Automation Enables Specialization: Field Evidence

Jie Gong and I.P.L. Png*

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Abstract

Becker and Murphy (1992) proposed that task specialization raises productivity but is limited by the costs of coordinating workers. We propose that automation enables workers to specialize without coordination costs. To the extent that the cost of effort exhibits increasing differences, workers increase effort in non-automated tasks and productivity. The proposition is supported by a field experiment among supermarket cashiers. Conventionally, supermarket cashiers perform two tasks – scanning purchases and collecting payment. Cashiers exhibited increasing differences in the cost of effort: when they scanned faster, they took longer to collect payments. We rotated cashiers between the conventional job design and one in which they specialized in scanning. The new job design increased cashier productivity in scanning by over 10 percent. The faster scanning was not due to customer sorting or cashier learning. The proposition is also validated by a survey of taxi drivers. Drivers who reported that difficulties in way-finding affected their driving were more likely to use map apps.

Keywords: Automation; Job design; Task specialization; Productivity
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*Gong: University of Hong Kong, gongjie@hku.hk. Png: National University of Singapore, iplpng@gmail.com. We gratefully acknowledge the cooperation of a major supermarket group and taxi company, advice from the Department Editor, Associate Editor, referees, Daron Acemoglu, David Autor, Emek Basker, Niloofar Abolfathi, Simone Santamaria, Kai-lung Hui, Pushan Dutt, other NUS colleagues, and superb assistance by Yige Duan, Chun-beng Leow, Valerie Chuang, Fiona Lee, and Enqi Teo. The research protocols were approved by the National University of Singapore, Institutional Review Board, S-17-252 and LS-17-090E. This project was funded by the Singapore Ministry of Education, grant MOE2016-SSRTG-059, SPIRE.

Introduction

In *the Wealth of Nations*, Adam Smith famously argued that the specialization of work (division of labor) would increase productivity through worker learning, reduced task switching, and application of specialized equipment (West, 1964; Chandra, 2004). Indeed, the core of the Industrial Revolution was transforming craft work (a skilled craftsman who produced the entire item) to factory work (several workers, each specializing in a few tasks, jointly produced the item). If specialization increases productivity, what impedes it? 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. Ride hail and taxi drivers must find their way and operate the car; cashiers must scan items and collect payment; researchers must keep up with the state of the art and produce 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, the cost of communication, or idle time (Becker and Murphy, 1992; Batt et al., 2019; Friebel and Yilmaz, 2016; KC, 2020).

Becker and Murphy (1992) reasoned that technology reduces the cost of communication and thus increases specialization. (By contrast, Dessein and Santos (2006) emphasized the exploitation of local information, and argued that technology reduces specialization.) We propose a different role for technology. Automation substitutes machines for workers in particular tasks, which leaves workers to specialize in non-automated tasks. In that case, workers coordinate with machines rather than other workers. Drivers use Google Maps, cashiers work with customer self-payment machines, researchers use Google Scholar, and doctors consult UpToDate (a medical decision support system). Importantly, coordinating with machines is less costly than with other humans.

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

To investigate empirically, we study the automation of payment collection in retail stores. Conventionally, the job of a retail cashier comprises two tasks: scanning and packing purchases and collecting payment. Collecting payment, especially cash, is cognitively demanding and stressful (Png and Tan, 2021). East Asian supermarkets have adopted a "scan-only" checkout format, which divides the cashier's job into two, with the human performing the scanning and packing and a machine collecting payment from the customer. Technology enabled the job redesign.

We conducted a field experiment in four outlets of a Singapore supermarket group that were only partly configured with the scan-only format. By arrangement with store managers, cashiers rotated among checkout counters in a within-subjects experiment. The new job design relieved cashiers of collecting payment, and thus mechanically increased cashier productivity as measured by customer flow. We focused instead on productivity in the *non-automated task*: the rate at which they scanned customer purchases. Based on the preferred estimate, which controlled for cashier and day-and-hour fixed effects, cashiers scanned items over 10 percent faster at scan-only than conventional counters. Importantly, and consistent with the theory, the increase in scanning speed was more pronounced among cashiers who were relatively slower in the conventional job design.

Our interpretation of this finding is that relieving cashiers of the payment task reduced their cost of effort in scanning, and as a result, they scanned faster. Using data from conventional checkout counters, we found a negative relation between scanning speed and time to collect payment. According to the instrumental variable estimator, when cashiers scanned 1 percent faster, they took about 0.66 percent longer to collect payment. The relation is consistent with our premise that more effort in one task increased the marginal cost of the other task. We also examined alternative mechanisms, including customer sorting and learning (Staats and Gino, 2012; Coviello et al., 2019), and found no strong evidence of either. Nevertheless, we acknowledge that it is difficult to rule out customer selection completely, as even the same customer might behave differently at conventional vis-à-vis scan-only counters.

In an ideal experiment, we would compare productivity under three scenarios: integrated job design (conventional checkout format), division of labor (one worker scans and the other collects payment), and automation (scan-only format). In practice, supermarkets do not seem to practice division of labor, possibly due to the costs of coordination (Becker and Murphy, 1992) such as idle time (Coviello et al., 2015; KC, 2020). Our experimental design did not allow us to isolate the pure effect of automation from that of task specialization. Rather, we interpret the results as the gains from *automation-enabled specialization*.

This study extends our understanding of the effect of automation as a strategy to increase productivity. Previous research shows that automation raised worker productivity in contexts that include restaurants (Tan and Netessine, 2020); motorcar driving (Hsu et al., 2012; Chao et al., 2014); and marine navigation (Gould et al., 2009). We contribute by elucidating a mechanism by which automation raises productivity — automation enables task specialization without the cost of coordination, and specialization reduces the marginal cost of non-automated tasks, which induces the worker to increase effort. Our analysis provides a theoretical basis for the finding of Tan and Netessine (2020) that the effect of self-ordering technology was more pronounced among slower waiters.

The proposition that automation reduces the marginal cost of non-automated tasks flows directly from the premise that, in conventionally designed jobs, the worker's cost of effort exhibits increasing differences in multiple tasks. Conceived by Holmstrom and Milgrom (1991), this premise underlies empirical studies of multitasking 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] One reason for the increasing differences is the cognitive effort required to start a new task, which renders switching tasks costly (Staats and Gino, 2012; KC, 2014; Coviello et al., 2015; Friebel and Yilmaz, 2016; Duan et al., 2021).

In our studies, automation split jobs between the human and a machine. Interestingly, machines took over the relatively high-skilled task (Autor, 2015; Acemoglu and Restrepo, 2018b). Unlike splitting the job between two humans, splitting the job between human and machine avoids any cost of coordination; thus, automation was essential to increasing productivity.

This study also contributes to more nuanced appreciation of the effect of automation on

[1]The multitasking 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 multitasking: 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.

labor markets. In prior research, automation displaced 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 assumes that task-level productivity (whether undertaken by machines or humans) is additively separable. By contrast, in our theory the substitution of machines for workers in one task raises labor productivity in the non-automated task. From a macroeconomic perspective, this would also increase the demand for labor, countervailing the displacement effect.

This study also contributes to understanding the division of labor between business and customer—a dimension of vertical organization that is attracting increasing 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 has emphasized the upstream boundary of the firm (Baker and Hubbard, 2003; Rawley and Simcoe, 2013). Here, we consider the downstream boundary between the firm and customer; the scan-only checkout outsourced the payment task to customers. We show that the gain from self-service is not merely the difference in productivity between employee and customer (with the machine) in the automated task; customer self-service might also raise the productivity of workers in the remaining tasks. This additional factor might influence the priority with respect to which tasks should be switched to self-service.

Theory

Following Becker and Murphy (1992), 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 $\partial q/\partial e_1 \geq 0$ and $\partial q/\partial e_2 \geq 0$.

The worker incurs cost of effort

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

where $\partial C/\partial e_1 \geq 0$ and $\partial C/\partial e_2 \geq 0$. Let efforts, e_1^G and e_2^G, maximize the net product,

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

A key condition in our analysis is the sign of the cross-partial, $\partial^2 C/\partial e_1 \partial e_2$, i.e., whether the cost of effort exhibits decreasing or increasing differences in the separate tasks. Decreasing differences means that more effort in one task reduces the marginal cost of effort in the other task. By contrast, increasing differences means that more effort in one task increases the marginal cost of effort in the other task.

