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Abstract

In this study, we seek to investigate what influences children's intelligence in early childhood. The Singapore Cohort Study of the Risk Factors of Myopia (SCORM) is used in to assess determinants of childhood IQ and changes in IQ. This longitudinal data set, collected from 1999, includes a wealth of demographic, socioeconomic, and prenatal characteristics. The richness of the data allows us to employ various econometric approaches including the use of ordered and multinomial logit analysis. We find mother's education to be a consistent and key determinant of childhood IQ. We also find that father's education and school quality are key drivers for increasing IQ levels above the average sample movement.

Keywords

Childhood IQ

Prenatal characteristics

Socioeconomic determinants

Longitudinal Study

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1. Introduction and Background

Low levels of cognitive ability as a child are associated with numerous negative health and social outcomes later in life (Lawlor et al., 2005). There is an extensive debate regarding the significant determinants of childhood intelligence, including the nature versus nurture argument: do genetics ultimately determine our intelligence, or can early-life environment influence outcomes, and if so, by how much?

Studies that investigate the pre- and post-natal determinants of intelligence and the associated later life-cycle health outcomes can essentially be split into three broad categories. One group investigates pre-natal determinants such as birth weight[1], gestational age (Kirkegaard, Obel, Hedegaard, & Henriksen, 2006; Lawlor, et al., 2006), and birth order (Boat, Campbell, & Ramey, 1986; Lawlor, et al., 2005). A second group looks at post-natal determinants and/or interventions that may moderate or amplify pre-natal determinants. Included in this research cluster are early intervention studies and those that emphasize the socio-economic interfaces[2] and/or childhood measures of intelligence[3]. The final group investigates whether these effects continue into adulthood and how they manifest themselves in later health outcomes[4]. This final group is growing rapidly as more longitudinal studies become available, including the Singapore Cohort Study of the Risk Factors for Myopia (SCORM) used in this work.

In this study, we seek to investigate what influences children's intelligence in early childhood. We design our research specifically so that the results can inform micro simulation policy modeling of childhood interventions and consequently help manage life-cycle health costs from both an individual and public health system perspective. Micro simulation modelling uses transition probabilities to model shifts in 'agent' or individual

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[1] See for example Alderman & Behrman, 2004; Boardman, Powers, Padilla, & al., 2002; Breslau, Chilcoat, DelDotto, & al., 1996; Cesur & Kelly, 2010; Lawlor, Clark, Davey-Smith, & Leon, 2006; Richards, Hardy, Kuh, & al., 2001, 2002; Richards, Hardy, Kuh, & Wadsworth, 2001; Shenkin, Starr, & Deary, 2004; Shenkin, Starr, Pattie, & al., 2001.

[2] Examples include Gomez-Sanchiz, Canete, Rodero, & al., 2003; Guo & Harris, 2000; Jefferis, Power, & Hertzman, 2002; Kramer, Allen, & Gergen, 1995; McLoyd, 1998; O'Callaghan, Williams, Andersen, & et al, 1995; Osler, Andersen, Due, & et al, 2003; Rowe, Jacobson, & Van den Oord, 1999; Turkheimer, Haley, Waldron, & al., 2003.

[3] Including G.D. Batty et al., 2002; G.D. Batty & Deary, 2004; G. David Batty, Deary, & Gottfredson, 2007; Deary, Whiteman, Starr, Whalley, & Fox, 2004; Hart, Taylor, Davey Smith, & et al, 2003; Kuh, Richards, Hardy, & et al, 2004; Lawlor, et al., 2005; Starr, Taylor, Hart, & et al, 2004; Taylor, Hart, Davey Smith, & et al, 2003.

[4] See for example G.D. Batty & Deary, 2004; G. David Batty, et al., 2007; Deary, et al., 2004; Illsley, 2002 ; Sorensen, et al., 1997; Starr, et al., 2004; Taylor, et al., 2003; Whalley & Deary, 2001.

characteristics such as IQ. More specifically, agents are allocated attribute constants (characteristics a child has at birth that do not change over the life cycle, such as gender, birth weight, ethnicity, mother's age at delivery, etc.) and an initial condition for health and socio-economic characteristics. The latter includes variables that can change over the life cycle, such as income, school characteristics, mother's working status, etc.

