Identifying and Decomposing Peer Effects in Decision-Making Using a Randomized Controlled Trial

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Abstract

This paper investigates how firms' decisions to participate in three one-day seminars on export promotion are affected by their information exchange peers. We find that peers' participation in the seminars has a positive effect overall. We distinguish between peers participating on the same day and other days, finding that the former has a positive effect while the latter has no significant effect. These results imply that peer effects arise mostly through a reduction of psychological cost of participation. Our results suggest that multiple equilibria in terms of the share of participants within each network of firms may emerge.

Keywords: peer effects, social networks, social utility, information confirmation, free riding, randomized controlled trials

JEL classification: C93, D22

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The effects of peers' behavior on actors' own behavior through social networks, i.e., peer effects, have been recognized in the theoretical and empirical economics literature (Lawrence E Blume et al., 2011, Matthew O Jackson and Yves Zenou, 2014). Although many studies examined effects of peers on performance, e.g., effects of classmates on students' test scores (Joshua D Angrist and Kevin Lang, 2004, Bruce Sacerdote, 2001, David J Zimmerman, 2003), one particular strand of this literature focuses on peer effects on decisions to participate in social programs. For example, Esther Duflo and Emmanuel Saez (2003) analyzed the role of social interactions in employees' decisions to enroll in a retirement plan. They conducted an experiment in which they provided monetary incentives to randomly selected employees to participate in information fairs and found a positive peer effect on participation in a business program for information dissemination.

Peer effects may affect participation in social and business programs, in particular those for information dissemination, for three reasons. First, actors may be more likely to participate in a program if their peers also participate, as doing so lowers the psychological costs of participation. Following Leonardo Bursztyn et al. (2014), we refer to this channel as social utility. Second, the participation of actors is encouraged by their peers' participation if they expect to be able to discuss the information that is provided in a program with their participating peers and thus to be able to increase their understanding of the information. In a similar context, Damon Centola (2010) found that the reinforcement of the same information from multiple peers promotes behavioral adoption; we refer to this channel as information confirmation. Finally, actors are discouraged to participate in programs based on their peers' participation because they may be able to obtain the information that their peers receive in the program at no personal cost ("free riding").[1] In short, social utility and information confirmation lead to strategic complementarity of behaviors among peers, which results in positive peer effects, while free riding results in strategic substitution and negative peer effects.

Whether the behaviors of actors are strategic complements or substitutes largely affects equilibrium characteristics Matthew O Jackson and Yves Zenou (2014). On the one hand, if strategic complementarity dominates owing to, for example, social utility, no

[1] Another possible channel of peer effects is word-of-mouth, which was examined by, for example, Sinan Aral and Dylan Walker (2011) and Abhijit Banerjee et al. (2013). In this study, we do not examine this channel because the time span between the seminars for diffusion of word-of-mouth is too short. Hongbin Cai, Yuyu Chen and Hanming Fang (2009) isolate the effects of learning from others through observations from the effects through direct communication. Our focus is not the distinction of these two types of effects.

participant within a network participates in the program in a Nash equilibrium. In this situation, if only one actor participates, her welfare may decline because of the great psychological costs of participation without any peer participants. However, in another Nash equilibrium, everyone in a network participates because the peer effects lower the costs of participation. On the other hand, if strategic substitution due to free riding dominates in a typical equilibrium, only a few actors participate and diffuse the information that they obtain in the program, while others free ride and thus also obtain the information (Yann Bramoullé and Rachel Kranton, 2007). In either case, the peer effects may result in a low participation rate in programs for information dissemination. In practice, the take-up rate in social and business programs is indeed often quite low (Marianne Bertrand et al., 2004, Janet Currie, 2004, David McKenzie and Christopher Woodruff, 2013). For example, Nicholas Bloom et al. (2013) provided free consulting on management practices to Indian firms, but only 26 percent of the 66 targeted firms participated in the program.

Therefore, to improve take-up rates, the empirical question of how peer effects work in such programs is important for program organizers and policy makers. However, empirically identifying peer effects is difficult because of the reflection problem argued by Charles F. Manski (1993) and because of the endogeneity in peer behavior. The reflection problem arises because average group behaviors are a mirror image of individual behaviors, so it is difficult to identify causality from the correlations between behaviors. Endogeneity arises because of the self-selection of peers and unobserved group effects.

To correctly identify peer effects, some recent studies have utilized natural and randomized experiments in peer formation or selection of participants (Sinan Aral and Dylan Walker, 2011, Abhijit Banerjee et al., 2013, Gustavo J Bobonis and Frederico Finan, 2009, Gordon B Dahl et al., 2014, Giacomo De Giorgi et al., 2010, Esther Duflo and Emmanuel Saez, 2003, Armin Falk and Andrea Ichino, 2006, Bruce Sacerdote, 2014, 2001, David J Zimmerman, 2003). The present study follows this literature on the identification of peer effects based on randomized experiments. In particular, we conducted a randomized controlled trial (RCT) in which we invited 151 firms randomly selected from nearly a population of 296 registered small and medium-sized enterprises (SMEs) in 16 traditional garment and textile clusters in Vietnam to seminars on export promotion. Before the RCT, we conducted a survey among all of the SMEs to capture the entire information exchange network of the firms within each cluster. The firm peers are defined as their information exchange partners. Because the number of invited peers of each SME is randomly determined based on the total number of its peers, the peer effects can be identified by two-stage least squares (2SLS) estimations in which the number of the participating peers, which is the key variable to examine peer effects, is instrumented by the number of invited peers.

This study contributes to the literature on the identification of peer effects in the following three ways. First, peer effects are often identified among individuals, e.g., students and employees. However, peer effects can also work among firms and affect firm participation in business training programs, which could (although not always) improve firm performance (David McKenzie and Christopher Woodruff, 2013). This paper is the first attempt to identify peer effects among firms in terms of participation in business programs.

Second, most of the existing studies defined peers by group members, such as roommates and classmates in colleges (Giacomo De Giorgi, Michele Pellizzari and Silvia Redaelli, 2010, Bruce Sacerdote, 2001, David J Zimmerman, 2003) and employees in the same department (Esther Duflo and Emmanuel Saez, 2003). However, all of the members in a particular group are not necessarily connected closely for information or utility exchange, and estimates from these studies are thus difficult to interpret (Scott E. Carrell et al., 2011). Therefore, some recent studies defined peers more precisely. For example, Leonardo Bursztyn, Florian Ederer, Bruno Ferman and Noam Yuchtman (2014) and Armin Falk and Andrea Ichino (2006) examined peer effects between two actors who were matched in experiments. One disadvantage of these studies is that the number of peers is always one and has no variation among the observations. Alternatively, Sinan Aral and Dylan Walker (2011), Abhijit Banerjee, Arun G Chandrasekhar, Esther Duflo and Matthew O Jackson (2013), Antoni Calvó-Armengol et al. (2009), and David Card and Laura Giuliano (2013) targeted whole networks of many actors to identify all of the peers for each actor. The current study follows this line of the literature and identifies all of the peer firms within the cluster with which firms exchange business information by asking firm representatives directly. Then, we estimate the effects of the number of peers participating in the seminars on firm decisions to participate while controlling for the total number of peers. Because this specification is analogous to the linear-in-means model of Charles F. Manski (1993), our results are more comparable to those of the previous studies.

