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A Multilevel Analysis of the Relationship Between Birth-Order and Intelligence

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Abstract

Many previous studies have found relationships between birth order and intelligence, but use cross-sectional designs or manifest other threats to internal validity. Using the National Longitudinal Survey of Youth Children (NLSY) data and multilevel analyses with control variables, we show that when these threats are removed, two major results emerge : (a) Birth order has no measurable influence on children's intelligence; and (b) Control variables provide strong evidence that earlier-reported birth order effects on intelligence are attributable to environmental and genetic factors that vary between, not within families. Identical sets of analyses on 7-8 and 13-14 year-old children from the NLSY support these conclusions. When hierarchical data structures, age-variance of children, and within-family vs. between-family variance sources are taken into account, previous research is seen in a new light.

Keywords: multilevel model, birth order, NLSY, hierarchical data

The topic of birth order may have drawn more attention from a wider variety of psychologists for a longer time than any other topic in our field. Psychologists interested in social processes, in development, in the family, in children, in reproduction, and in methodology have participated in birth order research. Other disciplines have also investigated birth order in a serious way, including anthropologists, sociologists, demographers, medical researchers, and even financial historians. Sir Francis Galton (1874) may have published the first research on birth order and intellectual ability (he noted a disproportionate number of first-borns among British scientists), but the topic of birth order has ancient status. For example, the birth order of Cain and Abel was relevant to the original Bible story. Even if Adam and Eve lacked training in psychology or research methods, they must have been among the very early observers of the effects of birth order patterns.

However, birth order is not easy to study. The methodological difficulties of properly accounting for birth order are belied by its apparent simplicity. As Schooler (1972, p. 174) noted, “it may well have been the seeming simplicity of birth order as an independent variable that provides the answer to ... its attractiveness to researchers.” Methodological critiques have been published at regular intervals, including Kammeyer (1967), Adams (1972), Schooler (1972), Schvaneveldt and Ihinger (1979), Ernst and Angst (1983), Rodgers and Thompson (1985), and Sulloway (1996).

Birth order patterns have been observed in relation to a wide array of dependent variables. Rodgers and Thompson (1985, p. 158) noted that “birth order ... is expected to predict the behavior of almost anyone: strippers and presidents, dentists and soldiers, assassins, authors, athletes, alcoholics, adult smokers, and assorted others” These topics notwithstanding, the most attention by far in the research literature has been given to the relation between birth order and intelligence.

Early attention to birth order and intelligence was impressive from both theoretical and methodological perspectives. Studies by Galton (1876), Thurstone and Jenkins (1929), Outhit (1933), Koch (1954) and Anastasi (1956) are exemplary of the early attention that was paid to the relation between birth order and intelligence by prominent psychologists. Unfortunately, even with such talent, coherence was lacking in the research: Kammeyer (1967) described the state of the birth order research enterprise at that time as “best characterized as a disparate, disconnected, aggregation of research findings” (p. 73).

In 1973, Belmont and Marolla published a study of the relation between birth order and intelligence from which the birth order literature has still not yet recovered. The Belmont and Marolla study was a simple empirical compilation of Raven Progressive Matrices scores from a cross-section of almost 400,000 Dutch men of different birth orders. When the IQ scores were disaggregated by levels of birth order and family size, a remarkably systematic pattern emerged, which suggested declining intelligence with increasing birth order and family size. The belief that large families and later birth order had a causal influence on intelligence preceded the Belmont and Marolla study. Nevertheless, the graphical patterns in their study were so clean, and the sample size so large, many viewed their results as the “final accounting.” Belmont and Marolla cautioned that the differences, though highly systematic, “appear to be small.” But the caution was not heeded. For example, in a published interview with Robert Zajonc, Elizabeth Hall (1986, p. 47) noted that “the sheer volume of data (400,000 observations) convinced Zajonc ... that the findings were no accident.”

Since then, both the scientific and popular presumption has been that the "negative birth order" effect on intelligence is a phenomenon searching for an explanation. Explanations that have been developed typically start by citing the Belmont and Marolla data, then referencing other cross-sectional datasets for further support and confirmation. The confluence model (Zajonc and Markus, 1975) is one example that posited a family environmental influence on children's intellectual development. The more adults and older children, the richer the environment, and the more intellectual facilitation provided to the developing child. The confluence model also contained a "tutoring effect," in which intellectual value was accrued through the tutoring provided to their younger siblings by all non-last-born children; the tutoring effect was added to the confluence model to help explain an IQ discontinuity among last-borns in the Belmont and Marolla data. Blake (1981) adapted the dilution model that had been proposed previously (see, e.g., Kellaghan & MacNamera, 1972; Lasko, 1954; Strodtbeck & Creeland, 1968; Walberg & Marjoribanks, 1976) to help explain the negative birth order finding. Her theory was that more children dilute the parental resources that provide nurture – including support for intellectual development – among developing children.

