Peers and Motivation at Work:
Evidence from a Firm Experiment in Malawi

Lasse Brune
Yale University

Eric Chyn
University of Virginia

Jason Kerwin
University of Minnesota

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Abstract: This paper sheds light on the nature of workplace peer effects by analyzing an experiment with a tea estate in Malawi. We randomly allocate tea-harvesting workers to locations on fields to estimate the impact of peers on worker performance. Using data on daily productivity, we find strong evidence of positive effects from working near higher-ability peers. Our estimates show that increasing the average of co-worker ability by 10 percent increases own-productivity by about 0.5 percent. We find nonlinearities in the magnitude of peer effects across the distribution of own-ability: peer effects are the largest for the lowest ability workers. Since workers receive piece-rates and there is no team production, peer effects in our setting are not driven by production or compensation externalities. In additional analysis, we find evidence against learning or worker socialization as mechanisms. Results from an incentivized choice experiment suggest instead that peer effects in this context are driven by co-workers as a source of "motivation." When given a choice to be re-assigned, the majority of workers want to be assigned to be near a fast (high-ability) coworker, even if switching is assigned an explicit cost. In open-ended survey responses, workers with demand for high-ability peers state that working near faster peers provides motivation to work harder.

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I. Introduction

Social scientists and policymakers have a long-standing interest in understanding how peers shape an individual's behavior. A key question is whether peers affect productivity in the workplace. The answer to this question has particular importance for determining the optimal allocation of labor and designing firm incentives.

While an emerging literature provides compelling evidence that peer effects exist in workplace settings, the mechanisms behind these peer effects are less clear.[1] Several studies show worker effort is sensitive to the social pressure that arises in settings where there are externalities from effort due to joint production and team compensation (Mas and Moretti, 2009; Gould and Winter, 2009; Kaur et al., 2010; Bandiera et al., 2013; Babock et al., 2015; Cornelissen et al. 2015).[2] Yet few studies test whether peer effects on productivity may also arise from mechanisms such as motivation or norms – channels not directly controlled by firms.

This paper provides new evidence on the mechanisms that drive workplace peer effects by conducting a unique field experiment with an agricultural firm. We partner with a tea estate in Malawi to randomly allocate about 1,000 piece-rate workers to different locations on tea fields. Each worker is assigned a specific plot area to pick tea leaves each day, and our design creates exogenous, within-worker variation in the composition of plot neighbors. We focus on estimating the effect of the average of peers' ability (permanent productivity) on workers' output.

Importantly, several aspects of this setting allow us to test for the existence of social influences on worker's performance that are unrelated to spillovers in the production process or in the compensation scheme. Unlike much of the previous work examining peer effects, workers in

[1] See Herbst and Mas (2015) for additional discussion and a list of previous studies on peer effects in the workplace.

[2] Another well-studied channel for workplace peer effects is knowledge spillovers (i.e., learning). Notable studies testing for this form of peer effect include Waldinger (2012), Azoulay et al. (2010), Jackson and Bruegmann (2009), and Guryan et al. (2009).

our setting are paid piece rates, and there is no cooperation in the process of collecting tea. Hence, any impact of peers on productivity in our setting is likely to be due to learning or psychological mechanisms related to "motivation" (e.g., self-control or norms).[3]

We find that a worker's daily volume of tea collected is affected by the average ability (i.e. permanent productivity) of his or her coworkers that are located nearby. Increasing the average ability of coworkers by 10 percent raises a tea worker's productivity by about 0.5 percent. In terms of the previous literature, Mas and Moretti (2009) and Falk and Ichino (2006) find effects that are about twice as large in very different settings.

In addition to our main estimates on the effects of mean peer productivity, we also test for non-linear peer effects. We find notable heterogeneity in the effects on productivity, which is consistent with the broader peer effects literature despite the markedly different contexts (Sacerdote 2001; Falk and Ichino, 2006; Carrell et al., 2009; Mas and Moretti, 2009; Carrell et al., 2013; Cornelissen et al., 2013). The least able workers are the most responsive to the average ability of their peers, while there is no detectable impact of peer productivity on higher-ability workers. This pattern of heterogeneity is notable because it suggests that there is potential for aggregate gains for the firm from sorting workers to ensure that the least able workers are near higher ability peers.

These estimates differ from Bandiera et al. (2010), who study peer effects among U.K. fruit-farm piece-rate employees who are friends. They find evidence that having a higher ability friend nearby increases a workers' productivity. Similarly, workers have lower productivity when they work near lower-ability friends. They argue that workers' desire to socialize with their friends

[3] In our setting, it is also possible that workers may synchronize their productivity and effort in an attempt to socialize with other workers nearby. We discuss and provide evidence against this hypothesis in greater detail in our analysis.

is the driver of this pattern of peer effects between friends.[4] In contrast, we measure peer effects from all co-workers, not just for friends. While we find similar conformism patterns (for all but the highest productivity workers), our analysis suggests that socialization is unlikely to be an important mechanism in our setting. Using data on workers' social networks, we find that friends have no detectable impact on productivity while there are positive and significant effects for non-friends.

To learn more about the mechanisms driving the peer effects in our setting, we conduct a choice experiment to measure demand for working next to specific peers. We conduct a survey of a subset of employees in the season following our first experiment and implement an incentivized choice experiment. We find that 71 percent of respondents state they would prefer having a high-productivity co-worker nearby if re-assignment were possible. When asked for the main reason for their choices in an open-ended question 79 percent workers state that the higher-productivity peers provide motivation. Moreover, workers are willing to pay for faster peers. We give workers the option to exchange all or part of the respondent gift that they receive for taking the survey (two bars of soap) in order to be re-assigned next to a high-productivity co-worker. Among those who stated a preference for being reassigned next to a fast plucker, 71 percent are willing to give up one bar and 55 percent are willing to give up two bars of soap – equivalent to 18 percent of average daily earnings. Our choice experiment also allows workers to pay to work next to any other worker of their choice, but almost none of them do so. This indicates that workers place value specifically on having high-ability coworkers, rather than on other traits that are correlated with ability.

