Social Network, Peer Effects, and Work Effort

Julie Beugnot[a], Guy Lacroix[b], Bernard Fortin[c], Marie-Claire Villeval[d]

[a] *Department of economics, Université Laval, CIRPÉE*
[b] *Department of economics, Université Laval, CIRPÉE and CIRANO.*
[c] *Department of economics, Université Laval, CIRPÉE and CIRANO.*
[d] *University of Lyon, F-69007, France; GATE, CNRS, 93, Chemin de Mouilles, F-69130, Ecully, France.*

Abstract

This paper extends the standard work effort model by allowing social interactions through social networks. In Manski (1993) nomenclature, our linear-in-means model takes into account individual effects, endogenous effects (i.e., impact of peers' performance), and contextual effects (i.e., impact of peers' piece rate wage and other peers' characteristics). Our model is tested with a real-effort laboratory experiment with two types of exogenous social networks: one in which participants interact recursively and one in which they interact simultaneously. The nature of the recursive treatment allows us to solve the Manski's identification (reflection) problem. In the Simultaneous treatment, individuals are arrayed on an undirected line and receive information on peer(s) to which they are connected. At each period, individuals play a number of rounds to allow the model to converge to a Nash equilibrium. Given the structure of the network, this model is also identified (Bramoullé, Djebbari, Fortin, 2009) Our findings show that in social networks with recursive interactions the participant's work effort is positively influenced by his own piece rate and his peers' mean performance. The social multiplier is estimated at a value of 1.17. In social networks with simultaneous interactions, the existence of endogenous peer effects strongly depends on the individuals' gender. The endogenous peer effect is positive and large on men's work effort but do not significantly influence women's one.

Keywords: Peer effects, social networks, work effort, piece rate, experiment.

JEL-codes: C91, J16, J24, J31, M52

Email addresses: Julie.Beugnot@ecn.ulaval.ca (Julie Beugnot), guy.lacroix@ecn.ulaval.ca (Guy Lacroix), Bernard.Fortin@ecn.ulaval.ca (Bernard Fortin), villeval@gate.cnrs.fr (Marie-Claire Villeval)

1. Introduction

Everyday life offers many examples whereby individual labor supply and performance not only depend on a worker's wage and characteristics but also on the wage and performance of other workers within his reference group. For peer effects to arise a worker must directly observe his co-workers' performance or the latter must be made known to him. Since Kandel and Lazear (1992)'s seminal paper, several empirical studies have found positive peer effects in settings as varied as tournaments, piece-rate (Azmat and Iriberri, 2010; Blanes i Vidal and Nossol, 2011) and fixed compensation schemes (Falk and Ichino, 2006; Mas and Moretti, 2009; Tafkov, 2013). Concern for conformity, competitiveness, monitoring or any combination thereof are potential candidates to explain the relationship between individual and peer performances.[1] Other studies, however, have found a relatively weak positive link (Guryan et al., 2009; Bellemare et al., 2010), while still others have even found peer effects to adversely impact the lowest-performing employees (Barankay, 2012) and the disappointment-averse workers (Gill and Prowse, 2012).

Most studies assume individuals interact in groups[2] and ignore the true structure of interactions between them (save for Mas and Moretti (2009) who study peer effects within a so-called directed network). This omission is essentially due to a lack of information about the true structure of interactions between individuals. This raises concern given the pervasiveness of social networks (Jackson, 2010, 2011) in which each person may have his own reference group. Yet, while peer effects within social networks have been studied in various fields of inquiry[3] their analysis on labor markets has been limited to the transmission

[1] It has also been shown that outperforming others is associated with an activation of the neural circuitry involved in the processing of rewards in the brain (Dohmen et al., 2011).

[2] This means that the population is partitioned in subsets (or groups), and that individuals are affected by all others in their group and by none outside of it.

[3] See Bertrand et al. (2000) on welfare participation, De Weerdt and Dercon (2006) on the provision of informal health insurance in developing countries, Munshi (2010) on labor and credit networks on economic activity in developing countries, Karlan et al. (2009) on risk-sharing, Calvó-Armengol et al. (2009) on education, Patacchini and Zenou (2008) on criminal activity, Cassar (2007) on coordination and cooperation, and Chen et al. (2010) on contributions to on-line communities.

of information about job opportunities (Laschever, 2011; Calvó-Armengol et al., 2009) and the role of referrals (Topa, 2011). The role of social networks on work effort has been largely ignored.[4] One aim of this paper is to partly fill this gap.

Empirical studies of peer effects generally rely upon a linear-in-means model (see Blume et al. (2011)). These linearly relate individual outcome to own characteristics and reference group mean outcome (endogenous peer effects) and mean characteristics (contextual peer effects). However, it is well known since Manski (1993)'s seminal paper that this model is plagued with two identification problems. The first relates to the difficulty of distinguishing the endogenous peer effects from spurious correlated effects caused by self-selection in peer groups (e.g., homophily) or common shocks. The second concerns distinguishing between endogenous peer effects and contextual effects due to the simultaneity of individual decisions, even assuming away correlated effects. Thus, when individuals interact in groups and their reference group includes themselves, the simultaneous decision making introduces a perfect collinearity between the mean outcome of each group and its mean characteristics. Manski (1993) refers to the identification problem as the "reflection problem".

Correlated effects can be overcome by means of random group assignment. For example, Sacerdote (2001) analyzes peer effects in student outcomes using information on roommates who were randomly assigned to dorms. Stinebrickner and Stinebrickner (2006) argue, however, that such assignment may make the reference group irrelevant, or partially observed, thus underestimating the true peer effect. In the absence of correlated effects, several approaches have been proposed to solve the reflection problem. First, group interactions that exclude oneself can identify both the endogenous and the contextual effects if there is sufficient group size variation (Lee, 2007). Second, non-linearities in social interactions (Brock and Durlauf, 2001; Fortin et al., 2007; Grodner et al., 2011) as well as recursive interactions (Bellemare et al., 2010) have been shown to ease identification. Finally, iden-

[4]Exceptions are Bandiera et al. (2005, 2009, 2010) who show using field experiments how friendship affect the impact of various incentive schemes on worker productivity.

tification obtains under quite general conditions when interactions are structured through social networks (Bramoullé et al., 2009, henceforth BDF)(Goldsmith-Pinkham and Imbens, 2012).

The paper focuses on the relationship between individuals and their reference group performances. The empirical analysis is based upon data obtained from a laboratory experiment involving real-effort tasks under a piece-rate scheme. The laboratory setting was chosen for a number of reasons. First, by randomly assigning participants to various sessions, we avoid the issue of correlated effects (e.g., due to self-selection in networks). Likewise, random assignment across networks ensures knowledge of the true reference group. In addition, individual characteristics and performance as well as those of the members of the reference group are perfectly known, as required by the linear-in-means model. Finally, we can afford to experiment with various types of interactions. In particular, we have chosen to experiment with two types of interactions: recursive and simultaneous. By recursive interactions, we refer to a setup in which participants in a given session are matched to participants who have played in isolation in a previous session. In both cases, participants interact within specific network structures.

From a methodological point of view, the aim of the paper is to compare the estimated peers' mean performance effect obtained using the Recursive and the Simultaneous treatments. It can be shown that both treatments should yield the same estimate under relatively innocuous assumptions. This is because the peers' mean performance effect is exogenous in the Recursive treatment while the network structure intrinsically generates powerful instruments that can be used to correct for the endogeneity of the peers' mean performance effect in the Simultaneous treatment. Our findings indicate that participants in the Recursive treatment respond positively to their own piece rate as well as to their peers' mean performance. Interestingly, males are much more responsive than females both to their own piece rate and to their peers' performance. In the Simultaneous treatment, on the other hand, the peer effect is gender specific. Men respond very strongly to their peers' performance whereas women are totally unaffected by their peers' behavior. The implications of these results are twofold: first, recursive and simultaneous interactions are distinct treatments despite being setup with the exact same parametric framework. In other words, learning about your colleagues' output on the assembly line in the previous shift, and being told about their performance in real time does not induce the same response. Second, conformism and competitiveness in the workplace seems to matter considerably more for men.

The remainder of the paper is structured as follows. Sections 2 presents a theoretical model of peer effects at work. Section 3 describes the experimental design and procedures. Section 4 presents the preliminary experimental results. Section 5 discusses these results and Section 6 concludes.

2. Theory

In their precursory work, Falk and Ichino (2006) were amongst the first to use a real-effort laboratory experiment to investigate the importance of peer effects on labor supply.[5] Experiments have since been successfully used to investigate peers effects in such diverse areas as worker productivity (Delfgaauw et al., 2009; Eriksson et al., 2009; Bellemare et al., 2010; Barankay, 2012; Gill and Prowse, 2012) and quitting behavior (Rosaz et al., 2012). Recently, Grodner et al. (2011) have provided ample theoretical arguments and empirical evidence as to why peer effects should matter on the labor market.

While all the aforementioned papers explicitly control for peers effects, none do so in the context of a social network. Yet the latter has been shown to matter in the transmission of information about job opportunities and referrals (Calvó-Armengol et al., 2009; Laschever, 2011; Topa, 2011). Very little research has considered the role of social networks on the

[5] In their experiment, participants had to wrap envelopes either alone in a room or alongside a co-worker. Working in pair induced a higher output level and a lower within-pair variance.

behavior of individuals who are already employed.[6] Mas and Moretti (2009) investigate peer effects on cashiers' productivity with data from a large grocery chain. The study does not focus on social networks *per se* but uses the spatial distribution of workers and the amount of time they have previously spent working together to proxy peer effects. Both Mas and Moretti (2009) and Falk and Ichino (2006) find that a 10% increase in the co-worker's productivity increases individual productivity by roughly 1.6%. In this context, social interactions are akin to a monitoring device.

