(e_1^D, e_2^D)$, at cost, $C(e_1^D, 0) + me_2^D - F$.

The difference in cost between division of labor and automation would be

$$\begin{aligned}\Delta_{DA} &= C(\kappa e_1^D, 0) + C(0, \kappa e_2^D) - C(e_1^D, 0) - me_2^D - F \\ &\geq C(e_1^D, 0) + C(0, \kappa e_2^D) - C(e_1^D, 0) - me_2^D - F = C(0, \kappa e_2^D) - me_2^D - F.\end{aligned} \tag{9}$$

Since $me_2 \leq C(0, e_2) \leq C(0, \kappa e_2)$, then $\Delta_{DA} > 0$ if κ is sufficiently large and F is sufficiently small.

Under division of labor, the worker's marginal cost of effort in task 1 would be $\frac{\partial C(\kappa e_1^D, 0)}{\partial e_1}$.

With automation, the marginal cost would be $\frac{\partial C(e_1^D,0)}{\partial e_1}$. The difference in marginal cost

$$\Delta_c = \frac{\partial C(\kappa e_1^D, 0)}{\partial e_1} - \frac{\partial C(e_1^D, 0)}{\partial e_1} > 0, \tag{10}$$

since $\kappa \geq 1$. QED.

Compared to division of labor, automation increases efficiency by avoiding the cost of coordination. Automation would reduce the number of jobs but not affect the degree of specialization.

Importantly, the conditions for automation to increase efficiency in Propositions 2 and 3 do not depend on the gain in productivity from specialization or synergies in production (i.e., $\partial^2 q/\partial e_1 \partial e_2$). By contrast, if the worker's cost of effort does not exhibit increasing differences, then, the right-hand sides of (7) and (8) would not be positive. Hence, automation would increase efficiency over the integrated job design (Proposition 2) only if the cost of effort exhibits increasing differences.

Further, automation could still increase efficiency even if the machine is not more efficient than the human worker. Suppose that $me_2 = C(0, e_2)$. Then (7) would simplify to

$$\Delta_{GA} = C(e_1^G, e_2^G) - C(e_1^G, 0) - me_2^G - F = C(e_1^G, e_2^G) - C(e_1^G, 0) - C(0, e_2^G) - F \geq 0,$$

if the increasing differences are sufficiently large and F is sufficiently small. Further, (9) would simplify to

$$\begin{aligned} \Delta_{DA} &= C(\kappa e_1^D, 0) + C(0, \kappa e_2^D) - C(e_1^D, 0) - me_2^D - F \\ &\geq C(e_1^D, 0) + C(0, \kappa e_2^D) - C(e_1^D, 0) - C(0, e_2) - F = C(0, \kappa e_2^D) - C(0, e_2) - F \geq 0, \end{aligned}$$

if κ is sufficiently large and F is sufficiently small.

3 Context

Evidence from various empirical studies is consistent with Proposition 2. In late 19th century U.S. manufacturing, production that involved machines was more specialized and more productive than purely human work (Atack et al., 2017, 2019). Auto-pilot systems reduced the workload of pilots and likely improved flight safety (Roscoe, 1993). A large U.S. restaurant chain which installed customer self-ordering systems increased sales and the speed of meals, and the effects were more pronounced among waiters who were ex-ante less productive (Tan and Netessine, 2020). While these empirical results are consistent with Proposition 2, they can be explained in other ways. A more compelling test requires a causal design as well as task-level data by worker. Accordingly, we carried out a field experiment in a Singapore supermarket chain.

Grocery retailing in Singapore, as elsewhere, is a labor-intensive industry. The setting of the present research is a major supermarket group in Singapore. As of December 2017, the group operated 44 stores with 404,000 square feet of retail space, yielding annual sales revenue of $830 million (US$621 million).

The supermarket group had employed foreign workers to the maximum allowed by government quota. However, beginning in 2010, the government reversed its previously liberal foreign worker policy. In 2015, to attract more locals to work as cashiers and increase productivity, the group introduced a new "scan-only/self-pay" job design. Conventionally, the job of supermarket cashier encompasses three tasks – scanning purchases, packing, and collecting payment. Supermarkets in Japan, China, and Singapore, including the subject of this study, have re-designed the job, with cashiers specializing in scanning and packing, and machines collecting payment (Jiang, 2017; Sankei News, 2020).

– Figure 1 –

Referring to Figure 1, in the new format, the cashier scans and packs the customer's purchases at the checkout counter, then directs the customer to a separate, designated kiosk which accepts payment in cash or by card. (Note that the scan-only format differs from the self-service checkout typical in Western countries, which requires the customer to both scan and make payment, and so, completely replaces the human cashier.) In a related study, Ong and Png (2020) show that the scan-only job design increased job quality and the supply of labor to the supermarket.

4 Experimental Design

In the conventional job design, the cashier must perform three tasks – scan the customer's purchases, pack, and collect payment. By contrast, in the new job design, the cashier specializes in the two tasks of scanning and packing, which, for brevity, will be called scanning.

To investigate the effect of the job redesign on cashier productivity, we conducted a field experiment at four stores which were (temporarily) equipped with both the conventional and scan-only checkout formats. The largest of the four stores was set up in a neighborhood where the group had no previous presence. Management was concerned that consumers in the area might not be familiar with the self-payment system. As a transitional measure, the group equipped the store with four scan-only checkout counters and four conventional counters. The next largest was spread over two floors. When building a new entrance on the upper floor, the group first converted the checkout counters on that level to scan-only. The other two stores were much smaller and were partly converted to scan-only owing to site constraints. Subsequently, all four stores were converted completely to scan-only.

Over 38 days in December 2017 and May 2018, we arranged with the store managers to rotate cashiers among the checkout counters on a daily basis. For instance, at the largest store, which was equipped with four conventional checkout counters, numbered 1 to 4, and four scan-only counters numbered, 5 to 8, a cashier would be assigned to counters 1 to 4 on Monday to Thursday respectively, and then counters 5 to 8 on Friday, Saturday, Monday, and Tuesday respectively (assuming that Sunday was her day off). By contrast, another cashier might be assigned to counters 7, 8, 1, and 2 on Monday to Thursday, and 3, 4, 5, and 6 on Saturday to Tuesday (assuming that Friday was her day off).

The experiment increased the frequency of rotation from the normal policy, which was to rotate the cashiers among the counters on a weekly basis. Thus, by design, this experiment identified the effect of the job redesign on cashier productivity within subjects, with each cashier providing her own control against which to measure the effect of the scan-only treatment.

Consider the following equation for the productivity of cashier c in store s handling transaction i at time t,

$$\ln Y_{icst} = \beta_0 + \beta_1 \cdot \text{Scan-only}_{cst} + \gamma X_i + \gamma_c + \gamma_t + \epsilon_{icst}. \qquad (11)$$

In (11), Y_{icst} represents cashier productivity, Scan-only_{cst} is an indicator which equals 1 when cashier c worked at a scan-only checkout counter, X_i are characteristics of the transaction such as purchase categories and payment method, γ_c and γ_t are fixed effects for cashier and time, and ϵ_{icst} is random error. Further, the parameters, β_0, β_1, and γ are coefficients to be estimated, and the estimates are clustered by cashier.[3]

Referring to (11), the parameter of interest is the coefficient of Scan-only$_{cst}$, β_1. This represents the difference in the productivity of cashiers between the scan-only and conventional job designs. Importantly, the rotation of cashiers between the two job designs abstracts the estimate of the coefficient from personal characteristics of cashiers and differences in purchases and payment method.

