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Quantile Regression Analysis between the After-School Exercise and the Academic Performance of Korean Middle School Students

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Abstract: This study deepens our understanding of the prediction and structural relationship between a student's academic performance and his/her regular after-school exercise by estimating models based upon the quantile regression and the instrumental variable quantile regression methods, respectively. Using data on Korean middle school students, we found that negative relationships were dominant for the prediction models, whereas the relationships were reversed for the structural models, affirming the theoretical and experimental hypotheses observed in prior literature. Furthermore, we also found that the low-performing students, in terms of the academic performance, had stronger associations between the two variables than the high-performing students, overall.

Keywords: after-school exercise; academic performance; structural relationship; quantile regression; instrumental variable quantile regression

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1. Introduction

Investigating the relationship between mental health and physical activity has been a popular research topic in literature. For example, Correa-Burrows et al. [1] and Tomporowski et al. [2] reviewed theoretical works on the relationship, indicating a positive structural association between a student's regular physical exercise and his/her academic achievement. Furthermore, Shin, Yoo, and Kim [3] empirically examined students' academic performance and after-school exercise using Korean middle school student data, affirming the theoretical and experimental hypotheses.

Nevertheless, we note that every student does not behave according to the same theoretical hypothesis, and the extent of the relationship between the academic performance and regular exercise is different from student to student, although the theoretical hypothesis may still be valid overall.

This aspect motivates the current study. The goal of this study is to empirically identify the relationship between students' academic performance and their after-school exercise by separately estimating structural models for the students belonging to different groups, thereby deepening the prior empirical results on the two variables. For this purpose, we classified the students according to the quantile levels of their academic performance score and examined whether the students belonging to each quantile level behaved according to the hypothesized theory or not. In addition to this, we also further examined which quantile level of students were more strongly supported by the hypothesized theory on the two variables.

For the purpose of this study, we investigated the empirical data collected by the National Youth Policy Institute (NYPI) in Korea from middle school students in 2011, using both quantile regression (QR) and instrumental variable quantile regression (IVQR) methods. The QR method, developed by Koenker and Bassett [4], estimates the quantile prediction model by using observations belonging to the different quantile levels of the dependent variable, and it does not necessarily estimate the structural relationship between the variables of interest. On the other hand, the IVQR method, developed by Chernozhukov and Hansen [5], in parallel to the two-stage least squares (TSLS) estimation, estimates the structural model by using the observations belonging to the different quantile levels of the dependent variable, similarly to the QR method. To the best of our knowledge, the IVQR method has not been applied to the quantile structural equation between a student's academic performance and his/her physical activity. This study contributes to the literature by providing empirical evidence on the positive structural relationship between Korean middle school students' physical activity and their academic performance by applying the IVQR method.

The paper is organized as follows. In Section 2, we discuss the motivation for the use of the IVQR method in comparison with the QR method, in parallel to the comparison between the ordinary least squares (OLS) and the TSLS methods. In addition, we provide the models estimated by QR and IVQR and the variables used for the empirical analysis, describing our strategy to estimate the quantile structural relationship between the two variables, along with the instrumental variables that are employed for the application of the IVQR method. The prior literature relevant to the current study goal is also provided. In Section 3, the estimation results are provided, and we compare the results with the hypotheses given in the existing literature and discuss them. Concluding remarks are provided in Section 4.

2. Model Estimation Strategy and Literature

2.1. Benchmark Model

Our study concept is based upon the following model:

$$\log(acps_i) = \alpha_* + \beta_* excd_i + \gamma_* prvl_i + \delta_* \log(yinc_i) + u_i, \tag{1}$$

where *acps* stands for the student's average exam scores of Korean, English, mathematics, science, and social science, which measures students' academic performance; and *excd* and *prvl* denote the dummy variables for weekly after-school exercise and weekly after-school private lessons for Korean, English, mathematics, science, or social science, respectively. For example, *excd* is equal to 1 if the student attends after-school private lessons for exercise and is 0, otherwise. This model was specified to capture the effect of the after-school exercise on the student's academic performance. Therefore, the exam score of physical education was not included in *acps*. In addition, *yinc* stands for the parent's yearly income measured in 10,000 Korean won. The logarithm was taken to *acps* and *yinc*, so that we could interpret the coefficient δ_* as the income elasticity of the academic performance. Finally, the subscript i denotes the student index.

This empirical model was motivated by the hypothesis that regular exercise positively affects students' academic performance. For example, Alkadhi [6], de Greeff, Bosker, Oosterlaan, Visscher, and Hartman [7], Tomporowski, McCullick, Pendleton, and Pesce [8], and Xiang et al. [9], among others, provided theoretical bases for a positive association between physical and cognitive or mental activities. Furthermore, Belcher et al. [10] reported experimental results indicating that regular exercises modified the structure and function of brain, positively affecting brain activities. These theoretical and experimental works imply that students' regular after-school exercises are helpful in raising their academic performances, and Model (1) was specified to capture this effect empirically. Here, a student's regular exercise is denoted as any form of after-school exercise lessons, but excludes casual exercises, such as irregular or regular gym classes held at the school. They are excluded because such classes are common for all students in Korea, and therefore it is difficult to capture the different activities among different students and their affection to the academic performance.

Models similar to (1) have been empirically investigated in prior literature. For example, using Korean middle school student data, Shin, Yoo, and Kim [3] showed that the academic performance was positively and structurally associated with after-school exercise hours, although their relationship was negative in terms of the prediction model. In obtaining this result, Shin, Yoo, and Kim [3] employed the OLS and TSLS estimation methods. The OLS method estimates the prediction model, and a negative relationship is captured between the two variables. Meanwhile, the TSLS method estimates the structural relationship between the two variables, estimating a positive relationship, affirming the structural hypothesis on the two variables in the literature.