[4] Park (2016) also provides evidence that manufacturing workers value socializing with their friends despite such interactions resulting in earnings losses. In this case, peer effects due to socializing are associated with compensating differentials: workers forgo monetary compensation to enjoy non-pecuniary benefits of socializing with their friends.

Overall, our analysis contributes to the literature by providing evidence that workplace peer effects may be driven by a particular class of psychological mechanisms. As discussed, our setting rules out the possibility that the effects are driven by externalities in the production process or the terms of the financial contract. Supplementary analysis also suggests that learning does not drive the estimates in our study because there no evidence that peer effects vary by experience of workers. Further, the choice experiment that we conduct shows that workers in our sample are willing to pay to work near high-productivity peers, a pattern that is inconsistent with standard models of rank preferences, last-place aversion, shame or reputational concerns (Tincani, 2015; Kuziemko et al., 2014; Kandel and Lazear, 1992; Breza and Chandrasekhar, 2015). Overall, our results are consistent with models of contagious enthusiasm or limited self-control (Mas and Moretti, 2009; Kaur et al., 2014).

II. Background

To conduct our study, we partner with Lujeri Tea Estates, a large agricultural firm in Malawi. Our sample is a group of roughly 1,000 employees who hand-pick ("pluck") leaves from tea bushes (hereafter, we refer to these workers as pluckers). Workers temporarily store plucked leaves in baskets and empty their baskets at a central weighing station. There is no explicit cooperation involved in this process, and tea pluckers are paid a constant piece rate for each kilogram of plucked tea.

Production at the firm is organized by assigning workers to "gangs" which are each managed by a supervisor. The size of a gang is typically around 45 pluckers, but the sizes range from 29 on the low end to 76 on the high end. Each gang is responsible for plucking tea from a pre-determined set of fields over the course of a harvesting "cycle" (7 to 12 calendar days). In our analysis sample, there are 78 fields for the 22 gangs we study.

On each tea field for a gang, the supervisor assigns workers to pluck tea from a specific set of plots (between 1 to 3 per day depending on the characteristics of the field and day of the week). Each field has between 30 and 120 plots, and workers must pluck on their assigned plots before moving on to other plots.[5,6] At the completion of a harvesting cycle, the gang returns back to the initial field for a new round of plucking – unlike with other crops that are harvested once or a few times, tea bushes grow continuously throughout the season.

Figure 1 illustrates the general assignment of workers to plots on a given field and the rotation of workers throughout the harvesting cycle.[7] Panel A shows that each worker is assigned two contingent plots (blue squares). The example highlights three workers who are colored red, green and yellow. The illustration shows that workers B and C are the immediate plot neighbors of worker A. Panel B provides an illustration showing how workers change assignments across fields covered during a 6-working-day harvesting cycle. On each day of the harvesting cycle a given worker has an assigned set of plots for that day's specific field. Across days in the harvesting cycle, a worker will have different neighbors. In the example, the three hypothetical workers are sometimes separated as shown for Cycle Days 3, 5 and 6. On these days, the workers will have different plot neighbors.

III. Random Assignment of Workplace Peers

We designed our experimental intervention to randomly assign workers to plots on tea fields in order to generate random variation in exposure to workplace peers. To implement this, we obtained the roster of workers in each gang and a "plucking program" for each gang. The plucking program

[5] Pluckers are expected to finish their assigned plots in accordance with the cycle schedule. Pluckers who finish their plots can ask for additional plots that are not assigned to other workers. If a worker is absent on a given day, the supervisor will assign the plot to other workers for the day.
[6] Fixed plot assignment is done so that workers internalize the negative effects of over- and under-plucking bushes on their plots.
[7] Note that in reality the fields and plots are often not evenly-sized rectangles.

is a predetermined list of which field (or fields) a gang works during each day of its cycle and the number of pluckers that should be assigned to each field. In the simplest case, there is one field on each cycle day with all the pluckers working on it.[8] We use this information to generate randomly ordered lists of pluckers for each day of a gang's harvesting cycle. On cycle days where a gang works on multiple fields, we also randomly determine which workers are on each field.

These randomized lists are used to determine the order in which pluckers are assigned to plots on each field. The random assignment takes advantage of the usual assignment process in which pluckers stand in a queue and are assigned to plots in the order in which they are standing. The supervisor does the assignments by "snaking" back and forth across the field and taking the next plucker from the queue for each plot. Our random assignment scheme alters this system by giving the supervisors a randomly-ordered list to use in this snake pattern.[9] Each gang supervisor was responsible for assigning workers using the randomly generated list of worker assignments in February 2015. We verified compliance with these assignments by having our project managers visit each gang in the week after randomization. As a result of our intervention, workers are randomly assigned to plots within a field for different cycle days as illustrated in Panel B of Figure 1.

IV. Data

To study the impact of workplace peers, we use three main sources of data. First, we rely on administrative data from the firm on worker productivity. Productivity is defined as kilograms of tea plucked per day and is electronically recorded by the firm for the purpose of paying employees.

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8 Many gangs have more complicated schedules, spending multiple cycle days on some fields, and splitting the gang across more than one field on certain days of their cycle.

9 An exception to our randomization is the first work day ("Cycle Day 1") in a gang's cycle. We intentionally did not randomize work assignments in this data. On these days, supervisors assigned workers using the usual method, in which the plots are still assigned using the snaking pattern across the field, but the order of the pluckers comes from the order in which they stand in the queue. We use this non-random assignment on the first work day to test for endogenous assignment and sorting of workers to locations on a field in Section 5.

As a result, it is measured with minimal error. This data on worker productivity is available from December 2014 to April 2015 (the beginning and end of the main tea harvest season, respectively). Second, we hired project staff to record information on the plot neighbors assigned to each worker as a result of the randomized assignment that we implemented. Third, we collected survey data to obtain measures of worker characteristics such as background demographics and social networks.