The most obvious threat to identification is that store managers might assign cashiers to scan-only vis-a-vis conventional counters according to their productivity. Cashiers did indeed vary considerably in their productivity as measured by scanning speed: the average scanning speed ranged from 9 to 22 items per minute, with mean of 13 and standard deviation of 3.2 items per minute. However, this concern is substantially mitigated by the experimental arrangement to rotate cashiers among the checkout counters. By design, each cashier was assigned to treatment and control regardless of their personal skill. In addition, the preferred estimate include fixed effects for cashiers.

A related, subtler issue is that store managers opened and closed counters selectively, according to the flow and ebb of customers. When not working at their assigned checkout counter, cashiers were deployed to pack at other counters or help with shelving. Store managers tended to open checkout counters in a particular order, some of which might be busier than others. Cashiers assigned to busier counters would be under more pressure to work fast. Again, this concern is also mitigated by the experimental arrangement to rotate cashiers among the checkout counters. By design, each cashier was rotated through all checkout counters.

Notwithstanding the experimental design, one concern is that, at times when both scan-only and conventional counters were open, customers could freely choose among counters. To the extent that different customers chose the scan-only as compared with the conventional counters, the cashier's work might have differed systematically between the two checkout formats. Yet, it is important to note that, at both scan-only and conventional counters, the cashier performed the tasks of scanning and packing. For the customer, the only difference was having to pay at a self-pay kiosk rather than to a

[3]To adjust for possible under-estimation of standard errors due to the small number of clusters, we apply the Wild cluster bootstrap (Roodman et al., 2019), and report the p-value.

human cashier. Nevertheless, to abstract from the effects of possible customer selection, a set of additional estimates included control for characteristics of the transaction such as purchase categories and payment method.

5 Data

Owing to resource constraints, the period of study was not long enough to observe every cashier at both scan-only and conventional counters. Accordingly, the study was limited to cashiers who worked at both scan-only and conventional counters during the period. (A robustness test includes all cashiers including those who worked at only one format throughout.)

The experiment involved 38 cashiers processing over 152,000 transactions, of which 64.4 percent were served at scan-only checkout counters and 35.6 percent at conventional counters. Management provided records from the point-of-sales systems, and time logs of every counter (recorded by the millisecond). For each transaction, the sales records included a transaction identifier, the identity of the cashier, details of the purchases, classified into 19 categories and 41 subcategories, prices, and method of payment. For each counter, the time logs recorded the transaction identifier, the start and end times for scanning, and time at which payment was made.

The variables for this study were drawn or constructed from the point-of-sales records and time logs of counters. Possibly owing to gaps in the records and logs, and the merging of the datasets, some of the constructed data were implausibly large. Accordingly, the top 1 percent of all variables except scan-only, cash payment, proportion of closed counters, indicator of Wednesday and cumulative customers up to 30 minutes earlier were dropped, and in a robustness test, these were Winsorized rather than dropped.

An immediate issue was how to measure the productivity of cashiers. The metric should reveal the cashier's effort in the non-automated tasks, which are scanning and packing. The time logs accounted for the start and end of scanning, but did not track packing time. Accordingly, we focused on the rate of scanning as the measure of the cashier's productivity in the non-automated task, represented by Y_{icst} in the regression equation, (11). The scanning speed was calculated as the number of items purchased (from point-of-sales record) divided by the elapsed time between start and end of scanning (from time log).

Table 1 reports summary statistics and Appendix Table A1 describes the construction of the variables. Owing to the opening and closing of counters according to customer demand, cashiers tended to work less time at scan-only than conventional counters. Yet they served the same number of customers in the course of their shift, likely because they did not have to collect payment.

– Table 1 –

As for the outcome of interest, cashiers scanned at an average speed of 14.02 items per minute (0.23 items per second) at scan-only counters and 14.70 items per minute (0.25 items per second) at conventional counters. The scanning speeds somewhat exceed the range of 0.16 to 0.20 item per second at a U.S. supermarket chain studied by Mas and Moretti (2009, Table 2). The apparent disparity might be due to the higher pressure of work in Singapore grocery retailing or differences in working practices (such as whether the cashier must weigh fruit and vegetables).

Seemingly, as measured by the raw scanning speed, cashiers scanned more slowly at scan-only than conventional counters. However, this difference is an artifact of outliers. A logarithmic transformation would mute the positive skew of the scanning speed distribution. With scanning speed specified in logarithm, cashiers scanned 6 percent faster at scan-only as compared with conventional counters.

When both scan-only and conventional counters were open, customers could freely choose among the two types of checkout. Apparently, consumer behavior differed significantly between scan-only and conventional counters. Referring to Table 1, the economically largest differences were in the mode of payment and Wednesday shopping. Roughly 68 percent of customers at scan-only counters paid in cash as contrasted with over 76 percent at conventional counters. Further, 15 percent of customers at scan-only counters were served on Wednesdays (when the supermarket gives a discount to senior citizens), as compared with 14 percent of customers at conventional counters.

Since the chief difference for customers between the two checkout formats was whether they made payment via a kiosk or to a cashier, it is intuitive that methods of payment differed considerably between the two checkout formats. Regarding the higher proportion of checkouts at scan-only on Wednesdays, store managers reported that older customers paying with large quantities of coins preferred the scan-only checkout (and then using the self-pay kiosk which automatically counts coins) rather than bother cashiers.

6 Estimates

For a first look at the effect of the scan-only job design on the productivity of cashiers, Figure 2 depicts the distributions of scanning speeds at scan-only and conventional checkout counters. That the distribution for the scan-only format lies to the right of that for the conventional format is a preliminary indication that cashiers scanned relatively faster in the scan-only job design.

– Figure 2 –

While informative, the patterns in Figure 2 might be confounded by differences among stores. For instance, owing to site constraints, the distribution of counters differed across stores. If coupled with differences in the frequency of transactions at scan-only vis-a-vis conventional counters across stores, the result might be spurious correlation between the checkout format and scanning speed.

To abstract from such differences, Table 2 presents ordinary least squares regression estimates of (11) with the dependent variable being the scanning speed, specified in logarithm.[4] First, Table 2, column (a), reports an estimate including scan-only as an explanatory variable and controlling only for the length of time that the cashier worked at the counter. (As discussed above, store managers opened and closed counters according to customer flow. Owing to store layouts, cashiers spent relatively less time attending to scan-only counters.) The coefficient of scan-only, 0.060 ($p = 0.413$), is positive but not significant.

– Table 2 –

Next, Table 2, column (b), reports an estimate including store fixed effects. The store fixed effects account for differences among stores in average scanning speed. One reason for such differences is disparities in store layout. Specifically, the largest of the four stores was equipped with four scan-only and four conventional counters, in two side-by-side clusters. By contrast, the next largest store was equipped with two scan-only and four conventional checkout counters, but the scan-only counters were on the upper level, which attracted fewer customers than the lower level. Including store fixed effects, the

[4]The regression estimates were tabulated using Stata routine, outreg (Gallup, 2012).

coefficient of scan-only, 0.141 ($p < 0.001$), is positive, significant, and over twice as large as the estimate with control for just counter work time.

Table 2, column (c), reports an estimate including cashier fixed effects. The cashier fixed effects account for individual differences among cashiers in scanning speed. The coefficient of scan-only, 0.108 ($p = 0.002$), is positive and significant, but smaller than the coefficient with store fixed effects. The smaller coefficient of scan-only in the estimate with cashier fixed effects as compared to that with store fixed effects suggests that the latter was inflated by differences in the average scanning speed between cashiers in the same store. The fixed effects for cashiers would absorb any such differences, and so, more precisely reveal the effect of the scan-only checkout format.