The above papers need all address the issue of identification of the endogenous peer effect. Group size variation, exogenous team formation, *etc.* are all clever workarounds that have been used to that end. In this paper we purposefully design a specific social network to identify the endogenous peer effect. The information flows between members follow a particular pattern. Membership to a given network is randomized to avoid homophily issues. Our contention is that social networks offer a powerful means by which peers effects can be identified in a statistically efficient manner.

2.1. Baseline treatment

Individual interactions within a social network need not occur simultaneously. Information concerning peer behavior may be predetermined in some sense. For example, workers on an assembly line may learn about the output level of their peers in a previous work shift. In other cases, individuals do interact simultaneously. A salesperson may learn about the sales figures of his peers in real time as is often the case with pharmaceutical representatives. For our purpose, we need to design different treatments to accommodate these possibilities. From an econometric point of view, both the simultaneous and the recursive cases should identify the same peer effect under some assumptions. We begin by defining the Baseline treatment that will be used to form pairs in the Recursive treatment.

[6]For a survey of laboratory experiments using networks see Kosfeld (2004). We are not aware of any experiment conducted within a network structure that aims to investigate the link between peers and individual behavior.

Each treatment includes s sessions indexed by l, with $i = 1, \ldots, n_l$ participants who play a total of $t = 1, \ldots, T_l$ periods. To simplify notation, we assume there is a single session per treatment (with $n_l = n$ and $T_l = T$). Total work time per period is fixed and allocated between on-the-job leisure and *work* (or effort). Effort is proxied by individual production per period.[7] Individuals are isolated, that is, they choose their effort without knowledge about other participants' production or characteristics. Individuals are paid a piece-rate for each unit of production. Finally, we assume preferences for consumption and on-the-job leisure can be represented by a utility function that rationalizes the following semi-log effort function when maximized under the budget and time constraints (see Heckman (1974)):

$$e_{it} = \alpha + \alpha_1 w_{it} + \boldsymbol{\alpha}_2' \boldsymbol{z}_{it} + \varepsilon_{it} \quad \text{with } E\left[\varepsilon_{it} | \boldsymbol{X}_i\right] = 0, \tag{1}$$

where e_{it} is individual's i effort at period t, w_{it} is his piece-rate wage (in log), $\boldsymbol{z}_{it}$ is a vector of observable characteristics, ε_{it} is a random term and $\boldsymbol{X}_i$ denotes the matrix of explanatory variables for all periods, that is, $\boldsymbol{X}_i = (\boldsymbol{w}_i, \boldsymbol{Z}_i)$. As written, all the explanatory variables are assumed strictly exogenous.[8]

2.2. Recursive treatment

Participants in the Recursive treatment are each associated with a specific reference group, N_i, that comprises n_i isolated individuals drawn from the Baseline treatment. They are informed about the average effort and wage as well as the mean characteristics of their reference group. The information flow is thus unidirectional and may influence production level through imitation, conformism, or competition. Social interactions is introduced in the

[7]In principle, we could specify a production function relating output to work effort, other inputs and unobservable shocks. However, it would be difficult to identify technology from preferences in the model. Thus, following Dickinson (1999), we simply assume that work effort is proxied by output.

[8]In the general case we allow for session fixed effect (for $l = 1, \ldots, s$). These may possibly be correlated with the explanatory variables and aim at capturing a changing laboratory environment (weather, daytime *etc.*). Conditional on α_l, though, the explanatory variables are assumed to be strictly exogenous. This framework includes the likely case where the session effects are random and uncorrelated with the explanatory variables.

model by assuming that the utility function has two additively separable components: an individual sub-utility function à la Heckman (1974) and a social sub-utility function. The arguments of the latter include consumption, leisure and information about the reference group. We assume that maximization of this utility function with respect to consumption and leisure under the budget and time constraints yields the following work effort function:

$$e_{it} = \beta + \beta_1 w_{it} + \boldsymbol{\beta}_2' \boldsymbol{z}_{it} + \beta_3 \frac{1}{n_i} \sum_{j \in N_i} e_{jt} + \beta_4 \frac{1}{n_i} \sum_{j \in N_i} w_{jt} + \boldsymbol{\beta}_5' \frac{1}{n_i} \sum_{j \in N_i} \boldsymbol{z}_{jt} + \varepsilon_{it} \tag{2}$$

A comparison of equations (1) and (2) shows that peer effect and contextual effects are implicitly captured by the constant in the Baseline treatment. Equation (2) thus corresponds to the linear-in-means semi-log effort function. In this model, social conformity is equivalent to having $\beta_3 > 0$. The reflection problem does not arise in the Recursive treatment since peer mean effort is strictly exogenous. This follows from the fact that $E\left[\varepsilon_{it} | \boldsymbol{e}_{-}, \boldsymbol{X}\right] = 0$, where $\boldsymbol{e}_{-}$ is the vector of effort of all individuals from the *Baseline treatment* in all periods and $\boldsymbol{X}$ is the matrix of all other explanatory variables in all periods from both the Baseline and the Recursive treatments. Social interaction effects are unlikely to arise through the error terms since all the information about the *Baseline* treatment is controlled for in the determinist part of the model.

In our model, peer mean effort and contextual effects are captured by β_3, and $(\beta_4, \boldsymbol{\beta_5}')$, respectively. Under the assumption that $\alpha = \beta$, $\alpha_1 = \beta_1$, $\boldsymbol{\alpha_2} = \boldsymbol{\beta_2}$, the pooled set of Baseline and Recursive individuals are said to form a *directed bipartite network*. It is as if the population contained two distinct groups with those in the Recursive group corresponding to "unconnected" peers to those in the Baseline group. If the above assumption holds, equations (1) and (2) can be combined into single *pooled* model:

$$\boldsymbol{e}_t = \beta \boldsymbol{\imath}_t + \beta_1 \boldsymbol{w}_t + \beta_2 \boldsymbol{Z}_t + \beta_3 \boldsymbol{R} \boldsymbol{e}_t + \beta_4 \boldsymbol{R} \boldsymbol{w}_t + \boldsymbol{\beta}_5' \boldsymbol{R} \boldsymbol{Z}_t + \boldsymbol{\varepsilon}_t \text{ with } E\left[\boldsymbol{\varepsilon}_t | \mathbb{R}\boldsymbol{e}, \boldsymbol{X}\right] = 0, \tag{3}$$

where $\boldsymbol{e}_t$ is the concatenated vector of effort levels at period t, $\boldsymbol{\imath}_t$ is an appropriately dimensioned unit-vector, $\boldsymbol{w}_t$ is the vector of wages, $\boldsymbol{Z}_t$ is the matrix of the individual characteristics, $\boldsymbol{R}$ is the social interaction matrix, where $\boldsymbol{R}_{ij} = 1/n_i$ if j is a member of the Baseline treatment and is a peer of individual i in the Recursive treatment, and $\boldsymbol{R}_{ij} = 0$ otherwise, $\mathbb{R} = \text{diag}(\boldsymbol{R})$ is a block-diagonal matrix with $\boldsymbol{R}$ on its diagonal. The vector $\boldsymbol{R}\boldsymbol{e}_t$ corresponds to the mean effort of each reference group at t and is equal to 0 for Baseline individuals. The vector of all reference groups' mean effort in all periods is given by $\mathbb{R}\boldsymbol{e}$, where $\boldsymbol{e}$ is the concatenation of $\boldsymbol{e}_t\,\forall t$, and is strictly exogenous in equation (3). This model is identified and can be estimated using pooled OLS or a RE panel model.[9] Session fixed effects can easily be introduced in this specification.

2.3. Simultaneous treatment

In the Simultaneous treatment, two-way interactions between n individuals are structured through an exogenous network designed by the experimenter. As before, individual i is assigned to a specific reference group N_i which is composed of n_i peers. He behaves non-cooperatively and ignores the impact his own output level may have on other members of the network. We assume that each individual maximizes a utility function subject to his budget and time constraints and conditional upon his expectations about his reference group's mean work effort and characteristics. We assume that the model has reached a non-cooperative Nash social equilibrium with *self-consistent* expectations. In other words, the expected and the equilibrium effort levels are equal. This is true for all network members.