Third and most importantly, we separate peer effects through social utility from the other two channels, namely information confirmation and free riding. In our experiment, we invited each participant to one of the one-day seminars that were held over three consecutive days. The invited representatives were allocated to the three seminars randomly, and they were not allowed to change the date of participation. This unique experiment structure enables us to isolate the peer effect through social utility. A firm representative who is invited to participate in the seminar is affected by her peers who participate in the seminar on the same day through all of the three above-enumerated channels. However, she is affected by her peers who participate in the seminar on one of the other two days through only two channels, namely, information confirmation and free riding, because social utility does not work when two actors participate in different seminars (although the contents are the same). Therefore, the difference between the effects of peers participating on the same day and the effects of peers participating on other days should constitute the peer effect through social utility.

A decomposition of peer effects is provided by Leonardo Bursztyn, Florian Ederer, Bruno Ferman and Noam Yuchtman (2014), who examined how individuals' decisions on purchasing a financial asset affect their peers' decisions. In particular, they distinguished between two channels of peer effects: (1) social learning due to a diffusion of information on an asset and (2) social utility due to the mutual possession of the same asset. However, because our study focuses on decisions to participate in seminars for information dissemination that involve the possibility of free riding on others' information, peers' participation may have a negative effect on the actor's participation. This possible negative effect through free riding is not incorporated in Leonardo Bursztyn, Florian Ederer, Bruno Ferman and Noam Yuchtman (2014).

To preview our results, we find a positive, statistically significant, and quantitatively large effect of participating peers on decisions to participate in seminars. Further, the positive peer effect is mostly due to social utility, i.e., a reduction in the psychological costs of participation due to peers' participation. The positive peer effect through social utility is consistent with the findings of Leonardo Bursztyn, Florian Ederer, Bruno Ferman and Noam Yuchtman (2014). Moreover, the sum of the positive effect due to information confirmation and the negative effect due to free riding is not statistically significant, although we cannot further distinguish between the two. Leonardo Bursztyn, Florian Ederer, Bruno Ferman and Noam Yuchtman (2014) find a positive peer effect through social learning, which is analogous to our information confirmation. However, their finding is not necessarily contradicting to ours, because the negative peer effects through free riding are theoretically absent in Leonardo Bursztyn, Florian Ederer, Bruno Ferman and Noam Yuchtman (2014).

Our results that support positive peer effects imply multiple equilibria due to strategic complementarity. In other words, the rate of firms' participation in the seminars may vary across clusters of firms, depending on the cluster characteristics that determine the firms' beliefs about their peers' participation. We find evidence that supports this argument of multiple equilibria: there was no participation in some of the clusters among the 16 in our sample, while the take-up rate was quite high in others. This argument is also consistent with the literature. For example, Leonardo Bursztyn, Florian Ederer, Bruno Ferman and Noam Yuchtman (2014) reported that the peer effects they found would result in herd behaviors in decisions to purchase financial assets. Lawrence E Blume, William A Brock, Steven N Durlauf and Yannis M Ioannides (2011) theoretically showed that in the presence of peer effects, or social interactions, the rate of adoption of a new technology jumps when it is adopted by a certain critical mass. Steven Durlauf (2006) proposed that poverty traps may arise when group membership affects individual decisions.

Our results provide important implications for organizers and policymakers of business seminars and social programs. As we mentioned earlier, the take-up ratio of business and social programs is often low despite their potential benefits. This study suggests that program organizers should invite firms and individuals in a dense network at the same time to lower the psychological costs of participation and to encourage participation.

I. Methodology

A. *Conceptual framework*

The actions taken by people may be influenced by their peers in their social networks. The recent development of network game theory helps to theoretically explain how a player’s actions can be positively or negatively affected by her peers’ actions (Matthew O Jackson and Yves Zenou, 2014).

In this study, as we will explain in detail later, firms are invited to business seminars, and they decide whether they will participate. If the firms’ expected payoffs are positively affected by their peers' participation, they are more likely to participate in the seminars when their peers participate. This strategic complementarity can arise from two sources. First, the costs of, or psychological barriers to, participation may be lower when their peers participate. Leonardo Bursztyn, Florian Ederer, Bruno Ferman and Noam Yuchtman (2014) found that individual investors' utility increases when they hold a financial asset that is also held by their peers, referring this source of peer effects as social utility. Social utility is also applicable in our case, as the participants may feel more comfortable when they are with their friends in the seminars. Second, the invited individuals may consider that their participation would be more useful if they confirmed the information that they learned in the seminars with each other to deepen their understanding of the information. This second channel of peer effects is related to the findings of Damon Centola (2010) based on a social experiment on the Internet that showed that people are more likely to adopt new health behaviors when a social network within a group is dense, i.e., when most of a group's members know each other. Centola interpreted this finding to indicate that the reinforcement of the same knowledge from multiple peers results in a deeper understanding of the knowledge and thus promotes its adoption. By contrast, if the information obtained in seminars is easily diffused among peers, they can free ride on the information obtained by their peer participants. Such a situation leads to strategic substitution and a negative correlation between an individuals' participation and their peers' participation.

A unique feature of our experiment enables us to separate a positive peer effect due to social utility from the other two effects (information confirmation and free riding). We held one-day seminars on three consecutive days and invited each firm to the seminar on a particular day. The invited firms were not allowed to participate in the seminars to which they were not invited. Thus, from a participant's viewpoint, there are two types of peer participants: (1) those who participated in the same seminar in which she participated and (2) those who participated in the other seminars in which she did not participate. Although the contents of the three seminars were slightly different from each other for the purpose of the impact evaluation of the different types of seminars (Yu Ri Kim et al., 2016), the invited firms did not know the differences at the time of invitation. Therefore, regardless of whether they participated, they assumed that the three seminars were the same.

Given this structure of our experiment, we found that peers participating in the seminar on the same day and those participating on other days differentially affected firms' decisions. Specifically, if a firm's peers participated in the seminar on the same day, the firm was affected by the peers through all the three channels described above, i.e., social utility, information confirmation, and free riding. However, firms whose peers participated in the seminar on other days were affected only by information confirmation and free riding. Firms can confirm the information that they obtain in seminars with peers who participate on any day and free ride on information that is obtained from any peer participant. However, the social utility of firm representatives is affected only by peers participating on the same day and not by peers participating on other days (Table 1). Therefore, the effect of peers participating on other days represents the sum of a positive peer effect due to information confirmation and a negative effect through free riding, while the difference between the effect of peers participating on the same day and the effect of peers participating on other days indicates a positive peer effect due to social utility.

B. *Estimation equation*

Based on the above conceptual framework, we empirically estimate how the decisions of firms' peers to participate in the seminar affect their own participation decisions. In the empirical analysis, one important issue concerns whether we should use the number of peers who were invited to the seminars or the number of peers participating in the seminars to measure the peer effects. Theoretically, it is often assumed that players make decisions simultaneously without observing others' decisions. If this is the case, a firm's decision is affected by its invited peers rather than the participating peers, as participation is not observed at the time of the decision. Thus, it is theoretically suggested to use the number of invited peers for the estimation of peer effects. In our study, using the invited peers provides a great advantage because the invited firms are randomly selected and thus the number of invited peers is exogenous given the number of all of the peers for each firm.

