Peer Effects in the Workplace: A Network Approach*

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Abstract

We use a network approach, together with data from an in-house call center, to study how co-worker productivity affects worker productivity. We show that contemporaneous worker productivity is positively affected by the contemporaneous productivity of a worker's co-worker network. We also find evidence of two important exogenous peer effects. First, worker productivity is affected positively by the average tenure of a worker's co-worker network. Second, worker productivity is affected positively by the number of co-workers who have received on-the-job training. We then demonstrate how a network model of worker productivity can be used to inform personnel policy.

Keywords: peer effects, on-the-job training, social networks, worker productivity.
JEL Classification: J24, M53, Z13.

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1 Introduction

There is a growing empirical literature showing that workers are sensitive to the output choices of their peers. Falk and Ichino (2006), Mas and Moretti (2009), Bandiera, Barankay and Rasul (2010), and Battiston, Blanes i Vidal, and Kirchmaier (2017), all demonstrate that co-workers can exert economically significant effects on their peers, via channels often not explicitly created by their firms. Understanding the mechanisms behind these effects and the policy consequences of such results may be of great value to firms and other organizations. The aim of this paper is to shed more light on this important topic by studying both endogenous and exogenous peer effects in the workplace using an explicit network approach.

We begin our investigation by presenting a formal model of worker productivity that encompasses the two main mechanisms behind productivity spillovers among workers that are hypothesized in the literature: social norms and knowledge spillovers. In our model, these mechanisms are captured by *local average* peer effects and *local aggregate* peer effects, respectively. The local average effect represents the role of social work norms, e.g. conformist behavior or peer pressure (Patacchini and Zenou, 2012; Liu et al., 2014; Blume et al., 2015; Topa and Zenou, 2015; Boucher, 2016), while the local aggregate effect represents strategic complementarities, e.g. knowledge spillovers (Ballester et al., 2006, 2010; Bramoullé et al., 2014; De Marti and Zenou, 2015). In the local-average model, deviating from the *average effort of one's peers* affects the utility of an individual *negatively.* The closer each individual's effort is to the average of her friends' efforts, the higher is her utility. In the local aggregate model, it is the *sum of the efforts of one's peers* that *positively* affects the utility of each individual. When peers exert more effort, the utility derived from own effort increases.

We use this model to guide the empirical part of our paper. We estimate the best reply function from the Nash equilibrium of our model using a high quality dataset from an in-house call center of a multi-national mobile network operator that covers a period of two years. The data include detailed information on the performance of individual workers, their direct co-workers, and the exact times that they punch in and out of work. We use this information to create co-worker networks for each week, where a weighted link between two agents indicates the amount of time they have been working together on the same team during a week. Because teammates sit close to each other, this provides us with very precise knowledge of the co-workers that a worker is exposed to during the week, as well as the intensity of this exposure. In contrast to many other network papers, we do not identify exposure to peers off of the stable part of a worker's co-worker network, which is prone to non-random sorting. In our setup, every worker receives a unique, exogenously varying dose of both co-worker productivity and co-worker characteristics. This dose changes from week to week due to worker turnover, due to changes in the scheduling needs of the company, and due to idiosyncratic changes in one's own work schedule and the work schedules of teammates. We demonstrate that this variation in co-worker exposure is plausibly exogenous after conditioning on team, week and individual fixed effects.[1]

We use this exogenous variation in exposure to various co-workers together with Bramoullé et al.'s (2009) "friends-of-friends" instrumental variable strategy to achieve identification of causal effects. We use the observable characteristics of a worker's co-workers' co-workers (whom she does not work with) as valid instruments for her co-workers' productivity.[2] This empirical approach takes care of simultaneity and, together with the fact that our network data are "incomplete" (i.e. everyone is not connected to everyone else), it also enables us to separately identify endogenous peer effects from exogenous (contextual) peer effects on worker productivity.

We find evidence of peer effects in worker productivity, both endogenous and exogenous. A 10% increase in the current productivity of a worker's co-worker network leads to a 1.3% increase in own current productivity. Our estimation results show that this effect can be attributed to conformist behavior (i.e. to *local average* peer effects), which means that workers' productivities adjust towards the average productivity of their co-worker network. We also find an important, exogenous (contextual) peer effect. A 10% increase in the average tenure of a worker's co-workers raises her own productivity by 0.3%.

[1] In essence, we adapt the identification strategy used by Bayer et al. (2009) to fit our explicit network approach. Bayer et al. (2009) designed their approach to study spillover effects in crime.

[2] The intransitivity of these triads generates valid exclusion restrictions.

In a second regression exercise, we include information about a week-long, firm-sponsored on-the-job training program (De Grip and Sauermann, 2012). One aim of this training program was to train workers on the best way to help their co-workers in order to facilitate spillover effects from on-the-job training. We find evidence of an additional exogenous peer effect: A 10% increase in the number of trained workers that a worker is exposed to raises her own productivity by 0.2%.

Previous studies have convincingly shown that there are meaningful peer effects in worker productivity.[3] Falk and Ichino (2006) randomize individuals to work with or without peers in the same room, and find that a 10% increase in co-worker productivity increases a worker's own productivity by 1.4%. Exploiting the quasi-random placement of supermarket cashiers, Mas and Moretti (2009) find remarkably similar peer effects in worker productivity. Cashiers work faster when being observed by highly productive workers, suggesting that co-workers may face sanctions from their peers for low output. A 10% increase in co-worker productivity raises worker productivity by 1.5%. Both Falk and Ichino (2006) and Mas and Moretti (2009) find that it is the less productive workers who respond to the more productive work norm set by their high productivity peers. Mas and Moretti (2009) show that peer pressure is driving the effects, which is in line with the arguments of Kandel and Lazear (1992). This implies that the firm could increase overall productivity by balancing skills across work shifts to overcome the problem of free-riding.

Using self-reported information on friendship networks among a sample of fruit pickers in the UK, Bandiera et al. (2010) find that workers adjust their effort upwards (downwards) if working with more (less) productive friends. The net effect on aggregate performance among fruit pickers in this firm is positive, which suggests that firms could harness these types of social incentives to boost aggregate production.[4]

[3]See Herbst and Mas (2015) for a meta-study on peer effects in worker productivity.

[4]The actual expression of potential peer effects in the work place and the role played by social connectedness may depend on the type of payment system in place in the firm. Chan, Li and Pierce (2014), for example, study peer effects among salespersons under individual-based and team-based pay: the presence of high ability peers improves performance for low ability peers under team-based compensation, but not under the individual-based pay system. Babcock et al. (2015) show that peer effects can arise from monetary team incentives and that these social incentives can be quite effective in motivating effort intensive tasks.

Battiston et al. (2017) study co-workers in a 911 emergency call center who must work together to receive calls and then assign emergency response units. Randomly assigned co-workers may either be sitting in the same room and close by or they may be sitting in a different room on the other side of town. Interestingly, they find that face-to-face communication generates larger peer effects in co-worker productivity than electronic communication does. If your co-worker is sitting neraby you in the same room, then the average speed with which you can handle calls and assign emergency response units goes up by 2%.

All of the above mentioned studies examine peer effects in worker productivity among workers performing relatively low skilled tasks, with most studies finding that peer effects are best explained by peer pressure or work norms in the workplace, and not by knowledge spillover effects.[5] For high-skilled occupations, the evidence points towards a different mechanism, namely knowledge spillovers. Jackson and Bruegemann (2009), for example, show that teacher output, measured by students' grades, is higher when the teacher has more effective colleagues. The effect is particularly large for less experienced teachers and it appears to persist over time, suggesting that these peer effects are driven by peer-to-peer learning. Azoulay et al. (2010) find that researchers collaborating with "super star" scientists experienced a lasting and significant decline in their quality adjusted publication rate after the unexpected death of their super star colleague. Waldinger (2010) provides evidence that the expulsion of high quality Jewish scientists from Germany by the Nazi government resulted in negative effects on the productivity of Ph.D. students that were left behind.

Studies on peer effects typically use data from specific occupations, for which worker productivity is measurable. In comparison to these studies, Cornelissen, Dustmann and Schönberg (2017) use linked employer-employee data for entire local labor markets in Germany, and find comparatively small average effects of peer productivity on own wages. A 10% increase in peer quality increases own wages by only 0.1%. When looking at the most repetitive and predefined occupations, which are likely to be most susceptible to peer pres-

[5] In contrast to the studies cited, which all analyze individual tasks, Hamilton, Nickerson and Owan (2003) demonstrate that peer effects among low skilled workers can also arise when production is team based and when team members have collaborative skills or when team members can specialize in different steps of the production process.

sure, they find that an effect of 0.6-0.9%, which is roughly half the number reported in Falk and Ichino (2006) and Mas and Moretti (2009). For high skilled and innovative occupations, they find spillover effects that are as small as those for the economy as a whole.

In this paper, we adopt a more explicit network approach to study the effect of contemporaneous co-worker productivity and characteristics on worker productivity. This approach provides us with a natural way of constructing plausibly exogenous variation in the "dose" of co-worker productivity and co-worker characteristics that a worker receives each week, which facilitates a causal interpretation of our estimated peer effects. Importantly, we measure the total network effect that arises from taking a worker's full network of co-workers into consideration, as opposed to only considering the effect from her immediate peers.

An explicit network approach also allows us to identify endogenous network effects separately from exogenous network effects. This is, of course, nothing unique to our study, but is merely a well known advantage of using an explicit network approach when studying peer effects (see, e.g., Bramoullé et al. (2009) and Blume et al. (2015)). We demonstrate how working with high tenure co-workers and/or co-workers that have recently received new skills through on-the-job-training raises a worker's own productivity via exogenous (contextual) peer effects. Importantly, our model also allows us to distinguish between *local average* effects, where deviations from the social norm of the reference group are costly, and *local aggregate* effects, where the activity of peers positively affects one's utility directly through the existence of complementarities.

Our first regression exercise, looking at the effect of contemporaneous co-worker productivity on contemporaneous worker productivity, is very similar to Mas and Morreti's (2009) experiment using data on grocery store cashiers. Like them, we also use detailed time clock data to measure exposure to peers and have very precise, automated measures of worker productivity. The main difference between the two papers is that we allow a worker to be influenced by her entire co-worker network, while the cashiers in Mas and Morreti's (2009) paper can only be influenced by persons working on the same shift. It is quite likely that this is, in fact, the most relevant specification in their context. In our context, however, we see that workers can be influenced by workers on their team whom they don't actually see during the week. That is, co-workers of co-workers also matter. They influence worker productivity indirectly by influencing the productivity of a worker's co-workers.

