Peer Effects, Social Networks, and Intergroup Competition in the Workplace

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April 2010

For Presentation at Syracuse University, April 13, 2010

Abstract
Using weekly data for defect rates (proportion of defective output) for all weavers in a Chinese textile firm during a 12 months (April 2003 - March 2004) period, we provide some of the first rigorous evidence on the presence and nature of peer effects in the manufacturing workplace. First, a worker is found to put in more effort and improve her performance when she is working with more able teammates. Second, by exploiting the well-documented fact that an exogenously-formed strong divide between urban resident workers and rural migrant workers exists in firms in Chinese cities, we provide novel evidence on the interplay between social networks (urban resident group and rural migrant group) and peer effects. Specifically, we find that a worker puts in more effort when she is working with more able outgroup teammates but not when working with more able ingroup teammates, pointing to intergroup competition as a powerful source of the peer effects. Such peer effects across the social network, combined with the presence of incentive to outperform teammates at this firm, are largely consistent with recent experimental evidence on the important role that group identities play in facilitating altruistic behaviors.

(Keywords: peer effects in the workplace; social networks; intergroup competition. JEL codes: M5, J24, L2)

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Peer Effects, Social Networks and Intergroup Competition in the Workplace

I. Introduction

Peer effects are present in the workplace when individual behaviors are influenced by the teammates' behaviors or characteristics. For example, a machine operator in a light manufacturing plant works harder when his/her teammates are working harder, or when he/she is working with more able teammates, even if he/she is solely responsible for his/her own output.

Interest in such peer effects among economists has been rising considerably. Naturally detecting peer effects in the workplace has been of great importance and interest for a growing field of behavioral economics and optimal incentive designs. Furthermore, peer monitoring, knowledge sharing and hence productivity spillovers among team members in the workplace play a central role in the theory of “high performance work system” or “high involvement work system” (Appelbaum, et. al., 2000; Gant, Ichniowski and Shaw, 2002; Boning, Ichniowski and Shaw, 2007). In addition, peer effects play an important role in economics of organization (e.g., Aoki, 1986; Kandel and Lazear, 1992), growth theory (e.g., Lucas, 1988), and FDI (e.g., Fosfuri, et. al., 2001).

However, direct evidence on peer effects in the workplace is relatively scarce, for such evidence requires researchers to go deep inside the black-box of the firm and obtain rare access to “insider” data on performance of individual workers. Pioneering works using internal personnel data in economic research include Medoff and Abraham (1980), and Baker, Gibbs, and Holmstrom (1994a, 1994b). More recently, a number of studies (e.g., Lazear, 2000, Kleiner and Helper, 2003, Fernie and Metcalf, 1999, Paarsh and Shearer, 1999, Knez and Simester, 2001, Bandiera, Barankay and Rasul, 2005, and Shi, 2007), use such “insider” data and study the effects on individual worker performance of a change in pay methods (e.g., the switch from time
rates to piece rates or to performance pay). A related line of work examines the effects on individual worker performance of the shift to team-based production (e.g. Batt, 1999, Hamilton, Nickerson and Owan, 2002, and Jones and Kato, 2007). None of these studies examine peer effects and performance spillovers.

New econometric case studies on the subject are emerging, however. Mas and Moretti (2009) use individual productivity data on supermarket cashiers at a large supermarket chain in California and provide direct evidence on performance spillovers though peer pressure. Bandiera, Barankay and Rasul (2009) use individual productivity data on fruit pickers at a leading U.K. agriculture firm and show that workers tend to conform to their friend’s productivity level. Finally, Guryan, Kroft and Notowidigdo (2009) exploit random groupings of professional golfers and test the presence of peer effects in professional golf tournaments. Unlike the first two studies, they find no evidence for peer effects.\(^1\)

In this paper we use individual performance data on weavers at a large textile firm in China and provide rigorous evidence on peer effects. Perhaps most importantly our study takes advantage of the well-documented social divide between urban resident workers and rural migrant workers in China’s transition economy and examines the potentially important interplay between peer effects and such exogenously-formed and clearly-defined social networks (rural migrant network vs. urban resident network). The potentially important role of social networks in worker’s decision making has been reported in the literature (e.g., Duflo and Saez, 2004 who find that female workers’ retirement investment decisions are correlated with the other female workers’ decisions in the same department, but not the male workers’). Recent experimental evidence also points to the important role that group identities play in overcoming self-interests.

\(^1\) Falk and Ichino (2006) provide experimental evidence on peer effects whereas Rees, Zax and Herries (2003) present early empirical evidence on productivity spillovers, using revenue data.
and fostering altruistic behaviors (e.g., Chen and Li, 2009). Bandiera, Barankay and Rasul (2009) also find that under a relative performance scheme, a high-ability worker would lower his/her performance in order to boost the pay for his/her friends.

In contrast to Bandiera, Barankay and Rasul (2009), we find stronger peer effects across the social network rather than within the network, i.e., a worker is found to put in more effort when she is working with more able outgroup teammates but not when working with more able ingroup teammates. Based on our own field research at the firm and our reading of the literature on group identity and its effects on behaviors, we interpret the finding as follows. Consider the arrival of a more able worker to the team. An average incumbent worker in the team is found to put in more effort and improve her performance in response to the arrival of the new high-ability worker to her team when the newcomer is an outgroup worker (belonging to the other social network) but not when the newcomer is an ingroup worker. The arrival of the high-ability outgroup worker is viewed as a threat to the supremacy of her own group over the other group (or to the group’s plan to establish its supremacy over the other group). Such intergroup competition pressure prompts the worker to put in more effort to maintain the supremacy of her group over the other group (or carry out the group’s plan to establish its supremacy without delay). The pervasiveness of “us against them” mentality generates powerful intergroup competition in the workplace which generates the cross-network peer effect. The weak peer effect within the network also suggests that knowledge sharing and contagious enthusiasm/role model may be relatively less powerful drivers of the peer effect.

