When Peers Count: Evidence from Randomized Peer Assignments in the Workplace*

(Preliminary; please do not circulate.)

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Abstract

This paper explores how the ability of coworkers affects individual productivity. I study a seafood-processing plant in Vietnam, where workers process fish individually and are compensated based on own output. Input (steamed fish) is allocated in groups (worktables), which on average consists of four workers. Managers keep track of each group's progress to ensure that input is allocated according to its work speed. For a period of five months, workers were randomly assigned to worktables on a daily basis. Using random variation in coworker composition, I find that an increase in the ability of coworkers at the same worktable leads to a decrease in worker productivity, measured as kilograms of fish processed per hour. This productivity decline is shown to be mitigated when a coworker is close to the focal worker either in physical distance or through a social tie. *JEL* Codes: J24, L23, M52.

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1 Introduction

In this paper, I investigate how and why the productivity of a worker varies as a function of the ability of her coworker. I study a production context in which manager attention is focused at the group level as a result of the input allocation process but, nonetheless, both production and compensation occur at the individual level. First, I identify a negative effect of average coworker ability on an individual worker's daily productivity. Then, I investigate the underlying mechanisms seeking to distinguish between specific forms of peer effects that could be at work.

To study peer influences on worker productivity, I conducted a field experiment at a processing plant in Vietnam that randomly assigned workers to workstations on a daily basis for five months.[1] For each worker, this created random variation in the composition of coworkers assigned to work at the same table, or in nearby positions, across workdays. Over the five month period, I observe daily measures on output, measured as kilograms of fillet produced, and time worked by each worker. Prior to the start of this experiment, I collected information on each worker's background, social relationships with coworkers, and personality skills through a baseline survey.[2]

I use a sample that consists of 104 workers who produce fish fillets at this processing plant. Production (i.e. cleaning and filleting fish) takes place on flat top worktables. Each worktable holds up to six working positions, or individual workstations. For production, the manager allocates steamed fish, the main input, to worktables. Workers produce individually combining own effort with fish allocated to their worktable. A designated employee at the weighing station records each processing worker's output and work time. Managers, who

[1]In a companion paper, Park (2016), I use outcomes from this field experiment to investigate the effect of working with friends on employee productivity.

[2]As a tool for measuring personality skills, I use the Big Five Inventory (BFI) which is a self-reported questionnaire designed to measure one's personality along the Big Five factors – extraversion, agreeableness, conscientiousness, neuroticism, and openness.

are in charge of the filleting stage, are responsible for organizing fish supply and allocation, supervising workers, and controlling the quality of output.

The firm compensates workers individually through a combination of a base wage plus a performance wage. The base wage is a fixed amount paid for each day of work attendance and is the same for all processing workers. The performance wage pays a fixed rate for each kilogram of fillet produced by an individual worker. Daily wages, including base and performance, are summed up and typically paid once a month. Both the base wage and piece rate were constant throughout the study period.

An attractive feature of this study is the random assignment of peers in an actual workplace environment.[3] Much of the previous studies on workplace peer effects rely on quasi-random variation in coworker composition (Mas and Moretti, 2009; Bandiera et al., 2010; Hjort, 2014), quality of inputs (Amodio and Martinez-Carrasco, 2017) or randomized peer assignments in a laboratory setting (Falk and Ichino, 2006).[4] An exception is Guryan et al. (2009) which investigates the effect of playing partner's ability on own performance using randomized group assignments in professional golf tournaments. In this study, workers are assigned to individual workstations using a code designed to generate random worker-workstation matches. As a result, a worker's peer group is assigned at random.

As a main result of this paper, I find *negative* effects from the presence of high ability coworkers on worker productivity. Estimates suggest that a 10 percent increase in the average ability of coworkers at the table is associated with a 1.2 percent *decrease* in the focal worker's productivity. While the estimate size is arguably close to estimates from other peer effects studies the sign is on the opposite side of the mean of study-level estimates (Herbst and Mas, 2015). The only other peer effects study reviewed in Herbst and Mas (2015) with a

[3]Manski (2000) suggests using experimental methods, such as random assignment of peers, to identify peer effects.

[4]In the educational context, Sacerdote (2001) and Zimmerman (2003) study peer effects on academic outcomes using random peer group assignments.

significantly negative estimate is Amodio and Martinez-Carrasco (2017) which I explain in more detail below.

Incentive problems pertinent to the current context arguably point to free riding as the main cause of this negative productivity spillover. To see this, consider the compensation for workers. Since part of wage is fixed (base wage), unlike a setting with full performance pay incentives, there still exists the possibility of moral hazard. From the manager's perspective, it is relatively easier to monitor each table's progress than keeping track of each individual worker's productivity. Then, taken together with the input allocation technology, it is reasonable to expect managers to supervise groups of workers at the same table rather than each individual worker at the table. In combination, these contextual factors provide incentives for a worker to reduce effort when high ability peers are present at her group but to put more effort when she is with low ability peers at the table to avoid manager criticism.

While this finding may appear to contrast the findings of positive peer pressure among simple task workers in a laboratory environment (Falk and Ichino, 2006) and among supermarket cashiers (Mas and Moretti, 2009), I present empirical evidence that consolidates the existences of a negative productivity spillover from high ability coworkers and positive peer pressure — as shown in previous studies — which when activated works against the negative spillover effect. Specifically, I show that a worker free rides only when a high ability peer is far enough such that it is relatively difficult to be monitored by that peer. That is, I find no negative productivity spillovers when a high ability peer works in an immediately adjacent position. This suggests that monitoring is crucial in activating positive peer pressure.[5]

To provide empirical support for the underlying mechanism, I rely on several sources of potentially exogenous variations in the workplace environment. First, I use natural variation in daily predicted performance incentive ratios, the ratio of predicted performance wage to

[5] Mas and Moretti (2009) also shows that peer pressure is most significant when the worker can be easily observed by the high ability peer in the same shift.

base wage. Consistent with the theoretical prediction from an effort provision model with varying performance incentives, I find that the negative effect is significant only on days with a low predicted performance to total wage ratio. Since incentives to provide effort is lower on those days workers are more likely to free ride on their high ability peers than on days with high performance incentive ratios. This finding may help understand why some studies fail to find peer effects, especially in occupations that consist of highly incentivized payment structures (Guryan et al., 2009; Cornelissen et al., 2017).

The second piece of evidence stems from random assignment of a worker's relative ability at the table. Specifically, a worker is exposed to coworkers who are on average more able on some days and to coworkers who are less able on other days. I exploit this variation to examine whether peer effects differ with respect to the focal's workers position in the table's ability distribution. Unlike Mas and Moretti (2009) and Bandiera et al. (2010), I consistently find a negative and significant effect regardless of the worker's relative ability at the worktable. This cannot be accounted by discouragement type behaviors since if it were a discouragement effect, then we should not observe decreases in productivity when a worker is relatively more able than her peers.

A concern of particular importance in peer effects studies is whether what we are estimating is a pure ability effect or instead picking up a confounding factor that happens to be correlated with ability and influencing worker productivity. For example, workers with high ability might also possess assertive personalities at the workplace which might be the main cause of affecting the productivity of their peers. In order to address concerns with confounding worker characteristics as the mechanism of peer effects, I show that the main estimate of peer effects is robust to inclusion of various worker characteristics, including personality skills. The statistical significance and magnitude of the coefficient estimate does not change after including workers' demographic characteristics and, if anything, only a minimal reduction in magnitude of ten percent once I include all Big Five personality factors.

Interestingly, similar to Bandiera et al. (2005, 2007, 2010) and Amodio and Martinez-Carrasco (2017), I find heterogeneous peer effects along social dimensions. The negative effect is nonexistent between workers with self-reported social ties, or friendships. This accords with findings in the social incentives literature that social pressure provides additional incentives for workers to increase effort which plausibly mitigates free riding behaviors in the workplace.

This study is closely related to Amodio and Martinez-Carrasco (2017) which study a Peruvian egg production plant and report evidence of negative productivity spillovers from the presence of highly productive coworkers due to high quality hens. I investigate a different production environment in which inputs are allocated to groups and workers are compensated individually.[6] Yet, I also find that high ability coworkers negatively influence productivities of other workers when manager's monitoring is focused on group-level performance. I argue that group-level monitoring creates free riding incentives even when the performance as a group is seemingly unrelated to the individual worker's compensation.