A further objective of the study us that our findings can be used in micro simulation modeling, the core determinants of movements in childhood cognition are important to ascertain, as well as the probabilities of shifting IQ over time. Given these aims, our study begins with initial exploratory regression analysis that considers the various determinants of childhood IQ at age 11, using the SCORM data source. The next step of this research and one of the key contributions this study makes is to split the IQ range of our sample into specific groups with repect to the five recognized intelligence levels, and make use of ordered logistic regression to empirically examine the factors that produce large shifts in IQ. Specifically, looking at drivers of movements between the IQ groupings. Subsequent to this, multinomial logit models are employed to determine characteristics that impact whether the movement in IQ is higher or lower than the average sample movement. Odds ratios obtained from both logistic models will be valuable in guiding the constructing of transition probabilities in future directions of this research that focus on micro simulation modeling.

This research is also distinctive in that the sample is based on two extremes of schooling quality. Half the data was collected from a top ranked school, and the remaining participants were collected from the reverse. This provided a diverse range of households and consequently a more enriched empirical analysis.

The final contribution this paper makes is to provide empirical investigation of the determinants of childhood IQ with a focus on Singapore. There is limited evidence from this country. Research by Boocock (1995) focused on the influence of attending preschool on Singaporean school children's ability to share and cooperate, as well as their proficiency in the English language. A recent study by Broekman et al (2009) focused more on the topic at hand (determinants of IQ) and also made use of the SCORM data, but concentrated on the influence of birth parameters[5] and used just linear regression models in their empirical analysis.

The remainder of this paper is organized as follows: Section 2 outlines the data sourced from Singapore; Section 3 explains the initial econometric strategies undertaken in this study (linear regression and ordered logit); Section 4 details the results obtained and consequent key findings; Section 5 covers the final econometric approach of using a multinomial logit model; and finally Section 6 provides a brief conclusion with indications of future directions for this research.

2. Data

This study uses SCORM data, which was initially collected in 1999 in Singapore. The schools surveyed in this dataset were selected based on prior National Examination results with half the sample collected from schools ranked among the top twenty schools (Seang-Mei Saw et al., 2002), and the other half collected from the reverse.

The child's IQ was collected at age 11, and all children who participated in SCORM undertook the Raven's Standard Progressive Matrices, which is extensively used to test nonverbal reasoning ability (Raven et al, 1998). Parents also completed a baseline questionnaire with respect to a range of demographic information. This included details on parental education, income, ethnicity, etc. Ethnicity was assessed by asking parents to classify their ethnicity, and the ethnicity of the child was determined by using the father's reported ethnicity (in accordance to the definition adopted by the Singapore Population Census[6]). There was some additional perinatal data available from the top ranked school, such as birth order, breast fed, mother's work status, etc[7]. Given the value of these additional covariates, all the upcoming empirical analysis in this study was conducted for both the full sample (n=662), as well as for the half sample (n=320) which had the additional independent variables. Such multiple analysis serves two functions: to the test the validity of results across a small sub-sample, versus the larger sample; and to investigate the importance of these additional variables in terms of the role they play in influencing childhood IQ levels.

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[5] The aim of Broekman et al (2009) was to contribute to the sparse literature on the relative importance of a variety of birth parameters (birth length, weight, head circumference, and gestational age) *within the normal birth size range.*

[6] See www.singstat.gov.sg/statsres/glossary/population.html

[7] Further details on this data set are reported elsewhere (Seang-Mei Saw, et al., 2002; 2005; 2006).

The next section of this paper outlines the various econometric strategies undertaken in this paper, as well as the motives behind their application using the SCORM data.

3. Econometric approaches

Initially, a simple linear regression model is employed, where IQ measured at age 11 is regressed against a range of individual, household, socio-economic and school determinants, consistent with the study undertaken by Cesur and Kelly (2010). Next, IQ is split into five groupings that are comparable to standard interpretations of intelligence levels (the interpretations are provided in parenthesis below):

1 if IQ < 90	(below average)
2 if 90<=IQ<=99	(low normal or average)
3 if 100<=IQ<=109	(high normal or average)
4 if 110<=IQ<=119	(superior)
5 if IQ=>120	(very superior)

Given the constructed ordinal and categorical nature of this dependent variable, the most appropriate econometric estimation method to apply is ordered logistic regression. The general form of this model is:

$$Y*_i = \beta X_i^{'} + u_i \qquad i = 1,2,...,N \tag{1}$$

with *Y** being a latent variable that is then ordered into the five IQ categories defined above.

