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Social Networks and Peer Effects on Academic Performance[1]

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Abstract

Peer effects in education—effects of peers' academic outcomes or characteristics on a student's academic outcomes—have been studied extensively but there is still no consensus on peer effects under university settings. This paper attempts to estimate peer effects on undergraduate students' GPA using a spatial autoregressive model with individual-specific social interactions in a group setting to separate endogenous peer effects from contextual peer effects. We conduct a survey of students' social networks to identify different types of peer groups: best friends, study groups, hangout groups and activity groups. We find positive and significant endogenous peer effects in all group types except best friends. The endogenous peer effect in study groups is the largest. This is intuitive since interactions in study groups may be aimed at improving academic performance whereas interactions among best friends may be more personal and thereby have no effect on

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academic outcomes.

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1. Introduction

Peer effects in educational settings have gained substantial interest among policymakers, researchers, educators and parents. It is common to believe that friends are an especially important determinant of a student's achievements and failures. A student's academic outcomes may benefit from having peers with high academic aptitudes while some may suffer from underperforming friends. Thus, a deeper understanding of how peers play a role in a student's academic performance would help design better educational environments.

Peer effects have been investigated extensively in various settings since the notable work of Coleman (1968). Many studies seek to explain the way peer effects work as well as measure the magnitude of those effects. However, identifying peer effects using empirical data can be very challenging because of two primary reasons. First, as described in many studies as a reflection problem (see Manski, 1993, 2000; Moffitt, 2001; Brock and Durlauf, 2001; Lin, 2010), it is difficult to isolate endogenous effects—effects of peers' outcome on an individual's own outcome—from contextual effects—effects of peers' characteristics on an individual's own outcome, as the propensity of each individual in the same peer group to behave in a certain way varies with the characteristics of the peer group. Furthermore, individuals in the same group tend to behave in the same way because they share similar characteristics or face similar institutional environments. This confounding effect is even more problematic when the formation of peer groups is endogenous.

The second challenge is a data problem. Typically, peer groups are not directly observable and it is unclear which type of peer group has an impact on educational outcomes. Many studies identify peer groups using non-social networks such as grouping students in the same class or school together. Such broad definitions of peer groups may bias the estimates of peer effects if students in the same presumed peer groups have no interactions with one another. Moreover, closer friends are more likely to produce stronger effects than distant ones but measuring peer closeness is even more difficult.

The goal of this paper is to estimate peer effects in the university setting while tackling both challenges mentioned above. To cope with the reflection problem, we employ a spatial autoregressive (SAR) model with individual-specific social interactions similar to Lin (2010). The SAR model enables us to separate endogenous effects from contextual effects. Despite advantages of the SAR model, there are only a few studies that use it to analyze peer effects mainly because the SAR model requires data on social networks to construct a spatial weight matrix. We estimate endogenous and contextual peer effects on GPA in various types of peer groups: best friends, study groups, hangout groups and activity groups. Using data from the Bachelor of Arts in Economics (EBA program) at Chulalongkorn University and surveys of student social networks, we find that significant and positive endogenous effects exist in study groups, hangout groups and activity groups, with the strongest effects existing in study groups, but there is no evidence of peer effects among best friends. The contextual effects are mostly insignificant in all group types. Lastly, we find strong complementarity of endogenous effects in hangout groups and activity groups.

Although there are several empirical evidences of favorable peer effects in primary and secondary schools, such as in Hoxby (2000), Boozer and Cacciola (2001), Hanushek et al. (2003) and Vigdor and Nechyba (2007), there is still no consensus about the impact of peer groups on student academic performance in higher education. A number of studies such as Sacerdote (2001), Zimmerman (2003) and Hoel et al. (2005) and Stinebrickner and Stinebrickner (2006) estimate peer effects in randomly-assigned dormmates or roommates, and find significant peer effects. Brunello et al. (2010) shows evidence of significant peer effects among roommates in the field of engineering, maths and the natural sciences. Lyle (2007) and Carrell, and Fullerton and West (2009) show beneficial peer effects in unique settings of military academies. Lin (2010) uses data from the National Longitudinal Survey of Adolescent Health to identify social networks and finds strong evidence for both endogenous and contextual effects in academic performance, but endogenous effects disappear when controlling for school fixed effects. In contrast, Foster (2006) finds no peer effects among dormmates. Several works including Hoel et al. (2005), Martins and Walker (2006) and Parker et al. (2008) find no evidence of peer effects in classrooms.