Finally, we will argue that such peer effects across the social network, combined with the presence of incentive to outperform teammates at this firm, are largely consistent with recent experimental evidence on the important role that group identities play in facilitating altruistic
behaviors (e.g., Chen and Li, 2009).

The paper is organized as follows. The next section discusses the data and the empirical setting. Section III illustrates the econometric strategies and presents our peer effect estimates. Section IV presents the results on the interplay between peer effects and social networks. Section V concludes.

II. Data and Setting

The Chinese textile firm in our case study, SCT, is based in Shijiazhuang, an industrial city and the capital of Hebei province in the northeastern China. Textile is one of the city's most prosperous industries. SCT was founded in 1921, originally as a state-owned enterprise (SOE). However, like many other large SOEs, SCT suffered from the financial crisis during the 1990's due to outdated facilities, an aging workforce, and shrinking market. In 1998 the firm was one of the first large-scale SOEs to be privatized. The ownership and management restructure saved the firm from the threat of bankruptcy. SCT employed about 3,500 workers during our study period.

In collaboration with Xiao-Yuan Dong and Derek C. Jones, we collected several kinds of data from the case.2 These were collected during a lengthy study period, highlighted by two separate site visits with extensive interviews with the Director of Human Resources, the Director of the Weaving Division, a line supervisor and two team leaders at the Weaving Division, and the Director of Data Management (who was in charge of all internal data). In addition, to get perspective from an outsider, the site visit was supplemented by an extensive interview with a long-term consultant for SCT who has been observing the firm for many years. As well as collecting various performance and personnel data, we also deepened our knowledge of the case by collecting data from a survey that we designed and administered to all team leaders.

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2 See Dong, Jones and Kato, 2007 for details on the data.
The detailed personnel data with which SCT generously provided us include personal characteristics, weekly performance measures and wage for all of its weavers in the weaving division over the 53-week span between March 2003 and April 2004. An advantage of this "insider" dataset is that the individual performance measures are recorded by machines and thus measured with little errors. For the purpose of this study, we dropped 12 weavers who have worked for only 1 week as well as 115 observations where the weaver worked for less than 2 days of the week, for we have too little data to accurately predict abilities for these weavers. They are also unlikely to receive or cause any peer effects with such short presence in the team. The resulting dataset has 9966 observations for 287 individual weavers. Table 1 provides the summary statistics of their personal characteristics. All but 9 weavers are female. They all have graduated from junior high school but not high school. About 67% of them are rural migrant workers, while the rest are urban resident workers.

Production Process and Performance Measures

A quick glance at the workplace gives observers a first impression that the role of weavers in the production process is rather limited since the operation appears to be fully automated and cloths are produced by automated looms rather than weavers. However, a longer and closer observation of the workplace reveals that automated loom machines are far from perfect and that problems do occur from time to time (such as broken threads). Each weaver's main task is to pay close attention to her assigned loom machines (multiple loom machines are assigned to each weaver).

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3 In addition, one outlier observation was dropped, where its defect rate was above 10% (the maximum in the rest of data is 2.5%) and its daily output was only 5 meters (the mean in the rest is around 500 meters).

4 Integrating careful field research into standard econometric analyses is a key element of “insider econometrics” (Bartel, Ichniowski and Shaw, 2004). For a compelling demonstration of the value of conducting careful field research before embarking on quantitative research, see Ichniowski, Shaw and Prennushi (1997).
and minimize the occurrence of such operational problems; and if problems arise, solve the problems quickly and effectively.

For example, “good weavers” will detect early signs of problems and make timely adjustments to the operation process so that problems will not fully materialize and hence no defective product will result. Should problems actually turn up, “good weavers” will solve them in a timely and effective manner so that defective output will be minimized. Due to the problem solving nature of their main task, SCT constantly tells their weavers how important quality is, and asks them to work toward "zero defect".

For each weaver in each week, the firm keeps three performance-related records: total output produced, days worked, and defective output produced. From these three variables, we calculated the following two performance measures:\footnote{The variables are scaled so that the regression coefficients are more readable: daily output is measured in 10 meters and defect rate is out of 100.}

Defect Rate (quality measure):

\[
\text{DefRate}_t = \{(\text{Defective Output}_t)/(\text{Total Output}_t)\} \times 100;
\]

Average Daily Nondefective Output (quantity measure):

\[
\text{DayOut}_t = \{(\text{Total Output}_t - \text{Defective Output}_t)/(\text{Days Worked}_t \times 10)\}.
\]

Table 1 shows the summary statistics of the performance measures. The mean of days worked is 6.3 days (a day is counted as an 8-hour work period, so it's possible for the maximal days worked to exceed 7). The mean of DayOut is around 545 meters with standard deviation of roughly 180 meters. The mean of defect rate is approximately 0.24% with standard deviation of 0.18%.

Although "zero defect" is emphasized in the workplace, there doesn't exist a week where zero defect rate is actually achieved.
The nature of weaving technology and the problem-solving nature of a weaver’s job at SCT as described above suggests that the key individual performance variable for weavers at SCT is DefRate (quality), and while their discretionary efforts matter significantly for DefRate, there appears to be little room for discretion in terms of pace of production (or DayOut). All weavers are required to fulfill planned output levels and they appear to do so on most occasions.  

In other words, on the one hand, DayOut is largely determined by the plan, and there will be very little if any room for weavers to have behavioral response to peer effects. Our wage regressions reported later also confirm that there is no monetary incentive to produce more than planned. Furthermore, it is difficult if not impossible to identify any peer effects when the output of the whole team is influenced by some aggregate demand shocks.  

On the other hand, the weavers have considerable discretion and monetary incentive to minimize defective output, and hence behavioral responses to peer effects in the quality measure are clearly plausible. Therefore, our investigation of peer effects will focus on defect rate as our key performance measure although we will pay appropriate attention to the quantity of output.  

