(1) TITLE PAGE

Bias from enrollment: Peer effects on the academic performance of university students in PUCE-Ecuador

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Bias from enrollment: Peer effects on the academic performance of university students in PUCE Ecuador

(2) ABSTRACT

This paper provides evidence of peer effects on academic achievement of university students in PUCE Ecuador, using a panel of academic-administrative data from students and each of their courses, for both semesters of 2018. To estimate the marginal effects of peer performance on individual academic achievement, a random effects model with controls is applied. The results show significant influence of the average group, high-achieving and low-achieving peers. Educational policy and course enrollment policies are discussed.

(3) KEYWORDS: higher education, achievement, Latin America, context factors, random effects, socioeconomic, segregation, classmates, gap, equality of opportunity

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Introduction

Despite recent efforts to improve higher education quality, students from developing countries show low academic performance. Starting with the seminal study by Coleman, (1966), literature has repeatedly shown that academic achievement is significantly influenced by associated factors, thereby conditioning student´s desertion or academic success (Vélez 2005 in Vargas, 2007). While embodied in the student´s socioeconomical, cultural, cognitive, and emotional dimensions (Vargas, 2007), these contextual factors can be analyzed with a hierarchical structure. The structure starts at the personal level, followed by the group or course level and the educational institution level (ibid)

At the personal level, factors such as the parents´ education, the number of household members and the socioeconomic situation are the most cited factors influencing academic performance (Coleman, 1966). Ethnicity and, more recently, gender disparities remain significant with respect to academic performance (Kao, 2019). At the course or classroom level, peer effects have proved statistically significant determinants of individual scores (Vargas, 2007). Peer effects may be defined as the impact of the study group over learning environment and academic achievement (Illanes, 2014). Therefore, the learning environment and the personal factors affecting classmates (peers), such as their sociocultural differences, family settings, parent´s educational level and socioeconomic context, may affect each individual according to the group they belong to.

At the educational institution level, non-personal factors involved in the education process may also influences academic achievement. Vargas (2007) found that besides their engagement with the subject and the difficulty of studies, the relation between students and teachers, teaching

quality, infrastructure conditions and the academic level of the educational institution are significant determinants of individual scores. Together, personal, course and educational institution levels hold key variables that influence academic achievement. Particularly, it is of interest to study the group effects over individual performance, as they tend to be greater in economic developed environments (Izaguirre & Di Capua, 2020).

Evidence of studies in neighboring countries suggest that peer effects may be strong determinants of academic performance in Ecuador. According to Barrera (2010), peer effects are significant in Colombian high schools. Moreover, Ferrara (2013), showed that socioeconomic factors, parent´s education, and peer scores as the strongest determinants over academic performance. Despite this evidence on the importance of peer effects, no research has been done in Ecuador, with particular relevance for universities such as PUCE, where its course enrollment mechanism may produce a strong bias in individual student performance.

In 2018, Ecuador showed a desertion rate in higher education of 32%, the third-largest in the region. The Pontifical Catholic University of Ecuador (PUCE) is one of the top universities in the country, as of 2018 hosting 19,828 students. The school of Economics at PUCE had a desertion rate of 38.46% in 2018. Since PUCE applies a course enrollment system that prioritizes course selection, according to the scores obtained on the previous semester, we speculate that this selection mechanism produces a bias against individual performance, depending on the high or low scores achieved by their peers. Consequently, by investigating to what extent do peer effects influence the academic achievement of students at the School of Economics at PUCE, may shine a light on the academic debate regarding their significance, as well as contributing with more consistent educational policy tools seeking to improve academic achievement of higher education students in the developing world.

The paper is organized as follows. Section 1 reviews the most relevant literature to enlighten the peer effects and education dynamics. Section 2 describes the methodology, the estimation model, and the data characteristics. Section 3 reports the results and their discussion. Section 4 concludes.

Literature Review

The study of the economics of education started in the early 60s, pioneered by Schultz & Becker (1964), who proposed education as an investment for the future. Later, Coleman (1966), with one of the first empirical works, found that student achievement depends on many contextual factors, being the mother´s education the most important.