Introduced by Holmstrom and Milgrom (1991), the property of increasing differences underlies much research on multitasking. Intuitively, this condition summarizes the interactions among tasks in the cost function and implies that task specialization would reduce costs and increase efficiency. Two psychological theories imply the condition. One is that setting up new tasks is mentally costly (Smith et al., 2001; Arrington and Logan, 2004), especially if the tasks are complex (Meuter and Allport, 1999). Another is that the separate tasks draw on a common limited mental resource. In psychology, ego depletion is a temporary reduction in the individual's capacity or ability to engage in volitional action such as decision-making (Baumeister et al., 1998).

To preview the theoretical analysis, we show that automation is a cost-efficient way to split the job into separate tasks (one performed by humans and the other by machines). Automation realizes the gain from task specialization without incurring the costs of coordination that would arise when the tasks are divided between humans.

Division of Labour

Suppose that the job is divided between 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 the 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 *If the increasing differences in the cost of effort are sufficiently weak relative to the cost of coordination, the integrated job design is more efficient than division of labor.*

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). If $C(\cdot, \cdot)$ does exhibit 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 weak relative to the cost of coordination, κ, then $\Delta_C < 0$. This implies that the integrated job design produces the same output as division of labor but at lower cost, and so, is thus 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 the net product,

$$q(e_1, e_2) - C(e_1, 0) - me_2 - F. \tag{6}$$

The next proposition presents our main theoretical insight and the focus of our empirical testing.

Proposition 2 *If the increasing differences in the cost of effort are sufficiently strong relative to the fixed cost of automation, automation is more efficient than the integrated job design, and it is optimal to increase the worker's effort to an extent that increases in the increasing differences.*

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

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

If $C(\cdot, \cdot)$ exhibits increasing differences to a sufficiently large degree and F is sufficiently small, then $\Delta_{GA} > 0$.

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 $\frac{\partial C(e_1^G, 0)}{\partial e_1}$. If $C(\cdot, \cdot)$ exhibits increasing differences, the difference in marginal cost

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

QED.

If the cost of effort exhibits increasing differences, 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 thus it would be optimal to increase the worker's effort in task 1. The stronger the increasing differences in the cost of effort, the more the worker should increase her effort. Note that automation reduces the number of tasks the worker performs, and so, increases job specialization.

An obvious question is whether increasing differences are a necessary condition for Proposition 2. What if the cost of effort were to exhibit decreasing differences? Owing to such decreasing differences (due for instance to worker preference for variety in tasks), the human marginal cost of effort would increase with task specialization. Then, whether automation is more efficient than the integrated job design depends on the balance between the increased cost of human effort vis-a-vis the lower variable cost of the machine. Accordingly, increasing differences are a sufficient but not necessary condition for Proposition 2.

On the other hand, provided that the cost of effort exhibits increasing differences, automation could still increase efficiency even if the machine itself 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.

Prior research on multi-tasking (Hong et al., 2018; Englmaier et al., 2017; Dumont et al., 2008; Bartel et al., 2017) provides indirect evidence that the cost of effort exhibits increasing differences. To examine the cost of effort directly, we interviewed a sample of 402 taxi drivers on their use of map apps, as reported in Appendix A. Operating a taxi involves two navigation tasks – way-finding and locomotion.[2] The interviews revealed that drivers' cost of effort in each task increased with effort in the other task (i.e., increasing differences). Further, drivers who reported that difficulties in way-finding affected their driving were more likely to use map apps, which provides suggestive evidence that automation-enabled specialization increased worker productivity by reducing the marginal cost of effort. However, the strength of these findings is limited by the correlational nature of the study and, more importantly, the absence of data on productivity by task. To

[2] "Navigation ... [includes] the two components of locomotion and way-finding. Locomotion is body movement coordinated to the local surrounds; way-finding is planning and decision making coordinated to the distal as well as local surrounds" (Montello, 2005).

avoid such limitations, we conducted a field experiment among supermarket cashiers.

Context: Supermarket Cashiers

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

The supermarket group 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 and packing purchases, and collecting payment. Supermarkets in Japan, China, and Singapore—including the subject of this study—have redesigned 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 that 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 thus completely replaces the human cashier.)[3]

Experimental Design

In the conventional job design, the cashier performed three tasks: scan and pack the customer's purchases, and collect payment. By contrast, in the new job design, the cashier specialized in the tasks of scanning and packing.

To investigate the effect of the job redesign on cashier productivity, we conducted a field experiment at four stores which, for administrative reasons, were temporarily equipped

[3]In a related study, Ong and Png (2021) show that the scan-only job design increased job quality and the supply of labor to the supermarket.

with both the conventional and scan-only checkout formats (Appendix B Section B1 reports the details). Over 38 days in December 2017 and May 2018, we arranged with store managers to rotate cashiers among checkout counters on a daily basis (Appendix B Section B2 presents an example). Hence, by design, the 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.

Several institutional details are worth noting. First, cashiers were paid a monthly wage and a substantial annual bonus. Store management said that cashiers were motivated to work hard by the desire to keep the job and the annual bonus. (The annual bonus depends on the profit of the entire group rather than individual productivity.) Second, store managers opened and closed counters according to the flow of customers, and cashiers who were relieved from counter duty helped with packing at other counters or shelving items. Third, the cashiers were not told about the experiment. Before our experiment, store managers rotated cashiers among the counters on a weekly basis. However, since our experiment changed the frequency of rotation to daily, the cashiers would have noticed the change and might have reacted. Accordingly, we tested for a Hawthorne effect.

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

$$\ln Y_{icst} = \beta_0 + \beta_1 \cdot \text{Scan-only}_{cst} + \gamma X_i + \gamma_c + \gamma_t + \epsilon_{icst}. \tag{9}$$

In equation (9), Y_{icst} represents cashier productivity, Scan-only_{cst} is an indicator that 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. Standard errors are clustered by cashier.[4]

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 the personal characteristics of cashiers and differences in purchases and payment method.

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

By rotating cashiers among the checkout counters, we mitigated potential identification concerns such as nonrandom assignment of cashiers to counters. For example, store managers might have assigned cashiers to checkout counters according to their productivity. Or, managers might have opened counters in a particular sequence and cashiers assigned to busier counters would be under more pressure to work fast. By design, each cashier was rotated through all checkout counters, regardless of their productivity and other characteristics. In addition, the preferred estimate included fixed effects for cashiers.

Notwithstanding the experimental design, one concern was customer sorting. 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 scanning and packing. For the customer, the only difference was having to pay at a self-pay kiosk rather than to a human cashier. Nevertheless, we conducted balance tests of the characteristics of the transactions and also included the same variables as controls in robustness checks. We did not find strong evidence of customer sorting.

Data

The management provided records from the point-of-sales systems and time logs for 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 of scanning, and the time at which payment was made.

An immediate issue was how to measure the productivity of cashiers. 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 regression equation (9). Scanning speed was calculated as the number of items purchased (from the point-of-sales record) divided by the elapsed time between start and end of scanning (from the time log).[5]

[5] Appendix B Section B3 discusses possible biases due to the time log not recording the adjustment process before scanning the first item or after scanning the last item.

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. Owing to resource constraints, the period of study was not long enough to observe every cashier at both scan-only and conventional counters. So, we limited the analysis 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.)

Table 1 reports summary statistics, and Appendix B Section B4 describes construction of the variables. The sample included 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. 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 similar number of customers in the course of their shift, likely because they did not have to collect payment. Overall, the data suggest that cashiers assigned to scan-only counters served more customers per hour while spending more time away from the counter.

– 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. These 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 1). The apparent disparity might be due to the higher pressure of work in Singapore grocery retailing and differences in working practices. Seemingly, as measured by 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 compared with conventional counters.

When not controlling for cashier- and time-specific effects, transactions differed significantly between scan-only and conventional counters. For example, roughly 68 percent of customers at scan-only counters paid in cash, compared with over 77 percent 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, the difference in payment mode is intuitive and expected. Further, 15 percent of customers at scan-only counters were served on Wednesdays (when the supermarket gives a discount to senior citizens), compared with 14 percent of customers at conventional counters. 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.