It is still possible, however, that aggregate demand shocks could affect actual defect rate. Using the planned performance measures as a control for demand, reassuringly our regressions show that there is no statistically significant relationship between the actual defect rate and demand shocks. These results will be discussed in more details in the next section.  

**Team environment**  

SCT uses a standard three-shift operation and each shift has six teams based on the

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6 Based on demand for its output, at the beginning of each week, SCT comes up with the upcoming week’s detailed production plan with specific numbers for planned output, days worked, and defective output assigned to each individual weaver. The correlation between the planned and actual daily output is 0.9562 whereas the correlation between the planned and actual defect rate is only 0.0957.
location of the weaving rooms. Thus, there are a total number of eighteen teams. As shown in Table 1, the average team size is around 10.5 with a standard deviation of 2.5. The weavers do not switch teams, but the composition of each team changes from week to week due to employee turnover and temporary absence. Our field research indicates that the firm does not use any systematic rule (explicit or implicit) on team assignment of new workers (such as assigning more able workers to teams which face more demanding assignments.) We will also confirm the suggested lack of systematic team assignment rules econometrically by testing the random team assignment hypothesis with the quantitative data below.

Assuming that changes in team composition are not correlated with the error terms, we have an exogenous source of variation that can be used to test whether a weaver puts in more effort and improves her performance when she is working with more able peers. While working alongside her teammates, the weaver is responsible for her own output. There is no team production at the weaving section of SCT, and no externality is generated by the production technology. Moreover, on-the-job interactions among weavers are extremely limited by the working environment, because 1) each weaver is required to pay undivided attention to her machines and 2) the machines are loud and the weavers are wearing masks. Thus, any peer effects could only come from either offline interactions or the simple presence of the teammates, or both.

SCT requires each of the 12 teams to hold team meetings during the meal break, once or twice a month to discuss issues concerning quality and exchange each other's experience of dealing with problems arising from production. Each team is also encouraged to hold "voluntary" team meetings after work as well. According to our own survey of all team leaders, nearly all teams meet once a week (four times a month). The average team meeting lasts about an hour. In
addition, each team is required to hold a training session and skill contest after work at least once a week. The purpose of such sessions is to help each other enhance skill level. Finally, each team selects a model worker during one of their team meetings. The company provides select model workers with bonuses and paid vacations. For example, during 2002 just before our data collection began, about 40 model workers were selected and awarded with a trip to Singapore, Malaysia, and Thailand, staying at 3-star hotels. Through various team activities described above, each weaver becomes clearly aware of her performance relative to her teammates.

Social Networks

In the context of an urban Chinese enterprise, there is a powerful social divide between urban resident workers and rural migrant workers. The relaxation of the regulations on rural-urban migration in 1988 encouraged many rural workers to look for a job in the urban areas and get paid higher than what they earn from doing agricultural work at home. However, it is not easy for rural migrant workers to gain an urban housing registration ("hu kou"), which serves as a considerable entry barrier to the buoyant urban labor market for rural migrants, and causes inequality between the rural and urban labor force. Without urban housing registration, rural workers are ineligible for many high-paying urban jobs as well as the urban welfare programs such as healthcare and schooling (Huang, 2001). A rural worker must also pay for a temporary residence permit in order to find a legal residence in the urban areas. There is significant adjustment cost for a rural migrant to work in the urban area, which does not incur for an urban worker. The sharp distinction between the urban and rural status tends to create powerful group identities among rural migrant workers as well as among urban workers.

Our informant (HR director) confirms that social interactions happen differently for the
rural and urban workers at SCT. The rural workers are mostly young single women from rural villages of Hebei Province. All of them live in the company dormitory free of charge (5 or 6 per room). After work they return to the same dorm, eat dinner in the same dining hall, and often socialize amongst themselves. It is thus highly likely that they create strong bonds among themselves, not only because they can relate more easily to each other, but also because they spend much more time together than with the urban workers. Since the rural workers form their own community, an urban worker will find it easier to be friends with other urban workers than breaking into the network of rural workers. Urban workers also prefer to communicate among themselves due to the commonality of their backgrounds (Nielsen, et. al., 2006 and Lu and Song, 2006).

Incentives

While confirming that weekly wage for weavers are tied to their performance and days worked for the week, our informant does not mention that SCT has any explicit relative performance pay scheme. Nonetheless, the existence of skill contests and competition for model workers point to the presence of incentive for workers to outperform other workers, however small the size of the incentive may be. To explore any possible implicit incentive in wage payment for a weaver to outperform her teammates, we run a wage regression with two dummy variables indicating whether or not the weaver outperforms her teammate's average performance in DefRate and DayOut as additional explanatory variables. As shown in Table 2, the fixed effect estimates of the wage equation first confirm our qualitative evidence from field research that individual wages are indeed related to individual performance (DefRate and DayOut) as well as days worked in a week. Most importantly, however, the estimated coefficient on the
outperformance dummy variable in DefRate is positive and significant at the 1 percent level, suggesting an implicit pecuniary incentive for a weaver to outperform her teammates in DefRate. Although such reward may not be written explicitly in the wage contract, peer effects would arise if the weavers are aware of the implicit competition.\footnote{To be consistent with the findings from our field research, there is no such incentive in DayOut. For more information on wage determination at SCT, see Dong, Jones and Kato (2007).}

**III. Estimating Peer Effects**

*Identification Strategy*

Consider the production function

\[
o_{it} = f(a_i, e_{it}, \varepsilon_{it})
\]

where \(o_{it}\) is the performance measure of weaver \(i\) in week \(t\), \(a_i\) is her innate, time-invariant ability, \(e_{it}\) is her effort in week \(t\), and \(\varepsilon_{it}\) is the error term. Weaver \(i\)'s performance is determined by her innate time-invariant ability, her time-varying effort, and other time-varying random factors. Peer effects are present if a weaver's effort is influenced by either the average effort of her teammates (how hard her teammates are working) or the average ability of her teammates (how capable her teammates are). We call the former "contemporaneous peer effects" and the latter "compositional peer effects". The contemporaneous effects are hard to identify due to the paucity of persuasive ways to separate \(\varepsilon_{it}\) from \(e_{it}\). Our observed correlation between \(o_{it}\) and \(\bar{o}_{it}\) (teammates' average performance excluding weaver \(i\)) could be due to correlation among the noises (for example, due to an aggregate demand shock.) Furthermore, regressing \(\bar{o}_{it}\) on \(o_{it}\) suffers from the "reflection problem" (Manski 2003) where the direction of causality cannot be identified. Thus, the satisfactory identification of the "contemporaneous effects" requires an instrument that influences the coworkers' average performance while not affecting one's own performance. By
definition, however, such an instrument does not exist, for every worker is a coworker of her colleagues at the same time.