This paper contributes to the literature in two ways. First, we are able to identify social relationships necessary for the spatial weight matrix by conducting a survey of student social networks. This is possible because our dataset includes all students in each class, unlike a sample survey. To our knowledge, no study has compared peer effects in different peer group types. This would help identify the group settings that have the largest impact on academic performance. Nevertheless, this more accurate data on peer groups come at the expense of having a smaller sample and non-random peer group formation. We believe the problem of endogeneity may not be severe since our models control for contextual effects which may in turn affect group formations. Also, the estimates in the specifications with randomly assigned groups appear to be robust. Second, we further modify the model to better reflect the actual social networks by relaxing assumptions that peer effects can exist only within peer groups. We propose measuring closeness of students by the number of peer group types they share. Under this assumption, the boundary of peer groups becomes blurry. Not only do peer effects extend beyond a single peer group type, but they can also be different across pairs of students.

This paper is organized as follows. Section 2 explains our methodology for estimating peer effects. Section 3 describes our dataset, estimation results and extensions. Section 4 provides a conclusion and discussions.

2. Methodology

To estimate peer effects, we employ the SAR model similar to Lin (2010). We assume that a student's GPA is a function of three components: the student's characteristics, endogenous effects and contextual effects. The model can be written as

$$Y = X\beta + \lambda WY + WX\gamma + \varepsilon$$

where Y is the vector of academic outcomes measured by GPA, X is the matrix of the student's characteristics and β is the vector of corresponding coefficients. The second component captures the effect of peers' GPA on an individual's GPA. The coefficient is the endogenous peer effect and the matrix W represents the student's social network. The matrix W is $m \times m$ an spatial weight matrix of known constants with zero diagonal elements where is the number of students in the dataset. Thus, the effect of peers' academic performance on a student's GPA is the product of endogenous peer effect and the weighted average GPA across students in her peer group. The spatial weight matrix is row-normalized so that each element w_{ij} represents the share of influence of student j on student i. The third component is the total effects of peers' characteristics on GPA. The vector γ denotes the contextual peer effects. In the baseline model, we assume that no peer effects exist and hence λ and γ are equal to zero.

The SAR model can identify and distinguish the endogenous effect from the contextual effect by means of the extra information contained in the spatially-correlated error terms as shown in Lee (2007) and Bramoulle et al. (2009). More precisely, the model includes a product of the spatial weight matrix and the individual characteristics which represent a weighted average value of explanatory variables across peers.

We construct the spatial weight matrix for different types of peer groups such as best friends and study groups. One of the important assumptions of the spatial weight matrix is that each of the peers' GPA uniformly affects a student's GPA. For example, if a student has four peers in her group, we assign the weight of 0.25 to each of these four friends. This is a strong assumption as different peers may have different levels of influence and the estimates may be biased if the actual weights are non-uniform. We later relax this assumption of uniform weighting.

3. Empirical analysis

3.1 Data

We obtain student data from EBA program. Our dataset consists of two classes of senior and junior students who graduated in 2014 and 2015 respectively. The 2014 and 2015 classes comprise 128 and 124 students respectively. The dataset includes two sets of variables: student characteristics provided by the EBA program office and students' social networks collected by means of survey.

Table 1 presents variable definitions and summary statistics of student characteristics. The average GPA of the students in the program at the time of the survey is 3.101 and 57 percent of the students are female. The EBA program's admission test consists of three parts: math, English and an interview, which have maximum scores of 75, 45 and 30 points respectively. The average high school GPA is 3.520. We also classify high schools as international or non-international schools as well as private or public schools. Around 30 percent of the students come from international schools. These students may have some advantage in their English language abilities. Around 51 percent of the students graduated from private schools.

