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It does not matter how hard you work: The importance of task allocation for worker productivity

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ABSTRACT

Using detailed high-frequency administrative data from a large retailer with an online presence in the UK we explore the determinants of worker productivity in a warehouse decant process. We distinguish between worker characteristics, time-specific effects, and task allocation as determinants of productivity and find a dominant role of the latter. This raises concerns about the assumption of random or identical task allocation made in studies when tasks are unobserved. This is especially relevant in the presence of output-related reward systems when workers will have an incentive to influence task allocation.

1. Introduction

Understanding the impact of heterogeneous inputs or task complexity (the terminology we use throughout) on worker productivity is important because in many real-world settings there is managerial and/or worker discretion over task allocation. In this paper, we use intra-firm administrative data to document that while worker ability/effort and time-specific effects both drive worker productivity, it's task allocation that plays the dominant role.

Our findings complement a recent but growing literature that explores the interaction between management practices, peer-effects, and task allocation (Bandiera et al., 2007; Burgess et al., 2010; Amodio and Martinez-Carrascoz, 2018; Adhvaryu et al., 2022). However, in this paper, we focus on the importance of task allocation relative to worker and time effects in driving worker productivity.[1] In this respect, we contribute to the broader literature on worker productivity which has identified the influence of incentive payments (Lazear, 2000), employee learning (Shaw and Lazear, 2007), peer effects (Mas and Moretti, 2009), managers (Lazear et al., 2015) and working time (Collewet and Sauermann, 2017). Yet, despite using intra-firm administrative data, task allocation is typically unobserved in these studies.

Our context is a manual decant process typical in a warehouse setting, for which we have high-frequency data on output specific to the worker, time period, and task. The data was made available by a large retailer with an online presence in the UK. We leverage this exceptionally granular information to explore the relative impact of task allocation on productivity. Our results indicate that the average worker is 4.6 times more productive when allocated tasks in the bottom decile of the task difficulty distribution relative to the top. However, at average task difficulty, workers in the highest decile of permanent worker productivity are only 1.9 times more productive than those in the least productive decile. Thus, the analysis highlights the importance of task allocation for worker productivity and the incentive for workers to influence task allocation in output-related reward systems.

2. Context, data and method

Our focus is decant activities at a company warehouse where workers perform a common job role using the same technology.[2] Workers operate independently, transferring heterogeneous products ('tasks') between a delivery and a storage state. Task

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[1] Amodio and Martinez-Carrascoz (2018) refer to input heterogeneity rather than task allocation.

[2] This role might be combined with others within the organisation (which are not considered here).

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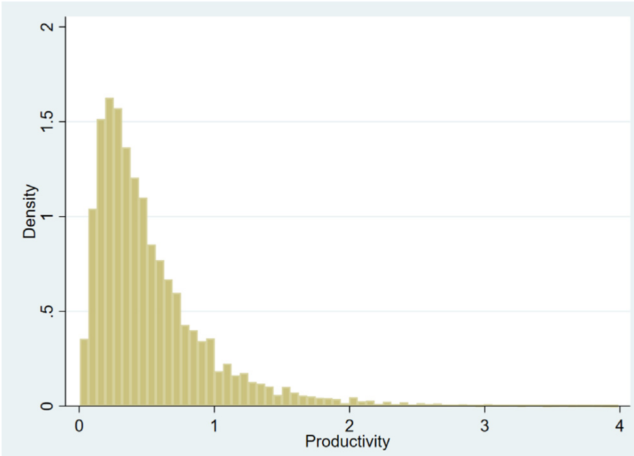

Fig. 1. Distribution of transaction productivity.
Notes: Author's calculations based on firm administrative data.

allocation across workers depends on product deliveries (determined by consumer demand) and is intended to be random, although in practice there is an element of discretion.[3] The work is structured around three equal length shifts plus occasional overtime, and across multiple workstations. It is a manual and labour-intensive task that requires few formal qualifications. Worker output depends on task allocation, as well as worker effort and ability (e.g. manual dexterity). Incentive pay rewards individual worker output above a pre-determined and known threshold.[4]

All decant transactions are monitored using an electronic system. For each transaction, output quantity (number of units decanted) and duration (in seconds) are recorded by worker, time, and task. This allows us to measure productivity at the worker-task-time level. After removing singleton observations on workers and tasks, our sample covers 230 days starting in January 2019, 2,640,987 transactions, 540 workers, and 26,051 tasks. Consistent with studies of this nature (Mas and Moretti, 2009; Amodio and Martinez-Carrascoz, 2018), worker productivity is calculated as output quantity per second of decant time. However, in this setting it is derived from each transaction rather than over a longer time interval.[5] Worker productivity varies instantaneously and is worker-time-task specific, facilitating analysis of variation by task for the *same* worker. Fig. 1 shows that the transaction-level productivity distribution has a long right tail, with productivity at the 90th percentile 7.8 times greater than at the 10th percentile.[6]