The study of peer effects received considerable importance since the Coleman report. Hanushek et al. (2003) found that as peers play a fundamental role for motivation, aspiration and interaction, it is expected a significant effect on group learning. Moreover, Macneil et al. (2009) found that, despite student and school heterogeneity, the average peers performance has a positive and significant effect on the learning process throughout the test score distribution. However, as showed by Vigdor & Ludwing (2010), peer effects may not only boost the learning process, but also jeopardize it, e.g. through class interruptions from low performance peers.

For Latin America and the Caribbean, a recent study by Izaguirre & Di Capua (2020) studied peer effects on primary education, using the data from the UNESCO (2015) - TERCE study. They applied a social interaction model, to show that the magnitude and significance of endogenous peer effects depend on the subject and the school type, where the influence of classmates plays a fundamental role on academic achievement. As the degree of peer effects is context-dependent, it is important to analyze it in other countries and education settings.

At the higher education or university level, research has shown that the peer effects vary according to the type of subject. Carrell et al. (2009) pioneered a controlled experiment on peer

effects and found that these are significant in mathematics and sciences, but non-significant in physical education and foreign languages. Later, Lavy et al. (2012) included parameters for the top 5% and bottom 5% of students. Their study showed a negative influence from low performance peers, but little or no influence from high performance peers. Finally, Androushchak et al. (2013) found that higher ability peers showed a positive effect on Economics, Mathematics and individual GPA, wheras no effect was found from low-ability peers. We build on these studies, with particular inspiration of Lavy et al. (2012), to develop our own random effects estimator, to be applied to the Ecuadorian higher education context, as described in the next section.

Methodology

Data Source

The study investigates causal effects between peer effects and academic achievement at the School of Economics at the Pontifical Catholic University of Ecuador (PUCE). First, academic data, including grades, courses and lecturers, were obtained from the School of Economics. Secondly, the Student Welfare Department at PUCE provided socioeconomic information about each student. The latter is possible due to a Socioeconomic Study performed each semester at PUCE, the SBS database, which aims to assign students into socioeconomic Categories and charge differentiated tuition fees according to socioeconomic categories. In this respect, Category A implies the lowest socioeconomic level, where students on this category pay the lowest fees, while Category F is the highest Category, where students pay large fees. We use 1,033 observations for the estimation model. All data corresponds to the first and second semesters of 2018. This includes missing data from the first and eighth semester students, from 2018-02 and 2018-01, respectively, since there is no ex-ante and ex-post semester to compare.

Identification problem

We generated one comprehensive database with individual (courses) of each semester and another with consecutive subjects. By applying the IDs of each student and their corresponding course, we created groups for each semester, that also identified the subject they took in that semester and the one that followed in the next semester. Thus, a comprehensive identifier was defined for each student, the student ID, the group of consecutive subjects they took in the first semester and the consecutive subject they took in the next semester, the current course and whether they repeated the course or not. Following this categorization, it was not possible to include students on their seventh and eight semesters, since at the School of Economics students take elective courses from their seventh semester. This identification process was key to perform regression analysis on our panel dataset, to enable an observation per period per person.

Variables Description

The variables applied in this study define personal, socio-economic and academic characteristics from students at School of Economics at PUCE. We follow the recommendations of most seminal and recent studies, including Coleman (1966) and Androushchak & et al. (2013), which strongly suggest the use of associated or context factors of academic achievement, such as the socioeconomic status. Consequently, we apply control variables such as: number of household members, parents´ income and family expenses. By also applying a panel dataset and our random effects model, these controls should contribute to isolate the causal effects of socioeconomic variables on student's academic performance.

Moreover, variables of students´ personal characteristics are used to account for their individual features and how these influences their academic performance. Therefore, following Vargas (2007), Lavy & al. (2012) and Androushchak & et al. (2013), we apply variables such as the number of credits taken in the semester (numbers of courses taken), any disabilities or illness

registered for the SBSS process, and the type of high school that the student attended. Finally, we use score data from each student, in each course (subject), at four grade stages per semester: three inter-semester exams and a final exam. Consequently, it is also important to account the number of absences in each subject and the teacher who taught the subject in that semester.

Lastly, we conducted an online survey to a 95% representative sample of 110 students at the School of Economics at PUCE, to collect information about teacher quality perception, as a proxy for teaching quality. Given the current SARS-COV-2 pandemic situation, the survey was sent via email and also responded online. The survey contained 10 questions regarding the quantity and quality of teaching methodology, teaching tools, academic standards, flexibility, among others.

