Peer Pressure and Manager Pressure in Organisations*

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Abstract

We study the interaction between horizontal (peer) and vertical (manager) social factors in workers' motivation. In our setting, individuals work using open-plan desks. Using a natural experiment, we identify a sharp increase in workers' productivity following the occupation of adjacent desks. We link this peer pressure effect to two key aspects of the worker-manager relation. First, we find stronger peer pressure when managers monitor workers less. Second, we find stronger peer pressure among workers performance-evaluated by the same manager. In a set of counterfactual exercises, we illustrate how organisations could take advantage of these interdependencies to increase worker productivity.

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1 Introduction

Motivating workers is one of the central challenges that firms and other organisations face. The limitations of contractual incentives in many settings (Gibbons and Roberts, 2013) have led to a rapidly expanding body of work examining the role that social factors play in workers' effort (for a review, see Ashraf and Bandiera 2018). This work has progressed along two main, largely independent, lines. One line has examined 'horizontal' (i.e. peer) effects, such as the potential of pressure between co-workers to alleviate free-riding in teamwork production processes. A separate 'vertical' line of enquiry has studied the effect that managers have on their direct subordinates' effort and performance.[1] While many insights have been gained from the above work, studying horizontal and vertical social factors separately ignores the fact that organisations and workplaces are complex social systems, characterised by subtle interdependencies between their parts (Brynjolfsson and Milgrom, 2013).

This paper shows that these interdependencies matter, thereby linking the two separately-studied sources of social incentives. Specifically, we examine the interaction between managers and how workers exert peer pressure on each other, in the context of a public sector occupation characterised by teamwork and low-powered incentives. We identify two key results. First, we show that peer pressure and manager pressure can play substitute roles, as peer pressure is empirically stronger when the manager's ability to directly monitor the worker is weaker. Second, we find that peer pressure is larger among pairs of workers exogenously performance-evaluated by the same manager. Importantly, this finding exists despite the fact that sharing a performance-evaluator does not determine a worker's team assignment or any other operational characteristic. Our paper therefore establishes that a key mechanism through which managers affect their subordinates is by shaping the milieu through which these subordinates interact with each other. In a set of counterfactual exercises, we illustrate how organisations could take advantage of these interdependencies to increase worker productivity.

Our study is based on the Operational Control Branch (OCB) of the Greater Manchester Police (GMP) between February 2012 and November 2014. Call handlers are responsible for answering emergency calls and describing the resulting incidents in the internal

[1] On peer pressure among co-workers, see Mas and Moretti (2009), Cornelissen et al. (2017), Silver (2021), and Lindquist et al. (2022). On the effects of social connections between managers and their subordinates, see Bandiera et al. (2009), Hjort (2014), Xu (2018), and Cullen and Pérez-Truglia (2023). On the wider effects of managers on their subordinates, see Lazear et al. (2015), Frederiksen et al. (2020), Hoffman and Tadelis (2021), Adhvaryu et al. (2022), Fenizia (2022), and Minni (2023).

computer system. All handlers working at the same time operate as a team, in the sense that they take calls from the same call queue and therefore an idle 'free-riding' handler would increase the workload of his colleagues.

Handlers are located in a single room, which is organized in rows of desks. Visibility of each other's work is highest among handlers in adjacent desks, and more limited among handlers with desks in different rows. Upon starting their shift, handlers can choose any desk that is empty, but they remain in the chosen desk until the end of the shift. Individual shift starting and ending times are set well in advance and staggered throughout the day in order to respond to expected demand smoothly. This generates frequent variation in whether the desks adjacent to a working handler are occupied.

We investigate how the productivity of a handler (e.g. number of calls taken per hour) in the middle of his shift is affected by whether the adjacent desks are occupied. To credibly identify causal effects we exploit high-frequency variation in this desk occupation, under the assumption that the sudden arrival or departure of nearby colleagues is orthogonal to idiosyncratic and sudden shocks to the handler's productivity (an assumption that we test). Our first finding is the presence of a peer pressure effect: handlers start to work harder when a colleague sits next to them and slack off when an adjacent colleague finishes his shift and departs. This effect is quantitatively large: the number of calls taken increases by 7% when the two desks adjacent to a worker become occupied.[2] A leads and lags analysis confirms that the effect is immediate, lasts for more than two hours, and is free from pre-existing trends. We find smaller effects for the occupation of non-adjacent desks with more limited visibility of the handler's position. We find no detrimental effects on the 'quality' of the handler's work following the occupation of adjacent desks.

Our main contribution is to relate the peer pressure effect to the two main roles played by managers in the OCB: *room supervisors* and *medium-term evaluators*. The room where the handlers operate includes desks reserved for managers performing their role as supervisors of the handlers' contemporaneous work (see Figure 1). On some shifts, a handler may sit right next to a supervisor, while, on other days, the same handler works on the other side of the room. We find that the peer pressure effect (i.e. the higher productivity when the adjacent desk becomes occupied by a peer) increases with the distance between the handler's desk

[2] To put this number into perspective consider the peer effects meta-analysis of Herbst and Mas (2015), in which the consensus is that an increase in the average productivity of a focus worker's peer group by 10% leads to the worker increasing his productivity by 1%. Therefore, our estimated effect is equivalent to increasing the productivity of a focus worker's peer group by 70%.

and the closest supervisor's desk. To reinforce a causal interpretation of this interaction, we use an instrument to generate exogenous variation in the distance between the desk where a handler sits during a shift and the closest supervisor. Our instrument is the average location of the empty desks at the time when the handler started his shift. This average location is strongly correlated with a handler's chosen desk, as one would expect given that arriving handlers can only choose from among empty desks. Furthermore, the instrument is plausibly exogenous because it depends on the earlier choices of handlers finishing their shifts just before the focus handler started his shift. We find qualitatively similar effects using this instrument and conclude that the peer pressure effect is stronger when the manager's ability to monitor the handler is weaker. Thus, peer pressure and direct manager monitoring substitute each other in motivating handlers to exert effort.

We next relate the peer pressure effect to managers' roles as evaluators of the handlers' performance over the medium term. In the OCB, each of the approximately three hundred handlers' performance is tracked and periodically reviewed by one of fifteen managers. This evaluation has a subjective component, given that (as in most jobs) objective measures of performance are insufficient to perfectly assess a worker's effort. We find that the peer pressure effect is 60% larger among handlers evaluated by the same manager (i.e. co-evaluated) relative to pairs of handlers that are not co-evaluated. We reinforce a causal interpretation of this effect by exploiting time variation in the assignment of handlers to evaluators. Specifically, we find that *the same pair of handlers* engage in higher peer pressure when they are being co-evaluated, relative to periods in which they have different evaluators.[3] Expanding our analysis from the desks adjacent to a worker to the overall OCB room, we further show that handlers work harder when their shifts coincide with a higher percentage of co-evaluated colleagues.

We interpret these empirical findings through the lens of a theoretical framework in which managers evaluate and reward workers' performance, and workers care about maximising this evaluation. In our stylised model, a manager cannot perfectly infer a worker's effort on the basis of objective measures or her own observations, and therefore partly relies on the worker's reputation among the other workers with whom the manager frequently communicates. Peer pressure then arises because a worker is aware that his co-workers' impressions

[3]Note that managers are not supposed to evaluate handlers relative to each other, but instead from an absolute perspective. 'Co-evaluated' here simply means that two handlers have the same evaluator, rather than that they are being formally compared to each other. Of course, it is still possible that managers informally compare their evaluatees. We expand on this possibility at the end of Section 2 and in Section 8.

about his effort could (with some probability) reach his manager, and this motivates him to work harder in front of them.[4,5] Interpreting the empirical findings through the lens of this conceptual framework suggests that the relation between peer pressure and manager pressure is nuanced. On the one hand, these two motivating forces play a substitute role, in that the value of peer pressure is higher when the manager is less able to directly monitor the worker. On the other hand there is an element of complementarity between them, as our model interprets the empirically observed 'peer pressure' effect as a mechanism through which managers indirectly monitor and therefore exert pressure on their subordinates.

Our findings have important policy implications, because they provide a framework that open-plan organisations could use to increase worker productivity through the optimal assignment of workers to seats and shifts. We illustrate the potential of this framework through a set of counterfactual exercises that take the number of handlers working at any one time as given. We first find that a seat allocation rule minimising the number of empty adjacent seats would increase productivity by 3%. An additional 5% increase would result from an algorithm optimising the shift patterns and seat assignments to ensure that co-evaluated handlers coincide and sit together whenever possible. These exercises underline how organisations could harness the interactions between horizontal and vertical factors to improve motivation and performance.

This paper creates a bridge between two sizeable literatures studying social determinants of workers' productivity (Ashraf and Bandiera, 2018). In the first literature on horizontal determinants, peer pressure has been a leading explanation for the existence of productivity spillovers among co-workers (Mas and Moretti 2009, Cornelissen et al. 2017, Silver 2021 and Lindquist et al. 2022).[6] An important yet unanswered question in this lit-

[4]Although they do not provide evidence in this respect, Mas and Moretti (2009) theorise this mechanism as a potential explanation of their findings when they write 'For example, if a worker is slow, other workers may impose a cost on her, for example, by reporting her to management(...).' It is important to note that we do not require that peers report a worker's shirking explicitly through a formal channel, as in Fiorin (2021). Instead, our mechanism simply requires that the worker's reputation for high or low effort spreads with some probability through the organisation and eventually reaches the worker's manager.

[5]While we argue that our framework provides the best explanation of the empirical findings, we discuss other potential explanations in Section 8. Importantly, all valid explanations must share the characteristic that the assignment of workers to evaluators determines the pressure that workers empirically exert on each other.

[6]In addition to peer pressure, the literature on co-worker productivity spillovers (or peer effects in the workplace) has studied mechanisms such as knowledge spillovers (Waldinger 2012, Sandvik et al., 2019), helping behaviour (Drago and Garvey, 1998) and socialising activities (Bandiera et al. 2010, Park 2019). The high-frequency variation that we exploit in this paper is not well-suited to the identification of knowledge spillovers. Helping behaviour is not a relevant mechanism in our setting, as handlers are not supposed to put a caller on hold to go and seek advice from colleagues who may be in the middle of their own calls (see,

erature is how peer pressure actually works in practice. Kandel and Lazear (1992) and Mas and Moretti (2009) hypothesise mechanisms through which workers could pressure their free-riding colleagues, but identifying these mechanisms empirically has remained elusive. We contribute to this literature by arguing that peers exert pressure on a worker (partly) through the channel of making the worker's manager better informed about his performance. In doing this, we provide evidence on a specific mechanism in which the horizontal pressure leverages the vertical relation between workers and their immediate superiors.

The second extensive literature that our paper bridges is on the channels through which middle managers affect their subordinates' effort and performance. Prominent examples include coaching and mentoring (Lazear et al., 2015), task and effort allocation (Bandiera et al. 2009, Adhvaryu et al. 2022), turnover-reducing interpersonal skills (Hoffman and Tadelis, 2021) and performance evaluations (Frederiksen et al., 2020). Some of this work highlights the mediating role that social connections between managers and subordinates can play (Bandiera et al. 2009, Hjort 2014, Xu 2018, Cullen and Pérez-Truglia 2023). Throughout all the above papers, the focus is on how managers affect their subordinates through their *direct* actions. We contribute to this literature by instead showing that managers can also affect subordinates *indirectly* by shaping the environment in which workers operate; specifically in terms of how co-workers influence each other.

Lastly, our paper links to studies on the effect of co-location on productivity (Catalini 2018, Battiston et al. 2021) and the more general debate about working from home (Bloom et al. 2015, Barrero et al. 2022). We contribute to this literature first by showing that proximity to peers increases productivity even when workers are based at the same physical location. Second, we show that this effect of proximity to peers is itself dependent on the distance between a worker and his supervisor.[7]

The article is organised as follows. Section 2 briefly discusses a simple theoretical framework to micro-found the peer pressure function and explore its relation to the manager's monitoring. Section 3 describes the institutional setting. Section 4 outlines the data and empirical strategy. Section 5 discusses the baseline peer pressure findings. Sections 6 and

however, Battiston et al. 2021 for evidence of helping behaviour between call handlers and radio operators dealing with the same incident). We consider socialising activities generating distraction in our theoretical framework, and argue that they are inconsistent with the positive peer effects that we find.

[7]The main source of variation in studies of peer pressure has been the composition of the peer group, typically in terms of the group average permanent productivity. By contrast, our main analysis leverages variation in the physical proximity between co-workers (for examples of this type of variation see Mas and Moretti 2009 in Table 6 of their paper, Falk and Ichino 2006 and Steinbach and Tatsi 2022.)

7 relate peer pressure to the relation between managers and workers. Section 8 discusses alternative explanations. Section 9 estimates the potential improvements in productivity following the reassignment of handlers to desks. Section 10 concludes and briefly discusses the external validity of our findings.

2 Conceptual Framework

We now outline a theoretical framework to understand: (a) how physical proximity among co-workers can affect productivity and, (b) how pressure among peers can interact with (or derive from) the pressure that workers receive from their managers. Our framework is very stylised, as our intention is simply to propose a simple mechanism and highlight the resulting predictions that we take to the data. We discuss other potential mechanisms and effects both in Section 8 and at the end of this section.

Assume an organization composed of a manager (she) and N workers (each of them a he), where N is a very large number. The production y_i of worker i, $y_i = f(e_i)$, depends exclusively on his own effort $e_i \geq 0$ and we assume $f' > 0$ and $f'' < 0$.

Direct and Indirect Signals The worker's manager does not observe his production but instead receives a *direct* noisy signal $z_i = y_i + u_i$ where u_i is an idiosyncratic shock.[8] Following Mas and Moretti (2009) we assume that the manager infers worker's output using a linear projection, based partly on the observed average (i.e. across all workers) production and signal. The manager *direct* inference is therefore:

$$\hat{y}_i = \bar{y} + b(z_i - \bar{z})$$

where $\bar{y} = \sum_{i=1}^{N} y_i/N$, $\bar{z} = \sum_{i=1}^{N} z_i/N$ and $b = \frac{cov(y_i,z_i)}{var(y_i)+var(u_i)}$.

The room where workers work is organized into $\frac{N}{2}$ blocks of two contiguous desks each. This implies that each worker i has an adjacent desk that can be free or occupied by co-worker j. We assume that the occupation of the adjacent desk is a continuous variable $t_{ij} \geq 0$ (e.g. the desk may be occupied only a fraction of the time).[9]

[8] As we discuss in Section 3, the best way to interpret production in our setting is as the contribution by the handler to minimising the call queuing time. The noisy nature of the signal received by the manager is motivated by the fact that she cannot evaluate this contribution precisely without accounting for the state of the call queue at every point in time, the characteristics of the calls taken, etc. In addition, the manager may have a limited attention span that allows her to focus during short periods of time on only a few workers, further limiting her ability to monitor them.

[9] The organisation of the room implies that if $t_{ij} > 0$ then $t_{ij} = t_{ji}$ and $t_{ih} = t_{jh} = 0$, $\forall h \neq \{i, j\}$. This

The nearby presence of worker j provides the manager with an additional *indirect* signal about i's effort, p_{ij}. Our main rationale for the existence of this signal is that i's effort is observable to j (when he occupies the adjacent desk), and j's information can reach the manager with some probability. Specifically, j's information can be directly communicated to the manager or, more indirectly, contribute to i's reputation within the company which is observed by the manager. We assume that

$$p_{ij} = -P[(e_j - e_i)t_{ij}]$$

where $P' > 0$ and $P'' < 0$. One way to interpret P is as the likelihood that a negative signal (e.g. a negative anecdote mentioned by a co-worker, which damages i's reputation) about i is generated. Intuitively, P is therefore increasing in j's effort and decreasing in i's effort. The multiplicative presence of t_{ij} captures the aforementioned notion that the indirect signal only depends on these relative efforts if the adjacent desk is occupied.[10]

Manager Evaluation and Manager Pressure The manager uses both the direct signal/inference $\hat{y}_i$ and the indirect signal p_{ij} to construct an evaluation of the worker's performance q_i, where

$$q_i = \alpha\hat{y}_i + \theta_{ij}p_{ij}$$

q_i is a linear combination of the two signals, with $\alpha > 0$ capturing the average relative weight given to the direct signal. The manager further weighs the indirect signal by $\theta_{ij} > 0$ to account for the fact that she may be more likely to receive (or to give weight to) an indirect signal about i if it comes through a specific peer j. For instance, certain peers may have a stronger relation with i's manager, which implies that their perceptions (when they sit next to i) may be particularly likely to reach said manager. For simplicity, we assume that $\theta_{ij} = \theta_{ji}$.

Effort entails disutility $C(e_i, t_{ij})$, which is increasing and convex on e_i. We also allow the cost of effort to depend on the nearby presence of j, t_{ij}, where we assume that $C_{et} = \frac{\partial^2 C(e_i,t_{ij})}{\partial e_i \partial t_{ij}} > 0$ to capture a potential 'distraction effect' (Park, 2019) generated by adjacent

simplifying assumption allows us to ignore spillovers that the occupation of other desks can have on the pair of workers i and j.

[10]We make two further simplifying assumptions. First $P > 0$ in the entire domain, which implies that there is always a strictly positive probability that a negative signal is generated. Second, we abstract from strategic transmission of information. Under the interpretation that p_{ij} captures the peer (directly or indirectly) revealing his signal to the manager, this revelation is assumed to be truthful.

colleagues.[11]

Finally, each worker chooses effort to maximize

$$U(w)q_i - C(e_i, t_{ij})$$

where $U(w)$ is the utility derived from the manager's reward.[12] Note that, despite effort being costly, the manager is able to pressure the worker to exert positive effort through two channels, both operating through her overall evaluation q_i. First, higher effort improves the direct signal/inference $\hat{y}_i$. Second, higher effort decreases the likelihood of a negative indirect signal being generated, if the adjacent desk is occupied. Note that, in this second mechanism, j generates 'peer pressure' because he can transmit his signal to the manager, who in turn can reward or punish i.

Equilibrium and Predictions We study the symmetric equilibrium where $e_i = e_j$ and (given the large N) workers take the effort of non-adjacent workers (and therefore $\bar{y}$ and $\bar{z}$) as given. All proofs are in Online Appendix B.

Proposition 1 (Peer Effect is Positive)
$\frac{\partial e_i}{\partial t_{ij}} > 0$ *if and only if* $\theta_{ij} U(w) P' > C_{et}$.

Proposition 1 implies that the response of effort to the occupation of the adjacent desk is ambiguous and depends on the pressure-distraction trade-off. Intuitively, the condition that the peer effect is positive is more likely to hold when: (a) the probability of generating a negative signal from the peer is more sensitive to reductions in effort (i.e. P' is large), (b) the manager is more likely to receive the signal observed by the peer (i.e. higher θ_{ij}), and (c) the distraction effect is less severe (i.e. lower C_{et}).

[11] There is no a priori reason why the occupation of adjacent desks should be detrimental to productivity from a marginal cost perspective. If $C_{et} < 0$, workers would instead be 'motivated' by working with colleagues nearby and there would be no trade-off between the peer's ability to generate the indirect signal p_{ij} and his provision of distraction opportunities. We do not analyse the case where $C_{et} < 0$ as it is conceptually less interesting but all conclusions from the model remain valid, with the caveat that $C_{et} < 0$ by itself cannot generate Propositions 2 and 3 (see Section 8).

[12] We regard the manager's reward broadly. One specific interpretation is that w denotes a fixed wage and q_i captures the worker's probability of keeping his job (for a similar interpretation, see Mas and Moretti 2009). In practice, managers have a range of mechanisms through which reward or punish a worker, even in settings without explicit performance pay or a realistic likelihood of firing the worker (Fenizia, 2022). For instance, the manager can allocate opportunities to earn overtime on the basis of her perception of the worker's performance. The manager can also use the range of social sanctions described in Kandel and Lazear (1992), potentially even more effectively than the worker's peers. This is especially the case in settings such as the OCB, in which managers have typically previously worked as handlers and are therefore socially proximate to their subordinates.

Proposition 2 (Peer Effect and Direct Manager Pressure)
If the peer effect is positive (i.e. $\frac{\partial e_i}{\partial t_{ij}} > 0$*), then* $\frac{\partial^2 e_i}{\partial t_{ij} \partial var(u_i)} > 0$.

Proposition 2 implies that (if the peer effect is positive) effort's response to the presence of nearby colleagues is larger when the manager has a less informative direct signal of the worker's productivity. Intuitively, this makes the manager have to rely more on j's signal, increasing i's reaction to the occupation of an adjacent desk.

Proposition 3 (Peer Effect and Peer/Manager Information Link)
If the peer effect is positive (i.e. $\frac{\partial e_i}{\partial t_{ij}} > 0$*), then* $\frac{\partial^2 e_i}{\partial t_{ij} \partial \theta_{ij}} > 0$.

Proposition 3 captures the idea that the occupation of an adjacent desk increases worker's effort more when the information link between the peer j and the manager is stronger (i.e. when θ_{ij} is larger). Intuitively, this makes the manager's reward w depend more strongly on j's observation, increasing i's reaction to the occupation of an adjacent desk.

Interpretation of $\mathbf{p_{ij}}$ We have interpreted the indirect signal received by the manager, p_{ij}, as arising from j's observation of i's effort, which can, with some probability, reach the manager. An alternative though very related interpretation is that the nearby presence of j allows the manager to better evaluate i's production. Consider, for instance, a manager visually monitoring worker i and observing that i is idle. The manager may be more likely to assign weight to this negative observation when there is an adjacent worker, j, who may instead appear busy. More generally, managers may find it easier to compare production levels across adjacent workers than to evaluate their absolute levels in isolation (Lazear and Rosen, 1981). We comment further on this interpretation in Section 8.

Note that we have not allowed peers to exert pressure other than through the channel of affecting the manager's evaluation, p_{ij}. In practice, peers may have a wider range of tools to directly discipline each other (Kandel and Lazear, 1992). The predictions that we highlight in this paper would remain unchanged if we added an additional channel of 'direct' peer pressure among co-workers.

In the remainder of the paper, we examine empirically whether the reaction of workers to the occupation of adjacent desks is consistent with Propositions 1-3. Proposition 1 has been examined empirically in previous work (Falk and Ichino 2006, Table 6 in Mas and Moretti 2009). Propositions 2 and 3 are unique to a framework that incorporates the vertical relation between the worker and manager.

3 Institutional Setting

We study the effect of co-worker proximity on productivity in the Operational Communications Branch (OCB) of the Greater Manchester Police (GMP). The OCB is the GMP unit in charge of: (1) answering 999 calls from members of the public, and (2) allocating police officers to the resulting incidents.[13] These two roles are the responsibility of two separate types of workers, with (1) being undertaken by 'call handlers' and (2) being done by 'radio operators'. Our study focuses exclusively on call handlers. Throughout our sample period, all handlers were based in a single room in a building in the Trafford area of Manchester.[14]

Nature and Allocation of Work The role of call handlers is to answer 999 calls, question and if necessary provide guidance to the callers, decide whether an official incident must be created and, if so, categorise the incident and record in an electronic log any information deemed relevant. The categorisation of the incident includes assigning a grade (determining the official urgency of the incident) and an opening code (describing horizontally the type of issue that the incident relates to). Handlers' work is strictly individual in that there is very little scope for giving or receiving help from other handlers.[15]

Incoming calls are assigned to handlers using a standardised computer system, as follows. If no handler is available when a call arrives, it joins the back of a call queue. A newly available handler is then allocated the call at the front of the queue. If the call queue is empty and several handlers start to become available, they form their own queue. The system then matches the handler at the front of the handler queue with the next incoming call. Following the completion of a call, a handler then indicates his status as 'not ready' (which allows the handler to take a break) or instead as 'ready to receive new calls'. Ready handlers will immediately receive a call if the call queue is not empty. Handlers can learn the status of the call queue from large screens located throughout the room.

[13]The UK 999 emergency line is the equivalent of 112 in the European Union and 911 in the United States.

[14]Throughout our sample period, radio operators were located separately from call handlers. In a companion paper (Battiston et al., 2021) we study whether the ability of handlers and operators to communicate in person when co-located allowed them to operate more efficiently. Our focus in Battiston et al. (2021) is on the period prior to 2012, when handlers and operators were (sometimes) based in the same location. By contrast, we focus in the current paper on the period after 2012, in which handlers and operators were never co-located.

[15]The main reason for this is that other handlers will typically be themselves busy dealing with their own calls, and it is not considered acceptable to interrupt colleagues in the middle of their calls. If handlers need help to deal with an incident, they can ask one of the handler supervisors in the room. Unfortunately, our data does not include the identity of the specific supervisors that are present at any one point in the handlers' room.