In our second regression exercise, we use our network model to replicate and then extend the findings of De Grip and Sauermann (2012) concerning spillover effects from on-the-job training.[6] Whereas De Grip and Sauermann (2012) only use the share of treated peers as a proxy for peer effects, the approach of this paper allows us to use the full sample, and to estimate the externalities on all workers employed in the call center.

In the policy section of our paper, we show how these empirical findings can be used in conjunction with our model-based network approach to address several important personnel management questions. Having a model allows us, for example, to identify "key workers" whom the firm should strive to retain and train. Who should the firm strive to retain? Who should they train? And how should the firm organize teams and shifts? We show that the answers to these questions hinge upon the presence of externalities in worker productivity, the underlying mechanism(s) of such peer effects, and on the structure of co-worker networks.

The rest of the paper unfolds as follows. In the next section, we present our theoretical framework. We then present the institutional setting and the definition of co-worker networks in Section 3. Section 4 is devoted to our first regression exercise concerning the effects of co-worker productivity and characteristics on worker productivity. Section 5 focuses on our second regression experiment, which studies spillover effects from on-the-job training. In Section 6, we demonstrate the relevance of our findings by using them to answer a number of practical policy questions faced by a typical personnel manager. Section 7 concludes.

[6] De Grip and Sauermann (2012) estimate the returns to training using a field experiment with random assignment to training. They also show productivity increases from a subset of these trained workers may have spilled over onto teammates who were themselves waiting to be trained. For reviews of the literature on the returns to training, see Leuven (2005), Dearden, Reed and Van Reenen (2006) and De Grip and Sauermann (2012).

2 Theoretical Framework

2.1 Notations and Preferences

A co-worker network, g, is a collection of $N = \{1, \dots, n\}$ workers and the links between them. The adjacency matrix $\mathbf{G} = \{g_{ij}\}$ keeps track of these links, where $g_{ij} = 1$ if i and j are co-workers, and $g_{ij} = 0$, otherwise. In this paper, co-worker links are defined as those who work the same shift on the same team in the same company.[7] Links are reciprocal so that $g_{ij} = g_{ji}$. We also set $g_{ii} = 0$ so that individuals are not linked to themselves. The adjacency matrix is thus a $0-1$ symmetric matrix describing the architecture of a co-worker network. Let $\mathbf{G}^* = \left\{g^*_{ij}\right\}$ denote the row-normalized matrix of $\mathbf{G}$, where $g^*_{ij} = g_{ij}/g_i$ and where $g_i = \sum_{j=1}^n g_{ij}$ is the number of links (co-workers) of individual i.

Individuals decide how much productive effort to exert on the job. We denote the effort level of individual i by y_i and the population effort profile by $\mathbf{y} = (y_1, ..., y_n)'$. Each agent i selects an effort $y_i \geq 0$, and obtains a payoff $u_i(\mathbf{y}, g)$ that depends on the effort profile $\mathbf{y}$ and the underlying network g, in the following way:

$$u_i(\mathbf{y}, g) = (a_i + \eta + \epsilon_i)\ y_i - \frac{1}{2}y_i^2 + \lambda_1 \sum_{j=1}^n g_{ij} y_j y_i - \frac{1}{2}\lambda_2 \left(y_i - \sum_{j=1}^n g^*_{ij} y_j\right)^2 \tag{1}$$

where $\lambda_1 \geq 0$, $\lambda_2 \geq 0$. The structure of this utility function is an extension of the one usually used in games on networks (Ballester et al., 2006; Calvó-Armengol et al., 2009; Patacchini and Zenou, 2012; Bramoullé et al., 2014; Jackson and Zenou, 2015) where both *local-aggregate* and *local-average effects* are incorporated in (1). This utility function has been introduced by Liu et al. (2014) and is referred to as the *hybrid utility function*. Indeed, there are two endogenous network effects in (1). The first network term $\sum_{j=1}^n g_{ij} y_j y_i$ represents the *aggregate* effort of i's co-workers with the *social-multiplier* coefficient λ_1. As individuals may have different locations in the network, $\sum_{j=1}^n g_{ij} y_j y_i$ is heterogeneous in i even if every individual in the network chooses the same effort level. The second network

[7] In Section 3.2, we explain the definition of the co-worker networks in our data more precisely.

term $\left(y_i - \sum_{j=1}^{n} g_{ij}^{*} y_j\right)^2$ represents the cost due to deviation from the *social norm* of the reference group (i.e. the average effort of the peers) with the *social-conformity* coefficient λ_2. Thus, an individual's utility is positively affected by the total effort of her co-workers *and* negatively affected by the distance from the average effort of her co-workers. If $\lambda_1 = 0$, we obtain the *local-average model* since it is only the deviation from the *average of efforts of her peers* that *negatively* affects the utility of individual i, while, if $\lambda_2 = 0$, we have the *local-aggregate model* since it is only the *sum of the efforts of her peers* that *positively* affects the utility of individual i.

In (1), there is also an idiosyncratic exogenous part, $(a_i + \eta + \epsilon_i)\, y_i - \frac{1}{2}y_i^2$, where a_i represents the ex ante individual *observable* heterogeneity in the return to effort, ϵ_i captured the *unobservable* individual heterogeneity, η, the *network fixed effect*, and $-\frac{1}{2}y_i^2$ is a quadratic effort cost. To be more precise, a_i, the observable individual heterogeneity in productive ability, is assumed to be deterministic, perfectly observable by all individuals in the network, and corresponds to the observable characteristics of individual i (e.g. age, sex, participation in on-the-job training, etc.) and to the observable average characteristics of individual i's immediate co-workers. It can thus be written as:

$$a_i = \sum_{m=1}^{M} \beta_{1m} x_i^m + \frac{1}{g_i} \sum_{m=1}^{M} \sum_{j=1}^{n} \beta_{2m} g_{ij} x_j^m \tag{2}$$

where x_i^m belongs to a set of M variables accounting for observable differences in individual characteristics of individual i. β_{1m} and β_{2m} are parameters and $g_i = \sum_{j=1}^{n} g_{ij}$ constitute the total number of immediate co-workers of individual i.

2.2 Nash Equilibrium

We now characterize the Nash equilibrium of the game where agents choose their effort level $y_i \geq 0$ simultaneously. In equilibrium, each agent maximizes her utility (1). We obtain the following best-reply function for each $i = 1, ..., n$:[8]

$$y_i = \phi_1 \sum_{j=1}^{n} g_{ij} y_j + \phi_2 \sum_{j=1}^{n} g_{ij}^{*} y_j + \alpha_i \tag{3}$$

where $\phi_1 = \lambda_1 / (1 + \lambda_2)$, $\phi_2 = \lambda_2 / (1 + \lambda_2)$, and $\alpha_i = (a_i + \eta + \epsilon_i) / (1 + \lambda_2)$. As $\lambda_1 \geq 0$ and $\lambda_2 \geq 0$, we have $\phi_1 \geq 0$ and $0 \leq \phi_2 < 1$. The coefficient ϕ_1 is called the *local-aggregate* endogenous network effect. As $\phi_1 \geq 0$, this coefficient reflects *strategic complementarity* in efforts. The coefficient ϕ_2 is called the *local-average* endogenous network effect, which captures the *taste for conformity.* Note that, $\phi_1/\phi_2 = \lambda_1/\lambda_2$. That is, the relative magnitude of ϕ_1 and ϕ_2 is the same as the relative magnitude of the social-multiplier coefficient λ_1 and the social-conformity coefficient λ_2.

2.3 Key players

The concept of the key player in economics was introduced by Ballester et al. (2006) and was initially defined for criminal activities. The key player is the agent that should be targeted by the planner. Removing this agent generates the largest reduction in total activity. It has been tested empirically and applied to other activities than crime, such as financial networks, R&D networks, wars, etc. (see Zenou, 2016, for an overview of this literature). Here, the key player will be the worker that the firm would most like to retain because, if removed, total productivity will be reduced the most. In some sense, the key player(s) is (are) the critical worker(s) in a company.

[8] Denote by $g^{\max}$ the highest degree in the network, i.e. $g^{\max} = \max_i g_i$. Then, if $g^{\max}\phi_1 + \phi_2 < 1$, then the network game with payoffs (1) has a unique interior Nash equilibrium in pure strategies.

Formally, a *key player* is the agent whose removal from the network leads to the largest reduction in the aggregate effort level in a network. Let $\mathbf{M}(g, \phi_1, \phi_2) = (\mathbf{I} - \phi_1 \mathbf{G} - \phi_2 \mathbf{G}^*)^{-1}$, with its (i, j)-th entry denoted by $m_{ij}(g, \phi_1, \phi_2)$. Let

$$\mathbf{b}(g, \phi_1, \phi_2, \boldsymbol{\alpha}) = \mathbf{M}(g, \phi_1, \phi_2)\boldsymbol{\alpha}$$

with its i-th entry denoted by $b_i(g, \phi_1, \phi_2, \boldsymbol{\alpha}) = \sum_{j=1}^{n} m_{ij}(g, \phi_1, \phi_2)\alpha_j$. Let $B(g, \phi_1, \phi_2, \boldsymbol{\alpha}) = \sum_{i=1}^{n} b_i(g, \phi_1, \phi_2, \boldsymbol{\alpha}) = \mathbf{1}_n' \mathbf{M}(g, \phi_1, \phi_2)\boldsymbol{\alpha}$ denote the aggregate effort level in network g, where $\mathbf{1}_n$ is an $n \times 1$ vector of ones. Let $g^{[-i]}$ denote the network with agent i removed. Let $\mathbf{G}^{[-i]}$ and $\boldsymbol{\alpha}^{[-i]}$ denote the adjacency matrix and vector of covariates corresponding to the remaining agents in network $g^{[-i]}$. Then, the key player i^* in network g is given by $i^* = \arg\max_i d_i(g, \phi_1, \phi_2, \boldsymbol{\alpha})$, where

$$d_i(g, \phi_1, \phi_2, \boldsymbol{\alpha}) = B(g, \phi_1, \phi_2, \boldsymbol{\alpha}) - B(g^{[-i]}, \phi_1, \phi_2, \boldsymbol{\alpha}^{[-i]}). \tag{4}$$

The key player is the worker with the highest measure of *intercentrality*, $d_i()$.