Next, Table 2, column (d), reports an estimate including fixed effects for cashier, date, and hour. The fixed effects for date and hour account for differences in scanning speed over time such as between weekdays and weekends, and the beginning and end of shifts. The coefficient of scan-only, 0.100 ($p = 0.006$), is positive and significant, and somewhat smaller than that without control for date and hour.

Finally, Table 2, column (e), reports an estimate including fixed effects for cashier, and day of week interacted with hour. The fixed effects for day of week interacted with hour more precisely account for differences in scanning speed over time such as between weekday and weekend peak hours. The coefficient of scan-only, 0.109 ($p = 0.005$), is positive and significant. This estimate suggests that cashiers scanned items 10.9 percent faster at scan-only than conventional counters. Among the estimates, we prefer this one as it includes the most stringent set of controls.

Referring to Table 1, at conventional counters, cashiers took an average of 0.532 minute to scan and pack, and 0.126 minute to collect payments. Applying the estimate in Table 2, column (e), at a scan-only checkout, cashiers would take an average of $0.891 \times 0.532 = 0.474$ minute to scan and pack, and would not spend any time on collecting payment. Hence, the customer throughput would increase from $1 \div [0.532 + 0.126] = 1.52$ per minute to $1 \div 0.474 = 2.11$ per minute. Referring to Proposition 2, this increase in productivity comprises an increase from $1 \div 0.532 = 1.88$ to 2.11 per minute, or an increase of 0.23 per minute due to the cashier's increased effort in scanning, plus an increase of $1.88 - 1.52 = 0.36$ per minute due to the cashier being relieved from scanning. For the supermarket in the present study, the gain in overall productivity due to increased effort in the non-automated task was over 60 percent of the magnitude of the direct gain from relieving the worker of the automated task.

– Figure 3 –

The estimates so far present the average effect of scan-only on productivity in scanning. Yet, cashiers might differ in their cost of effort and response to the job redesign. To explore such heterogeneity, we regressed scanning speed (in natural logarithm) on fixed effects for cashiers, scan-only interacted with cashiers, and date and hour. Figure 3 plots the effect of scan-only on scanning speed, represented by the coefficients of the fixed effects of scan-only interacted with cashiers, against the scanning speed at the conventional checkout, represented by the coefficients of the cashier fixed effects. Apparently, the scan-only job design had a relatively larger effect on cashiers who were less productive in the conventional job design. Appendix Table A2 reports ordinary least squares estimates that buttress this conclusion.[5]

A possible interpretation of the result is that cashiers with low cost of effort already scanned fast in the conventional job design. Relief from the task of collecting payments did not affect their marginal cost of effort in scanning by much. By contrast, cashiers with high cost of effort scanned relatively slowly in the conventional job design. The relief from the task of collecting payments reduced their marginal cost of effort in scanning relatively more. Hence, scan-only increased their productivity relatively more. The negative correlation between productivity in the conventional job design and the increase due to scan-only would result in the productivity of cashiers being less dispersed.

Appendix Table A3 reports tests to check the robustness of the finding that cashiers scanned faster at scan-only than conventional counters. Table A3, column (a), reports the effect of scan-only on the entire dataset of cashiers, including cashiers who worked at only one checkout format during the period of study. Table A3, column (b), reports an estimate on the dataset with outliers Winsorized at the top 1 percent, rather than trimmed.

[5]In Figure 3, some coefficients are negative because the coefficients depend on the productivity of the reference cashier. A negative coefficient means that the baseline productivity or change in productivity was less than that of the reference cashier.

Alternative Explanations

The above estimates suggest that cashiers scanned about 11 percent faster in the scan-only as compared with the conventional job design. We interpret the cashier's higher productivity in the scan-only job design as being due to specialization in scanning. However, the empirical correlation between cashier productivity and job design might be explained in other ways. Table 3 reports additional tests to investigate these alternative explanations.

– Table 3 –

An obvious explanation is that customers at scan-only checkout counters differed from those at conventional counters in ways that sped up the scanning. For instance, older customers might prefer the conventional checkout and also be slower in presenting purchases to the counter. This would result in scanning being relatively slower at conventional counters.

For commercial reasons, the supermarket group declined to provide data on customers. Absent customer data, we used characteristics of purchases and payment to indirectly check the effect of differences in customers. Table 3, column (a), reports an estimate controlling for the customer's expenditure (basket value, in logarithm). The scanning speed decreased in basket value, which is consistent with customers taking more time to bring larger quantities to the counter. With the additional control, the coefficient of scan-only is only slightly larger than the preferred estimate.

Table 3, column (b), reports an estimate with additional, more stringent controls for purchase characteristics, viz., fixed effects for the 41 product sub-categories. Further, Table 3, column (c), reports an estimate with an additional control for mode of payment. Actually, payment took place after scanning, and so, the scanning speed could not reasonably vary with the mode of payment. Rather, the mode of payment represents possible differences between customers not characterized by other purchase characteristics, or store, date, or hour fixed effects.

Recall that the supermarket offered discounts to seniors on Wednesdays. If, indeed, seniors preferred conventional counters and moved more slowly, cashiers would scan more slowly at conventional counters on Wednesdays. To investigate, Table 3, column (d), reports an estimate with an additional control for Wednesday shopping interacted with scan-only. The estimate does not explicitly include the indicator of Wednesday shopping as that would be absorbed by the date fixed effects. The coefficient of Wednesday shopping interacted with scan-only is positive, quite small relative to the coefficient of scan-only, and not statistically significant.

In all of the estimates that controlled (indirectly) for differences among customers, the coefficient of scan-only is positive, significant, and somewhat larger than the preferred estimate. These results suggest that the correlation between scan-only and the speed of scanning was not due to customers at scan-only checkout counters differing from those at conventional counters in ways that sped up the scanning. (To the extent that customers self-selected between the scan-only and conventional checkout counters, characteristics of purchases and payments would be bad controls. Accordingly, the estimate which excludes these variables is preferred.)

Another conceivable explanation for the correlation between cashier productivity and job design is that the flow of work at scan-only checkout counters was more regular. Depending on whether their assigned counter was open, cashiers either manned their checkout, helped with packing at other counters, or shelved items. Such switching would disrupt the continuity of work and affect productivity, given that workers take time to recover from interruptions (Cai et al., 2018). However, the preferred estimate in Table 2, column (e), controls for counter work time. This accounts for differences in the time that cashiers worked at their assigned counter. Consistent with the theory that interruptions degrade productivity, the coefficient of counter work time is positive and significant. After controlling for counter work time, the coefficient of scan-only measures the pure effect of the scan-only job design on cashier productivity.

Another possible explanation of the correlation between cashier productivity and job design is that work at scan-only checkout counters was less tiring, and so, cashiers could scan faster. Table 3, column (e), reports an estimate including control for the time on shift (in inverse hyperbolic sine).[6] The coefficient of the time on shift is negative, but small and insignificant, suggesting that cashiers did not suffer from fatigue.[7] Still, the estimated coefficient of scan-only is positive, significant, and equal in magnitude to the preferred estimate. This result suggests that the estimated effect of scan-only was not confounded by differences in fatigue between scan-only and conventional counters.

[6] In this and other estimates, non-negative variables such as time on shift that might possibly be zero are specified as the inverse hyperbolic sine (Burbidge et al., 1988).

[7] In an estimate below which includes cumulative transactions as an additional explanatory variable, the coefficient of cumulative transactions is positive while the coefficient of time on shift is negative. This result can be interpreted as evidence of learning (positive effect of cumulative transactions) and fatigue (negative effect of time on shift).

