Peer Pressure and Manager Pressure in Organisations*

Diego Battiston† Jordi Blanes i Vidal‡

Tom Kirchmaier§ Katalin Szemeredi¶

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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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†School of Economics, University of Edinburgh. Email: diego.battiston@ed.ac.uk

‡Department of Management, London School of Economics and Center for Economic and Policy Research. Email: j.blanes-i-vidal@lse.ac.uk.

§Copenhagen Business School and Centre for Economic Performance, London School of Economics. Email: t.kirchmaier@lse.ac.uk.

¶Corvinus University of Budapest. Email: katalin.szemeredi@uni-corvinus.hu

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), Nguyen (2022) 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. The ability to observe each other is highest among handlers in adjacent desks, and goes down as the distance between the desks increases. 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 and long-lasting, 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). The supervisors either sit or often stand next to their desks, so that they can visually monitor the room. 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

[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%.

when the adjacent desk becomes occupied by a peer) increases with the distance between the handler's desk 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 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 communi-

[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 in Section 7.

cates. Peer pressure then arises because a worker is aware that his co-workers' impressions 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

[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 7. 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

literature is how workplace peer pressure actually works in practice. Kandel and Lazear (1992) and Mas and Moretti (2009) hypothesise mechanisms through which workers could put pressure on their free-riding colleagues, but identifying these mechanisms empirically has remained elusive. We contribute to this literature by showing that managers are important mediators of this peer pressure effect. We further show that our findings are consistent with a framework in which peers exert pressure on a worker through the channel of making the worker's manager better informed about his performance. In doing this, we provide evidence in support of 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 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.

Our paper is also related to the wider literature on the effects of firm monitoring of workers' performance (Nagin et al., 2002). In existing work the firm typically monitors workers directly, through either a dedicated unit (Nagin et al. 2002, Gosnell et al. 2020) or by requesting them to fill checklists (Jackson and Schneider 2015, Friebel et al. 2023). We contribute here by showing that a workers' peers can represent an additional channel through which managers monitor behaviour.[7]

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, 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]Additional monitoring may also bring drawbacks in terms of decreased trust and commitment (Falk and Kosfeld 2006, Friebel et al. 2023) or increased worker attrition (Friebel et al., 2023). Our high-frequency variation is not well-suited to studying effects on attrition. To the extent that being monitored decreases the commitment and intrinsic motivation of workers, our findings in Section 4 are consistent with this negative effect being more than outweighed by the positive effect of feeling pressure to work harder, at least in a short-term horizon.

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.[8]

The article is organised as follows. Section 2 describes the institutional setting. Section 3 outlines the data and empirical strategy. Section 4 discusses the baseline peer pressure findings. Sections 5 and 6 relate peer pressure to the relation between managers and workers. Section 7 briefly rationalises the findings with a simple theoretical framework and discusses alternative explanations. Section 8 estimates the potential improvements in productivity following the reassignment of handlers to desks and shifts. Section 9 concludes and briefly discusses the external validity of our findings.

2 Institutional Setting

The OCB is the GMP unit in charge of answering emergency calls from members of the public and allocating police officers to the resulting incidents. Call handlers answer calls and radio operators allocate officers. 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.[9]

Nature and Allocation of Work The role of call handlers is to answer calls, question and if necessary provide guidance to the callers, decide whether an official incident must be created and, if so, assign an urgency grade and record in an electronic log any information deemed relevant. Handlers' work is strictly individual in that there is very little scope for

[8]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.)

[9]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.

giving or receiving help from other handlers.[10]

Incoming calls are assigned to handlers using a queueing system such that the call at the front of the queue is assigned to the first handler that becomes available. If the call queue is empty, the next incoming call will be assigned to the handler who was available first. Following the completion of a call, a handler 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.

Two consequences follow from the call allocation system. 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 account for the work conditions being faced by that handler.[11]

Seating Architecture Figure A1 displays a screenshot of the actual Trafford room in which the handlers were based during our sample period.[12] The desks were arranged in rows of differing length and mostly facing in the same direction. Computer monitors and desk screens implied that workers could only imperfectly observe the colleagues in the rows in front or behind. 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. A natural set of hypotheses, which

[10]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.

[11]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 evidence that the characteristics of incoming calls are uncorrelated with our main source of variation in Figures A4 and A5.