Removing any worker from her co-worker network can change the total productivity of that network in four ways. Our measure of worker intercentrality, $d_i()$, quantifies these four effects. First, total productivity is lowered by the loss of the worker's own productivity. Thus, high productivity workers will (all else equal) tend to be more central workers. Second, removing a worker will change the structure of the network and may, therefore, change the total productivity of the network. This network structure effect will be particularly large when the worker inhabits a unique position in that network, such as a "bridge" position between two otherwise separated clusters of workers within the network. The existence of network structure effects requires that there exist meaningful endogenous network effects and that networks are not complete. Third, removing a worker may change the contextual effects faced by the remaining workers in important ways, e.g. if the worker has high tenure or is from an underrepresented sex. This contextual effect can be especially important when networks are not large. Fourth, the removing of a worker will generate spillover effects if ϕ_1 and/or ϕ_2 are greater than zero.

3 The Call Center Data

3.1 Institutional Setting

To study network effects, we use data from an in-house call center of a multi-national mobile network operator. The call center provides services for current and prospective customers and is divided into 5 departments, which are segmented by customer group. In this study, we use data from the largest department, which handles calls from private customers with fixed mobile phone contracts. Call center agents working in this department answer customer calls and make notes in their customer database for documentation.

Our data start in week 1/2008 and end in week 10/2010. The data contain information on 439 call center workers. Because we are missing important information on gender, age and tenure for 14 agents, we drop them from our sample. To create a panel, we also drop 9 workers whom we only observe once in our data. This leaves us with 416 workers and 14,070 worker-week observations.[9] On average, 124 agents work in this department each week.

All agents are placed in teams which are led by a team leader. The main purpose of grouping agents into teams is that it facilitates monitoring, evaluation, and coaching by the team leader. Teams are not specialized for specific types of calls, or specific customer groups. There are also no team-based incentives. We observe an average of 10 teams per week. Average team size is 12 workers.

Our panel data include weekly information on agents' individual performance. Workers' performance as well as other indicators are continuously, and automatically measured by the IT system of the call center. Throughout the sample period used in this paper, average handling time, i.e. the time an agent needs on average to handle a customer call, was used as

[9] We are also missing information on the age of an additional 29 workers. But instead of dropping them, we assign the mean age to them and create a dummy variable indicating that we are missing information about their age.

the main key performance indicator to evaluate agents. The management's aim is to reduce costs by reducing average handling time $aht_{i,t}$ without a loss in quality. We define worker performance as $y_{i,t} = \frac{100}{aht_{i,t}}$. A decrease in average handling time can thus be interpreted as an increase in worker performance. Team coaches receive weekly scorecards for each worker on this and other key performance indicators.

To study how networks affect performance in the workplace, we link these performance data to data on the exact time agents are present at their workplace. This information is gathered from the turnstiles where agents need to log in when entering and log out when leaving the call centre. Agents also need to log in and out when they have breaks. Since agents who belong to the same team sit next to each other while working, two agents who are present at the same time are exposed to each other. Thus, we will use team membership and overlap in hours worked to define links between co-workers and co-worker networks (more on this below).

The panel data consisting of performance and network information is complemented with information on agents' gender, age, tenure, the number of hours they work each weak, and the share of these weekly hours worked during peak hours (i.e. times during the week when the number of incoming customer calls is the largest). We know what day(s) of the week that they worked as well as the exact time of the day they work. Information on the overall work load (i.e. the volume of incoming calls) during a specific week is also available.

Descriptive statistics are shown in Table 1. Our estimation sample consists of 416 different workers and 14,070 worker$\times$week observations. Two-thirds of the workers are females. The average age of a worker is approximately 29 years old. Most workers work part-time (around 23 hours per week), on weekdays, during the midday shift. Worker performance $y_{i,t}$ varies quite substantially. One standard deviation is equal to 26% of the mean in average worker productivity (see the right hand panel of Table 1) and 31% of the mean productivity in our worker$\times$week panel (left hand panel of Table 1).

3.2 Defining Co-Worker Networks

Let us now describe how we define co-worker networks. As we saw above, most call agents are part-timers who work on average 23 hours per week. At the same time, the call centre is open during day time from Monday to Friday. All teams work on the same floor of the building. The physical workspace is organized into work islands, with up to eight agents. Agents who are part of the same team are sitting next to each other. There are two levels of co-worker interactions. First, each worker is assigned to a team. Then, each week, individuals work in shifts and interact with different persons within the team that they are allocated to.

To staff the call centre with the right amount of agents at any time, the scheduling department makes predictions about the number and types of customer calls *ex ante*. Based on these predictions, they infer the number of agents needed in a week, and for each 30-minute block of a day. This procedure allows for daily and hourly variation in customer demand. Four weeks ahead of their working week, call agents learn about their exact working hours.[10] These working hours also precisely state when agents can take breaks, e.g. for lunch.

We use the exact time when agents enter and leave the call centre to identify networks (which can, and will, be weighted by joint working hours between worker i and j). As a result, one can reconstruct the whole geometric structure of a co-worker network, which is summarized by the adjacency matrix $\mathbf{G}$. We define each network component r (henceforth network) such that all individuals belonging to a network are path-connected. We define time periods t as weeks to make the problem tractable.

Two employees are defined as co-workers if they both come from the same team τ and their work hours during week t overlap. In total, we have 114 weeks of data for 20 different teams. Over time, new teams are created and old teams are dissolved so that we observe roughly 10 teams each week. In total we observe 1,188 team by week networks. To keep the notation simple, we label networks by r, leaving the team and time aspect $r(\tau, t)$ implicit.

[10] Although agents are required to be available throughout the week, they can mention preferences when they would like to work. Depending on availability of other agents, agents may request to changing their slot.

As in Section 2, we first define an unweighted adjacency matrix $\mathbf{G}_r$, where each cell $g_{ij,r} \in \{0,1\}$ keeps track of whether team members i and j have worked together during week t or not. We can also define matrix $\mathbf{G}_r^*$, which is the row-normalized matrix of $\mathbf{G}_r$ where each cell $g_{ij,r}^* = g_{ij,r}/g_{i,r} \in [0,1]$, where $g_{i,r} = \sum_j g_{ij,r}$ is the total number of team members individual i has worked with during week t. We also define a matrix $\mathbf{H}_r$, in which each cell $h_{ij,r} \geq 0$ keeps tract of the number of hours team members i and j have worked together during week t. The weighted adjacency matrix $\mathbf{H}_r^w$ is such that each cell $h_{ij,r}^w = h_{ij,r}/h_{i,r}$, where $h_{i,r} = \max[h_{ij,r}]$. This normalizes the weights so that the weight on the link between worker i and the co-worker j that she works the most with is equal to one.

To illustrate this, consider the following network g_r as shown in Figure 1. There are three agents i in team τ. Agent 1 holds a central position whereas agents 2 and 3 are peripherals.

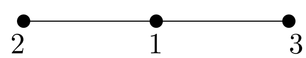

Figure 1: A network of 3 agents

The unweighted adjacency matrix $\mathbf{G}_r$ for this network is:

$$\mathbf{G}_r = \begin{pmatrix} 0 & 1 & 1 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix}$$

This means that, during the week t for which the network is observed, agents 1 and 2 as well as agents 1 and 3 have worked together while agents 2 and 3 have not. We can also define $\mathbf{G}_r^*$, which is the *row-normalized matrix* of $\mathbf{G}_r$ and defined as:

$$\mathbf{G}_r^* = \begin{pmatrix} 0 & 1/2 & 1/2 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix}$$

so that $g^*_{ij,r} = g_{ij,r}/g_{i,r} \in [0,1]$, where $g_{i,r} = \sum_j g_{ij,r}$ is the total number of persons individual i has worked with during week t.

Imagine that, during week t, agents 1 and 2 have worked 6 hours together while agents 1 and 3 have worked 10 hours together. We have:

$$\mathbf{H}_r = \begin{pmatrix} 0 & 6 & 10 \\ 6 & 0 & 0 \\ 10 & 0 & 0 \end{pmatrix}$$

Each link is given a weight by dividing through by the maximum value in each row. This means that we wait each link relative to the strongest link and the strongest link is normalized to 1. The weighted adjacency matrix $\mathbf{H}_r^w$ is given by:

$$\mathbf{H}_r^w = \begin{pmatrix} 0 & 6/10 & 10/10 \\ 6/6 & 0 & 0 \\ 10/10 & 0 & 0 \end{pmatrix} = \begin{pmatrix} 0 & 0.6 & 1 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix}$$

The row-normalized and weighted adjacency matrix $\mathbf{H}_r^{w*}$ is given by:

$$\mathbf{H}_r^{w*} = \begin{pmatrix} 0 & 0.6/1.6 & 1/1.6 \\ 1/1 & 0 & 0 \\ 1/1 & 0 & 0 \end{pmatrix} = \begin{pmatrix} 0 & 0.375 & 0.625 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix}$$

The weighted matrices reflect the fact that worker 1 works 2/3 more hours with worker 3 than she does with worker 2. Henceforth, we drop the superscript w and refer to our weighted adjacency matrix as $\mathbf{H}_r$ and our row-normalized weighted adjacency matrix as $\mathbf{H}_r^*$.[11]

Let $\overline{r}(\tau, t)$ be the total number of networks in the sample, n_r the number of individuals in the rth network, and $n = \sum_{r=1}^{r=\overline{r}} n_r$ the total number of sample observations. In our full

[11] Observe that all the results obtained in Section 2 hold true if we use the matrices $\mathbf{H}$ and $\mathbf{H}^*$ in (3) instead of $\mathbf{G}$ and $\mathbf{G}^*$.