III.A Main Analysis Sample

Our study centers on 1,046 pluckers who worked during the main season after we implemented our randomized work assignments in February 2015. Table 1 provides some summary statistics based on the survey and administrative data. The average age for workers is about 37 years and about 43 percent of the sample is female. Only 7 percent of workers are new and average experience is nearly 8 years. Over the course of our study period, the average daily output for each worker is 69 kilograms of plucked tea leaves.

As recorded in our data on work assignments, workers have on average about 5 assigned neighbors on any given day of work. We measure ability as the estimated permanent productivity for each worker in our sample (see Section 5 for details). Our study focuses on studying how working alongside peers of different ability affects daily output. To provide a sense of the variation in neighbor ability (measured as the logged average of co-worker ability), Table 1 shows that the standard deviation of co-worker ability is about twice the mean.

V. Empirical Strategy

The main question in this paper is whether working in close proximity to higher-ability co-workers increases productivity in our sample of tea pluckers. To address this question, we estimate the following linear model of peer effects for the productivity of worker *i*:

$$y_{ift} = \mu_i + \beta \overline{Ability}_{-ift} + \delta_t + \lambda_f + \epsilon_{ift} \tag{1}$$

where y_{ift} is the (logged) total kilograms of tea plucked on field *f* and date *t*. The key variable in Equation 1 is $\overline{Ability}_{-ift}$ which is the mean of ability of all co-workers who are assigned to work adjacent to the plots that worker *i* is assigned. The model also includes date and field fixed effects, δ_t and λ_f, to control for variation in harvest conditions over the course of the season and across the tea estate. Finally, we also control for time-invariant determinants of productivity – such as the worker's own plucking ability – by including individual-level fixed effects μ_i.

To measure ability in our sample of tea pluckers, we rely on an approach pioneered by Mas and Moretti (2009) which uses estimates of worker fixed effects as a measure of ability ("permanent productivity").[10] Specifically, we use the plucking data and estimate:

$$y_{ift} = \mu_i + \boldsymbol{M_{ift}}\gamma' + \delta_t + \lambda_f + \tau_{ift} \quad (2)$$

where the term $\boldsymbol{M_{ift}}$ is a vector of dummy variables which indicate whether worker *j* is working next to worker *i* in field *f* on date *t*.[11] The idea is that the vector γ contains a set of parameters that absorb any possible peer effects and allows us to obtain unbiased estimates of worker fixed effects μ_i, under the assumption that each individual worker can have any effect on his or her coworkers.[12] For Equation (1), we use these estimates to define $\overline{Ability}_{-ift} = \bar{\hat{\mu}}_{-ift}$ as our measure of peer influence.[13]

In models of peer effects such as Equation 1, the key assumption for identification of β is that there is no correlation between the average ability of one's peers and the unobserved

10 Similar approaches to estimating ability as permanent productivity have been used in Bandiera et al. (2010) and Park (2015).

11 To be clear, the set of possible co-workers is based on the gang for worker *i* so that $\boldsymbol{M_{ift}}$ is a vector of J_i -1 dummy variables. Here, J_i is the total number of pluckers in *i*'s gang.

12 One additional assumption for identification is that the form of any coworker peer effects is additively separable across workers.

13 Since $\overline{Ability}_{-ift}$ is based on estimated quantities, the correct standard errors for Equation (1) need to adjust for this additional source of sampling variability. In practice, we find that the standard errors change little when we use a repeated-split sample approach to estimate worker's permanent productivity so our main results report the naïve standard errors (results available upon request).

determinants of individual productivity: $cov(\overline{Ability}_{-ift}, \epsilon_{ift}) = 0$. One way this assumption could be violated is if supervisors assign workers with higher ability to work on particularly productive areas of a field that are physically close together. Our intervention eliminates this possibility by randomly assigning workers to plots within a field and makes it possible to purge estimates β of any endogenous sorting effects.

Table 2 shows that this random assignment is key for producing causal estimates of peer effects by presenting results from a series of regressions of worker' own ability on the mean of their co-workers ability.[14] Column (1) shows that the there is a positive correlation between own ability and peer ability on the sample of plucking days that correspond to "Cycle Day 1" of each gang's work cycle – these are days that we explicitly did not randomize workers and which gang supervisors implemented plot assignments through the status quo system. In line with our random assignment intervention, the results in Columns (3) and (4) show that this correlation does not exist for the remainder of the sample which supports the identifying assumption in our linear-in-means model.[15]

The chief threat to identification in our sample is the fact that a worker cannot be assigned to be her own neighbor. As a result, there is a mechanical negative correlation between a worker's own ability and that of her neighbors. Consider a worker who is at the top of the ability distribution. Her neighbors will necessarily be lower ability than her, and likewise for a worker at the bottom of the distribution. This issue, first noted by Guryan et al. (2009), leads to what Caeyers and Fafchamps (2016) call "exclusion bias": since the worker's ability typically appears in the error

[14] Note that we follow the recommendation of Guryan et al. (2009) and include the leave-one-out mean in our test of random assignment. The inclusion of this term corrects for exclusion bias in tests for random assignment, but only eliminates the bias in the case of non-overlapping peer groups (Caeyers and Fafchamps 2016).
[15] Column (2) shows that there is positive but not statistically significant correlation between own ability and peer ability using the sample of all cycle days. As expected, the magnitude of this positive correlation falls notably in the results shown in Columns (3) and (4) where Cycle Day 1 is excluded.

term of the regression, there is a negative correlation between peer ability and the error term and hence coefficient estimates are downward-biased. In most cases, solutions to this problem are fairly involved. We address it by exploiting the within-worker random assignment in our dataset, which allows us to include individual fixed effects μ_i in our regression model. These fixed effects eliminate any potential correlation between the ability of a worker and her peers, yielding unbiased estimates of β.