The current study deepens the empirical results in prior literature. Note that students' responses to the after-school exercise would not be the same for every student, and this can lead to various results in terms of raising their academic performance. For example, a student with high academic performance is expected to respond to the after-school exercise differently from a student with low academic performance. Specifically, if the academic performance is positively associated with the student's cognitive power and his/her regular exercise is helpful in raising the student's cognitive power, attending the after-school exercise class is expected to raise the cognitive power of the low-performing student more effectively than the high-performing student. It is mainly because the latter is likely to have already reached the level that cannot be easily raised by attending the physical exercise class. We estimated these different responses by specifying the QR model. Specifically, the responses were assumed to be different among the students belonging to the different quantile levels in terms of their academic performance, and we estimated the different coefficients by modifying Model (1) to have different parameters at different quantile levels. That is, if we let τ denote the quantile level of the student's academic performance, the parameters in Model (1) are modified to depend on τ, as follows: for each $\tau \in (0, 1)$,

$$\log(acps_i) = \alpha_{(\tau)*} + \beta_{(\tau)*} excd_i + \gamma_{(\tau)*} prvl_i + \delta_{(\tau)*} \log(yinc_i) + u_{(\tau)i}. \tag{2}$$

The parameters on the right side now depend on the quantile level τ, so that the top 10-% students can now be differently associated with the right-side variables from the bottom 10-% students.

We estimated Model (2) by the QR method. Koenker and Bassett [4] provided the estimation method for the model specified by the same motivation as that of this study, under a general model assumption, and showed that their estimator was consistent for the desired parameters and was asymptotically normal around the unknown parameter values. In addition, Koenker [11] demonstrated how to test hypotheses on the unknown parameters using the asymptotic normal distribution provided by Koenker and Bassett [4]. In particular, Koenker [11] employed the robust standard error to define the t-test and showed that its null limit distribution was a standard normal. Below, we exploit the technical advances in Koenker [11] to estimate Model (2).

Nevertheless, the QR method does not estimate the structural relationship between the academic performance and the after-school exercise. Note that when Model (2) is estimated by QR for different quantiles, their weighted average with respect to τ turns out to be identical to that estimated by OLS. This implies that the QR method cannot be associated with the structural relationship between the variables.

We therefore estimated the structural form of Model (2) by IVQR. Chernozhukov and Hansen [5] provided a method to estimate the structural parameters in Model (2) under the condition that proper instrumental variables are available. They showed that their estimator could consistently estimate the unknown structural parameters and, also, that its limit distribution was normal under some mild regularity conditions, that enables us to construct the t-test for the QR method. The model estimated by IVQR was different from that estimated by QR. For each quantile level, we emphasize that it consistently estimated the structural quantile equation instead of the quantile equation, viz., the quantile prediction model. The relationship between the QR and IVQR estimations is parallel to that between the OLS and TSLS estimations in terms of their structures. Exploiting the advances in Chernozhukov and Hansen [5], we estimated the structural quantile model and drew the model implications that were different from those of the QR method. (The following URL provides the stata code to estimate the model by the IVQR method: http://sites.google.com/site/dwkwak/dataset-and-code (accessed on 23 November 2021)).

The instrumental variables play a critical role in estimating the structural quantile model. For the goal of the current study, we employed the logarithms of the students' height, weight, and sleeping hours on the weekend. There were two motivations for these instrumental variables. First, a student's height and weight are closely associated with outside activities [12], so they are highly correlated. Second, a student attending the regular after-school exercise class tends to sleep more than other students on the weekend in order to recover from physical fatigue because they cannot oversleep during weekdays; hence, students' sleeping hours on weekends tend to be correlated with regular after-school exercise. Nihayah et al. [13] and Zeek et al. [14] also provided case studies on the relationship between students' sleeping hours and their academic performance. Based upon these two facts, the logarithms of students' height, weight, and sleeping hours on weekends were employed as our instrumental variables to apply to the IVQR method. The same instrumental variables were also selected by Shin, Yoo, and Kim [3] when estimating their structural model by TSLS.

In addition to the after-school exercise, the other explanatory variables on the right side of Model (2) were included in order to explain the variation of the academic performance score. The after-school private lessons for school subjects are certainly helpful in raising the academic performance score, which allows the after-school exercise (*excd*) to maintain its explanatory power. In addition, the parent's income level was also included on the right side, by noting that parent's high-income level provides the student with more opportunities to take high-quality private lessons, raising the student's academic performance. If these variables were to be omitted from the right side, the explanatory power of the after-school exercise may be overwhelmed by the variation of the error term. We called Model (2) our benchmark model and estimate it by both QR and IVQR.

2.2. Model Extensions

We next extended the model scope by including other explanatory variables on the right side and tested the robust model estimation property. For this goal, we applied the strategy taken by Shin, Yoo, and Kim [3] to our QR and IVQR models. As our first extension, we specified the following model:

$$\begin{aligned} \log(acps_i) &= \alpha_{(\tau)*} + \beta_{(\tau)*}excd_i + \gamma_{(\tau)*}prvl_i + \delta_{(\tau)*}\log(yinc_i) \\ &+\pi_{(\tau)*}gndr_i + \xi_{(\tau)*}expl_i + \rho_{(\tau)*}nsib_i \\ &+\eta_{(\tau)*}moed_{m_i} + \theta_{(\tau)*}moed_{h_i} + \kappa_{(\tau)*}moed_{p_i} \\ &+\lambda_{(\tau)*}moed_{u_i} + \mu_{(\tau)*}moed_{g_i} + u_{(\tau)i}, \end{aligned} \tag{3}$$

where *gndr* denotes students' gender, such that it is 1 and 0 for male and female students, respectively; *expl* denotes the monthly expenditure on the after-school private lessons measured in 10,000 KRW; *nsib* denotes the number of siblings; and *moed_x* denotes the mother's education level. The attachment x indicates the education level. That is, m, h, p, u, and g denote middle school, high school, polytechnic school, university, and graduate school, respectively. For example, if *moed_u* is 1, it implies that the student's mother was educated up to the university education.