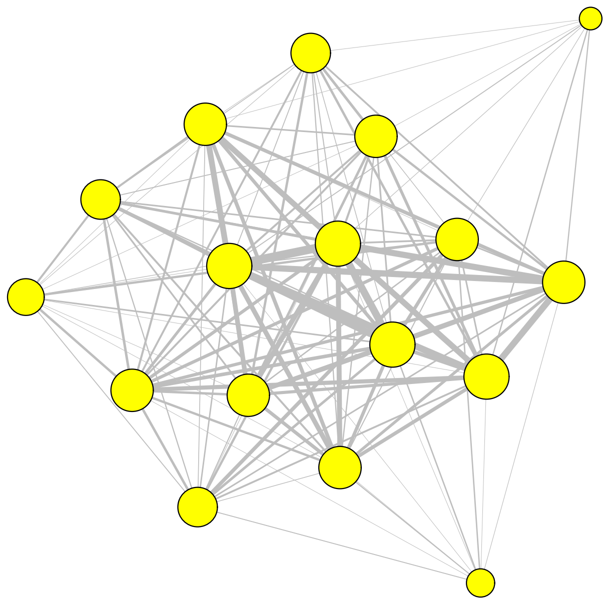

Figure 2: A real-world co-worker network.

dataset, n = 14,070 and $\overline{r}(\tau, t)$ = 1,188. The minimum network size is one. The average network size is 12. The median size is 13 and the maximum is 36.

In Figure 2, we plot the graph of one such (randomly chosen) co-worker network. In this week, 17 workers work together as a team. Each node represents a worker. The size of the node reflects how many co-workers from the same team a worker has worked on the same shift with during that particular week. The thickness of the lines represents the number of hours each pair of workers worked side by side during this particular week. This network is not complete. All workers are not directly connected to each other. Note also that there are large differences in the amount of time each pair of workers is exposed to each other.

4 Peer Effects in Worker Productivity

We now want to estimate the best reply function of workers given by Equation (3) where we replace the matrices $\mathbf{G}$ and $\mathbf{G}^*$ by $\mathbf{H}$ and $\mathbf{H}^*$ and add the subscript r to all variables to indicate which network each individual belongs to. We want to see if $y_{i,r}$, the productivity of individual i belonging to network r (measured by the average time needed to handle inbound customer calls), is positively influenced by the productivity of the team members who work the same shift as individual i during the week weighted by the number of hours worked together during that week. This is the endogenous network (peer) effect. We also want to know if the exogenous characteristics of a worker's co-workers can make her more or less productive. These are known as exogenous network (peer) effects.

The econometric model corresponding to the best-reply function (3) of agent i belonging to network $r(\tau, t)$ can be written as:[12]

$$y_{i,r} = \phi_1 \sum_{j=1}^{n} h_{ij,r}\, y_{j,r} + \phi_2 \sum_{j=1}^{n} h^*_{ij,r}\, y_{j,r} + \sum_{m=1}^{M} \beta_{1m} x^m_{i,r} + \sum_{m=1}^{M} \sum_{j=1}^{n} \beta_{2m} h^*_{ij,r} x^m_{j,r} + \epsilon_i + \tau + t + \varepsilon_{i,r}. \quad (5)$$

Parameters ϕ_1 and ϕ_2 represent the local aggregate and the local average endogenous network effects (respectively); β_{2m} represent the exogenous network effects; $\varepsilon_{i,r}$ represents i.i.d. innovations with zero mean and variance σ^2 for all i and r. The characteristics $x^m_{i,r}$ and $x^m_{j,r}$ are gender, age, tenure, total work hours during the week, share of peak hours worked, day(s) of the week worked and the time of the day worked (morning, midday, evening). Inference will be made using standard errors that are clustered on individual workers.

4.1 Threats to Identification

It is well-known that when estimating peer effects using linear-in-means model endogenous peer effects (ϕ_1 and ϕ_2) and contextual effects (β_{2m}) cannot always be separately identified due to the *reflection problem* (Manski 1993). When individuals are influenced by the

[12] Where, as stated above, we replace the matrices $\mathbf{G}$ and $\mathbf{G}^*$ by $\mathbf{H}$ and $\mathbf{H}^*$. Subsequently, we suppress the subscript t to simplify notation.

members of their own group, but not by individuals outside their group, there arises a simultaneity in the behavior of individuals within the group that introduces a perfect collinearity between the endogenous peer effect and the contextual effects. In this very special case, one cannot disentangle these two effects.

Using the terminology of social networks, the reflection problem arises when networks are complete. That is, when all agents are connected to (and influenced by) all other agents in the network. However, most networks (such as those studied in this paper) are not complete; everyone is not connected to everyone else. Bramoullé et al. (2009), Lee et al. (2010), Liu and Lee (2010), Liu et al. (2012), Patacchini et al. (2017) and others have shown us how the architecture of social networks can be used to identify endogenous peer effects.[13] Loosely speaking, endogenous peer effects and exogenous contextual effects are identified if at least two individuals in the same network have different links (Bramoullé et al., 2009). This condition is generally satisfied in any real-world network. In practice, a priori knowledge of $\mathbf{H}_r$ and $\mathbf{H}_r^*$ provides us with a set of restrictions on the coefficients in the reduced form equation that are used to identify the structural model.

While our network approach does allow us to separately identify endogenous effects and contextual effects, it does not necessarily identify the causal effect of peers' influence on individual behavior. In our context, we face three sources of potential bias arising from (i) *correlated effects*, (ii) *endogenous network formation* (non-random sorting), and (iii) *simultaneity bias*.

Individuals within the same network who share the same environment and face the same set of incentives and/or shocks are likely to behave in a similar manner. We control for these types of correlated effects by adding team and week fixed effects. Team members share the same physical environment and answer to the same team leader who may have her own personal management style, may be more or less experienced, etc. Shift members may share typical workloads and/or shift-specific shocks. We, therefore, control for week fixed effects and also for the day(s) of the week worked and the time of day worked (morning, midday,

[13] See Blume et al. (2011 and 2015), Graham (2015) and Boucher and Fortin (2016) for recent overviews of the literature on the identification of social interactions and for a set of original contributions on the topic.

evening). Recall also that we control for the share of a worker's hours that are worked during peak work hours. These controls should deal with correlated effects.

Unlike the networks in most applications, our networks are not formed by individuals who self-select into them. Workers do choose to work for the firm and they also state the shifts that they would be willing and able to work. For example, homemakers may want to work in the middle of the day, while students may only be available evenings and weekends. But it is the firm that places these workers into teams and sets the weekly work schedule.

The firm, however, clearly has the power to place like with like if they so desire. The firm could choose to place all homemakers into one team and all students into another. They could also choose to take workers' requests to work together into account when forming teams if they thought it to be in the best interests of the firm. If teams are formed through a process of assortative matching, then we would find ourselves in a situation with endogenous network formation. This would result in a positive bias to our estimated peer effect, since similar people would be placed into the same groups and are likely to have positively correlated outcomes even in the absence of true peer effects.

We have four explicit ways of dealing with the potential issue of endogenous team and shift formation (i.e. network formation). First, we control for the observable characteristics of co-workers, $\sum_{m=1}^{M}\sum_{j=1}^{n}\beta_{2m}h^{*}_{ij,r}x^{m}_{j,r}$. Second, we control for both team and week fixed effects. Third, we control for both observable, $\sum_{m=1}^{M}\beta_{1m}x^{m}_{i,r}$, and unobservable, ϵ_i, characteristics of each individual worker using an important set of observables controls and individual fixed effects. Fourth, we rely on our exogenous exposure matrices $\mathbf{H}$ and $\mathbf{H}^{*}$ to provide exogenous variation in co-worker productivity. We are not using the stable part of the co-worker network (that is potentially endogenous) to identify network effects. We are identifying network effects off of changes in the dose of co-worker productivity that each individual worker faces from week to week due to non-systematic changes in the make-up her network of co-workers.

There is a considerable amount of week-to-week variation in the dose of co-worker productivity that each worker is exposed to even after controlling for team, week, and individual fixed effects. The standard deviation of the residualized variation in $\mathbf{H}y$ is 0.86, while the mean of $\mathbf{H}y$ is 2.14. The standard deviation of the residualized variation in $\mathbf{H}^*y$ is 0.07. The mean of $\mathbf{H}^*y$ is 0.34.

Lastly, in order to deal with potential simultaneity bias, we adopt Bramoullé et al.'s (2009) "friend-of-friend" instrumental variable strategy. Under the assumption that $\mathbf{H}_r^*$ is conditionally exogenous, they show how $\mathbf{H}_r^*\mathbf{H}_r^*x_{j,r}$ can be used as valid instruments for the endogenous variable $\mathbf{H}_r^*y_{j,r}$ in the local-average model. Liu et al. (2012) show that $\mathbf{H}_r^*\mathbf{H}_r^*x_{j,r}$ can also be used as valid instruments for the endogenous variable in the local-aggregate model, $\mathbf{H}_r y_{j,r}$. They also demonstrate the validity of additional instruments for $\mathbf{H}_r y_{j,r}$, such as $\mathbf{H}_r\mathbf{H}_r^*x_{j,r}$ and the number of links, $\mathbf{HL}$.

4.2 Diagnostic Test of Identifying Assumption

Our main identifying assumption is that the within-worker, -team and -week variation in co-worker networks is essentially random, i.e. that $\mathbf{H}_r$ and $\mathbf{H}_r^*$ are conditionally exogenous after controlling for worker, week and team fixed effects. Our argument is that this variation is as good as random since it is based on variation in the overlap of hours worked (shifts) within teams of co-workers, due to non-systematic events (e.g. idiosyncratic changes in availability, own illness, sick children, holidays, school schedule changes – affecting both mothers with school children and college students, exam periods, school holidays, etc.) and due to new hires and quits (i.e. co-worker turnover). If this assumption holds, then we should see no correlation between this variation and the average observable characteristics of a worker's peers. Nor should we be able to detect any correlation between a worker's own observable characteristics and her co-workers' characteristics after controlling for worker, team and week fixed effects.

But before we test this assumption, we would like to examine whether or not we actually see evidence of non-random link formation between co-workers in networks. To do this, we estimate a logistic model of link formation using the variables age, gender and tenure as covariates. What we find is that men only have a 0.05 higher odds of linking with another man (as opposed to linking with a woman) and that people aged +/- 5 years apart only have a 0.04 higher odds of being linked with each other.[14] In contrast to these very small amounts of non-randomness, we see that people with similar tenure (+/− 12 weeks) have a 2.6 higher odds of being linked with each other.