Unfortunately, data on students' family backgrounds are not available to us. Although factors such as household income have been identified as important determinants of academic performance, we expect that the omitted variable bias in our analysis is small because of several reasons. First, the tuition fees of the EBA program are relatively high compared to other undergraduate programs. The tuition fee prior to 2013 was approximately 2,400 US dollars per semester. In comparison, the per capita annual income in Thailand in 2013 was 5,780 US dollars. Hence, EBA students are likely to have come from upper-middle to upper class families and their family backgrounds tend to be uniform. Second, omitted factors that potentially affect academic performance in university and high school may be similar and these factors may have already been captured by the high school GPA and admission scores.

The other crucial set of variables contains students' peer group information. We define four different types of peer groups: best friends, study groups, hangout groups and activity groups. Table 2 shows the description of each peer group type and the criteria used to identify peer group memberships. Peer groups are not mutually exclusive. Another group type of interest is the first-year sections, which can be regarded as a random assignment. During the first year of the EBA program, students are assigned alphabetically to sections of approximately 40 students each. Students in each section study the same courses and remain in the same section throughout their first year. Students in the same first-year section could form tighter peer groups, or the peer effects in these sections may exist only in the first year. On the contrary, the student peer groups are self-selected and thus students in the same peer group may share similar backgrounds or common interests. Hence, peer effects are more likely to exist within social networks since students in the same peer group typically have more social interactions with one another than those in the same first-year sections.

To collect the social network data, we asked all students in each class to respond to a survey of peer groups using the criteria in Table 2. Table 3 shows the average, minimum and maximum numbers of peers of each student for each of the peer group types. On average, best friend groups are the smallest, followed by study groups, hangout groups, activity groups and first-year sections, respectively. GPAs of students who do not belong to any peer group are determined solely by their own characteristics.

3.2 Estimation Results

We estimate the baseline model and four SAR models using different spatial weight matrices for the four peer group types. The estimation results are shown in Table 4. Model (1) or the baseline model does not include the endogenous and contextual effects. Models (2) to (5) define the peer groups as best friends, study groups, hangout groups and activity groups, respectively.

The estimation results show significant and positive endogenous effects in study groups, hangout groups and activity groups, while the effects are insignificant among best friends. The endogenous effects in study groups are the largest among all peer group types. Since the primary objective of study groups is to create a supportive learning environment, the main interactions among these peers are most likely to have an effect on academic performance. Hangout and activity groups have smaller endogenous peer effects than study groups, since interactions in hangout and activity groups are likely to be less related to studying. Interestingly, the endogenous effects among best friends are statistically insignificant. Although best friends may have the closest relationships, the group interactions among them may be more related to personal matters rather than academics.

The contextual effects are insignificant in all models except in a few instances. The peer effects are mostly endogenous. Our finding is in contrast to Lin (2010) which finds that both endogenous and contextual effects exist. The difference may be due to the feature of our samples in which the EBA students' characteristics and backgrounds are fairly uniform.

In all models, the individual effects of student characteristics have the expected signs and their significances are the same. That is, high school GPA, math score, English score and international school attendance have positive and significant effects on GPA. This is as expected as academic performance in an international degree program in Economics would require good math and English skills. In contrast, gender has no significant effect on GPA. Also, private or private school attendance does not significantly affect GPA. The fact that the effect of interview scores is insignificant is not surprising because the program's admissions interview aims to evaluate applicants on their interpersonal and social skills which may not have direct effects on academic performance.

We estimate several additional models to test for robustness and find that the peer effects are robust to specifications. The additional estimation results are shown in Table 5. Model (6) uses first-year sections as the random assignment groups to construct the spatial weight matrix. However, the first-year sections have no significant peer effects. With an average of 38.7 students per section, the first-year sections are so large that some students in the same section may have little chance to interaction with one another. The endogenous peer effects may exist only within subgroups in the section. Moreover, the first-year sections are formed only during freshman year and thereby any endogenous peer effects may have worn off.

Models (7) to (16) are similar to Models (2) to (5) except that Models (7) to (10) exclude the contextual effects whereas Models (11) to (14) exclude the endogenous effects. The coefficients of all individuals' characteristics appear robust in terms of significances, signs and magnitudes. When peers' characteristics are excluded, the endogenous effects in study groups become slightly larger and are statistically significant. However, the endogenous effects become insignificant in hangout and activity groups and remain insignificant in best friends. When peer endogenous effects are removed as in Models (11) to (14), all contextual effects stay insignificant except for high school GPA in hangout groups.