The second type of peer effects arises when changes in $\bar{a}_{it}$ (her teammates’ average innate ability excluding weaver $i$) caused by changes in her team composition will bring about changes in $e_{it}$ (her own effort level). Such compositional peer effects do not suffer the same econometric problems since neither the error term nor the worker’s effort at time $t$ should influence the innate ability of the coworkers. This is the approach that the recent peer effect literature has taken and is also explored in this paper.\(^8\)

There are a number of possible reasons why such compositional peer effects may arise at SCT. First, as discussed in Mas and Moretti (2009), when working with more able teammates, a weaver may put in more effort to satisfy her competitive spirit. The presence of explicit and implicit incentives for weavers to outperform their teammates at SCT (which we described in the previous section) amplifies such competitive spirit-induced peer effects. Second, peer effects may arise also from contagious enthusiasm and role models. For example, consider the arrival of a “superstar” worker. The “superstar” worker may become a role model for her teammates and hence inspire them to achieve higher performance. Third, it is certainly possible that peer effects stem from knowledge sharing among teammates. For instance, the newly-arrived “superstar” worker comes up with a new and better solution to a quality problem. Provided that she shares such a new and better solution with her teammates, her teammates will improve their performance.

In addition to those three reasons, Mas and Moretti (2009) consider social pressure as a primary source of peer effects. Unlike in the case of supermarket cashiers in Mas and Moretti (2009), Bandiera, Barankay and Rasul (2009), and Guryan, Kroft and Notowidigdo (2009).
(2009), however, there is no obvious negative externality of underperformance in our case.
Recall that there is no team production at SCT and that workers do not interact with their teammates while operating machines. As such, producing defective output from her assigned machines will make her teammates’ work no more difficult. In fact, the presence of explicit and implicit pecuniary incentive for a weaver to outperform her teammates points to some positive externality of underperformance. As such, social pressure does not appear to be directly relevant to the peer effects at SCT. However, once we introduce social networks and group identity, social pressure turns out to be relevant in the context of intergroup competition as we elaborate in the next section.

**Predicting Abilities**

To estimate peer effects successfully using the aforementioned compositional effect approach, we need to use a comprehensive set of covariates and predict with precision the true innate time-invariant ability of each individual weaver, $a_i$. To this end, we estimate the following equation with an extensive list of covariates:

$$\text{DefRate}_{it} = \alpha + a_i + \lambda M_{it} + \gamma C_{jt} + \beta \text{DayOut}_{it} + \varepsilon_{it}$$

where $M_{it}$ is a set of 287 coworker dummy variables controlling for the presence of coworkers. For instance, the dummy variable "coworker1" in week $t$ takes a value of 1 if weaver $i$ works with weaver 1 in week $t$ in the same team, zero otherwise. $C_{jt}$ is the set of additional controls including week fixed effects and week times team fixed effects. $\text{DayOut}_{it}$ is included so that we can measure each weaver’s ability to maintain high quality of the output, holding the quantity of the output constant. To see if endogeneity of $\text{DayOut}_{it}$ is a problem, we used planned $\text{DayOut}$ as an instrument for actual $\text{DayOut}$. Reassuringly the results changes little in general and Hausman
test cannot reject the null that the IV estimate of $\beta$ is not different from the OLS estimate of $\beta$. As such, we do not believe endogeneity poses any serious problem.\(^9\)

We exclude planned DefRate from the right-hand side of Eq. (4), for we are not measuring the ability to outperform the plan. If high ability performers also get more demanding assignments, then controlling for planned performance would underestimate the spread in ability.

As we argued before, DayOut is mostly demand-determined and individual weavers appear to have little room for discretionary effort. Hence, predicted innate ability differences in DayOut are expected to be of less consequence for our analysis. However, we also estimated a similar equation to predict the true innate time-invariant ability of each individual weaver in DayOut as well. As expected, all of our results are insensitive to the inclusion of predicted innate ability of each individual weaver in DayOut.

Random Assignment

Before turning to our main task of estimating peer effects, we first need to check whether the abilities of the team members at a given time are correlated with each other. If they are, then our ability to identify the peer effects will be constrained considerably. Reassuringly our field research at SCT points to the absence of any rule (written or unwritten) of assigning the weaver to different teams based on her ability. To confirm the absence of such systematic assignment rule at SCT, we further test the random assignment hypothesis statistically. Since weavers do not switch teams, their predicted abilities also include team fixed effects, for instance as the different teams may be producing different textile products. Thus, we cannot identify whether a more able

\(^9\) As discussed earlier, we focus on DefRate as the only relevant performance measure for weavers at SCT. However, we also considered DayOut as an additional performance measure. As expected, considering DayOut as an additional performance measure was found to yield similar results. These as well as all other unreported results are available upon request from the authors.
worker is assigned to a more able team, as the abilities are measured on different scales across the teams. We can, however, test whether a high-ability weaver is working with other high-ability teammates at any given time.