Finally, in addition to producing estimates from Equation (1), we are also interested in testing whether there are non-linear peer effects in terms of a worker's own-ability. Specifically, we estimate the following more general model of peer effects:

$$y_{ift} = \mu_i + \sum_{q=1}^{q=4} \theta_q \, D_i^q \times \overline{Ability}_{-ift} + \delta_t + \lambda_f + \epsilon_{ift} \tag{3}$$

where the terms D_i^q are indicators which equal one if a person is in the q quartile of the distribution of worker ability. Previous research in education settings has used this type of specification and found evidence of notable heterogeneity in peer effects across the distribution of student ability (Hoxby and Weingarth, 2005; Carrell et al., 2009; Imberman et al., 2012; Carrell et al., 2013).

VI. Main Results

To test whether the average ability of co-workers affects productivity, Table 3 reports estimates from Equation 1. Column (1) shows that there is a positive and significant effect of the mean ability of peers on worker productivity. Specifically, a 10 percent increase in mean ability of peers is associated with a 0.5 percent increase in the daily amount of kilograms of tea plucked for each worker. Column (2) shows that our estimates are essentially unchanged when we condition on date-by-location fixed effects. Relative to the literature, these estimates are about half the size of estimates produced in a lab setting by Falk and Inchino (2006) and studying supermarket cashiers by Mas and Moretti (2009).

In addition to exploring peer effects in a linear-in-means model, we also test for the existence of peer effects that are vary across workers with different ability. Importantly, the existence of non-linear effects implies that there would be aggregate gains from selectively choosing workers' peer groups.[16] Table 4 sheds light on this in our sample by presenting results from Equation 3. We see that there is notable heterogeneity in the estimates for workers of different ability. Workers in the first quartile of the distribution of ability have the strongest effects: for a 10 percent increase in average coworker ability, the lowest ability worker increases his output by nearly 1 percent. The remaining estimates show there are no detectable effects of peers on any other ability-type of workers. Despite the fact that these estimates are somewhat noisy, Figure 2 shows that the point the smallest point estimates are consistently decreasing in magnitude for higher ability workers.[17] In terms of policy, these results suggest that low ability workers benefit the most from having high-quality co-workers nearby.

VII. Robustness

Our measure of individual ability is estimated using the same sample as we use for our main peer effects regressions, which creates the possibility of a correlation between the estimated ability of a worker's peers and the error term in their output equation. Suppose that one corner of a specific field has higher productivity – maybe due to better sun exposure. This will raise the output of all the workers located in that corner on each day, and also increase their estimated ability. This sort of spatial correlation in the productivity of specific plots could plausibly create spurious "peer

[16] If peer effects were constant across individuals, then re-assigning a high-ability peer from one group to another would have equal and offsetting effects.
[17] Note that we can reject the null hypothesis of equal effects for the highest and lowest ability workers (p-value=0.01).

effects", since a worker's output would be positively correlated with the estimated ability of her peers. A similar issue could arise due to spatially-correlated shocks, such as fertilizer being distributed on the fields unevenly: workers near one another would experience similar shocks, which will drive both their ability estimates and output levels in the same direction.

We address this issue by constructing an alternative measure of individual ability (permanent productivity. This measure uses a double leave-one-out process, that is similar in principle to a jackknife estimator. First, when estimating equation (2), we use a sample composed of all *other* fields for a specific gang. So the ability estimates we use for Field 5 for Gang 3 leave out Field 5. Second, we construct the leave-self-out average of this ability measure – i.e. a worker's peer ability excludes his own ability, as usual. As a result, our estimates of equation (1) always use mean peer ability estimates that exclude both a) data for the same date for which we observe output, b) any other data for the same field, and c) the worker's own ability estimate. This procedure ensures that spatial correlation in plot quality, or spatially correlated shocks, do not cause violations of the assumption that $cov(\overline{Ability}_{-ift}, \epsilon_{ift}) = 0$.

Table 5 shows that the double leave-one-out approach generates a similar finding on worker peer effects relative to our main estimates. The point estimate of β is about 0.04 which is about one percentage point (20%) smaller than the point estimate we obtained in Table 3. This shows that our main findings are robust to concerns about spatially-correlated plot quality and output shocks, but may be slightly upward-biased due to the correlation between the error in the output equation and estimated peer ability.

VIII. Discussion and Interpretation

The evidence presented thus far shows that co-worker ability has an impact on productivity. A range of mechanisms could generate positive peer effects in general, but our setting allows us to rule out two of these immediately. First, unlike in many previously studied settings, our context rules out the possibility of peer effects being driven by externalities in the production process since there is no cooperation and no need for workers to coordinate. Second, the fact that workers receive piece-rates also rules out that our peer effects are driven by the firm's compensation scheme. With this in mind, this section proceeds to consider three other types of mechanisms that could be driving our estimates of peer effects.

One potential mechanism to explain our findings is learning ("knowledge spillovers"). It is conceivable that plot neighbors learn from observing each other work, thereby generating the positive effects that we observe.[18] To explore this possibility, we test whether peer effects in our setting are heterogeneous with respect to workers' past experience. Under the learning hypothesis, we would expect the effects of average peer ability would be largest for workers who have no prior or relatively less experience.

Table 6 presents results from augmented versions of Equation (1) in which we add measures of worker experience. The results in Column (1) replicate the estimate from our baseline specification for the sample of workers for whom we have self-reported experience. Column (2) builds on our main specification by adding an interaction between a dummy indicating status as a new worker (no prior experience) and our measure of peer ability. The estimate for this interaction is significant and implies that the effect of higher-ability peers is actually *negative* for new workers. As an alternative test for heterogeneity in peer effects by experience, we create dummies based on the quartiles of worker experience observed in our sample. We interact these dummies with our measure of average peer ability and present the results for these terms in Column (3). Although

[18] Among previous studies testing for the existence of knowledge spillovers, Jackson and Bruegmann (2009) find evidence of knowledge spillovers among teachers while Waldinger (2012) finds no evidence among university scientists.

the results for this specification are not precise, the point estimates for the least experience and most experienced workers are remarkably similar which is not consistent with the idea that learning drives peer effects in our setting.