However, there are also disadvantages to using invited peers. In particular, although pure theory often assumes the simultaneous decisions of players, this may not be the case in our setting. From our interviews with firms, we found that some of the firms discussed whether they would participate in the seminar with their peers. Therefore, the number of participating peers, and not the invited peers, may be a more accurate measure of the peers affecting their own decisions.

We thus consider the following linear probability model:

$$(1)\quad PAR_i = \beta_0 + \beta_1 PAR\_SAME_i + \beta_2 PAR\_OTHER_i + \boldsymbol{\gamma}\mathbf{X_i} + \varepsilon_i,$$

where PAR_i is a dummy variable for firm i's participation in the invited seminar. PAR_SAME_i is the number of firm i's peers participating in the same seminar to which firm i is invited, whereas PAR_OTHER_i represents the number of firm i's peers participating in a seminar on one of the other two days. As we will explain later in the data section, the peers of i are defined as the firms that were reported by firm i as information exchange partners or those that reported firm i as an information exchange partner. $\mathbf{X_i}$ is a vector of attributes of firm i and its representative, including the total number of peers (i.e., the degree centrality). It is important to include the total number of peers, as the number of invited and participating peers tends to be larger when the total number of peers is larger. By including the total number of peers, we can distinguish between the effect of the firms' attributes and the effect of peers.

According to the discussion in Section 2.1, which is summarized in Table 1, β_1 indicates the sum of a positive effect of peers due to information confirmation and a negative effect due to free riding. In addition to the two effects, β_2 includes a positive peer effect through social utility. Therefore, the difference between β_1 and β_2 signifies the peer effect through social utility.

C. *Identification strategy*

Identifying peer effects is known to be a difficult task (Lawrence E Blume, William A Brock, Steven N Durlauf and Yannis M Ioannides, 2011). In particular, Charles F. Manski (1993) argues that the channels behind the correlation between the behavior of an individual and her group members can be decomposed into three types. The first channel is the direct effect of peers' behaviors on an individual's behavior, or the endogenous effects according to Charles F. Manski (1993). In our case, this can be further decomposed into effects through social utility, information confirmation, and free riding, as argued in Section 2.1. The second channel comprises the effects of the exogenous characteristics of the group, or the exogenous (contextual) effects. Suppose, for example, that firms tend to form networks based on their owners' ages and that the owners are stimulated more by their younger peers for business expansion. Then, the firms are encouraged to participate in the seminar by their young peers, regardless of whether the young peers actually participate. The third channel comprises the correlated effects that simply represent correlation between a particular group's attributes and the group's behaviors without any reference to causality. For example, if firms with high productivity tend to be connected with firms with similarly high productivity and if high productivity promotes participation in the seminar, group productivity may be correlated with participation.

Our estimation equations focus on (decomposed) endogenous effects, and we investigate how the decisions of a particular firm's peers to participate in seminars affect its decision to participate. However, its peers' participation decisions are also affected by the firm's decision and are determined endogenously by common group characteristics. Thus, biases due to simultaneity and endogeneity arise in the estimation of equation (1). To avoid these problems and to identify the endogenous effects, we employ a 2SLS approach by using the exogenous number of the invited peers to instrument the endogenous number of participating peers. In our experiment, the firms are randomly invited to one of three one-day seminars. In this setting, given the total number of a firm's peers, the number of its peers that are invited to the same seminar to which the firm is invited and the number of peers that are invited to the seminar on another day are exogenously determined. Thus, the first-stage equations can be expressed as follows:

(2) $PAR\_SAME_i = \beta_{11} + \beta_{12} INV\_SAME_i + \beta_{13} INV\_OTHER_i + \boldsymbol{\lambda_1 X_i} + u_{1i}$

(3) $PAR\_OTHER_i = \beta_{21} + \beta_{22} INV\_SAME_i + \beta_{23} INV\_OTHER_i + \boldsymbol{\lambda_2 X_i} + u_{2i}$

where INV_SAME_i is the number of firm *i*'s peers that are invited to the same seminar to which firm *i* is invited and INV_OTHER_i represents the number of firm *i*'s peers that are invited to a seminar on another day. The total number of firm *i*'s peers is included in $\mathbf{X_i}$.

II. Data and Randomized Experiment

A. *Sampling and survey*

In this study, we focus on SMEs in village-based industrial clusters in the apparel and textile industry in the Red River Delta surrounding Hanoi, which is the capital city of Vietnam. Village industry clusters are traditionally developed agglomerations of SMEs, including micro enterprises in a particular industry such as the apparel, wood furniture, and ceramic industry within the village boundary. We focus on village industrial clusters because it is possible to observe the networks within the village through which firms exchange business information. Additionally, because we focus on participation in seminars on export promotion, we target SMEs in the apparel and textile industry, which have a reasonable share of current exporters, at approximately 10 percent.

We first identified such village clusters by using data from the Vietnam Enterprise Survey (VES), which was conducted by the General Statistical Office of Vietnam (GSO) in 2010. We chose villages or communes, which are the smallest administrative unit, with more than five registered firms in the textile and apparel industries (industry codes 13 and 14, based on the Vietnamese system of industry classifications) in the 10 provinces in the Red River Delta in the VES data. Because not all of the firms are formally registered and because smaller firms in the VES are randomly selected,[2] villages with more than five registered firms in the apparel and textile industry in the VES data are most likely to be industrial clusters of a specific industry. Through this process, we identified 19 villages in six provinces. Then, we visited the selected villages and found that two villages among the 19 are not apparel and textile clusters in the sense that most manufacturing firms in the villages do not necessarily engage in apparel or textile production. We also omitted one village from our sample because it was found that the village had already received business management training through another RCT and because it had been surveyed several times for impact evaluation (Yuki Higuchi et al., 2015). We assumed that firms in this village are already systematically different from firms in other villages.

The target of our study is registered firms in the remaining 16 apparel and textile village clusters. For each of the 16 villages, we obtained the full updated list of registered firms from the municipal governments. The total number of all registered firms in our target villages is 354. In December, 2014 and January, 2015, we requested face-to-face interviews with the owners, managing directors, or top-level managers of the 354 firms and obtained responses from 296. Thus, the response rate was 84 percent. The questionnaire consists of questions on standard firm characteristics, such as sales, number of workers, main products, and ownership. In addition, to identify firm networks within a cluster, we presented to a representative of each firm the full list of registered firms in the village and asked the representative to list the firms with which the firm regularly exchanges business information. Because we surveyed most of the registered firms within a village, we can identify a nearly complete network of the registered firms within each

[2] The VES targets all firms with 30 employees or more and randomly selected 10 percent of firms with 10-29 employees.

village.