The system of allocating calls that we have just described has two important consequences for our study. First, all handlers working at one point in time are engaged in 'team' production, as they are jointly responsible for dealing with a single call queue. Potential free-riding within this large team follows from the fact that a handler taking long breaks between calls will not be contributing to decreasing the length of the call queue, thereby increasing his colleagues' workload. Second, two workers on duty at the same time will not differ (in expectation) in the amount and type of work assigned to them by the system, or in the number and characteristics of the colleagues that share their workload. Therefore, controlling for the (narrowly-defined) time period during which a handler is working should largely account for the work conditions being faced by that handler.[16]

Seating Architecture Figure A1 displays a screenshot of the actual Trafford room in which the handlers were based during our sample period.[17] As we can see from the figure, the desks were arranged in rows of differing length and mostly facing in the same direction. Physical barriers such as computer monitors and desk screens implied that workers could only imperfectly observe the colleagues in the rows in front or behind, at least without standing up. On the other hand, workers on row-adjacent desks could easily observe and monitor each others' behaviour, as well as potentially engage in casual conversation and distract each other. Therefore, in this paper our main focus is on how workers react to their row-adjacent desks becoming occupied or disoccupied. However, we do also investigate empirically how handlers react to the seats in their row behind or their row in front being occupied. Consistently with the framework in Section 2 we initially posit that the effects on productivity could be either positive (i.e. peer pressure) or negative (i.e. distraction).[18]

[16]In Battiston et al. (2021) we provide extensive evidence that, after controlling for hour (i.e. year/month/day/hour of day) fixed effects, the characteristics of incoming calls are uncorrelated with the characteristics of the handlers assigned to these calls by the system. We provide complementary evidence in Figures A5 and A6.

[17]The screenshot is taken from the first episode of the documentary series 'The Force Manchester', broadcast in the United Kingdom by the Sky 1 TV channel. During very busy periods some handlers would also work from an additional adjacent room (not visible in Figure A1) separated from the main room by a glass panel. As we discuss below, our research design includes a full set of shift identifiers, where a shift is a combination of a specific handler and a specific date. Because handlers (almost) never changed their desk during a shift, these shift identifiers perfectly account for all the characteristics of the desk where a handler was based on a particular day, including whether the desk was in the main room or in the adjacent room.

[18]Note that the characteristics of our workplace imply that the set of co-workers that a handler can observe from his desk largely coincides with the set of co-workers being able to observe his. Therefore, we are not able to exploit any asymmetry between observable and observing sets to help isolate the mechanism at work (Mas and Moretti, 2009).

Seating Allocation The assignment of workers to desks took the form of 'hot-desking', as follows. Handlers were free to sit in any desk that was available at that time that they started their shift.[19] Once seated, however, they were expected to remain in their positions throughout the full duration of the shift.

The non-random assignment of handlers to desks requires a careful empirical design. We cannot, for instance, regard handlers who typically sit by themselves as good counterfactuals of handlers who tend to sit alongside other colleagues. Similarly, the same handler may choose desks with different exposure to colleagues in a way that is correlated with shocks to his productivity on that specific day. As we discuss in Section 4, our empirical strategy takes a handler on a desk as fixed within a shift (a realistic assumption in our setting) and exploits the high-frequency of the data to estimate the immediate reaction of that handler to the sudden occupation or disoccupation of the desks adjacent to his.

Measures of Productivity A core objective of the organisation we study (and particularly of the call handling unit) is to minimize the time that the average call spends waiting in the queue. Consequently with this objective, we use two measures of productivity: (1) the number of calls answered by a handler during a half-hour period, and (2) the number of minutes in a half-hour that the handler spends on the phone with callers. As is common in organisational studies from the field, these measures do not fully account for every dimension of performance that our organisation is concerned with. Despite this, we believe that the number of calls and the time on the phone are measures of productivity that are well-suited to the purposes of this study, for several reasons. First, these measures are regularly monitored by the organisation and statistics on the number of answered calls and waiting times are reported to the public (e.g. in the GMP website and its annual reports). These measures are also observed and evaluated by the handler's evaluator (see below). Second, previous studies based on call-center workers have used the number of calls as the main productivity

[19] Handlers' shifts were staggered to maintain continuity of service and therefore only a small proportion of handlers started or ended their shift at the same time. Figure A2 displays the distribution of starting and end time of the shifts, in half hour intervals. There are no shifts starting between 12 A.M. and 6 A.M., or ending between 7 A.M. and 10 A.M., but otherwise there is positive density throughout the workday. The relative smoothness of the incomings and outgoings of handlers is the result of three features of the working environment. First, the relatively sophisticated model that the GMP uses to predict the number of calls and therefore the number of needed handlers at any point in time implies that a sudden large turnover in the room is suboptimal. Second, handlers can only end their shift following the completion of a call, and call duration is to a large extent outside their control. Lastly, the GMP provides some flexibility to handlers in terms of their starting times, to account for contingencies such as those caused by traffic conditions.

measure (Batt et al. 2000, Bloom et al. 2015). Third and most important, (1) the number of calls taken represents the main channel through which a handler's behaviour exerts externalities on his colleagues, as discussed above, and (2) the time spent on the phone is the variable that can be most easily monitored by nearby co-workers.[20]

We complement our baseline 'quantity' measures with other performance measures that more directly reflect how handlers deal with the calls that they take. For instance, we use the response time of the incident (i.e. the time between the incident creation by the handler and the arrival of response officers to the incident's location). In addition we study whether, for the subset of calls reporting crimes, a suspect was identified. These 'quality' dimensions of performance do not generate obvious direct externalities on other handlers, and are difficult to observe by nearby peers.[21] Furthermore, our quality measures are not shaped exclusively by handlers, but instead reflect the input of other GMP workers, such as radio operators and police officers (Blanes i Vidal and Kirchmaier 2018, Battiston et al. 2021). Nevertheless, we use these quality measures to study whether any potential improvement in quantity caused by co-worker proximity is at the expense of the quality of work.

Supervisors and Performance Evaluators At any point in time, there were around twelve to seventeen individuals with the job title of handler 'manager' in the OCB. Each manager performed two related but conceptually different roles, which in this paper we distinguish with the labels of 'supervisor' and (performance) 'evaluator'.[22]

First, the OCB handlers' room always had to contain two to three managers, whose responsibility was to keep track of the state of the call queue, visually monitor handlers' work and provide them with support if necessary. We refer to managers performing these duties as acting in their role as 'supervisors'. As is the case with handlers, managers acting in their supervisory functions worked in shifts and followed standard rotation patterns.

Second, each manager was assigned an average of twelve handlers, for whom she performed the additional role of (performance) 'evaluator'. Performance evaluators were in charge of evaluating and supporting the performance of their assigned handlers *over the*

[20]Conceivably, handlers might respond to the presence of nearby colleagues by either taking more calls but spending little time on each one, or by dragging the duration of each call. Therefore, we also study in Table A5 any potential effects on the average call duration.

[21]To a large extent, evaluating the contribution of a handler to lowering response time or improving the clearance of crimes is also difficult for handlers' evaluators. This is both because these measures reflect the contribution of many workers, and because they are not regularly computed by the GMP.

[22]Note that these are labels created by the authors of this paper, to describe the economic content of the roles that managers undertake. In practice, the managers in the OCB are not referred to by these labels.

medium term. To do this, they regularly: (1) examined their handlers' objective performance measures (e.g. the average number of calls taken per hour or the percentage of time on the phone) during the previous weeks or months, (2) audited their assigned handlers' calls to monitor and ensure quality, and (3) had individual formal and informal meetings with their handlers, in which past performance, future objectives and the state of the working environment were discussed. In addition, performance evaluators were also responsible for more bureaucratic tasks such as approving handlers' vacation requests.

Incentives As is common in public sector organisations, the handlers in the OCB did not face highly-powered incentives (Fenizia, 2022). Despite this, handlers attached importance to their performance evaluators' perception of their performance, for two reasons. First, the views of their managers (and their corresponding reports) could influence their pay and job security.[23] Second and perhaps as importantly, performance evaluators could exert informal pressure on underperforming subordinates, using the same informal mechanisms that co-workers often use to exert peer pressure on each other (Kandel and Lazear, 1992).

It is also important to note that the perceptions of evaluators contained an important subjective component. Managers routinely accessed objective statistics such as the average number of calls per hour. However, these statistics were not deemed sufficient to fully evaluate the performance of a handler. For instance, a handler might have been assigned to shifts in which the call queue was often empty, resulting in low calls per hour through no fault of his own. More generally, aggregate statistics could not lead to a fully accurate evaluation given that managers were not able to fully account for the average working conditions being faced by the handler. The insufficiency of objective measures in turn generated a complementary role for subjective perceptions, based on the line manager's direct observations or on the general reputation of a handler among those with whom the performance evaluator interacted.

Co-Evaluated Handlers Throughout this paper, we refer to handlers assigned to the same evaluator as 'co-evaluated' handlers. Our discussions with OCB workers suggest that handlers are typically aware of who their co-evaluated handlers are.

[23]For example, managers' views affected the choice of handlers for 'difficult' shifts (e.g. those coinciding with important football events) which were compensated with overtime pay. In terms of job security, during this period the countrywide reduction in police budgets implied that the GMP reduced the total number of handlers through both redundancy and redeployment to other posts. Performance evaluators were perceived as transmitting information to the final decision-makers about who the most efficient handlers were.

The assignment of handlers to evaluators was not designed to be 'random', although in practice it had an important idiosyncratic component. For example, a new handler would typically be assigned to the evaluator with the lowest number of current evaluatees. The sudden departure of several evaluatees of the same evaluator might prompt a reassignment of handlers across evaluators to reestablish approximate parity. In Table A1, we test whether co-evaluated handlers are more similar to each other than to other handlers across a range of demographic, shift, and desk choice characteristics. We do not find any dimensions in which co-evaluated handlers resemble each other disproportionately.

An exception is the coincidence in the shifts of co-evaluated colleagues. We take in Figure A3 a sample of handlers in half-hour periods, and display the distribution of the share of handlers working at that point in time that are co-evaluated colleagues of the focus handler. We find that, while handlers are more likely to coincide with their co-evaluated colleagues than with other colleagues, the difference is small in magnitude.[24]

Two last points. First, co-evaluated handlers did not operate as a 'team', in the economic sense of being jointly responsible for a common output. Instead and as discussed earlier, it was *all* handlers working at the same point in time that operated as an economic team. Second, there was no expectation of relative performance evaluation in this setting: evaluators were not expected to evaluate the performance of their assigned handlers relative to each other but instead from an absolute perspective.

4 Data and Empirical Strategy

In this section we present and discuss the dataset and main variables of the paper. We also outline the baseline empirical strategy to estimate the effect of co-worker proximity on handler productivity.

[24]To reach this conclusion, we plot in Figure A2 both the observed distribution of the share of handlers in the room that are co-evaluated handlers, and the distribution that would arise if the handlers in our dataset were randomly allocated to shifts. We find that the two distributions are remarkably similar, although the observed distribution is slightly to the right of the counterfactual random distribution. For instance, random allocation would imply that, in 22% of observations, the percentage of handlers that are in the room that are co-evaluated lies between 0 and 2.5. In our data, we find that the $[0, 2.5]$ percentage occurs for 17% of observations. Unfortunately, we are not able to study empirically whether the supervisor in the room when a handler is working is more likely to be his performance evaluator, as opposed to a different manager. This is because we do not observe the rotation patterns for managers in their supervisory role.

Dataset We follow the shifts worked by OCB call handlers between February 2012 and November 2014. Our dataset is constructed using the computerised shift logs, which automatically record every change in handler activity (e.g. the end of a call and the start of 'not ready' time) together with the exact time at which the change occurred. We use these logs to calculate the number of calls and the total number of minutes that a handler spends on the phone for every half-hour period within his shift.

Thus, our baseline dataset is organized as a panel of *shift* × *half-hour* periods, where a shift is the combination of an individual handler working on a specific date (i.e. John Smith on the 1st of December 2012). For each shift we observe the number of the desk at which the handler sat, and we use this number and digitised floorplans to calculate the handler's spatial position inside the room.[25]

We use a dataset of incidents to add further information to the baseline dataset. For instance, we compute the average grade (i.e. official urgency) and type of incident (including whether it is a crime) of the calls taken by each handler in each half-hour period. We also calculate the average response time, which is the time between incident creation and arrival of the response officers to the incident location. For incidents classified as crimes, we record whether suspects were identified or detained. Lastly, we add HR information such as handlers' demographics and career information to the baseline shift/half-hour dataset.

Our final dataset includes 343 handlers. During a total of 71,673 shifts and 1,168,863 shift/half-hour periods, these handlers answered a total of 3,124,059 calls. Table A2 cross-tabulates the observations in our dataset based on the number of *adjacent* desks, and *adjacent and occupied* desks.[26] Note that 72% of observations involve handlers sitting in desks that have only one adjacent desk. In 64% (respectively, 24%) of shift/half-hours, handlers are sitting alongside one other (respectively, no other) colleague. In 45% of the observations with two adjacent desks, both of these desks are occupied. Table A3 provides summary statistics of the main variables in the empirical analysis.

[25] We constructed floorplans by combining spreadsheet information of the seat identifiers with our own measurements of the seat positions within the room. In this way, we identified the desks adjacent to every position. We then overlapped a grid with x-y coordinates and used this to calculate the distance between seats. We used this distance, for instance, to calculate how far a handler is sitting from the closest supervisor position (Section 6).

[26] Note that a seat is considered occupied in Table A2 if it was used by a handler for at least one minute during a half-hour period. Throughout the rest of the paper, we instead use a continuous measure of occupation that captures the minutes in the half-hour period during which the seat was actually occupied.

Intuition of Empirical Strategy We exploit the granularity of our dataset to study how productivity reacts to high frequency variation in the occupation of adjacent desks. Remember that handlers do not change their desks in the middle of their shifts. Consider a handler sitting alongside a colleague and imagine that, in the next half-hour, the colleague finishes his shift and the desk adjacent to the focus handler becomes unoccupied. Under the assumption that the end of the colleague's shift does not coincide with an unrelated shock to the productivity of the focus handler, we can identify the causal effect of the adjacent seat occupation. Notice that any confounding shock would have to be both sudden (in a first-differences regression with high-frequency data) and idiosyncratic (in a regression controlling for common shocks affecting all handlers working during the specific half-hour in which the seat became unoccupied).

Our empirical strategy also exploits *increases* in adjacent seat occupation. The assumption here is that handlers starting their shifts do not choose to sit next to handlers experiencing a sudden and idiosyncratic change in productivity, relative to other handlers in the room. In Section 5 we provide empirical evidence in support of our identification assumption.

Baseline Estimating Equation Consider the productivity y_{sh} of a handler in the half-hour period h of shift s, where s absorbs the identity of the handler and the date in which the shift started (e.g. 'John Smith/01-12-2012'). Make y_{sh} depend on the following factors:

$$y_{sh} = \beta Occupied_{sh} + \gamma_s + \theta_h + \lambda_{t(sh)} + \gamma MW_{sh} + \epsilon_{sh} \tag{1}$$

where γ_s is a shift identifier, θ_h is an identifier for the half-hour period within the shift and $\lambda_{t(sh)}$ is an identifier for the half-hour t (i.e. year/month/day/half-hour) corresponding to the sh combination.[27]

$Occupied_{sh} \in [0, 2]$ is the main independent variable of interest. It captures the number of desks row-adjacent to the handler in shift s *that were occupied* in period h. We allow $Occupied_{sh}$ to take non-integer values when an adjacent seat changes in occupation in the middle of a period. The variable then reflects the percentage of the period when such occupation occurred. Measuring the occupation of adjacent desks in a continuous way implies that we also need to control for the number of minutes that the handler actually worked in

[27] For instance the fourth half-hour of shift 'John Smith/01-12-2012' may correspond to the half-hour 15:00-15:30 1st December 2012.

the half-hour period, MW_{sh}. With this control, we rule out any effects driven by half-hour periods when the handler was not fully active (e.g. his first or last periods in the shift).

The controls in (1) account for several sources of unobserved heterogeneity. First, the inclusion of γ_s implies that only within-shift variation is exploited. This eliminates potential confounders such as inherently less productive workers (or workers feeling unproductive on a particular date) choosing isolated desks upon arrival. It also controls for all features of a desk (e.g. the amount of noise or the proximity to supervisors) which might be independently affecting productivity. Importantly, it also captures the number of desks that are adjacent to the one occupied during the shift. Because desks are fixed within a shift, variation in $Occupied_{sh}$ is instead due to *other* workers occupying (or not) adjacent seats. Second, θ_h accounts flexibly for average changes to productivity within a shift (e.g. handlers becoming tired as time passes). Lastly, $\lambda_{t(sh)}$ accounts for productivity shocks that are time-varying but affect all handlers in the room equally (e.g. environmental factors, the number of on-duty colleagues sharing the workload or the condition of the call queue).

Even in the presence of such a rich set of controls, the absence of experimental variation requires caution in the interpretation of β. A potential bias may arise if, for instance, handlers are more likely to be alone in periods when they are unproductive, relative to themselves in that specific shift, to the average handler in that specific period and to the average within-shift period effect. To overcome this concern we exploit high-frequency variation in $Occupied_{sh}$, resulting from the sudden arrival or departure of colleagues from adjacent desks. We do this by taking within-shift s differences in (1). Our baseline estimating equation becomes:

$$\Delta y_{sh} = \beta \Delta Occupied_{sh} + \pi_h + \mu_{t(sh)} + \gamma \Delta MW_{sh} + \Delta\epsilon_{sh} \tag{2}$$

where $\pi_h \equiv \Delta\theta_h$ is an identifier for the average change in productivity between consecutive within-shift periods and $\mu_{t(sh)} \equiv \Delta\lambda_{t(sh)}$ is an identifier for the average (across all handlers working contemporaneously in the room) change in productivity between consecutive half-hours. Standard errors are clustered at the shift level.

As discussed earlier, estimating (2) by OLS provides consistent estimates of β under the assumption that the desks adjacent to the desk where a handler is working during a shift do not change in occupation levels in periods of sudden change in productivity of the focus handler, relative to his average productivity in that shift, to the OCB-wide change in productivity between $t(sh)$ and $t(sh) - 1$ and to the average change in productivity among handlers entering the within-shift period θ_h. We provide several tests of this assumption below.

5 The Average Peer Pressure Effect

In this section we show and discuss the baseline results of the paper. We also provide empirical evidence in support of the identification assumption. Results from this section relate to Proposition 1 of the theoretical framework and thus we aim to establish if the overall effect of peer proximity is positive or negative.

Baseline Estimates Columns 1 and 2 of Table 1 estimates (2) and displays the baseline results of the paper. We find that time on the phone is 6% higher for every adjacent seat that becomes occupied (as discussed, this is up to a maximum of two). The number of calls is 3.5% higher for every adjacent occupied seat. In the framework of Section 2, the finding of positive coefficients provides support for the pressure effect being larger in magnitude than any potential distraction effect.[28]

Dynamic Effects of Changes in Occupation Equation (2) imposes the effect of a change in occupation to occur exclusively in the exact half-hour in which the change in occupation takes place. In this subsection, we instead investigate the presence of anticipatory and deferred effects. We do this by introducing a set of lead and lag variables to the main specification:

$$\Delta y_{sh} = \sum_{j=-4}^{4} \beta_j \Delta Occupied_{s(h+j)} + \pi_h + \mu_{t(sh)} + \gamma \Delta MW_{sh} + \Delta\epsilon_{sh} \tag{3}$$

where β_4 (respectively, β_{-4}) represents the index handler change in productivity in response to the occupation of an adjacent desk two hours (i.e. four half-hour periods) into the future (respectively, past), and the other coefficients are interpreted similarly.

The core objective of the lead analysis is to study whether productivity was already trending prior to the change in adjacent seat occupation. This analysis represents a test of the identification assumption, as the existence of such a 'pre-trend' would suggest that

[28] Our baseline panel dataset is constructed at the shift/half-hour period. In Table A4 we investigate the robustness of the baseline results to decreasing or increasing the duration of the time period. We find very similar coefficients (always highly statistically significant) when using either a shift/15 minutes panel or a shift/hour panel. Overall, the results do not appear to depend strongly on the frequency of the panel.

the change in occupation might be endogenous to shocks to the productivity of the focus handler. The main objective of the lag analysis is to examine whether the Table 1 immediate reaction of productivity to the change in adjacent seat occupation is sustained over longer horizons.

Figure 2 plots the estimated coefficients from (3). The first finding is that productivity does not appear to trend strongly prior to the change in occupation. As discussed earlier, this for instance rules out colleagues choosing to sit next to handlers whose productivity was already going up (e.g. to avoid being subjected to distracting chat) or down (e.g. to instead seek distraction opportunities). Instead, Figure 2 reveals that any potential confounding shock to productivity should have coincided *exactly* with the half-hour period in which the change in occupation ocurred.

The second finding from Figure 2 is the absence of apparent lagged effects. The fact that there are no lagged positive effects suggests that the immediate reaction to the change in occupation is not followed by similar changes over future periods. The absence of negative effects indicates that the immediate change in productivity is largely persistent. We can observe this persistence more clearly in Figure A4, where we plot the cumulative estimates corresponding to the Figure 2 coefficients. For instance, the cumulative effect at $t = 2$ (i.e. one hour after the period of the change in occupation) is equal to $\sum_{j=-2}^{4} \hat{\beta}_j$ (i.e. from four periods before the change to two periods after the change). We find that the change in productivity remains broadly constant and statistically significant until at least two hours after the change in occupation.

To summarise, Figures 2 and A4 reveal the existence of a sharp discontinuity in productivity that coincides exactly with the change in occupation of adjacent desks. We interpret this sharp discontinuity as evidence in support of the identification assumption. In addition, Figures 2 and A4 suggest that the effect is highly persistent, as it is still present more than two hours after the initial shock.

Further Tests of Identification Assumption A potential productivity shock correlated with the change in adjacent seat occupation could be caused by a change in the type of calls that the focus handler receives. The description in Section 3 of the assignment of incoming calls to available handlers suggests that this is an unlikely confounding effect. Nevertheless, we confirm the absence of this confounding effect in Figures A5 and A6. We study there whether the average official urgency of the calls assigned to a handler appears to be correlated with the change in adjacent seat occupation.[29] Contrary to Figures 2 and 3, we do not observe any change in the average official urgency coinciding with the change in occupation.

As we discuss above, a potential source of endogeneity when exploiting increases (although not decreases) in occupation consists of colleagues at the beginning of their shift choosing to sit alongside handlers who, in that specific half-hour period, are subject to a sudden and idiosyncratic productivity shock. Because this confounding effect relies on colleagues' ability to choose where to sit, we posit that it should be larger in magnitude when most seats are empty and handlers starting their shift enjoy ample choice. On the other hand, the potential bias should be smaller when the room is very busy, and arriving handlers have very little discretion in where to sit.

We can therefore provide an indirect test of the identification assumption by interacting the baseline effect in (2) with dummies for the four quartiles of room occupation. We plot the corresponding coefficients in Figure A7. We find very similar coefficients regardless of whether arriving handlers are constrained in their desk choices or instead have a lot of discretion. This suggests that the 'endogenous choice of seat' confounding mechanism does not appear to be empirically relevant. We interpret the evidence here as providing support for the identification assumption.

Individual-Level Effects Columns 1 and 2 Table 1 and Figure 2 reveal that the *average* effect of adjacent seat occupation is positive. However, it may still be the case that any potential distraction effect outweighs the pressure effect for a subset of the handlers. This (hypothetical) distraction effect for some handlers may not be apparent in our estimates if it is more than offset by the existence of a few handlers experiencing large productivity gains when their adjacent seats are occupied. In this subsection, we therefore estimate the effect of co-worker proximity on productivity separately for each of the handlers in the data. We do this by interacting $\Delta Occupied_{sh}$ with a set of dummies $\eta_{i(s)}$ taking value one for the handler i corresponding to shift s:

$$\Delta y_{sh} = \sum_{i(s)=1}^{343} \beta_{i(s)}(\Delta Occupied_{sh} \times \eta_{i(s)}) + \pi_h + \mu_{t(sh)} + \gamma \Delta MW_{sh} + \Delta\epsilon_{sh} \qquad (4)$$

[29] There are three main official levels of urgency. We display the coefficients from regressions where the dependent variables are the shares of highest and lowest grades. While the grades are assigned by the handlers themselves, discussions with GMP workers suggest that there is very little discretion in this assignment. The rigid set of instructions that handlers must follow imply that the urgency of an incident is best understood as a variable that is pre-determined to the involvement of the handler.

Figure A8 plots the distribution of the estimated $\beta_{i(s)}$ coefficients.[30] In Figure A9, we display only the coefficients that are statistically different from zero at the 10% level. We can see that the vast majority of handlers are positively affected by the presence of co-workers. For instance, the estimated $\hat{\beta}_{i(s)}$'s for the number of calls are positive for 80% of the handlers, and around half of these positive coefficients are significant at the 90% confidence level. On the other hand, only two handlers (out of around 300) display a negative and significant $\hat{\beta}_{i(s)}$.