Descriptive Statistics

The Pontifical Catholic University of Ecuador (PUCE), categorizes student socioeconomic status (SBS) according to family income, assets, household members, expenditures, debt, among other. This information, not only self-declared but also crosschecked via tax information, is used by the university to charge differentiated tuition fees according to the SBS. For the sample of 190 students applied in our study, 24.20% belong to Category A, the lowest SBS, with an average monthly income of $793.33. A higher category B, holds 23.14% of students, with an average income of $1318.89, while 26.04% belong to category C, with an average income $1593.15. The higher SBS categories hold 17.62% of students in category D, 7.55% in E and 1.4 % in F, with an average income of $2.103.58, $3.692.59 and &5.000, respectively. We also consider a variable of family income per capita (incomepc) for each student, which consists of the sum of all sources of income, divided by the number of household members. The family income per capita variable shows an average of $427.19 and a standard deviation of +/-$334.59. This relatively-high variance is consistent with the socioeconomic disparities reflected in the SBS categorization.

Since most of students live with their parents, 51.02% of them live in their own house, 17.33% of pay rent, 15.20% live in borrowed/ other family housing without paying rent, and 16.46% are paying mortgage on their homes. Most of them have full public service access, as well as 92.45% with internet access. On the other hand, 63.99% of students attended a private high school, 15% a fiscomisional (mixed partnership) high school, 20.04% a public high school and 0.97% a high school from abroad.

The study uses 1033 observations in total. The average number of credits taken by each student is 21.19, i.e. an average of 5 courses per semester. The grades consist of three inter-semester exams over 10 points and a final exam over 20 points, which together account for a semester grade over 50 points. For our sample, the average semester grade is 36.29/50 points, 7.5/10 points for the inter-semester exams and 14.25/20 points for the final exam. As suggested by Lavy et al. (2012), we also identify top ($phigh$) and bottom achieving students ($plow$). Taking into account that each course has an average of 15 students, we consider that the upper and lower boundaries should be 10%, instead of the 5% assumed by Lavy et al. (2012) in a much larger sample. It is worth noting that our results remained robust to the application of 5% boundaries, as reported in Table A1 – Appendix. Therefore, $plow$ represents the students at the bottom 10% of group performance (lowest grades), while $phigh$ are those students at top.

Estimation Model

Our models are consistent with the foundations provided by the educational production function by Levin (1974) and Hanushek (1979 in Ferrera, 2013), as defined in Equation 1:

$$A_{ij} = f(S_{ij}, B_{ij}, P_{ij}, I_{ij}) \qquad \textbf{Equation 1}$$

The model considers academic performance of student *i*, at the school j (A_{ij}), as a function of school input (S_{ij}), student socio-economic characteristics (B_{ij}), peer effects (P_{ij}) and the innate ability of the student (I_{ij}). This basic function has been widely applied in the literature, as we

do, adjusted for the requirements and specific characteristics of each study. For example the model applied by Androushchak et al. (2013) in Equation 2, estimated an index of student achievement (Y_i). This performance is defined on a vector of individual characteristics X_i, a vector of exogenous characteristics of peer students $-i$ who study with student i (X_{-i}^{peer}), and index of peer student achievement (endogenous effects) (Y_{-i}^{peer}), as well as shared characteristics of the students and his peers (correlated effects) (Z_{-ii}).

$$Y_i = \alpha + \beta X_i + \gamma X_{-i}^{peer} + \phi Y_{-i}^{peer} + \theta Z_{-ii} + \varepsilon_i \qquad \textbf{Equation 2}$$

Moreover, the model by Lavy et al. (2012) displayed in Equation 3 proposed a production function with peer effects of high and low-achieving students at ages 11 and 14.

$$A_{iqst} = \alpha_i + \beta_q + \gamma_{st} + \beta_q x\ Gender_i + \delta_1 P_{qst} + \delta_2 P_{qst}^h + \delta_3 P_{qst}^l + \varepsilon_{iqst} \qquad \textbf{Equation 3}$$

Their estimated achievement for student i in subject q at school s in cohort t (A_{iqst}), depends on student fixed effects (α_i), subject-specific effects (β_q), school * cohort effect (γ_{st}), average ability of peers (P_{qst}), and the fraction of high-ability (P_{qst}^h) and low-ability peers (P_{qst}^l) in the cohort of each student.