These additional explanatory variables were included in order to examine how they are associated with the academic performance score. First, according to Alkadhi [6], and de Greeff, Bosker, Oosterlaan, Visscher, and Hartman [7], among others, male and female students have relative advantages in different disciplines, so a student's academic performance score for different disciplines can be gender-dependent. Therefore, we expected the coefficient of *gndr* in Model (3) to be significantly different from zero, and to further diverge depending on the quantile levels. Second, we included the monthly expenditure on private lessons (*expl*) and the number of siblings (*nsib*) in order to explain the partial effect of the parent's income on the academic performance. If the parents' income is spent on the student's private lessons in order to raise the academic performance, the income effect can be better explained by including the expenditure on the private lessons in addition to parent's income. Similarly, the income effect of parents with multiple children can reduce if the total parents' income is divided for each child's private lessons. We therefore included the number of siblings on the right side and capture the split-income effect. Finally, we included the mother's education level on the right side and detected the parental-involvement effect. Bogenschneider [15], Boonk, Gijselaers, Ritzen, and Brand-Gruwel [16], and Glick and Hohmann-Marriott [17], among others, pointed out that a student's academic performance was closely related to parental involvement and, further, that parental involvement can exist in various forms, suggesting that the parent's education level can be a proper form for parental involvement, although it is generally difficult to measure it objectively. By following the suggestions in prior studies, we included the mothers' education level to measure parental involvement and examined how it affected the student's academic performance at the different quantile levels [15,17–19].

By estimating Model (3) by both QR and IVQR, we can examine the hypothesis for the newly included explanatory variables on the right side. The given hypothesis may be relevant to some quantile levels but not to all of the quantile levels, or it may be relevant at all quantile levels. There can be many different results depending on the quantile levels. Below, we empirically examine whether the given hypothesis is valid or not at each quantile level, and from this we draw detailed empirical inference on the Korean middle school students.

As our final model extension, we further included more explanatory variables in Model (3). As mentioned above, parental involvement is a critical variable that explains a student's academic performance but including only the mother's education level on the right side may be insufficient to capture the effect of parental involvement on a student's academic performance. We, therefore, compensated the mother's education level by complementing it with the father's education level, as follows:

$$\begin{aligned}\log(acps_i) &= \alpha_{(\tau)*} + \beta_{(\tau)*}excd_i + \gamma_{(\tau)*}prvl_i + \delta_{(\tau)*}\log(yinc_i) \\ &+\pi_{(\tau)*}gndr_i + \xi_{(\tau)*}expl_i + \rho_{(\tau)*}nsib_i \\ &+\eta_{(\tau)*}moed_{m_i} + \theta_{(\tau)*}moed_{h_i} + \kappa_{(\tau)*}moed_{p_i} + \lambda_{(\tau)*}moed_{u_i} \\ &+\mu_{(\tau)*}moed_{g_i} + \sigma_{(\tau)*}faed_{m_i} + \tau_{(\tau)*}faed_{h_i} + \phi_{(\tau)*}faed_{p_i} \\ &+\psi_{(\tau)*}faed_{u_i} + \omega_{(\tau)*}faed_{g_i} + u_{(\tau)i},\end{aligned} \tag{4}$$

where *faed_x* is a dummy variable indicating the father's education level, and the attachment x denotes the same education level as for the mother's education level.

We estimated the extended models in Models (3) and (4) in order to affirm the estimation results made by both QR and IVQR. If the quantile prediction and structural quantile equations in Model (2) are consistently estimated by both QR and IVQR, respectively, they should be similar to those obtained by Models (3) and (4). By estimating these multiple models, we attempted to ensure that our model estimates were robust to model variation.

3. Estimation and Inference

3.1. Data

The data set for our study was collected by the NYPI in South Korea. The NYPI panel survey is collected to understand the comprehensive conditions and environmental changes in youth and childrens' education in South Korea. For our study goal, we used the second wave that provides the observations for the variables in 2011. Shin, You, and Kim [3] also estimated the prediction and structural models by OLS and TSLS, respectively, using the same data. There were 2280 students in the data set, but some students did not provide information. We estimated the models by excluding the missing observations, and the number of missing observations was different from model to model.

3.2. Estimation and Inference Results

3.2.1. Estimation and Inference Results Using Model 2

Tables 1 and 2 report the estimation results of Model (2) obtained by QR and IVQR, respectively. The selected quantile levels were 0.1, 0.2, . . . , 0.8, and 0.9, and the total number of observations was 2099 after removing the missing observations. The estimated coefficients are provided in Tables 1 and 2, and figures in parentheses denote the p-values of the t-tests, testing whether the estimated coefficient was zero or not. We also provide the OLS and TSLS estimation results at the final columns of Tables 1 and 2, respectively, and affirm that the averages of the coefficients estimated by QR and IVQR approximate the corresponding coefficients obtained by OLS and TSLS, respectively.

Table 1. Estimation results obtained by quantile regression.

Variables\Quantiles	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**OLS**
const	2.223	1.946	2.310	2.706	3.073	3.373	3.648	3.890	4.182	2.907
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
excd	0.011	−0.084	−0.105	−0.118	−0.070	−0.051	−0.059	−0.054	−0.026	−0.067
	(0.828)	(0.245)	(0.038)	(0.281)	(0.089)	(0.028)	(0.003)	(0.006)	(0.185)	(0.047)
prvl	0.249	0.277	0.264	0.234	0.177	0.145	0.094	0.057	0.026	0.157
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.013)	(0.000)
$\log(yinc)$	0.158	0.219	0.193	0.161	0.133	0.108	0.086	0.065	0.038	0.143
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.126)
Sample size	2099	2099	2099	2099	2099	2099	2099	2099	2099	2099

Figures in parentheses are the p-values of the t-test statistics computed by robust standard error. The dependent variable is $\log(acps)$. R^2 of the OLS model is 0.1262.