Overall, Figures A8 and A9 support the idea that the baseline effect in Table 1 is not driven by a few handlers with abnormally high responses to our treatment, but is instead widely present among our sample of handlers.[31]

Effects on Quality In this subsection, we study the effect of adjacent seat occupation on other dependent variables, arguably more related to the 'quality' with which handlers deal with their incidents.[32]

We study three variables: (1) the (change log) in average response time of the calls received during the half-hour period, (2) the (change log) in average allocation time of the calls, and (3) the (change log) share of crimes for which a suspect is identified or detained. We posit that these variables partially reflect the quality of a handler's work because a more able and committed handler will extract the caller's information faster and more comprehensively, which will translate into a faster and more successful police response.

Note that in our setting the outcomes outlined above are not immediately observed by nearby colleagues. In addition, there is no obvious element of free-riding (along these dimensions) among colleagues working in the room at the same time. We study potential effects on these variables because a handler who is observed by his colleagues may allocate effort towards improving observable outcomes (such as the number of calls and time on the

[30] Note that we omit $\Delta Occupied_{sh}$ from (4). As a result, the estimated $\hat{\beta}_{i(s)}$ can be interpreted in absolute terms, as opposed to relative to an omitted individual.

[31] Instead of estimating different effects depending on the identity of the focus handler, we can also interact the effect of the adjacent seat occupation with dummies for the identity of the *peer*. Conceptually, different peers may have different effects on the same focus handler. For instance, some peers may be noisier or more willing to engage in distracting conversations, while other peers may be more willing to monitor and put pressure on their colleagues. In Figures A10 and A11, we display the distribution of effects on the basis of the peer. Again, we find that the overwhelming majority of the effects are positive, especially those effects that are statistically significant at the 10% level.

[32] Note that this analysis is possible because of our earlier finding that calls' characteristics are exogenous to the adjacent seat occupation, as predicted by the existence of a common call queuing system. The fact that calls are on average identical across different levels of adjacent seat occupation implies that we can potentially attribute different call outcomes to being caused by the occupation itself.

phone) and potentially away from non-observable outcomes.

We also examine potential effects on the average call duration. In principle, handlers might respond to the presence of nearby colleagues by either taking more calls but spending little time on each one, or by dragging the duration of each call. We restrict the sample to half-hours in which the handler took at least one call, and take the average call duration as the dependent variable.

Table A5 displays the results of estimating the baseline specification with the (change log) quality measures above as dependent variables.[33] Throughout, we find non-significant effects, which we interpret as indicating that the quality of the handler's work is not affected by the presence of nearby colleagues.[34]

Increases vs Decreases in Occupation Equation (2) imposes the effect of a change in occupation to be invariant to its sign. In Columns 3 and 4 in Table 1, we instead allow for different effects depending on whether $\Delta Occupied_{sh}$ is positive or negative. We find that both types of effects are positive and statistically significant. The implication is that productivity increases when a vacant adjacent seat becomes occupied *and* it also decreases when an adjacent worker finishes his shift and leaves. The coefficients are statistically different from each other, with the effect of an increase in occupation being larger than the effect of a decrease in occupation.[35]

We next estimate the effect of adjacent seat occupation non-parametrically, splitting non-zero values of $\Delta Occupied_{sh}$ into intervals of equal size, and regressing:

$$\Delta y_{sh} = \sum_{j=1}^{8} \beta_j \Delta Occupiedj_{sh} + \pi_h + \mu_{t(sh)} + \gamma \Delta MW_{sh} + \Delta \epsilon_{sh},$$

where $\Delta Occupiedj_{sh} = 1$ if the change in period sh falls into interval j. For instance,

[33] Note that the allocation and response times are only relevant for calls classified as official incidents, and requiring an actual police response. The clearance dummy variable is only relevant for incidents classified as crimes. These restrictions explain the lower number of observations in Table 3, relative to Table 2.

[34] The coefficients in Table 1 indicate that handlers increase their time on the phone by 6% and the number of calls by 3.5%. It might seem from comparing these coefficients that the average call duration must have increased. The analysis in Table A5 includes only half-hour periods in which at least one call was taken, and the regression gives equal value to all half-hours regardless of the number of calls taken by the handler. These differences explain the qualitatively different findings in Table A5, relative to Table 1.

[35] One potential explanation for this difference is in terms of 'the technology of shirking'. An isolated handler who is shirking and in 'not ready' status can quickly press 'ready' and immediately receive a call (if the call queue is not empty) when he is suddenly observed by an arriving colleague. On the other hand, a handler in the middle of a call who eyes the departure of a nearby colleague and intends to start shirking must first complete his current call.

$\Delta Occupied8_{sh} = 1$ if, in the current half hour, the handler changes from not having any nearby colleague to having more than 1.5 nearby colleagues over the half-hour period.[36]

We display the estimated coefficients in Figure A12 and find that the effects are monotonic and broadly linear. We can also see in the figure that the effects are economically large. For instance, moving from having no nearby colleagues to having more than 1.5 nearby colleagues increases the number of calls by 10%.

Seats in the Row Behind and Seats in the Row in Front To conclude this section, we expand the range of seats under study. As we mention in Section 3, the presence of computer screens and dividing panels implies that handlers are not as easily monitored from other rows as they are from the adjacent seats in the same row. This is the reason that we have so far only studied the effect of row-adjacent seats' occupation. Nevertheless, we study now whether handlers situated directly behind or directly in front of the focus handler may also have a, perhaps smaller, effect on his productivity. We repeat the baseline estimation (2) but also including the change in occupation of the seats directly in the row in front of and behind the focus handler. We define 'directly' as immediately behind (or in front), plus one position in diagonal. Therefore, a maximum of three seats are considered to be behind (or in front).

Two conclusions arise from the results in Columns 5 and 6 Table 1. First, the coefficients for the positions behind and in front are positive and statistically significant. Second, they are much smaller than the effect of adjacent seats' occupation. Overall, we conclude that handlers finely regulate their levels of effort to colleagues' degree of visibility of their work.

6 Peer Pressure and Direct Manager Monitoring

The previous section has shown robust evidence that the average effect of peer proximity on handler productivity is positive, consistently with Proposition 1 of the conceptual framework in Section 2. We now examine the empirical evidence regarding Proposition 2, which predicts

[36] To be clear about the construction of these dummies, the $[1.5, 2]$ dummy takes value one when the handler moves from having 2 empty adjacent seats to having at least 1 adjacent seat occupied for the full half-hour and the other adjacent seat occupied for 15 minutes. Equivalently, it also takes value one when the handler moves from having 2 empty adjacent seats to having both adjacent seats occupied for at least 20 minutes. Any other combination where the number of minutes corresponding to an adjacent seat occupied is more than 45 (across the two half-hours corresponding to the two adjacent seats) will result in the dummy taking value one.

that handlers will respond more strongly to the presence of nearby colleagues when their managers' *direct* ability to observe their performance is lower. The intuition is that, lacking a precise direct signal of the worker's performance, the manager will assign higher weight to the indirect signal that she can obtain through the worker's peer.[37]

Manager Monitoring and the Distance to the Supervisor Desk We test Proposition 2 by taking advantage of the fact that, in the OCB room, supervisors do not typically monitor each desk position with the same intensity. Instead, supervisors are based at their own desks, and as a result are much better able to observe the performance of workers sitting nearby than the performance of workers on the other side of the room.[38] In Figure 1 we display this idea with a stylised representation of the OCB room which includes both handler positions and supervisor positions.

Our dataset contains information about the seats designated as supervisor positions.[39] We convert the OCB floorplan into a matrix in the (x, y) format and calculate the euclidean distance between each handler desk and the closest supervisory position, $Distance_s = \sqrt{(x_s - x_{m(s)})^2 + (y_s - y_{m(s)})^2}$, where x_s and y_s are the coordinates corresponding to the desk where the handler is sitting during shift s, and $x_{m(s)}$ and $y_{m(s)}$ are the coordinates of the closest supervisor desk.[40]

We now examine empirically the relevance of $Distance_s$, in terms of predicting the supervisor monitoring ability and the associated worker performance. To do this, we restrict the sample to including only the time periods in which the seats adjacent to a handler are unoccupied. We then estimate the equation below to study whether handlers exert less effort

[37] An alternative mechanism generating this prediction is that, in a setting with a convex effort cost, workers exerting less effort (because they are not closely observed by their managers) have a higher potential to increase their effort following the arrival of a peer.

[38] During our visits, supervisors were often sitting at their desks, sometimes standing around their desks (perhaps in conversation with other OCB workers) and occasionally walking around the room. Overall, we concluded that the closer a handler sat to the supervisor desk, the better the supervisor was able to observe the handler's work.

[39] Unfortunately, we do not have any information regarding the supervisors' activities. For instance, we do not know the identity of the specific managers who are on duty performing the supervisory roles. We do not even know how many supervisors there are in the room during a specific half-hour, or which supervisory desks are being used during that period. As a result, our measure of distance to the closest supervisory position should be interpreted as capturing the supervisor's monitoring abilities with non-negligible measurement error.

[40] Our constructed floorplan is not fully to scale, which prevents us from measuring distance in metric units and is likely to introduce further measurement error in the handler-supervisor seat distance variable.

when sitting further from their supervisors:

$$y_{sh} = \alpha Distance_s + \eta_{i(s)} + \theta_h + \lambda_{t(sh)} + \gamma MW_{sh} + \epsilon_{sh}, \tag{5}$$

Note that (5) is in levels rather than in within-shift changes as, within shifts, handlers do not change desks and the variable $Distance_s$ is therefore fixed. The introduction of handler fixed effects $\eta_{i(s)}$ implies that we are comparing the productivity of the same handler on shifts where he is sitting at different distances from the closest supervisor. The introduction of half-hour fixed effects $\lambda_{t(sh)}$ implies that we are comparing handlers working at the same point in time, but in different areas of the OCB room and therefore at different distances from the closest supervisor.

In Figure A13 we find that handlers sitting far away from the supervisory desks spend less time on the phone and take less calls. Note that, despite our extensive array of controls, the absence of within-shift high-frequency variation implies that we cannot interpret the estimates here as causal effects. It is conceivable, for instance, that handlers determined to work less hard during a specific shift choose to place themselves as far as possible from their supervisors. Nevertheless, the evidence in Figure A13 is at least consistent with the intuition that managers are better able to observe and monitor handlers located nearby. Overall, we interpret Figure A13 as validating the notion that the distance to the closest supervisor can represent an empirical proxy for the informativeness of the manager's signal, $var(u_i)$, that forms the basis of Proposition 2.

Peer Pressure as Substitute of Direct Manager Pressure We now test Proposition 2, which predicts that peers will have a stronger effect on handlers' productivity when supervisors' ability to monitor is weaker. To test this, we expand the baseline regression by including the interaction between $\Delta Occupied_{sh}$ and the distance to the closest supervision position. The estimating equation becomes:

$$\Delta y_{sh} = \beta_1 \Delta Occupied_{sh} + \beta_2 (\Delta Occupied_{sh} \times Distance_s) + \pi_h + \mu_{t(sh)} + \gamma \Delta MW_{sh} + \Delta \epsilon_{sh},$$

We find in Columns 1 and 2 of Table 2 that the estimated coefficients for the interaction are positive and significant, indicating that workers react more strongly to the occupation of an adjacent seat when they are sitting further away from the supervisory position.

We provide intuition regarding the economic magnitude of the interaction coefficient in Figure A14. We display there the five coefficients that result from interacting $\Delta Occupied_{sh}$

with five bins for different distances between the handler and the closest supervisor position. We find that handlers sitting right next to a supervisor increase the time on the phone (respectively, the number of calls) by 3.8% (respectively, 2.4%) following the occupation of an adjacent desk. These effects are more than twice higher (10% and 6.2%) for handlers at the most distant positions, suggesting that the managers' ability to monitor workers is a salient factor in the degree to which workers react to pressure from their peers.

Interpreting the Interaction as a Causal Effect While strongly suggestive, the coefficients from Columns 1 and 2 Table 2 (and Figure A14) must be interpreted with the standard caution associated with heterogeneity analyses. Even in studies in which the baseline regression isolates causal effects, the heterogeneity regression incorporating an interaction may be difficult to interpret if one of the two variables comprising the interaction is not exogenously generated. We address this issue here in two ways.

First, we control in the specification for two expansive sets of interactions. The first set is the interactions between $\Delta Occupied_{sh}$ and the handler dummies $\eta_{i(s)}$. This allows us to compare the reactions (to the occupation of an adjacent seat) of the same individual handler across days in which he is sitting closer or further away from a supervisory desk. The second set is the interactions between $\Delta Occupied_{sh}$ and the half-hour fixed effects. By doing this, we are comparing the reactions of handlers working at the same exact time but in different areas of the OCB room and therefore at different distances to the closest supervisor. Together, these two sets of interactions control for the fact that handlers sitting further away from the supervisor (or in half-hours in which the room is perhaps busier and more handlers are sitting farther away from the supervisor) may, for whatever reason, be inherently associated with a stronger or weaker reaction to the occupation of an adjacent seat. In Columns 3 and 4 Table 2, we find that the coefficients of interest are essentially identical with or without these expansive interaction controls.

Our second strategy to evaluate whether the estimates for the interaction between the occupation of adjacent seats and the distance to the supervisor can be given a causal interpretation is to exploit an instrument for this interaction. The intuition behind our instrument is as follows. Remember that, upon starting their shifts, handlers can choose where to sit *conditional on those desks being unoccupied*. The average location of unoccupied seats (at the time at which a handler starts his shift) will be often idiosyncratic, as it will depend on the earlier choices of handlers finishing their shifts just before the focus handler started his. This implies that, on some days, an arriving handler will find that a large proportion of the available seats are close to a supervisor desk and, on average, the handler will sit relatively close to a supervisor. Conversely, on other days the empty desks will on average be far from the supervisor positions and the handler will tend to sit far. As a result, two handlers working at the exact same time may be at different distances from the closest supervisors purely due to the location of the desks that were empty at the different times at which they started working. Hence, we use the average distance of the free seats at the time at which the handler started his shift as an instrument for his current distance to the supervisor's desk.[41]

Table 3 displays the estimates of this 2SLS approach. Notice first that our instrument is very strong (Kleibergen-Paap F = 2,666), suggesting that arriving handlers are strongly constrained in their seating choices. Columns 1 and 2 display the reduced form estimates, which indicate that on days in which the empty desks at the start of the shift are far from the supervisor positions, the handler will react more to the occupation of adjacent seats. In Columns 4 and 5, we find that the 2SLS estimates are positive and highly statistically significant. They are also larger than the corresponding OLS estimates from Table 2.

Overall, we interpret the robustness of the interaction estimates to the alternative empirical strategies as supporting a causal interpretation of our main findings. We therefore conclude that, in our setting, peer pressure substitutes for the effect of (direct) manager pressure.

7 Peer Pressure Between Co-Evaluated Handlers

Proposition 3 predicts that a worker will react more strongly to the presence of a nearby peer if the information available to this peer is more likely to reach his manager. In this section we examine whether the empirical evidence is consistent with this prediction.

Co-Evaluation as a Proxy for Communication Link Measuring communication links inside organisations is notoriously difficult (Gant et al. 2002, Battiston et al. 2021, Impink et al. 2021). Our proxy for whether the focus handler's evaluator and the handler's peer regularly talk with each other is whether the focus handler's evaluator is also the peer's

[41] Strictly speaking, we use the interaction between the distance of the free seats and the change in occupation of adjacent desks as an instrument for the interaction between the distance to the closest supervisor and the change in occupation of adjacent desks.

evaluator. As discussed in Section 3, each OCB manager is assigned a specific set of handlers who she mentors, gives general advice, and produces performance reviews for. This 'evaluation' relation requires regular meetings and communication between the handler and his evaluator. As a result, we posit that a handler sitting alongside a co-evaluated colleague will often be conscious of the fact that his colleague has a direct communication link with his evaluator. Our corresponding prediction is that workers should react more to the presence of a nearby peer if that peer is a co-evaluated handler.

To test this prediction, we expand the baseline equation (2) with an interaction between $\Delta Occupied_{sh}$ and a dummy for whether the nearby peer and the focus handler have the same evaluator at that point in time. Column 1 Table 4 shows that this interaction is positive and statistically significant, indicating that handlers reaction to the presence of nearby colleagues is around 60% higher if these colleagues are currently evaluated by the same manager.

In Column 2 we again control for the set of interactions between $\Delta Occupied_{sh}$ and the handler dummies $\eta_{i(s)}$. We do this to account for the fact that handlers with a different propensity to react to the presence of nearby peers might, for whatever reason, be differentially likely to sit alongside co-evaluated colleagues. The coefficients remain essentially unchanged.

Interpreting the Interaction as a Causal Effect An immediate question in interpreting the interaction coefficient from the previous subsection is whether handlers allocated to the same evaluator might be similar along unobserved dimensions, as it might be these dimensions that cause the stronger reaction captured by the interaction coefficient. For instance, if all experienced handlers are assigned to the same manager, and peer effects are stronger for handlers of similar experience, we will be attributing the 'same experience' interaction effect to the 'co-evaluated' interaction effect. This is a concern in our setting because the allocation of handlers to evaluators cannot be regarded as random.[42]

We test this prediction by taking advantage of the fact that there are frequent reallocations of handlers across evaluators in our dataset. For instance, an evaluator losing several handlers (e.g. because of their retirements) will sometimes be assigned handlers from

[42]However, our discussions with members of the OCB suggest that this allocation has a strong idiosyncratic component, due to the need to maintain a broadly similar number of handlers per evaluator. For instance, handlers starting their OCB career are typically allocated to the evaluator that, at that point in time, happens to have more 'slack' (i.e. less handlers assigned at that point). We find in Table A1 that co-evaluated handlers are not disproportionately similar to each other, relative to non-co-evaluated handlers.

other evaluators, until parity in the number of evaluatees per manager is regained.

These re-allocations imply that we can observe pairs of handlers that do not share the same evaluator in the present but either shared it in the past or will share it in the future. Using these pairs can provide the basis of a placebo test because the potential confounding effect discussed above should largely extend to the interactions of $\Delta Occupied_{sh}$ with these 'co-evaluated in the past' and 'co-evaluated in the future' dummies.

We introduce these interactions in Column 3 Table 4 and find that handlers do *not* react more strongly to the presence of nearby peers that do not share the same evaluator in the present but either will share it in the future or have shared it in the past. The coefficient on the interaction with co-evaluated in the present remains unchanged.

An alternative way to exploit the variation in the assignment of handlers to evaluators is to control for the set of interactions between $\Delta Occupied_{sh}$ and indicators for each pair of handlers. In this type of equation, we are comparing the reaction of the *same* focus handler to the nearby presence of the *same* peer, in periods in which they are and are not co-evaluated. In Column 4 Table 4 we find that the introduction of this expansive set of controls does not impact the estimated coefficients, although these become a bit noisier.

Lastly, it may be that co-evaluated handlers tend to sit together and that it is the history of working alongside each other that generates the positive effect captured by the interaction coefficient.[43] To investigate this, we compute the number of times that the focus handler and the nearby peer have sat alongside each other in the past. In Column 5 Table 4 we include the interaction between this variable and $\Delta Occupied_{sh}$. We find that handlers work harder when the nearby peer is a handler that has often sat close by in the past. However, the coefficient of the interaction with being co-evaluated remains essentially unchanged.

We conclude that the 'co-evaluated' interaction effect likely reflects the treatment of being evaluated by the same manager, as opposed to an unobserved characteristic that may link to co-evaluated handlers.

[43] Two comments regarding this potential mechanism: (a) consistently with the hot-desking policy discussed in Section 3, there is no rule in the OCB dictating that co-evaluated handlers must sit together, and (b) the issue discussed here is not necessarily an effect that confounds the co-evaluated effect, but instead a potential mechanism through which being co-evaluated affects productivity through the different channel of generating a history of interactions between two otherwise unrelated handlers.

The Share of Co-Evaluated Handlers in the Room Throughout this paper our focus has been on the effect of the occupation of adjacent seats, both in terms of the overall effect and in terms of the differential effects depending on the characteristics of the occupants. In this subsection, we instead study whether the presence of co-evaluated handlers *anywhere in the OCB room* affects the productivity of a focus handler.

There are two reasons why we might expect an effect. First, colleagues in other areas of the room may still be able to observe a handler's effort, albeit in a more limited way than if they were sitting alongside his. For instance, non-adjacent colleagues may observe the work of a focus handler if they step away from their desks to stretch their legs.[44] As discussed earlier, a handler may in turn be more incentivised if these potential observations are likely to reach his evaluator, relative to being held by colleagues with no direct connection to his evaluator. Second, an evaluator may be able to better evaluate a handler's effort if she is also evaluating and therefore closely tracking other handlers who work at the same time (and are affected by the same shocks) as that focus handler (see Section 8 for a further discussion of the relative performance evaluation channel).

In our baseline dataset there are, on average, 29.8 colleagues in that half-hour in the room, out of which 2.47 are co-evaluated handlers.[45] We calculate the share of handlers in the room that have the same evaluator as the focus handler, and estimate:

$$\Delta y_{sh} = \gamma \Delta ShareCoEvaluated_{sh} + \pi_h + \mu_{t(sh)} + \gamma \Delta MW_{sh} + \Delta \epsilon_{sh}, \qquad (6)$$

Note that our equation continues to be in first-differences and include time (half-hour) fixed effects. We are therefore comparing handlers working at the same exact time, on the basis of whether the colleagues starting or ending their shifts in that half-hour are co-evaluated. The identification assumption is that the arrival or departure of co-evaluated colleagues (typically scheduled weeks in advance) does not coincide with idiosyncratic shocks to the productivity of a handler in that specific half-hour.

Column 1 Table 5 shows that increasing the share of handlers in the room that are co-evaluated increases a handler's productivity. The average share of co-evaluated handlers is 2.47/29.8 = .083. The estimated coefficient implies that moving from having no co-evaluated handlers to having the average share increases a handler's time on the phone by

[44]Note that the introduction of half-hour fixed effects in (2) implies that we were estimating the baseline peer pressure effect β *net* of the pressure that an additional handler in the room exerts on the focus handler.

[45]These numbers do not include the desks that are adjacent to the focus handler. We do not include these desks either in the calculation of the share of handlers in the room that are co-evaluated that we use in Table 5.

$.083 \times .183 \times 100 = 1.5\%$. This is a plausible magnitude, as it is smaller than the effect of a single co-evaluated handler sitting right next to the focus handler. We also note in Column 1 Table 5 that the number of handlers that will be co-evaluated in the future or were co-evaluated in the past does not affect productivity.

In Column 2 Table 5 we add the occupation of adjacent desks, together with its interaction with whether these occupants are co-evaluated. We find that the two effects (i.e. the co-evaluation of handlers adjacent and non-adjacent to the focus handler) are largely orthogonal to each other. This is unsurprising given the vast array of controls in our estimating equation, and lends further credibility to our baseline identification strategy. Adding interactions in Columns 3 and 4 between the focus handler (or the focus/peer pair) and the occupation of adjacent desks does not, reassuringly, affect the coefficients.

Overall, Table 5 confirms that the assignment of handlers to evaluators and shifts/desks represents a channel through which firms can manipulate the generation and magnitude of peer pressure among co-workers.

8 Discussion of Alternative Interpretations

We now list our main findings below and interpret them in light of both the Section 2 conceptual framework and potential alternative explanations.

- F1: the average peer effect is positive (Table 1). When estimating separate peer effects for each handler, the overwhelming majority of the statistically significant effects are positive (Figure A9).

- F2: the peer effect is larger when the handler is sitting further away from a supervisor (Tables 3-4).

- F3: the peer effect is larger among handlers who have the same performance evaluator, relative to handlers who do not (Tables 4-5).

The Section 2 conceptual framework provides an explanation of all three findings. Handlers care about impressing their managers and these managers receive both direct (through their own observations) and indirect (through the reputation among the peers that the managers interact with) signals of the handlers' performance. The arrival and observation by a peer leads to increased effort (F1), especially if the manager cannot directly monitor the handler (F2) and the peer communicates with the manager frequently (F3).

Relative Performance Evaluation Objective measures of performance such as the average number of calls per hour are insufficient to fully assess a handler's effort, which implies that evaluators partly rely on other information (including their own observations) about how a handler is performing. This prompts the question of whether evaluators compare their evaluatees in informally assessing how well they are doing.

It is important to emphasise that it is not immediately clear how relative performance evaluation would predict F2 or F3. A potential explanation of F3 would be that evaluators in the room are somehow better able to visually assess the effort of their handler when that handler is sitting alongside another evaluatee, relative to sitting alongside a colleague who has a different evaluator. F3 would then arise because the manager receives a more precise signal of the handler's effort when a co-evaluated handler sits nearby. As we discuss at the end of Section 2, this mechanism is conceptually very similar to our preferred explanation, as both rely on the nearby presence of a peer improving the manager's signal of the handler's effort. The only difference between the two mechanisms is in whether the peer is actively (i.e. voluntarily transmitting information) or passively (i.e. through his presence improving the signal-to-noise ratio) improving the manager's information.[46]

Pro-Social Preferences All the handlers working at the same point in time are engaged in teamwork, and potentially under the temptation to free-ride on each other. A potential explanation of F1 would be that the arrival of a colleague at an adjacent desk triggers pro-social preferences in a handler, leading to a desire for cooperative behaviour and higher effort. Related to this, observing an adjacent colleague may somehow create motivation through the 'warm glow' of working alongside others.