[12]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.

we explicitly consider in the Section 7 model, is that the effects on productivity could be either positive (i.e. peer pressure) or negative (i.e. distraction).[13]

Seating Allocation Handlers were free to sit in any desk that was available at that time that they started their shift (i.e. hot-desking). 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.[14] Once seated they were expected to remain in their positions throughout the full duration of the shift.

The non-random assignment of handlers to desks implies that we cannot 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. Therefore, our empirical strategy does not rely on the exogeneity of seating arrangements. Instead, we just regard seating allocation as fixed within a shift (a realistic assumption in our setting) and exploit 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. This includes the sudden disoccupation of an adjacent seat because the pre-established schedule dictates that the neighbouring worker has reached the end of their shift.

Measures of Productivity Consistently with previous studies on call centres (Batt et al. 2000, Bloom et al. 2015), 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. These measures are regularly monitored both at the OCB level and at the individual handler level. They are well-suited to our purposes because (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

[13]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).

[14]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.

co-workers.[15]

The above 'quantity' measures of productivity do not capture how handlers deal with the calls that they take. Therefore, we also study other 'quality' measures such as the response time of the incidents (i.e. the time between the incident creation by the handler and the arrival of response officers to the incident's location) or the crime clearance rate. 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'.[16]

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 medium term* (i.e. typically one year). 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

[15]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 A7 any potential effects on the average call duration.

[16]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.

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.[17] 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 We refer to handlers assigned to the same evaluator as 'co-evaluated' handlers. Handlers were typically aware of who their co-evaluated handlers are.

The assignment of handlers to evaluators was not designed to be 'random', although it had a strong 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 and Figure A3, 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, with the exception of a small higher overlap in their shifts.[18]

[17]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.

[18]To reach this conclusion, we plot in Figure A3 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

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.

3 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.

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 stylised floorplans to compute which desks are adjacent to each other and, more generally, to calculate the distances between desks[19]

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

observed distribution is slightly to the right of the counterfactual random distribution. 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.

[19]Unfortunately, we do not observe and cannot calculate distances in meters because our floorplans are very stylised and do not record the cardinal locations of desks, but only their ordinal positions relative to each other (for an illustration, see Figure 1).

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 1,275,483 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.[20] 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.

Unfortunately, our dataset does not include the timing of any meetings between evaluators and evaluatees, or the content of the performance evaluations. We also cannot observe the identity of the supervisors that are on duty in the room at each point in time.

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 4 we provide empirical evidence in support of our identification assumption.

[20]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.

Baseline Estimating Equation Consider the productivity y_{sh} of a handler in the half-hour period h of shift s, where *importantly* 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:

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

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.[21]

$Occupied_{sh} \in [0, 2]$ 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.[22] The variable then reflects the proportion 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 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).[23]

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 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 take place in a specific half-hour (e.g. 14-14:30 1st of December 2012) and affect all handlers in the room

[21] 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.

[22] While handlers officially start and finish their shifts on the hour or half-hour, the actual timing sometimes deviates from these official conditions. For instance, handlers in the middle of a call as the official shift ends, must resolve the underlying issue before finishing for the day.

[23] MW_{sh} is not a bad control because it is not affected by the main independent variable (Angrist and Pischke, 2009). We include it only to deal with the first and last half-hour periods in the shift. In Table A4 we show that the baseline estimates from Table 2 are essentially identical when we do not control for MW_{sh} and limit the sample to interior full half-hours.

equally (e.g. environmental factors, the number of on-duty colleagues sharing the workload, the condition of the call queue, the number of total calls received, etc).

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. Following Mas and Moretti (2009), 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, the level at which the variation occurs (Abadie et al., 2023).

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.

4 The Average Peer Pressure Effect

In this section we aim to estimate the average effect of peer proximity on productivity.

Baseline Estimates Columns 1 and 2 of Table 1 estimate (2) and display 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.[24] In the framework that we introduce in

[24]Our baseline panel dataset is constructed at the shift/half-hour period. In Table A5 we investigate the robustness of the baseline results to decreasing or increasing the duration of the time period. We find very

Section 7, the finding of positive coefficients is consistent with the peer pressure effect being larger in magnitude than any potential distraction effect.[25]

Dynamic Effects of Changes in Occupation We investigate the presence of anticipatory and deferred effects by introducing a set of lead and lag variables to the main specification:

$$\Delta y_{sh} = \sum_{j=-8}^{8} \beta_j \Delta Occupied_{s(h+j)} + \pi_h + \mu_{t(sh)} + \gamma \Delta MW_{sh} + \Delta \epsilon_{sh} \tag{3}$$

where β_8 (respectively, β_{-8}) represents the index handler change in productivity in response to the occupation of an adjacent desk four hours (i.e. eight half-hour periods) into the future (respectively, past), and the other coefficients are interpreted similarly.