Table 2. Estimation results obtained by instrumental variable quantile regression.

Variables\Quantiles	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**TSLS**
const	2.256	1.862	2.384	2.619	3.046	3.419	3.618	3.877	4.173	2.910
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
excd	0.662	2.102	2.073	2.038	1.037	0.839	0.439	0.300	0.169	1.055
	(0.464)	(0.002)	(0.000)	(0.000)	(0.003)	(0.000)	(0.018)	(0.026)	(0.158)	(0.006)
Prvl	0.239	0.228	0.231	0.194	0.169	0.123	0.081	0.049	0.026	0.138
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\log(yinc)$	0.152	0.224	0.178	0.165	0.132	0.100	0.089	0.066	0.039	0.140
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sample size	2099	2099	2099	2099	2099	2099	2099	2099	2099	2099

Figures in parentheses are the p-values of the t-test statistics testing whether the estimated parameter was zero or not. The dependent variable is $\log(acps)$.

We summarize the estimation results as follows. First, in terms of the quantile prediction model, the effect of the after-school exercise on the academic performance is statistically significant or insignificant, depending on the quantile level, implying that the after-school exercise is not always significantly associated with the academic performance. This quantile effect was obtained by integrating both the direct and indirect effects of the after-school exercise on the academic performance. For the 1% level of significance, the after-school exercise is negatively significant on the academic performance only for τ =0.7 and 0.8. If the level of significance is raised to 5%, it becomes also significant for τ =0.3 and 0.6, but it is insignificant for the other quantile levels. This implies that the after-school exercise is most negatively associated with the academic performance for the students with $\tau = 0.7$ and 0.8. In other words, the loss of the academic performance score is more severe for the students with $\tau = 0.7$ and 0.8. In other words, the opportunity cost of attending the after-school exercise class is most expensively perceived for the students with $\tau = 0.7$ and 0.8. On the other hand, for the extremely high-performing students (i.e., $\tau = 0.9$), attending the after-school exercise class is not perceived as an opportunity cost.

Second, the after-school exercise is positively associated with the academic performance score for most of the quantile levels in terms of the quantile structural model. The estimated coefficients of the after-school exercise in Table 2 are positive and statistically significant for $\tau = 0.2$ to 0.8 at a 1% level of significance, implying that most students directly raise their academic performance by attending the after-school exercise class. These overall positive effects have to be sharply distinguished from the negative effects in Table 1 that are obtained by integrating the direct and indirect effects of the after-school exercise, and they also empirically ensure the hypothetical and experimental positive relationship between the two variables, posited by de Greeff, Bosker, Oosterlaan, Visscher, and Hartman [7], and Tomporowski, McCullick, Pendleton, and Pesce [8], among others. In addition to this, the effect of the after-school exercise diminishes as the quantile level increases. That is, the students with low τ receive more direct benefit from the after-school exercise than the students with high τ. That is, as τ increases from $\tau = 0.2$ to $\tau = 0.9$, the estimated coefficient of *excd* persistently decreases. This aspect implies that the after-school exercise does not raise the academic performance score of the high-performing students as much as for the low-performing students, excluding the extreme quantile levels. From this aspect, we affirm that the hypothetical and experimental positive relationship is more effective for the students with low academic performance.

Third, the overall average effects of the parent's income and the after-school private lessons for the other subjects are positively associated with the student's academic performance. These positive associations are more or less similar between the QR and IVQR estimations. The obtained quantile coefficients of the parent's income and the private lessons decrease as τ increases, excluding the low-performing students, i.e., $\tau = 0.2$. This implies that the overall average effect of these two variables is more effective for the students with low academic performance. For the students with high academic performance, the overall average effect is still positive, but not as strong as for the low-performing students. From this aspect, we conclude that the marginal effect of taking the private lessons is greater for the low-performing students, and this also holds for the parent's income effect.

3.2.2. Estimation and Inference Results Using Model 3

We next discuss the estimation results of Model (3) reported in Tables 3 and 4. As for Model (2), Tables 3 and 4 are estimated by QR and IVQR, respectively. After removing the missing observations, we used a total of 2083 observations.

We summarize the estimation results as follows. First, the estimation results of Model (2) are valid even for Model (3). All estimated coefficients are more or less similar to those in Tables 1 and 2, and their statistical significance is also similarly obtained.

Second, we observed different gender effects between the quantile prediction and structural equations. Voyer and Voyer [20] and Gneezy, Niederle, and Rustichini [21], among others, assert that students' academic performance exhibits a gender effect, but this effect cannot be observed from the prediction models reported in Table 3. None of the estimated gender coefficients are statistically significant. In contrast, the gender effect becomes more evident for low quantile levels if the IVQR method is applied. For $\tau = 0.1$, 0.2, and 0.3, Table 4 reports that the estimated coefficients are negatively valued and statistically significant, implying that the gender effect asserted in the prior literature is more easily verifiable for the students. The estimated coefficient increases as τ increases, from -0.16 to close to 0 as τ increases from 0.1 to 0.4, and it stays around 0 for τ greater than 0.4.

Third, we examined the effects of the after-school lesson expenditure for private lessons and the number of siblings. As expected in Section 2.2, for both prediction and structural models, the overall sign of *expl* is positive, whereas it is weakly reversed for *nsib*. Although the coefficients of the number of siblings are statistically insignificant for the quantile prediction model, some of them in the quantile structural model are statistically significant. On the other hand, for most of the quantile levels, the coefficients of *expl* are statistically significant for both the quantile prediction and the structural models. This result implies that the parent's income effect can be better captured by including the expenditure effect rather than the number of siblings. In addition, the expenditure effect is stronger for the low-performing students than the students with high academic performance. The estimated coefficient of *expl* overall decreases as τ increases, implying that the academic performance of the low-performing students can be more easily raised by taking the private lessons than the high-performing students.