Yet another potential explanation of the correlation between cashier productivity and job design is that cashiers at scan-only checkout counters were more likely to get assistance with packing, and so, could scan faster. Given the limited number of cashiers in each shift, a cashier would be more likely to get assistance with packing when other counters were closed. To check, Table 3, column (f), reports an estimate which controls for the proportion of counters closed. Consistent with the argument that a cashier is more likely to get help if other counters are closed, the coefficient of the proportion of counters closed is positive and significant. Yet, the estimated coefficient of scan-only is just slightly smaller than the preferred estimate. This suggests that the estimated effect of scan-only was only slightly confounded by differences in assistance with packing.[8]

7 Mechanism

The estimates reported above suggest that cashiers scanned about 11 percent faster in the new scan-only job design compared to the conventional job design. How did automation-enabled specialization in the task of scanning raise cashiers' productivity? According to Proposition 2, if the worker's cost of effort exhibits increasing differences, automation would increase productivity by enabling the worker to specialize in one task, thus reducing her marginal cost of effort and inducing her to increase effort in that task.

Hence, the key issue is whether the cashier's cost of effort exhibited increasing differences in the tasks of scanning and collecting payments. Table 4 reports regressions of the time that cashiers took to collect payment on the speed of scanning, limited to transactions at conventional checkout counters. (Such estimates would not be meaningful for transactions at scan-only checkout counters, where cashiers did not collect payment.)

Table 4, column (a), reports an OLS (ordinary least squares) estimate, controlling for counter work time, payment in cash, and basket value, and including fixed effects for cashier, date, and hour. The coefficient of scanning speed, specified as the logarithm of items scanned per minute, 0.256 ($p < 0.001$), is positive and significant. This is consistent with more effort in the task of scanning being associated with a higher marginal cost of effort in the task of collecting payment. Accordingly, when the cashier scanned faster, she

[8]A high proportion of closed counters also indicates that the store was not busy. By this interpretation, in the estimate of scanning speed, the coefficient of the proportion of other counters closed should be negative, not positive.

also took more time to collect payment. Interestingly, the coefficient of payment in cash is negative and significant. Apparently, cashiers collected payments in cash more quickly than payments by card (payment by check is unusual in Singapore and mobile payment had not yet caught on at the time of the study). Further, the coefficient of basket value is positive and significant, suggesting that cashiers took more time and were more careful with larger payments.

– Table 4 –

Yet, a serious concern is that effort in both the tasks of scanning and collecting payment might be driven by common factors. For instance, cashiers might be motivated to complete both tasks more quickly when there are more customers in line (Wang and Zhou, 2018). To address such endogeneity, we instrumented for the speed of scanning by the quantities that the consumer purchased in four categories – alcoholic beverages, floral, prepaid cards, and (pre-packed) vegetables. The quantities of such purchases would affect the speed at which the cashier scans, but not affect the time needed to collect payments.

Table 4, column (b), reports the first-stage estimate of the scanning speed. Alcoholic beverages, which require age verification, and floral items, which must be handled with care, were scanned more slowly. In contrast, prepaid cards and vegetables (which are typically pre-packed, and need not be weighed and priced) were scanned more quickly. The coefficients of the instruments are significant, and a diagnostic suggests that the instruments are not weak (Kleiberger-Paap F-statistic 22.80).

Table 4, column (c), reports the second-stage IV (instrumental variable) estimate. The coefficient of the scanning speed, 0.305 ($p = 0.064$), is positive and marginally significant. Subject to the imprecision of the estimate, it suggests that if a cashier scanned 1 percent faster, then she took about 0.3 percent longer to collect payment. The IV estimate is one-fifth larger than the OLS estimate, suggesting that any bias in the OLS estimate is downward.[9]

The estimates in Table 4 suggest that, when cashiers at conventional checkout counters scanned faster, they were slower in collecting payment. We interpret this as evidence of the premise that the cashier's cost of effort exhibited increasing differences in the tasks of

[9]Table A4 reports two robustness tests: one with outliers Winsorized at the top 1 percent, rather than trimmed, and the other on the entire dataset, including cashiers who worked at only one checkout format during the period of study. In both robustness tests, the coefficient of the scanning speed is positive, significant, and larger than the estimate in Table 4, column (c) for cashiers who worked at both checkout formats and with outliers trimmed.

scanning and collecting payments. Hence, the cashier's marginal cost of effort in collecting payment increased with her effort in scanning. This supports the explanation for the cashier's higher productivity in the scan-only job design as being due to a lower marginal cost of effort in scanning.

Other Mechanisms

Besides reducing the marginal cost of effort in scanning, the scan-only job design might have increased productivity through mechanisms typically associated with the division of labor. Division of labor can raise productivity as workers learn from experience, and avoid the set-up costs involved in switching tasks (Staats and Gino, 2012; Coviello et al., 2019; Friebel and Yilmaz, 2016; Duan et al., 2021).

Table 5 reports estimates to investigate the effects of learning and reduction in switching costs. A cashier who specialises in scanning might become more proficient by learning on the job. Within a shift, if the cashier need not switch between scanning and collecting payments, she might better keep in mind details of the scanning task, such as gifts and special offers not recorded in the bar code, and so, scan faster. Similarly, across shifts, if the cashier need not switch tasks, she might become more proficient in the single task of scanning.

– Table 5 –

To investigate, Table 5, column (a), reports an estimate which considered the effect of cashier's counter assignment on the previous day as well as the day itself. If the cashier had worked at a scan-only counter on both days, she would have been more specialized than if she had switched from a conventional to a scan-only counter. To the extent that specialization increased performance through learning, the coefficient of scan-only on both days should exceed the coefficient of conventional followed by scan-only.

The inclusion of the previous day's counter assignment reduced the sample by more than one-third (in part because all observations where the cashier had rested on the previous day were dropped). The coefficient of scan-only on both days, 0.108 ($p = 0.013$), is positive and significant. The coefficient of scan-only with conventional the previous day, 0.033 ($p = 0.213$), is also positive but not significant. While it is smaller than the coefficient of scan-only on both days, the difference between the two coefficients is not statistically significant ($t(36) = 1.453,\ p = 0.267$). This suggests that scan-only did not significantly reinforce learning across days.

To further investigate the effect of learning, we considered the productivity of cashiers within shifts. Learning would increase with the number of customers served. However, a possible econometric issue with OLS estimation is that the number of customers might be endogenous. A particular concern is reverse causation: the faster the cashier works, the more customers she would be able to serve. To address possible endogeneity, we applied IV estimation. A reasonable instrument for cumulative transactions is cumulative transactions in the preceding 30 minutes. Cumulative transactions in the preceding 30 minutes are included in cumulative transactions, and so, the two measures would be closely related. However, the cashier's speed in scanning at any particular time should not be affected by the number of transactions she completed in the preceding 30 minutes.

Table 5, column (b), reports the first-stage regression of cumulative transactions on cumulative transactions in the preceding 30 minutes, with each variable specified as the difference from the respective sample mean. The coefficient of the instrument is positive and significant, and a diagnostic test suggests that the instrument is not weak (Kleiberger-Paap F-statistic = 376.7). Table 5, column (c), reports the second-stage IV estimate. The estimate also controls for time on shift, to represent possible fatigue, so that cumulative transactions would more cleanly represent the effect of learning. Consistent with learning from experience, the coefficient of cumulative transactions is positive and significant. The coefficient of time on shift is negative, but marginally significant, which suggests that cashiers did slow down over the shift.[10]

To investigate whether specialization increased productivity through learning, Table 5, column (d), reports an IV estimate including the interaction between scan-only and cumulative transactions. If the new scan-only job design increased learning, the coefficient of this interaction should be positive. By contrast, the coefficient is negative, albeit imprecise, which suggests that cashiers did not learn faster in the scan-only job design. The reason could be that the rate of learning diminished with additional customers, and so, the additional experience in the scan-only job design contributed relatively less to learning. It seems reasonable to conclude that the increase in productivity in the scan-only job design was not due to increased learning.