Another leading mechanism for explaining workplace peer effects is socialization between workers. In a relatively similar setting, Bandiera et al., (2009) detect evidence of peer effects among friends who pick fruit at a large agricultural firm in the UK. Their analysis suggests that socialization drives their estimates. When slow fruit pickers work near friends who are typically fast, they work harder to catch up. Similarly, relatively fast pickers slow down for their slower friends.

Using data on social networks, we provide evidence that suggests the peer effects in our sample are not driven by the desire to socially interact. Specifically, we use self-reported friendship between pluckers to identify when workers are plucking on plots near their friends. We then compute the average ability of nearby co-workers who are friends. Similarly, we calculate the average ability of co-workers who are not friends. On the average day in our sample, a worker has about three plot neighbors that are friends. We use these two separate measures of average co-worker ability in our basic linear-in-means specification and report the results in Column (3) of Table 7. The point estimates show that there is an effect of working near higher ability non-friends while there is no detectable impact for the average ability of friends.[19]

This pattern of results suggests that our peer effects are not driven by either learning or socialization. A final prominent possibility that we consider is that the peer effects we measure might operate through motivation and "contagious enthusiasm". A key prediction of this mechanism is that exposure to faster coworkers is beneficial, and thus workers should be willing

[19] While these point estimates appear quite different, we cannot reject a test of the null hypothesis that the effects of non-friends and friends are equal (*p*-value = 0.22).

to pay for higher-ability peers. To test this prediction, we conducted a supplementary survey and choice experiment for a subset of tea workers during the 2015-2016 harvesting season. In this experiment, we asked workers whether they wanted higher-ability peers, and whether they would be willing to give up part of the compensation that they received for taking part in the survey (workers were each given two bars of soap as a token of thanks for taking the survey).

Panel A of Table 8 reports that 71 percent of workers would like to be assigned next to a fast (high ability) peer in their gang. Further, Panel B shows that these workers seeking re-assignment are *willing to pay* for these peers: 71 percent of workers who want a fast peer would be willing to give up one bar of soap while 55 percent would be willing to give up two bars of soap. When asked for the main reason for their choices in an open-ended question, 83 percent workers state that faster peers provide motivation. Only 15 percent state learning as a reason for wanting higher-ability peers.

The results from our willingness to pay experiment strongly suggest that motivation is the key driver of the peer effects we measure in this study. They rule out a range of other potential mechanisms posited in the literature, such as shame or a desire to avoid being last (Kandel and Lazear, 1992; Kuziemko, 2014). Since workers are willing to pay for faster peers, shame-type mechanisms can only be the operative mechanism inasmuch as it serves as a commitment device, inducing workers to reach a higher level of effort that they truly would like to achieve.

IX. Conclusion

This paper provides evidence on workplace peer effects by conducting an experimental intervention with an agricultural firm in Malawi from February 2015 to April 2015. We randomly assigned tea pluckers to plot assignments on fields and use this variation in peer composition to examine the effect of mean coworker ability (permanent productivity) on workers' output. In addition, our analysis also explores whether the effect of peer ability varies by workers' own ability of workers.

Using administrative data on daily productivity, we find that the average of coworker ability has a positive and significant effect: increasing the average of coworker ability by 10 percent increases own-productivity by about 0.5 percent. Further, supplementary analysis suggests that these peer effects are non-linear, with the lowest ability workers being the most responsive to working near higher ability peers. This finding is notable because it implies that re-sorting workers on the basis of ability could generate gains in aggregate productivity, which is only possible if peer effects are non-linear.

To shed light on the mechanisms driving our peer effect estimates, we conducted a choice experiment in the next harvesting season that allowed workers to choose new coworkers as plot neighbors. In this experiment, we find that 71 percent of workers wanted to be assigned to a fast (high-ability) coworker. Moreover, workers were willing to pay for faster coworkers: 55 percent of workers were willing to give up two bars of soap (worth 18 percent of daily wages) that we had given them as a gift for survey participation. In open-ended follow-up questions, 83 percent of workers state that working near faster peers motivates them.

This analysis provides strong evidence that workplace peer effects in our setting stem from the effect that peers have on motivation. In additional analysis, we do not find evidence that the effects we detect are driven by learning or worker socialization. Finally, the fact that workers receive piece rates and there is no cooperation in tea plucking rules out that the effects in our setting stem from production externalities or incentives of the firm's compensation scheme.

References:

Bandiera, Oriana, Iwan Barankay, and Imran Rasul. 2010. “Social Incentives in the Workplace.” *The Review of Economic Studies* 77 (2): 417–58.

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

Caeyers, Bet, and Fafchamps, Marcel. 2016). Exclusion Bias in the Estimation of Peer Effects (Working Paper No. No. 22565). NBER.

Carrell, Scott E., Richard L. Fullerton, and James E. West. 2009. “Does Your Cohort Matter? Measuring Peer Effects in College Achievement.” *Journal of Labor Economics* 27 (3): 439–64.

Carrell, Scott E., Bruce I. Sacerdote, and James E. West. 2013. “From Natural Variation to Optimal Policy? The Importance of Endogenous Peer Group Formation.” *Econometrica* 81 (3): 855–82.

Cornelissen, Thomas, Christian Dustmann, and Uta Schönberg. 2013. “Peer Effects in the Workplace.” IZA Discussion Paper 7617. Institute for the Study of Labor (IZA).

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

Gould, Eric D, and Eyal Winter. 2009. “Interactions between Workers and the Technology of Production: Evidence from Professional Baseball.” *Review of Economics and Statistics* 91 (1): 188–200.

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

Herbst, Daniel, and Alexandre Mas. 2015. “Peer Effects on Worker Output in the Laboratory Generalize to the Field.” *Science (New York, N.Y.)* 350 (6260): 545–49.