Recently however, it has been suggested that the "negative birth order" phenomenon may have been a methodological illusion. Researchers using cross-sectional data – collected from individuals in different families at a specific point in time – have typically assumed that those cross-sectional patterns would match those across siblings within families. Researchers are familiar with the challenges involved when inferring longitudinal change processes from cross-sectional data, but have been forced to assume that patterns in cross-sectional data would hold when subjected to longitudinal scrutiny. Unfortunately this assumption has not always been borne out. Rodgers, Cleveland, van den Oord, and Rowe (2000) compared the patterns from cross-sectional data to those from the few within-family studies that have been run, and found them to be entirely different. The negative birth order phenomenon simply disappeared when actual siblings' IQs were compared to one another. They explained this result by noting that, in the cross-section, birth order can be an indirect measure of literally thousands of potential biases, including SES, maternal health, nutrition, parents' education, parental IQ, quality of schooling, and dozens of other less obvious processes. If patterns in cross-sectional data and within-family data do not match, then the assumption that birth order in the cross-section is actually measuring differences between siblings in a family, i.e., real birth order patterns, is untenable. The finding that hundreds of cross-sectional birth order-IQ patterns (which match one another) do not match the dozen or so within-family patterns (which also tend to match one another) is disturbing. A conservative view would be that the absence of a birth order-IQ relationship in within-family studies suggests that there is no birth order effect on intelligence.

However, existing within-family studies have methodological problems as well, even though their within-family matching partially controls for the thousands of between-family biases that plague the cross-sectional studies. What are these problems? Age matching is one. Researchers have repeatedly expressed concern over age variance, because the confluence model predicts different birth order-IQ patterns at different ages (e.g., Zajonc and Mullaley, 1998; Zajonc, 2001). Others (e.g., Steelman and Mercy, 1980; Michalski and Shackelford, 2001) have expressed concern over age confounding. Another concern is statistical. Failure to properly separate between-family variance from within-family variance (see, e.g., Jensen, 1980 for discussion) has kept researchers from determining what are the actual sources of influence on IQ observed in studies of birth order effects. Modeling critical between-family differences that account for large parts of children's variance in intelligence is a design innovation that can help identify the location of the actual sources of shared variance between birth order and IQ (if any exists at all). In this paper, we will use design and statistical innovations to address these concerns.

In our opinion, there are only two types of past birth order research that shed light on underlying causal processes. The first, already discussed, is research using within-family comparisons. When actual siblings are compared one to another, within-family and between-family sources of variance can be separated. We note, however, that uncontrolled within-family variance is still a problem (though much reduced). For example, as parents age, they typically increase in SES level, and may also spend more time at work and less time with their children. Thus, later-born children may on average mature in a slightly higher SES environment than their earlier-born siblings, but one in which parents spend less time with them. If later-born children have lower IQs, are we observing an effect of being a later-born child (a real birth order effect), or an indirect effect of SES? Obviously, within-family studies are no panacea.

The second type of birth order research includes the few studies that have used design innovations to study the relationship between birth order and IQ. These studies are substantially undervalued in past treatment of the birth order literature. We will carefully examine several of these to illustrate how design innovations can solve many of the problems with past birth order research. Typically, these design innovations require the use of within-family data.

Design Innovations in Past Birth Order Research

Most past birth order research has been based on one of two design approaches. In one approach, a cross-section has been obtained, observed on some outcome, and that outcome has been classified by birth order/family size category. In the other, individuals with some interesting feature in common (e.g., presidents, strippers, smokers, birth order researchers, etc;

see Rodgers & Thompson, 1985) have been studied to determine if their birth order is the same as that in the general population. Both designs have many deficiencies (see Adams, 1972; Kammeyer, 1967; Schooler, 1972; Rodgers & Thompson, 1985).