Again, it is not clear why this trigger in pro-social preferences should be stronger when the handler is sitting further away from a supervisor (F2), or why this desire would be

[46]Consider a similar, if less plausible, explanation. A handler finishes a shift having taken very few calls, and an evaluator wonders the reason behind the low objective measure of performance. One potential reason would be that few calls (or calls of particular difficulty and length) were received during the shift, and the other would be that the handler shirked. The presence of a co-evaluated colleague in the same shift might allow the evaluator to compare the relative performance of the focus handler and the co-evaluated colleague, determining which explanation is more likely to be correct, and increasing the pressure on the focus handler to perform. There are some deficiencies with this intuition as a potential explanation of F3. First, the comparison above could be made with any co-evaluated colleague working at the same time rather than those sitting nearby. Second, evaluators have access to the average number of calls for all OCB handlers rather than just their evaluatees, so it is not clear how the presence of a co-evaluated colleague in a shift would generate better information. Nevertheless, even if it is less plausible, this explanation again relies on the presence of the peer generating a more precise signal of the focus worker's effort, and is therefore conceptually similar to our preferred framework in Section 2.

stronger if the adjacent colleague happens to be evaluated by the same manager (F3). One might expect these pro-social preferences to arise more strongly among colleagues who are similar to each other, or who often sit next to each other (as we find in Column 5 Table 4). However, co-evaluated handlers are not more similar to each other (Table A1) and do not interact with each other much more strongly or frequently as a result of being co-evaluated. Furthermore, note that F3 is quantitatively unchanged in Column 5 Table 4 when controlling for both the pair fixed effects and the pair's past interactions (interacted with the main effect), suggesting that the co-evaluated variable is not proxying for the similarities or intensity of contact between the pair.

Peers as Reference Points Imagine that a handler is unaware about the minimum amount of calls that are regarded as acceptable (or the 'minimum norm'), either in the organisation in general or for his evaluator in particular. The arrival of a colleague to an adjacent desk might provide the handler with a point of reference in this respect, leading to an adjustment in the focus handler's effort.

An immediate problem with this explanation is that the corresponding effort adjustment need not be in a positive direction. Instead, around half of the handlers will find that they are exerting more effort than they want to (given that effort is costly, and that they are exceeding the minimum norm), and therefore adjust downwards when a colleague sits nearby. However, this prediction is inconsistent with F1, especially in light of Figure A9 which shows that the overwhelming majority of handlers react positively to the arrival of a nearby peer. It is also unclear how the hypothesis that an adjacent colleague creates a reference point would predict that the arrival of a such a colleague has a stronger (positive) effect if the focus handler is sitting far from a supervisor (F2).

Conformity to a Norm Related to the interpretation above, Kandel and Lazear (1992) mention the possibility of peer pressure to not exceed a maximum amount of effort (or a 'maximum norm'). The logic here is that, in the presence of a ratchet effect, hard workers (i.e. 'rate busters') may be ostracised if they alert management to the possibility of greater productivity (see also Jones, 1984). As a result, rate busters may be pressured to decrease their effort when they are observed by their colleagues.

Again, the prediction here would be that the presence of an adjacent worker decreases rather than increases effort. While this is possible in some organisations, it is difficult to reconcile with our empirical finding F1.

Other Peer Effects Lastly, we comment on types of peer effects affecting productivity without necessarily affecting effort. One such channel would entail knowledge spillovers arising across adjacent workers (Waldinger 2012, Sandvik et al. 2020). However, this slow-moving mechanism is unlikely to be the cause of the rapid reaction of productivity to the occupation of an adjacent seat that we document in this paper.

Another potential channel is mutual help among adjacent workers. We have indeed documented such an effect in previous work (Battiston et al., 2021). However, we studied there communication as help between two workers engaging sequentially with the same incident. In the GMP, it is regarded as acceptable for the latter worker (i.e. the operator) to solicit additional information from the former (i.e. the handler), about the case that they are both assigned to. However, we study in this paper only the handlers, who work in parallel on separate cases to each other. Therefore, there is little scope for mutual help in this paper. It is also unclear how this mechanism would predict F2 or F3.[47]

9 Counterfactual Exercises

In this section we use our earlier estimates to compute the potential productivity gains that could arise from alternative assignments of workers to seats and shifts. Throughout these counterfactual exercises, we keep every shift observed in the data, and therefore the number of handlers working at each point in time, unchanged.[48] We also maintain the practice that handlers do not change seats in the middle of their shifts. We make three additional simplifying decisions. First, we rearrange the desks within the room to create rows of ten contiguous seats each. Second, we perform all exercises on the median month in our sample period (May 2013).[49] Lastly, our focus is on illustrating how incorporating information on

[47] For instance, there is no reason why handlers with the same evaluator should help each other more. Handlers who are similar to each other or interact often with each other might help each other more, but F3 is unchanged when controlling for these characteristics.

[48] The length and starting time of each shift is determined by the OCB to meet the expected call volume while adhering to formal and/or informal constraints on the shift patterns. For instance, shifts are not expected to last beyond a certain maximum number of hours. It is also inadvisable for shifts to start at, say, 3am. We do not know the precise set of restrictions that OCB central planners operate under, so we conservatively keep every shift unchanged. Instead, we vary the assignment of handlers to desks and, in our second counterfactual, the identity of the handlers working in each shift.

[49] This sample restriction is motivated by the fact that counterfactually assigning handlers to desks in a continuous and dynamic fashion is a computationally demanding problem. This computational complexity

the vertical relations between workers and managers can help to augment the strength of horizontal incentives. Because of this, we design a first counterfactual to leverage F1 and a second counterfactual to leverage F1 + F3.

Increasing Horizontal Incentives while Ignoring Vertical Relations In this counterfactual exercise we increase the strength of the average peer pressure, but do not leverage how such a horizontal incentive depends on the vertical relations between workers and their managers. In our context, this implies increasing the number of adjacent seats that are occupied to exploit F1, while ignoring the finding that co-evaluated handlers in the same shift and adjacent seats will exert stronger peer pressure on each other (F3).

We use the following heuristic algorithm to allocate handlers to seats. At every point in time, we keep track of every seat being occupied and the remaining time left in the shift of its occupying handler. For each handler starting a shift we identify all empty seats and compute, for each of these seats, a score based on the time left in the shifts of the handlers occupying the adjacent seats.[50] We then allocate the starting handler to the empty seat with the highest score.

We have also used mixed-integer programming to solve the full dynamic problem (see Online Appendix C for a description of the optimal allocation problem). We favour the heuristic approach for three reasons. First, its simplicity increases the likelihood of implementation by real-world organisations, relative to time-consuming approaches relying on complex optimisation techniques. To illustrate, in our setting the heuristic algorithm can be calculated in a small fraction of the many hours required to implement the mixed-integer programming approach. Second, the heuristic algorithm performs quite well relative to the programming approach, in a dataset comprising of a single day (details available upon request). Lastly, the heuristic algorithm also performs well from an absolute perspective, more than doubling the average occupation of adjacent seats from .8 to 1.7.

We compute the predicted productivity increase under the counterfactual allocation of handlers to seats as follows. For each handler and half-hour period, we use the number of adjacent seats occupied and the regression coefficients from Columns 1 and 2 Table 1 to

increases exponentially with the length of the time horizon. We have confirmed that very similar conclusions result from using alternative months (available upon request).

[50] The score is the sum of the time left in each of the adjacent seats. Naturally, an adjacent seat unoccupied is regarded as a zero in this addition. Similarly, an adjacent seat that does not exist (because the focus seat is at the end of a row) is also a zero.

calculate the associated increases in the measures of productivity. We then aggregate across all the handlers in the room and then across all the half-hours in the sample period. We display the results from this counterfactual exercise in Column 1 Table 6. We find that the total time that handlers spend on the phone increases by 4.84% and the number of calls increase by 2.88%.[51,52]

Leveraging Both Horizontal and Vertical Relations In this counterfactual exercise we leverage information on what handlers are co-evaluated to further increase the magnitude of the peer pressure effect. We utilise this information in two ways. First, we modify the score determining the seat assigned to an incoming handler so that it gives a higher weight to empty seats adjacent to co-evaluated colleagues. Second, we use another heuristic algorithm to reassign handlers to shifts in a way that increases the likelihood that co-evaluated handlers work at the same time.

This shift-assignment algorithm works as follows. We start with the first shift of the month (say, 12am-9am 1st May 2013) and assign handlers from the first evaluator to that shift. We repeat this process with the second shift, and then the third shift, until we have exhausted the handlers from the first evaluator. We then take the next shift and start assigning handlers from the second evaluator to that shift, and proceed until the handlers from the second evaluator are exhausted. When we have finished the handlers from the last evaluator, we start assigning handlers from the first evaluator again and proceed in this fashion until the last shift of the month. It is easy to see that this process significantly increases the likelihood that co-evaluated handlers coincide in the room.

Note that the reassignment of shifts and the reassignment of seats complement each other because the increased shift overlap between co-evaluated handlers both leverages the findings from Table 4 and makes it easier to find co-evaluated handlers who can sit alongside each other thereby leveraging the findings from Table 5. Overall, this process increases: (1) the average occupation of adjacent seats from .8 to 1.6, (2) the occupation of adjacent

[51] Table 6 reports standard errors calculated from 200 bootstrap repetitions, clustered at the handler level. Each bootstrap repetition accounts for the underlying variation in the counterfactual seating allocation as well as drawing a new coefficient from a normal distribution with mean and standard deviation equal to the estimated coefficient and standard error from the regression in Table 1.

[52] An important implicit assumption in our counterfactual exercises is that the call queue permits the increase in productivity resulting from higher effort, at least to the same extent as it does in the observed sample period generating the baseline estimates in Table 1. To the extent that the call queue might start to empty when productivity increases, any organisation should be able to achieve the same number of calls taken while reducing its payroll.

seats by co-evaluated colleagues from .04 to 1.08, and (3) the average share of co-evaluated handlers in the room from .06 to .27.

We compute the predicted productivity increase under the counterfactual allocation of handlers to shifts and seats in the same way as in the previous subsection. We find in Column 2 Table 6 that this second counterfactual is associated with increased time on the phone of 11.98% and increased number of calls of 7.64%.

Discussion The two exercises above illustrate the potential for using alternative seat and shift arrangements to increase the size of the peer pressure. In Figure A15 we confirm this potential improvement by displaying the simulated distributions of our dependent variables, together with the observed distribution. We find that the counterfactual distributions are shifted to the right of the observed distribution, indicating an increase in average productivity along the whole support.

The key message from this section is that accounting for the vertical assignment of handlers to evaluators (Column 2 Table 6) more than doubles the productivity gains, relative to an approach that uses seat assignment to increase peer pressure but ignores the interdependencies between horizontal and vertical incentives (Column 1 Table 6).

10 Concluding Remarks

We have provided evidence on the interplay between peer pressure and manager pressure in organisations. Handlers exert more effort when a colleague sits in an adjacent desk, and this effect is mediated by the relation between workers and their managers. Through a series of counterfactual exercises we have illustrated how organisations could leverage these effects to increase worker productivity.

The richness of our analysis has been made possible thanks to our focus on a single organisation, for which we have been able to gather uniquely precise data and exploit its advantageous features. While this focus has substantial benefits in terms of the identification of causal effects and the range of questions that we can tackle, it also poses the question of how our findings might extend to other settings. We believe that the characteristics at the centre of our findings are likely present in many other contexts. For instance, team production and the potential to free-ride are pervasive features of modern workplaces. Similarly, many workers are co-located and can mitigate free-riding through peer pressure. The vertical relations in this paper are not atypical either. In many firms, managers are in charge of monitoring and evaluating their subordinates, and observe only imperfect measures of performance. Together, these ingredients make the interrelation between managers and peer pressure a likely mechanism in many other settings.

REFERENCES

Adhvaryu, A., Kala, N., and Nyshadham, A. (2022), "Management and Shocks to Worker Productivity", *Journal of Political Economy*, 130(1): 1-47.

Ashraf, N., and Bandiera, O. (2018), "Social Incentives in Organizations", *Annual Review of Economics*, 10: 439-463.

Bandiera, O., Barankay, I., and Rasul, I. (2009), "Social Connections and Incentives in the Workplace: Evidence from Personnel Data", *Econometrica*, 77(4): 1047-1094.

Bandiera, O., Barankay, I., and Rasul, I. (2010), "Social Incentives in the Workplace", *Review of Economic Studies*, 77(2): 417-458.

Barrero, J. M., Bloom, N., and Davis, S. J. (2022), "Long Social Distancing", *Working Paper*.

Batt, R., Colvin, A. J., Katz, H., and Keefe, J. (2000), "Telecommunications 2000: Strategy, HR Practices and Performance".

Battiston, D., Blanes i Vidal, J., and Kirchmaier, T. (2021), "Face-to-Face Communication in Organizations", *Review of Economic Studies*, 88(2): 574–609.

Blanes i Vidal, J., and Kirchmaier, T. (2018). "The Effect of Police Response Time on Crime Clearance Rates", *Review of Economic Studies*, 85(2): 855-891.

Bloom, N., Liang, J., Roberts, J., and Ying, Z. J. (2015), "Does Working from Home Work? Evidence from a Chinese Experiment", *Quarterly Journal of Economics*, 130(1): 165-218.

Brynjolfsson, E., and Milgrom, P. (2013), "Complementarity in Organizations ", *Handbook of Organizational Economics*, 11-55. Princeton University Press.

Catalini, C. (2018). "Microgeography and the Direction of Inventive Activity." *Management Science*, 64(9): 4348-4364.

Cornelissen, T., Dustmann, C., and Schönberg, U. (2017). "Peer Effects in the Workplace.", *American Economic Review*, 107(2): 425-56.

Cullen, Z., and Pérez-Truglia, R. (2023). "The Old Boys' Club: Schmoozing and the Gender Gap." *American Economic Review*, forthcoming

Drago, R., and Garvey, G. T. (1998). "Incentives for Helping on the Job: Theory and Evidence." *Journal of Labor Economics*, 16(1):1-25.

Falk, A., and Ichino, A. (2006). "Clean Evidence on Peer Effects." *Journal of Labor Economics*, 24(1), 39-57.

Fenizia, A. (2022). "Managers and Productivity in the Public Sector." *Econometrica*, 90(3): 1063-1084.

Fiorin, S. (2021). "Reporting Peers' Wrongdoing: Experimental Evidence on the Effect of Financial Incentives on Morally Controversial Behavior." *Working Paper*

Frederiksen, A., Kahn, L. B., and Lange, F. (2020). "Supervisors and Performance Management Systems." *Journal of Political Economy*, 128(6): 2123-2187.

Gant, J., Ichniowski, C., and Shaw, K. (2002), "Social Capital and Organizational Change in High-Involvement and Traditional Work Organizations ", *Journal of Economics and Management Strategy*, 11(2): 289-328.

Gibbons, R., and Roberts, J. (2013), "Economic Theories of Incentives in Organizations ", *Handbook of Organizational Economics*, 56-99. Princeton University Press.

Herbst, D., and Mas, A. (2015), "Peer Effects on Worker Output in the Laboratory Generalize to the Field ", *Science*, 350(6260): 545-549.

Hjort, J. (2014), "Ethnic Divisions and Production in Firms", *Quarterly Journal of Economics*, 129(4): 1899-1946.

Hoffman, M., and Tadelis, S. (2021), "People Management Skills, Employee Attrition, and Manager Rewards: An Empirical Analysis", *Journal of Political Economy*, 129(1): 243-285.

Impink, S. M., Prat, A., and Sadun, R. (2021), "Communication Within Firms: Evidence from CEO Turnovers", *Working Paper.*

Jones, Stephen R. G. *The Economics of Conformism.* Oxford: Blackwell, 1984.

Kandel, E., and Lazear, E. P. (1992), "Peer Pressure and Partnerships", *Journal of Political Economy*, 100(4): 801-817.

Lazear, E. P., and Rosen, S. (1981), "Rank-order Tournaments as Optimum Labor Contracts", *Journal of Political Economy*, 89(5): 841-864.

Lazear, E. P., Shaw, K. L., and Stanton, C. T. (2015), "The Value of Bosses", *Journal of Labor Economics*, 33(4): 823-861.

Lindquist, M. J., Sauermann, J., and Zenou, Y. (2022), "Peer Effects in the Workplace: A Network Approach", *Working Paper.*

Mas, A., and Moretti, E. (2009), "Peers at Work", *American Economic Review*, 99(1): 112-145.

Minni, V. (2023), "Making the Invisible Hand Visible: Managers and the Allocation of Workers to Jobs", *Working Paper.*

Park, S. (2019), "Socializing at Work: Evidence from a Field Experiment with Manufacturing Workers", *American Economic Journal, Applied Economics*, 11(3): 424-55.

Sandvik, J. J., Saouma, R. E., Seegert, N. T., and Stanton, C. T. (2020). "Workplace Knowledge Flows", *Quarterly Journal of Economics*, 135(3): 1635-1680.

Silver, D. (2021), "Haste or Waste? Peer Pressure and Productivity in the Emergency Department", *Review of Economic Studies*, 88(3): 1385-1417.

Steinbach, D. and Tatsi, E. (2022), "Short-Term and Long-Term Measures of Peer Behavior", *Working Paper*.

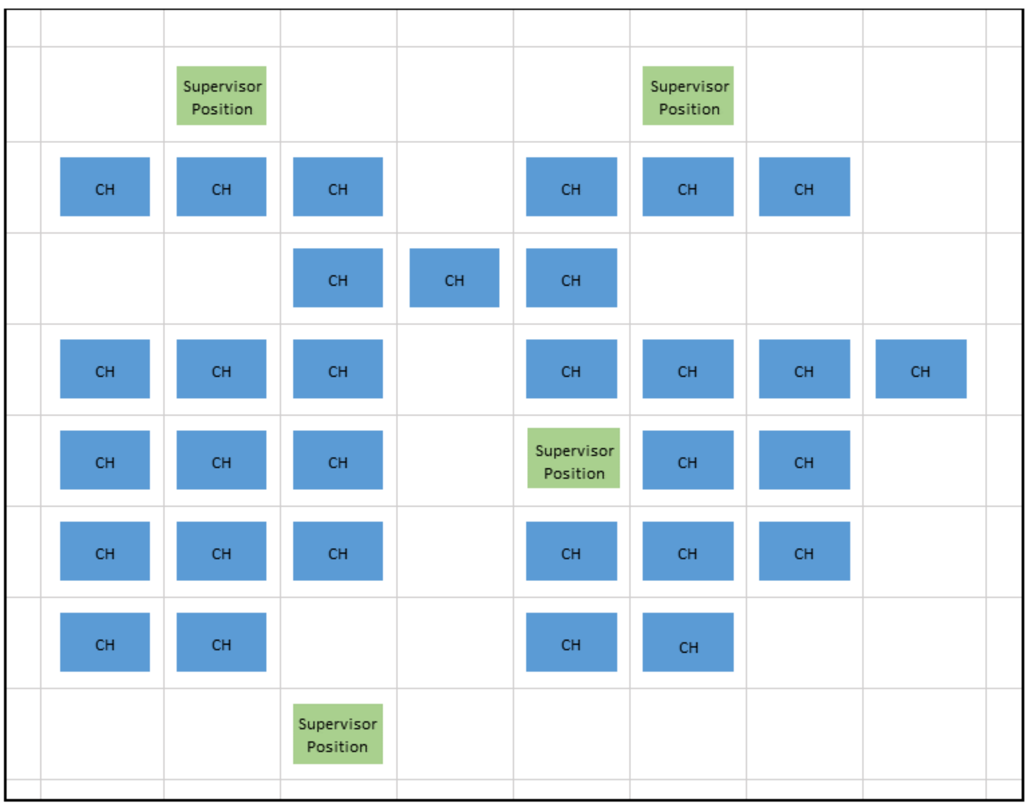
Waldinger, F. (2012), "Peer Effects in Science: Evidence from the Dismissal of Scientists in Nazi Germany ", *Review of Economic Studies*, 79(2): 838-861.

Xu, G. (2018), "The Costs of Patronage: Evidence from the British Empire ", *American Economic Review*, 108(11): 3170-98.

FIGURES

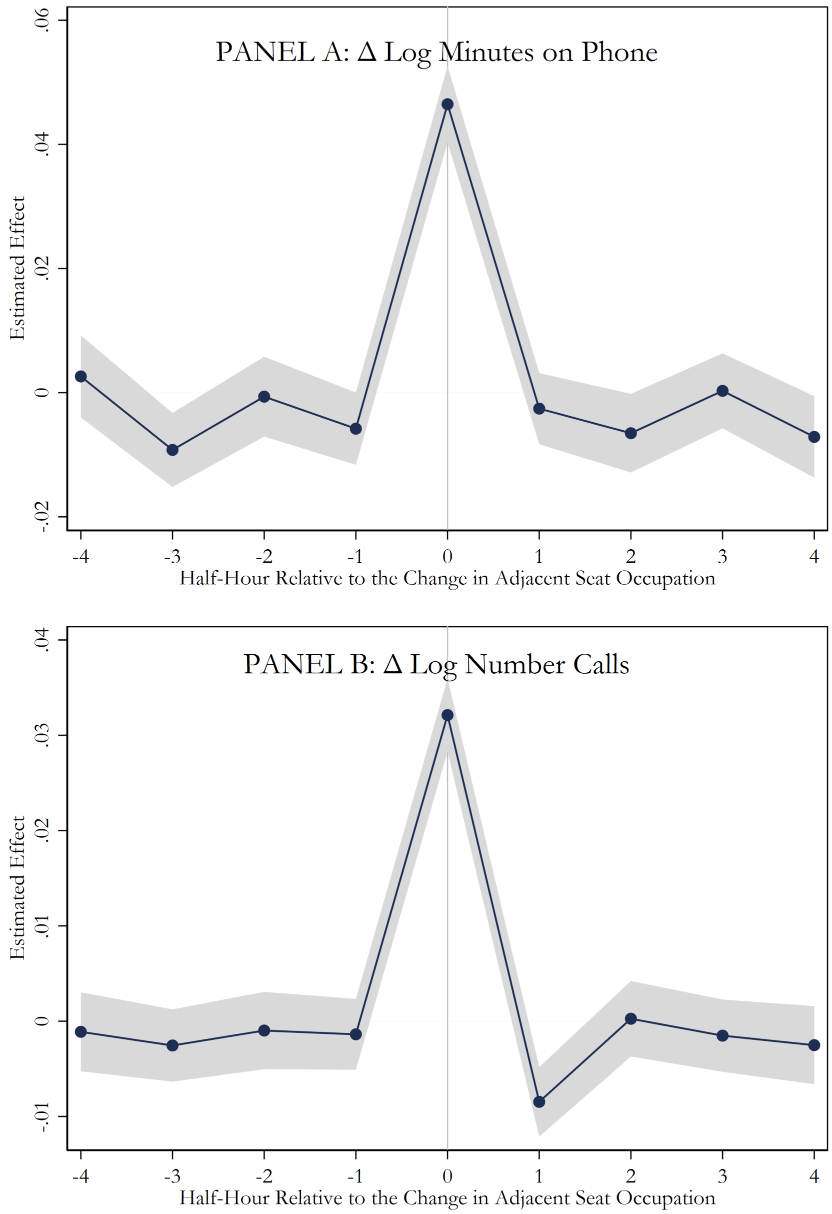
FIGURE 1: THE CALL HANDLING ROOM AT THE GREATER MANCHESTER POLICE

EXAMPLE OF OCB ROOM FLOORPLAN



This figure displays an example of the OCB room. The figure is not realistic, either in the number of seats or in the relative location of the seats. The purpose of the figure is to illustrate that the supervisory positions are scattered throughout the room and at different distances from different handler desks.

FIGURE 2: LAGS AND LEADS EVIDENCE



This figure displays the coefficients and 95% confidence intervals of regressions of productivity on the leads and lags of the (change in the) number of adjacent seats that are occupied next to a handler. The unit of observation is a half-hour unit h within a shift s, where a shift is defined as the combination of a specific handler and a specific date (e.g. an observation is the fourth half-hour of the shift of handler John Smith that starts on 1st December 2012). The estimating equation is:

$$\Delta y_{sh} = \sum_{j=-4}^{4} \beta_j \Delta Occupied_{s(t+j)} + \pi_h + \mu_{t(sh)} + \gamma \Delta MW_{sh} + \Delta\epsilon_{sh},$$

The dependent and independent variables are in first-differences within a shift. In Panel A the dependent variable is the (change in the) log of the number of minutes that the handler spends on the phone in the half-hour. In Panel B the dependent variable is the (change in the) log of the number of calls answered by the handler in the half-hour. All regressions include the (change in the) log of the number of minutes worked by the handler, indicators π_h for the half-hour period in which the handler is within the shift, and indicators $\mu_{t(sh)}$ for the natural unit of time (i.e. year X month X day X half-hour of day). Standard errors are clustered at the shift level.