The lead coefficients reveal whether productivity was already trending prior to the change in adjacent seat occupation. The existence of such a 'pre-trend' would suggest that the change in occupation might be endogenous to shocks to the productivity of the focus handler. The lag coefficients reveal whether the reaction of productivity to the change in adjacent seat occupation is sustained over longer horizons.

Figure 2 plots the estimated coefficients from (3), together with the cumulative effects. Productivity does not appear to trend strongly prior to the change in occupation. 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, any potential confounding shock to productivity should have coincided *exactly* with the half-hour period in which the change in occupation occurred.

The absence of lagged effects indicates that the immediate change in productivity is long-lasting. We can observe this persistence more clearly in looking at the cumulative effects. For instance, the cumulative effect at $t = 2$ (i.e. one hour after the period of the change in occupation) is equal to $\sum_{j=-2}^{8} \hat{\beta}_j$ (i.e. from eight 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 four hours after the change in occupation.[26]

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.

[25]Throughout the paper, we cluster the standard errors at the shift level. In Table A6 we examine the robustness to alternative clustering strategies. For instance, we allow for arbitrary correlation across handlers working in the same row (i.e. line of adjacent desks) and date. We also explore two-way clustering, at the shift and half-hour level. The standard errors are very similar throughout.

[26]To evaluate the length of the persistence that we estimate, note by comparison that Mas and Moretti

Further Tests of Identification Assumption In Figures A4 and A5 we study whether the average official urgency of the calls assigned to a handler appears to be correlated with the change in adjacent seat occupation.[27] Consistently with our description of the assignment of calls to handlers, the type of calls that handlers receive are uncorrelated with the occupation of adjacent desks.

A potential source of endogeneity when exploiting increases (although not decreases) in occupation consists of arriving colleagues 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, the resulting bias should be larger in magnitude when most seats are empty and handlers starting their shift enjoy ample choice. In Figure A6 we interact the baseline effect in (2) with dummies for the four quartiles of room occupation. We find very similar coefficients regardless of whether arriving handlers are constrained in their desk choices or instead have a lot of discretion.[28] This suggests that the 'endogenous choice of seat' confounding mechanism does not appear to be empirically relevant.

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 the effect may be negative for a subset of the handlers. This (hypothetical) negative 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 $\Delta Occupied_{sh}$ in (2) with a set of dummies $\eta_{i(s)}$ taking value one for the handler i corresponding to shift s:

Figure A7 plots the distribution of the estimated $\beta_{i(s)}$ coefficients. In Figure A8, 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. This suggests that the baseline effect in Table 1 is not driven by a few handlers

(2009) display an estimated persistence of 70 minutes.

[27] 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.

[28] Likewise we show in Table A9 that our findings do not rely on whether the peer is seated in one of their preferred desks. To investigate this question, we define the most preferred seats of the adjacent peer based on the proportion of times the peer chooses a seat when the seat is available. We find that our baseline findings are very similar regardless of whether the adjacent peer is seated in a preferred desk or not.

with abnormally high responses to our treatment, but is instead widely present among our sample of handlers.[29]

Effects on Quality We now study the effect of adjacent seat occupation on variables related to the 'quality' with which handlers deal with their incidents. We study three variables: (1) the average response time of the calls received during the half-hour period, (2) the average allocation time of the calls, and (3) the share of crimes for which a suspect is identified or detained. A handler who is observed by his colleagues may allocate effort towards improving observable 'quantity' outcomes and potentially away from 'quality' outcomes that cannot be easily observed by colleagues.

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 A7 displays the results of estimating the baseline specification with the quality measures above as dependent variables.[30] Throughout, we find non-significant effects.[31]

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

[29] 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 A9 and A10, 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.

[30] 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 A7, relative to Table 2.