3.3 Non-uniform peer effects

In the previous estimations, all models assume that there is no interaction across peer groups and thus peer effects exist only within peer groups. In reality, social networks can expand beyond group settings as any pair of students from different peer groups can potentially interact with each other to some extent. We expect that more social interactions lead to stronger endogenous effects. In this section, we relax the assumption that each peer has a uniform effect on a student's GPA. Instead of assigning an equal weight to all peers, we assume that peers who share more activities with a student have larger effects on the student's GPA. Let x_{ij}^t equal to one if students i and j are in the same peer group for group type t where

$$t \in T \subseteq \{\text{best friends, study groups, activity groups, hangout groups}\}$$

Thus, for any subset of group types T, we can construct a spatial weight matrix by row-normalizing an influence matrix where each of its element $x_{ij} = \sum_{t \in T} x_{ij}^t$.

We estimate several models with the endogenous and contextual peer effects similar to Models (2) to (5), using different peer group combinations to construct the spatial weight matrix. Table 6 shows the estimated endogenous effects for different peer group combinations, ordered by magnitude. Note that the table omits the individual characteristics and contextual effects as their signs, significances and magnitudes are similar to the estimates in Table 4. Estimates of endogenous peer effects within a single group type are repeated here.

Interestingly, including best friend groups may weaken the beneficial endogenous effects of other peer group interactions. When combining best friend with other group combinations except for combinations (10) and (11), best friends lower the endogenous effects of other group combinations. For example, the endogenous effect is 0.289 in the combination of study, hangout and activity groups but the effect falls to 0.268 after adding best friends to the group combination. On the other hand, hangout and activity groups can increase the endogenous peer effects of all other group combinations, including best friend groups. We observe strong complementarity in endogenous effects when combining hangout and activity groups.

4. Conclusion

In this paper, we estimate endogenous and contextual peer effects on GPA by employing a SAR model on various types of peer groups. Using data from the EBA program at Chulalongkorn University and surveys of student social networks, we find that significant and positive endogenous effects exist in study, hangout and activity groups, with the strongest peer effects existing in study groups. However, there is no evidence of peer effects among best friend groups. It implies that peer effects on academic performance may not exist in a group with close personal interactions. Nevertheless, best friend groups may affect other non-academic outcomes such as drug use or teenage pregnancy which can indirectly affect academic performance. There is no student with such non-academic conditions in our sample. The peer effects of different group types on non-academic outcomes are still unexplored and studies would be required to better inform policy decisions. We later relax the assumption that peers have influence within only a particular peer group and find even larger endogenous effects when considering combinations of interactions in study, hangout and activity groups.

The compelling evidence of beneficial peer effects on academic performance in different group types has important implications. A policy to encourage students to form study groups should be endorsed in the university setting. Aside from study groups, other group activities should also be considered as viable instruments as well.

This study has some limitations. First, the samples are collected from a single academic program and thus the results may not be applicable to other settings. Second, although our models allow different types of social relationships, we implicitly assume that the relationships exist only among students in the same class. The actual social networks may expand beyond a single class or even academic program. Third, having a small sample makes it impractical to include school fixed effects as in Lin (2010). However, the confounding effects of varying educational environments may be minimal in our dataset since all students studied the in the same program at the same university and the estimates appear robust across specifications.

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Table 1: Variable Definitions and Summary Statistics

Variable	Definition	Mean	S.D.	Min	Max
GPA	Cumulative Grade Point Average (4.0 scale)	3.101	0.468	1.97	4.00
Female dummy	Female = 1, Male = 0	0.574	0.495	0	1
Entrance (Math)	Mathematics score	64.216	4.582	50.63	75
Entrance (English)	English language proficiency score	37.921	2.655	30.44	45
Entrance (Interview)	Interview score	22.423	3.700	12.6	30
High school GPA	High school grade point average	3.520	0.327	2	4
International school	Graduated from international high school = 1, otherwise = 0	0.306	0.462	0	1
Private school	Graduated from private high school = 1, otherwise = 0	0.512	0.501	0	1

Note: the number of observations is 252.