Estimates

Figure 2 depicts the distributions of scanning speeds at scan-only and conventional checkout counters. The fact 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. While informative, the patterns might be confounded by differences among stores, such as the distribution of counters as a result of different site constraints.

– Figure 2 –

To abstract from such differences, Table 2 presents ordinary least squares (OLS) regression estimates of (9) with the dependent variable being the scanning speed, specified in logarithm. First, Table 2, column (a) reports an estimate that includes scan-only as an explanatory variable and controls only for the length of time the cashier worked at the counter, which accounts for differences in the time cashiers worked at their assigned counter.[6] The coefficient of scan-only, 0.060 ($p = 0.455$), is positive but not significant.

– Table 2 –

Next, Table 2, column (b) reports an estimate that includes store fixed effects, which account for differences among stores in average scanning speed.[7] The coefficient of scan-

[6]Counter work time also accounts for differences in the flow of work. Depending on whether their assigned counter was open, cashiers either operated 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).

[7]One reason for such differences is disparities in store layout. Specifically, the largest store 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 four conventional and two scan-only checkout counters, but the latter were on the upper level which attracted fewer customers.

only, 0.141 ($p = 0.004$), is positive, significant, and over twice as large as the estimate that only controls for counter work time.

Table 2, column (c) reports an estimate that includes cashier fixed effects, which account for individual differences among cashiers in scanning speed. The coefficient of scan-only, 0.108 ($p = 0.004$), is positive and significant, but smaller than the coefficient with store fixed effects. This suggests that the estimate with store fixed effects 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 thus more precisely reveal the effect of the scan-only checkout format.

Next, Table 2, column (d) reports an estimate that includes 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 different dates, and the beginning and end of shifts. The coefficient of scan-only, 0.100 ($p = 0.005$), is positive and significant, and slightly smaller than that without the control for date and hour.

Finally, Table 2, column (e), reports an estimate that includes 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 ($p = 0.003$), 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 because it includes the most stringent set of controls.

Appendix B Section B5 reports a battery of robustness checks, including a full sample of cashiers, outliers Winsorized at the top 1%, excluding top 5% of main variables, and excluding the first day of the experiment to test Hawthorne effect (Table B2), [8] and estimates with standard errors clustered by store and day to account for possible differences in the practices of store supervisors in charge each day (Table B3). Reassuringly, the estimates remain stable and significant.

Our preferred estimate suggests that the scan-only job design increased cashier productivity in scanning speed by 10.9 percent. Is the impact economically meaningful?

[8] Experimental demand effects are likely to be moderate even in the laboratory (De Quidt et al., 2018). Moreover, in the field, Leonard and Masatu (2006) found that the Hawthorne effect vanished by the second day. Accordingly, we conducted a robustness check by excluding the first day of the experiment and found no change in the estimated effect of the scan-only job design.

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 our preferred 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, customer throughput would increase from $1 \div [0.532 + 0.126] = 1.52$ per minute to $1 \div 0.474 = 2.11$ per minute. 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's being relieved from payment. For the supermarket in this 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.

We further estimated the effect on the rate at which cashiers served customers, measured as the number of customers served per counter hour (in logarithm). As reported in Appendix B Table B2, column (e), scan-only raised the service rate by around 21 percent. The coefficient combines the effect of relieving the cashiers of collecting payments and faster scanning.

The estimates so far present the average effect of scan-only on productivity in scanning. Yet, Proposition 2 predicts that cashiers whose marginal cost of effort in the integrated job design was greater would respond relatively more to automation. 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 scanning speed at the conventional checkout, represented by coefficients of the cashier fixed effects. Consistent with the theoretical proposition, the scan-only job design had a relatively larger effect on cashiers who were less productive in the conventional job design. Appendix B Section B6 reports ordinary least squares estimates that buttress this conclusion.[9]

– Figure 3 –

Our interpretation of the result is that cashiers with low cost of effort already scanned quickly in the conventional job design. Relief from the task of collecting payments did

[9] 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.

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. Being relieved of 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 cashiers' productivity being less dispersed.

Alternative Explanations

An obvious alternative 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 placing purchases on the counter. This would result relatively slower scanning at conventional counters.

For commercial reasons, the supermarket group declined to provide data on customers. Absent customer data, we first conducted balance tests of purchase characteristics and found no significant difference in basket size, basket value, average item price, and purchased quantity in major product categories between scan-only and conventional counters (Appendix B Section B7).[10] Second, we included purchase characteristics as additional controls (Table 3, columns (a) to (c)) but found little impact on the estimated effect on scanning speed.

Recall that the supermarket offered discounts to seniors on Wednesdays. If seniors preferred conventional counters and moved more slowly, cashiers would scan more slowly at conventional counters on Wednesdays. Table 3, column (d) reports an estimate with an additional control for Wednesday shopping interacted with scan-only. The coefficient of the interaction term is positive, small relative to the coefficient of scan-only, and not statistically significant.

– Table 3 –

Across all specifications that controlled for differences among customers, the coefficient of scan-only is positive, significant, and slightly larger than the preferred estimate. (The

[10]Purchases at scan-only counters were more likely paid by cash, which is expected since the primary difference between the counters was the payment mode. Although the estimated coefficients on the quantity of dried food, florist, and frozen food are statistically significant, the magnitudes are very small compared with the sample mean.

scanning speed decreased in basket value, which is intuitive as it takes more time to bring larger quantities to the counter for scanning.) These results suggest that customer sorting is unlikely to explain the higher productivity of cashiers at scan-only counters. Still, we acknowledge that it is difficult to rule out selection completely, even with data on customers, since the same customer might behave differently at conventional vis-à-vis scan-only counters.

Another possible explanation is that work at scan-only checkout counters was less tiring, and so cashiers could scan faster. Table 3, column (e), reports an estimate that controls for the time on shift. The coefficient of the time on shift is negative, but small and insignificant, which suggests that cashiers did not suffer from fatigue. 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.

One concern might be that cashiers at scan-only checkout counters were more likely to get assistance with packing, and thus could scan faster. Given the limited number of cashiers in each shift, a cashier would be more likely to get assistance when other counters were closed. Table 3, column (f), reports an estimate that controlled for the proportion of counters closed, the coefficient of which is positive and significant. Yet, the estimated coefficient of scan-only is close to the preferred estimate, which suggests that the estimated effect of scan-only was only slightly confounded by differences in assistance with packing.

Finally, the higher productivity might be the result of an increase in the effective wage. The scan-only checkout format was cognitively less demanding, and with no change in the wage, cashiers may have felt that their (effort-adjusted) wage had increased and were obliged to work harder. However, this explanation seems improbable. Cashiers were paid a monthly wage and annual bonus not contingent on individual productivity. To attribute faster scanning to an increase in the perceived wage, the cashiers' perception must have changed as they were rotated among conventional and scan-only checkouts on a daily basis.

Mechanism

The estimates reported above suggest that cashiers scanned over 10 percent faster in the new scan-only job design compared with the conventional job design. How did automation-enabled specialization in the task of scanning raise cashiers' productivity?

Reduced marginal cost of effort in scanning. By Proposition 2, if the worker's cost of effort exhibits increasing differences, specialization would reduce the worker's marginal cost of effort in the non-automated task and induce her to increase effort in that task. Did the cashier's cost of effort exhibit increasing differences in the tasks of scanning and collecting payments? Table 4, columns (a) to (c) report regressions of the time 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 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, 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 also took more time to collect payment.[11]

– Table 4 –

A serious concern is that efforts in scanning and collecting payment might both be affected by other factors. For instance, cashiers might be motivated to complete both tasks more quickly when there are more customers in line (Wang and Zhou, 2018). This would lead to a downward bias in estimating the relationship between scanning speed and payment time.[12] To address such endogeneity, we applied an instrumental variables (IV) estimator, instrumenting for the speed of scanning by the quantities of vegetables purchased. The supermarket group typically sells fresh vegetables pre-packed in plastic

[11]The coefficient of payment in cash is negative and significant, implying that 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, which suggests that cashiers took more time and were more careful with larger payments.