In a few cases, innovative and unusual approaches have been used to study birth order, and we review several of those. One early study anticipated recent criticisms of birth order literature. Thurstone and Jenkins (1929) obtained IQ information from the Institute for Juvenile Research for over 10,000 observations, which contained many siblings. After observing trends in the cross-sectional data, they noted that "The summary … is defective for our purposes in that several antagonistic factors are there at work without any control" (p. 644). They were concerned about the biases built into cross-sectional data, and thus limited their analysis to the study of siblings. Their interpretation of their findings has, unfortunately, gone unheeded by most birth order researchers since then: "If the intelligence of children is improved by the experience of parents in bringing up children, then it is conceivable that such experience would affect the comparison of first and second born children. … It is more probable, however, that the causal relation is more strongly in the reverse direction, namely that … the children are bright because the parents are bright" (p. 645).

Koch (1954) followed Thurstone and Jenkins' (1929) lead by using an even more restricted family design. Her study was based on "360 five- and six-year-olds from two-child, intact, native-born, white, urban families (Koch, 1957, p. 176). She, too, obviously appreciated the value of controlling the selection biases inherent in cross-sectional designs.

Although most past birth order research was based on cross-sectional designs, a few other studies followed the example that Thurstone and Jenkins (1929) and Koch (1954) set by using within-family data. Included among those are Olneck and Bill (1979), Berbaum and Moreland

(1980), Pfouts (1980), Galbraith (1982), Rodgers (1984), Retherford and Sewell (1991), and Rodgers et al. (2000). Rodgers et al reviewed the consistent non-relationship between birth order and IQ/achievement found in those studies.

McCall (1984) used an innovative approach to test a prediction of the confluence model, that the birth of a child should cause a discontinuity in the IQ scores of older siblings. He investigated whether there were IQ fluctuations among older siblings after the birth of a younger sibling. He found evidence for such a fluctuation, one of the few examples in the literature suggestive of a within-family influence in intelligence.

Guo and Van Wey (1999) used difference models to partially control for unobserved heterogeneity (i.e., selection bias) in studying birth order and family size relations to achievement scores. They used two types of these difference models, one a within-individual model, the other a model in which siblings were compared to one another. In cross-sectional versions of their data they found the usual negative relation between birth order/family size and IQ. When the unobserved factors that came from differences between families were partially controlled through their difference models, the relationship virtually disappeared.

We review these design innovations for two reasons. First, they help frame the logic of what information is informative about what causes birth order/IQ patterns. Obviously, theoretically-based research (that derives from predictions emerging from theoretical statements about within- and between-family processes) and within-family data are important features of past research contributing to our understanding. Second, they set the stage for design innovations that we present in the current paper. These include the use of longitudinal within-family data that can be used to obtain samples of siblings at fixed ages. In addition, an analytic approach that has not previously been applied to birth order data – multilevel modeling - will be used to explicitly separate within- and between-family sources of variance.

In order to implement these innovations, we used data that contained two types of information. First, we needed variables with information about individual children's intellectual ability, and second, family-level variables to help us remove the influence of between-family factors from that of within-family factors affecting intelligence.

These goals were met through the use of data from the National Longitudinal Survey of Youth (NLSY79), a project begun in the 1960's by the U.S. Department of Labor, which contracted with the Center for Human Resource Research (CHRR) at The Ohio State University to conduct the survey. Initial data collection on a nationally representative household sample of individuals between 14 and 21 years of age began in 1979. Data collection was later expanded to include the children of the 14-21 year-old women who were assessed in the original 1979 sample. Beginning in 1986 and continuing biannually through the present, measures have been collected of these children's cognitive ability, temperament, motor and social development, behavior problems, home environment, and of their attitudes toward self and others. These characteristics, along with the large sample size, made this data set ideal for this project. In the original NLSY79 sample, there were 6283 women. By 1998, a total of 10,918 children had been born to these women and included in the NLSY79 data set. We used data from the NLSY79 from the beginning of the child data collection program, in 1986, up to 1998.