What we see in the data is that firms tend to hire more than one new person at a time. These new people tend to be placed in the same team (or teams) for training and then stay closely linked to each other for many months to come. Thus, links are significantly non-random in tenure. Since productivity is strongly increasing in tenure (we show this below), those who are linked together will tend to have correlated productivities generated by this correlation in tenure. It is exactly this type of threat to identification that we need to be wary of and motivates our use of control variables together with the use of individual, team and week fixed effects.

Thus, a test of our main identifying assumption must demonstrate that variation in $\mathbf{H}_r$ and $\mathbf{H}_r^*$ is unrelated with average co-worker characteristics (age, gender and, in particular, tenure) after conditioning on our set of fixed effects. We run several versions of this basic test.

In our first test, we use age, tenure and gender along with individual, team and week fixed effects to predict work productivity, $\widehat{y}$. We then regress this measure (or index) of the productive characteristics of workers on to our two measures of endogenous network effects: the local-aggregate network effect $\sum_{j=1}^{n} h_{ij,r}\, y_{j,r}$ and the local-average network effect $\sum_{j=1}^{n} h_{ij,r}^{*}\, y_{j,r}$ In Panel A of Table 2, we see that our index of worker characteristics, $\widehat{y}$, is correlated with our two measures of endogenous network effects. However, in Panel B, we see that these correlations completely disappear when we include individual, team and week fixed effects. This result speaks in favor of the conditional exogeneity of $\mathbf{H}_r$ and $\mathbf{H}_r^*$ and of our main identifying assumption.

In Column (2) of Table 2, we relate our index of worker characteristics, $\widehat{y}$, to the average observable characteristics of her co-workers, $\sum_{m=1}^{M}\sum_{j=1}^{n}\beta_{2m}h_{ij,r}^{*}x_{j,r}^{m}$. Once again, we see that

[14]Note that 0.05 and 0.04 are extremely small values of assortative matching relative to what is typically seen in the literature (e.g. Currarini et al., 2010).

the correlations that appear to exist (see Panel A) disappear once we include individual, team and week fixed effects (see Panel B).

In a similar fashion, we can test whether or not the number of predicted (weighted) links an individual has, $\sum_{j=1}^{n} \widehat{h_{ij,r}}\, \mathbf{1}_{j,r}$, is related to the average observable characteristics of her co-workers. We also test to see if the predicted values of our two measures of endogenous network effects, $\sum_{j=1}^{n} \widehat{h_{ij,r}}\, y_{j,r}$ and $\sum_{j=1}^{n} \widehat{h_{ij,r}^{*}}\, y_{j,r}$, are correlated with the average observable characteristics of a worker's co-workers. In Panel B of Table 2, we clearly see that the variation in co-worker productivity that is used to identify a causal network effect is uncorrelated with the average characteristics of co-workers within networks after conditioning on individual, team and week fixed effects. Once again, these results all speak in favor of our main identifying assumption.

4.3 Results

Estimation results of Equation (5) are reported in Table 3. We begin, in Column (1), by reporting the raw associations between our two different network effects and contemporaneous worker productivity. The local average network effect has a strong positive association with worker productivity equal to 0.54 (0.035), while the local aggregate network effect has a negative and insignificant association -0.002 (0.002). After including individual, team and week fixed effects in Column (2), the large positive association between the average network effect and worker productivity is reduced to 0.203 (0.057), while the local aggregate effect becomes more negative. In Column (3), we add controls for individual characteristics, including day of the week dummies and dummies for working in the morning, midday and/or evening. We also include average co-worker characteristics. Recall that these represent contextual network effects. These additional controls reduce the estimate of the local-aggregate network effect and render it insignificant. Our estimate of the local-average effect, on the other hand, is only slightly reduced. It is now equal to 0.179 (0.059).

From these initial exercises we conclude that the local-average network model fits the data better than the local-aggregate model does. This is our first empirical finding. According to our structural model, this result implies that a worker's current productivity is affected by her co-workers' current productivity through her desire to conform to the local work norm and not through strategic complementarities. In Column (4) of Table 3, we present the model of worker productivity, which includes the local-average network effect only.[15]

In Column (5), we provide our instrumental variable results using $\mathbf{H}_r^* \mathbf{H}_r^* tenure_{j,r}$ as an instrument for the local-average network effect, $\mathbf{H}_r^* y_{j,r}$. Recall that all $\mathbf{H}_r^* \mathbf{H}_r^* x_{j,r}$ are valid instruments. But in our regressions, we see that $\mathbf{H}_r^* tenure_{j,r}$ is a strong predictor of $y_{i,r}$, which, in turn, makes $\mathbf{H}_r^* \mathbf{H}_r^* tenure_{j,r}$ a highly relevant instrument with an F-stat of 27.

Our new IV estimate of 0.13 (0.17) implies that a 10% increase in average co-worker productivity produces a 1.3% increase in a worker's own productivity. This is an economically meaningful effect and is quite similar to the effects reported in previous studies by Falk and Ichino (2006) and Mas and Moretti (2009). These earlier studies report effects of 1.4% and 1.5%, respectively. Importantly, both of these studies also present evidence that these productivity spillovers are driven by social norms.

However, unlike these previous studies, our IV estimate is very imprecise. When moving from the OLS estimate to the IV estimate the point estimate drops by 28% (due to the elimination of any existing simultaneity bias). But the standard errors are three times larger. As such, one should interpret this estimate with caution.

A second important finding is that there is also a strong contextual network effect. The average tenure of a worker's co-workers, $\mathbf{H}_r^* tenure_{j,r}$, affects her contemporaneous productivity even after controlling for their average productivity, $\mathbf{H}_r^* y_{j,r}$. A 10% increase in the average tenure of worker i's co-workers leads to a 0.2% increase in her contemporaneous productivity, $y_{i,r}$.

What explains this exogenous peer effect? Do workers become more productive because they are learning from their more tenured peers? Are they being aided by their more tenured peers? Or is it that they feel more strongly monitored when working with more tenured colleagues? Since, our model allows us to separately identify exogenous from endogenous

[15]When we estimate the model including the local-aggregate effect only, it is still not significant. In the local-aggregate model, the aggregate network effect is equal to 0.002 (0.0018).

effects, and since the endogenous effect does not change if we exclude $\mathbf{H}_r^* tenure_{j,r}$, we are inclined to interpret this exogenous effect as a form of positive knowledge spillover from high to low tenure workers.

5 Peer Effects in Worker Productivity from On-the-Job Training

In 2008, the firm decided to introduce a new on-the-job training program. To asses the effectiveness of this new program, it was first introduced in the form of a randomized experiment. De Grip and Sauermann (2012) designed and evaluated this training experiment and found that it raised worker productivity by 8.8%. Interestingly, they also provide evidence of potential spillover effects from one group of recently trained workers to another group of their (as yet) untrained teammates. Our goal here, is to model these potential spillover effects from on-the-job training (OJT) more formally in our network model of worker productivity. We include them as an additional exogenous (contextual) network effect.

The training program took place over the course of 27 weeks, starting in week 10/2009. The training took place in an in-house training center and consisted of 10 half-day sessions that were held from Monday to Friday. Half of these sessions contained group discussions led by the training coach and the team leader. These discussions were about which skills the agents were missing when executing their task, how these could be improved, and *how agents could help each other on the work floor*. Agents were also trained in conversational techniques designed to decrease average handling time. During the other half of the sessions, agents handled incoming customer calls that were routed to the training center. Training coaches and team leaders assisted these calls and gave feedback.

In our next regression exercise, we incorporate on-the-job training (OJT) and spillover effects from OJT into our network model of worker productivity. When estimating this extended model, we use data for all weeks and all persons who were trained in this program, i.e. we include those trained during the experimental phase of the program and those who were trained during the role out phase of this program that occurred after the original field experiment was complete.[16]

We include OJT as an exogenous contextual effect. We are agnostic about the functional form that this effect should have and, instead, include both the local-aggregate, $\sum_{j=1}^{n} h_{ij,r} ojt_{j,r}$, and the local-average, $\sum_{j=1}^{n} h^{*}_{ij,r} ojt_{j,r}$, contextual effect.

$$y_{i,r} = \gamma_1 ojt_{i,r} + \gamma_2 \sum_{j=1}^{n} h_{ij,r}\, ojt_{j,r} + \gamma_3 \sum_{j=1}^{n} h^{*}_{ij,r}\, ojt_{j,r} + \\ \phi_2 \sum_{j=1}^{n} h^{*}_{ij,r}\, y_{j,r} + \sum_{m=1}^{M} \beta_{1m} x^{m}_{i,r} + \sum_{m=1}^{M} \sum_{j=1}^{n} \beta_{2m} h^{*}_{ij,r} x^{m}_{j,r} + \epsilon_i + \tau + t + \varepsilon_{i,r}. \quad (6)$$

Estimation results are reported in Table 4. Column (1) of Table 4, simply repeats our previous estimates from Column (5) of Table 3; i.e the estimates from our network model without OJT. Column (2) includes OJT. Our results both replicate and extend those reported in De Grip and Sauermann (2012).

In the first week after training, *post training*$_{t=1,i,r}$, we see a drop in the productivity of trained workers. This was also noted by De Grip and Sauermann (2012). This is followed by a seven week period of higher productivity, *post training*$_{t=2-8,i,r}$, resulting from the on-the-job training program. Importantly, we also see a significant exogenous peer effect working through the aggregate number of trained co-workers (and hours) that a worker is exposed to, but not the average. Nor is the average significant when it is entered on its own (see Column (3)). Trained workers return to their teams and are able to pass on a portion of their new skills to their teammates (in fact, this element of "teaching" may be one reason why we observe a one week dip in own productivity in the week after they receive training).

Column (4) in Table 4, presents the estimates form our preferred empirical model. We observe three important network (peer) effects; one endogenous network effect and two exogenous network effects.

[16]The data used in De Grip and Sauermann (2012) are a small subset of the data used here.

First, a 10% increase in the average productivity of a worker's co-workers raises her own productivity by 1.2%. In our structural model this local average effect is due to a desire to conform to the contemporaneous work pace set by a worker's current set of co-workers. This endogenous effect is slightly smaller than our previous estimate from Column (5) of Table 3, and those reported by Falk and Ichino (2006) and Mas and Moretti (2009); but similar in nature (i.e. it represents a response to the contemporaneous work norm).