At the Nash equilibrium, the effort level of individual i at period t, e_{it}, is a function of his own wage and characteristics, as well as the average effort level, wage and other

[9]This property is also consistent with a theorem in BDF which states that the model is identified whenever $\boldsymbol{R}^2 = 0$ (which is the case here), $\beta \neq 0$ and at least one individual is isolated in the social network (see Appendix A in BDF paper).

characteristics of his reference group at the same period:

$$e_{it} \quad = \quad \gamma + \gamma_1 w_{it} + \boldsymbol{\gamma_2}' \boldsymbol{z}_{it} + \gamma_3 \frac{1}{n_{it}} \sum_{j \in N_i} e_{jt} + \gamma_4 \frac{1}{n_i} \sum_{j \in N_i} w_{jt} + \boldsymbol{\gamma_5}' \frac{1}{n_i} \sum_{j \in N_i} \boldsymbol{z}_{jt} + \varepsilon_{it}, \quad (4)$$

with $E\left[\varepsilon_{it}|X\right] = 0$ and where $|\gamma_3| < 1$. In matrix notation, our structural model is given by:

$$\boldsymbol{e}_t = \gamma \boldsymbol{\imath}_t + \gamma_1 \boldsymbol{w_t} + \boldsymbol{\gamma}_2' \boldsymbol{Z}_t + \gamma_3 \boldsymbol{G} \boldsymbol{e}_t + \gamma_4 \boldsymbol{G} \boldsymbol{w}_t + \boldsymbol{\gamma_5}' \boldsymbol{Z}_t + \boldsymbol{\varepsilon}_t, \quad (5)$$

with $E\left[\varepsilon_t|\boldsymbol{X}\right] = 0$, where $\boldsymbol{G}$ is a row-normalized social interaction matrix, with $\boldsymbol{G}_{ij} = 1/n_i$ if j is a peer of i, and 0 otherwise. It is worth emphasizing that equations (3) and (5) differ in one important aspect. Indeed, the variable $\boldsymbol{R}\boldsymbol{e}_t$ is exogenous in equation (3) whereas $\boldsymbol{G}\boldsymbol{e}_t$ is endogenous in equation (5). It is therefore crucial to establish the conditions under which the Simultaneous treatment model is identified. To do so, we start by deriving its reduced form. By assuming that $|\gamma_3| < 1$, it follows that $\boldsymbol{I} - \gamma_3 \boldsymbol{G}$ is invertible. The reduced form of model (5) is thus given by:

$$\begin{aligned} \boldsymbol{e}_t \quad &= \quad \gamma(\boldsymbol{I} - \gamma_3 \boldsymbol{G})^{-1} \boldsymbol{\imath}_t + (\boldsymbol{I} - \gamma_3 \boldsymbol{G})^{-1} (\gamma_1 \boldsymbol{I} + \gamma_4 \boldsymbol{G}) \boldsymbol{w}_t \\ &+ \quad (\boldsymbol{I} - \gamma_3 \boldsymbol{G})^{-1} \left(\gamma_2 \boldsymbol{I} + \boldsymbol{\gamma}_5' \boldsymbol{G}\right) \boldsymbol{Z}_t + (\boldsymbol{I} - \gamma_3 \boldsymbol{G})^{-1} \boldsymbol{\varepsilon}_t \end{aligned} \quad (6)$$

Since the inverse matrix is unique, the model is coherent and the Nash equilibrium is unique. The *macro* reduced form, which includes all periods, is given by:

$$\begin{aligned} \boldsymbol{e} \quad &= \quad \gamma(\mathbb{I} - \gamma_3 \mathbb{G})^{-1} \boldsymbol{\imath} + (\mathbb{I} - \gamma_3 \mathbb{G})^{-1} \left(\gamma_1 \mathbb{I} + \gamma_4 \mathbb{G}\right) \boldsymbol{w} \\ &+ \quad (\mathbb{I} - \gamma_3 \mathbb{G})^{-1} \left(\gamma_2 \mathbb{I} + \gamma_5' \mathbb{G}\right) \boldsymbol{Z} + (\mathbb{I} - \gamma_3 \mathbb{G})^{-1} \boldsymbol{\varepsilon}, \end{aligned} \quad (7)$$

where $\mathbb{G} = \text{diag}(\boldsymbol{G})$ is the block-diagonal social interaction matrix for the T periods. The intercept is γ if the individual is isolated and $\gamma/(1 - \gamma_3)$ if not. Equation (7) enables us to evaluate the impact of a marginal shock in γ (*i.e.*, a common exogenous change within the network) on an individual's output when the endogenous peer effect is taken into account. When there are no isolated participants this is equivalent to $\partial(E(\boldsymbol{e}_{it}|\cdot)/\partial\gamma = 1/(1-\gamma_3)$ and corresponds to a "social multiplier" in our model.[10] When $\gamma_3 > 0$ (*strategic complementarities* in work effort), the social multiplier is larger than 1 and the initial shock is amplified by the social interactions.

As for identification, BDF have shown that if $\boldsymbol{I}$, $\boldsymbol{G}$, and $\boldsymbol{G}^2$ are linearly independent then peer effects are identified.[11] This condition is satisfied whenever there are *intransitive triads* in the network, that is, whenever at least two individuals are separated by a link of distance 2. For example, if workers A and C are not peers but are linked through peer B, then peer effects are identified.[12] When session fixed effects are possibly correlated with the explanatory variables, the BDF condition becomes more restrictive. In the latter case the model is identified if $\boldsymbol{I}$, $\boldsymbol{G}$, $\boldsymbol{G}^2$, and $\boldsymbol{G}^3$ are linearly independent. This condition holds whenever two individuals are separated by a link of distance 3. A simple estimation strategy is to use session fixed effects along with an IV estimator whose instruments are $\mathbb{G}^2\boldsymbol{X}$, $\mathbb{G}^3\boldsymbol{X}$,... (see BDF).

3. Experimental design and procedures

Following the above theoretical discussion, our challenge is to devise experiments that can adequately measure peer and contextual effects in an efficient manner. In what follows, we describe the three treatments that were administered to participants and stress how they relate to the theoretical model. For that purpose, we use a between-subject design.

[10]When there are isolated participants, the social multiplier is a convex combination of the social multiplier when no individuals are isolated and when all individuals are isolated, that is, $(1-\delta)[1/(1-\gamma_3)] + \delta$, where δ is the fraction of participants who are isolated.

[11]Conceptually, $\boldsymbol{G}^2$ corresponds to the interaction matrix between an individual's peers with their own peers.

[12]More generally, peer effects are identified when individuals do not interact in groups.

3.1. The Baseline treatment

As mentioned in Section 2.1, Baseline participants play in isolation. Their performance is inherently interesting but the main purpose of this treatment is provide matches or peers to players in the Recursive treatment. Two sessions were organized, each one comprising 16 periods. Each session comprises 18 participants aligned along 3 rows. In each period, participants are invited to perform a task during two and a half minutes. The task consists in multiplying two-digit numbers by one-digit numbers (*e.g.* 15×3 or 22×7). To insure homogeneity of treatment across participants and sessions, the same tasks are asked from everyone in the same order. Once the two numbers have been displayed on the computer screen, participants enter the answer at will. If correct, a new task is displayed on the screen. Otherwise an error message is displayed and the answer must be entered anew. The screen keeps track of the number of correct answers and the remaining time until the period ends. Calculators, pen or electronic devices are prohibited. Before they begin, participants are informed that they are free to read the magazines that lay on their desk. These serve as a mimicking device to on-the-job leisure.

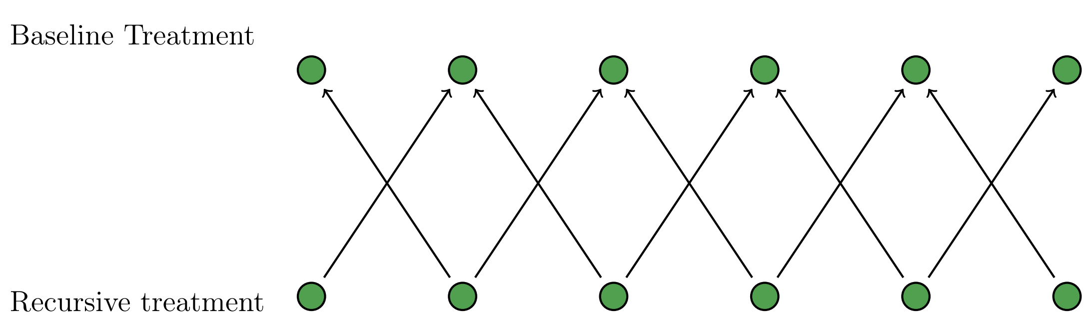
Compensation is based on a piece-rate system. At the beginning of each period, a piece-rate of either €0.10, €0.50, or €1 is randomly assigned to each participant and displayed onto the screen. Earnings in each period is simply the number of correct answers times the piece-rate. The number of correct answers and the potential earnings are displayed at the end of each period. When the session ends, actual compensation corresponds to the earnings of a randomly selected period drawn independently for each participant. In addition, participants are paid a fixed randomly selected show-up fee of either €2, €4, or €6 at the beginning of the session. In a standard labor supply model this would correspond to unearned income.

3.2. The Recursive treatment

The setup of the Recursive treatment is similar to that of the Baseline treatment save for unidirectional interactions. Indeed, participants are informed that they are matched to either one or two peers. In addition they are told theirs peers played in a previous session and that the match will remain the same for the duration of the session. Those seated at the end of a row are matched to a single peer (their corresponding neighbor of a previous session), while all others are matched to two peers (their corresponding left and right neighbors of a previous session). This spatial configuration parallels that of the Simultaneous treatment although in both the Recursive and the Simultaneous treatments participants are not aware of this. Figure 1 depicts the graph of the directed bipartite network. The nodes correspond to the players and the arrows point towards their peers.

At the beginning of the session, information on peer characteristics are displayed on the screen. These include average age, school, number of school years, gender, relative family wealth, and show-up fee. At the beginning of each period, in addition to own piece-rate, information about average peer piece-rate and performance are displayed on the screen. Participants are also informed that their peers had to perform the exact same multiplications as themselves, and in the same order.. This ensures that the level of difficulty of the task is kept constant across participants. At the end of each period, a summary screen displays own performance, piece-rate and potential earnings as well as average peer piece-rate and performance.

Figure 1: Graph of a Directed Bipartite Network



3.3. *The Simultaneous treatment*

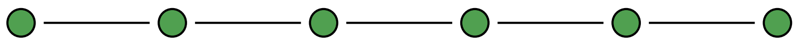
The setup of the Simultaneous treatment is similar to that of the Recursive treatment except that the interactions occur concurrently. The discussion of Section 2.3 has underscored the intimate link between the structure of a network, as described by its graph matrix $\boldsymbol{G}$, and the identifiability of the endogenous peer effect. In designing a specific network, we have tried to satisfy two separate criteria. First, identification requires that the network structure be such that the matrices $\boldsymbol{I}$, $\boldsymbol{G}$, $\boldsymbol{G}^2$, $\boldsymbol{G}^3$ be linearly independent. The lower the collinearity between the latter matrices, the more precise the resulting peer effect will be. Second, external validity requires the network to reflect real life interactions between individuals within their work environment.