We are interested in the relative importance of worker, time, and task effects in explaining transaction productivity. To this end we estimate the following model of decant productivity using Ordinary Least Squares:

$$lnP_{ijt} = \theta_i + \gamma_j + \delta_t + \boldsymbol{x_{ijt}\beta} + \varepsilon_{ijt} \quad (1)$$

[3] Task allocation is not determined by either managers or workers. There is an excess supply of products which are brought to workstations by delivery trucks. Workers perform tasks sequentially according to this allocation.

[4] The incentive system operates throughout the period. Thresholds (which are constant across workers and tasks at a point in time and are controlled for in the analysis) are updated to reflect seasonal variation and previous average worker productivity.

[5] Decant time excludes time spent working on non-decant activities and break periods.

[6] Appendix Figure A1 compares productivity per transaction, and average worker, task and hour productivity.

Table 1
Descriptive statistics.

Variable	Mean	Standard deviation
Workers per hour	20.44	4.83
Decant hours per worker	87.29	130
Tasks per worker	1,079.85	1,494.87
Tasks per hour	175.4	63.3
Tasks per worker-hour	5.54	4.25
Output per worker (thousands)	137.47	238.57
Output per hour (thousands)	13.60	5.4
Output per worker-hour	665.28	539.70
Output per transaction	28.11	23.43
Transaction productivity	0.54	0.50

Notes: Author's calculations based on firm administrative data. All figures are rounded to two decimal places. Hours (and worker-hours) refer to calendar hours rather than decant hours and include idle time.

lnP_{ijt} is the log productivity of worker i with task j at date/time t. Worker fixed effects (θ_i) capture variation in productivity driven by worker-related factors that are constant over time and tasks, reflecting innate ability and motivation. Task-specific effects (γ_j) are constant over workers and time, and capture task complexity. Time-specific (hour *x* date) effects (δ_t) capture time-varying conditions common across workers and tasks. $\boldsymbol{x_{ijt}}$ is a vector of work-related characteristics, including controls for permanent versus temporary contracts, workstation fixed effects and the incentive pay output threshold.[7] ε_{ijt} is the random error term.

To assess the contribution of each set of fixed effects to productivity dispersion, we follow Fox and Smeets (2011) and examine the change in residual productivity in response to introducing each set of variables. We focus on the change in the adjusted R^2 but also consider changes in standard deviation, and ratios of the 90th/10th and 75th/25th percentiles of the residual productivity dispersion (in levels).

3. Results

Table 1 presents selected descriptive statistics for the transaction-level data where workers undertake different decant tasks.[8] The average worker decants for relatively few (87) hours during the sample period, but our results are robust to excluding those in the bottom hours decile (see Appendix Table A3). The average worker performs an average of 6 different tasks per hour and 1,080 different tasks over the sample period. The average output per transaction is 28 units, and average transaction productivity is about half a unit per second.

Table 2 presents estimates of productivity dispersion. In Panel A, we model worker, task and time-specific fixed effects, as well as the control variables individually.[9] The adjusted R^2 values show that task fixed effects explain over half of the variation in productivity, while worker fixed effects explain only 12%, time-specific fixed effects explain 5%, and the control variables explain 4%.[10] Regardless of the precise measure of residual productivity dispersion, the variation is lower when controlling for task fixed effects relative to the other specifications.

Panel B shows the evolution of residual productivity dispersion as we sequentially introduce each set of fixed effects. Introducing task fixed effects into a regression with worker fixed effects increases adjusted R^2 fivefold from 0.12 to 0.59. The addition of time-specific fixed effects and the control variables has

[7] We have no further information on time-varying characteristics e.g. working hours or tenure.

[8] Appendix Table A1 provides additional measures.

[9] Appendix Table A2 provides coefficient estimates for the control variables.

[10] This is not simply a consequence of differences in the number of fixed effects between tasks, workers and time periods (see Appendix Table A4).

Table 2
Modelling transaction productivity.