[12]Note that an increase in scanning speed raises productivity, but an increase in payment time reduces productivity. When a cashier was motivated to complete both tasks more quickly, it would result in an increase in scanning speed and a decrease in payment time.

bags or boxes. Importantly, these need not be weighed and their barcodes are affixed in a uniform, easy to scan position. The quantities of vegetable purchases would affect the speed at which the cashier scans, but not the time needed to collect payments.

Table 4, column (b) reports the first-stage estimate of the scanning speed. Vegetables were indeed scanned more quickly. The coefficients of the instruments are significant, and a diagnostic suggests that the instruments are not weak. (Kleiberger-Paap F-statistic, 29.288, which exceeds the Stock and Yogo critical value, 16.38.) Referring to the second-stage estimate in Table 4, column (c), the coefficient of scanning speed is positive and statistically significant. The estimate suggests that, if a cashier scanned 1 percent faster, she took about 0.66 percent longer to collect payment. The IV estimate exceeds the OLS estimate, which suggests that any bias in the OLS estimate is downward. The result confirms our concern that simple OLS estimation may pick up correlation between cashier effort in the two tasks that arises from the motivation to turn around customers quickly.

The IV estimate suggests 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 scanning and collecting payments. At conventional counters, the tasks of scanning and collecting payments were integrated. To scan faster, the cashier had to exert more effort, which in turn raised the marginal cost of effort in collecting payment and hence slowed her in the task. By contrast, at scan-only counters, the cashiers did not collect payments, and so their marginal cost of effort (in scanning) was lower.

Less task switching. Another mechanism whereby automation-enabled specialization in scanning would raise cashiers' productivity is reduced task switching (Staats and Gino, 2012; Friebel and Yilmaz, 2016; Duan et al., 2021). This emphasizes the extensive margin of tasks, and is a possible reason for increasing differences in the cost of effort, as well as an independent explanation for the effect of specialization on productivity.

We use the average basket size to proxy for the frequency of task switching. 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 thus the size of the shopping basket should not affect scanning speed.

Table 4, column (d) reports an estimate that includes the average basket size (number of items in the transaction) since the start of a cashier's shift as well as the size of the basket in the particular transaction. 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 thus scan faster.

Next, Table 4, column (e) reports an estimate that includes the interaction of scan-only with average basket size. The coefficient of scan-only, 0.097 ($p = 0.012$), is smaller than our preferred estimate, 0.109 (in Table 2, column (e)) by 11 percent, suggesting that higher productivity at scan-only counters was only partly due to task switching. Yet, the coefficient of the average basket size, -0.022 ($p = 0.692$), is negative and insignificant, implying that cashiers at conventional counters did not scan faster with larger baskets. Further, the coefficient of the interaction, 0.118 ($p = 0.187$), is positive but not significant. The latter two results are somewhat inconsistent with the reasoning that, in the conventional job design, larger baskets reduce task switching and so increase productivity, and that such an effect would not arise in the scan-only job design in which cashiers do not switch tasks.

Learning. A cashier who specialises in scanning might become more proficient by learning on the job. If the cashier need not switch between scanning and collecting payments, she might better keep track of details, such as gifts and special offers not recorded in the bar code. We analyze cashier learning in Appendix B Section B8. There is no evidence of learning either across days (cashiers did not scan significantly faster after two consecutive days on scan-only compared with one scan-only day preceded by a conventional day) or within a shift (cashiers did not scan significantly faster when they served more transactions nor later in a shift at the scan-only checkout). The estimates are not consistent with scan-only increasing productivity through learning.

Target time per customer. Another explanation is that workers or supervisors aimed to meet a target for the customer's total service time, which encompassed scanning and payment at the conventional counters. Supervisors might have lowered the target time per customer for cashiers at scan-only counters. Empirically, however, scanning and payment time were positively not negatively related at conventional counters, is not consistent with the target time hypothesis. (The correlations were 0.19 and 0.17 with time measured in raw minutes and logarithmically transformed respectively.)

Differences in supervision. Although cashiers were closely overseen by supervisors, there might still have been gaps in monitoring. In particularly, it might be more difficult for supervisors to monitor workers in the conventional job design, since cashiers were engaged in multiple tasks and payments are harder to monitor than scanning. As such, cashiers would be forced to exert more effort at scan-only counters. By this argument, cashiers should prefer the conventional format. Yet in a survey experiment, Ong and Png (2021) 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.

Overall, we find strong evidence of automation-enabled specialization. As to the mechanism for the higher productivity in the scan-only job design, we slightly favor increasing differences in the cost of effort (due to a fixed cognitive capacity or set-up costs of new tasks). This is supported by estimates showing that, in the conventional job design, faster scanning was associated with slower collection of payment. Still, we acknowledge that reduction in the costs of task switching may account for some of the increase in productivity. Table 5 summarizes the empirical results on how automation-enabled specialization in scanning increased cashiers' productivity.

Concluding Remarks

We analyzed the effect of the automation of one task in an integrated job comprising multiple tasks. Theoretically, if the worker's cost of effort exhibits increasing differences in the separate tasks, the automation of one task would reduce the worker's cost of effort in the non-automated tasks, and thus induce the worker to increase effort and productivity. The effect of automation-enabled specialization on productivity is more pronounced among those with a higher degree of increasing differences (whose marginal cost of effort in one task is more sensitive to their effort in the other tasks).

In a field experiment, we rotated supermarket cashiers between the conventional job design (in which they scanned goods and collected payments) and a new job design that specialized them in scanning. The new job design increased cashier scanning speed by over 10 percent, which we interpret as due to the lower marginal cost of the scanning task and task switching.

Following our experiment, the supermarket group completely converted all stores to scan-only checkout. Management cited two reasons for the conversion. One was to attract more local workers to work as cashiers (Ong and Png, 2021), and thus comply with government restrictions on employing foreign workers. The other reason was to increase productivity.

We conducted a conservative back-of-the-envelope payback analysis of the scan-only job design. In December 2014, the supermarket group employed 471 full-time cashiers to staff 193 counters. The total wages of cashiers in the following 12 months, up to when the group started the conversion to scan-only, were \$11.79 million. If the number of cashiers could be reduced by 21 percent (based on our estimate of the effect on customer service rate), that would save $\$11.79 \times 0.21 = \$2.48$ million a year. The group planned to equip each scan-only checkout counter with two self-pay kiosks, which would cost a total of \$7.72 million (386 self-pay kiosks at an average cost of \$20,000). In addition, the kiosks required additional space costing \$1,770 per machine per year, or \$683,220 per year in total (based on the operating margin per square foot and 10 square feet per kiosk). Hence, the self-pay kiosks would pay for themselves in roughly 4.3 years.

Our research yields several managerial and policy implications. First, the automation-enabled task specialization studied here differs from specialization between two workers (Becker and Murphy, 1992). The specialization only became cost-effective with the automation: shifting the payment task to the self-pay kiosk. By contrast, if cashiers had delegated collecting payments to another worker, they would incur costs of coordination. Automation enables humans to specialize in tasks without incurring costs of coordination. This insight provides managers and policymakers with a new perspective on automation.

Second, automation contributes not only the gain in productivity from the substitution of machines for humans in the automated tasks, but also the increased productivity of humans in the non-automated tasks. This perspective is meaningful for economic policy, and also provides managers with more precise guidance. In technology strategy, managers must consider the effects on productivity in both the automated and non-automated tasks.

Third, in our setting, automation relieved human workers of the relatively high-skilled task (Autor, 2015; Acemoglu and Restrepo, 2018b): collecting payment for supermarket cashiers. In technology strategy, managers must consider all tasks, regardless of skill, as candidates for automation.

Finally, the redesign of the supermarket cashier's job can be interpreted as an automation-enabled division of labor between cashier and customer, with each specializing in the task in which they have a comparative advantage. Similarly, in airport check-in, retail banking, and call centers, service providers exploit automation to shift tasks to customers. To do so optimally, managers must consider the relative advantage of worker vis-à-vis automation-enabled customer. Relatedly, there might be a cognitive cost that is shifted to customers, which should be accounted for along with other customers disamenities. Future research can examine 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).

Here, we focused on the automation of one task in an integrated job. Yet many conventional jobs are specialized: for instance, cooks work with wait staff in restaurants, pilots team with navigators on ships' bridges, and surgeons consult radiologists. In these contexts, automation (replacing wait staff with robots, navigators with navigation systems, and radiologists with intelligent imaging systems) might increase productivity by avoiding the cost of coordinating the specialized workers. An important direction for future research is to investigate the effect of automation on the division of labor among humans.