Based on these two criteria, we have chosen an undirected line social network. Thus each row of six participants in the laboratory constitutes a network whose graph is depicted in Figure 2. Such a network ensures that at least two participants are separated by a link of distance 3, a sufficient condition for identification of the peer effect to hold. The degree of collinearity within this type of network can be ascertained by computing the *condition number* of the matrix resulting from the vectorization and concatenation of the above four matrices (see BDF).[13] Our undirected line network has a *condition number* of 7.7 which is quite low and should thus yield relatively precise estimates of the peer effects. An undirected line network is also likely to have good external validity properties. Indeed, it mimics many work environments in which employees work in isolation but have the ability to observe their colleagues' pace and performance (as in open space offices or workshops).

As shown in Figure 2, participants located at the end of a row are matched to a single peer while all others are matched to two peers. Participants are not aware of the network structure. They are not told that their peers are their direct neighbors but we checked that they understood that their peers are present in the same room. While the Recursive

[13]The condition number of a matrix $\boldsymbol{A}'\boldsymbol{A}$ is given by the square root of the ratio of its maximum and minimum eigenvalues. A condition number above 30 is indicative of serious collinearity.

Figure 2: Graph of the Undirected Line Network



and Simultaneous treatments share many features, there is nevertheless a major difference between the two. In the former, peer influence runs one way. In the latter, influence between peers runs both ways. Consequently, the interaction between two participants may trickle down indirectly through the whole network in a cascading fashion.

Contrary to the Baseline and Recursive treatments, a session consists of only four periods. Each period comprises up to five rounds of two and a half minutes each to allow convergence to the Nash equilibrium. The duration of the Simultaneous sessions is thus similar to the other two. Comparisons between treatments should therefore not be contaminated by fatigue.

The Simultaneous session unfolds pretty much like the Recursive session. Information on peer characteristics are displayed on the screen at the beginning of the session. As each period begins, information is provided on own piece-rate as well as average peer piece-rate. At the end of each round, average peer performance is displayed on the screen. Next participants are told whether the period has ended or whether a new round is about to begin. The period ends once the difference in average output between two successive rounds within a given network is less than 5%. When this criterion is satisfied, the model is said to have reached a non-cooperative Nash social equilibrium with *self-consistent* expectations. In other words, expected and contemporaneous peer mean performance are almost equal for each network member.[14]

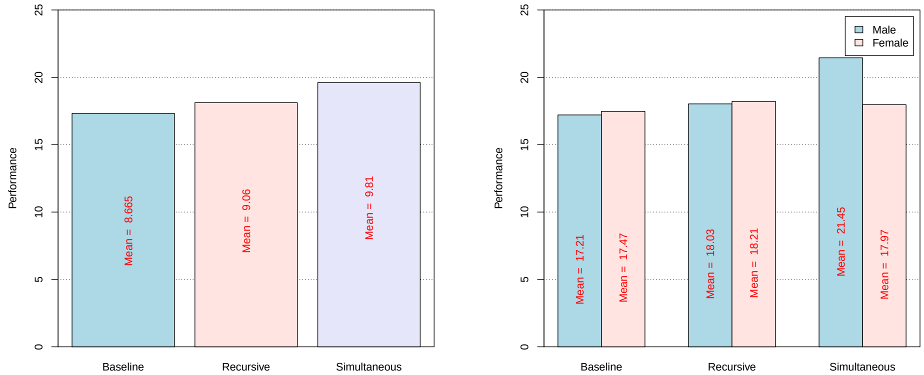
[14] They are only "almost" equal for two reasons: First, the convergence criterion is not zero. Second, for reasons of tractability, the criterion is applied at the network level, not at the individual level. This may generate measurement errors that is taken into account by using an IV approach.

3.4. Experimental procedures

The experiment was programmed using the Z-Tree software (Fischbacher (2007)). All sessions were conducted at GATE (Groupe d'Analyse et de Théorie Economique) in Lyon, France. Undergraduate students from the local engineering and business schools were invited via the ORSEE software (Greiner (2004)). Between 6 and 18 participants took part in each session, for a total of 219 participants. As outlined in Table A1 of Appendix 1, two sessions of the Baseline treatment were held with 18 participants each, three sessions of the Recursive treatment involved 39 participants and finally, 13 sessions of the Simultaneous treatment involved 75 participants. Participants in the Simultaneous treatment are more numerous since each session consists of only four periods.

Upon arrival in the laboratory, participants drew a ticket from a bag assigning them to a specific computer terminal. The instructions describing the task, the payment scheme and the available set of information throughout the experiment were distributed and read aloud (see Appendix 2). Once reading was completed, participants were distributed a questionnaire to assess their understanding of the rules. Answers were verified individually. They next had to report their age, gender, school, number of years of study, and belief about the wealth of their family relative to that of the other students of the same school on a scale from 1 to 10. This was followed by a practice period of two and a half minutes after which the experiment *per se* began.

At the end of the final period, participants were told which period (and which round in the Simultaneous treatment) was randomly selected for payment along with their payoff. They next had to complete an exit survey. On average, a session lasted 60 minutes and participants earned €14.36 with a standard deviation of €8.76, including an average €4 show up fee (minimum = €2, maximum = €40).



(a) Treatment (b) Treatment and Gender

Figure 3: Performance, by Treatment and Gender

4. Results

We start by presenting descriptive statistics on the pool of participants and on performance in each treatment before proceeding to our econometric analysis. Table 1 displays summary statistics and non-parametric statistics about the pool of participants and the mean characteristics of the peers in each treatment.

4.1. Summary statistics

In Figure 3, panel A displays the mean performance achieved in the task in the three treatments in the whole sample. For the Simultaneous treatment, we only consider the last round of the periods in which convergence has been reached in the network. Panel B displays the same information, by gender.

When one compares the three treatments (panel A), mean performance looks higher in both the Recursive and the Simultaneous treatments compared with the Baseline. However, these differences are not significant according to Mann-Whitney tests in which the mean performance across periods per individual is conservatively taken as one independent observation (two-tailed; $p = 0.996$ for the comparison between Baseline and Recursive

Table 1: Summary statistics

Treatments	Baseline		Recursive		Simultaneous		R/B	S/B	R/S
	Average	Std-Err	Average	Std-Err	Average	Std-Err			
Males (%)	52.78	(50.63)	51.28	(50.64)	47.37	(50.15)	0.897	0.571	0.673
Age	20.78	(1.77)	23.38	(5.21)	22.07	(3.52)	<0.001	0.003	0.127
Relative wealth	5.19	(1.85)	4.49	(1.86)	5.15	(1.82)	0.052	0.593	0.041
Engineering Central School (%)	22.78	(45.43)	28.21	(45.58)	31.58	(46.69)	0.967	0.666	0.693
Endowment (show up fee)	4.22	(1.49)	3.79	(1.88)	4.16	(1.62)	0.279	0.866	0.262
Number of male peers			1.03	(0.87)	0.96	(0.87)			0.665
Age of peers			20.82	(1.79)	21.99	(2.34)			<0.001
Wealth of peers			5.26	(1.51)	5.14	(1.82)			0.381
Peers in Engineering Central School (%)			28.21	(37.69)	33.77	(41.27)			0.521
Endowment (show up fee) of peers			4.08	(1.16)	4.16	(1.36)			0.697
Number of individuals	36		39		114				
Piece rate	0.52	(0.38)	0.54	(0.38)	0.54	(0.37)	0.332	0.469	0.944
Piece rate of peers			0.53	(0.31)	0.55	(0.30)			0.308
Performance	17.33	(7.85)	18.12	(8.92)	19.62	(7.76)	0.996		
Performance of peers			17.34	(6.21)	19.86	(6.28)			
Number of observations	576		624		294				

Note: Columns 2 to 4 report the mean values of variables and standard deviations are in parentheses. Columns 5 to 7 report the p-values of various non-parametric tests, all two-tailed. Column 5 compares the Recursive and the Baseline treatments; column 6 compares the Simultaneous and the Baseline treatments; column 7 compares the Simultaneous and the Recursive treatments. For the proportion of males, of participants in Engineering Central School and of peers in Engineering Central School, tests are proportion tests. All the other tests are Mann-Whitney tests (M-W, hereafter). In the upper panel of the Table, each individual is considered as one independent observation. In the lower panel of the Table, each observation is taken as one independent observation.

treatments, $p = 0.390$ for the comparison between Baseline and Simultaneous treatments, and $p = 0.440$ between the Recursive and Simultaneous treatments).

However, considering performance by gender (panel B) delivers interesting information. In the Baseline and the Recursive treatments, there is no significant gender difference in performance ($p = 0.669$ in the Baseline and $p = 0.736$ in the Recursive treatment). In contrast, there is a significant gender gap in performance in the Simultaneous treatment ($p = 0.027$). In this treatment, males outperform females but tend also to perform better on average than in the Baseline ($p = 0.094$) and in the Recursive treatment, but no significantly so ($p = 0.114$); they perform similarly in the Baseline and the Recursive treatment ($p = 0.822$). In contrast, females perform similarly in the three treatments. Indeed, no significant difference is found between the Baseline and respectively the Recursive treatment ($p = 0.899$) and the Simultaneous treatment ($p = 0.675$) or between the Recursive and the Simultaneous treatments ($p = 0.649$).