[31] 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 A7 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 A7, relative to Table 1.

each other, with the effect of an increase in occupation being larger than the effect of a decrease in occupation.[32]

In Figure A11 we estimate the effect of adjacent seat occupation non-parametrically, splitting non-zero values of $\Delta Occupied_{sh}$ into intervals of equal size. We find that the effects are monotonic and 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%.[33]

Seats in the Row Behind and Seats in the Row in Front 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. Nevertheless, it is still possible to observe imperfectly (e.g. if the peer is standing) and to hear whether the focus worker is on a call. To examine potential effects at longer distances, we study now whether handlers situated directly behind or directly in front of the focus handler may also have a effect on his productivity. 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 observability of their work.[34]

5 Peer Pressure and Direct Manager Monitoring

We now examine how handlers' reaction to the presence of nearby colleagues depends on their managers' ability to monitor their performance.

[32]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.

[33]Figure A11 also allows us to separately evaluate the 'intensive' and the 'extensive' margins. We find that both are sizeable: moving from zero (adjacent occupied seats) to one increases productivity, but moving to two increases productivity even more.

[34]In Table A8 we interact the baseline effects with characteristics of the match between focus handler and peer. We find that handlers increase their productivity more when the arriving peer is more productive than them, a result consistent with Mas and Moretti (2009). We find that the differences in experience or in gender do not appear to determine the strength of the baseline effect.

Manager Monitoring and the Distance to the Supervisor Desk We examine the relation between peer pressure and manager monitoring 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 (see Figure 1).[35]

Our floorplans record the seats designated as supervisor positions (Figure 1).[36] Unfortunately, the floorplans are quite stylised and fail to record the cardinal positions of desks (i.e. in meters). To compute our measure of distance to a supervisory position, we convert the floorplans into a matrix in the (x, y) format and calculate, $Distance_s = \sqrt{(x_s - x_{m(s)})^2 + (y_s - y_{m(s)})^2}$, 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. We posit that managers are better able to observe and monitor handlers when these handlers are located nearby.[37]

Baseline Estimates We now study whether peers 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. 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

[35]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.

[36]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 some measurement error.

[37]In Figure A12 we find that handlers without adjacent seats occupied are less productive when seated further away from a supervisor (as measured by $Distance_s$). The variation in this figure is across rather than within shifts, as handlers do not change their desk in the middle of their shift. For this and other reasons, we do not interpret these estimates as causal effects. Nevertheless, the finding in Figure A12 is consistent with the notion that managers supervising abilities decrease with $Distance_s$.

Figure A13. 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 A13) 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.[38]

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 shifts 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.

6 Peer Pressure Between Co-Evaluated Handlers

In this section, we study the relation between peer pressure and the evaluation relation between manager and worker. Specifically, we study whether peer pressure differs depending on whether two workers are evaluated by the same manager.

Baseline Estimates As discussed in Section 2, 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

[38]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.

handler and his evaluator. We study now whether workers react more to the presence of a nearby peer if that peer is a co-evaluated handler, and provide a plausible mechanism for this relation in Section 7.

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. This is a concern in our setting because the allocation of handlers to evaluators is not explicitly random, although it has a strong idiosyncratic component.

We test this prediction by taking advantage of the fact that there are sufficiently frequent re-allocations 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 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.[39]

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.[40] 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.

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. While we have posited (and confirmed empirically in Section 4) that observability is highest from adjacent desks and smaller in the rows in front and behind, other desks may still provide some degree of observability.

[39] An intriguing, albeit statistically very weak, finding is that the coefficient for the co-evaluated in the past interaction is negative and of a reasonable economic size. A potential interpretation is that handlers who shared an evaluator in the past may have become inured to reacting to each other's presence, and react less than average after ceasing to be co-evaluated. We do not emphasise this potential result as the estimates are noisy and they may just reflect sample variation.

[40] 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.

For instance, colleagues in other desks may observe the work of a focus handler if they step away to stretch their legs.[41] Therefore, we study whether the characteristics of the average handler in the room, in terms of whether they are co-evaluated with the focus handler, affect the focus handler productivity.

In our baseline dataset there are, on average, 29.8 colleagues in that half-hour in the room, out of which 2.47 are handlers that are co-evaluated with the focus handler.[42] For each observation, we calculate the share of handlers in the room that have the same evaluator as the focus handler, and estimate:

$$\Delta y_{sh} = \gamma \Delta ShareCoEvaluated_{sh} + \pi_h + \mu_{t(sh)} + \gamma \Delta MW_{sh} + \Delta \epsilon_{sh}, \tag{4}$$

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) does not coincide with idiosyncratic shocks to the productivity of a handler in that specific half-hour (we are still controlling for any productivity shock affecting all handlers in the room).