Method

Sampling Technique

Our sampling technique minimized the threats to validity that other studies on this topic have faced. An *age-snapshot* technique was used to minimize cohort and maturation influences on criterion variables while maintaining large sample size. We applied this technique to produce two samples, one comprised of 7-8 year old children, and the other of 13-14 year old children. In the NLSY data set, children were assessed on our chosen criterion variables (described below) every two years starting in 1986 and continuing through 1998. We extracted children's age-standardized criterion scores from the total NLSY sample at that assessment time point between 1986 and 1998 when the child was within the target age range. By holding constant the children's age with the snapshot technique, we reduced the threat to validity of differential, child-age related, within-family maturation influences that might covary with the children's different ages. To improve the generalizability of our results, we chose two different target age ranges, consisting of separate samples of 7-8 year olds (84-96 months), and of 13-14 year olds (156-168 months), respectively. All children who were in the target age range (84-96 months or 156-168 months) at any time between 1986 and 1998 were included in each sample. This yielded 3,322 7-8 year olds and 1,974 13-14 year olds. Both samples were skewed with respect to birth order, such that there were relatively few 6th and 7th born children, and many more 1st and 2nd born children. Therefore, to improve the reliability of our analyses, we analyzed the 1st to the 5th born children for the 7-8 year old sample, and the 1st to the 4th born children for the 13-14 year old sample. Table 1 shows the number of children of each birth order in each sample.

--Insert Table 1 about here.--

When 6th and 7th born children were removed from the 7-8 year old sample and 5th, 6th, and 7th born children were removed from the 13-14 year old sample, our total sample sizes for the two age-snapshots were 3,306 children (nested within 2365 mothers) and 1,959 children (nested within1494 mothers), respectively. The number of valid cases available on our different criterion and predictor variables caused sample size to vary slightly across subsequent analyses. Due to our age snapshot approach, 1270 children were sampled twice, once when they were between 7 and 8 years, and once when they reached the 13-14 year age range. This overlap does not impact our conclusions. When we examined the parameters of our final model after removing these overlapping children from the 7-8 year old sample (leaving 2036 children nested within 1691 mothers), the pattern of results and significance levels were identical to the model run on the larger sample.

Outcome Variables Investigated

A set of cognitive ability measures was selected to operationalize child's intelligence, along with two control variables to permit better disentanglement of between-family and within-family influences on intelligence. We operationalized children's intelligence by using the different sections of the Peabody Individual Achievement Test (PIAT) (Dunn & Dunn, 1981; Dunn & Markwardt, 1970). Age-standardized PIAT Mathematics, Reading Recognition, and Reading Comprehension subtest scores were used. For all PIAT subtests, higher scores indicate greater cognitive ability. More detailed information on the PIAT assessments is available from Dunn and Dunn (1981) and Dunn and Markwardt (1970).

Although children's average performance level has increased since the PIAT was normed in the late 1960's, this increase was not reflected in the age-standardized scores in a way that threatened the validity of our analyses. The original mean of the norming sample from the late 1960's was 100, with a standard deviation of 15 (Center for Human Resource Research, 1999). Means on the three subtests for NLSY children sampled in 1998 were roughly 5 points higher (Center for Human Resource Research, 1999), presumably as a function of social changes since the 1960's. Because birth order is correlated with birth year in our samples (7-8 year olds' r =

.272; 13-14 year olds' *r* = .262), we checked for a positive correlation of birth year with PIAT subtest scores. A positive correlation would suggest that a lack of observed birth order effects on intelligence might be due to cohort differences in PIAT mean subtest scores, rather than to the between-family factors we suggest here. In our samples, subtest scores are essentially uncorrelated with child's birth year. For 7-8 year olds (N = 3,322), correlations between child birth-year and the respective standardized PIAT subtest scores ranged from *r* = -.08 for Reading Recognition to *r* = -.03 for Reading Comprehension. The pattern was similar for the 13-14 year old sample (N = 1,974), with the corresponding correlations ranging from *r* = -.05 for Reading Recognition to *r* = -.04 for Reading Comprehension. If these correlations were to have any effects on analyses, they should work against our test of the hypothesis that birth order effects are largely due to between-family factors.

Control Variables

Mother's Intelligence. In addition to birth order as the central predictor variable, we chose to investigate the effects of two control variables on the relationship between birth order and children's intelligence. Because family size is correlated with many variables, birth order itself is also correlated with many factors that vary between families. These factors include cultural norms influencing family size, socioeconomic status (SES), access to birth control information or methods, or even mother's intelligence. This was the first control variable we selected. Variance in intelligence is partly heritable (e.g., Bouchard & McGue, 1981), and research indicates that mother's intelligence is correlated with family size in our culture (Rodgers et al., 2000). Mother's intelligence (MIQ) was operationalized as her Armed Forces Qualifying Test (AFQT) score, which was measured in 1980 for this sample.