Guryan, Kroft and Notowidigdo (2009) point out that the typical estimate of regressing the teammates' average ability at time t on one's own ability is biased downward, for one cannot be assigned to herself. In other words, the pool of peers that the teammates at time t are drawn from have a lower average ability for a high-ability focal worker than for a low-ability worker, as the focal worker is excluded from the otherwise identical pool. The bias is more severe when the pool is small. Following the bias-correction method in Guryan, Kroft and Notowidigdo (2009), we run the following regression:

\[ a_{it} = \pi_0 + \pi_1 \bar{a}_{-i} + \pi_2 (\bar{a}_{-it} - \bar{a}_{-i}) + \text{team fixed effects} + \epsilon_{it} \]

where \( a_{it} \) is the predicted ability in defect rate of person i who shows up at time t, \( \bar{a}_{-i} \) is the average ability of the teammates who are actually working with weaver i at time t, and \( \bar{a}_{-it} \) is the average ability of all of weaver i’s teammates including those not working at time t (in other words, any weaver who works with weaver i at least one time during the time period under study). By construction, \( a_i = \bar{\alpha} N - \bar{a}_{-i}(N-1) \) where \( \bar{\alpha} \) is the average ability of the whole team including weaver i and N is the total number of weavers in the team. Thus \( \pi_1 \) should be close to the mean of -(N-1), which according to Table 1 is about -15. The coefficient \( \pi_2 \) indicates whether more able workers are matched with other more able teammates at time t, holding the average ability of the pool that the teammates are drawn from constant. The null hypothesis of random assignment means that \( \pi_2 \) is zero.

Column (1) and (2) in Table 3 present the regression results. As expected, \( \pi_1 \) is significant at the 1 percent level and close to -15, and more importantly we cannot reject the null that \( \pi_2=0 \).
supporting our field observation that there is random assignment. The results are robust to the inclusion of week fixed effects.

**Peer Effect Estimates**

We use the following first-difference model to estimate peer effects:

(6) $\Delta \text{DefRate}_{it} = \theta \Delta \bar{a}_{-it} + \kappa \Delta \text{DayOut}_{it} + \text{additional controls} + \Delta \epsilon_{it}$

where $\Delta$ indicates the first difference between week $t$ and $t-1$. $\theta$ measures the compositional peer effects. $\text{DayOut}_{it}$ is included to control for pace of production and hence possible quantity-quality tradeoff (in theory a weaver can lower DefRate by simply slowing down her pace of production). To make sure that the estimated coefficient on $\Delta \bar{a}_{-it}$ is capturing the pure compositional peer effect, we include a variety of additional controls. First, we include a set of variables controlling for demand, which include: actual days worked, team size (at time $t$), planned defect rate. Planned daily output is excluded in equation because it is highly collinear with actual daily output, $\text{DayOut}$. Second, we include constant (to capture a firm-wide time trend), individual fixed effects (to capture individual-specific time trends), month fixed effects and/or week fixed effects (to capture firm-wide time-specific effects), and month*team fixed effects (to capture team-specific time effects). Third, the positive compositional peer effect ($\theta > 0$) means that when a weaver is working with more able teammates, she will put in more effort and improve her performance. However, for the same reason, her teammates also put in more effort and improve their performance. In other words, the positive compositional peer effect will likely accompany an increase in average effort of her teammates which may cause her effort to rise and hence improve her performance through the contemporaneous peer effect. As such, unless we control for average effort of her teammates, our estimates will be subject to omitted variable bias.
To address this problem, we add $\Delta \bar{e}_{-i,t}$ as an additional control variable where $\bar{e}_{-i,t}$ is average effort of weaver i’s teammates in week t (the effort level of each teammate, weaver k, is calculated by subtracting her estimated ability, $a_k$ from her DefRate$_{kt}$).

The first difference model is preferred to the fixed-effect level model, for as discussed above, we cannot separate the underlying team fixed effects from the individual predicted abilities. Thus, in the level model, team fixed effects will show up on both sides of the equation causing spurious correlations.

Table 4 presents the OLS estimates of Eq. (6). The estimates of $\theta$ (the effect of the change in teammates' average ability in defect rate on the change in the focal weaver's defect rate) are positive and mostly significant ($t=1.40, 2.13, \text{ and } 2.29$), pointing to the presence of peer effects at SCT. The size of the estimated peer effect appears to be plausible. When the average innate ability of her teammates in defect rate improves by 0.1 percentage point (or a 0.1 percentage point decrease in defect rate) as a result of team compositional changes, the weaver’s own defect rate will fall by 0.03 percentage points, ceteris paribus.

Finally, as expected, we find no evidence for the quality-quantity tradeoff (weavers reducing defect rate by simply slowing down the production pace). The estimated coefficients on DayOut are small and in fact negative rather than positive.

**IV. Peer Effects and Social Networks**

As discussed earlier, we believe there are four possible sources of the peer effects at SCT: (i) competitive spirit; (ii) contagious enthusiasm/role model; (iii) knowledge sharing; and (iv) social pressure. We now explore how the presence of strong social networks (rural vs. urban) at SCT may be interacting with those probable drivers of the observed peer effect.
The possible interplay between social networks and contagious enthusiasm/role model is rather intuitive and straightforward. The peer effect through contagious enthusiasm/role model is more likely to arise within the social network rather than across the social network. Again consider the arrival of the “superstar” worker to the team. The peer effect through contagious enthusiasm/role model arises when an incumbent team member will be inspired by the arrival of the “superstar” worker and perhaps even start emulating her as a role model, resulting in better performance for herself. When the “superstar” worker is an ingroup worker as opposed to an outgroup worker, the incumbent team member is more likely to be inspired by her and try to emulate her as a role model.\textsuperscript{10}

Likewise, the peer effects stemming from knowledge sharing among teammates are also more likely to arise within the social network rather than across the network. First, as explained in Section II, there is little pecuniary incentive to share knowledge with teammates (in fact there are explicit and implicit incentives for a weaver to outperform her teammates and hence not to share knowledge) and as shown in the recent experimental literature on group identity and altruistic behavior (e.g., Chen and Li, 2009), group identity facilitates workers to overcome their self-interests and engage in knowledge sharing among workers within the social network. Second, the cost of knowledge sharing tends to be lower among workers within the same social network than across the network (e.g., rural migrant workers are from the same rural region and speak the same dialect, and literally eat and sleep in the same dorm).