B. *Seminars on export promotion*

We conducted an RCT in which we randomly selected about a half of the 296 firms that were surveyed and invited each of the selected firms to one of the three one-day seminars on export promotion, which took place from March 14 to March 16, 2015. The seminar consisted of four common classes on: an introduction to the development of the global economy by a business school professor; basic procedures for exporting by an official from the Vietnam export promotion agency; tips for exporting to Japan by officials from the Hanoi office of the Japan External Trade Organization (JETRO); and an overview of experiences for beginning an exporting business by current exporters. Strictly speaking, the content of the seminars was slightly different across the three days: there was an additional class on e-customs on the second and third days, and there was a reception dinner after the seminar on the third day. However, we can ignore these differences when we estimate peer effects, as the invitees were not informed of such differences upon invitation and their decisions to participate should therefore not have been affected by the differences among seminars.

The venue of the seminars was a three-star hotel located at the center of Hanoi. We chose a three-star hotel to attract participants. It took a minimum of 30 minutes by motorbike to a maximum 2 hours by bus from the sample villages to the hotel. For several villages that are located far from the hotel, we chartered buses for the participants' transportation. We reimbursed the actual cost to those who used their own means of transportation, such as public buses or motorbikes. No compensation was provided except for meals at the hotel. We did not collect any participation fee from the participants.

C. *Selection and participation of firms*

We randomly selected 50 or 51 firms for each day (151 firms in total) by a stratified sampling strategy at the village level. Then, we sent an enumerator of the firm-level survey to each firm for face-to-face invitations to the seminars in early March and provided a formal letter that explained the details of the seminar. In the letter, we noted that only the owner, the managing director, or a top-level manager can participate in the seminars, although the seminar participants and respondents to our surveys may be different. A few days before the seminars, we made phone calls for further invitation. If the firms were not willing to participate at the time of the first phone call, we made another phone call a day before the seminar.

No firms were allowed to participate in the seminar unless they were invited. Thus, our estimations are based on a sample of firms that were invited to one of the seminars. We had to drop 20 firms that failed to report the necessary information for the estimations in the survey. Consequently, our baseline sample consists of 131 invited firms. Note that although we held three one-day seminars, the invited firms were not allowed to participate in a seminar that was different from the seminar to which they were invited. However, five firms came to a seminar to which they were not invited, although they were invited to a seminar on another day. We eventually had to allow them to participate for ethical reasons. In the analysis, we keep the five firms in the sample, as their decisions to change the date of the seminar for participation are obviously endogenous, whereas the instruments remain exogenous. To check the robustness of the results, we further dropped the five firms from the sample in alternative estimations.

Among the invited firms, only a small number of the invited firms participated in our seminars. Among the 50 firms that were invited on the first day, only 9 participated, whereas there were 15 among 50 on the second day and 14 among 51 on the last day. In total, of the 151 invited firms, 38 firms participated; thus, the participation rate is 25.2 percent. This low participation rate is comparable to that in the management consultation program in India conducted by Nicholas Bloom, Benn Eifert, Aprajit Mahajan, David McKenzie and John Roberts (2013).

D. *Construction of variables*

As we mentioned in Section 2.2, the dependent variable is a dummy variable that takes a value of one if firm *i* participated in one of the three seminars and zero otherwise. The key independent variables are *PAR_SAME* (*INV_SAME*) and *PAR_OTHER* (*INV_OTHER*), i.e., the number of firm *i*'s peers participating in (invited to) the seminar on the same day that firm *i* was invited to participate and the number of firm *i*'s peers participating in (invited to) the seminar on another day, respectively. The peers of firm *i* are defined to be the firms that were reported by the survey respondent of firm *i* as information sharing partners or those that reported firm *i* as information sharing partners. In other words, we assume no direction in information exchange networks. Although our estimations are based on 131 invited firms with complete information, the number of peers is defined based on the information exchange partners of all of the registered firms within each village, including those who did not respond, those who were not invited, and those who are dropped due to missing information.

The control variables include firm attributes that contain the log of the total number of workers, the share of exports in total sales, the log of the firm age, and the attributes of the top-level manager, such as the president and the owner, of each firm, including the log of his or her age, the log of his or her years of education, and a dummy that indicates whether the respondent was a female. In addition, we experimented with specifications incorporating the averages of firm and manager attributes above of the invited peers of each firm to control for correlated effects of Charles F Manski (1993), or possible effects of the group attributes on participation decisions. Finally, some of our specifications include dummy variables that indicate on which day firm *i* was invited to the seminar. This is primarily to control for possible differences between weekdays and weekends because our seminars were held on Saturday, Sunday, and Monday.

E. *Descriptive statistics*

Table 2 analyzes whether we succeeded in the random invitation to the firms by conducting *t* tests for systematic differences in the control variables for the firm and manager attributes that are used in the estimation between the invited and non-invited firms. None of the variables show a statistically significant difference between the two groups. Therefore, there should be no correlation between the number of invited peers and the error term in equation (1), and our identification strategy utilizing the RCT that is described in Section 2.3 should work.

Table 3 shows the descriptive statistics of the variables that are used in the later estimations for the sample of 131 firms. The average number of peers is 4.015, of which approximately one half, i.e., 1.977, were invited to one of the three seminars. The average number of peers participating in any of the seminars is 0.618. Because the target firms are in traditional garment and textile clusters, the average number of workers, 25.985, is relatively small. On average, the share of exports in total sales is 19.0 percent, the firm age is 6.57 years, the age of managers is 42.9 years, and their years of education are 13.8 years. We also found that 19.8 percent of the managers are female.

III. Results

A. *Peer effects in total*

We start by estimating a simpler version of equation (1), where the two types of peers are not distinguished, by using the total number of invited peers to instrument the total number of participating peers. We experimented with several sets of independent variables by incorporating dummies for the invited day in some specifications and averages of firm and manager attributes of the peers in others. The results from the first-stage regressions are shown in Table 4. The instrument, the number of invited peers, is highly correlated with the endogenous variable, the number of participating peers, in all of the specifications. Kleibergen-Paap Wald rk F statistics (Frank Kleibergen and Richard Paap, 2006) are shown in the second row from the bottom. The F statistic becomes smaller as we incorporate more independent variables that are mostly insignificant but greater than its critical value at the 20-percent maximal size, which is 6.66 (James H Stock and Motohiro Yogo, 2005), indicating that the instrument is not weak. The results from the second-stage regressions are presented in Table 5. In all of the specifications, the effect of the number of participating peers is positive and significant at least at the 10-percent level (significant at the 5-percent level in column [1] where the F statistic is the largest).

As we mentioned in Section 3.3, five firms participated in a seminar that was different from the seminar to which the firms were invited. To check the robustness of the above results, we dropped these five firms and repeated the same estimations. The results shown in Table 6 are mostly similar to those in Tables 4 and 5, except for the insignificant effect of participating peers when all of the control variables are incorporated (column [4]).

B. *Decomposing peer effects*

Subsequently, we decompose the peer effects as discussed in Section 2 and isolate those due to social utility and those due to information confirmation and free riding by disaggregating the firms' peers participating in the seminars into two types, i.e., those participating on the same day and those participating on other days. We experimented with the same four alternative sets of control variables as we did in Tables 4 through 6, and the results are shown in Table 7. In all of the specifications, the instruments, the numbers of the invited peers participating on the same day and that of those participating on other days, are significantly correlated with the endogenous variables, which include the number of participating peers on the same day and that of those participating on other days. In addition, the Kleibergen-Paap Wald rk *F* statistics (Frank Kleibergen and Richard Paap, 2006), shown in the second row from the bottom, are greater than its critical value for the 20-percent maximal size of 3.95, and they are mostly greater than that of the 15-percent maximal size of 4.58 (James H Stock and Motohiro Yogo, 2005). Therefore, we conclude that the instruments are not weak. The second-stage results of the 2SLS estimations demonstrate a positive and statistically significant effect of peers participating on the same day but no significant effect of peers participating on other days.