Eventual Family Size. The second control variable selected was a measure of the eventual size of each mother's family. We expected that eventual family size (EFS) would account for a substantial portion of any birth order effects because it should encapsulate a myriad of between-family influences affecting the home environment and parenting behaviors. Mothers' environments can affect both the number of children they have, and the conditions under which their children develop. Environments influence access to potential mates and can play important roles in influencing mating behavior and the desire to have children. Arguably, environments which facilitate having many children do not simultaneously facilitate mothers' education and career success, for women who attain a high level of education and/or invest considerable time and effort into a career would seem likely to delay child-bearing. These women may be more likely to support the intellectual development of their children, and they may be likely to value education and to model behaviors that help children succeed in school. However, the delayed childbearing onset of these mothers gives them fewer fertile years to have children, resulting in smaller families. Thus, EFS is not only a measure of the number of children a mother will eventually have above and beyond the children we analyzed in our samples, but is a measure that captures many between-family environmental influences on children's intelligence. We expected that larger EFS values would be negatively associated with child intelligence.

EFS was computed based on the number of children a mother had by the time she reached age 35 or 36. We used this cut-off age because many of the women in our sample were premenopausal, and we did not want to differentially truncate EFS values based on the number of children each woman had by 1998. Operationally, EFS is equal to the number of children the mother had by age 35 for mothers turning 35 in even years from 1992 to 1998. For mothers who turned 35 in odd years from 1992 to 1998, EFS is equal to the number of children these mothers had by age 36. No mothers in our sample reached age 35 before 1992. EFS is positively correlated with birth order; by definition, the families of 4th born children do not have EFS values smaller than 4. However, the birth order of an individual child is quite different from the total number of children a mother has by her mid-thirties. First, each family has only one EFS score, which captures some of the influence of many environmental factors on *all* of the members of that family. Although each family has only one EFS score, each family has as many birth order values as it has children included in our analyses. Because birth order varies within family and EFS between families, the hierarchical partitioning of these variables makes it impossible for them to be equivalent to one another. That is, birth order is a level-1 variable, and EFS is a level-2 variable. Second, because EFS is a measure of the total number of children a mother will have by her mid-thirties and is not limited to the number of children meeting our inclusion criteria, each family's EFS value is often larger than the number of children who are being analyzed in our sample. This measure may even occasionally represent the contribution of children who were not yet born at the time the focal children took the PIAT subtests.

Multilevel Modeling and Nested Data.

The extraction of these variables for each age-snapshot sample led to the creation of a nested, hierarchical data structure, where each child was nested within its mother (i.e., the particular family). This nesting means that scores on outcome variables exhibit variance both within and between families. Our explanatory variables allow the examination of both within-family (birth order) and between-family (EFS, MIQ) sources of this variance. Within-family influences include birth order, changes in the family's socio-economic status over time, or other factors varying from child to child within a family. These within-family influences can be obvious, or they can be subtle. For instance, research on physical attractiveness (Eagly, Ashmore, Makhijani & Longo, 1991; Snyder, Tanke, & Berscheid, 1977) implies that variation in children's attractiveness within the same family may influence parenting behavior. Between-family influences include such factors as mother's intelligence or the quality of schools in a given district, and do not vary across children in a family. Although the level of a particular between-family influence may vary across families, different children within a family are not exposed to different levels of these influences (i.e. a mother's intelligence is approximately constant for all children in her family).

Researchers have known for some time that it can be misleading to analyze group-level data (e.g. family-level data) and use these results to draw inferences about individuals within the groups (e.g. Robinson, 1950). Kreft, de Leeuw, and Aiken (1995) considered a case where data were analyzed at the level of individual workers, and educational level was positively associated with income, but when these data were analyzed at the higher level of industry, the relationship reversed. Previous studies of birth order and intelligence have faced just this problem. Birth order is an individual level variable, and individuals are nested within families. However, birth order has often been analyzed in an aggregated fashion, ignoring the child's family membership. The consequence is that the influences of family level variables (such as mothers' intelligence) on the outcome measure are not partialled out of any within-family birth order effect. Because less intelligent mothers tend to have less intelligent children, and because they tend to have more children, analyses of birth order effects that do not discriminate between-family from within-family factors deliver misleading results. In order to determine any valid effects of birth order, such between-family influences must be controlled. In addition to the potential invalidity of analyses that do not take between-family influences into account when within-family effects are being estimated, analyses of this type violate the assumptions of traditional regression analysis (e.g. see Barcikowski, 1981; Moulton, 1986; Scariano & Davenport, 1987; Scott & Holt, 1982; Walsh, 1947). Specifically, they violate the assumption that errors are independent. When units of observation are nested within units at another level (e.g. children within families), regression errors exhibit lack of independence. It is entirely possible that effects reported in previous studies that have used traditional regression techniques for analysis may owe their significance to the use of an inappropriate statistical model that does not appropriately partition the sources of variance present in nested data.