Second, we observe that a 10% increase in exposure to trained co-workers increases a worker's contemporaneous productivity by 0.2%. We argue here that this is exogenous network effect is due to a learning (or aiding) effect.[17] The source of this new productivity comes from a specific on-the-job training program that was implemented in the firm. The aim of the program was to raise worker productivity by learning new techniques to help customers more efficiently. One explicit goal of the training was how agents could help their peers on the work floor.

Third, as mentioned in the previous section, working with higher tenure co-workers also raises a worker's current productivity. In fact, a 10% increase in the average tenure of a worker's co-workers raises her current productivity by 0.3%. Here, there may be two factors at play. More tenured workers can more readily aide and teach less senior co-workers. But it may also be that junior colleagues feel that they are being more heavily monitored. However, we are inclined to interpret this effect as a learning effect, since excluding this variable does not change our estimate of the endogenous network effect (which itself represents the effect of workers adhering to a contemporaneous work norm).

[17] By "aiding", we simply mean that a worker can turn to one of her trained co-workers for help with an immediate question and/or problem. This works the same as Battiston et al.'s face-to-face communication.

6 Personnel Policy as Seen Through the Lens of Our Network Model

In this section, we demonstrate how our network model of worker productivity can be put to use to inform personnel policy and to increase firm productivity. We start by asking our model three questions. Who should the firm strive to retain? Who should the firm let go? Who should the firm train? We contrast our answers to the answers from a standard model of worker productivity *without* network effects. We then continue with a brief discussion of the implications of our model for the design of shift schedules and work teams.

6.1 Worker retention and dismissal: Who are the key workers?

Imagine that we ask a personnel manager to pick out 10 workers that she feels the company should work the hardest to retain. One reasonable strategy would be to pick out the 10 workers with the highest observable *own* productivities. In contrast to this, our model-based strategy would instead pick out the 10 workers with the highest average *intercentrality measures*. These are our key workers. These are the workers who generate the largest overall productivity gains for the firm according to our model.

Recall that our measure of intercentrality (defined by Equation (7)) positively depends on a worker's own productivity. But it also depends on the network effects that this worker generates. There are two sources of spillover effects in our local average model.[18] There are contextual peer effects and endogenous peer effects. The size of these effects depend not only on workers' own characteristics (including own productivity), but also on the unique position in the structure of the network occupied by each worker.

After picking our 10 key workers, we compare them to the 10 most individually productive workers chosen by the firm's personnel manager. Although we do see a correlation between our measure of intercentrality and individual productivity (0.37), there are only 2 workers that are on both of our lists. According to our measure of intercentrality, the

[18] Our focus here is on the model presented in Column (5) of Table 3.

total productivity loss incurred by losing our 10 key workers is 170% larger than the loss incurred by the 10 workers picked using the naive strategy based solely on a worker's own productivity. In other words, our 10 key workers have a much higher overall value to the firm than the 10 workers with the highest average individual productivity.

But how can there be such a large difference? Who are these key workers?

In Table 5, we regress our measure of intercentrality onto a number of individual characteristics to see how they correlate. We standardize all of the variables, except for our indicator for *male*. We also include a new variable, *degree*, which gives the degree centrality of each worker.[19] Clearly, key workers are identified by their tenure. It is the large exogenous peer effect generated by the average tenure of a worker's co-workers that matters most in our model. In Column (1) of Table 5, we see that having a one standard deviation higher than average tenure generates a 0.97 standard deviation in one's measure of intercentrality. Interestingly, in Column (2) we see that high intercentrality workers are both well connected (high degree) and have high tenure. These workers generate the largest productivity spillover effects. According to our model, these are the key workers that the firm should strive to retain.

The average productivity of the 10 most productive workers is 0.51. They have (on average) 3.1 years of tenure. The average productivity of the 10 workers with the highest intercentrality measure is 0.40. They have (on average) 11.2 years of tenure. Given the average productivity in our data of 0.31 (see Table 1), we are not picking out low productivity workers, but rather high tenure workers among those with above average productivity.

If we are, instead, forced to layoff 10 workers, and we want to minimize the aggregate productivity loss associated with these dismissals, then the firm should layoff the 10 workers with the lowest measures of intercentrality and not necessarily those with the lowest own productivity. According to our model, firing the 10 workers with the lowest average productivity leads to a productivity loss that is 21% larger than the loss that would be incurred if the firm had instead laid off the 10 workers with the lowest average measures of intercentrality.

[19]Degree centrality is the number of direct links of distance one that a worker has to her co-workers.

6.2 Which workers should be trained?

Our measure of intercentrality (given by Equation (7)) allows us to identify individuals who lead to the largest drop in firm productivity if permanently removed from the firm. These are our key workers. On the-job training (OJT), however, is a very different type of policy. The goal of OJT is to raise a worker's productivity and then place this worker back into the job or position in the network that she occupied before being trained. Training alters this worker's productivity, but not her other personal characteristics and, hence, there are no changes in contextual effects other than those related to the fact that she has received OJT. Training worker j affects j's own productivity, $\gamma_1 ojt_{j,r}$, and it alters the exogenous contextual effect, $\gamma_2 \sum_{j=1}^{n} h_{ij,r} ojt_{j,r}$, faced by worker i.

Furthermore, training does not alter the structure of the network. We must, therefore, adapt our measure of intercentrality so that it measures an individual worker's impact on total productivity via the local average endogenous effect, $\mathbf{H}_r^* y_{j,r}$, and the local aggregate contextual effect, $\mathbf{H}_r trained_{j,r}$, that we see in Column (4) of Table 4, while (at the same time) shutting down other contextual effects. The size of this spillover effect will depend on each worker's unique position in her co-worker network. People who generate large spillovers are the ones that the firm should train.[20]

We adapt our measure of intercentrality accordingly. First, we assume that all workers have been trained. Then we use the parameter estimates from Column (4) in Table 4 to calculate the total bonacich in each network, $B(g, \phi_2, \boldsymbol{\alpha})$, where $\boldsymbol{\alpha}$ now includes two additional terms, $\gamma_1 ojt_{i,r}$ and $\gamma_2 \sum_{j=1}^{n} h_{ij,r} ojt_{j,r}$. We call this new term $\boldsymbol{\alpha}_{train}$. We then set agent i's training to zero and calculate the subsequent loss in aggregate productivity:

$$d_{i,train}(g, \phi_2, \boldsymbol{\alpha}_{train}) = B(g, \phi_2, \boldsymbol{\alpha}_{train}) - B(g, \phi_2, \boldsymbol{\alpha}_{train}^{[train_i=0]}). \qquad (7)$$

[20] Alternatively, the firm can redesign the structure of co-workers in such a way so that the network structure itself generates the largest aggregate spillover effect (more on this below).

Workers with high $d_{i,train}$ are the ones that our network model tells us that the firm should train.[21]

Between week 50/2008 and week 36/2009, the firm picked out 88 workers to be trained. We choose 88 workers using our index of training intercentrality. The overlap in these two lists is not large; only 26 people are on both. According to our model, the productivity gain from training our 88 workers is 70% larger than the productivity gain achieved when training the 88 workers chosen by the firm. This additional productivity gain is due to the additional spillover effects that are generated by training workers who occupy important positions in their co-worker networks. Training these people maximizes spillover effects.

6.3 Optimal network design

In the *local average model*, the optimal network structure (from a worker's perspective) is the empty network.[22] This, however, is not allowed by the firm. The second-best, again from the worker's perpective, would be to have a small network in which a single worker can influence average productivity. Employers, on the other hand, may want to have larger teams in order to rationalize organization and monitoring. In the local average model, employers have no incentive to manipulate the structure of the network given a fixed productivity level. They will, however, have incentives to try and maximize average productivity across networks, perhaps by moving key workers to new teams.

The optimal network in the *local aggregate model* is either the complete network or a nested split graph (König et al., 2016; Billand et al., 2015; Belhaj et al., 2016).[23] Once again, such an extreme result is not likely to be of any practical use to the firm.

[21] In our model, returns to training are homogeneous. Hence, the firm can focus on the spillover effect only and ignore the direct effect that training has on a worker's own productivity. In a world with heterogeneous returns to training, the firm would also need to consider which workers have the most to gain from training.

[22] Indeed, for the local-average model, the utility function is given by (1) for which $\lambda_1 = 0$. Since social interactions with others only involve a cost (the cost of conforming to the norm), it should be clear that the optimal network that maximizes the sum of the utilities of all workers is the empty network.

[23] A nested split graph is a hierarchical structure such that the neighborhood of an agent with low centrality is a subset of the neighborhood of another agent with higher centrality, i.e. neighborhoods are nested. See König et al. (2014) for a precise definition.

There are no such analytical results available for a hybrid model (that includes both average and aggregate network effects). Instead, there is a built-in tension between the complete network and the empty network, subject to the constraints of the firm (e.g. total hours worked, the timing of customer demand, etc.). The optimal network structure in the hybrid model will have some "smoothing" properties (network effects spread more rapidly in more complete networks) and workers who work more than one shift during the day will play an important role. These "bridge" workers are necessary to facilitate the spread of network effects across shifts (Burt, 1992). More generally, larger more well connected networks should dominate, but the optimal size and degree of connectedness should fall well short of the complete network.

To illustrate these ideas, we run several descriptive regressions at the network level using our local average model (shown in Column (5) of Table 3). First, we examine the role played by network connectedness as measured by the average betweenness centrality of a co-worker network.[24] We do this by regressing the average betweenness of our networks onto the predicted productivity of each network, using the estimates from our local average model. A 10% increase in the average betweenness of a network is associated with nearly a 1% higher average predicted productivity.

We also examine the optimal network size. We do this by regressing average network productivity from our local average model onto a quadratic function of network size. The resulting function is presented in Figure 3. Currently, the mean network size is 12, while the optimal network size is 16. Increasing the mean network size by four individuals is associated with an increase in average network productivity of 8.6%.

Our policy conclusions concerning the optimal structure of co-worker networks can be summarized as follows: (i) the firm should increase team size, (ii) the firm should increase the average betweenness in each network, and (iii) the firm should spread out high tenure workers in order to increase other workers' exposure to them.