The ordered response model is defined as:

$$\Pr(Y = j | X, \alpha, \beta) = F_j(\alpha_j - X^{'}\beta) - F_{j-1}(\alpha_{j-1} - X^{'}\beta) \tag{2}$$

where $j = 1,2,...5$, $\alpha_0 = -\infty$, $\alpha_{j-1} \leq \alpha_j$, $\alpha_m = \infty$ and F is the cumulative distribution function of the logistic distribution $F_j = 1/(1 + \exp(-(\alpha_j - X^{'}\beta)))$.

Employing logit regression also permits greater interpretation through the use of odds ratios. These are useful in understanding the odds of moving from one IQ category to another, and as already indicated, will guide future directions of this research in terms of the micro simulation modelling.

Both econometric approaches (OLS and ordered logit regression) have advantages. The OLS results serve to validate past empirical research on determinants of childhood cognitive ability, especially since linear regression is often the tool used in much research on this front, and was the econometric technique used in the one relevant study from Singapore (Boeckman et al, 2009). Logistic results offer a unique perspective, in that they provide readily interpretable odds of moving from one IQ classification to another, and to our knowledge have not been applied to understanding determinants of childhood cognition within the Singaporean setting.

All econometric models are run with both the full and the half sample, where the additional covariates are available. The underlying IQ function for the full sample is:

$$
\begin{aligned}
IQ = \alpha &+ \beta * \text{Birth weight} + \beta * \text{Birth weight squared} + \beta * \text{Male} + \beta * \text{Chinese} \\
&+ \beta * \text{Malay} + \beta * \text{Income} + \beta * \text{Father education} + \beta * \text{Mother education} \\
&+ \beta * \text{Mother age} + \beta * \text{Mother age squared} + \beta * \text{School dummy} + u
\end{aligned} \tag{3}
$$

The IQ function for estimation with the half sample is specified as:

$$
\begin{aligned}
Q = \alpha &+ \beta * \text{Birth weight} + \beta * \text{Birth weight squared} + \beta * \text{Male} + \beta * \text{Chinese} \\
&+ \beta * \text{Malay} + \beta * \text{Income} + \beta * \text{Father education} + \beta * \text{Mother education} \\
&+ \beta * \text{Mother age} + \beta * \text{Mother age squared} + \beta * \text{School dummy} \\
&+ \beta * \text{Breastfed} + \beta * \text{Birth order} + \beta * \text{Number of children} \\
&+ \beta * \text{Mother working} + u
\end{aligned} \tag{4}
$$

Estimated coefficients and odds ratios for both the full sample and the part-sample are detailed and discussed in Section 4; the modelling is subsequently extended with the application of a multinomial logistic regression in Section 5.

4 Results

4.1 *Linear IQ Regression*

As explained in Section 3, the first step in this empirical analysis was to run a simple OLS regression with the dependent variable of childhood IQ at age 11. The independent variables included a range of child, household and school characteristics (as shown in Table 1). The same regression was also re-run for the half sample that had the additional covariates. The school variable was omitted from this half sample analysis as the additional data was only collected from participants enrolled at one of the schools. The results from both of these regressions are presented in Table 1.

< Insert Table 1 here >

Table 1 points to only one determinant that is consistently significant across both the half and full sample - Mother's education. School was also significant and importantly positive in the full sample. This result is expected as the school dummy is 1 if enrolled in a top ranked school, and 0 otherwise. Weakly significant results hold for income and ethnicity. Specifically, in the full sample, total combined household income was positive and significant at the 10% level, and a similar result was found for being Chinese (relative to ethnicities other than Malay) in the half sample regression. Finally, while several other determinants are not statistically significant in Table 1, many are in the direction expected. For example, the positive impact of being breast fed and the higher the father's education, a negative impact the higher the birth order, and a U-shaped pattern in terms of the impact of Mother's age.

4.2 *Logistic Regression of IQ groups*

IQ is measured using the Raven's Standard Progressive Matrices at approximately age 11 for the children participating in the SCORM project. It is split into five groups based on the widely recognized and standard interpretations of intelligence levels: Below average; Low normal to average; High normal to average; Superior; and Very superior. Ordered logit analysis is appropriate given the ordinal and categorical nature of the dependent variable. Additionally, the main advantage of this approach, as opposed to OLS and making use of continuous information on IQ (as shown in the regression in Table 1), is that it allows easily interpretable odd-ratios to be calculated. Odds ratios are a way of comparing whether the probability of a certain event/outcome is the same for two groups. For example, an odds ratio of 1 indicates an event is equally likely in both groups/circumstances (See Tarling, 2009).