To overcome these limitations and potential pitfalls, we used multilevel models to investigate the association between birth order and intelligence (Goldstein, 1995; Kreft & DeLeuw, 1998; Raudenbusch & Bryk, 2002). Unlike traditional regression analyses, multilevel models allow hierarchical partitioning of variance and reduce the magnitude of the above threats to validity. With data such as ours, these models yield more accurate standard error estimates, leading to more accurate significance tests. Additionally, multilevel models allow simultaneous estimation of group and individual-level parameters, as well as estimation of cross-level interaction terms, where the effect of a between-family variable (such as mother's intelligence) on a within-family variable (child's intelligence) can be more accurately modeled.

Description of Multilevel Model Sequence:

Within each age-snapshot, we fit 7 models to children's PIAT subtest scores. To begin, we fit a traditional regression model to demonstrate how the birth order effect appears to obtain when the multilevel structure of the data is ignored. In the interest of building a model able to detect even non-linear birth order effects, this and all subsequent analyses with birth order used dummy variables to represent birth order. Next, we used a baseline (also called totally unconditional or null) multilevel model to estimate how much of the variance in the outcome measures was due to between- and within-family factors. To this basic variance-partitioning model we then added birth order to estimate its effects. We examined the basic birth order effect using two, sequential, multilevel models. One model specified each of the birth order effects to be invariant; it did not estimate their variability across the population of families. The next model estimated the between-family variance in each of the birth order effects by specifying them as varying randomly at L2, between families.

Following these basic models, we systematically added control variables chosen to encapsulate conceptually important between-family influences on the effect of birth order. Control variables were used to predict the PIAT intercept score, then the birth order effect. Eventual Family Size (EFS) was included first as a control variable to assess its effect on the intercept term. Second, cross-level interactions of EFS with birth order were added to assess effects of EFS on birth order effects. Third, mother's intelligence (MIQ) was added as a predictor of intercept. To compare the explanatory power of each of our models, we conducted χ^2 tests of difference in fit between nested models, using the deviance statistics produced by our model-fitting software. In the following, we present our model specifications using standard notation (c.f. Nezlek, 2001), followed by a table summarizing the purpose of each model. Parameter estimates are reported in the results section.

Multilevel models can be fit using a variety of software packages. These programs vary in their flexibility, options, and computational robustness, but they all effectively implement multilevel random coefficient modeling (MRCM). MLwiN, LISREL's multilevel modeling module, HLM, and PROC MIXED in SAS are all common programs used to fit these models. The rapid pace of software development makes it difficult to maintain a current or complete listing, but there are also many other programs that effectively fit multilevel models. For our analyses, we used LISREL's multilevel modeling module (see Joreskog, Sorbom, du Toit, & du Toit, 2001).

Traditional Regression Model. In this model, children's PIAT scores were regressed on birth order terms. We initially used birth order as one discrete predictor variable, and found that it had statistically significant effects on all outcome measures in both samples. However, this type of model does not permit the detection of non-linear effects. Therefore, in the interest of building a model maximally sensitive to birth order effects, we coded birth order as a series of dummy variables. The first-born child was coded as the comparison child. Thus, for *K* birth orders we constructed *K-1* dummy variables for the *i* children in our sample, $d_{i(k)}$. For birth order 1, all $d_{i(k)} = 0$. For birth order 2, $d_{i(1)} = 1$ and $d_{i(2)} = d_{i(3)} = ... = d_{i(K-1)} = 0$. Generally, for birth order = *k*, $d_{i(k-1)} = 1$, and all other dummy variables are 0. Given this coding, regression coefficients for the dummy variables indicate predicted differences between each successive child and the first born-child. This coding additionally means that the value of the intercept term provides an estimate of the predicted average PIAT score of the first-born child.