In contrast, the peer effects arising from competitive spirits are likely to be stronger across the social network as opposed to within the network. As discussed earlier, when a weaver finds herself competing with more able weavers in the workplace, she increases her effort and

\textsuperscript{10} The positive effects on student outcomes of having teachers of the same gender or race as role models are reported in the economics of education literature (see, for instance, Rask and Bailey, 2002; Dee, 2004; Bettinger and Long, 2005 for recent evidence).
improve her own performance to satisfy her competitive spirit. We argue that in general her competitive spirit will be more acutely awakened when the increase in the average ability of her teammates originates in her outgroup teammates (such as the arrival of the “superstar” worker who belongs to the other social network). In addition, the nature of group identity and social networks generated by the powerful divide between rural migrant and urban workers in Chinese factories makes the aforementioned competitive spirit story particularly relevant and compelling at SCT.

As discussed earlier, the deep rural/urban social divide causes weavers to form powerful group identity and a pervasive mentality of “us against them”, resulting in informal yet vigorous intergroup competition within the team. In this context of intergroup competition, the arrival of new and able weaver from the other social network is viewed as a threat to the supremacy of her group over the other group (or the group’s plan to establish its supremacy without delay). Social pressure to respond strongly to such a threat to the status of the social network will be evoked. As discussed and supported by evidence in Mas and Moretti (2009), such social pressure prompts a weaver competing with more able outgroup teammates to exert herself more to satisfy her group’s collective competitive spirit. The failure to do so may result in shame, reputational loss, and social sanctions.

In contrast, when the increase in the average ability of her teammates comes from the rising average ability of ingroup teammates (e.g., the arrival of the “superstar” worker who belongs to her own social network), the aforementioned social pressure and collective competitive spirit are largely irrelevant.

To explore the interplay between peer effects and social networks, we modify Eq. (6) to

---

11 The relationship between inter-group competition and intra-group cooperation has been studied in experimental economics (see, for instance, Bornstein, Gneezy and Nagel, 2002, Tan and Bolle, 2007, and Reuben and Tyran, 2009).
allow for the interaction between peer effects and social networks:

\[
\Delta \text{DefRate}_{ijt} = \theta_1 \Delta \bar{a}_{-ijt} + \theta_2 \Delta \bar{a}_{-i-jt} + \kappa \Delta \text{DayOut}_{it} + \text{additional controls} + \Delta \varepsilon_{it}
\]

where j denotes person i’s social network, \( \bar{a}_{-ijt} \) is the average ability of the teammates who are in the same network as weaver i, and \( \Delta \bar{a}_{-i-jt} \) is the average ability of the teammates who are in the other network. We use the same set of control variables as in Eq.(6) except that we control for the size of the rural and urban networks in the team separately (instead of controlling for the total team size). We run the regression separately for the rural migrant workers and urban workers. Tables 5 and 6 present the results for the rural and urban workers respectively.

For the rural migrant worker, as shown in Table 5, the estimated coefficients on the average ability of her *outgroup* teammates (or urban teammates) are positive and significant at the 5 percent level in columns (1) and (2) without controlling for team-specific time effects and still significant at the 10 percent level even when additionally controlling for team-specific time effects. In contrast, the estimated coefficients on the average ability of her *ingroup* teammates (rural) are not significant and relatively small (especially when team-specific time effects are controlled for). In short, for the average rural migrant worker, changes in the average ability of her *ingroup* (rural) teammates are found to have little impact on her own effort, whereas she is found to put in more effort and improve her performance in output quality when the average ability of her *outgroup* (urban) teammates increases. The magnitude of such intergroup peer effects appears to be again sensible. For instance, as her *outgroup* (urban) teammates’ average ability in defect rate improves by 0.1 percentage point (or a 0.1 percentage point drop in defect rate), the average rural migrant weaver will put in more effort and improve her own defect rate by 0.02 percentage points.

The results for urban weavers are similar to those for rural weavers although they are
slightly less significant. The estimated coefficients on the average ability of the urban worker’s *outgroup* teammates (rural) are positive and significant at the 10 percent level with team-specific time effects controlled for and close to significant without team-specific time effects (t=1.59 and 1.60). The estimated coefficients on the average ability of her *ingroup* teammates (urban) are, however, much smaller and not at all significant. As such, similar to the case of rural workers, on the one hand, an urban weaver is found to change her effort level very little in response to a change in her *ingroup* (urban) teammates’ average ability. On the other hand, she is found to put in more effort and lower her own defect rate by 0.03 to 0.04 percentage points when her *outgroup* (rural) teammates’ average ability rises by 0.1 percentage point.

In sum, we find that the peer effects arise amongst weavers across the social network rather than within the network. It follows that the peer effects at SCT are likely to be driven by each weaver’s competitive spirit in general and her collective competitive spirit in the presence of intergroup competition, combined with social pressure (shame, social sanctions and reputational damages), in particular. In contrast, the lack of significant peer effects within the network suggests that contagious enthusiasm/role model and knowledge sharing may be of less relevant at SCT.

The regression results in Tables 5 and 6 also suggest that our peer effect estimates are unlikely to be driven by common noise, for otherwise $\theta_1$ and $\theta_2$ should both be significant for both groups of workers. For instance, suppose an increase in the average ability of the urban team members is accompanied by some positive shocks to everyone's productivity. If that is the case, we should expect $\theta_1$ to be as large, positive and significant as $\theta_2$ for urban workers, which we do not observe.
V. Conclusions

Using weekly data for defect rates (proportion of defective output) for all weavers in a Chinese textile firm during a 12 months (April 2003-March 2004) period, this paper has provided some of the first rigorous evidence on the presence and nature of peer effects in the manufacturing workplace. First, we have found that a worker increases her effort level and improves her performance when working with more able teammates. Second, by exploiting the well-documented fact that an exogenously-formed deep divide between urban workers and rural migrant workers exists in firms in Chinese cities, we have provided novel evidence on the interplay between social networks (urban resident group and rural migrant group) and the peer effects. Specifically, workers have been found to put in more effort when working with more able outgroup teammates but not when working with more able ingroup teammates.