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 $.083 \times .183 \times 100 = 1.5\%$. 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

[41] 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.

[42] 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.

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.

7 Potential Mechanisms

Our main empirical findings are as follows:

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 A8).

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).

In this section we briefly outline a conceptual framework micro-founding the pressure that peers exert on each other. We argue that the predictions of this framework are compatible with all three findings above, and therefore that our framework provides a mechanism through which to interpret the empirical results. We also discuss the extent to which alternative mechanisms can reconcile our results. Note however that our objective in this paper is not to isolate a narrow mechanism and rule out all others. Instead, we aim to show that managers are important mediators of the pressure that workers exert on each other, and that these observed interdependencies can be rationalised through a plausible theoretical framework.

Peers Improving the Manager Information In Online Appendix B we outline and solve a model micro-founding peer pressure among workers, which we briefly summarise here. A manager (she) wants to encourage a focus worker (he) to exert effort. Because effort is costly, the manager offers a reward that depends positively on her evaluation of the worker's effort. The manager receives a *direct* but noisy signal of such effort (e.g. on the basis of her own observations and objective performance measures). A peer sitting in a desk

adjacent to the focus worker can also observe the focus worker's effort. This observation can reach the manager with some probability (e.g. because the manager and the peer talk with each other), so the presence of the peer in an adjacent desk potentially generates an *indirect* signal. The manager constructs her optimal evaluation of the worker's effort using both the direct (i.e. her own) and the indirect (i.e. the peer's) signals.

In addition to the peer observing effort and improving the manager's information, our model also allows the peer to distract the worker (e.g. by being noisy or chatty). This distraction effect directly reduces the worker's productivity (Park, 2019). Our model has three predictions :

Prediction 1: The arrival of a peer can increase the worker's productivity. The intuition of this prediction is that the additional signal transmitted by the peer allows the manager to evaluate effort more accurately. The focus worker then becomes more motivated because he knows that the reward depends more strongly on his choice of effort. Therefore in our model the peer 'pressures' the focus worker to exert effort through the channel of making the manager better informed about this effort (see the Mas and Moretti 2009 discussion in footnote 4). When this positive effect outweighs the negative distraction effect, a peer sitting in an adjacent seat increases the focus worker's productivity.

Prediction 2: The arrival of a peer increases the worker's productivity more when the manager's direct signal is more noisy. The intuition of this prediction is that the manager evaluates the worker's effort using both the direct and indirect signals, such that higher noise in one signal results in higher weight assigned to the other. When the manager has very little direct information about the worker's effort, she has to rely more on the signal generated by the peer. It follows that the worker increases his effort more when the peer arrives.

Prediction 3: The arrival of a peer increases the worker's productivity more when the peer's observation is more likely to reach the manager. This intuition is immediate. The positive peer pressure effect results from the positive likelihood that the peer's information is transmitted to the manager. When this likelihood is higher, the arrival of the peer motivates the worker more.

The conceptual framework above provides an explanation of all three findings F1-F3. Handlers care about impressing their managers and these managers receive both direct (through their own observations) and indirect (through the signals observed and transmitted by the peers that the managers interact with) signals of the handlers' performance. The arrival and observation by a peer therefore leads to increased effort (F1). This is especially if the manager cannot easily monitor the handler (F2). As discussed in Section 2 evaluators meet regularly with their evaluatees, both in a formal and in an informal manner. A focus handler observing the arrival of a co-evaluated peer will therefore be aware that the observation of that peer has a higher chance of reaching his evaluator, relative to the arrival of a non-co-evaluated peer. The finding that handlers increase their productivity more when a co-evaluated peer arrives (F3) is therefore consistent with Prediction 3.

Lastly, note that our model does not allow the peer to exert pressure other than through the channel of affecting the manager's evaluation. This is for simplicity, and because the predictions that we highlight in our model would remain unchanged if we added an additional channel of 'direct' peer pressure among co-workers.

Peers as Comparison Group In our conceptual framework above the precision of the manager's evaluation increases because the peer *actively* transmits her observation. This transmission could be direct to the manager or even indirect (i.e. talking with other colleagues who then talk with the manager). An alternative though very related interpretation of our model is that the peer improves the manager's evaluation *passively*. Specifically, a manager may find it easier to compare efforts across adjacent workers than to evaluate their efforts from an absolute perspective.[43] There are two potential consequences of the manager using the peer to better evaluate the focus worker's effort.