Based on the argument in Section 2.2 summarized in Table 1, the difference between the coefficients on the two types of participating peers represents the peer effect due to social utility, while the coefficient on the participating peers on the other days indicates the sum of the positive peer effect due to information confirmation and the negative effect due to free riding. Thus, we conducted Wald tests to examine the null hypothesis that the difference between the two coefficients is zero, i.e., that there is no peer effect due to social utility. The bottom row shows *p* values from the Wald tests. The null hypothesis is rejected at the 10 percent level in columns (3) and (4) in Table 7, while it is not in columns (1) and (2). Thus, the Wald test provides contradicting results across the specifications. However, we rely more on the results in columns (3) and (4) for two reasons. First, the specifications in columns (3) and (4) utilize more control variables, including average peer attributes that may affect the similarity of the decisions among peers. Second, even in columns (1) and (2) of Table 7, the number of peers participating on the same day has a positive and significant effect. In addition, the results in Tables 5 and 6 show a positive and significant effect of the participating peers overall. These results suggest that there are positive peer effects of some kind. Therefore, it would be more contradictory if we were to rely more on the specifications in columns (1) and (2) and to conclude that no peer effect due to social utility, information confirmation, or free riding exists.[3]

IV. Discussion and Conclusion

In this study, by utilizing a RCT in traditional clusters of apparel and textile SMEs in

[3] For robustness checks, we dropped the five firms that participated in the seminars different from the seminars to which the firms were invited and repeated the estimations, as we did in Table 6. We found that the results were qualitatively the same and quantitatively similar to the results in Table 6.

Vietnam, we investigate the peer effects on firms' participation in seminars on export promotion. To identify the peer effects, we apply 2SLS estimations by using the number of peers invited to the seminars, which was randomly determined, to instrument the number of peers participating in the seminars. We further distinguish peers participating in the same seminar to which a particular firm was invited from peers participating in the seminars on the other days. In this way, we can isolate the peer effect by reducing in the psychological costs of participation, or social utility, from the positive effect through information confirmation among peers and the negative effect through free riding on peers' information.

The results in Tables 4 through 7 can be summarized as follows. First, the identified peer effects are quite large. An additional participating peer increases the probability of participation in the seminars by 21.9 percentage points (column 1 of Table 4), whereas the average participation rate is only 25.2 percent (Table 3).

Second, peers participating in seminars on the same day increase the probability of participation, while peers participating in seminars on other days do not. Further, the difference between the effects of peers on the same day and the effects of peers on other days is significant in our preferred specifications. Therefore, we conclude that peer effects arise mostly due to social utility, i.e., increases in firm representatives' utility when their peers are with them. This finding is consistent with the findings of Leonardo Bursztyn, Florian Ederer, Bruno Ferman and Noam Yuchtman (2014), who found that investors tend to hold the same financial assets as their peers.

Third, there may be two other types of peer effects: a positive effect due to information confirmation among peers and a negative effect due to free riding on peers' information. Our results suggest that the two opposing effects may cancel each other out or that both of them are negligible.

The positive peer effects that are found in this study lead to strategic complementarity in firms' participation decisions. Because of the strategic complementarity, it is theoretically likely that there are multiple equilibria across the groups, as argued in David Card and Laura Giuliano (2013): firms are better off by participating in a seminar if many peers participate, but they are worse off if only a few peers participate. This situation is similar to the majority game, for which there are two equilibria: one in which all firms participate and the other in which no firm participates, depending on the beliefs of the firms (Matthew O Jackson and Yves Zenou, 2014). In the case of our experiment, we indeed found that there are some villages in which most of the invited firms did not participate in any seminar (Panel A of Figure 1) while most of the invited firms participated in some seminars (Panel B).

The actual situation in this study is more complicated because we found positive effects of peers participating on the same day while there was no effect of peers participating on other days. In the latter case, depending on how many firms in the village were invited to the seminar on each of the three days, the participation rate within the village may vary. Suppose, for example, that three firms that are linked to each other in a village were invited to the seminar on the first day but that only one firm in the same village was invited on each of the other two days. Then, all or none of the former three firms would participate, depending on their beliefs about their peers' behaviors. However, the last two might not participate, which leads to a participation rate of either 60 or 0 percent.

Based on this conjecture, we would expect that the take-up rate among invited firms varies substantially across villages although it may skew toward zero. Panel A of Figure 2 shows the distribution of the take-up rate among the invited firms in each village. The dominant take-up rate is about 0-10 percent, but there are many firms and villages with a rate of 50-70, 70-90, and 90-100 percent. Panel B shows the take-up rate among invited firms in the ego network of each invited firm, i.e., among the invited firm and its invited peers. The distribution at the firm level is similar to that at the village level. These dispersed distributions are consistent with the argument that there are multiple equilibria owing to peer effects.

Based on the argument above, our results provide implications to organizers and policymakers of social and policy programs. As we mentioned in Section 1, the participation rate in policy and social programs is often found to be low in practice. Our results suggest that the low participation rate is partly due to peer effects. In other words, actors hesitate to participate in such programs because of the high psychological costs of participation. The participation of their peers can reduce such costs, but if peers are not informed about or invited to the program, or if the actors believe that their peers would not participate, they will not participate either. Therefore, organizers of social and business programs should target actors that are closely linked, and invite and inform all of them at the same time to raise the participation rate.

Although we successfully isolated the peer effect due to social utility, we could not distinguish between the other two possible channels of peer effects, namely, information confirmation and free riding. However, whether actors tend to avoid participation in social and policy programs due to free riding and, if so, how this negative peer effect affects the overall performance of actors remain topics for further analysis. Future research should attempt to address these issues.

References

Angrist, Joshua D and Kevin Lang. 2004. "Does School Integration Generate Peer Effects? Evidence from Boston's Metco Program." *American Economic Review*, 94(5), 1613-34.

Aral, Sinan and Dylan Walker. 2011. "Creating Social Contagion through Viral Product Design: A Randomized Trial of Peer Influence in Networks." *Management Science*, 57(9), 1623-39.

Banerjee, Abhijit; Arun G Chandrasekhar; Esther Duflo and Matthew O Jackson. 2013. "The Diffusion of Microfinance." *Science*, 341(6144), 1236498.

Bertrand, Marianne; Sendhil Mullainathan and Eldar Shafir. 2004. "A Behavioral-Economics View of Poverty." *American Economic Review*, 94(2), 419-23.

Bloom, Nicholas; Benn Eifert; Aprajit Mahajan; David McKenzie and John Roberts. 2013. "Does Management Matter? Evidence from India." *Quarterly Journal of Economics*, 128(1), 1-51.