The main contribution of this paper lies in providing randomized evidence of peer effects in a hybrid compensation environment. Most studies on peer effects have investigated settings that are either largely fixed wage (Falk and Ichino, 2006; Mas and Moretti, 2009; Amodio and Martinez-Carrasco, 2017) or entirely performance-related pay (Guryan et al., 2009; Bandiera et al., 2010).[7] In this study, the ratio of performance to fixed wage ranges from 1:1 to 3:1 fitting in between the two extreme types of worker compensation schemes. This result can be potentially useful in predicting the change in worker incentives from a change in the performance incentive as a ratio of performance to fixed wage.

This paper relates to other papers in the peer effects literature. Gould and Winter (2009)

[6] In Amodio and Martinez-Carrasco (2017), inputs (batch of laying hens) are assigned to individual workers while performance evaluation or termination policy is more team-based.

[7] Bandiera et al. (2005) exploit a field experiment to investigate the effect of a relative compensation scheme compared to a performance pay scheme on worker productivity. They report increases in worker effort under the latter and suggest that workers coordinate effort under the former.

investigate production externalities among team members in professional baseball and show how baseball players' effort choices depend on the technology of production. Brown (2011) which uses variation in the presence of superstars in golf tournaments identifies negative spillovers on the performance of other golf players. However, the author attributes the spillover effect to performance decline driven by golf players' lower expectations on the probability of winning a prize when competing with a superstar.

The remainder of this paper is organized as follows. Section 2 describes the production setting. Section 3 describes the econometric specification. Section 4 presents estimates of the effect of coworker ability on worker productivity and provides test results with potential mechanisms. Section 5 concludes.

2 The Production Setting

This study is based on a field experiment that I conducted at a seafood processing plant in Vietnam. I use the plant's employee records data to obtain a measure of productivity of seafood processing workers. For each worker and workday, I observe the weight of fish processed, in kilograms, and the start time and end time on the processing job.[8] Using this information, I define individual productivity as the average kilograms of fish processed per hour during a workday.

The main task of employees is to fillet fish. This process takes place on rectangular shaped work tables with typically four to six workers per table. However, the filleting task is performed individually and workers are compensated through a combination of a fixed daily wage plus a piece rate wage. The piece rate pays a fixed amount per kilogram of fish processed by the individual worker.

[8]The start and end time is recorded inside processing rooms by clerical workers and is a better measure of actual production time than a measure that uses employee timesheet records which is entered when a worker enters or leaves the workplace.

Distribution of work material (i.e. steamed fish) occurs at the table level. Specifically, for each batch arrival of steamed fish, a table receives one tray per person working at that table. Since workers may differ in their processing ability, some tables may be faster than others. To ensure that every table has enough material to work on, it is the manager's job to reallocate fish across tables according to each table's progress.

Worker positions, including the table and position at that table, were randomized within rooms on a daily basis over a period of five months from August 1 to December 30, 2014. Random assignment of workers to work stations are based on the use of a random sequence generator. To avoid systematic absences (e.g. workers choosing not to show up at work under specific assignments) the assignment form was delivered to workers on the beginning of each workday through their managers. Park (2016) provides more details about the implementation of the random assignment process.

I administered a baseline survey two weeks prior to the start of randomization to collect information on worker characteristics. Specifically, each worker was asked to report about her demographics (e.g. age, education, months of experience on the job, and marital status), social relationship with other workers in her processing room (e.g. collect self-reported information on friends and family members in the room), and to complete a 44 short-itemed questionnaire on the Big Five Inventory.[9]

3 Econometric Specification

I begin by specifying a model that characterizes determinants of a worker's productivity in the setting of this study. I assume that productivity of worker i, working in room r, at time

[9]The questionnaire, originally from John et al. (1991) and John et al. (2008), was translated in Vietnamese and back translated in English by a professional translation company. Both versions were additionally checked by a native Vietnamese with experience in Vietnamese-English translations. The original version of the BFI is available for research purposes at `http://www.ocf.berkeley.edu/~johnlab/bfi.php`

d can be written as

$$y_{ird} = \theta_i + \mathbb{P}_{ird}(\theta_1, \ldots, \theta_{i-1}, \theta_{i+1}, \ldots, \theta_k) + \pi N_{ird} + \phi F_{ird} + \eta F_{-ird} + \lambda_{rd} + \epsilon_{ird}, \quad (1)$$

where θ_i denotes worker fixed effects; $\mathbb{P}_{ird}(\theta_{-i}; \nu_{-i})$ is a peer effects function that affects an individual's productivity depending on her coworker's ability; N_{ird} denotes the number of workers that are spatially contiguous to worker i on a given day; F_{ird} denotes the vector of dummy variables that indicate the presence of a focal worker's friend at specific proximities (low, medium, and high proximity)[10]; F_{-ird} is an indicator equal to one if there is at least one coworker $j \neq i$ near worker i working alongside a friend and zero otherwise; λ_{rd} is a vector of all possible room×day and room×workstation fixed effects. As in the conceptual framework, I interpret the parameter θ as a measure of a worker's ability, or permanent productivity to distinguish from contemporary productivity.

Following Mas and Moretti (2009), I parametrize the peer effects function whereby it consists of the average of coworker productivity. That is, the peer effects function is written in the form of

$$\mathbb{P}_{ird}(\theta_1, \ldots, \theta_{i-1}, \theta_{i+1}, \ldots, \theta_k) = \bar{\theta}_{-ird}. \quad (2)$$

Combining equation (1) and (2), I then obtain my baseline estimating equation:

$$y_{ird} = \theta_i + \beta\bar{\theta}_{-ird} + \pi N_{ird} + \phi F_{ird} + \eta F_{-ird} + \lambda_{rd} + \epsilon_{ird}. \quad (3)$$

The coefficient of interest is β. If there are no externalities from coworker productivity then $\beta = 0$.

I estimate (3) in two steps. In the first step I estimate the θ_i terms. To estimate these terms it is necessary to take into account the fact that an individual's productivity may be

[10]Park (2016) finds that productivity drops when a friend is working at a high proximity position but does not drop, otherwise.

affected by coworker composition. The purpose of the first step is therefore to estimate θ_i in a model that is consistent with (3). To accomplish this, I estimate

$$y_{ird} = \theta_i + \mathbb{V}'\mathcal{C}_{-ird} + \pi N_{ird} + \phi F_{ird} + \eta F_{-ird} + \lambda_{rd} + \epsilon_{ird} \tag{4}$$

where $\mathcal{C}_{-ird} = \{I_1, \ldots, I_{i-1}, I_{i+1}, \ldots, I_k\}$ is a set of dummy variables, one for each worker that shares the same processing room with worker i. Each $I_{j\neq i}$ is equal to one if worker j is working at the same table with worker i and zero, otherwise. The vector $\mathbb{V}$ contains k parameters, one for each worker $1, \ldots, k$. The term $\mathcal{C}_{-ird}$ accounts for worker-specific influences on productivities of their coworkers. This allows consistency between equation (3) and (4) because the peer effects function is absorbed by $\mathcal{C}_{-ird}$. Note that this approach is analogous to that used by Arcidiacono et al. (2017) where the authors estimate player specific effects on their teammates' scoring chances in a professional basketball context.

I use the estimated worker fixed-effects, $\{\hat{\theta}_i\}_{i=1}^{k}$, to construct a measure of average coworker productivity, denoted $\bar{\theta}_{-ird}$. The critical assumption is that the variation of a worker's productivity across days is orthogonal to changes in the average permanent productivity of coworkers at the same table, aside from that originating from peer effects. This is plausible if worker positions are randomly assigned. For this purpose, I draw on data from the random assignment period and use the assigned coworker composition as an instrument for realized coworker composition. In the next section, I check the validity of the assumption of random assignment during this period. Specifically, I test the relationship between the focal worker's characteristics, including estimated ability, and average characteristics of coworkers assigned to work at the same table or nearby.

The parameter β represents the effect of coworkers' permanent productivity on worker i's current productivity. However, a general concern that applies to peer effects estimation is that I cannot empirically distinguish between permanent and contemporaneous effects

(Manski, 1993, 2000; Brock and Durlauf, 2001; Moffitt, 2001). Accordingly, a possible interpretation is that both effects are present in my estimate of β.

4 Estimates of Peer Effects

In this section, I begin by presenting the data and test of random assignment. Then, I present main estimates of how the productivity of worker i depends on her coworkers' ability. I then investigate a more general model where I include additional worker characteristics to the baseline specification.