Table 3. Estimation results obtained by quantile regression.

Variables\Quantiles	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**OLS**
const	3.086	2.907	2.934	3.252	3.513	3.665	3.926	4.122	4.283	3.355
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
excd	−0.019	−0.089	−0.101	−0.093	−0.077	−0.049	−0.050	−0.043	−0.025	−0.064
	(0.868)	(0.060)	(0.148)	(0.129)	(0.087)	(0.067)	(0.033)	(0.027)	(0.210)	(0.058)
prvl	0.097	0.203	0.220	0.171	0.148	0.122	0.073	0.037	0.014	0.111
	(0.060)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.007)	(0.182)	(0.000)
log(*yinc*)	0.057	0.089	0.101	0.087	0.068	0.057	0.048	0.033	0.024	0.082
	(0.076)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)
gndr	−0.064	−0.039	−0.011	0.014	0.010	0.009	0.004	0.002	−0.004	−0.012
	(0.148)	(0.166)	(0.617)	(0.418)	(0.441)	(0.400)	(0.621)	(0.794)	(0.559)	(0.360)
expl	0.004	0.003	0.002	0.001	0.001	0.001	0.000	0.000	0.000	0.002
	(0.030)	(0.001)	(0.004)	(0.001)	(0.005)	(0.000)	(0.016)	(0.038)	(0.006)	(0.000)
nsib	−0.008	−0.024	−0.017	−0.029	−0.018	−0.006	−0.012	−0.008	−0.008	−0.016
	(0.743)	(0.300)	(0.499)	(0.156)	(0.134)	(0.499)	(0.125)	(0.155)	(0.114)	(0.143)
moed_m	−0.113	−0.074	−0.109	−0.144	−0.078	−0.010	−0.065	−0.039	0.006	−0.059
	(0.183)	(0.243)	(0.430)	(0.188)	(0.524)	(0.890)	(0.200)	(0.409)	(0.876)	(0.294)
moed_h	−0.017	0.074	0.088	0.061	0.082	0.107	0.037	0.043	0.021	0.041
	(0.706)	(0.148)	(0.254)	(0.404)	(0.046)	(0.013)	(0.212)	(0.051)	(0.312)	(0.206)
moed_p	0.057	0.226	0.239	0.176	0.153	0.144	0.066	0.062	0.027	0.114
	(0.714)	(0.000)	(0.004)	(0.020)	(0.000)	(0.001)	(0.032)	(0.009)	(0.210)	(0.002)
moed_u	0.186	0.261	0.267	0.209	0.179	0.167	0.085	0.082	0.047	0.146
	(0.030)	(0.000)	(0.001)	(0.004)	(0.000)	(0.000)	(0.005)	(0.000)	(0.023)	(0.000)
moed_g	0.166	0.294	0.319	0.250	0.210	0.197	0.101	0.094	0.046	0.139
	(0.294)	(0.098)	(0.000)	(0.001)	(0.000)	(0.000)	(0.002)	(0.000)	(0.049)	(0.011)
Sample size	2083	2083	2083	2083	2083	2083	2083	2083	2083	2083

Figures in parentheses are the p-values of the t-test statistics computed by robust standard error. The dependent variable is log($acps$). R^2 of the OLS model is 0.1660.

Fourth, we examined the effect of the parental involvement on the academic performance measured by the mother's education level. Overall, for each quantile level, the effect of the mother's education level is positive and becomes statistically more significant as the mother's education level increases for the quantile prediction model. On the other hand, for the quantile structural model, the effect of the mother's education level is maximized when the mother receives education up to university level. If the mother is educated only up to the middle school or high school level, it does not affect the student's academic performance significantly for neither the prediction nor the structural model. Furthermore, the effect of the mother's education level is most influential for $\tau = 0.2$ or 0.3 for both models.

3.2.3. Estimation and Inference Results Using Model 4

We finally discuss the estimation of Model (4) reported in Tables 5 and 6. As for Models (1) and (2), Tables 5 and 6 are estimated by QR and IVQR, respectively. After removing the missing observations, a total of 2083 observations remained.

Table 4. Estimation results by obtained instrumental variable quantile regression.

Variables\Quantiles	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	TSLS
const	2.882	2.903	2.924	3.274	3.484	3.681	3.955	4.072	4.288	3.353
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
excd	2.480	2.292	2.641	1.818	1.151	0.692	0.624	0.439	0.214	1.655
	(0.028)	(0.017)	(0.000)	(0.001)	(0.008)	(0.061)	(0.004)	(0.056)	(0.131)	(0.007)
prvl	0.070	0.158	0.157	0.139	0.116	0.112	0.055	0.029	0.009	0.078
	(0.184)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.009)	(0.207)	(0.007)
$\log(yinc)$	0.078	0.085	0.098	0.075	0.066	0.054	0.042	0.037	0.022	0.077
	(0.044)	(0.009)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
gndr	−0.160	−0.127	−0.086	−0.036	−0.023	−0.013	−0.016	−0.015	−0.010	−0.065
	(0.001)	(0.002)	(0.004)	(0.142)	(0.237)	(0.441)	(0.087)	(0.141)	(0.102)	(0.018)
expl	0.004	0.002	0.001	0.001	0.001	0.001	0.001	0.000	0.000	0.002
	(0.003)	(0.006)	(0.020)	(0.050)	(0.009)	(0.004)	(0.003)	(0.144)	(0.000)	(0.002)
nsib	−0.013	−0.020	−0.034	−0.033	−0.021	−0.007	−0.015	−0.009	−0.007	−0.022
	(0.615)	(0.420)	(0.051)	(0.020)	(0.078)	(0.488)	(0.011)	(0.148)	(0.111)	(0.186)
moed_m	−0.030	−0.059	−0.097	−0.100	−0.058	−0.016	−0.047	−0.022	0.010	−0.026
	(0.806)	(0.579)	(0.204)	(0.127)	(0.269)	(0.724)	(0.070)	(0.432)	(0.590)	(0.728)
moed_h	0.027	0.124	0.149	0.127	0.122	0.107	0.058	0.057	0.021	0.088
	(0.744)	(0.068)	(0.003)	(0.003)	(0.000)	(0.000)	(0.001)	(0.001)	(0.065)	(0.066)
moed_p	0.027	0.185	0.182	0.164	0.150	0.115	0.067	0.051	0.022	0.094
	(0.773)	(0.017)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.013)	(0.110)	(0.084)
moed_u	0.219	0.319	0.335	0.280	0.217	0.168	0.110	0.093	0.047	0.197
	(0.013)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
moed_g	0.100	0.274	0.263	0.253	0.203	0.168	0.101	0.086	0.040	0.124
	(0.483)	(0.023)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.008)	(0.064)	(0.147)
Sample size	2083	2083	2083	2083	2083	2083	2083	2083	2083	2083