Our finding of the significant peer effects across the social network yet not within the social network sheds light on the actual mechanisms though which the peer effects arise. As in the case of U.S. supermarket cashiers studied by Mas and Moretti (2009), the peer effects we detected for Chinese weavers are driven probably neither by knowledge sharing nor by contagious enthusiasm/role model, for if knowledge sharing and contagious enthusiasm/role model were key drivers of the peer effect, we should have found more significant peer effects within the social network rather than across the social network. However, unlike Mas and Moretti (2009)’s cashiers, our weavers do not impose any direct negative externality on their teammates by underperforming. In fact, there are explicit and implicit incentives for them to outperform their teammates (or positive externality imposed on their teammates by underperforming). Hence social pressure (e.g., shame, reputational damage and social sanctions) to minimize negative externality imposed on her teammates by her own underperformance
(which turned out to be the primary source of the peer effects among cashiers in Mas and Moretti, 2009) is of less relevance to our weavers.

Instead we believe that strong group identity and intergroup competition have much to do with the peer effect that we have observed. In the context of the pervasive divide between rural migrant workers and urban resident workers in the manufacturing workplace in Chinese cities, each weaver’s competitive spirit is more powerfully awakened when the increase in the average ability of her teammates stems from the rising ability of her outgroup teammates as opposed to her ingroup teammates. The increase in the average ability of the worker’s outgroup teammates is regarded as a threat to her group’s relative standing against the other group. Hence there is social pressure for her (and all other ingroup teammates) to counter such a rise in the average ability of her outgroup teammates by putting in more effort and improving her performance.

Such competitive behavior is further amplified by the presence of explicit and implicit pecuniary incentive for each weaver to outperform her teammates. The rising average ability of the worker’s ingroup teammates may stimulate her individual competitive spirit (which is also consistent with the presence of the aforementioned relative performance incentive) yet such individual competitive spirit appears to pale compared to collective competitive spirit (or collective social pressure on each teammate to counter the rise in the average ability of her outgroup teammates).

A recent study of fruit pickers in the U.K. (Bandiera, Barankay and Rasul, 2009) reports stronger peer effects within the network than across the network. Group identity of their fruit pickers appears to be largely personal and certainly not based on deep-rooted social and historical institutions (such as rural migrant versus urban resident workers in our case), it is quite possible that intergroup competition (“us versus them” mentality) which prevails between rural
migrant and urban resident workers in the workplace in Chinese factories may not be as pervasive among those fruit pickers. Such lack of powerful intergroup competition among fruit pickers may account for their contrasting finding.

Economists have been increasingly aware of the potentially important behavioral effects of group identities (see for example Akerlof and Kranton, 2000), and lately rigorous evidence on such behavioral effects of group identities has been provided by economists. Most of the evidence is experimental and evidence from the actual workplace is still rare. For instance, Chen and Li (2009) report intriguing experimental evidence on the significant role of group identities in overcoming self-interests and facilitating altruistic behaviors. Our weavers display similar group identity-induced altruistic behaviors when competing with their teammates in the presence of pecuniary incentives to outperform their teammates. Specifically, when competing with more able teammates, the weaver is less likely to win skill contest and model worker competition, and hence prizes, and her wage will be more likely to be lower since she is less likely to outperform the average performance of her teammates (as shown in our wage regression results). As such, there is an incentive for her to respond to the rising ability of her teammates by putting in more effort and enhance her performance. However, she will not act on this incentive insofar as the source of the rising average ability of her teammates is the presence of more able ingroup teammates. In other words, a weaver appears to be willing to let her teammates win the prize and earn higher wages insofar as they belong to the group with which she strongly identifies. Such altruistic behaviors do not arise if the rising average ability of her teammates comes from more able outgroup teammates. As such, our finding on the interplay between peer effects and social networks represents one of the first field evidence from the actual workplace on the role of group identities in altruistic behaviors.
Lastly, our finding of stronger peer effects across the network than within the network implies that peer effects are stronger in the integrated workplace than in the segregated workplace, and that inter-network competition in the integrated workplace may lead to better overall performance in the integrated workplace than in the segregated workplace.\textsuperscript{12}

\textsuperscript{12} Charness and Villeval (2009), based on new experimental evidence, draws a similar implication for the advantage of workplace diversity in the context of mixing senior with junior workers. In addition, Kurtulus (2009) uses subjective evaluations of individual workers as performance measures and provide evidence for the performance-enhancing effect of workplace diversity in terms of gender, narrowly-defined tenure within division, education and wage.
References