Specification	Adjusted R^2	Standard deviation	90th/10th percentiles	75th/25th percentiles
Panel A				
Worker fixed effects	0.115	1.13	6.82	2.71
Task fixed effects	0.517	0.64	3.96	2.02
Time fixed effects	0.046	1.19	7.45	2.85
Control variables	0.040	1.21	7.48	2.87
Panel B				
Worker fixed effects	0.115	1.13	6.82	2.71
Task fixed effects	0.587	0.56	3.46	1.85
Time fixed effects	0.593	0.55	3.42	1.83
Control variables	0.594	0.55	3.41	1.83

Notes: Author's calculations based on firm administrative data. The number of observations is 2,640,987 throughout. Panel A relates to specifications including the relevant set of variables only. In Panel B variables are included sequentially. Error term in levels. The adjusted R^2 includes the influence of fixed effects.

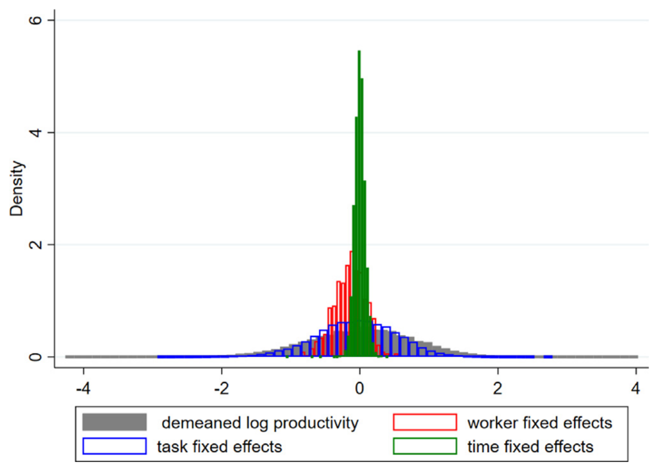

Fig. 2. Distribution of task, worker and time-specific fixed effects along with log transaction productivity.
Notes: Figure presents demeaned log productivity and estimates for task, worker and time-specific fixed effects based on the most comprehensive specification of Eq. (1).

little further impact. This indicates that task allocation is the key driver of productivity variation in this context and explains four times more variation in output than permanent worker productivity.[11] Consistent with this, controlling for task variation in addition to worker effects halves the 90th/10th percentile ratio in residual transaction productivity (from 6.82 to 3.46).

To further illustrate the importance of task allocation, in Fig. 2 we plot the distribution of task, worker and time-specific fixed effects in Panel B, alongside transaction productivity. The distributions of time-specific fixed effects and worker fixed effects exhibit little dispersion (standard deviation of 0.07 and 0.22 respectively) and so offer limited explanation for the long tail of the productivity distribution. In contrast, the distribution of task fixed effects is wider (standard deviation of 0.57) and more similar in shape to the productivity distribution. This graphically demonstrates that its controlling for tasks that brings predicted productivity far closer to its actual distribution.

Our analysis demonstrates the importance of task allocation to worker productivity. In the presence of output-related incentive pay, task allocation will have implications for wage inequality and incentivise workers to influence task allocation.[12] As an illustration, over a course of one hour, output of the average worker continuously allocated difficult tasks (10th percentile of the task fixed effects distribution) would be 4.6 times less productive than when allocated straightforward tasks (90th percentile). At average task difficulty, the most productive workers (90th percentile of worker fixed effects distribution) will decant 1.9 times the least productive workers (10th percentile).

4. Conclusion

In an intra-company warehouse setting and within a narrowly defined job role, we find that worker productivity depends heavily on task allocation. Indeed, task allocation is far more important than permanent worker productivity. Put simply, some products are far more difficult to decant than others. In this context, output-related reward systems provide a motivation for employees to influence task allocation. Consequently, where there is potential discretion in allocation, our findings question the assumption of identical or random task allocation often made in studies on worker productivity when task allocation is unobserved. Our findings are consistent with Amodio and Martinez-Carrascoz (2018) and Adhvaryu et al. (2022) who find task allocation important in different contexts and encourage further investigation of task allocation across countries and sectors to assess the generalisability of these relationships.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data

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The data are made accessible under a non-disclosure agreement from an anonymous large retailer with an online presence in the UK. We are grateful to the company for their support during this project, and their advice and guidance on using and interpreting these data. We also thank the editor (Audra Bowlus),

[11] Appendix Table A5 shows that including an interaction between worker and task fixed effects improves the fit of the model, consistent with worker-task complementarities.

[12] Discussions with managers at the firm suggest there is concern that employees seek to influence task allocation by delivery truck drivers.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.econlet.2023.111115.

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