The first consequence is that the manager's signal will be more precise when a worker sits alongside a peer. This higher precision will make the worker more motivated and be compatible with F1.[44] Note that this 'peers as comparison' mechanism is conceptually very similar to the one in our model, as both rely on the nearby presence of a peer improving the manager's signal of the handler's effort. The difference between the two mechanisms

[43]Evaluators are not supposed to 'grade on a curve' in our setting. Therefore, any potential relative performance evaluation is likely to be implicit, and for the purposes of filtering out common noise such as the level of demand.

[44]F2 and F3 are perhaps harder to rationalise by this mechanism. To rationalise F3, we would need to assume that evaluators are better able to assess the effort of their handlers when those handlers are sitting alongside co-evaluatees, relative to sitting alongside colleagues with different evaluators.

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.

The second potential consequence is that the peer's effort might make the manager revisit the threshold of effort required from the focus worker. As we explain on our discussion on reference points below, this type of effect need not lead to higher effort. A large proportion of focus workers will observe that the new threshold requires less effort, and slack off correspondingly. This is incompatible with the evidence in Figure A8.

Therefore, our baseline finding F1 is compatible with the manager using the peer as a comparison group, as long as this comparison takes the form of higher precision through the filtering of common noise, as opposed to a change in the discrete threshold (i.e. a reference point) that the focus worker must meet.

Social Image and Hedonic Motives Bursztyn and Jensen (2017) refer equivalently to 'social pressure' and to 'concerns about social image', in their discussion of studies examining individuals behaving differently in front of others in a variety of settings. In examining the reasons for this differential behaviour, they distinguish between instrumental (i.e. improving social image helps individuals to achieve future gains) and hedonic (i.e. social image enters directly into the utility function) motives. Our conceptual framework above describes a specific instrumental mechanism. To reconcile a hedonic motive with F3, we would need to assume that handlers *particularly* care (from a hedonic perspective) about how they are perceived by their co-evaluated colleagues. While it is difficult to fully rule out this possibility, note that the co-evaluation relation is not proxying for the similarity or length of contact between handlers (Table 4). Furthermore, the broad message of the paper (i.e. that the assignment of workers to managers affects the strength of the peer pressure effect) remains valid under both an instrumental and a hedonic interpretation of the underlying mechanism.

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.

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 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 A8 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.[45]

8 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.[46] 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

[45]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.

[46]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.

contiguous seats each. Second, we perform all exercises on the median month in our sample period (May 2013).[47] Lastly, our focus is on illustrating how incorporating information on 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.[48] 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.

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

[48] 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.

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 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%.[49,50]

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

[49]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.

[50]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.

findings from Table 5 and makes it easier to find co-evaluated handlers who can sit alongside each other thereby leveraging the findings from Table 4. Overall, this process increases: (1) the average occupation of adjacent seats from .8 to 1.6, (2) the occupation of adjacent 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 A14 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.

There are however two caveats to our exercise. The first caveat is that extrapolating from our estimates based on high-frequency variation may not be valid if workers get accustomed to being around their peers, and therefore become insensitive to such monitoring. Figure 2 shows that this is not a strong concern *within* a shift, as the productivity increase persists for at least four and a half hours after the occupation of an adjacent seat, with no decreasing trend. Nevertheless, there is the possibility that long-term exposure to peer pressure may eventually decrease its effect. To evaluate empirically this concern, we estimate a regression in which the change in occupation is interacted with dummies for the percentage of the previous two weeks that the handler has spent with his adjacent seats occupied. We find no evidence in Figure A15 of decreased sensitivity to peer pressure: if anything the interactions have a slight positive trend. We conclude that, at least within sample, this concern may not be empirically relevant.[51]

The second caveat is that increased effort may change the handlers' participation constraints, requiring additional compensation to avoid increased turnover. Turnover is quite low in our setting, which leads to empirical investigations in our sample to be somewhat

[51]The evidence in Figure 15 is robust to using different time windows, such as a week or a month. Results are available upon request.

underpowered. We therefore cannot rule out this potential obstacle to the extrapolation undertaken in this section.