TABLES

TABLE 1: AVERAGE PEER PRESSURE EFFECT

Feb2012-Nov2014; Handlers=343; Shifts= 71,589; Half-Hours= 48,033.

Dependent Variable:	**(1) Δ Log Minutes on Phone**	**(2) Δ Log Number Calls**	**(3) Δ Log Minutes on Phone**	**(4) Δ Log Number Calls**	**(5) Δ Log Minutes on Phone**	**(6) Δ Log Number Calls**
Δ Occupied	.06***	.035***			.059***	.035***
	(.003)	(.002)			(.003)	(.002)
Δ Occupied × 𝟙(Δ Occupi			.078***	.041***		
			(.004)	(.003)		
Δ Occupied × 𝟙(Δ Occupi			.04***	.03***		
			(.005)	(.003)		
Δ Occupied (Seat in Row Behind)					.016***	.009***
					(.003)	(.002)
Δ Occupied (Seat in Row in Front)					.012***	.006***
					(.003)	(.002)
Δ Log Minutes Worked	Yes	Yes	Yes	Yes	Yes	Yes
Time (Half-Hour) F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Half-Hour within Shift F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,120,440	1,120,440	1,120,440	1,120,440	1,120,440	1,120,440

This table displays estimates of OLS regressions of productivity on the number of adjacent seats that are occupied next to a handler. The unit of observation is a half-hour period h within a shift s, where a shift is defined as the combination of a specific handler and a specific date (e.g. an observation is the fourth half-hour of the shift of handler John Smith that starts on 1st December 2012). The estimating equation in Columns (1)-(2) is:

$$\Delta y_{sh} = \beta \Delta Occupied_{sh} + \pi_h + \mu_{t(sh)} + \gamma \Delta MW_{sh} + \Delta \epsilon_{sh},$$

The dependent and independent variables are in first-differences within a shift. The independent variable ranges between -2 (when both seats next to a handler were fully occupied in the previous half-hour and became fully unoccupied in the current half-hour) and +2 (when both seats were unoccupied and they became occupied). The variable is continuous, as it reflects the percentage of the half-hour that the seats are occupied. In Columns (1), (3) and (5), the dependent variable is the (change in the) log of the number of minutes that the handler spends on the phone in the half-hour. In Columns (2), (4) and (6), the dependent variable is the (change in the) log of the number of calls answered by the handler in the half-hour. In Columns (3)-(4) we split $\Delta Occupied_{sh}$ by whether it has a positive or a negative sign. In Columns (5)-(6) we add the change in occupation for the three seats in the row in front (exactly in front plus the two diagonals) and for the three seats in the row behind. All regressions include indicators π_h for the half-hour period in which the handler is within the shift, indicators $\mu_{t(sh)}$ for the natural unit of time (i.e. year X month X day X half-hour of day), and the (change in the) log of the number of minutes worked by the handler. Standard errors are clustered at the shift level.

TABLE 2: HETEROGENEOUS EFFECTS BY DISTANCE TO CLOSEST SUPERVISOR POSITION

Feb2012-Nov2014; Handlers=341; Shifts= 64,089; Half-Hours= 48,022.

	(1)	(2)	(3)	(4)
Dependent Variable:	**Δ Log Minutes on Phone**	**Δ Log Number Calls**	**Δ Log Minutes on Phone**	**Δ Log Number Calls**
Δ Occupied	-.001	-.001		
	(.0134)	(.0081)		
Δ Occupied × (Log) Distance to Supervisor	.026***	.016***	.025***	.016***
	(.0064)	(.0038)	(.0074)	(.0045)
Δ Log Minutes Worked	Yes	Yes	Yes	Yes
Time (Half-Hour) F.E.	Yes	Yes	Yes	Yes
Half-Hour within Shift F.E.	Yes	Yes	Yes	Yes
Δ Occupied × Focus Handler F.E.	No	No	Yes	Yes
Δ Occupied × Time (Half-Hour) F.E.	No	No	Yes	Yes
Observations	982,861	982,861	982,861	982,861

This table displays estimates of OLS regressions of productivity on the number of adjacent seats that are occupied next to a handler, interacted with the (log of the) distance between the handler's desk and the closest supervisor position. The unit of observation is a half-hour period h within a shift s, where a shift is defined as the combination of a specific handler and a specific date (e.g. an observation is the fourth half-hour of the shift of handler John Smith that starts on 1st December 2012). The estimating equation is in Columns (1)-(2):

$$\Delta y_{sh} = \beta_1 \Delta Occupied_{sh} + \beta_2(\Delta Occupied_{sh} \times Distance_s) + \pi_h + \mu_{t(sh)} + \gamma \Delta MW_{sh} + \Delta\epsilon_{sh},$$

The dependent and independent variables are in first-differences within a shift. The occupied variable ranges between -2 (when both seats next to a handler were fully occupied in the previous half-hour and became fully unoccupied in the current half-hour) and +2 (when both seats were unoccupied and they became occupied). The variable is continuous, as it reflects the percentage of the half-hour that the seats are occupied. In Columns (1),(3) the dependent variable is the (change in the) log of the number of minutes that the handler spends on the phone in the half-hour. In Column (2),(4) the dependent variable is the (change in the) log of the number of calls answered by the handler in the half-hour. All regressions include indicators π_h for the half-hour period in which the handler is within the shift, indicators $\mu_{t(sh)}$ for the natural unit of time (i.e. year X month X day X half-hour of day), and the (change in the) log of the number of minutes worked by the handler. Columns (3)-(4) include interactions between the change in the occupation of adjacent seats and: (a) a set of focus handler identifiers $\eta_{i(s)}$, and (b) a set of half-hour identifiers. Standard errors are clustered at the shift level.

TABLE 3: HETEROGENEOUS EFFECTS BY DISTANCE TO CLOSEST SUPERVISOR POSITION TWO STAGE LEAST SQUARES MODEL

Feb2012-Nov2014; Handlers=342; Shifts= 71,488; Half-Hours= 47,899; Observations= 981,915

	Reduced Form		First Stage	Second Stage	
Dependent Variable:	**(1) Δ Log Minutes on Phone**	**(2) Δ Log Number Calls**	**(3) Δ Occupied × (Log) Distance to Supervisor**	**(4) Δ Log Minutes on Phone**	**(5) Δ Log Number Calls**
Δ Occupied × (Log) Av. Distance Free Seats	.114***	.08***	1.572***		
	(.0478)	(.0289)	(.0304)		
Δ Occupied × (Log) Distance to Supervisor				.072***	.051***
				(.0304)	(.0184)
Δ Log Minutes Worked	Yes	Yes	Yes	Yes	Yes
Time (Half-Hour) F.E.	Yes	Yes	Yes	Yes	Yes
Half-Hour within Shift F.E.	Yes	Yes	Yes	Yes	Yes
Δ Occupied × Focus Handler F.E.	Yes	Yes	Yes	Yes	Yes
Δ Occupied × Time (Half-Hour) F.E.	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F				2666.66	

This table displays estimates of Two-Stage Least Square models of productivity on the number of adjacent seats that are occupied next to a handler, interacted with the (log of the) distance from the handler's seat to the closest supervisor seat. The instrument is the interaction between the number of adjacent seats that are occupied next to a handler and the distance between the average free seat at the time that the handler started her shift and the closest supervisory seat. The unit of observation is a half-hour period h within a shift s, where a shift is defined as the combination of a specific handler and a specific date (e.g. an observation is the fourth half-hour of the shift of handler John Smith that starts on 1st December 2012). The estimating equation is in Columns (4)-(5):

$$\Delta y_{sh} = \beta_1 \Delta Occupied_{sh} + \beta_2(\Delta Occupied_{sh} \times Distance_s) + \pi_h + \mu_{t(sh)} + \gamma \Delta MW_{sh} + \Delta\epsilon_{sh},$$

The dependent and independent variables are in first-differences within a shift. The occupied variable ranges between -2 (when both seats next to a handler were fully occupied in the previous half-hour and became fully unoccupied in the current half-hour) and +2 (when both seats were unoccupied and they became occupied). The variable is continuous, as it reflects the percentage of the half-hour that the seats are occupied. All regressions include indicators π_h for the half-hour period in which the handler is within the shift, indicators $\mu_{t(sh)}$ for the natural unit of time (i.e. year X month X day X half-hour of day), the (change in the) log of the number of minutes worked by the handler, interactions between the change in the occupation of adjacent seats and: (a) a set of focus handler identifiers $\eta_{i(s)}$, and (b) a set of half-hour identifiers. Standard errors are clustered at the shift level.

TABLE 4: HETEROGENEOUS EFFECTS BY EVALUATOR AFFILIATION OF PEER

Feb2012-Nov2014; Handlers=343; Shifts= 71,589; Half-Hours= 48,033.

	(1)	(2)	(3)	(4)	(5)
Panel A: Dependent Variable - Δ Log Minutes on Phone					
Δ Occupied	.057***				
	(.0036)				
Δ (Occupied × Current Co-Evaluated)	.027***	.029***	.027***	.029*	.029*
	(.0103)	(.0106)	(.0107)	(.0153)	(.0153)
Δ (Occupied × Past Co-Evaluated)			-.023*	-.017	-.022
			(.0124)	(.0185)	(.0185)
Δ (Occupied × Future Co-Evaluated)			-.013		
			(.0207)		
Δ (Occupied × Number Past Interactions)					.011***
					(.0015)
Panel B: Dependent Variable - Δ Log Number Calls					
Δ Occupied	.033***				
	(.0021)				
Δ (Occupied × Current Co-Evaluated)	.02***	.018***	.017***	.018*	.017*
	(.0062)	(.0064)	(.0065)	(.0091)	(.0091)
Δ (Occupied × Past Co-Evaluated)			-.009	-.011	-.014
			(.0076)	(.011)	(.011)
Δ (Occupied × Future Co-Evaluated)			-.006		
			(.0123)		
Δ (Occupied × Number Past Interactions)					.006***
					(.001)
Δ Log Minutes Worked	Yes	Yes	Yes	Yes	Yes
Time (Half-Hour) F.E.d	Yes	Yes	Yes	Yes	Yes
Half-Hour within Shift F.E.	Yes	Yes	Yes	Yes	Yes
Δ Occupied × Focus Handler F.E.	No	Yes	Yes	No	No
Δ Occupied × Focus/Peer Pair F.E.	No	No	No	Yes	Yes
Observations	1,120,440	1,120,440	1,120,440	1,116,359	1,120,440

This table displays estimates of OLS regressions of productivity on the number of adjacent seats that are occupied next to a handler, interacted with whether the occupying peers are co-evaluated with the focus handler. The unit of observation is a half-hour period h within a shift s, where a shift is defined as the combination of a specific handler and a specific date (e.g. an observation is the fourth half-hour of the shift of handler John Smith that starts on 1st December 2012). The estimating equation in Column (1) is:

$$\Delta y_{sh} = \beta_1 \Delta Occupied_{sh} + \beta_2 \Delta(Occupied_{sh} \times CurrentCoEvaluated_{i(sh)}) + \pi_h + \mu_{t(sh)} + \gamma \Delta MW_{sh} + \Delta\epsilon_{sh},$$

where Columns (2)-(5) include additional interactions between the change in the occupation of adjacent seats and other characteristics. In (2), the interactions are with the focus handler indicators. In (3), we add the interactions are with the indicators for the interaction between the focus handler and the peer handler. In (4), we add the interactions with dummies for whether the The dependent and independent variables are in first-differences within a shift. The occupied variable ranges between -2 (when both seats next to a handler were fully occupied in the previous half-hour and became fully unoccupied in the current half-hour) and +2 (when both seats were unoccupied and they became occupied). The variable is continuous, as it reflects the percentage of the half-hour that the seats are occupied. The calls received in the room is the number of incoming calls arriving to the GMP router in the existing half-hour. In Columns (1),(3) the dependent variable is the (change in the) log of the number of minutes that the handler spends on the phone in the half-hour. In Column (2),(4) the dependent variable is the (change in the) log of the number of calls answered by the handler in the half-hour. All regressions include indicators π_h for the half-hour period in which the handler is within the shift, indicators $\mu_{t(sh)}$ for the natural unit of time (i.e. year X month X day X half-hour of day), and the (change in the) log of the number of minutes worked by the handler. Standard errors are clustered at the shift level.

TABLE 5: HETEROGENEOUS EFFECTS BY EVALUATOR AFFILIATION OF PEER AND EVALUATOR AFFILIATION OF SAME-ROOM HANDLERS

Feb2012-Nov2014; Handlers=342; Shifts= 71,575; Half-Hours= 47,903.

	(1)	(2)	(3)	(4)
Panel A: Dependent Variable - Δ Log Minutes on Phone				
Δ Share Current Co-Evaluated in the Room	.183***	.215***	.215***	.215***
	(.0493)	(.0492)	(.0492)	(.0512)
Δ Share Past Co-Evaluated in the Room	-.008	-.009	-.007	.001
	(.0422)	(.0422)	(.0422)	(.044)
Δ Share Future Co-Evaluated in the Room	-.028	-.025	-.026	-.023
	(.0425)	(.0425)	(.0425)	(.0447)
Δ Occupied		.057***		
		(.0036)		
Δ Occupied × Current Co-Evaluated		.028***	.03***	.033**
		(.0103)	(.0106)	(.0153)
Panel B: Dependent Variable - Δ Log Number Calls				
Δ Share Current Co-Evaluated in the Room	.115***	.134***	.134***	.125***
	(.0305)	(.0305)	(.0305)	(.0317)
Δ Share Past Co-Evaluated in the Room	.002	.001	.002	0
	(.0272)	(.0272)	(.0272)	(.0283)
Δ Share Future Co-Evaluated in the Room	.012	.014	.013	.018
	(.0271)	(.027)	(.027)	(.0283)
Δ Occupied		.033***		
		(.0021)		
Δ Occupied × Current Co-Evaluated		.021***	.018***	.02**
		(.0062)	(.0064)	(.0091)
Δ Log Minutes Worked	Yes	Yes	Yes	Yes
Time (Half-Hour) F.E.	Yes	Yes	Yes	Yes
Half-Hour within Shift F.E.	Yes	Yes	Yes	Yes
Δ Occupied × Focus Handler F.E.	No	No	Yes	No
Δ Occupied × Focus/Peer Pair F.E.	No	No	No	Yes
Observations	1,120,350	1,120,350	1,120,350	1,120,350

This table displays estimates of OLS regressions of productivity on the share of handlers in the room that are co-evaluated with the focus handler. The unit of observation is a half-hour period h within a shift s, where a shift is defined as the combination of a specific handler and a specific date (e.g. an observation is the fourth half-hour of the shift of handler John Smith that starts on 1st December 2012). The estimating equation in Column (1) is:

$$\Delta y_{sh} = \gamma \Delta ShareCoEvaluated_{sh} + \pi_h + \mu_{t(sh)} + \gamma \Delta MW_{sh} + \Delta \epsilon_{sh},$$

where the regression includes the handlers co-evaluated in the present, in the past and in the future. In (2), we include the occupation of adjacent seats, interacted with whether the occupants are co-evaluated. In (3), we add the interaction between the occupation of adjacent seats and indicators for the focus handler. In (4), we add the interaction between the occupation of adjacent seats and indicators for the interaction between the focus handler and the peer handler. The dependent and independent variables are in first-differences within a shift. In Panel A the dependent variable is the (change in the) log of the number of minutes that the handler spends on the phone in the half-hour. In Panel B the dependent variable is the (change in the) log of the number of calls answered by the handler in the half-hour. All regressions include indicators π_h for the half-hour period in which the handler is within the shift, indicators $\mu_{t(sh)}$ for the natural unit of time (i.e. year X month X day X half-hour of day), and the (change in the) log of the number of minutes worked by the handler. Standard errors are clustered at the shift level.

TABLE 6: COUNTERFACTUAL EXERCISES
AVERAGE PRODUCTIVITY INCREASES

	Counterfactual 1: Increasing Horizontal Incentives	Counterfactual 2: + Leveraging Vertical Relations
Hourly change (%) in:	**(1)**	**(2)**
Minutes on Phone	4.84***	11.98***
	(0.31)	(2.98)
Number of Calls	2.88***	7.64***
	(0.17)	(1.94)

This figure displays the average productivity increases resulting from alternative allocations of handlers to seats and shifts. We assume that the room layout consists of rows of ten contiguous seats. In both counterfactual exercises we maintain the starting time and duration of every shift observed in the data. As a result, the number of handlers working at each point in time is the same in the observed and counterfactual distributions. In Column 1 we reallocate handlers to seats to maximise the number of adjacent seats that are occupied. In Column 2 we reallocate handlers to shifts to maximise the number of adjacent seats that are occupied by a co-evaluated handler. We further reallocate handlers to shifts to increase the likelihood that co-evaluated handlers work at the same time. The estimated productivity increase in Column 1 is calculated as

$$y_1 = y_0 \left[1 + \hat{\beta}_1(Occupied_{counter} - Occupied_{observed})\right]$$

where y_0 is the observed productivity of the handler, $Occupied_{counter}$ is the simulated occupation of adjacent seats, $Occupied_{observed}$ is the observed occupation of adjacent seats and $\hat{\beta}_1$ is the coefficient from Table 2. The estimated productivity increase in Column 2 is calculated as

$$\begin{aligned} y_1 = y_0 \Big[& 1 + \hat{\beta}_1(Occupied_{counter} - Occupied_{observed}) \\ & + \hat{\beta}_2((Occupied \times CoEvaluated)_{counter} - (Occupied \times CoEvaluated)_{observed}) \\ & + \hat{\beta}_3(ShareCoEvaluated_{counter} - ShareCoEvaluated_{observed})\Big] \end{aligned}$$

where $(Occupied \times CoEvaluated)_{counter}$ is the simulated occupation of adjacent seats by a co-evaluated handler, and $ShareCoEvaluated_{counter}$ is the simulated share of co-evaluated handlers in the room (excluding co-evaluated handlers sitting in an adjacent seat). $\hat{\beta}_2$ is the coefficient from Column 2 Table 8 and $\hat{\beta}_3$ is the coefficient from Column 2 Table 9. Each cell reports the standard errors clustered at the handler level obtained by 200 bootstrap repetitions. Each bootstrap repetition additionally draws random coefficients β_1, β_2 and β_3 from normal distributions with mean and variance according to Tables 2 and 9. Asterisks denote significance based on the boostrapped distribution. The dependent variables are aggregated at the room-hour level.

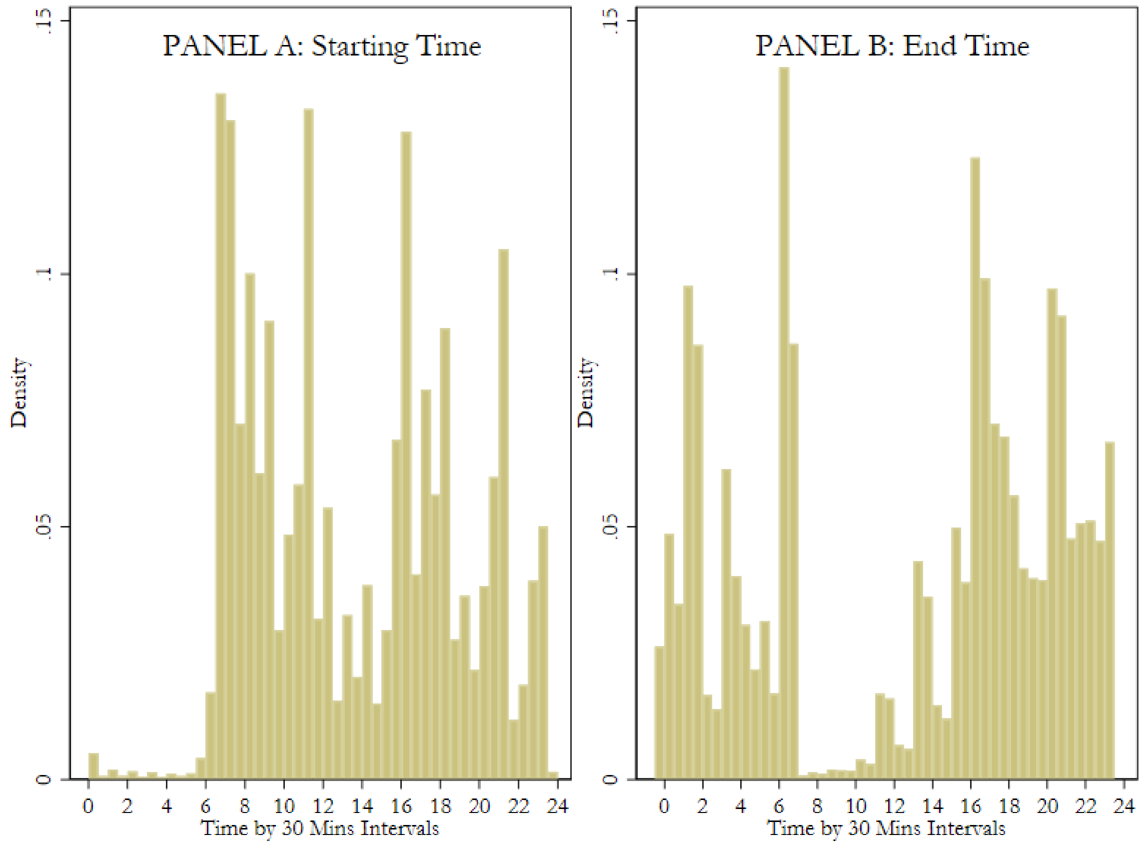
ONLINE APPENDIX A (NOT FOR PUBLICATION): ADDITIONAL TABLES AND FIGURES

FIGURE A1: THE CALL HANDLING ROOM AT THE GREATER MANCHESTER POLICE

SCREENSHOT FROM 'THE FORCE MANCHESTER'

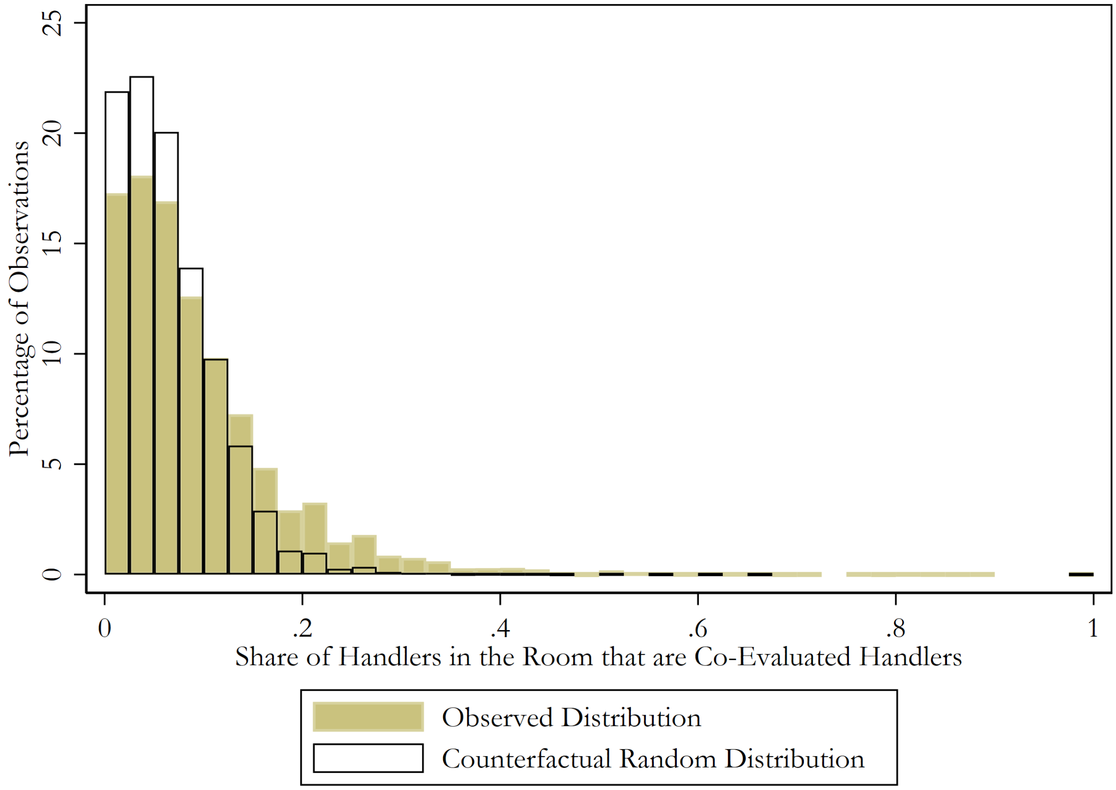
This figure displays a photograph of the actual room that we study in this paper. The screenshot is taken from the first episode of the documentary series 'The Force Manchester', broadcast in the United Kingdom by Sky 1 TV channel.