Finally, in Equation 4 we estimate the effects of high and low-achieving university peers influencing student performance at the School of Economics at PUCE. We do so by estimating academic performance (P_{imt}) of student i, in the subject (course) m, during the two periods (semesters) t corresponding to 2018-01 and 2018-02. **Equation 4:**

$$\boldsymbol{P_{imt} = \beta_0 + \beta_1 Peers_{mt} + \beta_2 phigh_{imt} + \beta_3 plow_{imt} + \beta_4 X_{imt} + \beta_5 Z_{it} + \beta_6 V_{imt} + \varepsilon_{it}}$$

The model estimates β_1, β_2 and β_3, the marginal (peer) effects on individual academic performance of student i, in the subject m and period t. While β_1 estimates the effects from average grades, obtained by peers in subject m and period t ($\boldsymbol{Peers_{mt}}$) the coefficients $\beta_2$and β_3 measures the effects of high-ability ($\boldsymbol{phigh_{imt}}$) and low-ability peers ($\boldsymbol{plow_{imt}}$),

respectively. The high and low ability peers are the number of students at the top and the bottom 10%, respectively. Equation 4 also includes control vectors for students' personal characteristics ($\boldsymbol{X_{imt}}$), as well as socioeconomic and household variables ($\boldsymbol{Z_{it}}$)**,** which includes family income per capita (***incomepc***), number of ***siblings***, a gender (***female***) dummy variable and the number of ***credits*** taken by each student. For each lecturer of subject m, we include a proxy variable for teaching quality ($\boldsymbol{V_{imt}}$, hereafter ***teachqual***), and we match it for each student according to their course taken. As mentioned, $\boldsymbol{phigh_{imt}}$, $\boldsymbol{plow_{imt}}$ and ***female*** are dummy variables. $\boldsymbol{\varepsilon_{it}}$ is the error term.

We estimate Equation 4 via a random effects estimator. We use random effects because the personal error components are not correlated with each other and are not correlated with time (Wooldridge, 2013). The random effects estimator is useful if we assume that the unobserved heterogeneity is not correlated with the controls. Therefore, we applied a Hausman Test, against the hypothesis of applying a fixed effects estimator, which would instead eliminate the unobserved heterogeneity**.** The results on the Hausman Test in Table A2 - Appendix suggest the use of a random effects estimator. Finally, this estimator assumes no perfect linear relationship among the explanatory variables (Wooldridge 2013). This assumption was verified through our test in Table A3 - Appendix.

Results and Discussion

According to the model introduced in Equation 4, we estimated the peer effects of the average, low-ability and high-ability students ($Peers, plow, phigh$), on individual academic performance. We control for the number of *credits* chose by each students for each semester, gender (*female*), *incomepc, siblings* and *teachqual*. We find that $phigh$ and $peers$ show both a positive and statistically significant effect on the individual academic performance of each student, in that course and semester. Also, as expected, we find that $plow$ shows a negative

and statistically significant effect on academic performance. Finally, the effects of *siblings* and *teachqual* are statistically non-significant.

As reported in Table 1, the estimated coefficients for low-ability peer effects is -13.31 and for high-ability peer effects is +8.89. Both coefficients are statistically significant at the 99% confidence. This implies that when the student belongs to the low-achievement group, the student final grade is expected to decrease in 13.31 points. For students who belong to the high-achievement group, their final grade is expected to increase in 8.89 points. Finally, the estimated coefficient for average peer effects is +0.70, implying a small-yet-positive and statistically significant effect at the 99% confidence. The estimated coefficient of family´s income and female are positive and statistically significant at the 99% confidence, whereas the coefficients of *siblings* and *teaching quality* where not statistically significant. We posit that this last result, may be explained by the influence of teaching attitude, even more than perceived quality, with respect to academic performance (see e.g. Heck & Marcoulides, 2006).

To reinforce the strong and statistically significant relations found for the variables of interest (Table 1), as suggested by Gonzalez & Resousudarmo (2019), this study will perform robustness check estimations and include new relevant variables, aiming to address omitted variable bias. As depicted in Table 2, the first model for robustness check (1) is a replacement of *income per capita (incomepc*) with *expenditure per capita (expenditupc*), in order to validate that the socioeconomic effect is being captured from either side of the circular flow of income. The second model for robustness check removes teaching quality (2) from the original equation, while the third and forth models remove credits (3) and female (4). These estimations were performed as individual Random Effect regressions, with the aforementioned changes to the original equation. The results for the four models depicted in Table 2 are consistent with the results of the variables of interest in Table 1. In other words, low-ability students have a strong and significant negative influence on academic performance, while high-ability students

have a strong and significant positive influence on academic performance and the academic performance of the course is also positive and statistically significant at the 99% confidence.