The percentage of participants who choose to exert no effort is very low in the three treatments: 2.60% in the Baseline treatment (15 out of 276 observations), 1.60% in the Recursive treatment (10 out of 624) and 1.02% in the Simultaneous treatment (3 out of 294).

4.2. Econometric analysis

Table 2 reports the results of four work effort models for the entire sample. Model (1) is for the Baseline treatment and model (2) for the Recursive treatment. Model (3) pools the data of the Baseline and the Recursive treatment, under the assumption (tested below) that the pooling restrictions are not rejected. This corresponds to a situation where a directed bipartite network links the subjects participating in the Recursive treatment and their peers from the Baseline treatment. Model (4) is for the Simultaneous treatment where participants are linked through an undirected line network. Two sets of regressions are provided for each model.

Regarding models (1) to (3), which assume no simultaneity problems, panel OLS and

RE estimates are provided. In each of these cases, we assume standard composite random terms, that is, which are equal to the sum of an individual effect invariant over time and an idiosyncratic error. Therefore, valid inference requires robust standard errors clustered at the individual level. While panel OLS provided consistent estimators they are not asymptotically efficient as they do not exploit the structure of the covariance matrix. RE estimators are consistent and more asymptotically efficient as they are based on a feasible generalized least squares approach.[15]

To estimate the Simultaneous model, we use an IV or random effects IV approach. The choice of the instruments raises difficult issues given that the number of networks is small in our set-up. Indeed, using a generalized IV approach based on the reduced form of the macro model (as suggested by BDF) is likely to yield biased estimates in small size samples. After a number of attempts, we have decided to use $\mathbb{G}^2\boldsymbol{X}$ as the matrix of instruments at the network level.[16] Observations used for estimation are limited to rounds where our criterion for convergence to the Nash equilibrium is satisfied. One additional advantage of using an IV approach is that it may take into account the presence of measurement errors in peers' labor supply as expected by a worker. Indeed, our convergence criterion is not perfect and is defined at the network rather than at the individual level. Therefore, the individual contemporary peers' labor supply may differ from its expected value.

The independent variables in model (1) include a time trend to account for learning effects,[17] session fixed effects and the following individual effects: the piece-rate (in log) paid in the period, the relative wealth of his family, his age, his gender, his initial endowment and a dummy indicating whether or not he studies in the Engineering Central School. 22.8% of the subjects belong to the engineering school which students are selected based on very

[15] We also estimate this model using a fixed effects approach which allows the individual effect to be correlated with the explanatory variables. A Hausman test never rejects that the difference between random and (identifiable) fixed effects estimated coefficients were jointly equal to zero.

[16] Introducing $\mathbb{G}^3\boldsymbol{X}$ and $\mathbb{G}^4\boldsymbol{X}$ did not qualitatively change the results.

[17] Introducing a time squared variable to account also for fatigue effects did not qualitatively affect the results.

high abilities in mathematics. Considering the nature of the task, we expect that knowing that your peers belong to this school has a specific influence. Models (2) to (4) augment the previous model with the corresponding mean values of the individual variables for the player's peers (i.e., the contextual peer variables) and the peers' mean performance (i.e., the endogenous peer variable). In model (4) the maximum number of periods is limited to four while it is 16 in the other treatments. Within a period, we only include an observation in the regression as long as it corresponds to the round when convergence has been reached.

5. Discussion

Table 2 shows that when estimating the Baseline model using panel OLS, only the Period variable is positive and significant. The estimated coefficient (=0.264) indicates a learning effect in performing tasks (multiplications). However, when the same model is estimated but this time using the RE approach, the piece-rate effect on performance becomes significant ($p < 0.01$). According to our results, doubling his piece rate increases the individual's number of tasks by 0.765 per period.

Interestingly, when the Baseline model is estimated by gender (see Table 3 for males and Table 4 for females), our RE results indicate that the piece-rate effect on performance is much stronger for males (=1.091) than for females (=0.384).[18] This suggests that, at least in this treatment, males respond more intensively to financial incentives provided by a performance pay scheme than females. This result is in line with researches by psychologists (R. et al., 2001; Li et al., 2007) who find that men exhibit a greater sensitivity to rewards and a higher valuation of earnings than women, possibly for evolutionary reasons (Kanazawa, 2005). However, most of these results have been obtained using hypothetical questionnaires. In contrast, in a field experiment in a tree-planting firm in Canada, Paarsch and Shearer (2007) found no gender gap in the response to a higher individual piece rate.

[18]We performed joint tests of equality of coefficients for each male and female model. We reject the null hypothesis for all models (except the Baseline OLS one).

In the Recursive treatment, the participants receive information for each period on the mean number of tasks performed previously by their peers, their mean piece rate and their mean other characteristics. OLS results (see column 3 of Table 2) on the peers' mean performance coefficient suggest that when his peers perform an average of one additional task per period, an individual increases his number of tasks by 0.269. This result is consistent with the presence of a competitiveness or emulation effect. This result is quite the same (=0.262) but more precise ($p < 0.01$ as compared with $p < 0.10$) when the RE approach is used. Regarding the gender differences (see tables 3 and 4), our results show that males react more in terms of their work effort to the mean performance of their peers (RE coefficient =0.316) than females (RE coefficient =0.205).

Regarding the individual effects in the Recursive treatment (see Table 2), the piece rate effect is positive, significant at the 5% level and larger than in the Baseline model (=0.945 when the RE approach is used). Also, the age coefficient is positive, indicating that older individuals perform better than younger ones, maybe because they have more experience in accounting and arithmetics. Also students from Engineering Central School perform much better than the other participants. As suggested by the RE estimated coefficient, they make close to ten more tasks per period than the other individuals ($p < 0.01$). An interesting result is than the Endowment (the show-up fee) coefficient is negative. This could be interpreted as an income effect on work effort as long as on-the-job leisure is a normal good (see Dickinson (1999)).[19] Moreover, being a male reduces performance by four tasks per period ($p < 0.05$). This result is consistent with recent researches (see Else-Quest et al. (2010)) indicating that girls from countries where gender equity is more prevalent (*e.g.,* France) are more likely to perform better on mathematics assessment tests. It is also consistent with a recent study according to which girls perform better than boys at

[19]This interpretation does not seem to work in the case of females from the Baseline treatment. For them, the Endowment coefficient is positive and significant, which could reflect a gift exchange effect [see Akerlof (1982)].

arithmetic, and especially in tasks like simple subtraction and complex multiplication (see Wei et al. (2012)).

Results from tables 3 and 4 provide other interesting information regarding gender differences in the individual effects. Thus in the Recursive treatment, females do not react at all to a change in the piece rate while males react much more strongly than in the Baseline model to such a change (RE coefficient = 1.625). In short, females performs better than males but they respond much less than males to financial incentives and to their peers' performance. Another interesting result is that females whose family wealth is relatively high tend to perform much better, while this wealth effect is not significant in the case of males.

As far as the contextual peers effects are concerned, results from Table 2 show that only the peers' mean age effect is significant ($p < 0.1$) for the entire sample. Its negative sign suggests that when his peers are younger, this may induce the participant to provide a stronger performance to remain competitive. However, this effect seems only important for females (see Table 4) as it is not significant for males (see Table 3). Also, results for males indicate that an increase in his peers' mean piece rate induces a man to reduce his performance. Based on the RE approach, doubling his peers' average wage reduces a man's number of tasks by 0.5 per period. One explanation for this negative effect is that an increase in peers' wage rate associated with no change in their performance indicates that peers are leisure lovers (i.e., their income effect is equal to their substitution effect). Social conformity may thus induce a male to perform less at a same wage rate. The peers' mean piece rate effect is not significant in the case of females.

The Pooled model combines both Baseline and Recursive treatments under the null hypothesis that the parameters pooling restrictions are not rejected. This hypothesis is rejected at the 5% level but not at the 1% level ($p = 0.042$). Using a 1% rule of decision, the pooled model can be analysed as a linear-in-means model with a directed bipartite network. Results from Table 2 indicate that the OLS and the RE peers' mean performance coefficients are quite similar (=0.292 and 0.230), significant at the 1% level, and very close to the corresponding Recursive estimated coefficients. This latter result also holds in the case of males and females. The social multiplier for the full sample is equal to 1.15 (= 1/2 + 1/2[1/(1- 0.230]), based on RE approach. As regards the individual effects, the OLS and RE coefficients are smaller (in absolute value) than those from the Recursive treatment but larger (in absolute value) than those from the Baseline one. This is what should be expected, since the Pooled model combines these two treatments. Moreover, the Endowment and the Gender effects are no longer significant, as it was the case in the Baseline model. Like in the Recursive model, only the contextual effect for peers mean age is significant. However, the OLS and RE coefficients in the Pooled model are now much smaller in absolute value than in the Recursive model (-0.6 as compared with -1.5). Regarding males and females, the Pooled model confirms that males respond much more to their own piece rates than females and that older people, whatever their gender, perform better than younger ones. Also, the peers' mean piece rate has a negative effect on males' performance, but only based on the OLS coefficient. Finally, females react quite strongly and positively to an increase in their peers' Endowment level. One interpretation is that this reflects an horizontal equity effect which motivates a female to improve her performance and therefore her (expected) earnings when the mean show-up fee of her peers is higher.

Results from the Simultaneous model under self-consistent expectations are displayed in the two last columns of Table 2. IV and IV-RE estimators are provided. As in the other models, the period variable is positive and significant, which is consistent with a learning effect. Note however that the estimated coefficient is much higher than those in the Baseline, Recursive and Pooled models. This can be explained by the fact that in the Simultaneous model, contrary to the other models, a period includes many rounds, which is likely to be the source of a stronger learning effect.[20]

[20]We did not use a round rather than a period as a proxy for the learning effect since the number of rounds is not exogenous as it depends on the speed of convergence toward the Nash equilibrium.