To conclude, we emphasized increasing differences in the cost of effort in separate tasks, and ruled out complementarities such as workers appreciating task variety in work (Staats and Gino, 2012). However, the psychology of task-skill match suggests that such preferences might depend on the worker's skill level (Ong and Png, 2021). Hence, another important direction for future work is to examine the effect of complementarities among tasks on productivity.

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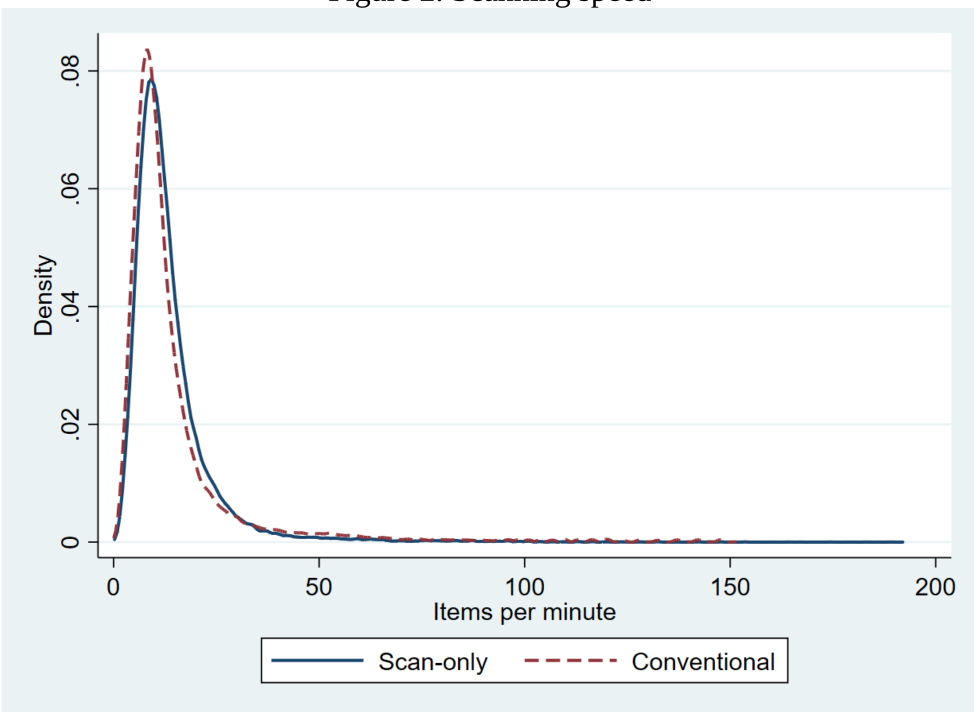
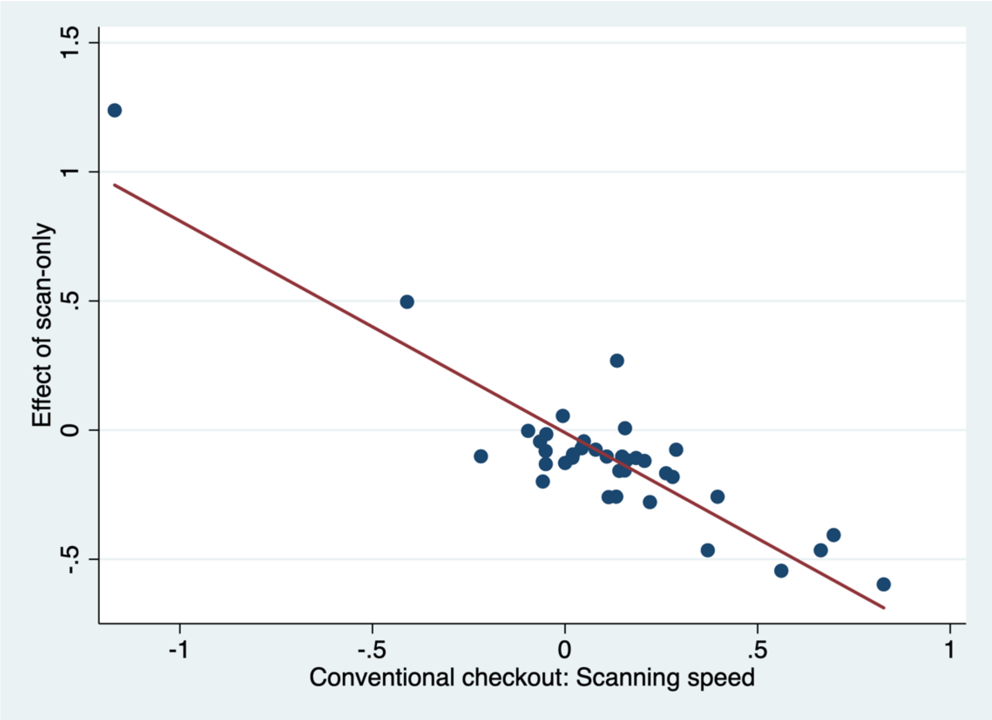
Figure 1. Scan-only/self-pay checkout

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 day*hour. The horizontal axis plots the coefficients of individual cashier fixed effects and 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. Cashier experiment: 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	<0.001
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		98,007	54,239			
Cashiers: 38						
Stores: 4						

Notes: Please refer to Appendix Table B1 for details of variable construction.

Table 2. Cashier productivity

VARIABLES	(a) Scan-only	(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***
	(0.455)	(0.004)	(0.004)	(0.005)	(0.003)
Counter work time (ln)	-0.002	0.004	0.012	0.015	0.021**
	(0.873)	(0.803)	(0.183)	(0.123)	(0.034)
Store A		0.121*			
		(0.074)			
Store B		0.265**			
		(0.014)			
Store C		0.173			
		(0.139)			
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	152,246	152,246	152,246	152,246	152,246
R-squared	0.002	0.027	0.074	0.080	0.081
Scan-only: confidence interval	[-0.109, 0.239]	[0.059, 0.221]	[0.046, 0.165]	[0.043, 0.151]	[0.047, 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, the p-value of the Wild cluster bootstrap (Roodman et al. 2019) is reported in parentheses. The last row of the table reports the 95% Wild cluster 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***	0.120***	0.120***	0.119***	0.109***	0.104***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
Counter work time (ln)	0.030***	0.027***	0.027***	0.027***	0.021	0.020*
	(0.002)	(0.002)	(0.002)	(0.003)	(0.269)	(0.052)
Basket value (ln)	-0.174***	-0.186***	-0.189***	-0.189***		
	(0.000)	(0.000)	(0.000)	(0.000)		
Payment in cash			-0.029*	-0.029*		
			(0.073)	(0.073)		
Scan-only x Wednesday				0.007		
				(0.736)		
Time on shift (ihs)					-0.000	
					(0.999)	
Counters closed (proportion)						0.109**
						(0.046)
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	[0.057, 0.168]	[0.066, 0.171]	[0.065, 0.170]	[0.063, 0.172]	[0.049, 0.164]	[0.045, 0.158]

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, the p-value of the Wild cluster bootstrap (Roodman et al. 2019) is reported in parentheses. The last row of the table reports the 95% Wild cluster 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)	(b)	(c)	(d)	(e)
	Payment time			Task switching	
	OLS	First stage	Second stage		
Scanning speed (ln)	0.256***		0.658**		
	(0.000)		(0.026)		
Counter work time (ln)	0.011	0.045*	-0.008**	0.024**	0.020**
	(0.355)	(0.064)	(0.032)	(0.024)	(0.036)
Payment in cash	-1.317***	-0.082	-1.284***		
	(0.000)	(0.100)	(0.000)		
Basket value (ln)	0.251***	-0.177***	0.316***		
	(0.000)	(0.000)	(0.000)		
Vegetables (ln quantity)		0.049***			
		(0.000)			
Scan-only counter				0.111***	0.097**
				(0.002)	(0.012)
Basket size (ln)				-0.114***	-0.114***
				(0.000)	(0.000)
Avg basket size (ln)				0.045**	-0.022
				(0.043)	(0.692)
Scan-only x avg basket size (ln)					0.118
					(0.187)
Cashier f.e.	Yes	Yes	Yes	Yes	Yes
Day x hour f.e.	Yes	Yes	Yes	Yes	Yes
Cashiers	38	38	38	38	38
Transactions	54239	54239	54239	152246	152246
R-squared	0.439	0.182	0.377	0.103	0.103
Kleiberger-Paap F-stat	.	.	29.29		
Scanning speed: confidence interval	[0.083, 0.377]	.	[0.072, 1.245]	[0.049, 0.168]	[0.029, 0.171]