Hoxby, Caroline M., and Gretchen Weingarth. 2005. “Taking Race out of the Equation: School Reassignment and the Structure of Peer Effects.” *Unpublished Manuscript.*

Imberman, Scott A, Adriana D Kugler, and Bruce I Sacerdote. 2012. “Katrina’s Children: Evidence on the Structure of Peer Effects from Hurricane Evacuees.” *American Economic Review* 102 (5): 2048–82.

Jackson, C. Kirabo, and Elias Bruegmann. 2009. “Teaching Students and Teaching Each Other: The Importance of Peer Learning for Teachers.” *American Economic Journal: Applied Economics* 1 (4): 85–108.

Kandel, Eugene, and Edward P. Lazear. 1992. “Peer Pressure and Partnerships.” *Journal of Political Economy*, 801–817.

Kaur, Supreet, Michael Kremer, and Sendhil Mullainathan. 2010. “Self-Control and the Development of Work Arrangements.” *American Economic Review* 100 (2): 624–28.

Kaur, Supreet, Michael Kremer, and Sendhil Mullainathan. 2014. “Self Control at Work.” *Journal of Political Economy*.

Kuziemko, I., R. W. Buell, T. Reich, and M. I. Norton. 2014. “Last-Place Aversion: Evidence and Redistributive Implications.” *The Quarterly Journal of Economics* 129 (1): 105–49.

Mas, Alexandre, and Enrico Moretti. 2009. “Peers at Work.” *American Economic Review* 99 (1): 112–45.

Park, Sangyoon. 2015. “Socializing at Work: Evidence from a Field Experiment with Manufacturing Workers.” *Unpublished Manuscript.*

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

Waldinger, Fabian. 2012. “Peer Effects in Science: Evidence from the Dismissal of Scientists in Nazi Germany.” *The Review of Economic Studies* 79 (2): 838–61.

Table 1. Summary Statistics, Lujeri Worker Sample

	(1) Average	(2) Std. Deviation	(3) 10th Percentile	(4) 90th Percentile	(5) Obs (N)
Age	37.43	10.64	25.00	52.00	944
Female (=1)	0.43	0.50	0.00	1.00	944
Married (=1)	0.63	0.48	0.00	1.00	944
New Worker (=1)	0.07	0.26	0.00	0.00	944
Experience (Yrs.)	7.72	8.31	0.08	15.50	944
Ability (Estimate)	0.03	0.20	-0.22	0.30	1,046
# Neighbors	4.69	1.82	2.00	8.00	35,460
Log(Mean Peer Ability)	0.05	0.10	-0.07	0.16	35,460
Output (kgs.)	69.41	36.17	27.00	118.00	35,460

Notes: This table presents descriptive statistics based on survey data we collected for a sample of tea pluckers at the Lujeri Tea Estates in Malawi.

Table 2. Balance Test: Comparing Own and Peer Ability

	Dependent Variable: Log(Own-Ability)			
	(1)	(2)	(3)	(4)
Log(Mean Peer Ability)	0.129*	0.0415	0.0201	0.00518
	(0.0737)	(0.0283)	(0.0308)	(0.00849)
Leave-One-Out Mean	-1.455***	-1.552***	-1.595***	-43.27***
	(0.404)	(0.390)	(0.394)	(0.672)
Cycle Day 1	Yes	Yes	No	No
Remaining Cycle Days	No	Yes	Yes	Yes
Worker Fixed Effects	No	No	No	Yes
Date Fixed Effects	No	No	No	Yes
Observations	9,531	45,058	35,460	35,460
R2	0.022	0.024	0.026	0.927

Notes: This table presents results from a regression of our measure of a worker's own ability on the mean ability of physically nearby co-workers. The underlying data is a panel at the worker and day level. The results in Columns (1) are from the sample of "Cycle Day 1" days which did not have random assignment of workers to plot assignments at the tea estate. Column (2) presents results using the full sample of all dates and cycle dates in our data. Columns (3) and (4) use the sample of all non Cycle 1 days -- this is the sample for which we randomly assigned workers to locations on fields. The measure of daily output comes from administrative data obtained from Lujeri Tea Estates. Information on neighbors was collected by staff for this project. Standard errors are clustered at the worker level.

Table 3. Effects of Workplace Peers, Linear Model

	Dependent Variable: Log of Daily Output	
	(1)	(2)
Log(Mean Peer Ability)	0.0560**	0.0497**
	(0.0238)	(0.0210)
Worker Fixed Effects	Yes	Yes
Date Fixed Effects	Yes	No
Location (Field) Fixed Effects	Yes	No
Date by Location Fixed Effects	No	Yes
Observations	35,460	35,460
R2	0.416	0.736

Notes: This table presents results from a regression of daily output (the log of kilograms of tea plucked) on the mean ability of physically nearby co-workers. The underlying data is a panel at the worker and day level. All specifications control for individual fixed effects. The results in Columns (1) and (2) use two different approaches to control for date and location effects. The measure of daily output comes from administrative data obtained from Lujeri Tea Estates. Information on neighbors was collected by staff for this project. Standard errors are clustered at the worker level.

Table 4. Effects of Workplace Peers, Non-Linear Model

	Dependent Variable: Log of Daily Output	
	(1)	(2)
Log(Mean Peer Ability) X Ability Quartile 1	0.123***	0.0926**
	(0.0460)	(0.0377)
Log(Mean Peer Ability) X Ability Quartile 2	0.0846	0.0679
	(0.0518)	(0.0500)
Log(Mean Peer Ability) X Ability Quartile 3	0.0728	0.0391
	(0.0491)	(0.0427)
Log(Mean Peer Ability) X Ability Quartile 4	-0.0438	0.00350
	(0.0406)	(0.0356)
Worker Fixed Effects	Yes	Yes
Date Fixed Effects	Yes	No
Location (Field) Fixed Effects	Yes	No
Date by Location Fixed Effects	No	Yes
Observations	35,460	35,460
R2	0.416	0.736

Notes: This table presents results from a regression of daily output (the log of kilograms of tea plucked) on the mean ability of physically nearby co-workers interacted with dummies for the worker's own ability level. The underlying data is a panel at the worker and day level. All specifications control for individual fixed effects. The results in Columns (1) and (2) use two different approaches to control for date and location effects. The measure of daily output comes from administrative data obtained from Lujeri Tea Estates. Information on neighbors was collected by staff for this project. Standard errors are clustered at the worker level.