Given these caveats, the key message from this section is that accounting for the vertical assignment of handlers to evaluators (Column 2 Table 6) could potentially double 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).

9 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. We leave further explorations of this interrelation to future work.

REFERENCES

Abadie, A., Athey, S., Imbens, G. W., and Wooldridge, J. M. (2023), "When Should You Adjust Standard Errors for Clustering?", *Quarterly Journal of Economics*, 138(1):1-35.

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

Angrist, J. D., and Pischke, J. S. (2009), "Mostly Harmless Econometrics: An Empiricist's Companion", Princeton University Press.

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.

Bursztyn, L., and Jensen, R. (2017), "Social Image and Economic Behavior in the Field: Identifying, Understanding, and Shaping Social Pressure ", *Annual Review of Economics*, 9: 131-153.

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.

Falk, A., and Kosfeld, M. (2006)."The Hidden Costs of Control. " *American Economic Review*, 96(5): 1611-1630.

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.

Friebel, G., Heinz, M., Hoffman, M., Kretschmer, T., and Zubanov, N. (2023), "Is This Really Kneaded? Identifying and Eliminating Potentially Harmful Forms of Workplace Control. " *Working Paper*

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

Gosnell, G. K., List, J. A., and Metcalfe, R. D. (2020), "The Impact of Management Practices on Employee Productivity: A Field Experiment with Airline Captains ", *Journal of Political Economy*, 128(4): 1195-1233.

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.

Jackson, C. K., and Schneider, H. S. (2015). "Checklists and Worker Behavior: A Field Experiment. ", *American Economic Journal: Applied Economics*, 7(4): 136-168.

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*.

Nagin, D. S., Rebitzer, J. B., Sanders, S., and Taylor, L. J. (2002). "Monitoring, Motivation, and Management: The Determinants of Opportunistic Behavior in a Field Experiment. ", *American Economic Review*, 92(4): 850-873.

Nguyen, K. T. (2022), "Trust and Innovation within the Firm: Evidence from Matched CEO-Firm Data", *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.

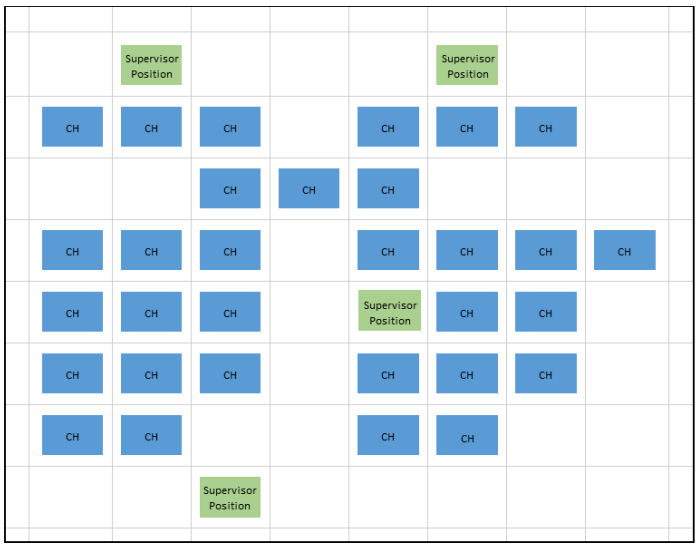
Steinbach, D. and Tatsi, E. (2022), "Short-Term and Long-Term Measures of Peer Behavior", *Working Paper*.