Notes: Sample: All transactions at conventional checkout counters; Unit of analysis: Transaction; Dependent variable: columns (a) and (c): Time to collect payment in minutes (ln); columns (b), (d) and (e): Items scanned per minute (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 pre-packed vegetables; Column (c): IV regression of payment time on scanning speed (items per minute (ln)). Column (d): Including basket size (ln) and average basket size (ln); Column (e): Including interaction of scan-only and average basket size (ln). All estimates include fixed effects for cashier and day x hour. Below each estimated coefficient, the p-value of the Wild cluster bootstrap (Roodman et al. 2019) is reported in parentheses. The last row of the table reports the 95% Wild cluster bootstrap confidence interval (Roodman et al. 2019) for the coefficient of Scanning speed. Number of bootstrap replications: 999.

Table 5. Alternative explanations and mechanisms

Mechanism	Evidence	Findings/reasoning
Customer sorting	No	Table 1: Transactions characteristics were similar between scan-only and conventional counters. Table 3, columns (a)-(c): Controlling for transaction characteristics did not affect estimated effects of scanning speed. Table 3, column (d): Faster scanning was not due to senior shoppers choosing conventional counters.
Cashier fatigue or assistance with packing	No	Table 3, column (e): Controlling for time on shift did not affect estimates; Table 3, column (f): Controlling for number of counters closed (likelihood to get assistance) did not affect estimates.
Increase in effective wage	Not likely	Cashiers were rotated daily between conventional and scan-only counters, but their wages did not vary with individual productivity.
Reduced marginal cost in scanning task	Yes	Table 4, columns (a)-(c): Costs of effort in the two tasks were negatively correlated: At conventional counters, cashiers took longer to collect payment when they scanned faster.
Less task switching	Mixed	Table 4, columns (d)-(e): Controlling for average basket size decreased the coefficient of scan-only by 11%. At conventional counters, cashier did not scan faster when the average baskets were larger.
Cashier learning	No	Appendix B Table B7, column (a): Cashiers did not scan significantly faster after two consecutive days on scan-only compared with one scan-only day preceded by a conventional day. Appendix B Table B7, columns (b)-(e): Cashiers did not scan significantly faster when they served more transactions, later in a shift at the scan-only checkout, or later in the days of the study.
Target time per customer	No	At conventional counters, payment and scanning time were positively correlated.
Different supervision, harder to shirk	No	Ong and Png (2021) 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.

Appendix A. Automation of way-finding among taxi drivers

To examine the basic predicate of increasing differences in driver's cost of effort in separate tasks, we studied taxi drivers. Operating a taxi involves two navigation tasks: way-finding and locomotion.[1] In recent years, mobile applications such as Google Maps and Waze have enabled taxi drivers to automate the way-finding task, allowing them to specialize in locomotion. Between January and March 2022, we interviewed 402 drivers affiliated with a major Singapore taxi company regarding their use of map apps. The interviews were administered in person by a student surveyor, mostly as drivers waited for routine vehicle maintenance, recorded in Qualtrics on an iPad, and took about 15 minutes. Each respondent was compensated with S$30 in cash or a shopping voucher.[2]

We asked respondents how often they used map apps and classified those who answered *never* as not map users and all others (*sometimes, frequently, always*) as map users. To investigate the effect of effort in way-finding on the cost of effort in locomotion, we asked three questions.[3] As reported in Table A1, Panel B, items (a), (b), and (g), among app users, over 40 percent agreed that, when they had difficulty finding their way, it affected their driving, and over 73 percent agreed that the app let them focus on driving and that, using the app, they were less tired. Except for way-finding (which might be confounded by age and facility with smartphones), the proportions were significantly higher among app users than non-users. These responses are consistent with less effort in way-finding reducing the cost of effort in locomotion, i.e., increasing differences in the cost of effort.

Further, we investigated how the map apps affected productivity. As shown in Table A1, Panel B, items (d) and (f), among map app users, 72.5 percent agreed that the app saved time and 50.2 percent agreed that the app enabled them to earn more and more quickly. To elicit the information less directly, we asked respondents how not using any map app would affect their operations. As shown in Table A1, Panel C, among app users, 26.9 percent said that either they would work the same hours and serve fewer rides or they would work more hours and serve the same or fewer rides.

Finally, we examined the drivers' decision whether to automate the way-finding task using ordered logit regressions. As shown in Table A2, columns (a) and (b), respondents who made more wrong turns and reported poor knowledge of the roads were more likely to use a map app.[4]

Table A2, column (c) reports an estimate that tests the effect of increasing differences, as characterized by the effect of way-finding on driving (Table A1, Panel B, item (a)). The coefficient of way-finding is positive but not statistically significant. Table A2, column (d) limited the estimate to respondents who agreed that difficulties in way-finding affected their

[1] "Navigation ... [includes] the two components of locomotion and way-finding. Locomotion is body movement coordinated to the local surrounds; way-finding is planning and decision making coordinated to the distal as well as local surrounds" (Montello, 2005).
[2] The survey experiment was registered with the Open Science Foundation, identifier JXQH9.
[3] The questions were randomly framed in positive and negative senses, on a 5-point Likert scale (1 = *strongly disagree,* 2 = *somewhat disagree*, 3 = *neutral*, 4 = *somewhat agree*, 5 = *strongly agree*).
[4] The coefficients should be interpreted as the change in the ordered log-odds. For example, a one-standard-deviation increase in the frequency of making wrong turns would increase the ordered log-odds of being in a more frequent app user category by 0.225.

driving. The coefficient of way-finding is an order of magnitude larger and marginally significant. Finally, Table A2, column (e), reports an estimate with all controls. The coefficient of the effect of way-finding is even larger and significant. These results are consistent with Proposition 2 that automation is more efficient to an extent that increases in the increasing differences.[5]

Overall, the study of taxi drivers provides clear evidence of increasing differences in the driver's cost of effort in the two tasks of way-finding and locomotion. Further, drivers who reported that difficulties in way-finding affected their driving were more likely to use map apps, which provides suggestive evidence that automation-enabled specialization increased worker productivity by reducing the marginal cost of effort. However, the strength of our findings with regard to the effect of automation on productivity is limited by the correlational nature of the study and, more importantly, the absence of data on productivity by task.

[5] The results are robust to controlling for competence in English. The coefficient of the way-finding variable is somewhat smaller and the standard error larger, possibly because app users and non-users did not differ significantly in English competence (Table A1, Panel B, item (i)).

Table A1. Taxi driver survey: Summary statistics

VARIABLES			
Panel A: Summary statistics	Mean	%	
Female (%)	2.2		
Age (years)	61.5		
Experience as a taxi driver (years)	20.2		
Days per month	27.1		
Hours per day	9.6		
Rides per day	14.7		
Take home income per day (SGD)	79.0		
Self-reported road familiarity (5-point Likert scale)	4.0		
Use map apps (0 = *never*, 3 = *always*)	1.5		
never		17.66	
sometimes		45.52	
frequently		10.95	
always		25.87	
Panel B: Percentage agreeing with the statement:	Use map apps	Never use map apps	Pearson χ^2 p-value
(a) When I have difficulty finding the way, it affects my driving.	40.5	45.1	0.38
(b) With the map app, I can now focus on driving.	73.4	50.7	<0.001
(c) The map app is distracting.	21.1	52.1	<0.001
(d) The map app saves me time per trip.	72.5	49.3	<0.001
(e) With the map app, the job is more relaxed and pleasant.	84.0	50.7	<0.001
(f) With a map app, I can earn more and more quickly.	50.2	16.9	<0.001
(g) With a map app, I am less tired.	73.1	50.7	<0.001
(h) With a map app, I have to think harder to find my way.	16.0	26.8	<0.001
(i) I understand English well.	60.1	56.3	0.36
(j) I am not good with a smartphone.	33.2	47.9	0.06
Panel C: Percentage responding with the following actions:	Without map app	With map app	
(a) Work fewer hours	3.6	2.8	
i. Fewer rides	2.4	0	
ii. Same rides	1.2	1.4	
iii. More rides	0	1.4	
(b) Work same hours	81.3	95.8	
i. Fewer rides	13.3	4.2	
ii. Same rides	67.7	80.3	
iii. More rides	0.3	11.3	
(f) Work more hours	15.1	1.4	
i. Fewer rides	9.4	1.4	
ii. Same rides	4.2	0	
iii. More rides	1.5	0	
Observations	331	71	