[10] In the estimate in Table 3, column (e), the coefficient of time on shift is negative, small, and imprecise. But that estimate did not include the cumulative transactions, and so, the time on shift variable captured the effects of both learning and fatigue.

Research in psychology shows that switching tasks is cognitively demanding (Smith et al., 2001; Arrington and Logan, 2004). A job that is specialized in a single task would naturally require less switching than a job that involves multiple tasks. To the extent that costs of switching are substantial, specialization would increase productivity (Staats and Gino, 2012; Friebel and Yilmaz, 2016; Duan et al., 2021).

In the conventional job design, cashiers switched between scanning and collecting payment. If consumers purchased larger baskets of goods, cashiers would switch tasks less frequently. To the extent that switching tasks was mentally taxing, cashiers should have scanned faster. By contrast, in the scan-only job design, cashiers need not switch tasks, and so, the size of the shopping basket should not affect scanning speed.

To investigate whether the scan-only job design increased cashier productivity by reducing switching, Table 5, column (e), reports an estimate including the average basket size (number of items in the transaction, specified as the difference from the sample mean). The estimate also controlled for the basket size at the subject time, as it would take relatively longer for a customer to present and the cashier to scan a basket of many items. (As Figure 1 shows, the check-out counter is quite small.) The coefficient of average basket size is positive, which is consistent with the reasoning that, if customers presented larger baskets, cashiers would have to switch tasks less frequently, and so, scan faster.

Next, Table 5, column (f), reports an estimate including the interaction of scan-only with average basket size. The coefficient of the interaction, 0.118 ($p = 0.175$), is positive but not significant. At the average basket size of 4.605 items at conventional counters, the estimated coefficient implies that, at scan-only counters, the cashier scanned $4.605 \times 0.118 = 0.54$ items per minute faster, which is quite small relative to the average scanning speed of 14.75 items per minute at conventional counters. Accordingly, it seems reasonable to conclude that the increase in productivity in the scan-only job design was not due to reduced switching of tasks.

Besides the mechanisms proposed in previous research into specialization, the increase in productivity in the scan-only job design might possibly be explained by differences in supervision. Realistically, the cashiers were closely overseen by supervisors, and so, it would have been difficult for them to shirk. Still, there might have been gaps in monitoring. One argument is that it was more difficult to monitor workers engaged in multiple tasks than a single task. Hence, it would be easier for cashiers to shirk in the conventional as compared with the scan-only job design. By this reasoning, in scan-only job design, the cashier would be forced to exert more effort. Another argument is that it is more difficult for supervisors to monitor payments than scanning. By this reasoning, in the conventional job design, cashiers could shirk while collecting payment, while in the scan-only job design, cashiers could not shirk.

Both arguments imply that it would be easier for cashiers to shirk in the conventional job design, and so, they should prefer that job design to the scan-only job design. Yet, in a survey experiment, Ong and Png (2020) found that 83 percent of cashiers preferred the scan-only to the conventional job design, by a median of 3.7 percent of monthly wages. This survey evidence is not consistent with the conventional job design allowing cashiers to shirk more.

Furthermore, consider the argument is that it is more difficult for supervisors to monitor payments than scanning. As shown above, the cost of effort has increasing differences in the separate tasks of scanning and collecting payment. Hence, in the conventional job design, shirking in collecting payment should reduce the marginal cost of effort in scanning. Thus, in the scan-only job design, the cashier's marginal cost of effort in scanning would be higher, and so, she should scan more slowly, which contradicts the empirical evidence.

8 Concluding Remarks

The present research analyzed the effect of automation of particular tasks in an integrated job comprising multiple tasks. If the worker's cost of effort exhibits increasing differences in the separate tasks, automation of a task would increase productivity in two ways. It would directly reducing the worker's cost of effort in the non-automated task. Moreover, it would reduce the worker's marginal cost of effort in the non-automated task, and so, she should increase effort to an extent increasing in the degree of increasing differences.

To test the proposition, we carried out a field experiment at four stores in a supermarket group which had partly automated the collection of payments. Owing to the partial automation, it was possible to conduct a within-subjects experiment of the effect of automation on the design of the cashier's job and productivity. In the redesigned job, cashiers specialized in the task of scanning, and scanned faster than in the conventional job design. We attributed the increase in productivity to the cashiers' cost of effort in the conventional job design exhibiting increasing differences in their effort in the separate tasks of scanning and collecting payments. Being relieved of the task of collecting payments, the cashiers' marginal cost of effort in scanning was lower, and they responded by exerting more effort in scanning. Importantly, the increase in effort was larger among those whose productivity in the conventional job design was lower (Tan and Netessine (2020) found a similar result).

Yet, the empirical results should be interpreted with caution. A limitation of the present study is that, while the assignment of cashiers to scan-only vis-a-vis conventional checkout counters was experimentally manipulated, the flow of customers and their purchases was not. Various alternative explanations of the relation between the job design and scanning speed were considered and rejected. Still, it is not possible to definitively rule out alternative explanations.

With caution, these empirical results support the general proposition that, in jobs where the cost of effort exhibits increasing differences in the separate tasks, automation of one task reduces the cost and marginal cost of the other, non-automated tasks, and raises productivity. Importantly, the scan-only job redesign is not the typical story of specialization in which splitting a job between two persons raises productivity. The job specialization only became cost-effective with the automation of the task of collecting payments.

Accordingly, the contribution of automation comprises not merely the gain in productivity from the substitution of machines for humans in the particular tasks, but possibly also the gain in productivity of humans in the non-automated tasks. This perspective is meaningful for economic policy, and also, from a managerial standpoint, provides more precise guidance as to the returns from automation. This perspective of automation complements that which emphasizes the possible gains in productivity due to humans performing new tasks (Autor, 2015; Acemoglu and Restrepo, 2019). Moreover, it suggests caution in redesigning jobs to include new tasks – to the extent that the worker's cost of effort exhibits increasing differences in the non-automated and new tasks, the new tasks would attenuate the increase in productivity due to automation.

The scan-only checkout system studied here unbundled the job of the supermarket cashier. This is consistent with a historical trend by which automation has raised productivity by increasing the division of labor (Atack et al., 2017, 2019). Here, labor was divided between worker and machine in conjunction with the customer. In the supermarket context (as well as many others such as airport check-in, retail banking, and call centers), automation is changing the boundary between the service provider and consumer. Hence, the gains from automation also depend on the relative advantage of worker vis-a-vis consumer with machine in performing the task.

It is reasonable to suppose that consumers have comparative advantage over cashiers in handling payments. Indeed, consumers might actually prefer paying a machine than a human cashier, as the machine would be less likely to make a mistake, still less cheat on change. An important direction for future research is the effect of automation on consumer self service, and more generally, the vertical boundary between service provider and customer (Xue et al., 2007; Buell et al., 2010; Field et al., 2012; Hui and Png, 2015; Basker, 2016; Basker et al., 2017; Tan and Netessine, 2020).[11]

Autor and Dorn (2013) reasoned that front-line service workers such as cashiers rely heavily on flexible interpersonal communication and physical dexterity. To the extent that it is difficult to substitute machines for humans in front-line service tasks, such jobs would be less affected by automation. However, the present study highlights that such tasks can be automated – in conjunction with customer self-service.

By dividing labor between worker and customer, the scan-only checkout system shrunk the vertical boundary of the retailer (and the Western-style self-service checkout systems that completely outsource the cashiers' job to consumers, even more so). This outsourcing of work to the consumer runs counter to the general direction of e-commerce which, by delivering goods to the consumer's doorstep, has extended the vertical boundary of retailers. Future research could study the reasons for these apparently conflicting trends in the division of work between retailers and consumers.