Table 5. Effects of Workplace Peers, Double Leave-One-Out Estimates of Linear Model

	Dependent Variable: Log of Daily Output
	(1)
Log(Mean Peer Ability)	0.043**
	(0.019)
Worker Fixed Effects	Yes
Date Fixed Effects	No
Location (Field) Fixed Effects	No
Date by Location Fixed Effects	Yes
Observations	35,540

Notes: This table presents results from a double leave-one-out, jackknife-style estimator of the effect of mean co-worker ability on daily output. As described in Section VII, we proceed in two steps. First, when estimating the ability of a worker's peers for a specific field, we leave that field out of the sample used to estimate equation (2). Second, we estimate peer group mean ability leaving out the worker's own ability estimate. The estimate is slightly attenuated but statistically significant, showing that our main results are not primarily driven by spatially correlated plot quality or shocks. Standard errors are clustered at the level of the randomized treatment, which is the intersection of worker and cycle day.

Table 6. Peer Effects by Experience Level

	Dependent Variable: Log of Daily Output		
	(1)	(2)	(3)
Log(Mean Peer Ability)	0.0585**	0.0692***	
	(0.0256)	(0.0268)	
New Worker (=1) X Log(Mean Peer Ability)		-0.158*	
		(0.0819)	
Quartile 1 Exp. X Log(Mean Peer Ability)			0.0693
			(0.0528)
Quartile 2 Exp. X Log(Mean Peer Ability)			0.0366
			(0.0526)
Quartile 3 Exp. X Log(Mean Peer Ability)			0.0675
			(0.0473)
Quartile 4 Exp. X Log(Mean Peer Ability)			0.0632
			(0.0527)
Worker Fixed Effects	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes
Location (Field) Fixed Effects	Yes	Yes	Yes
Date by Location Fixed Effects	No	No	No
Observations	32,921	32,921	32,921
R2	0.411	0.411	0.411

Notes: This table presents results from a regression of daily output (kilograms of tea plucked) on the mean ability of physically nearby co-workers. The underlying data is a panel at the worker and day level. All specifications control for individual fixed effects. The results in Column (2) and (3) are from specifications that include additional interactions based on the worker's self-reported experience at Lujeri. The measure of daily output comes from administrative data obtained from Lujeri Tea Estates; information on neighbors was collected by staff for this project; and, measures of experience are based on our survey data collection. Standard errors are clustered at the worker level.

Table 7. Effects of Friends and Non-Friends in the Workplace

	Dependent Variable: Log of Daily Output		
	(1)	(2)	(3)
Log(Mean Peer Ability), Non-Friends	0.052***		0.052***
	(0.020)		(0.020)
Any Non-friends (=1)	0.017		0.012
	(0.037)		(0.037)
Log(Mean Peer Ability), Friends		0.006	0.007
		(0.032)	(0.032)
Any Friends (=1)		-0.006	-0.007
		(0.007)	(0.007)
Worker Fixed Effects	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes
Location (Field) Fixed Effects	Yes	Yes	Yes
Date by Location Fixed Effects	No	No	No
Observations	35,445	35,445	35,445
R2	0.415	0.415	0.415

Notes: This table presents results from a regression of daily output (the log of kilograms of tea plucked) on measures of the mean ability of nearby co-workers who are friends and non-friends. The underlying data is a panel at the worker and day level. All specifications control for individual fixed effects. The results in Column (2) and (3) are from specifications that include additional interactions based on the worker's self-reported experience at Lujeri. The measure of daily output comes from administrative data obtained from Lujeri Tea Estates; information on neighbors was collected by staff for this project; and, measures of experience are based on our survey data collection. Standard errors are clustered at the worker level.

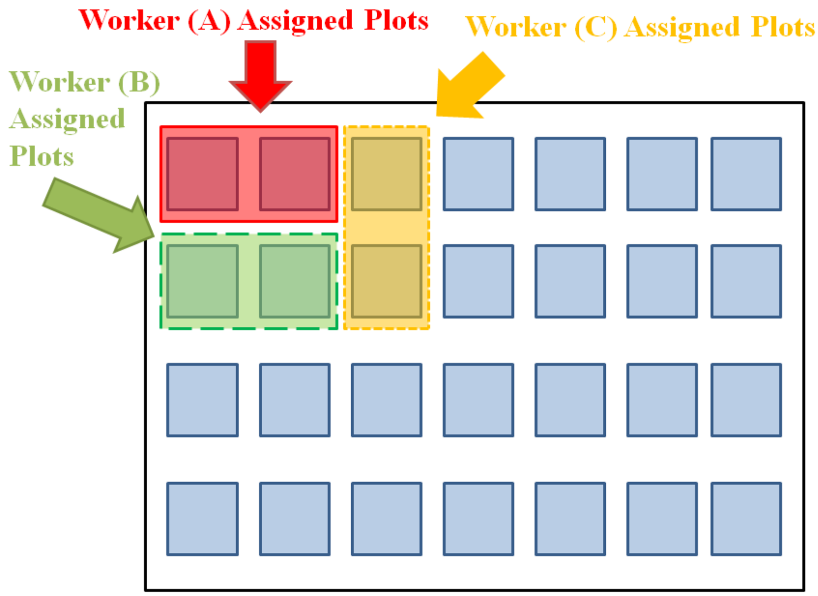
Table 8. Willingness to Pay for Fast Peers

	(1) Pct.	(2) Obs.
Panel A. All Survey Respondents		
Who do you want to be re-assigned next to?		
A fast plucker in your gang	0.71	724
A slow plucker in your gang	0.05	724
Any person of your choosing	0.11	724
No-reassignment	0.14	724
Panel B. Respondents who want to be next to fast pluckers		
If you could switch to be near a fast plucker…		
…would you be willing to give up 1 bar of soap?	0.71	515
…would you be willing to give up 2 bar of soap?	0.55	515