Figures in parentheses are the p-values of the t-test statistics testing whether the estimated parameter was zero or not. The dependent variable is $\log(acps)$.

Table 5. Estimation results obtained by quantile regression.

Variables\Quantiles	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	OLS
const	3.037	2.872	3.004	3.332	3.535	3.661	3.982	4.128	4.281	3.431
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
excd	−0.031	−0.054	−0.093	−0.069	−0.064	−0.055	−0.040	−0.049	−0.026	−0.062
	(0.815)	(0.385)	(0.098)	(0.259)	(0.166)	(0.042)	(0.065)	(0.008)	(0.236)	(0.069)
prvl	0.103	0.187	0.205	0.170	0.135	0.121	0.076	0.039	0.017	0.112
	(0.036)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.109)	(0.000)
$\log(yinc)$	0.061	0.094	0.078	0.063	0.058	0.057	0.040	0.034	0.024	0.069
	(0.086)	(0.001)	(0.002)	(0.009)	(0.003)	(0.000)	(0.001)	(0.001)	(0.004)	(0.000)
gndr	−0.085	−0.046	−0.014	0.007	0.014	0.009	0.003	0.001	−0.005	−0.013
	(0.034)	(0.137)	(0.499)	(0.674)	(0.294)	(0.378)	(0.711)	(0.942)	(0.474)	(0.350)
expl	0.003	0.003	0.001	0.001	0.001	0.001	0.000	0.000	0.000	0.002
	(0.026)	(0.006)	(0.022)	(0.003)	(0.000)	(0.000)	(0.010)	(0.148)	(0.012)	(0.000)
nsib	−0.015	−0.021	−0.015	−0.038	−0.020	−0.009	−0.013	−0.010	−0.007	−0.018
	(0.511)	(0.428)	(0.388)	(0.045)	(0.144)	(0.290)	(0.096)	(0.106)	(0.179)	(0.098)
moed_m	−0.038	−0.047	0.031	−0.062	−0.060	−0.004	−0.036	−0.048	−0.015	−0.040
	(0.690)	(0.508)	(0.764)	(0.610)	(0.713)	(0.948)	(0.556)	(0.427)	(0.777)	(0.505)
moed_h	−0.009	0.039	0.130	0.086	0.070	0.082	0.038	0.031	0.027	0.040
	(0.824)	(0.462)	(0.026)	(0.248)	(0.176)	(0.022)	(0.211)	(0.232)	(0.208)	(0.220)
moed_p	0.065	0.164	0.239	0.174	0.145	0.128	0.067	0.047	0.036	0.104
	(0.603)	(0.021)	(0.000)	(0.024)	(0.007)	(0.000)	(0.040)	(0.092)	(0.128)	(0.007)
moed_u	0.116	0.165	0.255	0.182	0.153	0.133	0.073	0.061	0.049	0.121
	(0.211)	(0.016)	(0.000)	(0.014)	(0.004)	(0.000)	(0.020)	(0.025)	(0.026)	(0.001)

Table 5. *Cont.*

Variables\Quantiles	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	OLS
moed_g	−0.001	0.184	0.285	0.219	0.188	0.169	0.099	0.080	0.041	0.109
	(0.993)	(0.179)	(0.001)	(0.005)	(0.001)	(0.000)	(0.004)	(0.008)	(0.102)	(0.052)
faed_m	−0.041	−0.065	−0.098	0.062	0.040	−0.009	−0.042	0.000	0.017	−0.005
	(0.630)	(0.342)	(0.259)	(0.676)	(0.742)	(0.890)	(0.457)	(1.000)	(0.681)	(0.927)
faed_h	0.037	0.043	0.081	0.091	0.062	0.037	−0.001	−0.001	−0.010	0.031
	(0.453)	(0.438)	(0.119)	(0.266)	(0.397)	(0.496)	(0.966)	(0.980)	(0.563)	(0.361)
faed_p	−0.015	0.074	0.143	0.118	0.066	0.009	−0.005	−0.009	−0.018	0.037
	(0.883)	(0.376)	(0.020)	(0.171)	(0.383)	(0.871)	(0.884)	(0.737)	(0.351)	(0.356)
faed_u	0.127	0.123	0.164	0.165	0.097	0.045	0.019	0.012	−0.007	0.069
	(0.087)	(0.031)	(0.003)	(0.046)	(0.201)	(0.408)	(0.512)	(0.585)	(0.693)	(0.054)
faed_g	0.245	0.163	0.208	0.180	0.093	0.034	0.000	0.007	0.003	0.084
	(0.049)	(0.067)	(0.003)	(0.043)	(0.235)	(0.535)	(0.998)	(0.779)	(0.890)	(0.072)
Samplesize	2083	2083	2083	2083	2083	2083	2083	2083	2083	2083

Figures in parentheses are the p-values of the t-test statistics computed by robust standard error. The dependent variable is $\log(acps)$. R^2 of the OLS model is 0.1687.