[11]In June 2018, the supermarket group completely converted Store D to scan-only checkout. As Appendix Table A5 reports, the complete conversion was associated with more customers but did not significantly affect sales. These results are consistent with consumers being willing to pay to a machine rather than a cashier.

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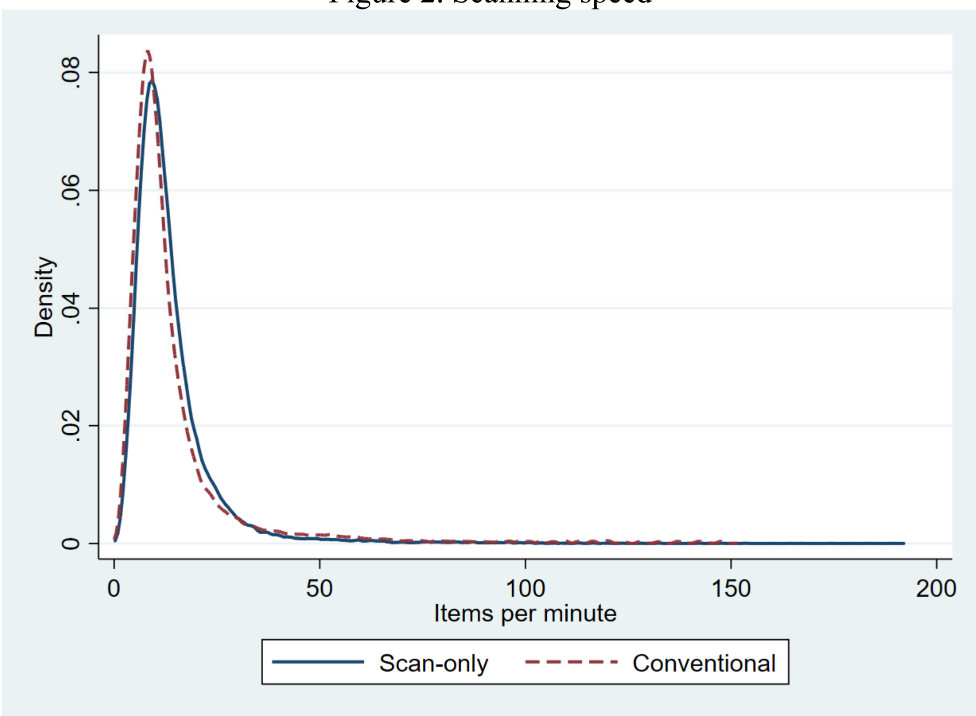
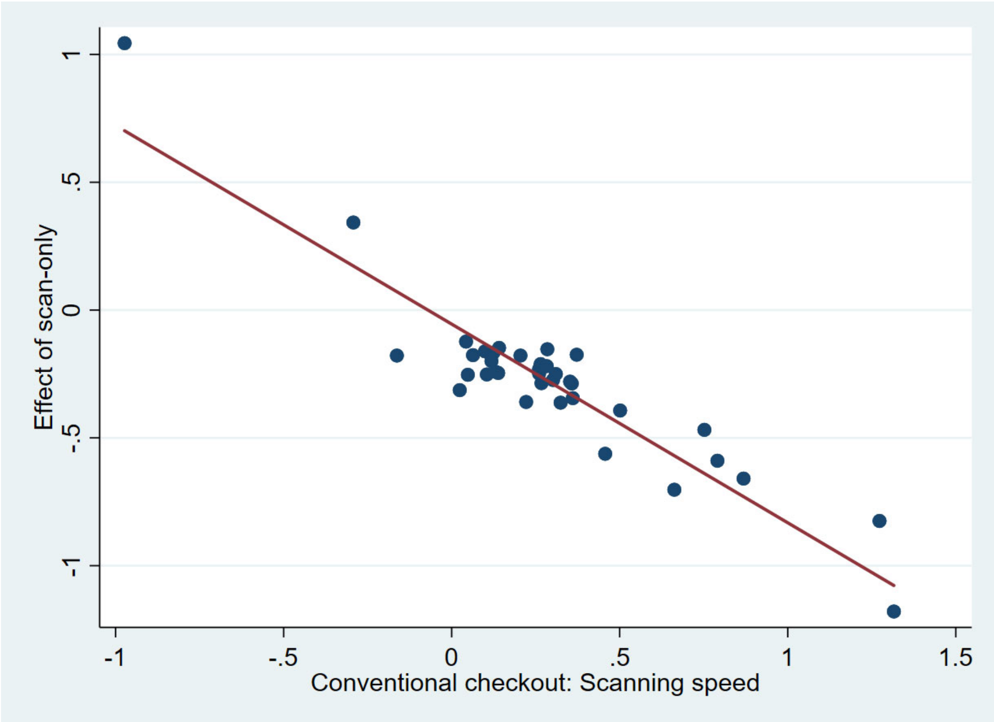
Figure 1. Scan-only/self-pay checkout

Figure 2. Scanning speed



Note: Figure depicts the kernel density of the scanning speed at scan-only and conventional checkout counters.

Figure 3. Cashier productivity: Individual



Notes: Figure plots the effect of scan-only on scanning speed against the scanning speed at the conventional checkout by individual cashier. The plot is based on an ordinary least squares regression of the natural logarithm of scanning speed on fixed effects for cashiers, scan-only interacted with cashiers, and date and hour. The horizontal axis plots the coefficients of the individual cashier fixed effects, while the vertical axis plots the coefficients of the fixed effects of scan-only interacted with cashiers. Some coefficients are negative because the coefficients depend on the productivity of the reference cashier. A negative coefficient means that the baseline productivity or change in productivity is less than that of the reference cashier.

Table 1. Summary statistics

VARIABLES	Unit	Scan-only checkout	Conventional checkout	Difference	Standard error	p-value
Scan time	Minute	0.508	0.532	-0.024	0.003	<0.001
Scanning speed	Per minute	14.021	14.701	-0.679	0.073	<0.001
Scanning speed (ln)		2.44	2.379	0.06	0.003	<0.001
Counter work time	Minutes per shift	103.488	127.994	-24.507	5.948	<0.001
Time on shift		404.451	377.52	26.931	15.129	0.075
Cumulative customers over shift		203.757	194.405	9.352	12.228	0.445
Counters closed	Proportion	0.379	0.334	0.045	0.001	<0.001
Cash payment		0.677	0.765	-0.088	0.002	<0.001
Basket size		4.723	4.605	0.118	0.024	<0.001
Basket value	$	16.466	16.913	-0.447	0.097	0.237
Item price	$	3.706	3.944	-0.239	0.016	<0.001
Wednesday		0.154	0.137	0.017	0.002	<0.001
Payment time	Minute	NA	0.126	NA	NA	NA
Observations		98007	54239			
Cashiers: 38						
Stores: 4						

Notes: Please refer to Appendix Table A1 for details of variable construction.