The findings of this paper are consistent with findings in literature. The research by Lavy et al. (2012) showed that peers from the bottom 5% affect negatively academic performance, while the peers from the top 5% contribute to the learning process. This finding was reinforced by the fact that they obtained an average peer quality coefficient of 0.30 in their model, which heavily decreased to 0.12, when the top and bottom 5% of students were included. The later suggests that, as our research also showed, the data tails can better capture the peer effects. Moreover, the study by Androushchak et al. (2013) also found that each student benefits from a group of high-achieving students. While they concluded that peers with higher academic performance have a positive effect on individual grades in Economics and Mathematics, the effect for low-achieving students was negative but not statistically significant. By contrast, we found in our study that not only high-ability peers influence their classmates positively but also that low-ability peers affected them negatively. Furthermore, our findings about the average peer effects are also consistent with the study by Hanushek et al., (2003). They found that average peer achievement positively and strongly influences the learning process and individual grades of the group. Aligned with Hanushek et al., (2003), our main results suggest that it is important to consider student reallocation policies, possibly accompanied with tutoring programmes. The Pontifical Catholic University of Ecuador implemented an academic and accompaniment tutoring program since 2017. However, the findings of our study highlight the possibililty of reevaluating the course enrollment system at PUCE. As this system prioritizes student´s course selection according to their previous scores, such selection mechanism produces a strong and significant bias in individual student´s performance, depending on the high or low scores achieved by their peers.

Conclusion

In this paper, we evaluated the peer effects on academic performance, motivated by a course enrollment system at the Pontifical Catholic University of Ecuador (PUCE). We use a panel of academic and administrative data from the total student population at the School of Economics at PUCE, for both semesters of 2018. Subsequently, we applied a random effects model to estimate the marginal effects of average, high-ability and low-ability peer performance on the individual academic achievement of each student. Personal, socioeconomic and teaching-quality control variables were included. Finally, we performed robustness check estimations.

Our results showed that individual academic achievement is strongly influenced by their peers', and that the course enrollment system at PUCE may be generating a perverse bias on individial academic perfornace. The estimations showed that individual grades are strongly influenced by the grades of their high (top 10%) and low-ability peers (bottom 10%). The average peer effects are positive and statistically significant, yet not large. Family income per capita, the number of credits taken by the student and their gender (female) were also positive and statistically significant. Thus, we can affirm that individual academic achievement is significantly influenced by their groups of peers: the average, top and the bottom group effects. Moreover, our study suggests a strong warning against course enrollment systems that prioritize course selection by students with the highest grades from the previous semester, as this polarization may trigger or exacerbate peer effects that significantly influece student performance across semesters and perpetuate segregation in student performance.

As a data limitation, we should acknowledge that our universe of students did not have the exact same timeframe for declared (and verified) income. This is because at PUCE, students report their income for socioeconomic re-categorization each two-three years, depending on each case. However, we expect that the majority of families did not experience significant

income changes across our time of study. This limitation would become very relevant when more data periods are analyzed, which we expect to do in a further study. Moreover, our dataset did not provide province of origin, as it was unavailable, thus we recommend that future studies on different datasets include this variable. Literature shows a lack of consensus on the influence of this variable on academic achievement. Finally, beyond our significant socioeconomic and peer effects, we did not have access to information on life habits, including sleep, exercise and eating behaviors, which may also be affecting student performance. Nevertheless, as literature shows, these habits are already correlated with ability, i.e. to our unobserved variable, which we addressed with the estimation method, robustness checks and tests applied in this study.

This research contributed to shine a light on the academic debate regarding the degrees, level and significance of peer effects with respect to academic performance of university students. It is therefore necessary to review and strenghten current university and government educational policies, ensuring consistency with our findings realting strong peer influence, and aiming to improve academic achievement of higher education students. Moreover, as our research concurred with literature, socioeconomic effects are strong predictors of academic performance. Therefore, policies should also aim to attenuate this gap and promote equality of opportunity for students and their peers in the developing world.