4.1 Data and Randomization Test

The dataset consists of daily worker level data on assigned and realized workstations, in addition to work time, measured in minutes, and weight of fish processed during the five month randomization period; for work days between August 1, 2014 and December 30, 2014. In total, I observe 104 seafood processing workers and approximately 5,500 worker-day observations with work attendance.[11] Table 1 reports descriptive statistics of the sample population. All workers are female. The average worker is married, 31 years old, and worked at this plant for around 20 months. Half of the workers in my sample finished secondary education (equivalent to completing grade 9 or junior-high school in the U.S context).

All processing workers perform the same task of producing mackerel fillets and are subject to the same payment schedule.[12] However, there is variation in productivity across workers. Figure 1 shows a distribution of estimated fixed effects ($\hat{\theta}_i$). The average 90-10 percentile differential in the estimated fixed effects is 0.28 (workers at the top of the distribution are 28 percent more productive than workers at the bottom of the ability distribution).

[11] Average absence rate during period was approximately 20 percent. I find no statistical relationship between a worker's assigned coworker characteristics and attendance which plausibly suggests successful implementation of the experiment.

[12] There is no seniority-based pay schedule at this firm.

The identifying assumption in equation (4) for the causal interpretation of β is that the changes in coworker permanent productivity across workdays is orthogonal to unobserved shocks affecting individual productivity. I check this assumption by directly testing random assignment of coworkers. Specifically, using various measures of individual worker characteristics, I test the claim that assignment of coworkers is random within a room-by-date cell. In practice, I use the bias-corrected method proposed by Guryan et al. (2009) and estimate the following model:

$$X_{ird} = \pi_1 + \pi_2 \overline{X}_{-irtd} + \varphi \overline{X}_{-ird} + \lambda_{rd} + u_{ird} \tag{5}$$

where $\overline{X}_{-irtd}$ denotes the mean characteristic of coworkers assigned to work at the same table t with worker i in room r on day d; $\overline{X}_{-ird}$ is the mean characteristic of all workers registered in room r on date d.[13]

Table 2 presents results from a series of randomization tests using different measures of characteristics of coworkers. Panel A shows estimates when using the average characteristic of coworkers assigned to work at the same table with the focal worker. To be careful, panel B provides an additional check by reporting results using coworkers assigned to work in spatially contiguous positions. This set is neither a superset nor subset of the set of coworkers at the same table. In column 1, I report the estimated π_2 using average coworker ability, or the average of estimated worker fixed effects of coworkers ($\bar{\theta}_{-irtd}$). In both panels, the coefficient on average coworker ability is small and insignificant. This result is consistent with coworker ability being randomly assigned for a given worker.

In columns 2-5, I test for random assignment using other observed and unobserved worker characteristics. Columns 2 and 3 report estimates using age and months of experience on

[13] The inclusion of the mean characteristic of all workers registered in the same room, including those that are not necessarily assigned to work nearby, is to account for the fact that the focal worker cannot be assigned to herself. With small samples, this may cause a negative bias in the estimate of π_2. For a full discussion, I refer the reader to Guryan et al. (2009).

job. In columns 4 and 5, I present results from selected Big Five personality measures (i.e. extraversion and conscientiousness). Estimation results on the remaining three personality dimensions (e.g. agreeableness, neuroticism, and openness) are reported in a separate appendix. Estimates of π_2 are all statistically insignificant under conventional levels. Overall, there is no evidence to suggest a systematic relationship in the characteristics between the focal worker and the average peer at the worktable.

4.2 Input Allocation

As described above, for each batch arrival, input (steamed fish) is distributed to each table based on the number of workers at that table. If a table produces faster than other tables and runs out of input the manager restocks it with undistributed input or by taking inputs from other tables that are expected to have surplus when the next batch arrives. However, if a manager slacks on her job and fails to supply more inputs to high speed tables then this would mechanically cause a negative externality similar to the implications of a zero sum game. [14]

I first visually check this possibility by plotting the relationship between a table's average output and the average ability of workers at that table. Assuming a constant conversion rate from a unit weight of input to output, a table's output can be used as a proxy for input allocated to that table on a given day.[15] Since output is likely to vary across workdays and influenced by time-invariant characteristics of the table itself (e.g. tables at the corners of

[14]It can also be the case that managers possess favoritism towards workers with social connections (Bandiera et al., 2009). For this study, I did not collect social network data on managers.

[15]A constant conversion rate would be maintained as long as workers do not cut off too less non-edible parts or too much edible parts from the input. Concerning the former, the quality control process at the end of the processing stage ensures that all non-edible parts are removed from the fillets. The management also has strict controls over the latter issue for a couple of reasons. Fish waste, including skin and bones, that come out during the filleting process is separately collected in yellow baskets by individual workers. They are strictly prohibited from throwing the waste down the water drain because of environmental regulations but also to minimize input cost. By checking individual yellow baskets, managers ensure that workers are not throwing away edible fish parts.

a room may be under less supervision from the manager), I adjust output using room$\times$day and room$\times$table fixed effects. Figure 2 presents a plot of residual table output against table's average ability. The red dashed line marks the slope with a proportional constant of one between ability and input: a one unit increase in average ability is associated with a one unit increase in input supplied to that table. The slope is positive and close to the red line implying that an increase in the average ability of a table is associated with an equally proportionate increase in the supply of inputs to that table. If there were no input reallocation, the slope would have been close to zero.

Next I formally estimate the input supply elasticity which shows the percentage change in supply of input, using output as a proxy, from a one percent change in the ability of workers at a table. This leads to estimating the following specification:

$$f_{trd} = \omega \cdot \bar{\theta}_{trd} + \delta \cdot \bar{\nu}_{trd} + \lambda_{rd} + \xi_{rt} \tag{6}$$

where f_{trd} is the log per-capita output at table t in room r on day d; $\bar{\theta}_{trd}$ is the average ability of workers at table t; $\bar{\nu}_{trd}$ is a vector of worker characteristics at table t; λ_{rd} and ξ_{tr} each denote room$\times$day and room$\times$table fixed effects, respectively. For each table, per-capita fish output is derived by dividing the sum of weight of fish processed by all workers at table t in room r on day d by the number of workers at table t. The coefficient ω measures the percentage change in the table's per-capita output from a percentage change in the average ability of workers at that table. The coefficient δ indicates how per-capita output (which is a function of per-capita fish input) relates to the table's average characteristic along dimensions other than ability. If there was any influence on the reallocation process based on characteristics other than the ability of workers at a table, then we could expect δ to at least partially capture this relationship.

Table 3 reports ordinary least squares estimates of equation (6). Column 1 estimates the coefficient on average ability without including other worker characteristics. Column 2 includes means of table's age, experience, and the number of friends. Column 3 also includes two personality factors, extraversion and conscientiousness.[16] The estimate on average permanent productivity is close to one: 0.973 in columns 1 and 3. This implies that a one percent increase in ability is associated with a roughly one percent increase in supply of inputs to the table. It also remains statistically significant across all columns. This exercise suggests that input allocation during the study period was successful in that faster tables received proportionately more input than slower tables and this process was not influenced by other characteristics of workers at a table.

4.3 Main Estimates

Before presenting the table with regression estimates, I first plot regression-adjusted productivities against average coworker ability. To do this, I run an Ordinary Least Squares (OLS) regression of equation (3) without the coworker ability variable. Then I take the residuals from this regression, compute means by each decile of the average coworker ability distribution, and graph the average residual against each decile bin. The graph is displayed in Figure 3.

For a baseline check, I first focus on coworkers that are working near the focal worker. If there are any productivity spillovers, then I expect to observe large spillovers between workers who are close to each other.[17] Panel (a) plots the estimates using the average ability of coworkers that are spatially contiguous to the focal worker. There appears to be no discernible trend in the residuals against the decile bins of average coworker ability: the

[16] Including other Big Five personality factors in the regression does not change the results. Here, I present results with only two of the five factors to save space.

[17] Mas and Moretti (2009) also uses spatial proximity and orientation to identify the specific channels of spillovers from high to low ability supermarket cashiers and finds that the spillover is most effective when the low ability worker can be observed by the high ability worker. In my context, workers are facing the center of the table such that workers can mutually observe each other if they are at the same table.

estimates are somewhat declining but remains close to zero. Next, I focus on the ability of coworkers at the same table. Panel (b) suggests evidence of negative productivity spillovers from high ability coworkers at the table. The graph displays a drop in residual worker productivity below zero when average coworker ability is in the upper part of the distribution. It also suggests positive productivity spillovers from low ability peers. Residual productivity is positive and noticeably different from zero when coworker ability falls into one of the three lowest decile bins.