Table 2. Cashier productivity

VARIABLES	(a) Counter work time	(b) Store fixed effects	(c) Cashier fixed effects	(d) Cashier, date, and hour fixed effects	(e) Cashier and day x hour fixed effects
Scan-only counter	0.060	0.141	0.108	0.100	0.109
	(0.413)	(< 0.001)	(0.002)	(0.006)	(0.005)
Counter work time	-0.002	0.004	0.012	0.015	0.021
(ln)	(0.867)	(0.824)	(0.144)	(0.128)	(0.024)
Store A		0.121			
		(0.076)			
Store B		0.265			
		(0.014)			
Store C		0.173			
		(0.136)			
Store f.e.	No	Yes	No	No	No
Cashier f.e.	No	No	Yes	Yes	Yes
Date and hour f.e.	No	No	No	Yes	No
Day x hour f.e.	No	No	No	No	Yes
Cashiers	38	38	38	38	38
Observations	152246	152246	152246	152246	152246
R-squared	0.002	0.027	0.074	0.080	0.081
Scan-only: confidence interval	[-0.095, 0.247]	[0.059, 0.220]	[0.047, 0.164]	[0.041, 0.153]	[0.044, 0.166]

Notes: Estimated by ordinary least squares (Stata routine, areg); Sample: All transactions; Dependent variable: Items per minute (ln); Column (a): Control for only counter work time; Column (b): Including store fixed effects; Column (c): Including cashier fixed effects; Column (d): Including cashier, date, and hour fixed effects (e): Including cashier, day x hour fixed effects. Below each estimated coefficient, p-value of Wild clustered bootstrap (Roodman et al. 2019) is reported in parentheses. The last row of the Table reports 95 percent Wild clustered bootstrap confidence interval (Roodman et al. 2019) for the coefficient of Scan-only counter. Number of bootstrap replications: 999.

Table 3. Cashier Productivity: Alternative Explanations

VARIABLES	(a) Purchase charact-eristics	(b) Product sub-categories	(c) Payment mode	(d) Wednes-day	(e) Fatigue	(f) Packing help
Scan-only counter	0.114 (0.001)	0.120 (0.002)	0.120 (0.001)	0.119 (0.001)	0.109 (0.004)	0.104 (0.004)
Counter work time (ln)	0.030 (0.001)	0.027 (0.005)	0.027 (0.002)	0.027 (0.005)	0.021 (0.253)	0.020 (0.049)
Basket value (ln)	-0.174 (< 0.001)	-0.186 (< 0.001)	-0.189 (< 0.001)	-0.189 (< 0.001)		
Payment in cash			-0.029 (0.064)	-0.029 (0.062)		
Scan-only x Wednesday				0.007 (0.725)		
Time on shift (ihs)					-3x10e-5 (0.996)	
Counters closed (proportion)						0.109 (0.039)
Product sub-cat f.e.	No	Yes	Yes	Yes	No	No
Cashier f.e.	Yes	Yes	Yes	Yes	Yes	Yes
Day x hour f.e.	Yes	Yes	Yes	Yes	Yes	Yes
Cashiers	38	38	38	38	38	38
Observations	152246	152246	152246	152246	152246	152246
R-squared	0.156	0.187	0.187	0.187	0.081	0.081
Scan-only: confidence interval	[0.053, 0.167]	[0.063, 0.173]	[0.064, 0.170]	[0.058, 0.173]	[0.049, 0.165]	[0.046, 0.156]

Notes: Estimated by ordinary least squares (Stata routine, areg); Sample: All transactions; Unit of analysis: Transaction; Dependent variable: Items scanned per minute (ln); Column (a): Including personal characteristics; item value specified as the inverse hyperbolic sine, which can be interpreted like a natural logarithm (Burbidge et al. 1988); Column (b): Including product subcategory fixed effects; Column (c): Including mode of payment; Column (d): Including interaction of scan-only with Wednesday purchases; Column (e): Including time on shift (ln); Column (f): Including proportion of counters closed. All estimates include fixed effects for cashier and day x hour. Below each estimated coefficient, p-value of Wild clustered bootstrap (Roodman et al. 2019) is reported in parentheses. The last row of the Table reports 95 percent Wild clustered bootstrap confidence interval (Roodman et al. 2019) for the coefficient of Scan-only counter. Number of bootstrap replications: 999.

Table 4. Mechanism: Effort cost

VARIABLES	(a) OLS	(b) First stage	(c) IV estimate
Scanning speed (ln)	0.256		0.305
	(< 0.001)		(0.064)
Counter work time	0.011	0.046	0.009
(ln)	(0.393)	(0.054)	(0.315)
Payment in cash	-1.317	-0.082	-1.313
	(< 0.001)	(0.115)	(0.275)
Basket value (ihs)	0.251	-0.167	0.259
	(< 0.001)	(< 0.001)	(0.009)
Alcohol (quantity)		-0.025	
		(0.067)	
Prepaid card (quantity)		0.095	
		(< 0.001)	
Floral (quantity)		-0.037	
		(0.148)	
Vegetables (quantity)		0.009	
		(< 0.001)	
Cashier f.e.	Yes	Yes	Yes
Day x hour f.e.	Yes	Yes	Yes
Cashiers	37	38	38
Transactions	54238	54239	54239
R-squared	0.439	0.181	.
Kleiberger-Paap F-stat	.	.	22.80
Scanning speed:	[0.094,	.	[-0.015,
confidence interval	0.381]		0.680]

Notes: Sample: All transactions at conventional checkout counters; Unit of analysis: Transaction; Dependent variable: Time to collect payment in minutes (ln). Column (a): OLS regression (Stata routine, areg) of payment time on scanning speed (items per minute (ln)); Column (b): First stage regression (Stata routine, areg) of scanning speed on basket value (inverse hyperbolic sine), indicator of payment by cash, and basket value (inverse hyperbolic sine), and instruments, quantities purchased of alcoholic beverages, prepaid cards, floral items, and vegetables; Column (c): IV regression of payment time on scanning speed (items per minute (ln)). All estimates include fixed effects for cashier and day x hour. Below each estimated coefficient, p-value of Wild clustered bootstrap (Roodman et al. 2019) is reported in parentheses. The last row of the Table reports 95 percent Wild clustered bootstrap confidence interval (Roodman et al. 2019) for the coefficient of Scanning speed. Number of bootstrap replications: 999.

Table 5. Other Mechanisms

VARIABLES	(a) OLS: Learning by day	(b) First stage	(c) IV: Learning within day	(d) IV: Learning within day	(e) OLS: Task switching	(f) OLS: Task switching
Scan-only current & previous days	0.108 (0.013)					
Scan-only current & conventional previous	0.033 (0.213)					
Scan-only counter		0.129 (< 0.001)	0.056 (0.043)	0.053 (0.084)	0.111 (0.004)	0.097 (0.008)
Counter work time (ln)	0.024 (0.035)	0.548 (< 0.001)	-0.215 (< 0.001)	-0.210 (< 0.001)	0.024 (0.021)	0.020 (0.032)
Time on shift (ln)		-0.023 (0.153)	-0.031 (0.069)	-0.031 (0.052)		
Cum. trans. 30 mins earlier (ln)		0.330 (< 0.001)				
Cum. trans. (ln)			0.272 (< 0.001)	0.282 (< 0.001)		
Scan-only x cum. trans. (ln)				-0.021 (0.197)		
Basket size (ln)					-0.114 (< 0.001)	-0.114 (< 0.001)
Avg basket size (ln)					0.045 (0.033)	-0.022 (0.694)
Scan-only x avg basket size (ln)						0.118 (0.175)
Cashier f.e.	Yes	Yes	Yes	Yes	Yes	Yes
Day x hour f.e.	Yes	Yes	Yes	Yes	Yes	Yes
Cashiers	37	38	38	38	38	38
Observations	110180	152246	152246	152246	152246	152246
R-squared	0.083	0.982	0.085	0.086	0.103	0.103
Kleiberger-Paap F-statistic	.	.	376.7	194.4	.	.
Scan-only: confidence interval	.	.	[0.002, 0.107]	[-0.008, 0.110]	[0.048, 0.167]	[0.026, 0.170]

Notes: Sample: All transactions; Unit of analysis: Transaction; Dependent variable: Items scanned per minute (ln). Column (a): Regression distinguishing scan-only current and previous days as compared with scan-only current and conventional previous day; Column (b): First stage regression of cumulative transactions (ln) on instrument, cumulative transactions up to 30 minutes earlier (ln); Column (c): Second-stage IV estimate of scanning speed on cumulative transactions (ln); Column (d): Including interaction of scan-only and cumulative transactions (ln); Column (e): Including basket size (ln) and average basket size (ln); Column (f): Including interaction of scan-only and average basket size (ln). All estimates include fixed effects for cashier and date x hour. Below each estimated coefficient, p-value of Wild clustered bootstrap (Roodman et al. 2019) is reported in parentheses. The last row of the Table reports 95 percent Wild clustered bootstrap confidence interval (Roodman et al. 2019) for the coefficient of Scan-only counter. Number of bootstrap replications: 999.

