Pre and post natal drivers of childhood intelligence: Evidence from Singapore

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Abstract

The Singapore Cohort Study of the Risk Factors of Myopia (SCORM) is used in this paper 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. Using 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.

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1. Introduction and Background

There is a substantial and growing literature that investigates the pre- and post-natal determinants of intelligence and the associated later life-cycle health outcomes. These studies can essentially be split into three broad categories. One group investigates pre-natal determinants such as birth weight [1-13], gestational age [7, 14], and birth order [15, 16]. 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 [15, 17-27] and/or childhood measures of intelligence [16, 28-36]. The final group investigates whether these effects continue into adulthood and how they manifest themselves in later health outcomes [3, 13, 29-31, 35-39]. 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.

Low levels of cognitive ability as a child are associated with numerous negative health and social outcomes later in life[16]. There is an extensive debate regarding the significant determinants of childhood intelligence, including the relative roles of individual characteristics of the child, household and socio-economic factors, etc. Such research is important in designing moderating interventions (for example, policies that are aimed at encouraging mothers to improve their nutrition during pregnancy to reduce the probability of low birth weight prevalence) and consequently managing life-cycle health costs from both an individual and public health system perspective.

While numerous studies have investigated a range of pre and post natal determinants of childhood IQ, this research is distinctive in that the sample is based on two extremes of schooling quality. Half of data was collected from a school ranked in the bottom twenty in Singapore and the remaining participants were from schools ranked in the top twenty. This provided a diverse range of households and consequently a more enriched empirical analysis. Additionally, besides initial exploratory regression analysis that considers the various determinants of childhood IQ at age 11, one of the contributions of this study is to empirically examine factors that produce large shifts in IQ (specifically looking at drivers of movement between IQ quintiles). Logistic regression is applied to ascertain factors influencing significant shifts in childhood IQ, and consequent 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.

The remainder of this paper is organized as follows: Section 2 outlines the data sourced from Singapore and summarizes the econometric strategies undertaken in this study; and Section 3 provides the results and consequent discussion.

2. Methodology

This study uses SCORM data, which was initially collected in 1999 in two schools located in the northeastern and southeastern parts of Singapore. In 2001 it was extended to include one school located in the west. The schools were selected based on prior National Examination results with the northeastern school ranked among the bottom twenty schools and the southeastern and western schools both being ranked among the top twenty schools [40]. The data set consists of comprehensive information on the perinatal and socio-economic situations at the time of birth and also when IQ was tested at age 11. There was some additional perinatal data available from the southeastern school (top twenty school), such as birth order, breast fed, mother's work status, etc. Further details on this data set are reported elsewhere [40-42].

Three separate types of analyses were undertaken in this research that will each be reported in sequence. Initially, IQ measured at age 11 was regressed against a range of individual, household/socio-economic and school determinants consistent with the study undertaken by Cesur & Kelly[6]. IQ was then grouped into five categories (quintiles) and an ordered logistic regression model run. Both of these analyses were run on the full sample and the half sample that had the additional perinatal variables from the southeastern school. Finally a multinomial logit model was run to produce the drivers of movement between IQ quintiles; in particular, whether the movement was higher or lower than the average sample movement.

3. Results

3.1 *IQ Regression*

Initially, a simple OLS regression was run across the full sample of 662 individuals, 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 data. 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.

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.

From the results presented in Table 1 it was found that the only determinant that was consistently significant across samples was 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 twenty school (i.e. the south eastern and western schools), 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 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.

3.2 *Logistic Regression of IQ Quintiles*

Of particular interest to this study was the impact of possible interventions and consequently the need to model the transition between life stages. Unfortunately, IQ was only collected at one point in time for children in this Singapore dataset, but given the early results where Mother's education was found to be strongly and consistently significant, this motivates its use as a proxy for cognition at birth.

Within the dataset Mothers' education is split into 5 categories: No formal education, primary, secondary, pre-degree/diploma, and university. Therefore it was sensible to split IQ into 5 categories too. These categories are based on the standard interpretation of IQ and broadly matching those interpretations to the Mother's education classifications. This resulted in the following five groups (standard interpretations of IQ to intelligence levels are shown in parenthesis):

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)

Changes in IQ from birth (using mother's education categories as the proxy) to age 11 are analysed with the use of a multinomial logit model in Section 3.3 of this paper. Before that, it is useful to first apply ordered logistic regression. This approach is appropriate given the constructed ordinal and categorical nature of the dependent variable IQ. 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. These can be used to understand the odds of moving from one IQ category to another. The general form of the ordered logit model is:

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

with the ordered responses, *Y*, being the five IQ categories defined above.

The ordered response model is defined as:

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

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 $F_j = 1/(1 + \exp(-(\alpha_j - X^{'}\beta)))$.

The underlying IQ function for estimation with the full sample can be specified as:

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

The IQ function for estimation with half the sample (with additional perinatal variables) can be specified as:

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

Results including coefficients and odds ratios[43] for both the full sample and the part-sample are given below in Table 2.

Table 2: Logistic regression analysis of IQ quintiles

Variables	Coefficients (Full sample)	Odds-Ratio (Full sample)	Coefficients (Half Sample)	Odds-Ratio (Half Sample)
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***	-	-
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.

Once again it is Mother's level of education that is strongly significant within both the full sample 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 [15, 23, 27, 32]. Interestingly, in contrast to other studies that found that birth weight was a significant determinant of childhood IQ [4-6], this study did not find that was the case. An odds-ratio of 1 indicates the irrelevance of birth weight in this sample. 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 parental education levels, income, housing quality and home environment. This explanation is supported by omitting the school dummy from the analysis (results not reported here), and finding that father's level of education and income both then become significant suggesting that the school variable is possibly indirectly capturing these effects.

3.3 *Multinomial logit model*

This model investigates the likelihood of moving across IQ quintiles between birth and age 11. As already explained in the previous section, mother's education level presents as a good proxy for cognition at birth and hence is not included as an independent variable in the following analysis. Preliminary inspection of IQ movements in our sample show that most children move up atleast one quintile between birth and age 11. Therefore, rather than using multinomial logit analysis to capture the drivers of movements up, down or no change in IQ quintile, we focus on movements above average and below average. This means that the average sample movement was the base outcome.

Additionally, 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.

Table 3: Movement in IQ quintile 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.

Discussion

The results from this analysis reinforce those found in the earlier regressions. Father's education 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 [45] and also to income. However, given the nature of our model set up, we have already controlled for mother's education.

School remains strongly significant. 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. Being at a top 20 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 the top 20 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).

The last important variable is birth weight. In the earlier regression analyses (in Section 3.1 and 3.2) 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 [6].

Overall, this analysis shows there are really only 3 important drivers of changes in childhood cognitive ability in this Singaporean sample – parental education, school attended, and to a small extent – birth weight.

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