Notes: Panel A: Take-home income is net of expenses for rental, fuel, and parking. Map app usage is the categorical response (*never, sometimes, frequently, always*) to the question "How often do you use map apps when operating your taxi?" Panel B: This reports the proportions of respondents who selected 4 or 5 on a 5-point Likert scale (1 = *strongly disagree* and 5 = *strongly agree*) of respondents who used or never used map apps. Questions (a), (b), and (g) were randomly posed as positive or negative ("does" or "does not", "can" or "cannot" and "less" or "more", respectively). For analysis, all answers were recoded to positive. Panel C: This reports responses to the hypothetical "If you do not use a map app" posed to respondents who used map apps and "If you use a map app" posed to respondents who never used map apps. Pearson χ^2 tests conducted for the responses to hours and rides, separately.

Table A2. Use of map app

Variables	(a) Wrong turns	(b) Road knowledge	(c) Increasing differences	(d) Increasing differences (sub sample)	(e) Full controls
Wrong turns	0.225**				0.069
	(0.028)				(0.646)
Road knowledge		-0.218**			-0.294**
		(0.026)			(0.049)
Way-finding affects driving			0.045	0.902*	1.012**
			(0.622)	(0.059)	(0.044)
Age	-0.040***	-0.037***	-0.045***	-0.052***	-0.039*
	(0.001)	(0.003)	(0.000)	(0.007)	(0.064)
Unfamiliar with smartphone	-0.514***	-0.530***	-0.520***	-0.515***	-0.547***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Observations	402	402	402	166	166

Notes: Estimated using ordered logit. Dependent variable is self-reported frequency of using map app when operating taxi, coded on 4-point scale (0 = *never*, 3 = *always*). Explanatory variables except age were normalized to mean 0 and standard deviation 1. Sample: Columns (a)-(c): all respondents to the survey; Column (d): drivers who responded “somewhat agree” or “strongly agree” with the statement, “When I have difficulty finding the way, it affects my driving.”

Appendix B. Cashier experiment: Supplementary information

B1. Experimental Stores

The largest of the four stores was set up in a neighborhood in which the group had no previous presence. The 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, by 2019, all four stores were completely converted to scan-only checkout counters in line with all other stores in the supermarket group.

B2. Rotation Schedule

The largest store was equipped with four conventional checkout counters, numbered 1 to 4, and four scan-only counters, numbered 5 to 8. As an example, 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).

B3. Time Log

One issue with the time log is that it did not record the adjustment process before scanning the first item or after scanning the last item. To understand the magnitude of the adjustment time and possible direction of bias, we computed the time lapse between the end of scanning the last item (or the completion of payment if at a conventional counter) in the previous transaction and starting to scan the first item in the current transaction. On average, the proxy for adjustment time was 29.6 seconds at conventional counters and 28.4 seconds at scan-only counters. The difference, 1.2 seconds, is small in magnitude. Moreover, the adjustment time was longer at conventional counters, and thus facilitating cashiers' scanning. Hence, the difference in the adjustment process, if any, tended to bias our estimates downward.

B4. Data Construction

Table B1 reports the details of construction of the variables.

Table B1. Cashier experiment: Data construction

VARIABLES	Construction
Scan-only	Indicator variable = 1 if transaction at a 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 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 in a shift
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 point-of-sales records and time logs of counters. Owing to gaps in the records and matching the data, the observations of some variables were extremely large. Hence, the top 1% of all variables—except scan-only, cash payment, proportion of closed counters, indicator for Wednesday and cumulative customers up to 30 minutes earlier—were trimmed.

B5. Scan-only: Robustness tests

This section reports robustness tests of the finding that the scan-only job design increased cashier productivity. Table B2 reports tests of robustness to sample selection.

Table B2. Cashier productivity: Robustness

VARIABLES	(a) All cashiers	(b) Winsorized data	(c) Exclude top 5%	(d) Exclude first day	(e) Customer service rate
Scan-only counter	0.106***	0.097**	0.101***	0.108***	0.213***
	(0.007)	(0.011)	(0.000)	(0.006)	(0.000)
Counter work time (ln)	0.008	0.007	0.022***	0.023**	-0.058***
	(0.252)	(0.206)	(0.004)	(0.030)	(0.000)
Cashier f.e.	Yes	Yes	Yes	Yes	Yes
Day x hour f.e.	Yes	Yes	Yes	Yes	Yes
Cashiers	81	38	38	38	38
Observations	243872	177264	105291	144359	152246
R-squared	0.100	0.074	0.089	0.080	0.819
Scan-only: confidence interval	[0.042, 0.166]	[0.031, 0.158]	[0.057, 0.142]	[0.044, 0.169]	[0.185, 0.241]

Notes: Estimated by OLS (Stata routine, areg); Dependent variable: Items per minute (ln). Column (a): Sample of all cashiers including those who worked at scan-only counter format during period of study; Column (b): Scanning speed and other variables Winsorized at the top 1% rather than trimmed. Column (c): Scanning speed and other variables dropped at top 5%; Column (d): Excluding the cashiers' first days in the experiment; Column (e): Customers per hour (ln) as the dependent variable. All estimates include cashier and day x hour fixed effects. Below each estimated coefficient, the p-value of Wild cluster bootstrap (Roodman et al. 2019) is reported in parentheses. The last row of the table reports the 95% Wild cluster bootstrap confidence interval (Roodman et al. 2019) for the coefficient of Scan-only counter. Number of bootstrap replications: 999.

Table B3 reports tests of robustness to the level of clustering of the estimated standard errors. Our experimental design (rotating cashiers among counters) is close to random within each store, and the effects are heterogenous among cashiers. In such a setting, Abadie et al. (2017: 19) recommend clustering standard errors by the unit of treatment. Accordingly, our estimation clustered by cashier. Still, we report a robustness check with clustering by store-and-day. The reason is that the various supervisors in charge of the store each day might differ in their policies with regard to opening and shutting counters and assigning off-counter cashiers to packing or shelving work. (Clustering by store alone would also account for such unobserved correlation but would present a problem of insufficient clusters and under-estimation of standard errors (Cameron and Miller 2015: 23)).

Table B3. Cluster by store-day

VARIABLES	(a) Scan-only	(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**
	(0.116)	(0.001)	(0.024)	(0.024)	(0.021)
Counter work time (ln)	-0.002	0.004	0.012**	0.015*	0.021**
	(0.760)	(0.675)	(0.040)	(0.076)	(0.010)
Store A		0.121***			
		(0.006)			
Store B		0.265***			
		(0.000)			
Store C		0.173***			
		(0.003)			
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	152,246	152,246	152,246	152,246	152,246
R-squared	0.002	0.027	0.074	0.080	0.081
Number of clusters	28	28	28	28	28
Scan-only: confidence interval	[-0.019, 0.148]	[0.083, 0.197]	[0.022, 0.175]	[0.014, 0.165]	[0.026, 0.176]

Notes: Estimated by ordinary least squares (Stata routine, areg); Standard error clustered at store-day level (e.g., store 1-Monday, etc); 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, the p-value of the Wild cluster bootstrap (Roodman et al. 2019) is reported in parentheses. The last row of the table reports the 95% Wild cluster bootstrap confidence interval (Roodman et al. 2019) for the coefficient of Scan-only counter. Number of bootstrap replications: 999.