< Insert Table 2 here >

Once again it appears that it is the Mother's level of education that is strongly significant within both the full and part-sample. This strong effect could be accounted for by the environment and learning support provided by a better educated mother. This is also entirely consistent with health literature that considers the home environment (Boat, et al., 1986; Hart, et al., 2003; Neligan & Prudham, 1976; Turkheimer, et al., 2003). Alternatively, Mother's level of education could be highly correlated with Mother's IQ, and be impacting the child's IQ via genetics.

Interestingly, in contrast to other studies that found that birth weight was a significant determinant of childhood IQ (Boardman, et al., 2002; Breslau, et al., 1996; Cesur & Kelly, 2010), this study did not find that was the case. An odds-ratio of 1 indicates the irrelevance of birth weight in this sample[8]. Similarly in the half sample, although an odds ratio of 1.316 for being breast fed indicates that children breast fed (relative to those not) are 1.3 times more likely to have a higher IQ, this is not statistically significant.

Besides mother's education, the only other significant determinant of childhood IQ was schooling quality. This is reflective of the Singaporean education system and the selection of the participant schools. The schools were chosen on their rankings in prior National Examination results therefore it would be expected that the school would reflect a number of confounding variables such as measures of the socio-economic status of the family including income, housing quality and home environment. In this case, the significance of the schooling quality supports the nurture argument that schooling, a childhood environmental factor, can influence childhood intelligence.

5 *Multinomial logit model*

The final econometric approach used in this study is multinomial logistic regression. This is an extension of logistic modelling and is relevant when the categorical dependent variable has more than two outcomes. In this study, we are particularly interested in the impact of possible interventions and the need to model the transition between life stages. Unfortunately, IQ was only collected at one point in time in this dataset and hence we must proxy individuals' early cognition level. As shown in Section 4 of this paper, results from the previous econometric approaches (OLS and ordered logit) point to a clear choice of proxy. Mother's education level is found to be strongly and consistently significant and this motivates its use as a proxy for cognition at birth. Additionally, mother's education is split into five categories that are broadly comparable to the standard interpretations of the IQ

[8] This may partially be due to a high proportion of babies in this sample born in a healthy weight range. Only 6.8% of the sample were born with low birth weight (i.e. below 2500g).

groupings used for the children in this analysis. These include no formal education, primary, secondary, pre degree / diploma, and university as the highest educational qualification attained.

Preliminary inspection of the changes in IQ indicate that, on average, most individuals move up one IQ category from birth to age 11. Consequently, rather than using multinomial logit analysis to capture the drivers of movements up and down, relative to no change in IQ group, we focus on movements above and below the average sample shift. The average movement in IQ is therefore our base / reference outcome.

The generalised form of this model is:

$$\Pr(Y_i = j | X_i) = \frac{\exp(X_i'\beta_j)}{\sum_{j=0}^{2} \exp(X_i'\beta_j)} \qquad j=0, 1, 2. \tag{3}$$

The estimated equations from (3) provide probabilities for each category (in this case 2 categories: movement in IQ above the average sample shift, and movement in IQ below the average sample shift) relative to the reference category (in this case j=0 is the reference / base outcome of the individual's movement in IQ being the same as the average sample shift).

The contribution of this econometric approach is that we are essentially controlling for the *Flynn Effect*. This effect deals with the issue of how general IQ scores of a population change over time. Flynn (1994) tested IQ scores for different populations over the past sixty years and found that in general, IQ scores increased from one generation to the next for all of the countries he tested. This phenomena has since been labelled the *Flynn Effect.* Consequently, by investigating the determinants of moving across IQ groups between birth and age 11, using mother's education as a proxy for cognition at birth, and using the average shift of the sample as the reference point, we attempt to control for the expected *Flynn Effect*.

Another advantage of this method is that we seek to isolate the impact of the environment on children's IQ, and so by using mother's level of education as the proxy for cognition at birth, we can infer, for a given level of mother's education, how environmental factors influence development of children's cognition. In essence this permits us to broadly split the influence of nature versus nurture. For a given level of nature (i.e. same level of mother's education), we can assess which environmental influences (i.e. nurture) are most significant in impacting childhood cognition.