[24]The betweenness centrality of a given worker is equal to the number of shortest paths between all pairs of workers that pass through the given agent. In other words, a worker is central if she lies on several shortest paths among other pairs of workers. See Jackson (2008) for definitions and discussions of the different centrality measures.

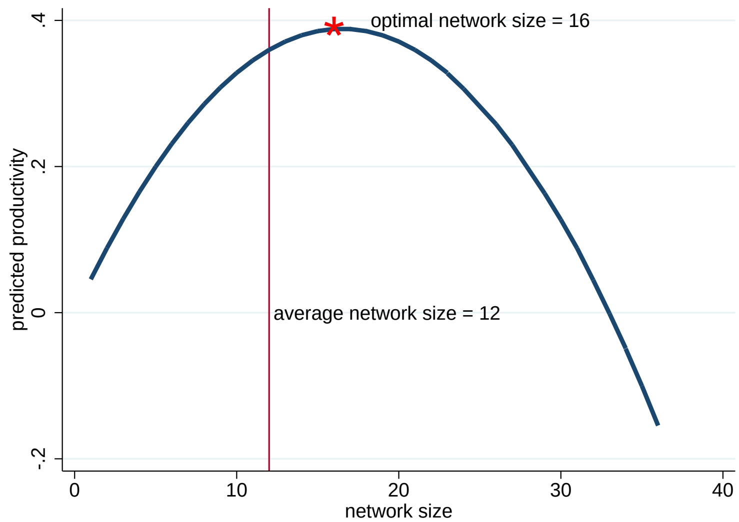

Figure 3: Optimal network size.

7 Conclusion

We present evidence that co-workers can exert economically significant effects on their peers through network effects. A 10% increase in the current productivity of a worker's co-worker network leads to a 1.3% increase in own current productivity. We attribute this endogenous peer effect to conformist behavior.

We also find evidence of two important exogenous (contextual) peer effects. First, a 10% increase in the average tenure of a worker's co-worker network increases her own productivity by 0.3%. In our policy experiments, we saw that the key workers in the firm tended to be well connected high tenure workers. Second, we saw significant spillover effects from on-the-job training. A 10% increase in the number of trained co-workers increases own productivity by 0.2%.

The existence of peer effects in the workplace affects the answer to a wide variety of policy questions faced by personnel managers on a daily basis. Our hope is that the literature on social networks will expand more vigorously into the field of personnel economics; a field that we believe is particular suited for network methods and models.

References

[1] Azoulay, P., Graff Zivin, J. and J. Wang (2010) "Superstar extinction," *Quarterly Journal of Economics* 125, 549-589.

[2] Babcock, P.S., Bedard, K., Charness, G., Hartman, J.L. and H. Royer (2015), "Letting down the team? Social effects of team incentives," *Journal of the European Economic Association* 13, 841-870.

[3] Ballester, C., Calvó-Armengol, A. and Y. Zenou (2006), "Who's who in networks. Wanted: The key player," *Econometrica* 74, 1403-1417.

[4] Ballester, C., Calvó-Armengol, A. and Y. Zenou (2010), "Delinquent networks," *Journal of the European Economic Association* 8, 34-61.

[5] Bandiera, O., Barankay, I. and I. Rasul (2010), "Social incentives in the workplace," *Review of Economic Studies* 77, 417-459.

[6] Battiston, D. Blanes i Vidal, J. and T. Kirchmaier (2017), "Is distance dead? Face-to-face communication and productivity in teams, " CEP Discussion Papers No. 1473.

[7] Bayer, P., Hjalmarsson, R. and D. Pozen (2009), "Building criminal capital behind bars: Peer effects in juvenile corrections," *Quarterly Journal of Economics* 124, 105-147.

[8] Belhaj, M., Bervoets, S. and F. Deroïan (2016), "Efficient networks in games with local complementarities," *Theoretical Economics* 11, 357-380.

[9] Billand, P., Bravard, C., Durieu, J. and S. Sarangi (2015), "Efficient networks for a class of games with global spillovers," *Journal of Mathematical Economics* 61, 203–210.

[10] Blume, L.E., Brock, W.A., Durlauf, S.N. and Y.M. Ioannides (2011), "Identification of social interactions," In: J. Benhabib, A. Bisin, and M.O. Jackson (Eds.), *Handbook of Social Economics, Vol. 1B*, Amsterdam: Elsevier Science, pp. 853-964.

[11] Blume, L.E., Brock, W.A., Durlauf, S.N. and R. Jayaraman (2015), "Linear social interactions models," *Journal of Political Economy* 123, 444-496.

[12] Boucher, V. and B. Fortin (2016), "Some challenges in the empirics of the effects of networks," In: Y. Bramoullé, B.W. Rogers and A. Galeotti (Eds.), *Oxford Handbook on the Economics of Networks*, Oxford: Oxford University Press, pp. 277-302.

[13] Boucher, V. (2016), "Conformism and self-selection in social networks," *Journal of Public Economics* 136, 30-44.

[14] Bramoullé, Y., Djebbari, H. and B. Fortin (2009), "Identification of peer effects through social networks," *Journal of Econometrics* 150, 41-55.

[15] Bramoullé, Y., Kranton, R. and M. d'Amours (2014), "Strategic interaction and networks," *American Economic Review* 104, 898-930.

[16] Burt, R.S. (1992), *Structural Holes: The Social Structure of Competition*, Harvard: Harvard University Press.

[17] Calvó-Armengol, A., Patacchini, E. and Y. Zenou (2009), "Peer effects and social networks in education," *Review of Economic Studies* 76, 1239-1267.

[18] Chan, T.Y., Li, J. and L. Pierce (2014) "Compensation and peer effects in competing sales teams," *Management Science* 60, 1965-1984

[19] Cornelissen, T., Dustmann, C. and U. Schönberg (2017), "Peer effects in the workplace, *American Economic Review* 107(2): 425-456.

[20] Currarini, S., Jackson, M.O., and P. Pin (2010), "Identifying the roles of choice and chance in network formation: Racial biases in high school friendships," *Proceedings of the National Academic of Sciences of the USA* 107, 4857-4861.

[21] De Grip, A. and J. Sauermann (2012) "The effects of training on own and co-worker productivity: Evidence from a field experiment," *Economic Journal* 122, 376-399.

[22] Dearden, L., Reed, H. and J. Van Reenen (2006) “The impact of training on productivity and wages: Evidence from British panel data,” *Oxford Bulletin of Economics and Statistics* 68, 397-421.

[23] De Marti, J. and Y. Zenou (2015), “Networks games under incomplete information,” *Journal of Mathematical Economics* 61, 221-240

[24] Falk, A. and A. Ichino (2006), “Clean evidence on peer effects,” *Journal of Labor Economics* 24, 39-57.

[25] Graham, B.S. (2015), “Methods of identification in social networks,” *Annual Review of Economics* 7, 465–485.

[26] Hamilton, B.H., Nickerson, J.A. and H. Owan (2003), “Team incentives and worker heterogeneity: An empirical analysis of the impact of teams on productivity and participation,” *Journal of Political Economy* 111, 465-497.

[27] Herbst, D. and A. Mas (2015), “Peer effects in worker output in the laboratory generalize to the field,” *Science* 350 (6260).

[28] Jackson, C.K., and E. Bruegmann (2009) “Teaching students and teaching each other: The importance of peer learning for teachers,” *American Economic Journal: Applied Economics* 1, 85-108.

[29] Jackson, M.O. (2008), *Social and Economic Networks*, Princeton: Princeton University Press.

[30] Jackson, M.O. and Y. Zenou (2015), “Games on networks,“ In: P. Young and S. Zamir (Eds.), *Handbook of Game Theory, Vol. 4*, Amsterdam: Elsevier, pp. 91-157.

[31] Kandel, E. and E. P. Lazear (1992), “Peer pressure and partnerships,” *Journal of Political Economy* 100, 801–817.

[32] König, M.D., Liu, X. and Y. Zenou (2016), "R&D networks: Theory, empirics and policy implications," Unpublished manuscript, Monash University.

[33] König, M.D., Tessone, C. and Y. Zenou (2014), "Nestedness in networks: A theoretical model and some applications," *Theoretical Economics* 9, 695-752

[34] Lee, L-F., Liu, X. and X. Lin (2010), "Specification and estimation of social interaction models with network structures," *Econometrics Journal* 13, 145-176.

[35] Leuven, E. (2005), "The economics of private sector training: A survey of the literature," *Journal of Economic Surveys* 19, 91-111.

[36] Lindquist, M., Sauermann, J. and Y. Zenou (2015) "Network Effects on Worker Productivity" CEPR Discussion Paper No. 10928.

[37] Liu, X. and L.-F. Lee (2010), "GMM estimation of social interaction models with centrality," *Journal of Econometrics* 159, 99-115.

[38] Liu, X., Patacchini, E. and Y. Zenou (2014), "Endogenous peer effects: Local aggregate or local average?" *Journal of Economic Behavior and Organization* 103, 39-59.

[39] Liu, X., Patacchini, E., Zenou, Y. and L-F. Lee (2012), "Criminal networks: Who is the key player?" CEPR Discussion Paper No. 8772.

[40] Manski, C.F. (1993), "Identification of endogenous effects: The reflection problem," *Review of Economic Studies* 60, 531-542.

[41] Mas, A. and E. Moretti (2009), "Peers at work," *American Economic Review* 99, 112-145.

[42] Patacchini, E., Rainone, E. and Y. Zenou (2017), "Heterogeneous peer effects in education," *Journal of Economic Behavior and Organization* 134, 190-227.

[43] Patacchini, E. and Y. Zenou (2012), "Juvenile delinquency and conformism," *Journal of Law, Economic, and Organization* 28, 1-31.

[44] Topa, G. and Y. Zenou (2015), "Neighborhood versus network effects," In: G. Duranton, V. Henderson and W. Strange (Eds.), *Handbook of Regional and Urban Economics, Vol. 5A*, Amsterdam: Elsevier Publisher, pp. 561-624.

[45] Waldinger, F. (2010), "Quality matters: The expulsion of professors and the consequences for PhD students outcomes in Nazi Germany," *Journal of Political Economy,* 118, 787-831

[46] Zenou, Y. (2016), "Key players," In: Y. Bramoullé, B.W. Rogers and A. Galeotti (Eds.), *Oxford Handbook on the Economics of Networks*, Oxford: Oxford University Press, pp. 244-274.