Table 4 presents my main estimate of β from fitting (3) to the data. To correct for sampling variability of worker fixed effect estimates, I derive standard errors from using a Bayesian Parametric Bootstrapping Method, adopted from Mas and Moretti (2009), and cluster the standard errors two-way by worker and room$\times$day level. Columns 1 and 2 report OLS estimates. In column 1 the estimate indicates no significant relationship between average ability of spatially contiguous coworkers and individual productivity. In column 2 I report the coefficient estimate for average ability of coworkers at the same table. The estimate is negative and statistically significant at the one percent level suggesting a negative correlation between average coworker ability and worker productivity.

Columns 3 and 4 show I.V. estimates of β using average ability of assigned coworkers as an instrument for realized average coworker ability. As in column 1, column 3 employs the average ability of coworkers nearby. The estimate is negative yet statistically insignificant. The estimated β, reported in column 4, suggests the existence of negative peer effects at the same table. It is both statistically and economically significant. The estimate suggests that a 10 percent increase in average coworker ability at the same table is associated with a 1.3 percent decrease in the focal worker's productivity.

The nonexistence of a similar effect from coworkers who are nearby but not necessarily at the same table imply that, in this context, the worktable is an important medium through which peer effects operate. This could possibly be the case if managers are monitoring work progress at the table level which induces workers to not only care about their own productivity but also to pay attention to their table's overall productivity. If my table is slower than other tables, I will speed up to avoid manager criticism and negative evaluation but if my table is fast compared to other tables I do not need to put in this extra effort. Since a table's work speed should be largely dependent on the ability of workers at that table, having high ability peers causes a worker to reduce effort while having low ability peers drives a worker to increase effort.

I have found a contemporaneous decline in worker productivity at the daily level as the ability of same-table coworkers increases. The implications of this effect can be different depending on whether the effect is temporary – limited to the current day – or persistent across workdays. In order to determine the persistence of this effect, I estimate a version of equation (3) that includes both the current period's average coworker ability and the average coworker ability from previous workdays as lags:

$$y_{ird} = \theta_i + \beta\bar{\theta}_{-ird} + \sum_{k=1}^{3} \beta_k \bar{\theta}_{-ir,d-k} + \pi N_{ird} + \phi F_{ird} + \lambda_{rd} + \epsilon_{ird}. \tag{7}$$

where $\bar{\theta}_{-ir,d-k}$ is the average ability of coworkers that shared the same table with the focal worker k days before day t. Through the coefficient on the lag term from this model, β_k, we can examine how a shock to the coworker ability composition may affect individual productivity over time.

In column 1 of Table 5, I present coefficient estimates of $\hat{\beta}$ and $\hat{\beta}_1$. The estimated coefficient on current period's average coworker ability is -0.128 and statistically significant at the one percent level where as the coefficient on previous workday's average coworker ability is estimated as 0.007. Columns 2 and 3 each use the average ability of coworkers from the past two and three workdays, respectively. In both columns, estimated current day coworker ability coefficient is similar in magnitude to column 1 and remains statistically significant at the five percent level. However, none of the coefficient estimates on past workdays are significantly different from zero. These results suggest that peer ability in previous workdays is not a determining factor of today's individual productivity.

4.4 Identifying Underlying Mechanisms of Peer Effects

In this section, I turn to identifying the mechanism for the decline in worker productivity associated with working with high ability coworkers. The specification thus far assumed it is the ability of peers that affects individual performance. An alternative hypothesis is that other peer characteristics, such as age or personality also matters. Furthermore, omitting these characteristics from the regression can be especially problematic if coworker ability is systematically correlated with, for instance, noncognitive skills which would lead to overestimating or underestimating the importance of peer ability effects depending on the sign of the correlation between a worker's ability and noncognitive skills. To investigate this possibility, I present variations of equation (3) that allows estimation of the relationship between average coworker's non-ability characteristics and own productivity:

$$y_{ird} = \theta_i + \beta\bar{\theta}_{-ird} + \gamma\bar{\nu}_{-ird} + \pi N_{ird} + \phi F_{ird} + \eta F_{ird} + \lambda_{rd} + \epsilon_{ird}. \tag{8}$$

where $\bar{\nu}_{-ird}$ is the average measure for a given characteristic across coworkers at the table. If there are no spillovers from these non-ability characteristics then $\gamma = 0$.

Table 6 presents estimates of β and γ from fitting (8) to the data. Column 1 includes average coworker measures on age and job experience. Both estimates of non-ability coworker coefficients are virtually zero. In column 2, I exploit information collected from the baseline survey on a worker's number of friends and wealth index, derived as the first principal component from an analysis based on questions about ownership of household assets. Again, both non-ability coefficient estimates are insignificant. Coworker ability is estimated close in magnitude to the main specification estimate (-0.125) and is statistically significant.

The last column reports estimates from including the average scores of coworkers' Big Five personality factors. Estimated average coworker ability is still negative and statistically significant. Compared to the main estimate the effect size shrinks by only 0.10 ($(0.125 - 0.112)/0.125$). All five estimates of average coworker personality coefficients are insignificant. Among the Big Five, extraversion has the largest estimated size of peer effect. The estimate suggests that a one standard deviation increase in average coworker extraversion is associated with a decline of 0.6 percent in the focal worker's productivity. To gauge its economic significance with respect to our main variable of interest, coworker's ability, I convert the effect size of coworker ability from a one percentage change to a one unit change in standard deviation. Since one standard deviation of ability is commensurate to about an 11 percent difference, a one standard deviation increase in coworker ability is associated with a 1.4 percent productivity decline ($-0.125 \times (0.11/0.10)$). Hence, holding other factors constant, coworker ability has more than twice the effect size than that of coworker extraversion.

One type of behavioral response that is consistent with the negative association between peer ability and worker productivity is a discouragement effect. This could be the case if workers are conforming to their position in the ability distribution when exposed to certain types of peers at the same table. If high ability peers are present workers reduce effort because they are discouraged by the presence of a higher ability peer. On the other hand, if low ability peers are present a worker is encouraged because now she is the high ability type and, accordingly, puts in more effort. The econometric implication of this behavioral response is that we should observe a productivity decline only when the worker is relatively less able to her coworkers at the table. We should not observe productivity drops among workers who have relatively higher ability.[18]

[18] In fact, one of the crucial pieces of evidence that Mas and Moretti (2009) provide to verify the existence of peer pressure (i.e. low ability workers increase their performance in response to the presence of high ability workers) is showing that the positive effect only exists when the focal worker's ability is below average.

To achieve this, I include interaction terms to equation (3) and estimate the models using an I.V. estimator for each interaction term. In column 1 of Table 7 I include an interaction term between average coworker ability and an indicator variable equal to one if the focal worker's productivity is higher than the average ability of coworkers at the same table. The coefficient estimate of the interaction term is statistically insignificant. This suggests that the negative effect does not depend on whether the focal worker is more able than the average coworker at the table. This seems inconsistent with the discouragement behavior explained above.

In columns 2 and 3, I use alternative measures of relative ability. Column 2 uses an indicator variable equal to one if the focal worker is the most able worker at the table. If the effect is driven by conforming behaviors then we should not expect a negative relationship between average coworker ability and worker productivity when a worker is the most able worker at the table. The estimated coefficient on β is negative and statistically significant while the estimate of the interaction term is close to zero and insignificant. This suggests that the peer effect is equally negative even for the fastest workers at the table. Column 3 uses an indicator for being the least able at the table. While the sign does suggest that a worker is likely to have larger negative effects from high ability peers when she is the least able worker than when she is not, the estimate is statistically insignificant.

In column 4 I use the absolute difference in estimated ability between the focal worker and her average coworker and I interact this measure with an indicator variable for whether the focal worker is more able or less able than the average coworker. I find that a 10 percent increase in the absolute difference in ability with coworkers is associated with a 0.9 percent increase when the focal worker is more able but a 1.6 percent decrease when the focal worker is less able. This further confirms that the effect of having high ability peers on individual productivity is negative regardless of whether the worker is more or less able than the average coworker at the table. These results run against the explanation of negative peer effects on productivity as discouragement from the presence of high ability peers.