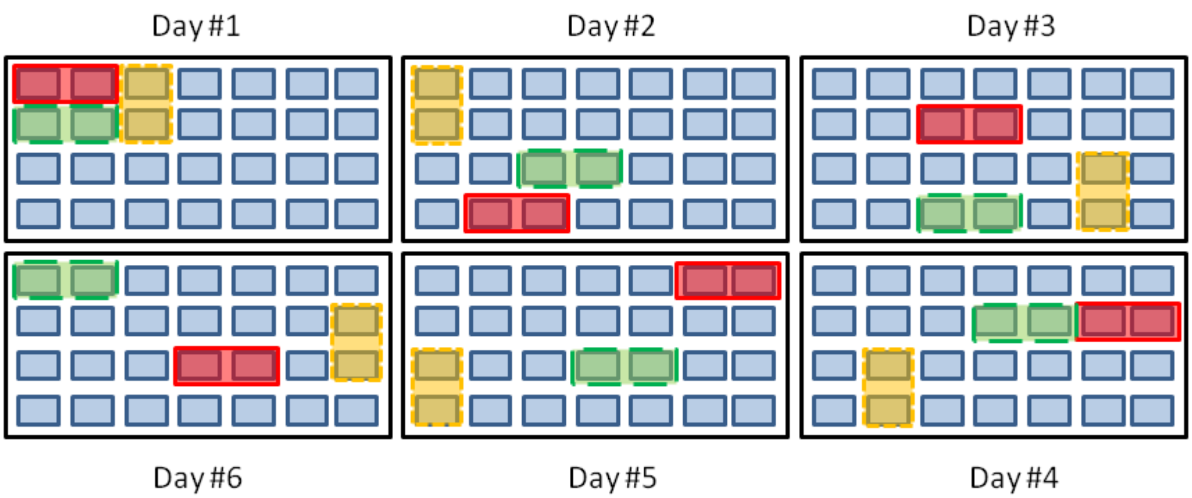
Notes: This table presents statistics from survey data that we collected for tea pluckers at the Lujeri Tea Estates. For the choice experiment, respondents were given a gift of two bars of soap (18 percent of average daily wages) and asked if they would be willing to give up soap in exchange for being re-assigned.

Figure 1. Tea Worker Field Assignment Illustrations

Panel A. Hypothetical Assignment for Three Tea Workers

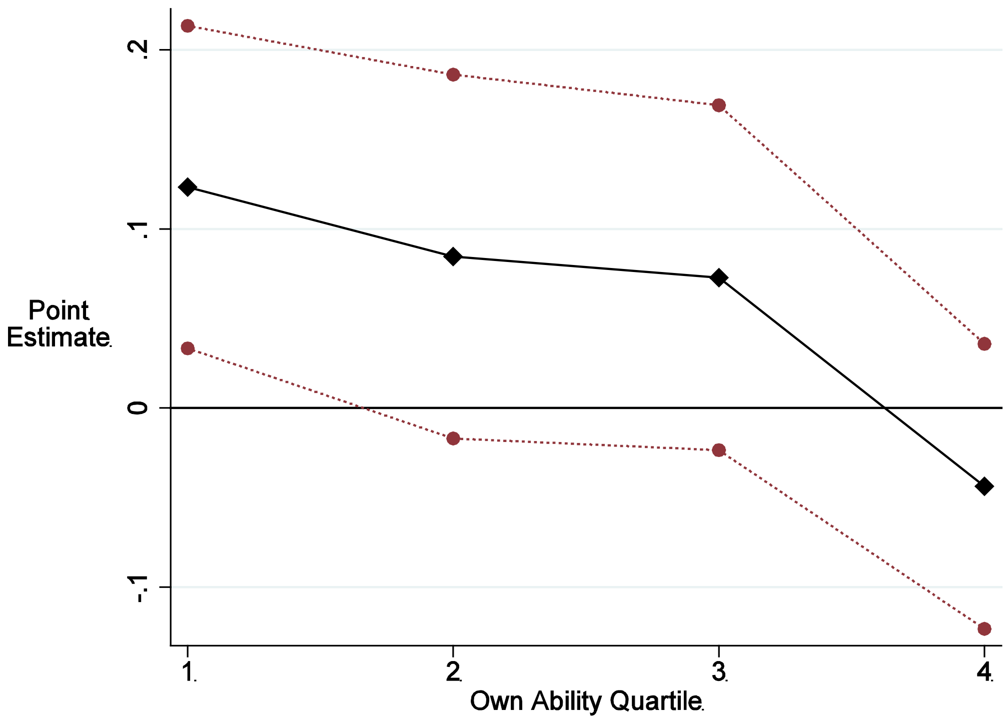


Panel B. Plot Assignments Change Over Days in Harvesting Cycle



Notes: The two panels illustrate work assignments for tea workers at the Lujeri Tea Estates in Malawi. Panel A shows how three workers would be assigned two plots each. For our analysis, all workers A, B and C would be neighboring co-workers. Panel B shows how plot work assignments change over the course of a harvest cycle that lasts 6 calendar days and visits distinctly different fields. On some days and fields, workers A, B and C are neighbors. Yet, there are also cases where they are not neighbors: for example, on Day #3, #5 and #6, workers A, B and C are not assigned to work in neighboring plots.

Figure 2. Non-Linear Peer Effect Estimates



Notes: This figure presents results from a regression of daily output (the log of kilograms of tea plucked) on the mean ability of physically nearby co-workers interacted with dummies for the worker's own ability level. The underlying data is a panel at the worker and day level. All specifications control for individual fixed effects. The results parallel Column (1) of Table 3, and control separately for date and location fixed effects. The measure of daily output comes from administrative data obtained from Lujeri Tea Estates. Information on neighbors was collected by staff for this project. 95% confidence intervals are shown with dashed lines; standard errors are clustered at the worker level.