In the Simultaneous model, the peers' mean performance effect is not significant for the entire sample, in contrast to results from the Recursive and Pooled models. However, an analysis of this effect broken down at the gender level provides the basic reason for such a result. Thus Table 3 show that males are very strongly influenced by their peers' mean performance. Indeed, the peers' performance effect is 0.677 based on the IV approach and reaches 0.723 based on the IV-RE approach. These levels are higher than those estimated in the Recursive or Pooled models (OLS coefficients ≈ 0.5 and RE coefficients ≈ 0.3). One interpretation is that when individuals play simultaneously, they know that, contrary to the Recursive or Pooled treatment, their peers are in the same lab unreal time. In the case of males, this information motivates them to be more competitive and therefore to increase their performance. In contrast, the peers' mean performance may simply reflect a reference point to be partly reached by the participant, since the peers are not in the same place in real time. On the other hand, the peers' performance effect for females (see Table 4) is negative but not significant. All in all, male and female peers' performance effects tend to cancel out so that the net effect becomes not significant for the entire sample.

Regarding the individual effects, the piece-rate effect for the entire sample is significant and large (=0.957) when the model is estimated using an IV-RE approach. Interestingly, in the Simultaneous treatment, in contrast to the other treatments, females respond to financial incentives as much as males, as their piece rate effect is high and significant (=0.984 as compared with 0.995 for males), which is now consistent with Paarsch and Shearer (2007) evidence. Also, results for the entire sample show that performance increases with age and is higher for students from the Engineering Central school. As regards the contextual effects, an important result is that the peers' endowment effect is positive (=0.736) and significant ($p < 0.1$). Moreover, at the gender level, while, in contrast to the Pooled model, this effect is not significant for females, it is large (=1.821) and significant ($p < 0.01$) for males. In short, it seems that female refuse to play an emulation game when their peers are in the same lab unreal time.

6. Conclusion

Most research on work effort ignores social interaction effects. This omission is partly due to the fact that non-experimental data rarely reveal a worker's reference group within the firm. Moreover, estimating a work effort model with peer effects raises notoriously difficult identification problems. First the formation of the social network within a firm is likely to be endogenous and second, it may be hard to disentangle the peers' performance effect from the peers' contextual effects. In this paper, we argue that a carefully designed laboratory experiment can be helpful in order to solve these problems. On the one hand, each participant's reference group can be exogenously determined by the experimentalist through his choice of a social network. On the other hand, recent developments on peer effects (e.g., Bramoullé et al. (2009)) characterize the networks for which all social interactions effects are identifiable in the standard linear-in-means model.

Our experiment (in which participants perform multiplications) allows to identify peer effects on work effort using two types of social networks. The first one is a bipartite directed network in which participants from a Baseline treatment are peers of participants in a Recursive treatment implemented afterwards. This network does not involve identification and simultaneity problems in the estimations. The second one is an undirected line network which does raise simultaneity issues but allows the model to be identified and estimated. One additional contribution of this paper is to analyse the peers effects at the gender level. Indeed, we find that social interactions effects are quite different depending on whether the participant is a male or a female.

Our three main findings are the following. First, males are influenced by their peers' performance, whatever the structure of the network. Moreover, their reaction is stronger when their peers are in the lab in real time (undirected line network). On the other hand, females either do not react to their peers' performance (in the undirected line network) or respond less than males to it (in the directed bipartite network). Thus, the emulation and competitiveness effects regarding the work effort seem to differ by gender in our application.

Second, an increase in their peers' endowment (show-up fee) motivates men to perform better in the undirected line network. This may reflect an incentive for males to earn a level of income similar to that of their peers when their show-up fee is higher. Besides, while females are not affected by this variable in the latter network, they respond to their peers' endowment in the directed bipartite network. Therefore, it seems that when their peers are in the same lab in real time, females do not accept to play a competitiveness game. Finally, as regards the piece rate effect, males strongly respond to financial incentives in terms of their work effort in all networks. On the other hand, females react much less to a change in their piece rate except in the indirected line network where there response is close to that of men.

Studies in lab as this one has its own limitations. Networks are formed artificially, for the sake of the experiment, which may raise a problem of external validity. Therefore, caution must be exercised when extrapolating our results to the population of workers.

References

Akerlof, G. A., 1982. Labor contracts as partial gift exchange. The Quarterly Journal of Economics 97 (4), 543–569.

Azmat, G., Iriberri, N., August 2010. The importance of relative performance feedback information: Evidence from a natural experiment using high school students. Journal of Public Economics 94 (7-8), 435–452.

Bandiera, O., Barankay, I., Rasul, I., August 2005. Social preferences and the response to incentives: Evidence from personnel data. The Quarterly Journal of Economics 120 (3), 917–962.

Bandiera, O., Barankay, I., Rasul, I., 07 2009. Social connections and incentives in the workplace: Evidence from personnel data. Econometrica 77 (4), 1047–1094.

Bandiera, O., Barankay, I., Rasul, I., 04 2010. Social incentives in the workplace. Review of Economic Studies 77 (2), 417–458.

Barankay, I., 2012. Rank incentives: Evidence from a randomized workplace experiment. Wharton School, University of Pennsylvania.

Bellemare, C., Lepage, P., Shearer, B., January 2010. Peer pressure, incentives, and gender: An experimental analysis of motivation in the workplace. Labour Economics 17 (1), 276–283.

Bertrand, M., Luttmer, E. F. P., Mullainathan, S., August 2000. Network effects and welfare cultures. The Quarterly Journal of Economics 115 (3), 1019–1055.

Blanes i Vidal, J., Nossol, M., 2011. Tournaments without prizes: Evidence from personnel records. Management science 57 (10), 1721–1736.

Blume, L. E., Vienna, I., Brock, W. A., Durlauf, S. N., Jayaraman, R., ESMT, B., 2011. Linear social network models. Tech. rep., mimeo University of Wisconsin.

Bramoullé, Y., Djebbari, H., Fortin, B., 2009. Identification of peer effects through social networks. Journal of econometrics 150 (1), 41–55.

Brock, W. A., Durlauf, S. N., December 2001. Interactions-based models. In: Heckman, J., Leamer, E. (Eds.), Handbook of Econometrics. Vol. 5 of Handbook of Econometrics. Elsevier, Ch. 54, pp. 3297–3380.

Calvó-Armengol, A., Patacchini, E., Zenou, Y., 2009. Peer effects and social networks in education. Review of Economic Studies 76 (4), 1239–1267.

Cassar, A., 2007. Coordination and cooperation in local, random and small world networks: Experimental evidence. Games and Economic Behavior 58 (2), 209–230.

Chen, Y., Harper, F. M., Konstan, J., Xin Li, S., 2010. Social comparisons and contributions to online communities: A field experiment on movielens. The American Economic Review 100 (4), 1358–1398.

De Weerdt, J., Dercon, S., 2006. Risk-sharing networks and insurance against illness. Journal of Development Economics 81 (2), 337–356.

Delfgaauw, J., Dur, R., Sol, J., Verbeke, W., 2009. Tournament incentives in the field: Gender differences in the workplace. Tinbergen Institute Discussion Paper 09-069/1.

Dickinson, D. L., 1999. An experimental examination of labor supply and work intensities. Journal of Labor Economics 17 (4), 638–670.

Dohmen, T., Falk, A., Fliessbach, K., Sunde, U., Weber, B., 2011. Relative versus absolute income, joy of winning, and gender: Brain imaging evidence. Journal of Public Economics 95 (3), 279–285.

Else-Quest, N. M., Hyde, J. S., Linn, M. C., 2010. Cross-national patterns of gender differences in mathematics: A meta-analysis. Psychological bulletin 136 (1), 103.

Eriksson, T., Poulsen, A., Villeval, M. C., 2009. Feedback and incentives: Experimental evidence. Labour Economics 16 (6), 679–688.

Falk, A., Ichino, A., 2006. Clean evidence on peer effects. Journal of Labor Economics 24 (1), 39–57.

Fischbacher, U., 2007. Z-tree: Zurich toolbox for ready-made economic experiments. Experimental Economics 10 (2), 171–178.

Fortin, B., Lacro, G., Villeval, M.-C., 2007. Tax evasion and social interactions. Journal of Public Economics 91 (11), 2089–2112.

Gill, D., Prowse, V., 2012. A structural analysis of disappointment aversion in a real effort competition. The American Economic Review 102 (1), 469–503.

Goldsmith-Pinkham, P., Imbens, G. W., 2012. Social networks and the identification of peer effects. mimeo.

Greiner, B., 2004. An online recruitment system for economic experiments. MPRA paper, University Library of Munich, Germany.

Grodner, A., Kniesner, T. J., Bishop, J. A., Aug 2011. Social interactions in the labor market. IZA Discussion Papers 5934, Institute for the Study of Labor (IZA).

Guryan, J., Kroft, K., Notowidigdo, M. J., October 2009. Peer effects in the workplace: Evidence from random groupings in professional golf tournaments. American Economic Journal: Applied Economics 1 (4), 34–68.

Heckman, J., 1974. Shadow prices, market wages, and labor supply. Econometrica 42 (4), pp. 679–694.

Jackson, M. O., 2010. Social and economic networks. Princeton University Press.

Jackson, M. O., 2011. An overview of social networks and economic applications. The Handbook of Social Economics., ed. Jess Benhabib, Alberto Bisin and Matthew O. Jackson. Elsevier Press.