4.5 Peer Effects and Heterogeneous Incentives

To alleviate moral hazard behaviors, the firm can potentially provide stronger performance incentives by increasing the proportion of total wage paid by piece rate performance (Lazear, 2000). Yet, an important question for the management is how much increase in the performance ratio is necessary to completely remove incentives to free ride in the workplace. To answer this question, I exploit natural variation in the performance to total wage ratio. Across workdays, average worker output is expected to positively covary with demand of fillet products.[19] Workers will need to produce more output the higher the demand which fluctuates with orders from buyers in the U.S. market, the main export destination. Thus, when demand is high workers' performance wage ratio also increases because the base wage is fixed at a daily rate. This provides a natural experiment to test how the negative peer effect differs across days with different performance incentives.

Define performance incentive ratio (PIR) as the ratio of performance wage to total wage. I use daily variation in the average PIR, obtained as the ratio of average performance wage (piece rate $\times$ average worker output) to total wage (average performance wage + base wage). Panel (a) of Figure 4 depicts a histogram of daily average worker output. It shows a substantial amount of variation in output per worker across workdays, ranging from 30 to 80 kilograms per worker. Next, in panel (b), I present a scatterplot between average worker output and individual PIRs. Two points are worthy of mentioning. First, there is dispersion in individual worker PIRs within the same day because of differences in worker output. Second, individual PIRs increase on days with higher worker output. This implies that workers have greater incentives to exert high effort on days with high average worker

[19] The firm mostly sources its fish input, frozen or unfrozen, from local fish suppliers. When supply is high the firm buys unfrozen fish but when it is low the firm buys frozen fish that were caught earlier but stored in freezers.

output than on days with low average worker output. Accordingly, if the negative peer effect is driven by free riding behavior then we should expect this effect to subside on days with high PIR and grow on days with low PIR.

Next, I visually check this implication by estimating the main specification at each decile of the average PIR. We would expect the estimated coefficients to be increasing with the deciles of average PIR. Figure 5 plots the coefficients in circles along each decile bin. The red solid line indicates the linear fit weighted by the inverse of the variance of each coefficient estimate. The line is positively sloped suggesting a decrease in the negative effect from high ability coworkers as the performance incentive increases. The coefficient estimates suggest that peer effects are largely absent when the performance incentive ratio is slightly below 0.70. That is, workers cease responding to the ability of peers at their table when the percentage of wage paid through performance pay is close to 70 percent.

Formally, I use a regression specification which adds an interaction term between average worker ability and average PIR to equation 3. Estimation results are reported in column 1 of Table 8. The estimate of PIR is positive and statistically significant at the ten percent level. It suggests that increasing the performance to total wage ratio from the mean (0.65) by one standard deviation (corresponds to a four percentage point increase) reduces peer effects by 84 percent (1.04/1.24). Column 2 divides the PIR into three equal size bins (high, medium, and low) and interacts each bin with coworker ability at the table. The peer effect estimate loses significance when the performance incentive is high. Coefficient estimates for medium and low PIR are all statistically different from zero and increasing in absolute size as PIR drops from medium to low. These findings are similar to the findings of Amodio and Martinez-Carrasco (2017) and show that workers' motives to free ride on coworker ability may depend significantly on performance incentives, especially those that motivate workers to exert more effort.

Several studies suggest that free riding behaviors can be mitigated through non-monetary modes in the form of providing peer pressure or social incentives (Kandel and Lazear, 1992; Mas and Moretti, 2009; Bandiera et al., 2013; Amodio and Martinez-Carrasco, 2017). I examine this hypothesis by investigating whether the effects of coworker ability on worker productivity is heterogeneous with respect to (i) the distance of the coworker's position to the focal worker (physical proximity) and (ii) whether there is a social tie between the coworker and focal worker (social proximity).

If peer pressure is applied through close monitoring, as suggested by Mas and Moretti (2009), then we would expect a worker to have less incentives to free ride when a high ability coworker is right alongside relative to when the coworker is further away. This is because it is much more difficult for the high ability peer to monitor the focal worker when in distance and, therefore, less pressure for the focal worker. Social proximity would also matter if peer pressure is more effectively utilized amongst socially related workers for example due to the credibility of threats made from friends or if workers possess social preferences (Bandiera et al., 2005, 2010, 2013; Amodio and Martinez-Carrasco, 2017).

Results of heterogeneous peer effects are presented in columns 3-5 of Table 8. For column 3, I divide the coworker composition into three groups (high, medium, and low proximity) with regard to the physical distance with the focal worker and calculate the average ability of coworkers at each proximity. For each proximity, the estimate shows how a worker's productivity is associated with the ability of coworkers in that specific proximity. The result shows increases in the estimate size, from -0.045 to -0.275, and statistical significance, from not significant at any conventional level to significant at the one percent level, as the distance between the focal worker and coworkers increases. The evidence accords with what peer pressure under monitoring predicts in this setting.

To test for heterogeneity with respect to social connections, I separate a worker's peer group into two non-overlapping groups: socially connected peers and non-connected peers. Then, I calculate the average ability of coworkers in each group and include both variables in the main specification, replacing the single average coworker ability variable. I.V. estimates are provided in column 4. The estimate on socially connected peers is statistically insignificant but also above zero while the estimate on not connected peers is negative and large (-0.165). This finding suggests that peer effects arise only between workers with no social connections. In the current setting with incentives to free ride, peer ability shows no influence on worker productivity possibly because of social pressure.

Column 5 uses an alternative specification to check for heterogeneity with the existence of socially connected peers at the table. Instead of including separate coworker ability variables based on social connection status I simply interact average coworker ability with the presence of at least one socially connect peer at the table. The coefficient on coworker ability when no friend is at the table is negative and larger in magnitude to that from the main specification. However, when at least one friend is working at the same table, I find no statistically significant effect. The reduction in free riding behaviors when connected coworkers are present can be explained as social pressure alleviating negative productivity spillovers.

5 Conclusion

I use the random assignment of workers to workstations at a seafood processing plant to test for whether and how coworker ability affects individual productivity. I find a negative effect on worker productivity when the ability of coworkers at the same table increases. Based on natural variations in the performance wage ratio and relative ability difference I argue that the main channel is through free riding behaviors when high ability peers are present. In addition, I document evidence to suggest that productivity spillovers are largely dependent on both monetary and non-monetary incentives.

A natural question to ask is why the firm did not adopt a full piece rate scheme in the first place; or even a higher proportion of wage based on piece rate. One possible explanation fomulated in Holmstrom and Milgrom (1991) is that piece rate alone is not an optimal compensation scheme in multi-task settings. Anecdotal evidence from interviews with management staff indicates that the management believes that if the performance portion is excessively high then workers will forgo quality of the products — which in this case directly relates to safety issues (removal of bones) — for quantity of output produced. Using the words of the CEO at this firm, the number one priority for food production companies is to ensure safety of their products. Another possible reason is to promote workers to develop processing techniques and share productivity enhancing information with other employees as well as with their managers. Studies suggest that it is not impossible for a complete piece rate payment structure to hinder diffusion or adoption of productivity improving technologies by workers (Lazear, 1986; Gibbons, 1987).

I do not find evidence of equal input sharing among coworkers at the table. Since performance can be easily monitored by workers nearby they could potentially engage in some type of collusion or agreement in which case we would expect one's productivity to not vary significantly with coworker ability. One potential explanation for the lack of such behavior is that in this study input is allocated across worktables and faster worktables receive more inputs than slower tables. This input allocation technology creates incentives, additional to that of manager monitoring, for workers to avoid colluding their work speeds with coworkers at the same table.

References

Amodio, F. and Martinez-Carrasco, M. A. (2017). Input Allocation, Workforce Management and Productivity Spillovers: Evidence from Personnel Data. McGill University, Working Paper.

Arcidiacono, P., Kinsler, J., and Price, J. (2017). Productivity Spillovers in Team Production: Evidence from Professional Basketball. *Journal of Labor Economics*, 35(1):191–225.

Bandiera, O., Barankay, I., and Rasul, I. (2005). Social Preferences and the Response to Incentives: Evidence From Personnel Data. *Quarterly Journal of Economics*, 120:917–962.

Bandiera, O., Barankay, I., and Rasul, I. (2007). Incentives for Managers and Inequality among Workers: Evidence from a Firm Level Experiment. *Quarterly Journal of Economics*, 122(2):729–74.