Tables

Table 1: Descriptive Statistics

	Worker×week observations N = 14,070				Within worker averages N = 416			
	mean	s.d.	min	max	mean	s.d.	min	max
$y_{i,t}$ (performance)	0.35	0.11	0.06	2.61	0.31	0.08	0.10	0.60
$age_{i,t}$	32.3	11.1	17.5	65.3	29.3	9.79	17.5	65.3
$male_i$	0.29	0.46	0	1	0.35	0.48	0	1
$tenure_{i,t}$ (in years)	2.78	3.62	0.02	13.48	1.54	2.85	0.03	12.42
$hours_{i,t}$ (weekly hours worked)	21.3	10.1	0.05	82.7	22.6	7.58	4.98	47.65
$share\ peak\ hours_{i,t}$	0.55	0.16	0	1	0.58	0.11	0	0.83
$morning_{i,t}$	0.32	0.47	0	1	0.30	0.23	0	1
$midday_{i,t}$	0.93	0.25	0	1	0.95	0.12	0	1
$evening_{i,t}$	0.28	0.45	0	1	0.29	0.27	0	1
$Monday_{i,t}$	0.76	0.43	0	1	0.75	0.20	0	1
$Tuesday_{i,t}$	0.77	0.44	0	1	0.76	0.20	0	1
$Wednesday_{i,t}$	0.75	0.45	0	1	0.75	0.22	0	1
$Thursday_{i,t}$	0.73	0.45	0	1	0.75	0.22	0	1
$Friday_{i,t}$	0.71	0.45	0	1	0.73	0.20	0	1
$Saturday_{i,t}$	0.32	0.47	0	1	0.31	0.21	0	1
$Sunday_{i,t}$	0.04	0.20	0	1	0.04	0.08	0	1

Table 2: Diagnostic Tests of Main Identifying Assumption

	(1)	(2)	(3)	(4)	(5)
Dependent variables:	$\widehat{y}_{i,r}$	$\widehat{y}_{i,r}$	$\widehat{h_{ij,r}\mathbf{1}_{j,r}}$	$\widehat{\sum_{j=1}^{n} h_{ij,r}y_{j,r}}$	$\widehat{\sum_{j=1}^{n} h^*_{ij,r}\, y_{j,r}}$
Panel A: No fixed effects					
$\sum_{j=1}^{n} h_{ij,r}\, y_{j,r}$	-0.003**				
	(0.0014)				
$\sum_{j=1}^{n} h^*_{ij,r}\, y_{j,r}$	0.538***				
	(0.0249)				
$\sum_{j=1}^{n} h^*_{ij,r} tenure_{j,r}$		0.007***	-0.216***	-0.023**	0.009***
		(0.0013)	(0.0357)	(0.0110)	(0.0009)
$\sum_{j=1}^{n} h^*_{ij,r} age_{j,r}$		0.001*	-0.024*	-0.007	0.000
		(0.0004)	(0.0140)	(0.0042)	(0.0003)
$\sum_{j=1}^{n} h^*_{ij,r} male_{j,r}$		-0.008	0.103	-0.090	-0.025***
		(0.0093)	(0.2573)	(0.0819)	(0.0061)
Panel B: With fixed effects					
$\sum_{j=1}^{n} h_{ij,r}\, y_{j,r}$	0.000				
	(0.0000)				
$\sum_{j=1}^{n} h^*_{ij,r}\, y_{j,r}$	-0.000				
	(0.0000)				
$\sum_{j=1}^{n} h^*_{ij,r} tenure_{j,r}$		0.000	-0.000	-0.000	-0.000
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\sum_{j=1}^{n} h^*_{ij,r} age_{j,r}$		0.000	0.000	0.000*	-0.000
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\sum_{j=1}^{n} h^*_{ij,r} male_{j,r}$		-0.000	0.000*	-0.000	0.000
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observations	14,070	14,070	14,070	14,070	14,070
Individuals	416	416	416	416	416

Note: All dependent variables are predicted values from a linear regression of the variable of interest on age, tenure, gender and individual, team and week fixed effects. *** indicates significance at 1% level, ** at 5% level, * at 10% level. Standard errors (in parentheses) are clustered at the individual level.

Table 3: Estimation Results

	(1)	(2)	(3)	(4)	(5)
Estimation method:	OLS	OLS	OLS	OLS	IV
Dependent variable:	$y_{i,r}$	$y_{i,r}$	$y_{i,r}$	$y_{i,r}$	$y_{i,r}$
$\mathbf{H}_r^* y_{j,r}$	0.539***	0.203***	0.179***	0.174***	0.126
	(0.0350)	(0.0569)	(0.0588)	(0.0564)	(0.1666)
$\mathbf{H}_r y_{j,r}$	-0.002	-0.005**	-0.001		
	(0.0016)	(0.0019)	(0.0019)		
$tenure_{i,r}$			0.039***	0.039***	0.040***
			(0.0098)	(0.0098)	(0.0108)
$hours_{i,r}$			-0.001***	-0.001***	-0.001***
			(0.0002)	(0.0002)	(0.0002)
$share\ peak\ hours_{i,r}$			-0.035***	-0.036***	-0.036***
			(0.0114)	(0.0110)	(0.0110)
$\mathbf{H}_r^* tenure_{j,r}$			0.003***	0.003***	0.003**
			(0.0009)	(0.0009)	(0.0016)
$\mathbf{H}_r^* hours_{j,r}$			0.000	0.000	0.000
			(0.0002)	(0.0002)	(0.0003)
$\mathbf{H}_r^* share\ peak\ hours_{j,r}$			0.017	0.016	0.016
			(0.0186)	(0.0183)	(0.0181)
$\mathbf{H}_r^* age_{j,r}$			-0.000	-0.000	-0.000
			(0.0003)	(0.0003)	(0.0003)
$\mathbf{H}_r^* male_{j,r}$			0.003	0.003	0.003
			(0.0070)	(0.0070)	(0.0070)
Individual fixed effects		Yes	Yes	Yes	Yes
Team & Week fixed effects		Yes	Yes	Yes	Yes
Day of week dummies			Yes	Yes	Yes
Morning/midday/evening dummies			Yes	Yes	Yes
Observations	14,070	14,070	14,070	14,070	14,070
Number of personid	416	416	416	416	416
First stage F-stat					27

Note: *** indicates significance at 1% level, ** at 5% level, * at 10% level. Standard errors (in parentheses) are clustered at the individual level. In Column (5), $\mathbf{H}_r^*\mathbf{H}_r^* tenure_{j,r}$ is used as an instrument for the local-average network effect, $\mathbf{H}_r^* y_{j,r}$, in a 2SLS regression.

Table 4: Estimation Results Including On-the-Job Training.

	(1)	(2)	(3)	(4)
$post\ training_{t=1,i,r}$		-0.025***	-0.023**	-0.026***
		(0.0094)	(0.0093)	(0.0094)
$post\ training_{t=2-8,i,r}$		0.016***	0.016***	0.015***
		(0.0050)	(0.0050)	(0.0050)
$\mathbf{H}_r^* trained_{j,r}$		-0.009	0.002	
		(0.0147)	(0.0112)	
$\mathbf{H}_r trained_{j,r}$		0.003*		$0.002^{\dagger}$
		(0.0016)		(0.0012)
$\mathbf{H}_r^* y_{j,r}$	0.126	0.128	0.127	0.115
	(0.1666)	(0.1716)	(0.1699)	(0.1717)
$tenure_{i,r}$	0.040***	0.050***	0.050***	0.050***
	(0.0108)	(0.0114)	(0.0113)	(0.0113)
$hours_{i,r}$	-0.001***	-0.001***	-0.001***	-0.001**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$share\ peak\ hours_{i,r}$	-0.036***	-0.036***	-0.036***	-0.036****
	(0.0110)	(0.0110)	(0.0110)	(0.0110)
$\mathbf{H}_r^* tenure_{j,r}$	0.003**	0.003*	0.003*	0.003*
	(0.0016)	(0.0016)	(0.0016)	(0.0016)
$\mathbf{H}_r^* hours_{j,r}$	0.000	0.000	0.000	0.000
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
$\mathbf{H}_r^* share\ peak\ hours_{j,r}$	0.016	0.016	0.018	0.017
	(0.0181)	(0.0179)	(0.0178)	(0.0180)
$\mathbf{H}_r^* age_{j,r}$	-0.000	-0.000	-0.000	-0.000
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
$\mathbf{H}_r^* male_{j,r}$	0.003	0.004	0.003	0.004
	(0.0070)	(0.0071)	(0.0071)	(0.0071)
Observations	14,070	14,070	14,070	14,070
Number of personid	416	416	416	416
First stage F-stat	27	27	27	28

Note: The Dependent variable is $y_{i,r}$. The Estimation method is 2SLS. $\mathbf{H}_r^*\mathbf{H}_r^* tenure_{j,r}$ is used as an instrument for the local-average network effect, $\mathbf{H}_r^* y_{j,r}$. *** indicates significance at 1% level, ** at 5% level, * at 10%, † at 11% level. Standard errors (in parentheses) are clustered at the individual level. Individual, team, and week fixed effects are included in each regression, as are day of week and time of day dummies.

Table 5: Who Are the Key Workers?

	(1)	(2)
Z-$tenure_{i,r}$	0.970***	0.837***
	(0.0023)	(0.0044)
Z-$degree_{i,r}$	0.031***	-0.005***
	(0.0018)	(0.0020)
Z-$tenure_{i,r}$ x $degree_{i,r}$		0.144***
		(0.0042)
Z-$y_{i,r}$	0.006***	0.006***
	(0.0018)	(0.0017)
Z-$hours_{i,r}$	-0.011***	-0.009***
	(0.0019)	(0.0018)
Z-$share\ peak\ hours_{i,r}$	-0.007***	-0.012***
	(0.0019)	(0.0018)
Z-$age_{i,r}$	0.006***	0.002
	(0.0023)	(0.0022)
$male_{i,r}$	0.008**	0.006
	(0.0039)	(0.0037)
Observations	13,622	13,622
R-squared	0.959	0.962

Note: The Dependent variable is $intercentrality_{i,r}$. The Estimation method is OLS. All variables have been standardized with the exception of $male_{i,r}$. *** indicates significance at 1% level, ** at 5% level, * at 10%.