Kanazawa, S., 2005. Is "discrimination" necessary to explain the sex gap in earnings? Journal of Economic Psychology 26 (2), 269–287.

Kandel, E., Lazear, E. P., 1992. Peer pressure and partnerships. Journal of Political Economy, 801–817.

Karlan, D., Mobius, M., Rosenblat, T., Szeidl, A., 2009. Trust and social collateral. The Quarterly Journal of Economics 124 (3), 1307–1361.

Kosfeld, M., 2004. Economic networks in the laboratory: A survey. Review of Network Economics 3 (1), 20–41.

Laschever, R., 2011. The doughboys networks: Social interactions and labor market outcomes of World War I veterans. mimeo.

Lee, L.-f., 2007. Identification and estimation of econometric models with group interactions, contextual factors and fixed effects. Journal of Econometrics 140 (2), 333–374.

Li, C.-s. R., Huang, C.-Y., Lin, W.-y., Sun, C.-W. V., 2007. Gender differences in punishment and reward sensitivity in a sample of taiwanese college students. Personality and individual differences 43 (3), 475–483.

Manski, C. F., 1993. Identification of endogenous social effects: The reflection problem. The Review of Economic Studies 60 (3), 531–542.

Mas, A., Moretti, E., March 2009. Peers at work. American Economic Review 99 (1), 112–45.

Munshi, K., 2010. Labor and Credit Networks in Developing Economies. Handbook of Social Economics. Elsevier Science, Ch. 23, pp. 1223–1254.

Paarsch, H. J., Shearer, B. S., 2007. Do women react differently to incentives? Evidence from experimental data and payroll records. European Economic Review 51 (7), 1682–1707.

Patacchini, E., Zenou, Y., 2008. The strength of weak ties in crime. European Economic Review 52 (2), 209–236.

R., T., Avilab, A., Moltob, J., Caserasa, X., 2001. The sensitivity to punishment and sensitivity to reward questionnaire (spsrq) as a measure of gray's anxiety and impulsivity dimensions. Personality and Individual Differences 31, 837–862.

Rosaz, J., Slonim, R., Villeval, M.-C., 2012. Quitting and peer effects at work.

Sacerdote, B., 2001. Peer effects with random assignment: Results for Dartmouth roommates. The Quarterly Journal of Economics 116 (2), 681–704.

Stinebrickner, R., Stinebrickner, T. R., 2006. What can be learned about peer effects using college roommates? Evidence from new survey data and students from disadvantaged backgrounds. Journal of public Economics 90 (8), 1435–1454.

Tafkov, I. D., 2013. Private and public relative performance information under different compensation contracts. The Accounting Reviews 88 (1), 327–350.

Topa, G., 2011. Chapter 22 - Labor markets and referrals. In: Jess Benhabib, A. B., Jackson, M. O. (Eds.), Handbook of Social Economics. Vol. 1 of Handbook of Social Economics. North-Holland, pp. 1193 – 1221.

Wei, W., Lu, H., Zhao, H., Chen, C., Dong, Q., Zhou, X., 2012. Gender differences in children's arithmetic performance are accounted for by gender differences in language abilities. Psychological science 23 (3), 320–330.

Table 2: Work performance, Entire sample

	Baseline (1)		Recursive (2)		Pooled (1) + (2)		Simultaneous† (3)	
	OLS	Random Effects	OLS	Random Effects	OLS	Random Effects	IV	IV - Random Effects
Intercept	-7.849	-7.685	26.653	26.566	3.129	3.037	-2.386	-3.09
	(16.848)	(16.788)	(24.875)	(25.342)	(6.057)	(6.019)	(9.038)	(7.99)
Period	0.264***	0.269***	0.154**	0.157***	0.203***	0.216***	1.04**	0.819**
	(0.065)	(0.066)	(0.063)	(0.048)	(0.044)	(0.042)	(0.469)	(0.400)
Peers' performance effect			0.269*	0.262***	0.292**	0.230***	-0.44	0.149
			(0.139)	(0.045)	(0.128)	(0.051)	(0.389)	(0.332)
Individual effects								
Wage (log)	0.532	0.765***	1.037**	0.945**	0.726**	0.852***	0.696	0.957***
	(0.437)	(0.297)	(0.410)	(0.392)	(0.305)	(0.247)	(0.465)	(0.298)
Wealth	-0.013	-0.016	0.343	0.341	0.268	0.265	0.016	0.057
	(0.739)	(0.739)	(0.655)	(0.656)	(0.477)	(0.480)	(0.365)	(0.345)
Age	0.871	0.871	0.553**	0.553***	0.526***	0.531***	0.304*	0.273*
	(0.548)	(0.548)	(0.211)	(0.208)	(0.199)	(0.200)	(0.171)	(0.158)
Endowment	1.188	1.198	-1.027*	-1.028**	-0.080	-0.072	-0.046	-0.207
	(0.954)	(0.955)	(0.522)	(0.524)	(0.456)	(0.456)	(0.457)	(0.439)
Gender (male=1)	-2.130	-2.123	-4.062**	-4.073**	-1.909	-1.962	2.546	2.229
	(2.434)	(2.436)	(1.682)	(1.695)	(1.507)	(1.515)	(1.587)	(1.397)
Engineering Central School	4.172	4.172	9.857***	9.881***	5.630***	5.701***	5.171**	5.915***
	(2.993)	(2.998)	(2.530)	(2.539)	(1.964)	(1.964)	(2.052)	(1.854)
Peers' contextual effects								
Wage (log)			-0.309	-0.208	-0.331	-0.156	0.342	-0.034
			(0.301)	(0.160)	(0.322)	(0.160)	(0.675)	(0.414)
Wealth			0.390	0.394	0.765	0.766	0.428	0.452
			(0.904)	(0.917)	(0.680)	(0.682)	(0.514)	(0.506)
Age			-1.478*	-1.473*	-0.680***	-0.640***	0.376	0.304
			(0.791)	(0.814)	(0.253)	(0.239)	(0.261)	(0.24)
Endowment			-0.186	-0.178	0.444	0.495	0.685	0.736*
			(1.107)	(1.092)	(0.867)	(0.841)	(0.452)	(0.423)
Gender (male=1)			2.831	2.842	3.030	2.934	1.14	0.392
			(3.041)	(3.057)	(3.088)	(3.118)	(2.026)	(1.899)
Engineering Central School			-1.371	-1.357	-1.419	-1.126	-2.314	-3.286
			(3.201)	(3.092)	(3.366)	(3.450)	(2.508)	(2.390)
Sessions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	576	576	624	624	1200	1200	294	294

†Panel-robust standard errors in parentheses. (a) Excluded instrumental variables: $\mathbb{G}^2\boldsymbol{X}$ where $\boldsymbol{X}$ is the set of exogenous individual variables in all periods of a network.

***Indicates 1% significance level, **Indicates 5% significance level, *Indicates 10% significance level.

Table 3: Work performance, Males

	Baseline (1)		Recursive (2)		Pooled (1) + (2)		Simultaneous† (3)	
	OLS	Random Effects	OLS	Random Effects	OLS	Random Effects	IV	IV - Random Effects
Intercept	2.499	2.881	-25.036	-22.672	4.778	6.112	21.455	16.647
	(23.521)	(23.280)	(34.983)	(35.625)	(7.281)	(7.316)	(19.606)	(17.449)
Period	0.237*	0.243**	0.052	0.100	0.128*	0.174**	-0.542	-0.507
	(0.121)	(0.121)	(0.085)	(0.067)	(0.074)	(0.072)	(0.575)	(0.509)
Peers' performance effect			0.486**	0.316***	0.551***	0.276***	0.677***	0.723**
			(0.183)	(0.068)	(0.178)	(0.082)	(0.333)	(0.303)
Individual effects								
Wage (log)	0.765	1.091**	1.831**	1.625**	1.257**	1.365***	0.937	0.995**
	(0.775)	(0.511)	(0.691)	(0.720)	(0.516)	(0.436)	(0.67)	(0.499)
Wealth	-0.332	-0.339	-0.388	-0.536	-0.295	-0.375	-0.534	-0.519
	(0.815)	(0.808)	(0.897)	(0.831)	(0.578)	(0.579)	(0.541)	(0.487)
Age	0.581	0.578	0.911***	0.883***	0.584***	0.536**	0.009	0.006
	(0.719)	(0.716)	(0.301)	(0.308)	(0.206)	(0.214)	(0.214)	(0.192)
Endowment	0.347	0.355	-0.439	-0.536	-0.080	-0.172	-1.062	-1.006
	(1.421)	(1.427)	(0.641)	(0.658)	(0.662)	(0.678)	(0.74)	(0.675)
Engineering Central School	3.745	3.741	8.872*	9.709**	5.116	5.484	8.488***	8.954***
	(4.371)	(4.384)	(4.448)	(4.262)	(3.377)	(3.383)	(3.065)	(2.791)
Peers' contextual effects								
Wage (log)			-1.071**	-0.500*	-1.088***	-0.398	0.384	-0.121
			(0.433)	(0.271)	(0.391)	(0.271)	(0.679)	(0.463)
Wealth			-0.009	-0.163	-0.824	-1.131	0.964	1.108
			(1.456)	(1.564)	(1.163)	(1.134)	(0.771)	0.73
Age			-0.009	0.082	-0.659	-0.380	-0.782	-0.694
			(0.914)	(0.938)	(0.395)	(0.388)	(0.682)	(0.609)
Endowment			2.112	2.334	0.830	1.303	1.778***	1.821***
			(1.539)	(1.581)	(0.956)	(0.938)	(0.597)	(0.554)
Gender (male=1)			3.135	1.930	3.118	0.689	-0.38	-0.469
			(4.970)	(5.972)	(4.896)	(4.996)	(3.213)	(2.888)
Engineering Central School			4.100	5.996	4.259	7.837	-11.256***	-11.865***
			(4.706)	(5.612)	(6.516)	(6.638)	(2.538)	(2.515)
Sessions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	304	304	320	320	624	624	139	139

†Panel-robust standard errors in parentheses. (a) Excluded instrumental variables: $\mathbb{G}_M^2\boldsymbol{X}$ where $\boldsymbol{X}$ is the set of exogenous individual variables in all periods of a network and where G_M is the matrix G but where the line is zero when the participant is a female.
***indicates 1% significance level, **indicates 5% significance level, *indicates 10% significance level.