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

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

Bandiera, O., Barankay, I., and Rasul, I. (2013). Team Incentives: Evidence from a Firm Level Experiment. *Journal of the European Economic Association*, 11(5):1079–1114.

Brock, W. A. and Durlauf, S. N. (2001). Discrete Choice with Social Interactions. *Review of Economic Studies*, 68(2):235–60.

Brown, J. (2011). Quitters Never Win: The (Adverse) Incentive Effects of Competing with Superstars. *Journal of Political Economy*, 119(5):982–1013.

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

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

Gibbons, R. (1987). Piece-rate incentive schemes. *Journal of Labor Economics*, 5:413–429.

Gould, E. and Winter, E. (2009). Interactions between workers and the technology of production: Evidence from professional baseball. *Review of Economics and Statistics*, 91(1):188–200.

Guryan, J., Kroft, K., and Notowidigdo, M. (2009). Peer Effects in the Workplace: Evidence from Random Groupings in Professional Golf Tournaments. *American Economic Journal: Applied Economics*, 1(4):34–68.

Herbst, D. and Mas, A. (2015). Peer effects on worker output in the laboratory generalize to the field. *Science*, 350:545–49.

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

Holmstrom, B. and Milgrom, P. (1991). Multitask principal-agent analyses: Incentive contracts, asset ownership, and job design. *Journal of Law, Economics, and Organization*, 7:24–52.

John, O., Donahue, E., and Kentle, R. (1991). The Big Five Inventory–Versions 4a and 54. Berkeley, CA: University of California, Berkeley, Institute of Personality and Social Research.

John, O., Naumann, L., and Soto, C. (2008). Paradigm shift to the integrative Big Five trait taxonomy: History, measurement, and conceptual issues. In John, O., Robins, R., and Pervin, L., editors, *Handbook of personality: Theory and research*. Guilford Press, New York, NY.

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

Lazear, E. (2000). Performance Pay and Productivity. *American Economic Review*, 90(5):1346–1361.

Lazear, E. P. (1986). Salaries and piece rates. *Journal of Business*, 59(3):405–431.

Manski, C. (1993). Identification of Endogenous Social Effects: The Reflection Problem. *Review of Economic Studies*, 60(3):531–542.

Manski, C. (2000). Economic Analysis of Social Interactions. *Journal of Economic Perspectives*, 14(3):115–136.

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

Moffitt, R. A. (2001). Policy Interventions, Low-Level Equilibria, and Social Interactions. In Durlauf, S. N. and Young, H. P., editors, *Social Dynamics*. Brookings Institution Press, Washington, DC.

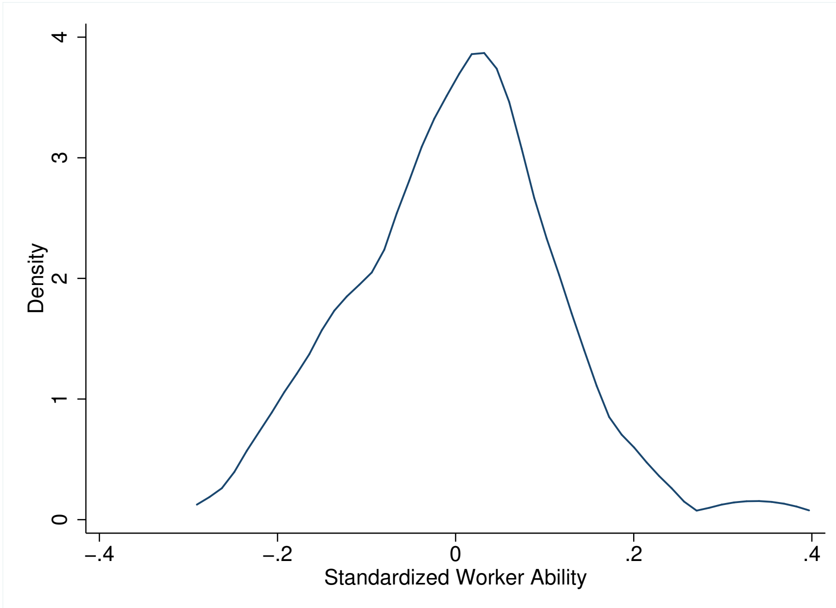
Park, S. (2016). Socializing at Work: Evidence from a Field Experiment with Manufacturing Workers. Working Paper.

Sacerdote, B. (2001). Peer Effects with Random Assignment: Results for Dartmouth Roommates. *Quarterly Journal of Economics*, 116(2):681–704.

Zimmerman, D. J. (2003). Peer Effects in Higher Education: Evidence from a Natural Experiment, Williams Project on the Economics of Higher Education. *Review of Economics and Statistics*, 85(1):9–23.

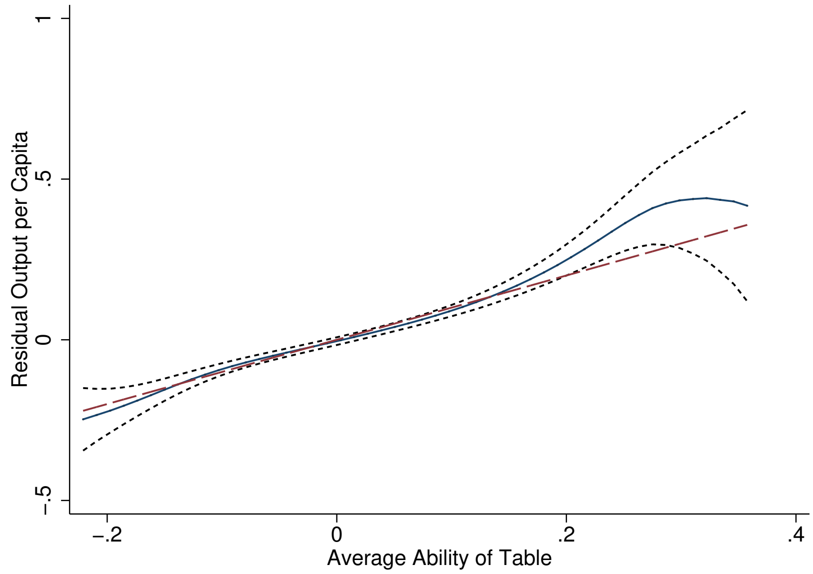
A Figures and Tables

Figure 1: Distribution of Estimated Worker Ability



Note: This figure shows a kernel density distribution of estimated worker ability of all 104 workers in the sample using equation (4). The estimate is standardized at the room level. I use an Epanechnikov kernel and optimal bandwidth.