FIGURE A2: DISTRIBUTION OF STARTING AND ENDING TIMES OF THE HANDLERS' SHIFTS



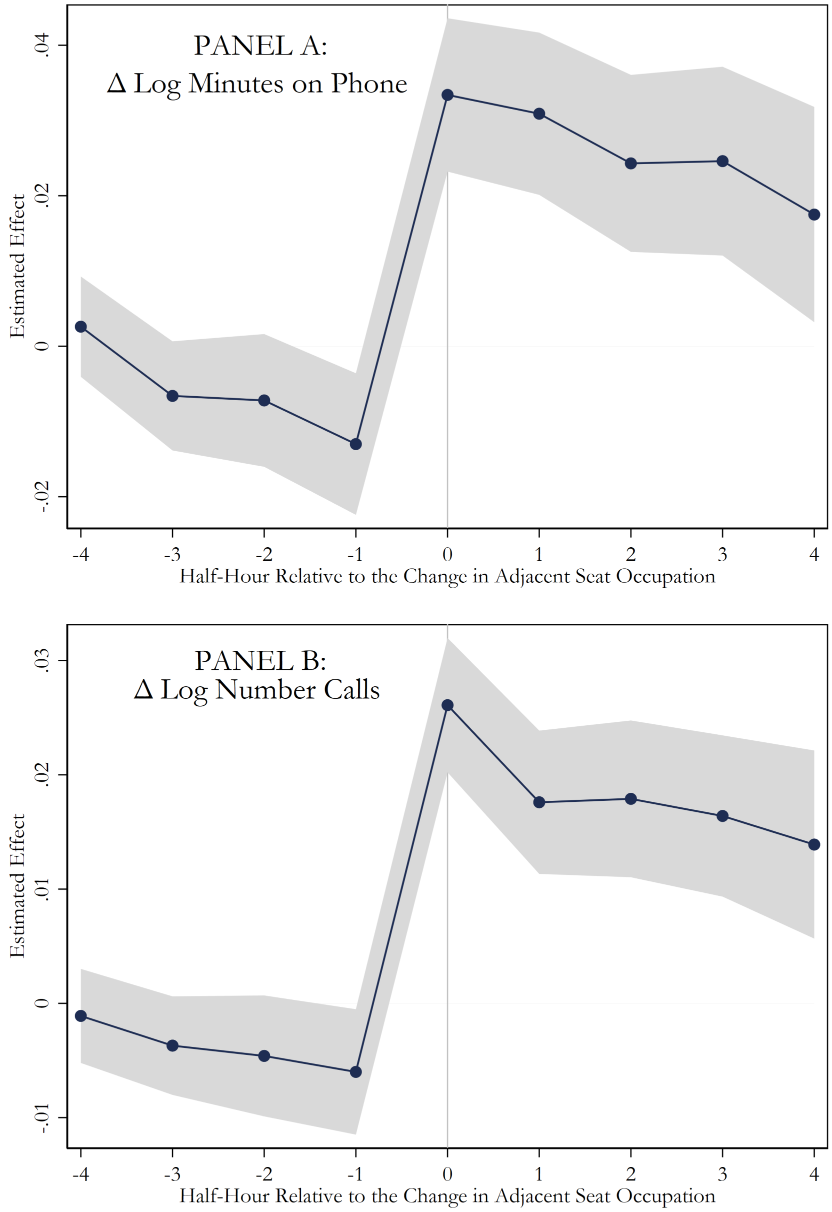
This figure displays the distributions of starting and end times for the shifts in our dataset. An observation is an individual shift.

FIGURE A3: DISTRIBUTION OF SHARE OF HANDLERS IN THE ROOM THAT ARE CO-EVALUATED HANDLERS



This figure displays the distribution of the share of handlers in the room that are co-evaluated. An observation is a shift/half-hour period, consistently with our baseline sample. For each observation, we calculate the percentage of handlers that are working in the room and who are co-evaluated with the focus handler. We also calculate and plot this percentage under a counterfactual in which the allocation of handlers to shift/half-hour periods is randomly created.

FIGURE A4: CUMULATIVE LEADS AND LAGS

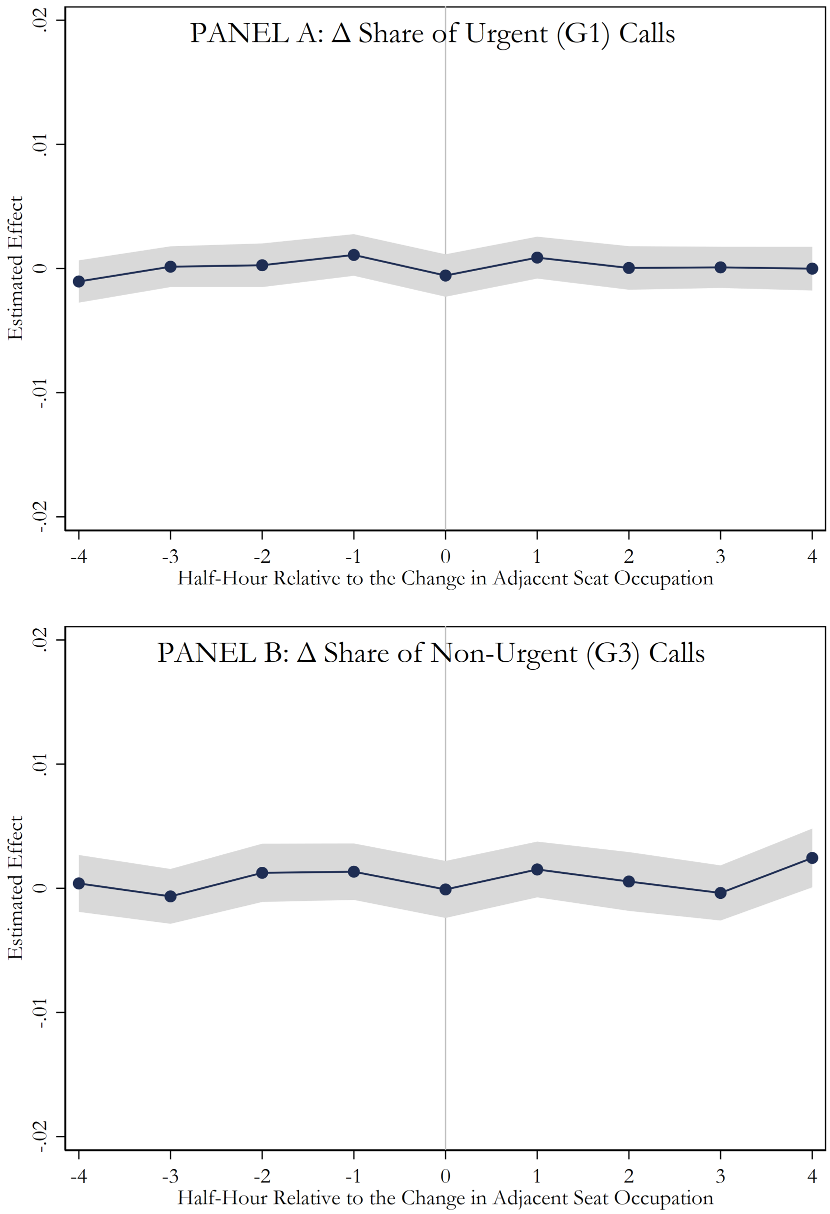


This figure displays the coefficients and 95% confidence intervals of regressions of productivity on the leads and lags of the (change in the) number of adjacent seats that are occupied next to a handler. The figures plot the cumulative effect over time, calculated as the sum up to a certain period and starting two hours before the change in occupation. For instance, the cumulative effect at $t = 2$ (i.e. one hour after the period of the change in occupation) is equal to $\sum_{j=-2}^{4} \hat{\beta}_j$ (i.e. from four periods before the change to two periods after the change). The unit of observation is a half-hour unit h within a shift s, where a shift is defined as the combination of a specific handler and a specific date (e.g. an observation is the fourth half-hour of the shift of handler John Smith that starts on 1st December 2012). The estimating equation is:

$$\Delta y_{sh} = \sum_{j=-4}^{4} \beta_j \Delta Occupied_{s(t+j)} + \pi_h + \mu_{t(sh)} + \gamma \Delta MW_{sh} + \Delta \epsilon_{sh},$$

The dependent and independent variables are in first-differences within a shift. In Panel A the dependent variable is the (change in the) log of the number of minutes that the handler spends on the phone in the half-hour. In Panel B the dependent variable is the (change in the) log of the number of calls answered by the handler in the half-hour. All regressions include the (change in the) log of the number of minutes worked by the handler, indicators π_h for the half-hour period in which the handler is within the shift, and indicators $\mu_{t(sh)}$ for the natural unit of time (i.e. year X month X day X half-hour of day). Standard errors are clustered at the shift level.

FIGURE A5: LAGS AND LEADS PLACEBO

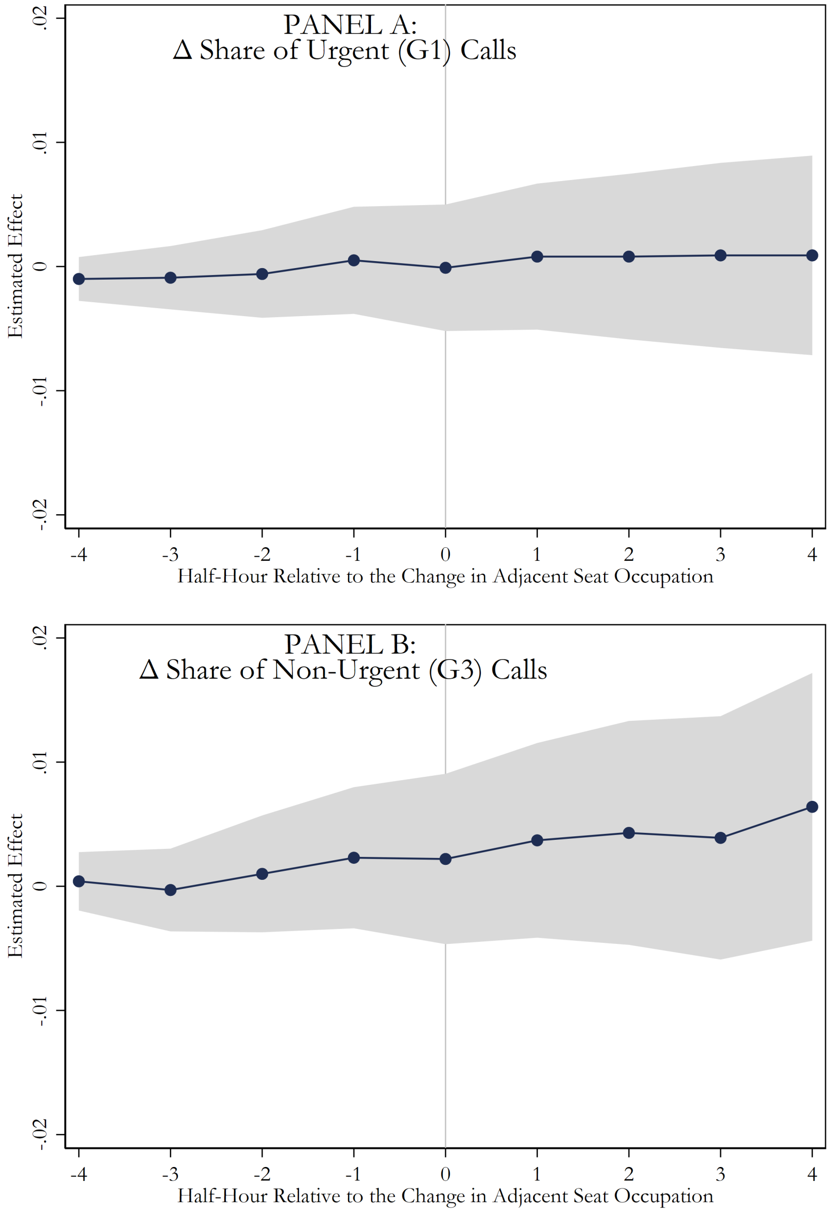


This figure displays the coefficients and 95% confidence intervals of regressions of pre-determined average call characteristics on the leads and lags of the (change in the) number of adjacent seats that are occupied next to a handler. The unit of observation is a half-hour unit h within a shift s, where a shift is defined as the combination of a specific handler and a specific date (e.g. an observation is the fourth half-hour of the shift of handler John Smith that starts on 1st December 2012). The estimating equation is:

$$\Delta y_{sh} = \sum_{j=-4}^{4} \beta_j \Delta Occupied_{s(t+j)} + \pi_h + \mu_{t(sh)} + \gamma \Delta MW_{sh} + \Delta \epsilon_{sh},$$

The dependent and independent variables are in first-differences within a shift. In Panel A the dependent variable is the (change in the) share of calls that are classified as Urgent (Grade 1 calls). In Panel B the dependent variable is the equivalent for Non-Urgent (Grade 3 calls). All regressions include the (change in the) log of the number of minutes worked by the handler, indicators π_h for the half-hour period in which the handler is within the shift, and indicators $\mu_{t(sh)}$ for the natural unit of time (i.e. year X month X day X half-hour of day). Standard errors are clustered at the shift level.

FIGURE A6: CUMULATIVE LAGS AND LEADS PLACEBO

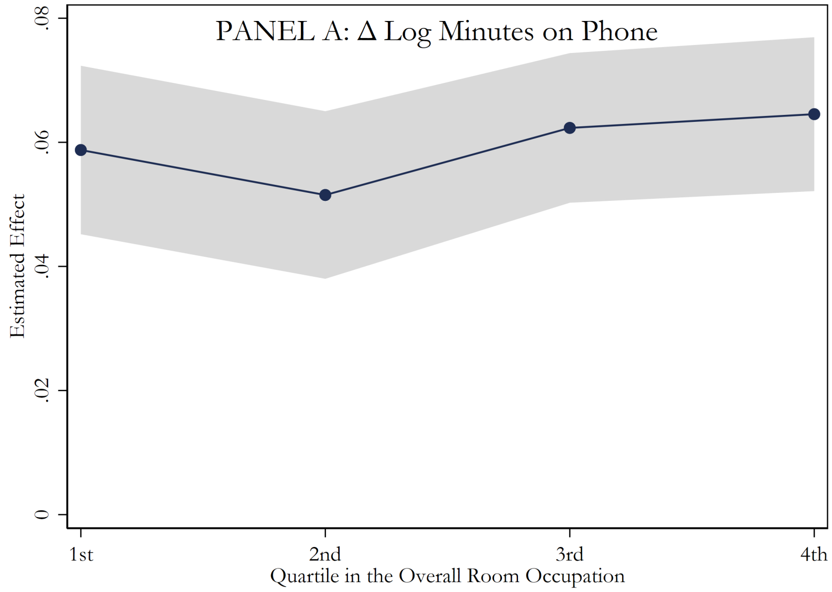


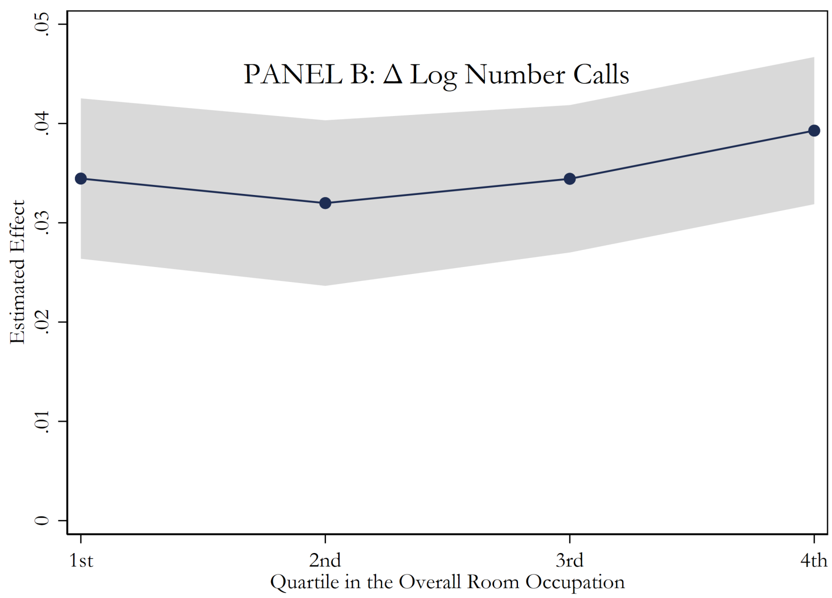
This figure displays the coefficients and 95% confidence intervals of regressions of pre-determined average call characteristics on the leads and lags of the (change in the) number of adjacent seats that are occupied next to a handler. The figures plot the cumulative effect over time, calculated as the sum up to a certain period and starting two hours before the change in occupation. For instance, the cumulative effect at $t = 2$ (i.e. one hour after the period of the change in occupation) is equal to $\sum_{j=-2}^{4} \hat{\beta}_j$ (i.e. from four periods before the change to two periods after the change). The unit of observation is a half-hour unit h within a shift s, where a shift is defined as the combination of a specific handler and a specific date (e.g. an observation is the fourth half-hour of the shift of handler John Smith that starts on 1st December 2012). The estimating equation is:

$$\Delta y_{sh} = \sum_{j=-4}^{4} \beta_j \Delta Occupied_{s(t+j)} + \pi_h + \mu_{t(sh)} + \gamma \Delta MW_{sh} + \Delta\epsilon_{sh},$$

The dependent and independent variables are in first-differences within a shift. In Panel A the dependent variable is the (change in the) share of calls that are classified as Urgent (Grade 1 calls). In Panel B the dependent variable is the equivalent for Non-Urgent (Grade 3 calls). All regressions include the (change in the) log of the number of minutes worked by the handler, indicators π_h for the half-hour period in which the handler is within the shift, and indicators $\mu_{t(sh)}$ for the natural unit of time (i.e. year X month X day X half-hour of day). Standard errors are clustered at the shift level.

FIGURE A7: HETEROGENEITY OF BASELINE EFFECT BY OVERALL OCCUPATION OF ROOM



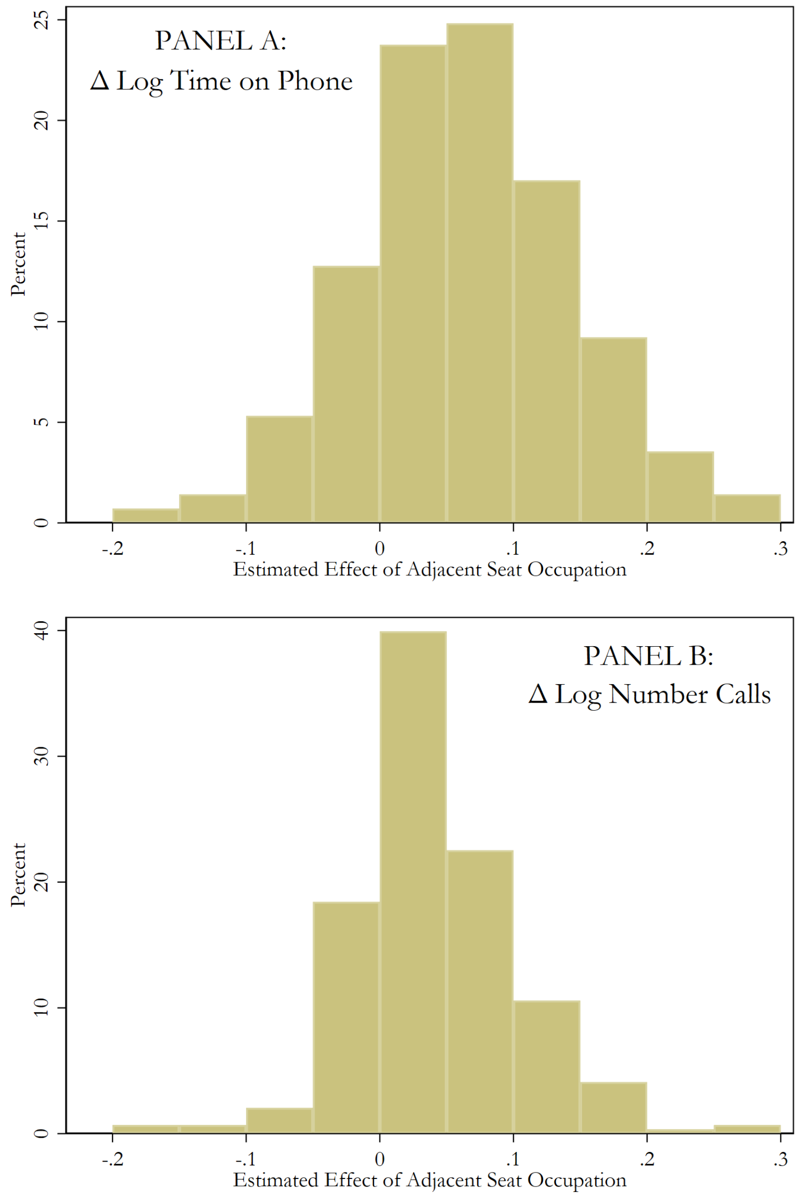


This figure displays the coefficients and 95% confidence intervals of regressions of productivity on the (change in the) number of adjacent seats that are occupied next to a handler, interacted with quartiles for the occupation of the room. The unit of observation is a half-hour unit h within a shift s, where a shift is defined as the combination of a specific handler and a specific date (e.g. an observation is the fourth half-hour of the shift of handler John Smith that starts on 1st December 2012). The estimating equation is:

$$\Delta y_{sh} = \sum_{j=1}^{4} \beta_j (\Delta Occupied_{sh} \times Qj_{t(sh)}) + \pi_h + \mu_{t(sh)} + \gamma \Delta MW_{sh} + \Delta \epsilon_{sh},$$

The dependent and independent variables are in first-differences within a shift. $Qj_{t(sh)}$ is a dummy variable for whether the half-hour (i.e. year X month X day X half-hour of day) t corresponds to the quartile j in terms of the overall occupation of the room. In Panel A the dependent variable is the (change in the) log of the number of minutes that the handler spends on the phone in the half-hour. In Panel B the dependent variable is the (change in the) log of the number of calls answered by the handler in the half-hour. All regressions include the (change in the) log of the number of minutes worked by the handler, indicators π_h for the half-hour period in which the handler is within the shift, and indicators $\mu_{t(sh)}$ for the natural unit of time (i.e. year X month X day X half-hour of day). Standard errors are clustered at the shift level.

FIGURE A8: DISTRIBUTION OF INDIVIDUAL-SPECIFIC EFFECTS (FOCUS HANDLER)

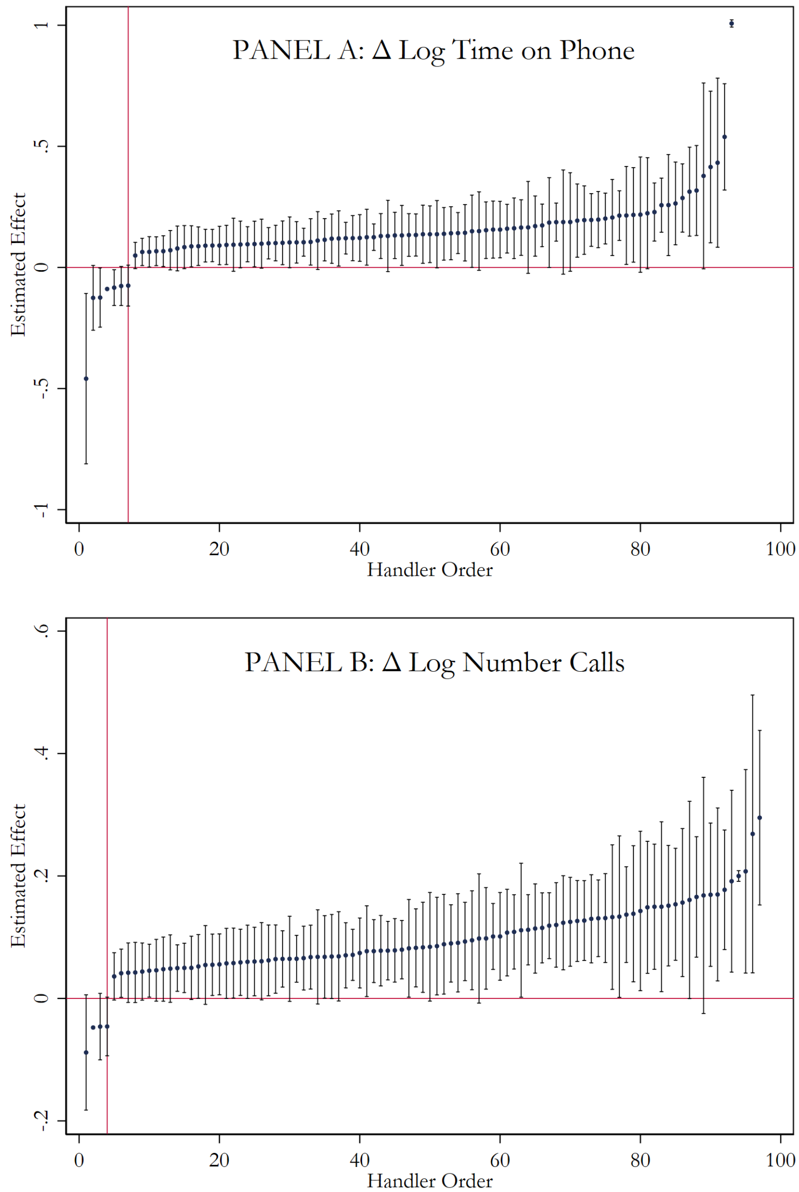


This figure displays the distribution of the individual-specific coefficients $\hat{\beta}_{i(s)}$ arising from regressions of productivity on the (change in the) number of adjacent seats that are occupied next to a handler. The unit of observation is a half-hour unit h within a shift s, where a shift is defined as the combination of a specific handler and a specific date (e.g. an observation is the fourth half-hour of the shift of handler John Smith that starts on 1st December 2012). The estimating equation is:

$$\Delta y_{sh} = \sum_{i(s)=1}^{343} \beta_{i(s)}(\Delta Occupied_{sh} \times \eta_{i(s)}) + \pi_h + \mu_{t(sh)} + \gamma \Delta MW_{sh} + \Delta\epsilon_{sh}$$

The dependent and independent variables are in first-differences within a shift. In Panel A the dependent variable is the (change in the) log of the number of minutes that the handler spends on the phone in the half-hour. In Panel B the dependent variable is the (change in the) log of the number of calls answered by the handler in the half-hour. The main independent variable $\Delta Occupied_{sh}$ is interacted with focus-handler dummies, $\eta_{i(s)}$. All regressions include the (change in the) log of the number of minutes worked by the handler, indicators π_h for the half-hour period in which the handler is within the shift, and indicators $\mu_{t(sh)}$ for the natural unit of time (i.e. year X month X day X half-hour of day). Standard errors are clustered at the shift level.