Blume, Lawrence E; William A Brock; Steven N Durlauf and Yannis M Ioannides. 2011. "Identification of Social Interactions," Jess Benhabib, Alberto Bisin and Matthew O. Jackson, *Handbook of Social Economics.*

Bobonis, Gustavo J and Frederico Finan. 2009. "Neighborhood Peer Effects in Secondary School Enrollment Decisions." *Review of Economics and statistics*, 91(4), 695-716.

Bramoullé, Yann and Rachel Kranton. 2007. "Public Goods in Networks." *Journal of Economic Theory*, 135(1), 478-94.

Bursztyn, Leonardo; Florian Ederer; Bruno Ferman and Noam Yuchtman. 2014. "Understanding Mechanisms Underlying Peer Effects: Evidence from a Field Experiment on Financial Decisions." *Econometrica*, 82(4), 1273-301.

Cai, Hongbin; Yuyu Chen and Hanming Fang. 2009. "Observational Learning: Evidence from a Randomized Natural Field Experiment." *American Economic Review*, 99(3), 864-82.

Calvó-Armengol, Antoni; Eleonora Patacchini and Yves Zenou. 2009. "Peer Effects and Social Networks in Education." *Review of Economic Studies*, 76(4), 1239-67.

Card, David and Laura Giuliano. 2013. "Peer Effects and Multiple Equilibria in the Risky Behavior of Friends." *Review of Economics and Statistics*, 95(4), 1130-49.

Carrell, Scott E.; Bruce I. Sacerdote and James E. West. 2011. "From Natural

Variation to Optimal Policy? The Lucas Critique Meets Peer Effects," National Bureau of Economic Research Working Paper No. 16865.

Centola, Damon. 2010. "The Spread of Behavior in an Online Social Network Experiment." *Science*, 329(5996), 1194-97.

Currie, Janet. 2004. "The Take up of Social Benefits," National Bureau of Economic Research Working Paper No. 10488.

Dahl, Gordon B; Katrine V Løken and Magne Mogstad. 2014. "Peer Effects in Program Participation." *American Economic Review*, 104(7), 2049-74.

De Giorgi, Giacomo; Michele Pellizzari and Silvia Redaelli. 2010. "Identification of Social Interactions through Partially Overlapping Peer Groups." *American Economic Journal: Applied Economics*, 241-75.

Duflo, Esther and Emmanuel Saez. 2003. "The Role of Information and Social Interactions in Retirement Plan Decisions: Evidence from a Randomized Experiment." *Quarterly Journal of Economics*, 118(3), 815-42.

Durlauf, Steven. 2006. "Groups, Social Influences and Inequality," S. Bowles, S. Durlauf and K. Hoff, *Poverty Traps.* Princeton: Princeton University Press, 141-75.

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

Higuchi, Yuki; Vu Hoang Nam and Tetsushi Sonobe. 2015. "Sustained Impacts of Kaizen Training." *Journal of Economic Behavior & Organization*, 120, 189-206.

Jackson, Matthew O and Yves Zenou. 2014. "Games on Networks," P. Young and S. Zamir, *Handbook of Game Theory.*

Kim, Yu Ri; Yasuyuki Todo; Daichi Shimamoto and Petr Matous. 2016. "Are Seminars on Export Promotion Effective? Evidence from a Randomized Controlled Trial," RIETI Discussion Paper, Research Institute of Economy, Trade and Industry.

Kleibergen, Frank and Richard Paap. 2006. "Generalized Reduced Rank Tests Using the Singular Value Decomposition." *Journal of Econometrics*, 133(1), 97-126.

Manski, Charles F. 1993. "Identification of Endogenous Social Effects: The Reflection Problem." *The Review of Economic Studies*, 60(3), 531-42.

Manski, Charles F. 1993. "Identification of Endogenous Social Effects: The Reflection Problem." *Review of Economic Studies*, 60(3), 531-42.

McKenzie, David and Christopher Woodruff. 2013. "What Are We Learning from Business Training and Entrepreneurship Evaluations around the Developing World?" *The*

World Bank Research Observer, lkt007.

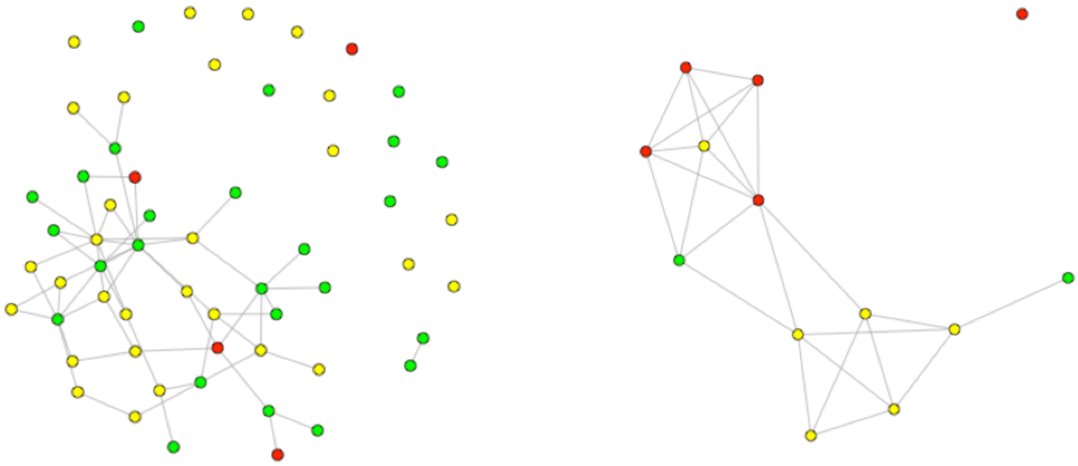
Sacerdote, Bruce. 2014. "Experimental and Quasi-Experimental Analysis of Peer Effects: Two Steps Forward?" *Annual Review of Economics*, 6(1), 253-72.

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

Stock, James H and Motohiro Yogo. 2005. "Testing for Weak Instruments in Linear Iv Regression," D. W. K. Andrews, J. H. Stock and T. J. Rothenberg, *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg.* Cambridge: Cambridge University Press,

Zimmerman, David J. 2003. "Peer Effects in Academic Outcomes: Evidence from a Natural Experiment." *Review of Economics and Statistics*, 85(1), 9-23.