Table 2: Definition of Peer Groups

Peer group type	Description	Criteria
Best friends	a group of close friends who always do activities together	Chat with each other everyday Share the same interest Have the same lifestyle
Study groups	a group of friends who usually enroll in the same class sections and study for exams together	Enroll in the same class section Study in the same major
Hangout groups	a group of friends who usually hang out together	Have the same lifestyle Hang out together
Activity groups	a group of friends who usually do general activities such as having lunch together or being a member of the same club	Chat with each other more than once a week Share the same interest Share the same activities
First-year sections	A group of students in the pre-assigned section	Randomly assigned by the program

Table 3: Group Definition and Characteristics

Peer group type	Number of Peers		
	Average	Min	Max
Best friends	2.53	0	14
Study groups	3.20	0	13
Hangout groups	4.09	0	14
Activity groups	9.93	0	18
First-year sections	38.69	33	46

Table 4: Estimation results

	1	2	3	4	5
	Baseline	**Best friends**	**Study**	**Hangout**	**Activity**
Endogenous peer effect		0.120	0.231*	0.196*	0.170*
		(0.134)	(0.013)	(0.028)	(0.050)
Individual characteristics					
Constant	-2.070**	-2.445**	-2.178**	-2.177**	-2.131**
	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)
Female	0.028	0.024	0.036	0.039	0.024
	(0.607)	(0.668)	(0.597)	(0.496)	(0.662)
High school GPA	0.643**	0.641**	0.619**	0.638**	0.613**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Entrance (math)	0.024**	0.025**	0.025**	0.024**	0.024**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Entrance (English)	0.035**	0.035**	0.034**	0.035**	0.036**
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Entrance (Interview)	-0.005	-0.005	-0.006	-0.004	-0.004
	(0.482)	(0.429)	(0.425)	(0.537)	(0.574)
International school	0.158*	0.186**	0.164*	0.162*	0.151*
	(0.025)	(0.006)	(0.016)	(0.018)	(0.027)
Private school	-0.048	0.071	0.048	0.029	0.051
	(0.369)	(0.170)	(0.352)	(0.571)	(0.330)
Contextual effect					
Female		0.047	-0.006	-0.110	0.087
		(0.530)	(0.951)	(0.213)	(0.317)
High school GPA		-0.019	-0.122	0.178	-0.233
		(0.882)	(0.483)	(0.250)	(0.106)
Entrance (math)		-0.001	0.025	-0.005	0.000
		(0.849)	(0.055)	(0.589)	(0.974)
Entrance (English)		0.012	-0.045	-0.016	0.016
		(0.360)	(0.073)	(0.311)	(0.320)
Entrance (Interview)		-0.017	-0.006	-0.006	-0.011
		(0.091)	(0.791)	(0.637)	(0.349)
International school		0.012	0.192	0.058	-0.011
		(0.911)	(0.285)	(0.661)	(0.926)
Private school		0.090	0.156	-0.029	0.050
		(0.307)	(0.266)	(0.759)	(0.570)
Class of 2014 dummy	0.070	0.075	0.089	0.056	0.073
	(0.185)	(0.169)	(0.130)	(0.330)	(0.188)
Log likelihood	Adj. R^2 = 0.281	-104.168	-98.276	-89.067	-107.769

Notes: Number of observations is 242. P-values are shown in parentheses. * and ** indicates significance at 5% and 1% levels, respectively.