Table 4: Work performance, Females

	Baseline (1)		Recursive (2)		Pooled (1) + (2)		Simultaneous† (3)	
	OLS	Random Effects	OLS	Random Effects	OLS	Random Effects	IV	IV - Random Effects
Intercept	4.848	4.927	150.937**	141.345**	-11.061	-9.270	-0.899	2.127
	(28.843)	(28.917)	(69.298)	(70.564)	(9.918)	(9.424)	(17.459)	(15.34)
Period	0.298***	0.295***	0.321***	0.246***	0.292***	0.270***	1.837***	1.766***
	(0.040)	(0.039)	(0.064)	(0.053)	(0.040)	(0.031)	(0.696)	(0.59)
Peers' performance effect			-0.039	0.205***	0.053	0.190***	-0.276	-0.215
			(0.122)	(0.066)	(0.150)	(0.066)	(0.472)	(0.46)
Individual Effects								
Wage (log)	0.500	0.384*	0.228	0.241	0.311	0.295*	0.597	0.984***
	(0.330)	(0.223)	(0.316)	(0.227)	(0.220)	(0.154)	(0.533)	(0.371)
Wealth	0.647	0.646	1.895**	1.751**	1.562*	1.522*	0.13	0.184
	(1.279)	(1.277)	(0.720)	(0.709)	(0.800)	(0.786)	(0.681)	(0.598)
Age	-0.306	-0.312	0.745**	0.614**	0.616*	0.550*	0.099	-0.0001
	(1.171)	(1.175)	(0.275)	(0.268)	(0.324)	(0.311)	(0.586)	(0.533)
Endowment	2.450***	2.440***	0.619	0.473	0.719	0.699	0.752	0.683
	(0.586)	(0.586)	(0.647)	(0.651)	(0.640)	(0.636)	(0.597)	(0.548)
Engineering Central School	6.781**	6.781***	11.440**	10.846**	3.429**	3.481**	4.727	4.764
	(2.373)	(2.377)	(4.430)	(4.963)	(1.604)	(1.639)	(3.176)	(2.971)
Peers' contextual effects								
Wage (log)			-0.011	-0.025	-0.182	-0.008	0.57	0.477
			(0.339)	(0.182)	(0.363)	(0.175)	(0.874)	(0.733)
Wealth			-2.306	-2.163	1.421*	1.300	-0.176	-0.316
			(1.759)	(1.822)	(0.794)	(0.795)	(0.739)	(0.674)
Age			-6.999**	-6.521**	-0.543	-0.567	0.716**	0.629**
			(2.729)	(2.818)	(0.405)	(0.425)	(0.322)	(0.275)
Endowment			-2.184	-2.071	1.390**	1.278**	0.551	0.702
			(1.690)	(1.732)	(0.675)	(0.601)	(0.673)	(0.604)
Gender (male=1)			1.377	1.165	1.937	1.698	-1.441	-1.46
			(3.726)	(3.871)	(4.682)	(4.607)	(2.535)	(2.262)
Engineering Central School			10.676*	8.926	-1.607	-1.961	0.951	0.938
			(5.842)	(5.928)	(4.931)	(4.832)	(2.854)	(2.58)
Sessions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	272	272	304	304	576	576	155	155

†Panel-robust standard errors in parentheses. (a) Excluded instrumental variables: $\mathbb{G}_F^2\boldsymbol{X}$ where $\boldsymbol{X}$ is the set of exogenous individual variables in all periods of a network and where G_F is the matrix G but where the line is zero when the participant is a male.

***Indicates 1% significance level, **Indicates 5% significance level, *Indicates 10% significance level.

Appendix A. Tables

Table A.5: Characteristics of the experimental sessions

Session number	Number of participants	Treatments
1	18	Baseline
2	18	Baseline
3	18	Recursive
4	12	Recursive
5	9	Recursive
21	18	Simultaneous
22	18	Simultaneous
23	12	Simultaneous
24	12	Simultaneous
25	18	Simultaneous
26	18	Simultaneous
27	18	Simultaneous
TOTAL	189	

Appendix B. Instructions for the Simultaneous treatment

(Other instructions available upon request) We thank you for participating in this experiment on economic decision-making. The session consists of 4 periods, each divided into several rounds during which you will be able to perform a task, as described in detail below.

One of these rounds will be randomly selected at the end of the session to determine your earnings in Euros. Your earnings in Euros depend on your performance during this round. Moreover, you will receive an initial endowment for the whole session. The amount of this endowment will be randomly selected among the following values: 2, 4 or 6 Euros. You will be informed on the amount of this endowment for the session before starting the first period.

Your earnings will be paid to you in cash and in private in a separate room. During the session, you will be matched with one or two participants, names "peers" in the rest of these instructions. You will keep the same peers throughout the experiment. You will never know their identity.

At the beginning of the session, you will be asked a few personal questions (gender, age, relative wealth of your family compared to the other students). Then, you will be informed on your peer's answers to these questions. If you have two peers, you will be informed of their mean answers to the questions about their age and the relative wealth of their family. "Men" indicates that your two peers are men; "women" indicates that your two peers are women; "mixed" indicates that one peer is a man and the other peer is a woman.

You will be also informed on the initial endowment of your peer or the average initial endowments of your two peers for the session. All your decisions during the session will remain anonymous. You will never have to enter your name in the computer.

Description of each period

Each of the four periods consists of several rounds. The number of rounds can change across periods. Each round lasts 2 minutes 30. During these 2 minutes 30, you are invited to perform the following task.

This task consists of multiplying two-digit numbers by one-digit numbers that are displayed on your screen (for example, 15×3, 22×7). You must enter a value in the corresponding box and submit your answer by clicking the "validate" button. You must make these calculations in your head. It is strictly forbidden to use a pen, a calculator, a mobile phone or any device to multiply the numbers, otherwise you will be immediately excluded from the session and the payoffs. One you have submitted an answer:

- If this answer is not correct, a message will inform you and you will be able to enter a new answer. Only a correct answer will make another multiplication appear.
- If this answer is correct, your score is increased by one unit and a new multiplication is displayed on your screen.

You can make as many multiplications as you like during each round. You are also allowed to read the magazines that are available on your desk.

Please note that before the beginning of the first period, a practice round of 2 minutes 30 will allow you to train at the task. Your performance during this round will be count for the determination of your earnings.

Determination of your earnings

Your earnings during this experiment depend on your piece-rate and your score (your number of correct answers) in a round of a period randomly drawn by the computer program at the end of the session. Your piece-rate for each correct answer is randomly selected at the beginning of each period. It can change across periods. In contrast, it remains constant across the rounds of a same period.

This piece-rate for each correct answer can take the following values: €0.10, €0.50, €1. Your earnings for the experiment are therefore calculated as follows:
Your total earnings = your initial endowment + (your piece-rate × your score in the randomly selected round). The incorrect answers are not accounted for in the determination of your earnings.

Information

At the beginning of the first round of each period, you are informed on the piece-rate for the period. You are also informed of the piece-rate of your peer in the same period. If you have two peers, you are informed on their average piece-rate. Indeed, your peers can receive different piece-rates than yours during a period. Their piece-rate is also randomly selected among the following values: €0.10, €0.50, €1. Note that the piece-rate of the other participants in this session in a given period can also differ from your piece-rate.

At the end of each round, you are also informed on your peer's final score in the round for his piece-rate in the period; if you have two peers, you are informed on the mean final score in this round. Please note that your peer or your peers had to solve exactly the same multiplications as you and in the same order as you during each round. Similarly, all the participants in the session have to solve the same multiplications and in the same order as you in each round.

You are permanently informed on your current score in the round and on the time remaining until the end of the round. At the end of each round, your final score in the round is displayed, as well as a reminder of your piece-rate for the period, your peer's piece-rate and final score or your two peers' average piece-rate and average final score.

You can find below a copy of the screenshot during the task. The numbers indicated are only an example.

To sum up:

- Each of the four periods consists of several rounds during which you can solve multiplication problems.
- From one period to the next, you keep the same peer or the same two peers. The piece-rates are randomly determined.
- , During a period, you keep the same piece-rate across rounds.
- From one round to the next, the multiplications are modified randomly. Your peer or your peers receive the same multiplications problems and in the same order than you.
- You are informed at the beginning of the period on your peer's piece-rate or on the average piece-rate of your two peers.
- At the end of each round, you are informed on your final score and your potential earnings for this round, and on your peer's score or on the average score of your two peers. You are reminded your piece-rate and your peer's piece-rate or the average piece-rate of your two peers.

Please read again these instructions and answer the questions on the questionnaire that has been distributed to you. If you have any question, please raise your hand and we will answer to your questions in private. Once we will have answered your questions, a questionnaire will be displayed on your computer screen. Then the practice period will start. The following periods will start automatically. At the end of eh session, you will be invited to fill out a final questionnaire.

You are not allowed to communicate with any other participant.