Table 6. Estimation results obtained by instrumental variable quantile regression.

Variables\Quantiles	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	OLS
const	3.133	3.088	3.052	3.417	3.576	3.767	4.000	4.125	4.298	3.504
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
excd	2.662	2.111	2.428	2.093	1.129	0.816	0.636	0.504	0.214	1.686
	(0.005)	(0.050)	(0.000)	(0.000)	(0.011)	(0.023)	(0.011)	(0.019)	(0.161)	(0.008)
prvl	0.071	0.158	0.146	0.130	0.115	0.108	0.059	0.029	0.010	0.078
	(0.109)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.174)	(0.008)
$\log(yinc)$	0.027	0.044	0.058	0.036	0.041	0.035	0.032	0.027	0.020	0.045
	(0.464)	(0.300)	(0.035)	(0.106)	(0.021)	(0.013)	(0.001)	(0.002)	(0.001)	(0.073)
gndr	−0.163	−0.111	−0.080	−0.050	−0.019	−0.017	−0.015	−0.019	−0.010	−0.066
	(0.000)	(0.015)	(0.007)	(0.040)	(0.330)	(0.275)	(0.160)	(0.040)	(0.121)	(0.018)
expl	0.003	0.002	0.001	0.001	0.001	0.001	0.001	0.000	0.000	0.002
	(0.003)	(0.039)	(0.017)	(0.018)	(0.005)	(0.003)	(0.010)	(0.065)	(0.001)	(0.002)
nsib	−0.025	−0.035	−0.034	−0.041	−0.023	−0.013	−0.016	−0.013	−0.008	−0.027
	(0.275)	(0.202)	(0.053)	(0.004)	(0.049)	(0.197)	(0.019)	(0.033)	(0.089)	(0.106)
moed_m	0.077	−0.002	0.042	−0.035	−0.049	0.022	0.005	−0.002	−0.007	0.005
	(0.489)	(0.986)	(0.612)	(0.609)	(0.387)	(0.637)	(0.862)	(0.929)	(0.735)	(0.949)
moed_h	0.035	0.127	0.147	0.112	0.094	0.103	0.064	0.057	0.031	0.078
	(0.585)	(0.084)	(0.003)	(0.005)	(0.005)	(0.000)	(0.001)	(0.000)	(0.009)	(0.100)
moed_p	0.047	0.148	0.156	0.127	0.120	0.115	0.074	0.053	0.032	0.079
	(0.551)	(0.095)	(0.008)	(0.009)	(0.003)	(0.000)	(0.001)	(0.007)	(0.029)	(0.167)
moed_u	0.208	0.273	0.291	0.235	0.174	0.162	0.108	0.091	0.057	0.173
	(0.006)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
moed_g	−0.015	0.226	0.201	0.171	0.159	0.171	0.095	0.085	0.042	0.087
	(0.894)	(0.103)	(0.030)	(0.023)	(0.011)	(0.001)	(0.008)	(0.004)	(0.087)	(0.331)
faed_m	0.038	0.023	0.004	0.131	0.078	0.022	−0.032	0.009	0.022	0.045
	(0.715)	(0.843)	(0.958)	(0.044)	(0.150)	(0.609)	(0.295)	(0.731)	(0.241)	(0.560)
faed_h	0.185	0.166	0.211	0.212	0.148	0.086	0.026	0.034	0.001	0.126
	(0.020)	(0.066)	(0.000)	(0.000)	(0.000)	(0.008)	(0.261)	(0.086)	(0.922)	(0.026)
faed_p	0.103	0.237	0.243	0.216	0.145	0.054	0.017	0.026	−0.006	0.126
	(0.255)	(0.021)	(0.000)	(0.000)	(0.001)	(0.144)	(0.512)	(0.260)	(0.741)	(0.052)
faed_u	0.238	0.243	0.269	0.251	0.172	0.086	0.035	0.040	0.002	0.147
	(0.004)	(0.008)	(0.000)	(0.000)	(0.000)	(0.008)	(0.125)	(0.044)	(0.895)	(0.009)
faed_g	0.382	0.342	0.342	0.310	0.188	0.082	0.037	0.038	0.014	0.191
	(0.001)	(0.006)	(0.000)	(0.000)	(0.001)	(0.075)	(0.250)	(0.179)	(0.509)	(0.018)
Sample size	2083	2083	2083	2083	2083	2083	2083	2083	2083	2083

Figures in parentheses are the p-values of the t-test statistics testing whether the estimated parameter was zero or not. The dependent variable is $\log(acps)$.

We summarize the estimation results as follows. First, the estimation results using Model (3) are still valid for Model (4). The estimated coefficients are more or less similar to those in Tables 3 and 4, and their statistical significance is also similarly obtained, ensuring that the model estimations are robust.

Second, we examined the effect of the father's education level on the student's academic performance as another form of parental involvement. In terms of the quantile prediction model, most of the father's education levels are not statistically significant. Nevertheless, for the students with $\tau = 0.4$, if his/her father receives education up to university level or more, it becomes statistically significant, implying that the highly educated fathers affect the academic performance of the student with $\tau = 0.4$.

Finally, we examined the effect of the father's education level on the student's academic performance in terms of the quantile structural model. Contrary to the quantile prediction model, the father's education level becomes significant, although the estimated coefficients are not significant, when the father receives education up to the middle school level. On the other hand, for each τ less than 0.7, the estimated coefficient overall increases as the father's education level increases, that is different from the effect of the mother's education level. For the structural model, the effect of the mother's education level is maximized when the mother receives education up to university level. In addition, the estimated coefficients are maximized for $\tau = 0.2$, 0.3, and 0.4.