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

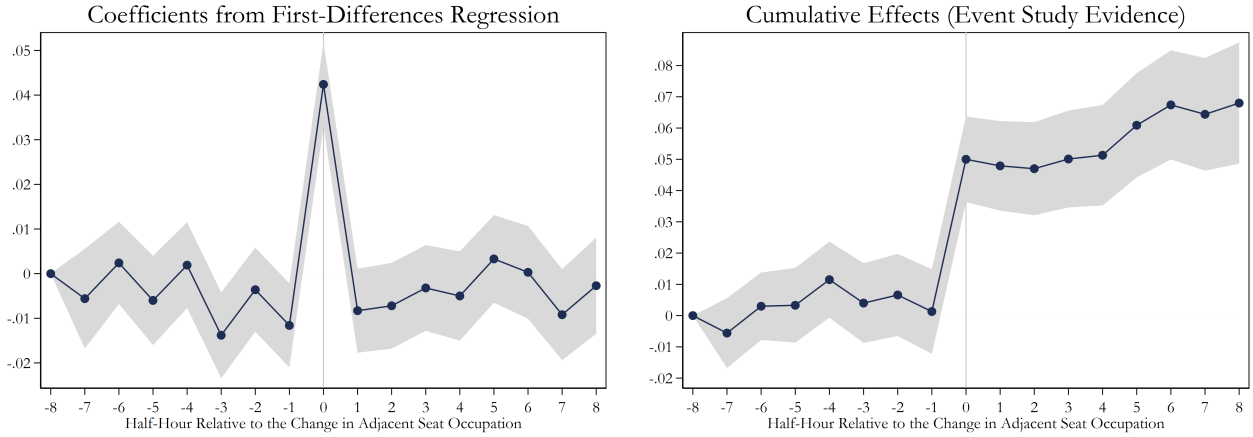
FIGURE 1: EXAMPLE OF OCB ROOM FLOORPLAN



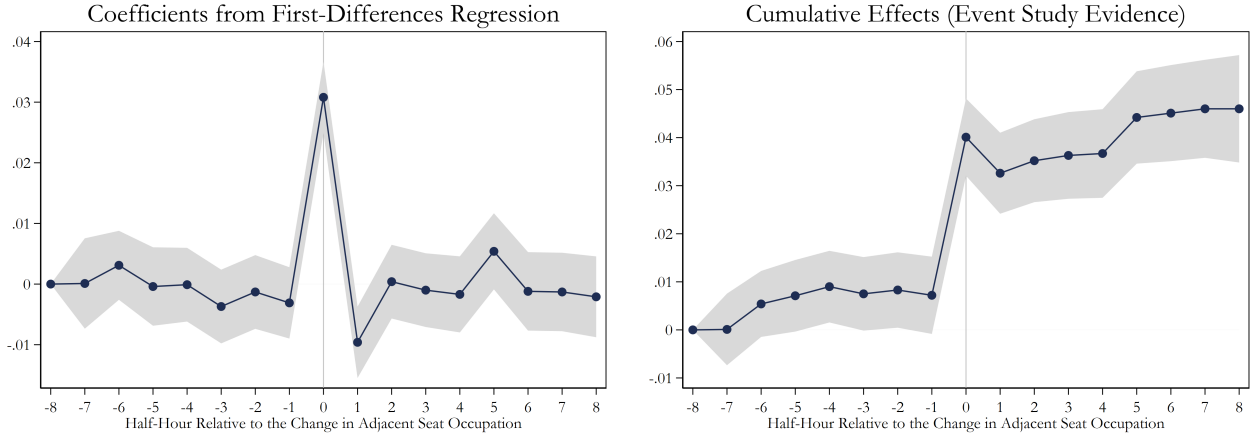
This figure displays an example of the OCB room. The figure is not realistic, either in the number of seats or in the relative location of the seats. The purpose of the figure is to illustrate that the supervisory positions are scattered throughout the room and at different distances from different handler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

FIGURE 2: LAGS AND LEADS EVIDENCE

PANEL A: Δ Log Minutes on Phone



PANEL B: Δ Log Number Calls



The left figures display 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 right figures plot the cumulative effects, calculated as the sum up to a certain period and starting four 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 $\sum_{j=-2}^{8} \hat{\beta}_j$ (i.e. from eight 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:

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

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.

TABLE 1: AVERAGE PEER PRESSURE EFFECT

Feb2012-Nov2014; Handlers=343; Shifts= 71,589; Half-Hours= 48,033; Observations= 1,120,440.

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 Occupied > 0)			.078***	.041***		
			(.004)	(.003)		
Δ Occupied × 𝟙(Δ Occupied < 0)			.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

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; Observations= 982,861.

Dependent Variable:	**(1)** **Δ Log Minutes on Phone**	**(2)** **Δ Log Number Calls**	**(3)** **Δ Log Minutes on Phone**	**(4)** **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

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; Observations= 1,120,440.

	(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

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)-(3), the interactions are with the focus handler indicators. In (4), we add the interactions are with the indicators for the interaction between the focus handler and the peer handler. In (5), we add the interaction with the number of times that the handler pair have sat next to each other in the past. 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. 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; Observations= 1,120,350.

	(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

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

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

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 acording to Tables 2 and 9. Asterisks denote significance based on the boostrapped distribution. The dependent variables are aggregated at the room-hour level.