FIGURE A9: INDIVIDUAL-SPECIFIC EFFECTS (FOCUS HANDLER)

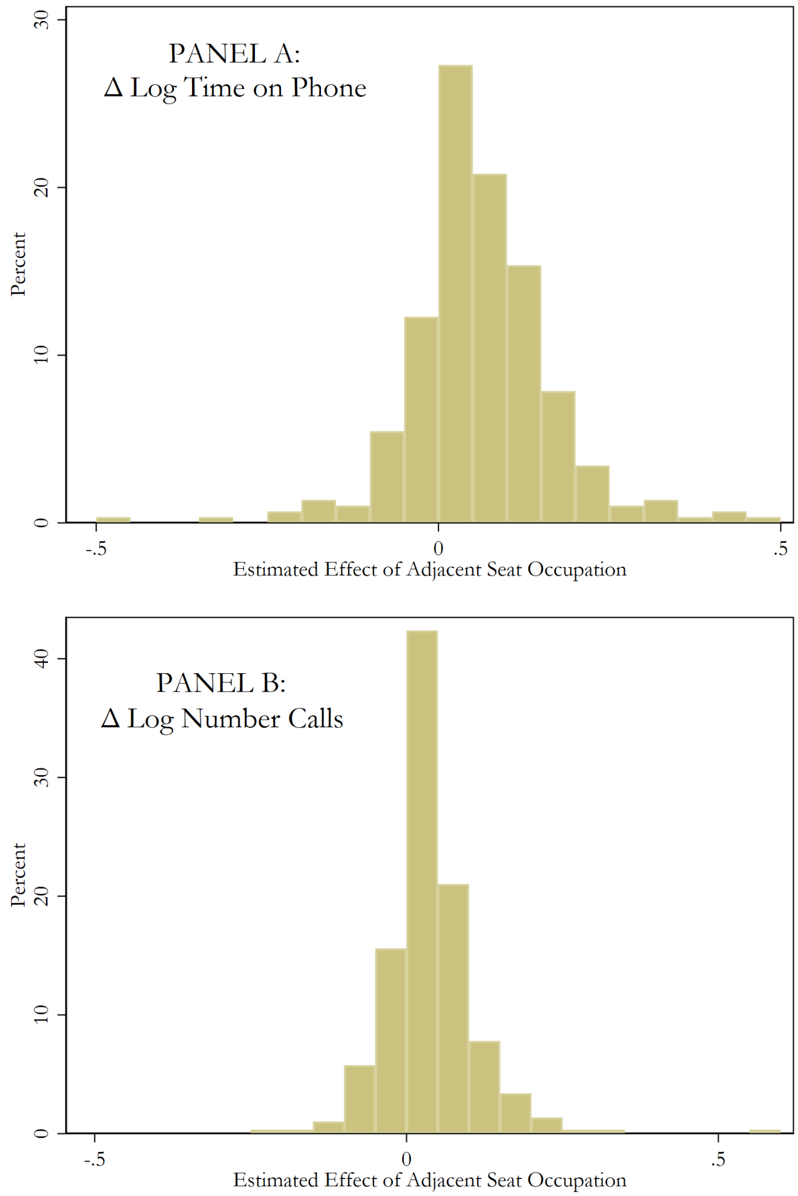


This figure displays the individual-specific coefficients $\hat{\beta}_{i(s)}$ arising from regressions of productivity on the (change in the) number of adjacent seats that are occupied next to a handler. Only the coefficients that are different from zero at the 10% are displayed, together with the 95% confidence levels. The unit of observation is a half-hour unit h within a shift s, where a shift is defined as the combination of a specific handler and a specific date (e.g. an observation is the fourth half-hour of the shift of handler John Smith that starts on 1st December 2012). The estimating equation is:

$$\Delta y_{sh} = \sum_{i(s)=1}^{343} \beta_{i(s)}(\Delta Occupied_{sh} \times \eta_{i(s)}) + \pi_h + \mu_{t(sh)} + \gamma \Delta MW_{sh} + \Delta\epsilon_{sh}$$

The dependent and independent variables are in first-differences within a shift. In Panel A the dependent variable is the (change in the) log of the number of minutes that the handler spends on the phone in the half-hour. In Panel B the dependent variable is the (change in the) log of the number of calls answered by the handler in the half-hour. The main independent variable $\Delta Occupied_{sh}$ is interacted with focus-handler dummies, $\eta_{i(s)}$. All regressions include the (change in the) log of the number of minutes worked by the handler, indicators π_h for the half-hour period in which the handler is within the shift, and indicators $\mu_{t(sh)}$ for the natural unit of time (i.e. year X month X day X half-hour of day). Standard errors are clustered at the shift level.

FIGURE A10: DISTRIBUTION OF INDIVIDUAL-SPECIFIC EFFECTS (PEER HANDLER)

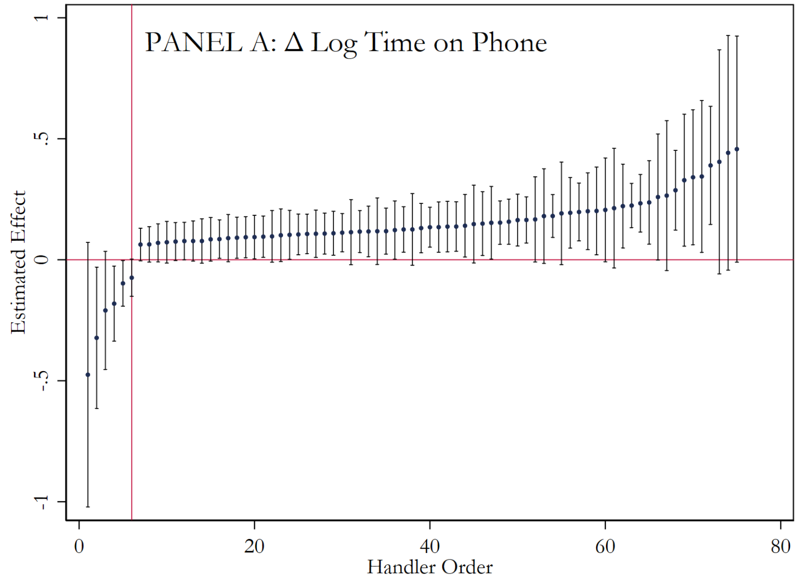


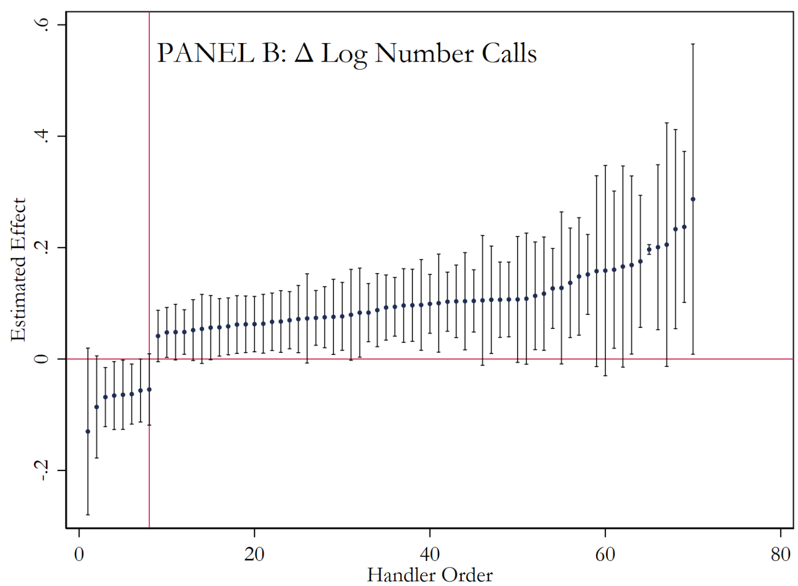
This figure displays the distribution of the peer-specific coefficients $\hat{\beta}_{i(s)}$ arising from regressions of productivity on the (change in the) number of adjacent seats that are occupied next to a handler. The unit of observation is a half-hour unit h within a shift s, where a shift is defined as the combination of a specific handler and a specific date (e.g. an observation is the fourth half-hour of the shift of handler John Smith that starts on 1st December 2012). The estimating equation is:

$$\Delta y_{sh} = \sum_{i(s)=1}^{343} \beta_{i(s)} (\Delta Occupied_{sh} \times \eta_{i(s)}) + \pi_h + \mu_{t(sh)} + \gamma \Delta MW_{sh} + \Delta\epsilon_{sh}$$

The dependent and independent variables are in first-differences within a shift. In Panel A the dependent variable is the (change in the) log of the number of minutes that the handler spends on the phone in the half-hour. In Panel B the dependent variable is the (change in the) log of the number of calls answered by the handler in the half-hour. The main independent variable $\Delta Occupied_{sh}$ is interacted with peer-handler dummies, $\eta_{i(s)}$. All regressions include the (change in the) log of the number of minutes worked by the handler, indicators π_h for the half-hour period in which the handler is within the shift, and indicators $\mu_{t(sh)}$ for the natural unit of time (i.e. year X month X day X half-hour of day). Standard errors are clustered at the shift level.

FIGURE A11: INDIVIDUAL-SPECIFIC EFFECTS (PEER HANDLER)



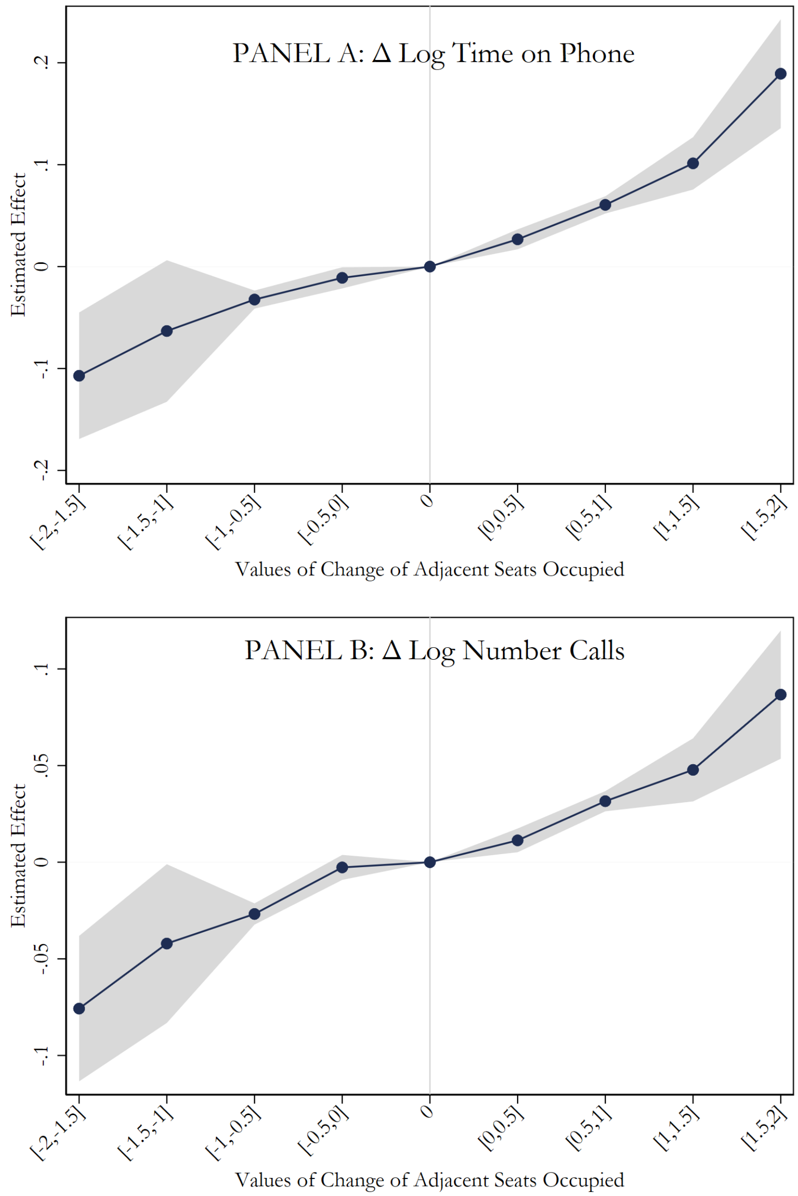


This figure displays the peer-specific coefficients $\hat{\beta}_{i(s)}$ arising from regressions of productivity on the (change in the) number of adjacent seats that are occupied next to a handler. Only the coefficients that are different from zero at the 10% are displayed, together with the 95% confidence levels. The unit of observation is a half-hour unit h within a shift s, where a shift is defined as the combination of a specific handler and a specific date (e.g. an observation is the fourth half-hour of the shift of handler John Smith that starts on 1st December 2012). The estimating equation is:

$$\Delta y_{sh} = \sum_{i(s)=1}^{343} \beta_{i(s)} (\Delta Occupied_{sh} \times \eta_{i(s)}) + \pi_h + \mu_{t(sh)} + \gamma \Delta MW_{sh} + \Delta \epsilon_{sh}$$

The dependent and independent variables are in first-differences within a shift. In Panel A the dependent variable is the (change in the) log of the number of minutes that the handler spends on the phone in the half-hour. In Panel B the dependent variable is the (change in the) log of the number of calls answered by the handler in the half-hour. The main independent variable $\Delta Occupied_{sh}$ is interacted with peer-handler dummies, $\eta_{i(s)}$. All regressions include the (change in the) log of the number of minutes worked by the handler, indicators π_h for the half-hour period in which the handler is within the shift, and indicators $\mu_{t(sh)}$ for the natural unit of time (i.e. year X month X day X half-hour of day). Standard errors are clustered at the shift level.

FIGURE A12: INCREASES VS. DECREASES IN ADJACENT SEATS OCCUPATION

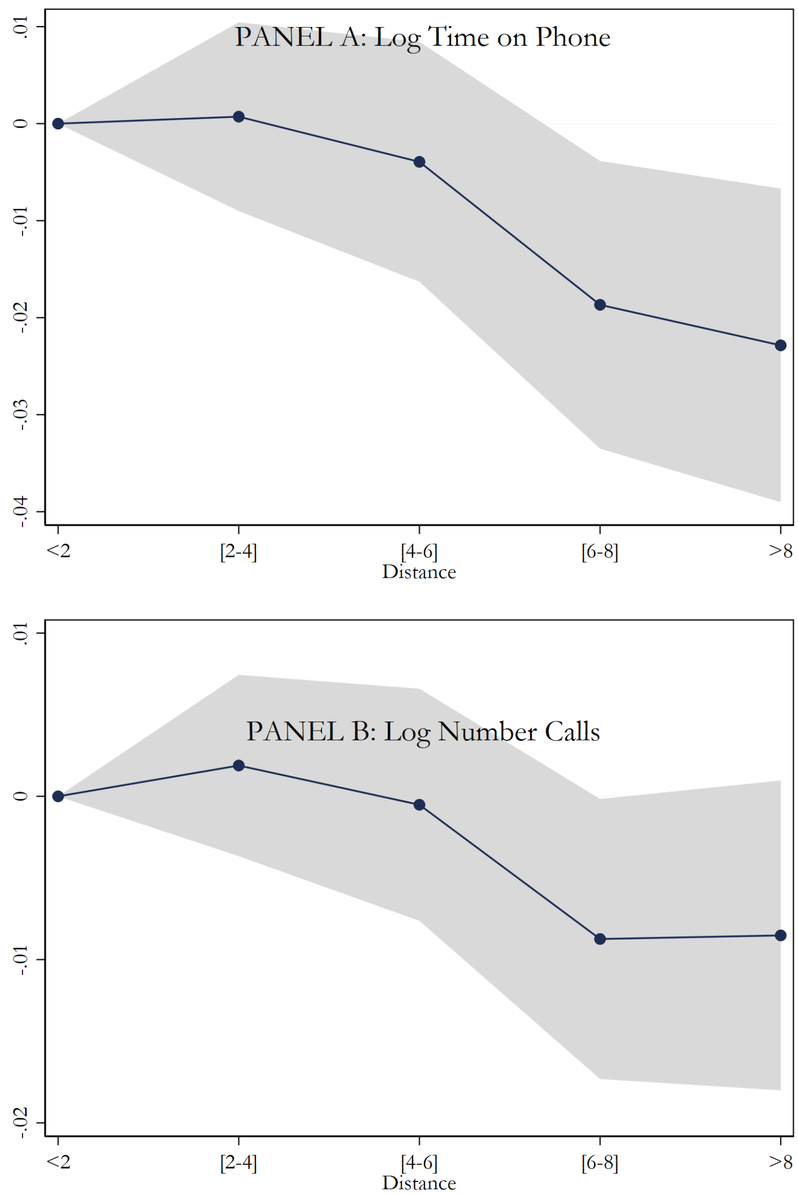


This figure displays the coefficients and 95% confidence intervals of regressions of productivity on the (change in the) number of adjacent seats that are occupied next to a handler. The changes are grouped non-parametrically into eight dummy variables $\Delta Occupiedj_{sh}$, where $\Delta Occupiedj_{sh} = 1$ if the change in period sh falls into interval j. For instance, $\Delta Occupied8_{sh} = 1$ if in the current half hour, the two seats adjacent to the handler change from being unoccupied to being occupied more than 75% of the time. The unit of observation is a half-hour unit h within a shift s, where a shift is defined as the combination of a specific handler and a specific date (e.g. an observation is the fourth half-hour of the shift of handler John Smith that starts on 1st December 2012). The estimating equation is:

$$\Delta y_{sh} = \sum_{j=1}^{8} \beta_j \Delta Occupiedj_{sh} + \pi_h + \mu_{t(sh)} + \gamma \Delta MW_{sh} + \Delta \epsilon_{sh},$$

The dependent and independent variables are in first-differences within a shift. In Panel A the dependent variable is the (change in the) log of the number of minutes that the handler spends on the phone in the half-hour. In Panel B the dependent variable is the (change in the) log of the number of calls answered by the handler in the half-hour. All regressions include the (change in the) log of the number of minutes worked by the handler, indicators π_h for the half-hour period in which the handler is within the shift, and indicators $\mu_{t(sh)}$ for the natural unit of time (i.e. year X month X day X half-hour of day). Standard errors are clustered at the shift level.

FIGURE A13: DESCRIPTIVE EVIDENCE OF THE RELATION BETWEEN PRODUCTIVITY AND DISTANCE TO THE CLOSEST SUPERVISORY DESK

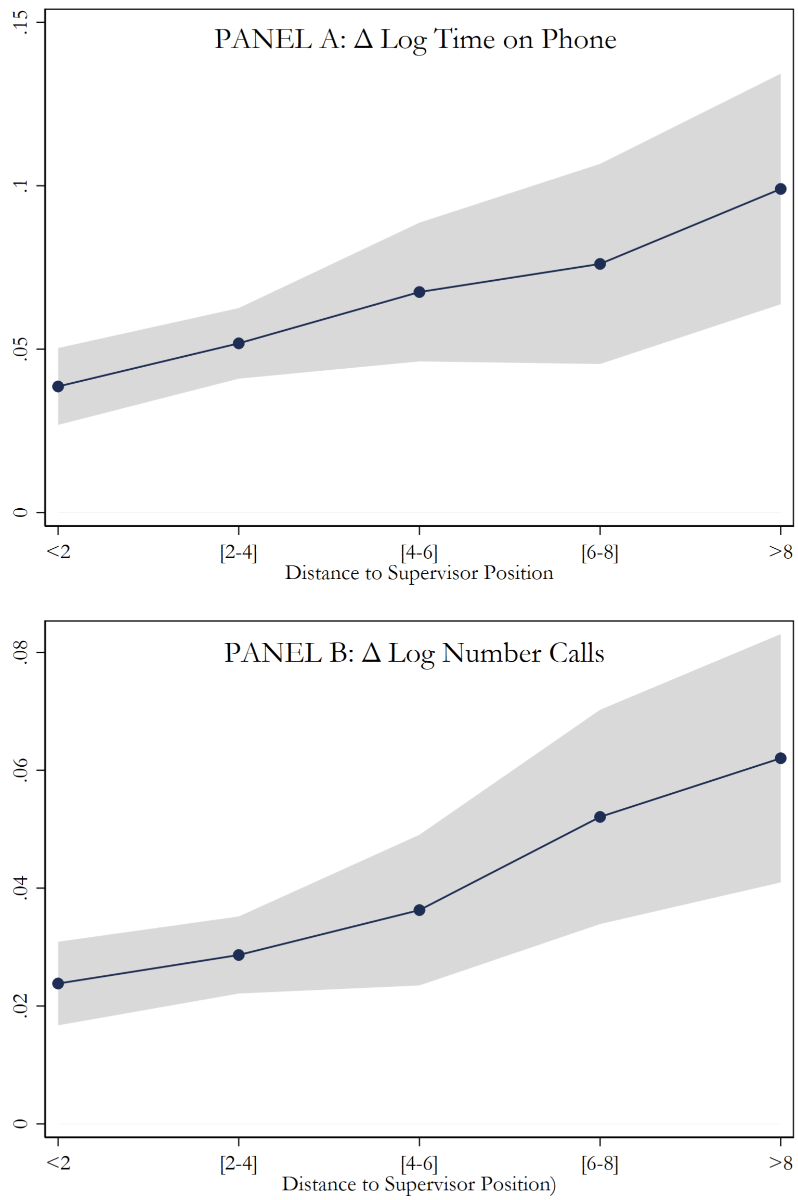


This figure displays the coefficients and 95% confidence intervals of regressions of productivity on the distance to the closest supervisory desk. The distance levels are grouped non-parametrically into five dummy variables. The unit of observation is a half-hour unit h within a shift s, where a shift is defined as the combination of a specific handler and a specific date (e.g. an observation is the fourth half-hour of the shift of handler John Smith that starts on 1st December 2012). The dataset includes only half-hours in which the seats adjacent to a handler are unoccupied. The estimating equation is:

$$y_{sh} = \alpha Distance_s + \eta_{i(s)} + \theta_h + \lambda_{t(sh)} + \gamma MW_{sh} + \epsilon_{sh},$$

In Panel A the dependent variable is the log of the number of minutes that the handler spends on the phone in the half-hour. In Panel B the dependent variable is the log of the number of calls answered by the handler in the half-hour. All regressions include the log of the number of minutes worked by the handler, indicators $\eta_{i(s)}$ for the handler corresponding to the shift, indicators θ_h for the half-hour period in which the handler is within the shift, and indicators $\lambda_{t(sh)}$ for the natural unit of time (i.e. year X month X day X half-hour of day). Standard errors are clustered at the shift level.