B6. Individual cashier productivity

Proposition 2 predicts that cashiers whose marginal cost of effort in the integrated job design was greater would respond relatively more to automation. To examine this empirically, we first estimated a regression of scanning speed (in natural logarithm) on fixed effects for cashiers, scan-only interacted with cashiers, and date and hour. Then, we regressed the increase in productivity at the scan-only checkout (as represented by the coefficient of the fixed effect of scan-only interacted with cashier in the first regression) on the individual cashier's productivity at the conventional checkout (as represented by the coefficient of the fixed effect for cashier in the first regression). Table B4 reports the results. Consistent with Figure 3, the increase in the cashier's productivity in scan-only was negatively related to their productivity at the conventional checkout.

Table B4. Individual cashier productivity: Heterogeneity

VARIABLES	(a) Baseline	(b) With store fixed effects	(c) Excluding outliers
Conventional checkout: Scanning speed	-0.744***	-0.640***	-0.322***
	(0.000)	(0.000)	(0.000)
Constant	0.254***	0.243***	0.179***
	(0.000)	(0.000)	(0.000)
Store fixed effects	No	Yes	Yes
Cashiers	38	38	35
R-squared	0.73	0.84	0.64

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.

B7. Balance tests

Tables B5 and B6 report balance tests with respect to purchase and product characteristics.

Table B5. Purchase characteristics: Balance tests

VARIABLES	(a) Basket Size	(b) Basket Value	(c) Average Item Price	(d) Payment in Cash
Scan-only counter	0.014	0.029	0.015	-0.016***
	(0.817)	(0.140)	(0.360)	(0.004)
Counter work time (ln)	0.263***	0.047***	-0.003	-0.004
	(0.000)	(0.000)	(0.559)	(0.223)
Cashier f.e.	Yes	Yes	Yes	Yes
Day x hour f.e.	Yes	Yes	Yes	Yes
Cashiers	38	38	38	38
Observations	152246	152246	152246	152246
R-squared	0.053	0.058	0.021	0.053
Scan-only: confidence interval	[-0.110, 0.158]	[-0.011, 0.074]	[-0.018, 0.052]	[-0.027, -0.006]

Notes: Estimated by ordinary least squares (Stata routine, areg); Sample: All transactions; Dependent variable: (a): Number of items in the basket; Column (b): Basket value (ln); Column (c): Average item price (ln); Column (d): Indicator of payment in cash. All specifications including cashier fixed effects and day x hour fixed effects. Below each estimated coefficient, the p-value of Wild cluster bootstrap (Roodman et al. 2019) is reported in parentheses. The last row of the table reports the 95% Wild cluster bootstrap confidence interval (Roodman et al. 2019) for the coefficient of Scan-only counter. Number of bootstrap replications: 999.

Table B6. Purchase categories: Balance tests

VARIABLES	(a) Dried Food	(b) Florist	(c) Frozen	(d) Fruits	(e) Grocery	(f) Meat	(g) Seafood	(h) Veget-ables
Scan-only	0.021*	-0.004**	-0.133***	-0.006	0.168	-0.009	0.003	-0.042
	(0.094)	(0.027)	(0.000)	(0.956)	(0.372)	(0.269)	(0.790)	(0.516)
Counter work time(ln)	0.023***	-0.000	0.072***	0.115***	-0.008	0.011***	0.007	0.135***
	(0.001)	(0.819)	(0.000)	(0.003)	(0.862)	(0.001)	(0.131)	(0.000)
Cashier f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dayxhour f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cashiers	38	38	38	38	38	38	38	38
Observations	152246	152246	152246	152246	152246	152246	152246	152246
R-squared	0.005	0.006	0.033	0.011	0.041	0.013	0.018	0.023
Scan-only: confidence interval	[-0.005, 0.047]	[-0.008, -0.000]	[-0.183, -0.082]	[-0.233, 0.211]	[-0.222, 0.599]	[-0.025, 0.007]	[-0.018, 0.023]	[-0.187, 0.094]

Notes: Estimated by ordinary least squares (Stata routine, areg); Sample: All transactions; Dependent variable: Quantity purchased in the corresponding categories. All specifications including cashier fixed effects and day x hour fixed effects. Below each estimated coefficient, the p-value of Wild cluster bootstrap (Roodman et al. 2019) is reported in parentheses. The last row of the table reports the 95% Wild cluster bootstrap confidence interval (Roodman et al. 2019) for the coefficient of Scan-only counter. Number of bootstrap replications: 999.

B8. Alternative Mechanisms: Learning

To examine the effect of the scan-only job design on cashier learning, Table B7, column (a), reports an estimate that considers the effect of cashier's counter assignment on the previous day as well as the day itself. If the cashier worked at a scan-only counter on both days, she would be 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 counter followed by scan-only.

Table B7. Alternative mechanism: Learning

	Learning by day	With a day: cumulative transactions			Within a day: counter work time
VARIABLES	(a) Learning by day	(b) First stage	(c) IV	(d) IV	(e) OLS
Scan-only current & previous days	0.108*** (0.006)				
Scan-only current & conventional previous	0.033 (0.242)				
Scan-only counter		0.129*** (0.000)	0.056*** (0.000)	0.053*** (0.000)	0.212*** (0.000)
Counter work time (ln)	0.024** (0.034)	0.548*** (0.000)	-0.215*** (0.000)	-0.210*** (0.000)	0.039** (0.012)
Time on shift (ln)		-0.023 (0.166)	-0.031*** (0.000)	-0.031*** (0.000)	
Cum. trans. 30 mins earlier (ln)		0.330*** (0.000)			
Cum. trans. (ln)			0.272*** (0.000)	0.282*** (0.000)	
Scan-only x cum. trans. (ln)				-0.021 (0.189)	
Scan-only x count work time (ln)					-0.023 (0.114)
Cashier f.e.	Yes	Yes	Yes	Yes	Yes
Day x hour f.e.	Yes	Yes	Yes	Yes	Yes
Cashiers	37	38	38	38	38
Observations	110180	152246	152246	152246	152246
R-squared	0.083	0.982	0.085	0.086	0.086
Kleiberger-Paap F-statistic	.	.	376.7	194.4	
Scan-only: confidence interval	.	.	[0.053, 0.059]	[0.050, 0.056]	[0.087, 0.373]

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). All estimates include fixed effects for cashier and date x hour. Below each estimated coefficient, the p-value of Wild cluster bootstrap (Roodman et al. 2019) is reported in parentheses. The last row of the table reports the 95% Wild cluster bootstrap confidence interval (Roodman et al. 2019) for the coefficient of Scan-only counter. Number of bootstrap replications: 999.

The coefficient of scan-only on both days, 0.108 (p = 0.006), is positive and significant, while the coefficient of scan-only with conventional the previous day, 0.033 (p = 0.242), is positive but not significant. 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. (Inclusion of the previous day's counter assignment reduced the sample by more than one-third, in part because all observations in which the cashier had been off work the previous day were dropped.)

We also tested the learning of cashiers within shifts, which would increase with the number of customers served. If the customer flow is exogenous, we can examine the effect of learning on scanning speed by estimating the following OLS specification:

$$\ln Y_{icst} = \beta_0 + \beta_1 \mathrm{Scan}_{cst} + \beta_2 \mathrm{CumTrans}_{cst} + \gamma_X X_i + \gamma_c + \gamma_t + \epsilon_{icst},$$

where $\mathrm{CumTrans}_{icst}$ is the cumulative transactions cashier c served that shift before transaction i at time t. However, the number of customers served might be endogenous. A particular concern is reverse causation: The faster the cashier works, the more customers she would be able to serve. As such, we use the number of transactions in the preceding 30 minutes to instrument for the cumulative transactions a cashier served. Transactions in the preceding 30 minutes are included in cumulative transactions, and thus the two measures would be closely related. Meanwhile, 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 B7, column (b), reports the first-stage results, and column (c) reports the second-stage IV estimate. 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). The IV 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.

While cashiers became more specialized at scanning as they served more customers, did this drive our main findings? In other words, were cashiers faster at scan-only counters because they could learn better? Table B7, column (d), reports an IV estimate that includes 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 the increase in productivity in the scan-only job design was not due to increased learning. Similarly, Table B7, column (e), reports an estimate that includes the interaction between scan-only and counter work time and the coefficient is negative and insignificant. Taken together, we do not find strong evidence that the effect from scan-only is mainly driven by cashier learning.

References

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