Given the small sample size for mother's education level of 1, and the limited room for movement for mother's education levels 4 and 5, we report results only for mother's education levels 2 and 3. For these two starting points, Table 3 presents the multinomial logit results showing determinants of movements in IQ above and below the average sample movement.

< Insert Table 3 here >

Some of the key findings in Table 3 enhance those found in the earlier regressions. School remains strongly significant after accounting for mother's level of education. This suggests the 'nurture' impact of the schooling environment positively influences childhood cognitive development. Sending your child to a good school appears to be of paramount importance, in terms of enabling them to move beyond the average shift in IQ of their peers born to mothers with similar educational attainment. Being at a top ranked school results in the child being more likely to move more than the average rise in IQ (as shown in the mother education = 2 column), and conversely, being at a top ranked school results in the child being less likely to move below the average (as shown by the negative and significant coefficient in the mother education = 3 column). Additionally, school also appears to have a larger impact the lower the starting point, i.e. more likely to move above the sample average shift in IQ when the mother's education level was 2 versus 3[9].

Father's education also has a positive and significant impact. The higher the father's educational attainment, the more likely children are to move above the average rise in IQ rankings (as shown in the mother education = 2 column), and conversely, the higher the father education, the less likely the child is to make a movement below the average (as shown in the mother education = 3 column). This result is potentially confounded by the father's level of education often being related to mother's education level, if an assortive matching model is used (Becker, 1993), and also to income. As per mother's education level, the significant result of father's education level could be accounted for by the environment and learning support provided by a better educated mother. However, it is ofcourse not possible to rule out the potential contribution through genetics.

[9] This was also found via additional multinomial logit estimates (results not reported here) where the school dummy was interacted with mother's education level. The coefficient was larger and more significant for the lower levels of mother's education versus the higher levels (when multiplied by the school dummy).

The last important variable is birth weight. In the earlier regression analyses (in Section 4) this was not found to be important, contrary to findings in past research. In the multinomial logit however it does become important and the way it does is consistent with other studies. There is no evidence of birth weight changes impacting on above average movement but a higher birth weight does make it more likely for the child to move below the average shift in IQ. Combining this result with the significant, but infinitesimally small negative coefficient on birth weight squared, indicates an inverted U shaped effect of birth weight. This is consistent with the studies investigating whether high birth weight matters as well as low birth weight (Cesur & Kelly, 2010).

6. Conclusions

This study has made use of the SCORM data set collected in Singapore, to assess determinants of childhood IQ and changes in IQ. Initial OLS regression pointed to the importance of mother's education in influencing childhood cognitive ability. Significant results were also found for schooling quality, household income, and ethnicity (specifically, Chinese relative to other ethnicities). Interestingly, in contrast to much past literature on this topic, birth parameters such as birth weight were insignificant. Similar findings were made with the ordered logit specification, with the added advantage of odds ratios being produced. Future research avenues of this study include micro simulation modelling, which models shifts in individual characteristics such as IQ, as well as the transition between life stages. Such odds ratios will provide preliminary transition probabilities for this future research.

Finally, this study employed multinomial logit analysis to empirically investigate changes in IQ, using mother's education level as a proxy for the cognition level of the child at birth. By allowing the average change in the sample's IQ level to be the reference category in this empirical specification, we attempt to control for the Flynn Effect in our estimated results. Additionally, by adopting this approach separately for each given level of mother's education, we also attempt to broadly split the impacts of nature versus nurture. Findings from this set of analysis are clear, there are three important drivers of changes in IQ: schooling quality, parental education, and to a small extent birth weight. Schooling quality is of importance for policy modelling, and the importance of birth weight in the final set of analysis was interesting, given its lack of significance in the OLS and ordered logit regressions. Consequently, it appears that while birth weight has an insignificant impact on IQ levels per se, it does seem to be important in reducing the probability of childhood IQ increasing at a slower rate, relative to your peers.