Figure 1. Inter-firm social network and participation in the seminars

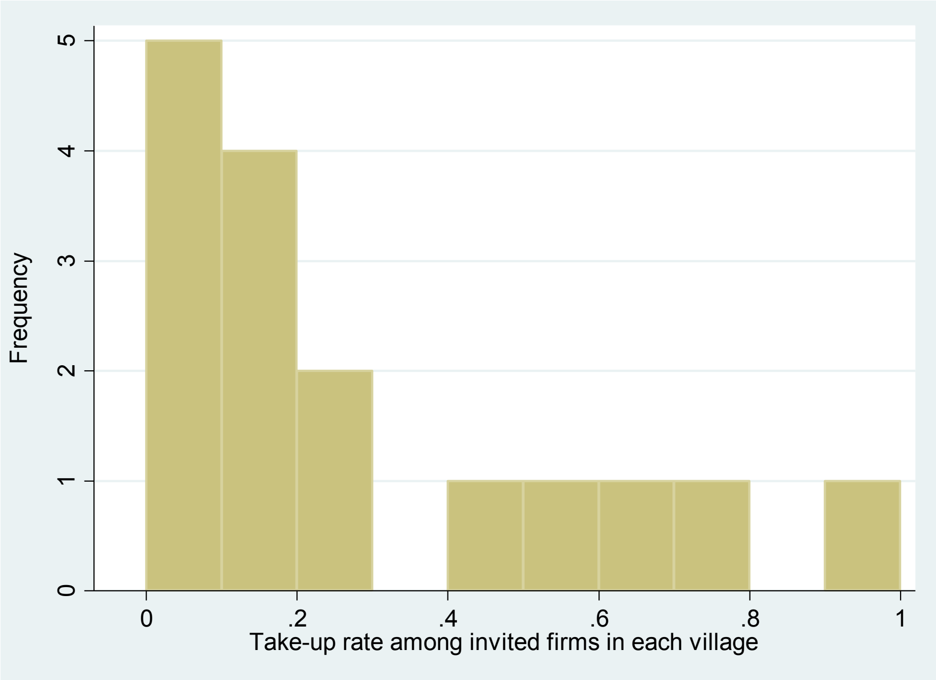


Panel (A) Panel (B)

Notes: Red, green, and yellow circles respectively indicate firms participating in a seminar, those invited but not participating in any seminar, and those not invited to any seminar.

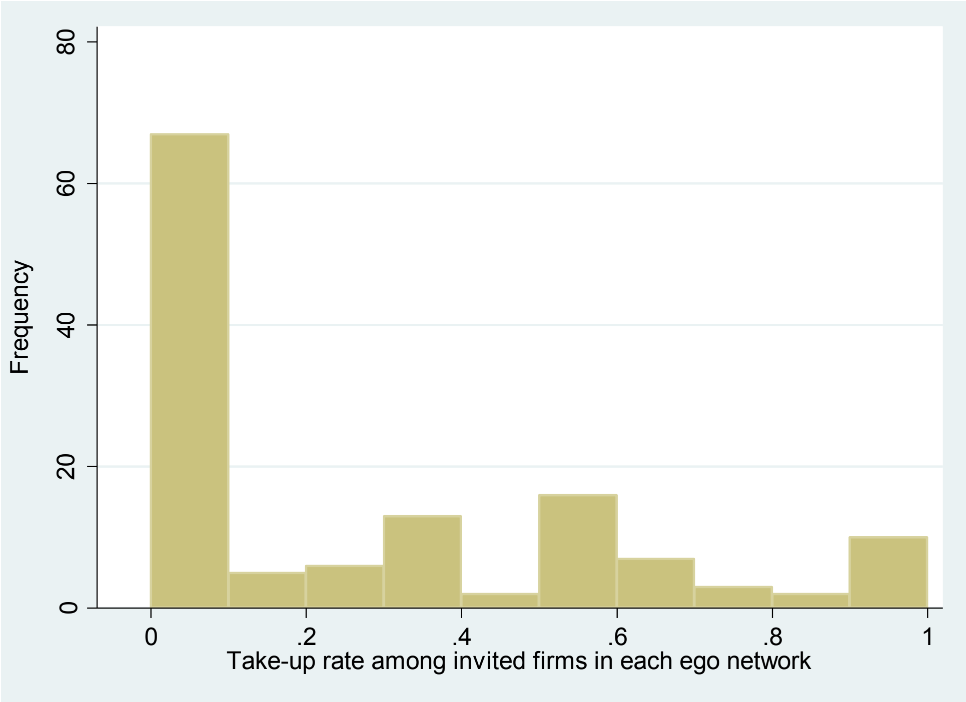
Figure 2. Distribution of the take-up rate

Panel (A): Village level



Notes: This figure shows the distribution of the take-up rate among the invited firms in each of the 16 villages used in this study.

Panel (B): Firm level



Notes: This figure shows the distribution of the take-up rate among the invited firms in the ego network, of each of the 131 invited firm used in the regressions, i.e., an invited firm and its invited peers.

Table 1. Channels of peer effects by day of invitation

	Peers participating in the seminar	
	on the same day that a particular firm is invited to	on other days that a particular firm is invited to
Social utility (+)	X	
Information confirmation (+)	X	X
Free rides (-)	X	X

Table 2. Differences between invited and non-invited firms

	Invited firms			Non-invited firms			Difference
Variable		Mean	S.D.	*N*	Mean	S.D.	invited – non-invited
Firm attributes							
Total number of peers	140	3.979	3.492	135	3.948	3.293	0.030
Number of workers	142	29.51	59.00	132	76.38	410.41	-46.87
Share of export in total sales	146	19.58	37.75	136	14.74	32.38	4.840
Firm age	144	8.681	5.467	136	8.610	6.010	0.070
Manager attributes							
Age	142	43.268	9.922	130	44.492	10.280	-1.225
Female dummy	146	0.192	0.395	138	0.217	0.414	-0.026
Years of schooling	142	13.831	2.134	133	14.083	2.306	-0.252

Notes: N and S.D. represent the number of observations and standard deviation, respectively.

Table 3. Descriptive statistics

Variables	Mean	S.D.	Min.	Max.
Participation dummy	0.252	0.436	0.000	1.000
Number of peers	4.015	3.517	0.000	16.000
Number of participating peers	0.618	1.026	0.000	4.000
-- on the same day	0.221	0.611	0.000	3.000
-- on different days	0.435	0.842	0.000	4.000
Number of invited peers	1.977	1.895	0.000	7.000
-- on the same day	0.649	0.793	0.000	3.000
-- on different days	1.328	1.378	0.000	6.000
Firm attributes				
Number of workers	25.985	56.466	0.000	500.000
-- in logs	3.003	1.407	0.000	6.908
Share of exports in total sales	19.031	37.370	0.000	100.000
Firm age	8.695	5.368	1.000	26.000
-- in logs	2.660	0.671	0.881	3.952
Manager attributes				
Age	42.878	9.794	25.000	69.000
-- in logs	4.426	0.230	3.912	4.927
Female dummy	0.198	0.400	0.000	1.000
Years of education	13.832	2.131	9.000	18.000
-- in logs	3.310	0.148	2.893	3.584
Which day a firm is invited to				
first day	0.313	0.465	0.000	1.000
second day	0.351	0.479	0.000	1.000
third day	0.336	0.474	0.000	1.000
Peers' average firm attributes				
Number of peers	22.467	34.380	0.000	185.194
Number of workers	2.622	1.831	0.000	5.915
-- in logs	2.174	1.564	0.000	5.227
Share of exports in total sales	12.359	29.978	0.000	100.000
Firm age	6.572	5.245	0.000	21.000
-- in logs	2.030	1.321	0.000	3.738
Peers' average manager attributes				
Age	32.050	20.946	0.000	65.000
-- in logs	3.238	2.007	0.000	4.868
Female dummy	0.103	0.216	0.000	1.000
Years of education	9.997	6.308	0.000	18.000
-- in logs	2.402	1.487	0.000	3.584

Notes: N=131. S.D. represents standard deviation.