FIGURE A14: HETEROGENOUS EFFECTS BY DISTANCE TO SUPERVISOR

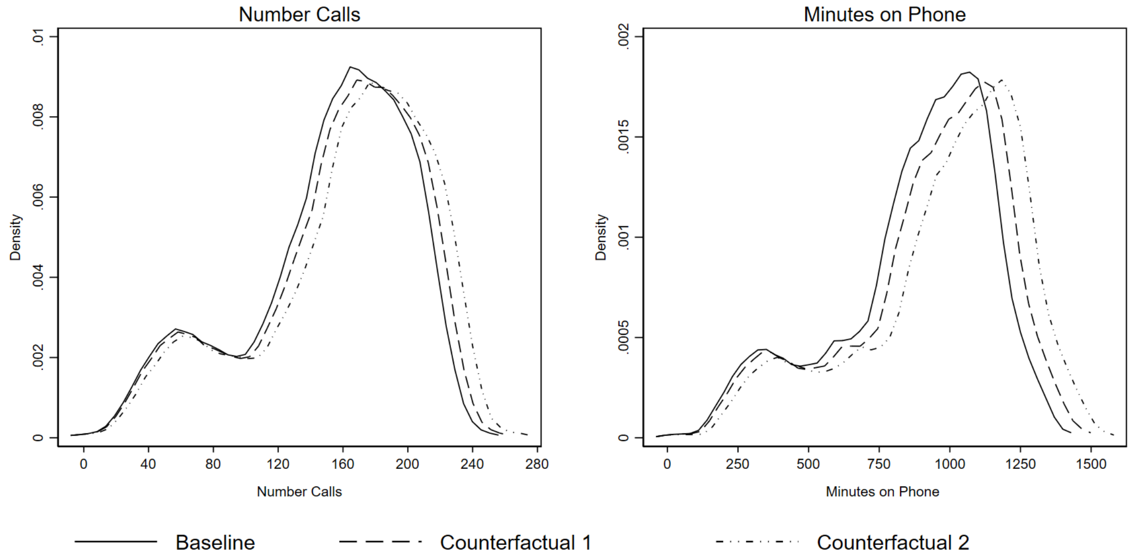


This table displays estimates of OLS regressions of productivity on the number of adjacent seats that are occupied next to a handler, interacted with dummies for the distance between the handler's desk and the closest supervisor position. The unit of observation is a half-hour unit h within a shift s, where a shift is defined as the combination of a specific handler and a specific date (e.g. an observation is the fourth half-hour of the shift of handler John Smith that starts on 1st December 2012). The estimating equation is:

$$\Delta y_{sh} = \sum_{j=1}^{5} \beta_j (\Delta Occupied_{sh} \times Distancej_s) + \pi_h + \mu_{t(sh)} + \gamma \Delta MW_{sh} + \Delta\epsilon_{sh}$$

The dependent and independent variables are in first-differences within a shift. $Distancej_s$ is a dummy variable for whether the desk corresponding to shift s is at j distance to the closest supervisor. In Panel A the dependent variable is the (change in the) log of the number of minutes that the handler spends on the phone in the half-hour. In Panel B the dependent variable is the (change in the) log of the number of calls answered by the handler in the half-hour. All regressions include the (change in the) log of the number of minutes worked by the handler, indicators π_h for the half-hour period in which the handler is within the shift, and indicators $\mu_{t(sh)}$ for the natural unit of time (i.e. year X month X day X half-hour of day). Standard errors are clustered at the shift level.

FIGURE A15: COUNTERFACTUAL EXERCISES OBSERVED AND COUNTERFACTUAL DISTRIBUTIONS



This figure displays the counterfactual distributions of productivity resulting from alternative allocations of handlers to seats and shifts, together with the observed distributions. Panel A shows the (kernel estimated) distributions of the hourly time spent in the phone across handlers. Panel B shows the equivalent distributions for the hourly number of calls taken. We assume that the room layout consists of rows of ten contiguous seats. In both counterfactual exercises we maintain the starting time and duration of every shift observed in the data. As a result, the number of handlers working at each point in time is the same in the observed and counterfactual distributions. In Counterfactual 1 we reallocate handlers to seats to maximise the number of adjacent seats that are occupied. In Counterfactual 2 we reallocate handlers to shifts to maximise the number of adjacent seats that are occupied by a co-evaluated handler. We further reallocate handlers to shifts to increase the likelihood that co-evaluated handlers work at the same time. The output in Counterfactual 1 is calculated as

$$y_1 = y_0 \left[1 + \hat{\beta}_1(Occupied_{counter} - Occupied_{observed})\right]$$

where y_0 is the observed productivity of the handler, $Occupied_{counter}$ is the simulated occupation of adjacent seats, $Occupied_{observed}$ is the observed occupation of adjacent seats and $\hat{\beta}_1$ is the coefficient from Table 1. The output in Counterfactual 2 is calculated as

$$\begin{aligned} y_1 = y_0 \Big[& 1 + \hat{\beta}_1(Occupied_{counter} - Occupied_{observed}) \\ & + \hat{\beta}_2((Occupied \times CoEvaluated)_{counter} - (Occupied \times CoEvaluated)_{observed}) \\ & + \hat{\beta}_3(ShareCoEvaluated_{counter} - ShareCoEvaluated_{observed})\Big] \end{aligned}$$

where $(Occupied \times CoEvaluated)_{counter}$ is the simulated occupation of adjacent seats by a co-evaluated handler, and $ShareCoEvaluated_{counter}$ is the simulated share of co-evaluated handlers in the room (excluding co-evaluated handlers sitting in an adjacent seat). $\hat{\beta}_2$ is the coefficient from Column 2 Table 4 and $\hat{\beta}_3$ is the coefficient from Column 2 Table 5. The dependent variables are aggregated at the room-hour level.

TABLE A1 - BALANCING TESTS
CO-EVALUATION OF HANDLERS

Feb2012-Nov2014; Handlers=280; Observations= 107,596.

	(1)	(2)
Same Gender	-.011	-.001
	(.019)	(.002)
Difference in Age	-.026	-.002
	(.017)	(.002)
Difference in Experience	-.037*	-.004
	(.021)	(.003)
Average Distance Within Room	-.004	0
	(.012)	(.001)
Overlap in the Night Shifts	-.017	-.003
	(.011)	(.002)
Overlap in the Morning Shifts	-.005	0
	(.009)	(.001)
Difference in Share of Urgent Calls	-.013	-.001
	(.011)	(.001)
Difference in Number of Hours Worked	-.02	-.001
	(.013)	(.001)
Difference in Share of Time with Adjacent Seats Occupied	.003	.001
	(.008)	(.001)
First Handler Fixed Effects	Yes	Yes
Second Handler Fixed Effects	Yes	Yes
Year/Semester Fixed Effects	Yes	Yes
F-Statistic Coefficients Jointly Equal to Zero		1.16

This table displays estimates of regressions of whether two handlers are co-evaluated in a specific semester on a set of characteristics of the handler pair. An observation is a pair of handlers in a semester (an observation only exists if both handlers were working during that semester). Average Distance within the Room is the average distance between the desks of the two handlers, calculated over all the half-hours in which the handlers coincide. Overlap in the Night Shifts is the difference in the share of time that the handlers spend on the night shift, relative to the afternoon shift. Overlap in the Morning Shifts is the difference in the share of time that the handlers spend on the morning shift, relative to the afternoon shift. Difference in the Share of Urgent Calls is the difference in the share of the Grade 1 calls received. Column 1 displays the estimates of nine separate regressions of the type:

$$Charack_{ijt} = \psi CoEvaluated_{ijt} + \theta_i + \lambda_j + \pi_t + \epsilon_{ijt}$$

where $Charack_{ijt}$ is characteristic k of the pair ij during semester t. $CoEvaluated_{ijt} = 1$ if the pair were co-evaluated in semester t. θ_i and λ_j are handler 1 and 2 fixed effects, and π_t are semester fixed effects. Column 2 displays the estimates of a single regression of the type:

$$CoEvaluated_{ijt} = \sum_{k=1}^{K} \beta_k Charack_{ijt} + \theta_i + \lambda_j + \pi_t + \epsilon_{ijt}$$

Standard errors are clustered at the Handler 1 and Handler 2 levels.

TABLE A2: VARIATION IN THE BASELINE SAMPLE CROSS-TABULATION BY NUMBER OF ADJACENT SEATS AND NUMBER OF ADJACENT OCCUPIED SEATS

Number of Adjacent and Occupied Seats	**Number of Adjacent Seats** 0	1	2	Total
0	7,645	230,132	39,409	277,186
1	0	610,793	137,724	748,517
2	0	0	143,160	143,160
Total	7,645	840,925	320,293	1,168,863

This table displays the main source of variation in the baseline sample. The unit of observation is a half-hour period h within a shift s, where a shift is defined as the combination of a specific handler and a specific date (e.g. an observation is the fourth half-hour of the shift of handler John Smith that starts on 1st December 2012). Along the column dimension, we display the number of seats that are row-adjacent to the seat that the handler is occupying during that observation. Along the row dimension, we display the number of seats that are both row-adjacent and occupied by other handlers. In this table, a seat is considered occupied if it was occupied by a handler for at least one minute during the half-hour period. Due to the construction of the table, below-diagonal cells take value zero.

TABLE A3: DESCRIPTIVE STATISTICS

Variable Name	Mean	SD	Min	Max	Observations
N Handlers in Room	30.86	9.44	1	64	1,275,483
Handler Age	39.13	11.47	19	65	1,274,731
Female Handler Dummy	.68	.47	0	1	1,274,731
Handler Experience (in Years)	5.6	5.73	.03	29.17	1,274,731
Shift Duration (in Hours)	8.99	1.69	.02	14.63	1,275,483
N Minutes Worked	26.96	8.23	0	30	1,275,483
N Calls	2.45	1.67	0	29	1,275,483
Time on Phone	13.7	8.46	0	30	1,275,483
N Calls Taken by All Handlers	75.93	27.14	0	208	1,275,483
Share of Desks Occupied	.53	.16	.02	1	1,275,483
Distance to Closest Supervisor	3.5	2.2	1	10.13	1,117,457
N Evaluators	14.97	1.37	12	17	1,273,138
N Handlers Managed by Evaluator	12.23	2.83	1	27	1,273,138
N Adjacent Desks	1.27	.46	0	2	1,275,483
N Desks in Row Behind	1.43	1.13	0	3	1,275,483
N Desks in Row in Front	1.58	1.11	0	3	1,275,483
Occupation of Adjacent Desks	.82	.59	0	2	1,275,483
Occupation of Adjacent Desks Current Co-Evaluated	.13	.35	0	2	1,275,483
Occupation of Adjacent Desks Past Co-Evaluated	.05	.23	0	2	1,275,483
Occupation of Adjacent Desks Future Co-Evaluated	.02	.15	0	2	1,275,483
Share Current Co-Evaluated in the Room	.09	.08	0	1	1,275,329

This table displays the summary statistics of the main variables used in the empirical analysis. All the statistics have been calculated at the shift/half-hour level, before the panel dataset is converted into first differences. N Handlers in Room is the total number of handlers that are present in the room in the specific half-hour. N Calls is the number of calls taken by the handler in the specific half-hour. Time on Phone is the number of minutes that the handler spent on the phone in the specific half-hour. Share of Desks Occupied is the percentage of the total desks in the room that are occupied in the specific half-hour. N Evaluators is the number of managers that are acting as performance evaluators at that point in time. N Handlers Managed by Evaluator is the number of handlers assigned to an average performance evaluator at that point in time. Occupation of Adjacent Desks is the main independent variable in the study, and it captures the number of desks adjacent to the focus handler that are occupied during that specific half-hour. Share Current Co-Evaluated in the Room is the percentage of handlers in the room during that half-hour that are evaluated by the same manager as the focus handler.

TABLE A4: ROBUSTNESS TO DIFFERENT TIME UNITS

Feb2012-Nov2014; Handlers=343; Shifts= 71,284.

	15 Minutes		30 Minutes		60 Minutes	
Dependent Variable:	**(1) Δ Log Minutes on Phone**	**(2) Δ Log Number Calls**	**(3) Δ Log Minutes on Phone**	**(4) Δ Log Number Calls**	**(5) Δ Log Minutes on Phone**	**(6) Δ Log Number Calls**
Δ Occupied	.059***	.03***	.06***	.035***	.083***	.049***
	(.003)	(.002)	(.003)	(.002)	(.004)	(.002)
Δ Log Minutes Worked	Yes	Yes	Yes	Yes	Yes	Yes
Time Period F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Period within Shift F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,253,316	2,253,316	1,120,440	1,120,440	552,534	552,534

This table displays estimates of OLS regressions of productivity on the number of adjacent seats that are occupied next to a handler. The unit of observation is a time unit h within a shift s, where a shift is defined as the combination of a specific handler and a specific date (e.g. an observation is the fourth time period of the shift of handler John Smith that starts on 1st December 2012). In (1)-(2), the time units are 15-minute periods. In (3)-(4), the time units are 30-minute periods. In (5)-(6), the time units are 60-minute periods. The estimating equation is:

$$\Delta y_{sh} = \beta \Delta Occupied_{sh} + \pi_h + \mu_{t(sh)} + \gamma \Delta MW_{sh} + \Delta \epsilon_{sh},$$

The dependent and independent variables are in first-differences within a shift. The independent variable ranges between -2 (when both seats next to a handler were fully occupied in the previous period and became fully unoccupied in the current half-hour) and +2 (when both seats were unoccupied and they became occupied). The variable is continuous, as it reflects the percentage of the period that the seats are occupied. In Columns (1), (3) and (5) the dependent variable is the (change in the) log of the number of minutes that the handler spends on the phone in the period. In Columns (2), (4) and (6) the dependent variable is the (change in the) log of the number of calls answered by the handler in the period. All regressions include indicators π_h for the period in which the handler is within the shift, indicators $\mu_{t(sh)}$ for the natural unit of time (i.e. year X month X day X period of day), and the (change in the) log of the number of minutes worked by the handler. Standard errors are clustered at the shift level.

TABLE A5: EFFECTS ON QUALITY

Dependent Variable:	(1) Δ Log Average Call Duration	(2) Δ Log Allocation Time	(3) Δ Log Response Time	(4) Δ Log Clearance Dummy
Δ Occupied	.005 (.0029)	.02 (.0165)	.012 (.0124)	-.026 (.0327)
Δ Log Minutes Worked	Yes	Yes	Yes	Yes
Time (Half-Hour) F.E.	Yes	Yes	Yes	Yes
Half-Hour within Shift F.E.	Yes	Yes	Yes	Yes
Observations	908,253	355,363	351,023	9,625

This table displays estimates of OLS regressions of quality measures on the number of adjacent seats that are occupied next to a handler. The unit of observation is a half-hour period h within a shift s, where a shift is defined as the combination of a specific handler and a specific date (e.g. an observation is the fourth half-hour of the shift of handler John Smith that starts on 1st December 2012). The estimating equation is:

$$\Delta y_{sh} = \beta \Delta Occupied_{sh} + \pi_h + \mu_{t(sh)} + \gamma \Delta MW_{sh} + \Delta \epsilon_{sh},$$

The dependent and independent variables are in first-differences within a shift. The independent variable ranges between -2 (when both seats next to a handler were fully occupied in the previous half-hour and became fully unoccupied in the current half-hour) and +2 (when both seats were unoccupied and they became occupied). The variable is continuous, as it reflects the percentage of the half-hour that the seats are occupied. In Column (1) the dependent variable is the (change in the) log of the average duration of the calls answered by the handler in the half-hour. In Column (2) the dependent variable is the (change in the) log of the average time between the handler creating the incident and the radio operator assigning an officer. In Column (3) the dependent variable is the (change in the) log of the average time between the handler creating the incident and the police officer reaching the scene of the incident. In Column (4) the dependent variable is the (change in the) ratio of incidents classified as crimes for which a suspect is identified by the police. All regressions include indicators π_h for the half-hour period in which the handler is within the shift, indicators $\mu_{t(sh)}$ for the natural unit of time (i.e. year X month X day X half-hour of day), and the (change in the) log of the number of minutes worked by the handler. Standard errors are clustered at the shift level.

ONLINE APPENDIX B (NOT FOR PUBLICATION): PROOFS OF PROPOSITIONS

Proof of Proposition 1 Given the large N, we assume that the worker ignores the (partial) effect that her own effort has on the average productivity observed by the manager (i.e. $\frac{\partial \bar{y}_i}{\partial e_i} \sim 0$ and $\frac{\partial \bar{z}_i}{\partial e_i} \sim 0$). It can be shown that the conclusions remain qualitatively similar if we relax this assumption. The first order condition of the worker's maximization problem is given by:

$$\Lambda = U(w)\left(\alpha b f' + \theta_{ij} P' t_{ij}\right) - C_e = 0 \tag{A1}$$

A symmetric Nash equilibrium of the game where the worker and the peer perform effort $e_i^* = e_j^*$ exists given the assumptions that $\theta_{ij} = \theta_{ji}$ and the fact that both workers choose their own effort taking the average effort in the room as given. Therefore, the first order condition of the problem is symmetric for i and j. By implicit differentiation we get:

$$\frac{\partial e_i}{\partial t_{ij}} = -\frac{\partial \Lambda / \partial t_{ij}}{\partial \Lambda / \partial e_i} = \frac{C_{et} - \theta_{ij} U(w)(P' + t_{ij}(e_j - e_i)P'')}{U(w)\left(\alpha b f'' - \theta_{ij} P'' t_{ij}^2\right) - C_{ee}} = \frac{\Gamma}{\Omega} \tag{A2}$$

In order to simplify notation, we have respectively defined Γ and Ω as the numerator and denominator in equation (A2). Note that $\Omega < 0$ in a local maxima since it corresponds to the second order condition of the maximization problem. Since $e_j = e_i$ in equilibrium, we can conclude that:

$$\frac{\partial e_i}{\partial t_{ij}} > 0 \quad \Leftrightarrow \quad \theta_{ij} U(w) P' > C_{et}$$

Notice that if $C_{et} < 0$ (i.e. the peer's presence does not create distraction thereby increasing the cost of additional effort, but instead reduces it), this condition trivially holds.

Proof of Proposition 2 We can differentiate equation (A2) with respect to $var(u_i)$ (applying the Envelope Theorem):

$$\frac{\partial^2 e_i}{\partial t_{ij} \partial var(u_i)} = -\frac{\Gamma U(w) \alpha f''}{\Omega^2} \frac{\partial b}{\partial var(u_i)} \tag{A3}$$

From the definition of $b = \frac{cov(y_i, z_i)}{var(y_i) + var(u_i)} = \frac{var(y_i)}{var(y_i) + var(u_i)}$,
we have that $\frac{\partial b}{\partial var(u_i)} = \frac{-var(y_i)}{(var(y_i) + var(u_i))^2} < 0$.
Noticing that $\Omega^2 > 0$, $f'' < 0$ and that $e_j = e_i$ in equilibrium, we conclude that:

$$\frac{\partial^2 e_i}{\partial t_{ij} \partial var(u_i)} > 0 \quad \Leftrightarrow \quad \theta_{ij} U(w) P' > C_{et}$$

Proof of Proposition 3 We can differentiate equation (A2) with respect to θ_{ij} (applying the Envelope Theorem):

$$\frac{\partial^2 e_i}{\partial t_{ij}\partial\theta_{ij}} = \frac{-\Omega U(w)(P' + t_{ij}(e_j - e_i)P'') + U(w)P''t_{ij}^2\Gamma}{\Omega^2} \tag{A4}$$

The first term in the numerator is positive since $\Omega < 0$, $P' > 0$ and $e_i = e_j$ in equilibrium. Since $P'' < 0$, we have that $\Gamma < 0$ is a sufficient condition for the sign of expression (A4) to be positive:

$$\theta_{ij}U(w)P' > C_{et} \quad \Rightarrow \quad \frac{\partial^2 e_i}{\partial t_{ij}\partial\theta_{ij}} > 0$$

Note two things. Firstly, strictly speaking, only the assumption $P''(0) \leq 0$ is required for Proposition 3 to hold. Secondly, this is a sufficient but not necessary condition. Given $\theta_{ij}U(w)P' > C_{et}$, even if $P''(0) > 0$, expression (A4) remains positive if $\frac{\partial e_i}{\partial t_{ij}} > \frac{P'(0)}{t_{ij}^2 P''(0)}$ (i.e. when the peer pressure effect is sufficiently high).

ONLINE APPENDIX C (NOT FOR PUBLICATION): DESCRIPTION OF THE OPTIMAL ALLOCATION PROBLEM

Consider a room with m seats per row, and a set of workers with shifts defined by their starting and ending times. The goal is to assign each worker to a seat in such a way that maximizes the total time during which workers have both adjacent seats occupied. Let S be the set of shifts, R be the set of rows, and A_r be the set of existing seats in row r. Each seat is labelled with the index (r, j) which identifies the row and number of seat within the row. Let T_i and D_i denote the starting and ending times of shift i, respectively. The overlapping time between shift i and shift k is represented by $\Omega_{i,k}$.

We partition the time frame of interest into discrete intervals, e.g., 5-minute intervals. Let t denote the index of these intervals.

The binary decision variable $x_{i,(r,j)}$ is equal to 1 if shift i is assigned to seat (r, j), and 0 otherwise. The optimization problem can be formulated as follows:

$$\max \sum_{i \in S} \sum_{k \in S} \sum_{i \neq k} \sum_{r \in R} \left(\sum_{j=1}^{m-1} \Omega_{i,k} \cdot \left(x_{i,(r,j)} \cdot x_{k,(r,j+1)} \right) + \sum_{j=2}^{m} \Omega_{i,k} \cdot \left(x_{i,(r,j)} \cdot x_{k,(r,j-1)} \right) \right)$$

subject to the following constraints:

1. Each shift must be assigned to exactly one seat:

$$\sum_{r \in R} \sum_{j \in A_r} x_{i,(r,j)} = 1 \quad \forall i \in S$$

2. No two shifts can be assigned to the same seat at the same time:[1]

$$y_{i,(r,j),t} + y_{k,(r,j),t} \leq 1$$

$$\forall i \neq k \in S, \forall r \in R, \forall j \in A_r, \forall t \text{ such that } T_i \leq t < D_i \text{ and } T_k \leq t < D_k$$

where the variable $y_{i,(r,j),t}$ is the time that shift i is allocated to seat (r, j) during the time interval t.[2] Notice that the objective function tracks the overlapping time between each seat and the adjacent seats to the left and to the right separately.

The solution for this problem is an optimal assignment of shifts to seats that maximizes the total overlapping time between adjacent seated workers, subject to the constraints of seat assignments and non-overlapping shifts in the same seat. The presence of discrete decision variables $x_{i,j}$ and linear constraints make this problem a mixed-integer linear programming (MILP) problem.

[1]This constraint states that for any two different shifts i and k, at most one of them can be assigned to the same seat (r, j) at any time interval t.

[2]If the time interval t is sufficiently short, $y_{i,(r,j),t}$ can be defined as a dummy variable. This prevents the same seat being occupied by two handlers in a non-overlapping way within the interval of time t. We follow this approach when implementing the solution algorithm. Alternatively, we can set the constraint as $y_{i,(r,j),t} + y_{k,(r,j),t-1} \leq 1$ which will allow for small overlapping (e.g. less than 5 minutes) in the occupation of seats.

MILP problems are characterized by the combination of continuous and integer variables, and they often arise in optimization scenarios involving discrete decisions. In general, MILP problems are NP-hard, meaning that their complexity increases rapidly with the size of the problem. Obtaining a feasible solution requires the use of modern solvers that uses algorithmic approaches that can find near-optimal solutions in an efficient way. Unlike continuous linear programming problems that can be efficiently solved using techniques such as simplex methods or stochastic gradient descent, MILP problems lack the convexity properties that facilitate fast optimization. Additionally, the combination of discrete and continuous variables often lead to a combinatorial explosion in the solution space. As a result, solving MILP problems optimally often entails exploring a vast solution space, potentially involving branching, backtracking, and enumerating numerous potential solutions. This exhaustive search process can be computationally expensive,

We use Gurobi, a widely-used commercial optimization solver which is capable of solving large-scale mixed-integer linear programming problems by employing cutting-edge algorithms, advanced heuristics, and parallel computing techniques for pruning the solution space efficiently. [3]

[3] One of the most widely used algorithms for solving MILP problems is the branch-and-bound algorithm, which is a systematic enumeration method that searches through the solution space by exploring and eliminating branches of a search tree. The algorithm uses linear programming relaxations to compute bounds on the optimal solution, which helps to prune branches that cannot contain the optimal solution. Another technique often employed in solving MILP problems is cutting-plane methods. These methods involve iteratively generating linear inequalities (cuts) that separate the optimal solution of the integer problem from the optimal solution of the linear programming relaxation. The generated cuts are then added to the linear programming relaxation, tightening the feasible region and potentially improving the quality of the bounds. Modern MILP solvers like Gurobi combine multiple techniques such as branch-and-bound, cutting planes, and various heuristics to efficiently explore the solution space and find an optimal or near-optimal solution. The difficulty of solving MILP problems depends on the specific problem instance, its structure, and the size of the problem. Some instances can be computationally challenging or even intractable.