Figure 2: Residual Table Output by Table's Average Ability

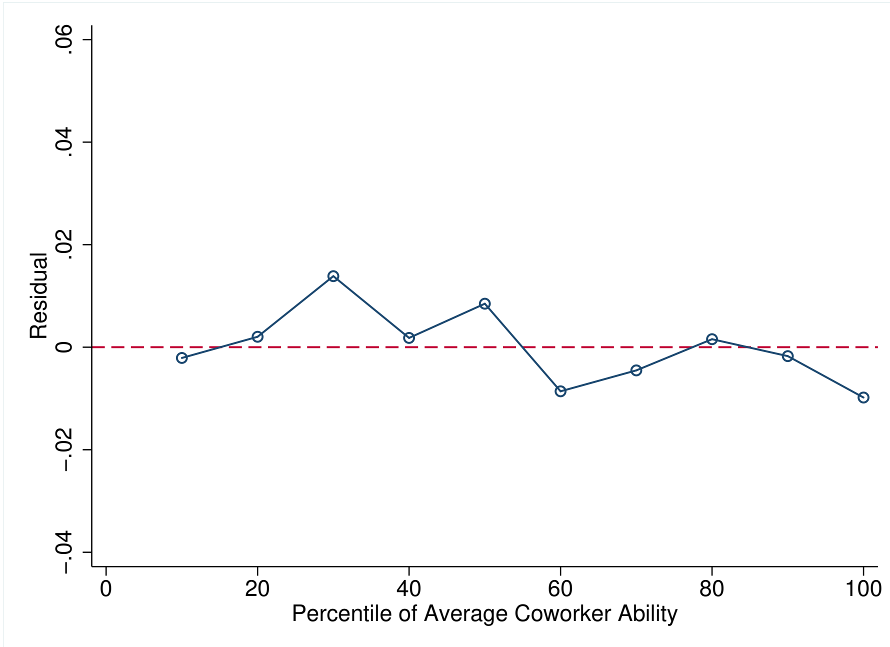


Notes: Residual table output is obtained as

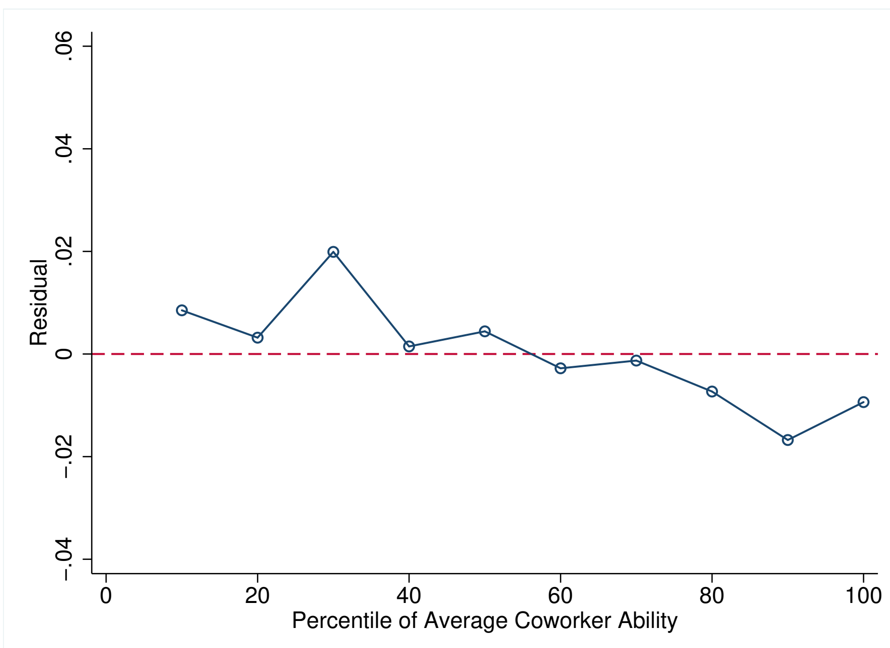
$$\hat{\epsilon}_{trd} = y_{trd} - \hat{\lambda}_{trd}$$

where y_{trd} is the per worker output of table t in room r on day d and $\hat{\lambda}_{trd}$ is a vector of estimated room×day and room×table fixed effects. 95 percent confidence intervals are shown in black dotted lines. The hypothetical line with a proportional constant of one is represented by the red dashed line.

Figure 3: Residual Productivity by Decile of Average Coworker Ability



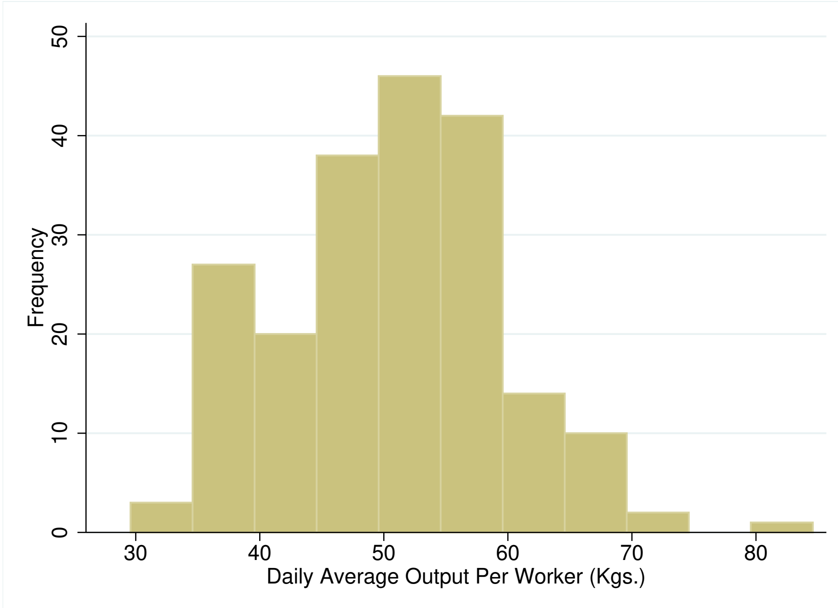
(a) Coworkers Spatially Contiguous to Focal Worker



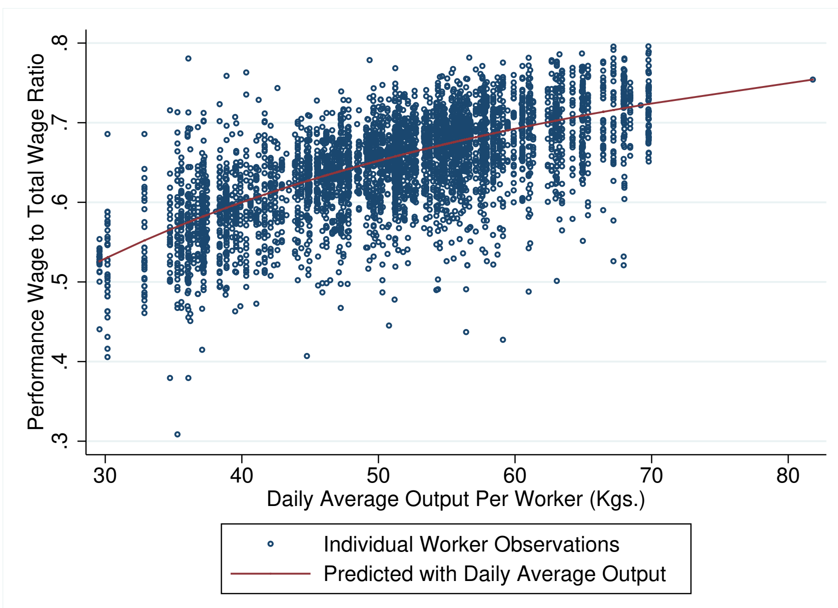
(b) Coworkers at Same Table

Note: This figure plots the average of a residual by decile of average ability of coworkers nearby (panel a) and of coworkers at same table as the focal worker ((panel b). The residual is from a regression of individual productivity on the number of workers nearby, presence of socially connected workers, and worker, room×day, and workstation fixed effects.

Figure 4: Variation in Worker Output and Performance Wage Ratio



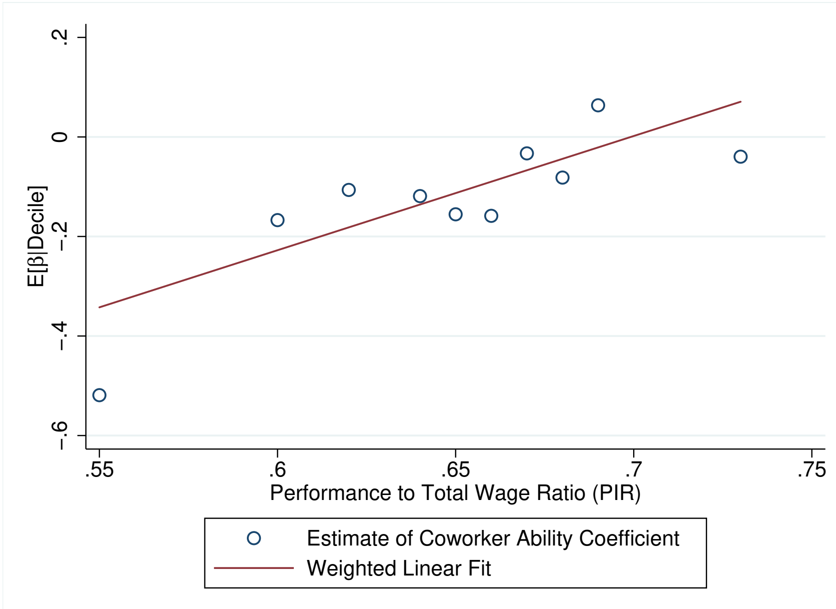
(a) Distribution of Daily Average Worker Output



(b) Variation in Performance-Total Wage Ratio

Note: Panel (a) plots a histogram of average worker output by room×day. Bins are set to have widths of five. Panel (b) presents a scatter plot between average worker output and the ratio of performance wage (paid by piece rate) to total wage (performance + base wage). The unit of observation, denoted by a hollow circle on the graph, is worker×day. The red solid line connects predicted performance-total wage ratios using the average worker output at the room×day level.