Table 4. Estimation results on total peer effects (1st stage)
Dependent variable: number of participating peers

	(1)	(2)	(3)	(4)
Number of invited peers	0.294	0.279	0.305	0.293
	(0.0938)	(0.0928)	(0.106)	(0.104)
Firm attributes				
Number of peers	0.0224	0.0308	-0.00369	0.00318
	(0.0488)	(0.0487)	(0.0503)	(0.0504)
Number of workers (log)	0.000534	0.00718	0.0139	0.0201
	(0.0646)	(0.0641)	(0.0645)	(0.0649)
Share of exports	0.00458	0.00446	0.00156	0.00156
	(0.00172)	(0.00179)	(0.00152)	(0.00162)
Firm age (log)	0.0154	0.0481	0.0107	0.0462
	(0.102)	(0.111)	(0.0869)	(0.0956)
Manager attributes				
Age (log)	-0.0206	-0.0331	0.0228	0.00691
	(0.303)	(0.298)	(0.308)	(0.306)
Female dummy	0.0228	0.0255	0.0535	0.0572
	(0.153)	(0.153)	(0.145)	(0.146)
Years of education (log)	-0.680	-0.795	-0.596	-0.720
	(0.409)	(0.417)	(0.470)	(0.492)
Which day a firm is invited to (reference: second day)				
First day		-0.207		-0.204
		(0.184)		(0.190)
Third day		-0.0264		-0.0762
		(0.189)		(0.188)
Average peers' firm attributes				
Number of peers			0.0333	0.0363
			(0.0266)	(0.0268)
Number of workers (log)			0.0726	0.0838
			(0.112)	(0.116)
Share of exports			0.00122	0.000896
			(0.00355)	(0.00365)
Firm age (log)			0.0511	0.0217
			(0.184)	(0.190)
Average peers' manager attributes				
Age (log)			0.976	0.960
			(0.350)	(0.359)
Female dummy			-1.558	-1.532
			(0.460)	(0.462)
Years of education (log)			1.096	1.097
			(0.385)	(0.395)
Observations	131	131	131	131
Kleibergen-Paap Wald rk F statistic	9.85	9.02	8.33	7.90
R-squared	0.420	0.427	0.499	0.504

Notes: Robust standard errors are in parentheses.

Table 5: Estimation results on total peer effects (2nd stage)

Dependent variable: dummy for participation

	(1)	(2)	(3)	(4)
Number of participating peers	0.219	0.200	0.206	0.193
	(0.106)	(0.114)	(0.106)	(0.113)
Firm attributes				
Number of peers	-0.0324	-0.0288	-0.0351	-0.0321
	(0.0210)	(0.0221)	(0.0181)	(0.0190)
Number of workers (log)	0.0327	0.0351	0.0316	0.0335
	(0.0284)	(0.0282)	(0.0309)	(0.0311)
Share of exports	0.00103	0.00102	0.00108	0.00103
	(0.00134)	(0.00132)	(0.00159)	(0.00156)
Firm age (log)	0.0296	0.0367	0.0298	0.0339
	(0.0659)	(0.0718)	(0.0674)	(0.0741)
Manager attributes				
Age (log)	-0.0291	-0.0233	-0.0853	-0.0750
	(0.175)	(0.172)	(0.163)	(0.162)
Female dummy	0.162	0.164	0.137	0.139
	(0.0907)	(0.0907)	(0.0879)	(0.0882)
Years of education (log)	-0.255	-0.289	-0.249	-0.268
	(0.264)	(0.280)	(0.272)	(0.287)
Which day a firm is invited to (reference: second day)				
First day		-0.0526		-0.0377
		(0.101)		(0.102)
Third day		0.0410		0.0592
		(0.0928)		(0.0967)
Average peers' firm attributes				
Number of peers			0.00314	0.00380
			(0.0170)	(0.0169)
Number of workers (log)			-0.0577	-0.0560
			(0.0685)	(0.0689)
Share of exports			0.00131	0.00127
			(0.00241)	(0.00239)
Firm age (log)			0.0342	0.0300
			(0.0765)	(0.0771)
Average peers' manager attributes				
Age (log)			0.0255	0.0297
			(0.212)	(0.211)
Female dummy			0.0245	0.0178
			(0.302)	(0.303)
Years of education (log)			-0.288	-0.294
			(0.196)	(0.202)
Observations	131	131	131	131
R-squared	0.071	0.093	0.107	0.123

Notes: Robust standard errors are in parentheses.

Table 6. Robustness checks

Sample dropped five firms attended the seminar in different day that they invited.

	(1)	(2)	(3)	(4)
Second stage				
	Dependent variable: dummy for participation in the seminar			
Number of participating peers	0.240	0.220	0.215	0.199
	(0.118)	(0.128)	(0.113)	(0.121)
First stage				
	Dependent variable: number of participating peers			
Number of invited peers	0.273	0.253	0.287	0.272
	(0.0946)	(0.0930)	(0.108)	(0.106)
Firm attributes	YES	YES	YES	YES
Manager attributes	YES	YES	YES	YES
Which day a firm is invited to	NO	YES	NO	YES
Average peers' firm attributes	NO	NO	YES	YES
Average peers' manager attributes	NO	NO	YES	YES
Observations	126	126	126	126
Kleibergen-Paap Wald rk F statistic	8.35	7.43	7.06	6.54

Notes: These estimations use an alternative sample without five firms that attended the seminar on a day different from the day they were invited. Robust standard errors are in parentheses.

Table 7. Estimation results from decomposition of peer effects

	(1)	(2)	(3)	(4)
A. Second stage				
Dependent variable: dummy for participation in the seminar				
Number of peers participating on same day	0.348	0.326	0.374	0.362
	(0.151)	(0.172)	(0.147)	(0.165)
Number of peers participating on other days	0.0822	0.0834	0.0270	0.0352
	(0.117)	(0.115)	(0.114)	(0.113)
B. First stage				
Dependent variable: number of participating peers on same day				
Number of invited peers on same day	0.387	0.373	0.388	0.375
	(0.104)	(0.0992)	(0.112)	(0.105)
Number of invited peers on other days	0.0834	0.0657	0.0927	0.0780
	(0.0624)	(0.0577)	(0.0638)	(0.0594)
C. First stage				
Dependent variable: number of participating peers on different day				
Number of invited peers on same day	-0.252	-0.260	-0.237	-0.240
	(0.113)	(0.112)	(0.125)	(0.123)
Number of invited peers on other days	0.256	0.261	0.260	0.266
	(0.0924)	(0.0943)	(0.107)	(0.107)
Firm attributes	YES	YES	YES	YES
Manager attributes	YES	YES	YES	YES
Which day a firm was invited to	NO	YES	NO	YES
Average peers' firm attributes	NO	NO	YES	YES
Average peers' manager attributes	NO	NO	YES	YES
Observations	131	131	131	131
Kleibergen-Paap Wald rk *F* statistic	5.171	4.853	4.656	4.526
H0: No peer effect due to social utility	0.1580	0.2135	0.0675	0.0980

Notes: Robust standard errors are in parentheses. The bottom row shows p values from Wald tests for the null hypotheses that there is no peer effect through a reduction in participation costs.