4. Concluding Remarks

This study deepens our understanding of the prediction and structural relationship between a student's academic performance and his/her after-school exercise by employing the QR and IVQR methods, respectively. Using Korean middle school student data, our empirical investigation shows that the QR method detects negative relationships for all of the quantile levels of consideration, whereas a positive structural relationship is dominant between the two variables. This affirms the theoretical and experimental hypotheses on the two variables in prior literature. Furthermore, the low-performing students, in terms of academic performance, have stronger associations between the two variables than the high-performing students, overall.

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References

1. Correa-Burrows, P.; Burrows, R.; Orellana, Y.; Ivanovic, D. Achievement in mathematics and language is linked to regular physical activity: A population study in Chilean youth. *J. Sports Sci.* **2014**, *32*, 1631–1638. [CrossRef] [PubMed]
2. Tomporowski, P.D.; Davis, C.L.; Miller, P.H.; Naglieri, J.A. Exercise and children's intelligence, cognition, and academic achievement. *Educ. Psychol. Rev.* **2008**, *20*, 111–131. [CrossRef] [PubMed]
3. Shin, K.; Yoo, S.; Kim, M. A comparison of Two-Stage Least Squares (TSLS) and Ordinary Least Squares (OLS) in estimating the structural relationship between after-school exercise and academic performance. *Mathematics* **2021**, *9*, 3105. [CrossRef]
4. Koenker, R.; Bassett, G. Regression quantiles. *Econometrica* **1978**, *46*, 33–50. [CrossRef]
5. Chernozhukov, V.; Hansen, C. An IV model of quantile treatment effects. *Econometrica* **2005**, *73*, 245–262. [CrossRef]
6. Alkadhi, K.A. Exercise as a positive modulator of brain function. *Mol. Neurobiol.* **2018**, *55*, 3112–3130. [CrossRef] [PubMed]
7. De Greeff, J.W.; Bosker, R.J.; Oosterlaan, J.; Visscher, C.; Hartman, E. Effects of physical activity on executive functions, attention and academic performance in preadolescent children: A meta-analysis. *J. Sci. Med. Sport* **2018**, *21*, 501–507. [CrossRef] [PubMed]
8. Tomporowski, P.D.; Mccullick, B.; Pendleton, D.M.; Pesce, C. Exercise and children's cognition: The role of exercise characteristics and a place for metacognition. *J. Sport Health Sci.* **2015**, *4*, 47–55. [CrossRef]
9. Xiang, M.; Gu, X.; Jackson, A.; Zhang, T.; Wang, X.; Guo, Q. Understanding adolescents' mental health and academic achievement: Does physical fitness matter? *Sch. Psychol. Int.* **2017**, *38*, 647–663. [CrossRef]
10. Belcher, B.R.; Zink, J.; Azad, A.; Campbell, C.E.; Chakravartti, S.P.; Herting, M.M. The roles of physical activity, exercise, and fitness in promoting resilience during adolescence: Effects on mental well-being and brain development. *Biol. Psychiatry Cogn. Neurosci. Neuroimaging* **2021**, *6*, 225–237. [CrossRef]
11. Koenker, R. *Quantile Regression*; Cambridge University Process: Cambridge, NY, USA, 2005.
12. Beets, M.W.; Beighle, A.; Erwin, H.; Huberty, J. After-school program impact on physical activity and fitness: A meta-analysis. *Am. J. Prev. Med.* **2009**, *36*, 527–537. [CrossRef] [PubMed]
13. Nihayah, M.; Ismarulyusda, I.; Syarif, H.L.; NurZakiah, M.S.; Baharudin, O.; Fadzil, M.H. Sleeping hours and academic achievements: A study among biomedical science students. *Procedia Soc. Behav. Sci.* **2011**, *18*, 617–621. [CrossRef]
14. Zeek, M.L.; Savoie, M.J.; Song, M.; Kennemur, L.M.; Qian, J.; Jungnickel, P.W.; Westrick, S.C. Sleep duration and academic performance among student pharmacists. *Am. J. Pharm. Educ.* **2015**, *79*, 63. [CrossRef] [PubMed]
15. Bogenschneider, K. Parental involvement in adolescent schooling: A proximal process with transcontextual validity. *J. Marriage Fam.* **1997**, *59*, 718–733. [CrossRef]
16. Boonk, L.; Gijselaers, H.J.; Ritzen, H.; Brand-Gruwel, S. A review of the relationship between parental involvement indicators and academic achievement. *Educ. Res. Rev.* **2018**, *24*, 10–30. [CrossRef]
17. Glick, J.; Hohmann-Marriott, B. Academic performance of young children in immigrant families: The significance of race, ethnicity, and national origins. *Int. Migr. Rev.* **2007**, *41*, 371–401. [CrossRef]
18. Daily, S.M.; Mann, M.J.; Kristjansson, A.L.; Smith, M.L.; Zullig, K.J. School climate and academic achievement in middle and high school students. *J. Sch. Health* **2019**, *89*, 173–180. [CrossRef] [PubMed]
19. Mann, M.J.; Kristjansson, A.L.; Sigfusdottir, I.D.; Smith, M.L. The role of community, family, peer, and school factors in group bullying: Implications for school-based intervention. *J. Sch. Health* **2015**, *85*, 477–486. [CrossRef] [PubMed]
20. Voyer, D.; Voyer, S.D. Gender differences in scholastic achievement: A meta-analysis. *Psychol. Bull.* **2014**, *140*, 1174. [CrossRef] [PubMed]
21. Gneezy, U.; Niederle, M.; Rustichini, A. Performance in competitive environments: Gender differences. *Q. J. Econ.* **2003**, *118*, 1049–1074. [CrossRef]