<table>
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<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>DefRate (out of 100)</td>
<td>0.239</td>
<td>0.181</td>
<td>9966</td>
</tr>
<tr>
<td>DayOut (in 10m)</td>
<td>54.555</td>
<td>18.285</td>
<td>9966</td>
</tr>
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<td>Days Worked in a Week</td>
<td>6.271</td>
<td>0.88</td>
<td>9966</td>
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<td>Wage</td>
<td>148.136</td>
<td>30.369</td>
<td>9966</td>
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<tr>
<td>Ability in DefRate (out of 100)</td>
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<td>287</td>
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<td>Ability in DayOut (in 10 meters)</td>
<td>1.299</td>
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<td>Female Dummy</td>
<td>0.969</td>
<td>0.175</td>
<td>287</td>
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<td>953</td>
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<td>18</td>
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<td>(3)</td>
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<td>--------------</td>
<td>--------------</td>
</tr>
<tr>
<td></td>
<td>(3.54)</td>
<td>(3.50)</td>
<td>(3.65)</td>
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<tr>
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<td>0.079***</td>
<td>0.078***</td>
<td>0.086***</td>
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<td>(3.39)</td>
<td>(3.44)</td>
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<td>24.632***</td>
<td>24.912***</td>
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<td>(49.73)</td>
<td>(47.74)</td>
<td>(48.94)</td>
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<td>5.382*</td>
<td>-8.855*</td>
</tr>
<tr>
<td></td>
<td>(1.19)</td>
<td>(1.81)</td>
<td>(1.78)</td>
</tr>
<tr>
<td>Teammates' Avg DayOut</td>
<td>-0.025</td>
<td>-0.001</td>
<td>0.006</td>
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<td>(0.58)</td>
<td>(0.03)</td>
<td>(0.12)</td>
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<td>Outperforming Teammates' Avg DefRate</td>
<td>6.768***</td>
<td>6.446***</td>
<td>6.776***</td>
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<tr>
<td></td>
<td>(10.79)</td>
<td>(11.23)</td>
<td>(10.86)</td>
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<td>Outperforming Teammates' Avg DayOut</td>
<td>0.402</td>
<td>0.424</td>
<td>0.335</td>
</tr>
<tr>
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<td>(0.63)</td>
<td>(0.68)</td>
<td>(0.52)</td>
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<td>Actual - Planned DayOut</td>
<td>-0.104**</td>
<td>-0.099*</td>
<td>-0.070</td>
</tr>
<tr>
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<td>(2.04)</td>
<td>(1.94)</td>
<td>(1.27)</td>
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<td>Team Size</td>
<td>-0.148</td>
<td>-0.079</td>
<td>-0.139</td>
</tr>
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<td>(0.73)</td>
<td>(0.66)</td>
<td>(0.50)</td>
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<td>Time FE</td>
<td>Month</td>
<td>Month</td>
<td>Week</td>
</tr>
<tr>
<td>Month*Team FE</td>
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<td>No</td>
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<td>0.751</td>
<td>0.733</td>
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</table>

Absolute values of t in parentheses
All standard errors are robust and clustered at the individual level.
All models include individual fixed effects.
* p<0.10  
** p<0.05  
*** p<0.01
Table 3 Random Assignment within a Team: Dep=Ability in DefRate

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</tr>
</thead>
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<tr>
<td>Teammates' Avg Ability in DefRate (entire team)</td>
<td>-14.796***</td>
<td>-14.792***</td>
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<tr>
<td>(48.94)</td>
<td>(48.74)</td>
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<td>Teammates' Avg Ability in DefRate (in week t) - Teammates' Avg Ability in DefRate (entire team)</td>
<td>0.003</td>
<td>-0.005</td>
</tr>
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<td>(0.32)</td>
<td>(0.54)</td>
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<tr>
<td>Week FE</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Team FE</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>Adj.R-squared</td>
<td>0.998</td>
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</tr>
<tr>
<td>N</td>
<td>9961</td>
<td>9961</td>
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</table>

Absolute values of t in parentheses

All standard errors are corrected for heteroskedascity and clustered at the team level.

* p<0.10

** p<0.05

*** p<0.01
Table 4 Peer Effects: Dep=First Diff. in DefRate

<table>
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<tr>
<td>Teammates' Avg Ability (FD DefRate)</td>
<td>0.270</td>
<td>0.333**</td>
<td>0.323**</td>
</tr>
<tr>
<td></td>
<td>(1.40)</td>
<td>(2.13)</td>
<td>(2.29)</td>
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<tr>
<td>DayOut(FD)</td>
<td>-0.005***</td>
<td>-0.004***</td>
<td>-0.004***</td>
</tr>
<tr>
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<td>(19.15)</td>
<td>(19.12)</td>
<td>(19.03)</td>
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<td>Time FE</td>
<td>Month</td>
<td>Week</td>
<td>Week</td>
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<td>Adj.R-squared</td>
<td>0.122</td>
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<td>N</td>
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Absolute values of t in parentheses
All standard errors are robust and clustered at the individual level.
All models include individual fixed effects, demand controls and teammates’ average effort.

* p<0.10
** p<0.05
*** p<0.01"
Table 5 Peer Effects and Social Networks: Sample=Rural Weavers; Dep=First Diff. in DefRate

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<tr>
<td>Rural Teammates' Avg Ability (FD DefRate)</td>
<td>0.141</td>
<td>0.121</td>
<td>0.055</td>
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<td></td>
<td>(1.49)</td>
<td>(1.28)</td>
<td>(0.54)</td>
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<td>Urban Teammates' Avg Ability (FD DefRate)</td>
<td>0.189**</td>
<td>0.178**</td>
<td>0.171*</td>
</tr>
<tr>
<td></td>
<td>(2.24)</td>
<td>(2.07)</td>
<td>(1.80)</td>
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<tr>
<td>DayOut(FD)</td>
<td>-0.004***</td>
<td>-0.004***</td>
<td>-0.004***</td>
</tr>
<tr>
<td></td>
<td>(15.19)</td>
<td>(15.46)</td>
<td>(15.46)</td>
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<tr>
<td>Time FE</td>
<td>Month</td>
<td>Week</td>
<td>Week</td>
</tr>
<tr>
<td>Month*Team FE</td>
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<td>No</td>
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<tr>
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Absolute values of t in parentheses
All standard errors are robust and clustered at the individual level.
All models include individual fixed effects, demand controls and teammates' average effort.

* p<0.10
** p<0.05
*** p<0.01
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<td>Rural Teammates' Avg Ability (FD DefRate)</td>
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<td>0.345</td>
<td>0.391*</td>
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<td>(1.59)</td>
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<td>(1.71)</td>
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<td>(1.00)</td>
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<td>DayOut(FD)</td>
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<td>-0.004***</td>
<td>-0.004***</td>
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<td>Week</td>
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<tr>
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</table>

Absolute values of t in parentheses
All standard errors are robust and clustered at the individual level.
All models include individual fixed effects, demand controls and teammates’ average effort.

* p<0.10  ** p<0.05  *** p<0.01"