Table 5: Robustness check

	6	7	8	9	10	11	12	13	14
	First year	**Best friends**	**Study**	**Hangout**	**Activity**	**Best friends**	**Study**	**Hangout**	**Activity**
Endogenous peer effect	0.053	0.090	0.251**	0.093	0.090				
	(0.824)	(0.145)	(0.003)	(0.117)	(0.133)				
Individual characteristics									
Constant	-2.533*	-2.651**	-2.661**	-3.085**	-2.420**	-2.464**	-2.380	-2.249**	-2.179**
	(0.013)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.396)	(0.002)	(0.001)
Female	0.033	0.012	0.026	0.047	0.006	0.019	0.033	0.036	0.029
	(0.633)	(0.829)	(0.627)	(0.380)	(0.907)	(0.754)	(0.663)	(0.544)	(0.606)
High school GPA	0.623**	0.663**	0.629**	0.635**	0.655**	0.644**	0.622**	0.654**	0.620**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Entrance (math)	0.027**	0.026**	0.023**	0.028**	0.024**	0.025**	0.027**	0.024**	0.025**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Entrance (English)	0.035**	0.037**	0.034**	0.048**	0.034**	0.035**	0.035**	0.036**	0.036**
	(0.002)	(0.001)	(0.001)	(0.000)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)
Entrance (Interview)	-0.005	-0.003	-0.005	-0.004	-0.001	-0.005	-0.005	-0.004	-0.004
	(0.446)	(0.621)	(0.431)	(0.568)	(0.938)	(0.428)	(0.460)	(0.510)	(0.542)
International school	0.170*	0.191**	0.152*	0.144*	0.167*	0.182*	0.170*	0.164*	0.153*
	(0.014)	(0.006)	(0.026)	(0.039)	(0.018)	(0.020)	(0.033)	(0.034)	(0.033)
Private school	-0.056	0.073	0.034	0.052	0.061	0.074	0.057	0.030	0.051
	(0.284)	(0.165)	(0.505)	(0.321)	(0.252)	(0.190)	(0.345)	(0.583)	(0.351)
Contextual effect									
Female	-0.007					0.052	-0.003	-0.123	0.102
	(0.949)					(0.497)	(0.977)	(0.159)	(0.262)
High school GPA	0.038					0.062	0.035	0.339*	-0.112
	(0.824)					(0.610)	(0.905)	(0.012)	(0.435)
Entrance (math)	0.028*					-0.001	0.028	-0.003	0.002
	(0.026)					(0.940)	(0.184)	(0.742)	(0.829)
Entrance (English)	-0.045					0.013	-0.045	-0.016	0.016
	(0.075)					(0.333)	(0.233)	(0.275)	(0.336)
Entrance (Interview)	-0.008					-0.019*	-0.008	-0.011	-0.014
	(0.723)					(0.049)	(0.822)	(0.337)	(0.239)
International school	0.252					0.041	0.256	0.127	0.041
	(0.162)					(0.708)	(0.227)	(0.317)	(0.742)
Private school	0.204					0.102	0.207	-0.027	0.076
	(0.147)					(0.267)	(0.217)	(0.791)	(0.432)
Class of 2014 dummy	0.098	0.098	0.052	0.097	0.073	0.078	0.102	0.064	0.076
	(0.116)	(0.059)	(0.313)	(0.063)	(0.167)	(0.147)	(0.118)	(0.248)	(0.186)
Log likelihood	-111.625	-106.296	-111.277	-96.258	-107.746	-105.114	-109.739	-92.308	-104.694

Notes: Number of observations is 242. P-values are shown in parentheses. * and ** indicates significance at 5% and 1% levels, respectively.

Table 6: Estimation of endogenous peer effects for different group combinations

Group combination	Best friends	Study	Hangout	Activity	Endogenous peer effect
1		Yes	Yes	Yes	0.289* (0.007)
2			Yes	Yes	0.282** (0.005)
3	Yes	Yes	Yes	Yes	0.268* (0.011)
4	Yes		Yes	Yes	0.264** (0.009)
5		Yes		Yes	0.258* (0.014)
6	Yes	Yes		Yes	0.234* (0.026)
7		Yes			0.231* (0.013)
8		Yes	Yes		0.229* (0.017)
9	Yes	Yes	Yes		0.227* (0.017)
10	Yes			Yes	0.223* (0.025)
11	Yes		Yes		0.201* (0.024)
12			Yes		0.196* (0.028)
13				Yes	0.170* (0.050)
14	Yes	Yes			0.165 (0.073)
15	Yes				0.120 (0.134)

Notes: Number of observations is 242. P-values are shown in parentheses. * and ** indicates significance at 5% and 1% levels, respectively. Estimated coefficient of individual characteristics and contextual effects are omitted.