(5) NOTES

Notes on Table 1: The dependent variable is academic performance, as measured by the end-of-semester grades achieved by each student. The results are coefficients of a single Random-Effects estimation, including all the mentioned variables. Standard deviations are reported in parentheses. ***p<0.01. N=1033.

Notes on Table 2: The dependent variable is academic performance, as measured by the end-of-semester grades achieved by each student. The results are coefficients of four different Random-Effects estimations, including the control variables shown in the Table. ***p<0.01.

Notes on Appendix Table A1: This random-effects estimation, which applies boundaries of 5% low-ability peers and 5% high-abilities peers (phigh), shows that the estimators of interest: plow, phigh and peers, remain statistically significant and in the same direction as with 10%.

Notes on Appendix Table A2: The Hausman Test analyzes the exogeneity of explanatory variables with respect to the random effects estimation. In this case, the value p>0.05 suggests that we should apply random effects instead of fixed effects (Montero, 2005).

Notes on Appendix Table A3: The variance inflation factor (VIF) measures the correlation and strength of correlation between the explanatory variables in a regression model. When the value is close to 1, it means that there is no correlation between an explanatory variable and any other variables in the model. Only values larger than 5 would suggest high correlation.

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(7) TABLES

Table 1. Peer effects on the academic performance of PUCE students

Dependent variable: Final grade (finalgr)	
VARIABLES	**RANDOM EFFECTS**
Low-ability students (plow)	-13.31*** (0.46)
High-ability students (phigh)	8.89*** (0.53)
Peer effects	0.70*** (0.041)
Credits	0.10*** (0.018)
Family income (incomepc)	0.001*** (0.00)

Siblings	-0.48 (0.64)
Female	1.17*** (0.29)
Teaching quality (teachqual)	-1.33 (0.75)
R-squared within	0.0973
R-squared between	0.6599
R-squared overall	0.6624
Wald chi2	2009.22
Prob > chi2	0.000

Table 2. Robustness check estimations

Dependent variable: Final grade (finalgr)				
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**
Low-able students (plow)	-13.28***	-13.25***	-13.64***	-13.32***
High-able students (phigh)	9.04***	8.90***	9.05***	9.03***
Mean course	0.69***	0.71***	0.69***	0.71***
Changes in Control Variables	Expenditure per capita (expenditupc)	No teach quality (teachqual)	No credits	No gender (female)
Observations	1033	1033	1033	1033
R-squared within	0.0974	0.0990	0.0958	0.0981
R-squared between	0.6573	0.6588	0.6495	0.6541
R-squared overall	0.6597	0.6614	0.6514	0.6569
Wald chi2	1984.87	2001.99	1915.00	1962.07
Prob > chi2	0.000	0.000	0.000	0.000

(9) APPENDICES

Table A1. Robustness check with top 5% and bottom 5% of students.

Dependent variable: Final grade (finalgr)	
VARIABLES	**RANDOM EFFECTS**
Low-ability students (plow)	-14.91***
High-ability students (phigh)	9.79***
Peer effects	0.79***

Credits	0.11***
Family income (incomepc)	0.002***
Siblings	0.32
Female	1.26***
Teaching quality (teachqual)	-1.49
R-squared within	0.2319
R-squared between	0.55
R-squared overall	0.5537
Wald chi2	1270.26
Prob > chi2	0.000

Table A2. Hausman Test

VARIABLES	Fixed Effects	Random Effects	Difference
Low-ability students (plow)	-4	-13.31	9.31
Peer effects	2.63	0.9677	1.93
chi2	0.62		
Prob > chi2	0.7339		

Table A3. Variance inflation factor (VIF)

Dependent variable: Final grade (finalgr)		Variance Inflation Factor
VARIABLES	**RANDOM EFFECTS**	**VIF**
Low-ability students (plow)	-13.31***	1.07
High-ability students (phigh)	8.89***	1.04
Peer effects	0.698***	1.08
Credits	0.10***	1.03
Family income (incomepc)	0.001***	1.03
Siblings	-0.05	1.03
Female	1.17***	1.03
Teaching quality (teachqual)	-1.32	1.03
Mean VIF	0.66	1.04
R-squared	0.66	
R-squared Adjusted	0.6598	
Prob > chi2	0.000	