Appendix

Table A1. Data Construction

VARIABLES	Construction
Scan-only	Indicator variable = 1 if transaction at scan-only counter
Cash payment	Indicator variable = 1 if transaction paid in cash
Basket size	Number of items in transaction
Average basket size	Average basket size for all the transactions from start of cashier’s shift
Basket value	Total bill for transaction
Item price	Basket value divided by basket size
Scanning speed	Basket size divided by time in minutes between start and end of scanning
Scan time	Time in minutes between start and end of scanning
Payment time (conventional counter)	Time in minutes between start and end of payment
Customer flow	Number of customers per hour served by a cashier at a counter
Cumulative customers	Number of customers from start of cashier’s shift
Cumulative customers up to 30 minutes earlier	Number of customers up to 30 minutes before the current transaction
Counter work time	Sum of scan time and payment time in minutes within hour
Wednesday	Indicator variable = 1 if transaction on Wednesday
Time on shift	Time in minutes from start of cashier’s shift
Proportion of closed counters	Ratio of closed counters to all counters
Post conversion	Indicator variable = 1 if the store was fully converted to scan-only counters
Scan-only current & previous days	Indicator variable = 1 if the cashier worked on the previous day and worked at a scan-only counter. The value is recorded as missing if the cashier did not work the previous day
Scan-only current & conventional previous	Indicator variable = 1 if the cashier worked on the previous day and worked at a conventional counter. The value is recorded as missing if the cashier did not work the previous day

Notes: All variables were constructed from the point-of-sales records and time logs of counters. Owing to gaps in the records and matching the data, observations of some variables were extremely large. Hence, the top 1 percent of all variables except scan-only, cash payment, proportion of closed counters, indicator of Wednesday and cumulative customers up to 30 minutes earlier were trimmed.

Table A2. Cashier productivity: Individual

VARIABLES	(a) Baseline	(b) With store fixed effects	(c) Excluding outliers
Conventional checkout: Scanning speed	-0.414	-0.636	-0.419
	(0.094)	(<0.001)	(<0.001)
Constant	0.288	0.350	0.232
	(0.001)	(<0.001)	(<0.001)
Store fixed effects	No	Yes	Yes
Cashiers	38	38	35
R-squared	0.33	0.82	0.74

Notes: Estimated by OLS (Stata routines, reg and areg); Data comprises coefficients from ordinary least squares regression of the natural logarithm of scanning speed on fixed effects for cashiers, scan-only interacted with cashiers, and date and hour. Dependent variable: Coefficient of fixed effect of scan-only interacted with cashier; Explanatory variable: Coefficients of individual cashier fixed effects. Column (a): Excluding store fixed effects; Column (b): Including store fixed effects; Column (c): Excluding outlier cashiers (with individual cashier fixed effect < -0.5 or > 1.0). Below each estimated coefficient, p-value in parentheses.

Table A3. Cashier productivity: Robustness

VARIABLES	(a) All cashiers	(b) Winsorized data
Scan-only counter	0.106	0.097
	(0.008)	(0.017)
Counter work time (ln)	0.008	0.007
	(0.256)	(0.214)
Cashier f.e.	Yes	Yes
Day x hour f.e.	Yes	Yes
Cashiers	81	38
Observations	243872	177264
R-squared	0.100	0.074
Scan-only: confidence interval	[0.036, 0.166]	[0.025, 0.156]

Notes: Estimated by OLS (Stata routine, areg); Dependent variable: Items per minute (ln). Column (a): Sample of all cashiers including those who worked at only counter format during period of study; Column (b): Scanning speed and other variables Winsorized at top 1 percent rather than trimmed. All estimates include cashier and day x hour fixed effects. Below each estimated coefficient, p-value of Wild clustered bootstrap (Roodman et al. 2019) is reported in parentheses. The last row of the Table reports 95 percent Wild clustered bootstrap confidence interval (Roodman et al. 2019) for the coefficient of Scan-only counter. Number of bootstrap replications: 999.

Table A4. Mechanism: Robustness

VARIABLES	(a) IV: Winsorized	(b) IV: All cashiers
Scanning speed (ln)	0.121	0.511
	(0.039)	(0.001)
Counter work time (ln)	0.010	0.051
	(0.490)	(0.112)
Payment by cash	-1.315	-1.340
	(0.329)	(0.284)
Basket value (ihs)	0.230	0.298
	(0.003)	(0.000)
Cashier f.e.	Yes	Yes
Day x hour f.e.	Yes	Yes
Cashiers	38	56
Transactions	63862	94993
Kleiberger-Paap F-stat	12.321	22.312
Scanning speed: Confidence interval	[0.005, 0.270]	[0.205, 0.854]

Notes: Sample: All transactions at conventional checkout counters; Unit of analysis: Transaction; Estimated by 2-stage least squares (Stata routine, ivreg2); Dependent variable: Time to collect payment in minutes (ln). Column (a): Scanning speed and other variables Winsorized at top 1 percent rather than trimmed; Column (b): Sample of all cashiers including those who worked at only counter format during period of study. All estimates include cashier and day x hour fixed effects. Below each estimated coefficient, p-value of Wild clustered bootstrap (Roodman et al. 2019) is reported in parentheses. The last row of the Table reports 95 percent Wild clustered bootstrap confidence interval (Roodman et al. 2019) for the coefficient of Scanning speed. Number of bootstrap replications: 999.

Table A5. Store D: Full conversion to scan-only

VARIABLES	(a) Customers (ln)	(b) Revenue (ln)
Post-conversion	0.035**	0.005
	(0.014)	(0.027)
Monday	-0.333***	-0.533***
	(0.018)	(0.042)
Tuesday	-0.315***	-0.533***
	(0.038)	(0.069)
Wednesday	-0.274***	-0.481***
	(0.021)	(0.037)
Thursday	-0.377***	-0.602***
	(0.029)	(0.047)
Friday	-0.402***	-0.582***
	(0.031)	(0.047)
Saturday	-0.156***	-0.118***
	(0.014)	(0.022)
Monday	0.001	-0.035
x post-conversion	(0.022)	(0.050)
Tuesday	-0.057	-0.062
x post-conversion	(0.041)	(0.077)
Wednesday	0.027	0.038
x post-conversion	(0.030)	(0.053)
Thursday	0.036	0.018
x post-conversion	(0.038)	(0.067)
Friday	0.012	0.056
x post-conversion	(0.035)	(0.062)
Saturday	0.030	0.010
x post-conversion	(0.019)	(0.034)
Constant	8.297***	11.576***
	(0.010)	(0.018)
Observations	152	152
R-squared	0.836	0.809

Notes: Sample: All transactions at Store D, which was converted from partial scan-only to complete scan-only on 19 June 2018. Estimated by ordinary least squares (Stata routine, areg); Unit of analysis: Day. Column (a): Dependent variable: Customers (ln); Column (b): Dependent variable: Sales revenue (ln). Robust standard errors (***p < 0.01 **p < 0.05 *p < 0.1).