Figure 5: Peer Effect Estimates by Deciles of Performance-Total Wage Ratio



Note: Each observation (circle) is an estimate of the average coworker ability coefficient obtained by running the main regression specification at each decile of the performance-total wage ratio distribution. The performance-total wage ratio is the predicted room×day level performance wage, using average worker output, divided by predicted total wage. I distribute these ratios into ten equal frequency bins. The red line is the linear fit weighted by the inverse of the variance of the estimate.

Table 1: Descriptive Statistics - Workers in Sample ($N = 104$)

Variable	Mean	Standard Deviation
Module A. Socioeconomics		
Female	1	
Age (years)	31.43	9.37
Married	0.68	0.47
Completed secondary school	0.49	0.50
Tenure at current job (months)	19.30	17.00
Experience in fish processing (months)	32.71	33.02
Number of reported friends in same room	5.01	1.80
Module B. Big Five Personality Traits		
Extraversion	3.60	0.57
Agreeableness	4.08	0.70
Conscientiousness	3.84	0.58
Neuroticism	2.59	0.72
Openness	2.75	0.61

Table 2: Test of Random Assignment - OLS Estimates

	Dependent variable, X =				
	Ability	Age	Months of Experience	Extra- version	Conscien- tiousness
A. Coworkers assigned to same table					
Average($\overline{X}_{-irtd}$)	−0.001	−0.008	−0.015	−0.007	−0.006
	(0.005)	(0.005)	(0.010)	(0.005)	(0.006)
Room×day fixed effects	Yes	Yes	Yes	Yes	Yes
Number of observations	7,289	7,289	7,289	7,289	7,289
B. Coworkers assigned to contiguous workstations					
Average($\overline{X}_{-irtd}$)	0.002	−0.002	−0.004	0.000	0.005
	(0.004)	(0.003)	(0.006)	(0.004)	(0.004)
Room×day fixed effects	Yes	Yes	Yes	Yes	Yes
Number of observations	7,289	7,289	7,289	7,289	7,289

Notes: All regressions include mean characteristic of workers in the room and room×day fixed effects. For instance, average ability of coworkers at room r is the average estimated fixed effects of coworkers assigned at room r, excluding the focal worker. Standard errors are clustered by worker and presented in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 3: Estimation of Per Capita Output and Table Characteristics

	log(per capita output by table)		
Averaged by table ($\overline{X}_{trd}$)	(1)	(2)	(3)
Ability	0.973***	0.939***	0.973***
	(0.082)	(0.095)	(0.103)
Age		0.000	0.000
		(0.001)	(0.001)
Months on job		−0.001	−0.001
		(0.001)	(0.001)
Number of friends		−0.002	−0.004
		(0.005)	(0.006)
Extraversion			−0.005
			(0.011)
Conscientiousness			−0.009
			(0.014)
Number of observations	1,224	1,224	1,224
Adjusted R^2	0.31	0.31	0.31

Notes: Robust standard errors are presented in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 4: Estimation Results

	Dependent variable = log(productivity)			
	OLS		I.V.	
Variable	(1)	(2)	(3)	(4)
Average ability of contiguous coworkers	−0.038		−0.051	
	(0.034)		(0.039)	
Average ability of coworkers at same table		−0.086***		−0.125***
		(0.033)		(0.040)
1st stage F statistic			6580.89	9863.35
Number of observations	5,454	5,490	5,454	5,490

Notes: All regressions control for the number of coworkers at contiguous positions, worker fixed effects and room×day and room×work-station fixed effects. Standard errors presented in parentheses are clustered two-way by worker and room×day and corrected for sampling variability of the fixed effect estimates using a Bayesian Parametric bootstrap procedure. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 5: Temporary or Persistent Effects?

	log(productivity)		
Average ability of	(1)	(2)	(3)
Coworkers at table on day d	−0.128***	−0.102**	−0.111**
	(0.044)	(0.049)	(0.054)
Coworkers at table on day $d-1$	0.007	−0.024	−0.030
	(0.035)	(0.035)	(0.042)
Coworkers at table on day $d-2$		0.009	0.019
		(0.040)	(0.041)
Coworkers at table on day $d-3$			−0.013
			(0.038)
Kleibergen-Paap Wald F stat	3375.17	1615.135	766.494
Number of observations	4,469	3,667	3,047

Notes: All regressions control for the number of coworkers at contiguous positions, worker fixed effects, room×day and room×workstation fixed effects. The average ability of coworkers on day $d-k$ is the average of all coworkers at the same table k days before current day d. I.V. estimates are reported. Standard errors are clustered two-way by worker and room×day and presented in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 6: Robustness Check with Additional Peer Characteristics - I.V. Estimates

	Dependent var. = log(productivity)		
Average of coworkers at table ($\bar{X}_{-i}$)	(1)	(2)	(3)
Ability	-0.136***	-0.120**	-0.112***
	(0.041)	(0.054)	(0.042)
Age	0.000		
	(0.001)		
Months on job	0.000		
	(0.001)		
Number of friends		0.000	
		(0.003)	
Wealth Index		-0.003	
		(0.003)	
Extraversion			-0.006
			(0.004)
Agreeableness			-0.004
			(0.005)
Conscientiousness			0.000
			(0.005)
Neuroticism			-0.005
			(0.006)
Openness			-0.002
			(0.003)
Number of observations	5,402	5,402	5,402

Notes: All regressions control for the number of coworkers at contiguous positions, worker fixed effects, room×day and workstation fixed effects. Standard errors are clustered two-way by worker and room×day and presented in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$. Wealth Index is the first principal component of a principal component analysis conducted using seven questions on household assets in the baseline survey. The Big Five personality measures use standardized scores from a self-reported survey (BFI).

Table 7: Heterogeneity by Worker Ability - I.V. Estimates

	Dependent var. = log(productivity)			
Variable	(1)	(2)	(3)	(4)
Average ability of coworkers at table	−0.149*	−0.133**	−0.096**	
	(0.077)	(0.053)	(0.043)	
× Focal worker is more able ($\theta_i > \bar{\theta}_{-i}$)	0.051			
	(0.127)			
× Focal worker is most able		0.021		
		(0.091)		
× Focal worker is least able			−0.079	
			(0.103)	
Absolute ability difference × Focal worker is more able				0.089
				(0.055)
Absolute ability difference × Focal worker is less able				−0.158**
				(0.070)
Number of observations	5,489	5,489	5,489	5,489

Notes: All regressions control for the number of coworkers at contiguous positions, room×day and workstation fixed effects. Standard errors are clustered two-way by worker and room×day and presented in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$. Focal worker is more able is an indicator variable equal to one if estimated ability of focal worker is greater than the average of the ability of coworkers at the same table, and zero, otherwise. Likewise, focal worker is most able or least able if estimated ability of focal worker is the highest or lowest among the workers at the same table. Absolute ability difference is the absolute value of the difference between the ability of the focal worker and average coworker ability.

Table 8: Peer Effects and Incentive Heterogeneity - I.V. Estimates

	log (productivity)				
Average ability of coworkers at	(1)	(2)	(3)	(4)	(5)
Table	−0.124***				
	(0.040)				
× Performance Incentive Ratio (PIR)	0.104*				
	(0.057)				
Table × High PIR		−0.041			
		(0.052)			
Table × Medium PIR		−0.108**			
		(0.053)			
Table × Low PIR		−0.227**			
		(0.097)			
High physical proximity to focal worker			−0.045		
			(0.031)		
Medium physical proximity to focal worker			−0.045**		
			(0.023)		
Low physical proximity to focal worker			−0.275***		
			(0.073)		
Average ability of coworkers with social connections to focal worker				0.036	
				(0.136)	
Average ability of coworkers without social connections to focal worker				−0.165***	
				(0.054)	
Table × No social tie at table					−0.156***
					(0.060)
Table × Social tie at table					−0.064
					(0.066)
Number of observations	5,375	5,375	5,064	5,454	5,489

Notes: All regressions control for the number of coworkers at contiguous positions, room×day and workstation fixed effects. Standard errors are clustered two-way by worker and room×day and presented in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$. Performance Incentive Ratio (PIR) is the fraction of performance to total wage standardized at the room level. No friend at table is equal to one if worker i has no friend at same table. High PIR is the top one third of the PIR distribution. Medium PIR is the middle and Low PIR is the bottom one third of the PIR distribution. High physical proximity indicates positions that are alongside each other. Positions with medium proximity are across each other and low proximity are diagonally facing positions. A social connection exists between two workers if either one reported the other as a friend or family member. Social tie at table is equal to one if worker i has at least one friend at same table.