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Table 1: Determinants of IQ age 11

Variables	IQ Full Sample	IQ Half Sample
Individual characteristics		
Birth weight	-0.006 (0.007)	-0.003 (0.008)
Birth weight squared	0.000 (0.000)	0.000 (0.000)
Male	-0.300 (0.872)	-1.205 (1.161)
Breast fed	-	1.007 (1.197)
Birth order	-	-0.936 (0.907)
Chinese	2.546 (1.697)	3.676* (2.185)
Malay	-2.771 (1.88)	-1.156 (2.644)
Household characteristics		
Total combined income	1.391* (0.784)	0.504 (1.069)
Father education	0.84 (0.596)	0.594 (0.803)
Mother education	2.078*** (0.637)	2.709*** (0.882)
Mother age	-0.372 (0.872)	-0.197 (1.387)
Mother age squared	0.005 (0.014)	0.004 (0.023)
Number of children	-	-1.147 (0.807)
Mother working	-	0.999 (1.34)
School characteristics		
School dummy	5.878*** (0.982)	-
Observations	662	320
R squared	0.233	0.178

***, **, and * denotes significance at 1%, 5%, and 10% levels, respectively.

Table 2: Logistic regression analysis of IQ groups

Variables	Coefficients (Full sample)	Odds-Ratio	Coefficients (Half Sample)	Odds-Ratio
Individual characteristics				
Birth weight	-0.001 (0.001)	1.000	-0.000 (0.001)	1.000
Birth weight squared	0.000 (0.000)	1.000	0.000 (0.000)	1.000
Male	0.087 (0.150)	1.091	0.012 (0.227)	1.012
Breast fed	-	-	0.274 (0.232)	1.316
Birth order	-	-	-0.252 (0.176)	0.778
Chinese	0.331 (0.283)	1.393	0.602 (0.416)	1.827
Malay	-0.373 (0.313)	0.689	-0.172 (0.505)	0.842
Household characteristics				
Total combined income	0.189 (0.135)	1.208	0.158 (0.204)	1.171
Father education	0.098 (0.102)	1.102	-0.008 (0.156)	0.992
Mother education	0.458*** (0.114)	1.581***	0.619*** (0.179)	1.857***
Mother age	-0.010 (0.146)	0.989	-0.072 (0.268)	0.931
Mother age squared	0.000 (0.002)	1.000	0.002 (0.004)	1.002
Number of children	-	-	-0.180 (0.157)	0.835
Mother working	-	-	0.021 (0.259)	1.021
School characteristics				
School dummy	1.102*** (0.171)	3.011***	-	-
Cuts				
When IQ group = 1	-1.158 (2.704)		-2.200 (4.555)	
= 2	0.027 (2.700)		-0.766 (4.539)	
= 3	1.085 (2.700)		-0.019 (4.535)	
= 4	3.277 (2.700)		2.285 (4.538)	
Observations	662	662	320	320
Pseudo R squared	0.102	0.102	0.081	0.081

***, **, and * denotes significance at 1%, 5%, and 10% levels, respectively.

Table 3: Movement in IQ group different from baseline

	Mother education = 2	Mother education =3
Above average		
Individual characteristics		
Birth weight	-0.001 (0.002)	0.001 (0.003)
Birth weight squared	0.000 (0.000)	-0.000 (0.000)
Male	-0.136 (0.484)	0.192 (0.256)
Chinese	-0.332 (0.873)	0.413 (0.553)
Malay	-0.536 (0.910)	-0.198 (0.641)
Household characteristics		
Total combined income	0.568 (0.599)	-0.036 (0.215)
Father education	0.930 (0.423)**	-0.110 (0.163)
Mother age	-0.205 (0.452)	-0.011 (0.285)
Mother age squared	0.004 (0.008)	0.000 (0.005)
School characteristics		
School dummy	1.157 (0.555)**	1.027 (0.318)***
Below average		
Individual characteristics		
Birth weight	0.016 (0.008)**	0.001 (0.004)
Birth weight squared	-0.000 (0.000)**	-0.000 (0.000)
Male	0.425 (0.571)	0.225 (0.333)
Chinese	-0.586 (1.138)	-0.449 (0.600)
Malay	0.819 (1.137)	-0.313 (0.657)
Household characteristics		
Total combined income	0.184 (0.726)	-0.460 (0.300)
Father education	0.342 (0.516)	-0.360 (0.223)*
Mother age	-0.139 (0.528)	0.018 (0.341)
Mother age squared	0.003 (0.009)	0.000 (0.006)
School characteristics		
School dummy	0.723 (0.671)	-1.270 (0.358)***
Observations	171	331
Pseudo R squared	0.154	0.106

***, **, and * denotes significance at 1%, 5%, and 10% levels, respectively.