Our regression model using dummy-coded birth order variables is expressed as follows:

$$y_i = \beta_0 + \sum_{k=1}^{K-1} \beta_k d_{i(k)} + r_i \qquad (1)$$

where *K* = 5 birth orders for the children in the 7-8 year old sample and *K* = 4 birth orders for the 13-14 year old sample. Further, y_i is the score on the outcome variable for child *i*, $d_{i(k)}$ is the value of dummy variable *k* for child *i*, β_0 is the intercept, β_k is the regression coefficient for dummy variable *k*, and e_i is the residual. This is the traditional regression model with which most researchers are familiar. However, as noted earlier, analyzing nested data as if all observations were independent can lead to biased parameter estimates and inflated Type I error rates. We include this model only to demonstrate how easily, when used with nested data, traditional regression can lead to incorrect conclusions.

Unconditional, or Variance Partitioning Multilevel Model. To obtain estimates of the variance in outcome measures partitioned into between-family (level 2; L2) and within-family (level 1; L1) factors, a baseline multilevel model (also called a "totally unconstrained" model, or a "null model"; see Kreft & De Leeuw, 1998) was applied to each outcome measure. This model contains no predictors, and includes an intercept term:

$$y_{ij} = \beta_{0j} + r_{ij} \qquad (2)$$

Here, y_{ij} is the score on the outcome variable (any of the PIAT measures in the current study) for child *i* in family *j*; β_{0j} is the intercept for family *j*, which is equivalent to the mean of *y* for family *j*; and r_{ij} is the deviation for child *i* from the mean for that child's family. Between-family (L2) variability in means is represented as:

$$\beta_{0j} = \gamma_{00} + u_{0j} \qquad (2a)$$

where γ_{00} is the mean of all family means, and u_{0j} is the deviation of family *j* from that overall mean. Substitution from Equation 2a into 2 yields the full expression of this null or baseline model.

$$y_{ij} = \gamma_{00} + (u_{0j} + r_{ij}) \tag{2b}$$

Equation 2b represents two aspects of variation of an individual child's score from the overall mean. The first, u_{0j}, is the family's deviation from the overall mean. The second, r_{ij}, is the child's deviation from its family's mean. Fitting this model to data yields estimates of three parameters: (a) γ_{00} , the mean of all family means; (b) $var(u_{0j})$, the variance of between-family (L2) deviations from this overall mean; and (c) $var(r_{ij})$, the variance of individual children's (L1) deviations from their own family's mean.

Model of Fixed Birth Order Effects. We next introduced predictors into this model consisting of the dummy variables representing birth order, resulting in the following L1 model:

$$y_{ij} = \beta_{0j} + \sum_{k=1}^{K-1} \beta_{(k)} d_{ij(k)} + r_{ij} \tag{3}$$

As in the previous model, the term β_{0j} is the intercept for family *j.* β_{0j} now represents the predicted value of *y* for the first-born child, because of the way that the dummy variables for birth order are coded. The coefficients $\beta_{(k)}$ are the weights for the dummy variables, each coefficient representing the predicted difference in *y* between a child of a given birth order and the first-born child. Note that in this model these coefficients are specified as being invariant across families. (No L2 variation in birth order effects is estimated—yet.) As in the previous model, between family (L2) variability in the intercept is represented by

$$\beta_{0j} = \gamma_{00} + u_{0j} \tag{3a}$$

where γ_{00} now represents the mean intercept, or equivalently the mean *y* for first-born children, and u_{0j} represents between-family variation around that value. Substitution of Equation 3a into Equation 3 yields the full model:

$$y_{ij} = \gamma_{00} + \sum_{k=1}^{K-1} \beta_{(k)} d_{ij(k)} + (u_{0j} + r_{ij}) \tag{3b}$$

Fitting of this model to data yields estimates of the following parameters: (a) the mean and variance of the intercepts, γ_{00} and $var(u_{0j})$; (b) the fixed coefficients, $\beta_{(k)}$, for the dummy variables representing birth order; and (c) the level-1 residual variance, $var(r_{ij})$. Of particular interest are the estimates of the $\beta_{(k)}$ coefficients, representing estimated differences between the first-born child and each successive child. This model allows for overall differences between families in its random intercept term, but by estimating only the fixed portion of each of the birth order coefficients, it requires that the effects of birth order on children's intelligence are the same in every family.

Model of Random Birth Order Effects. The previous model of fixed birth order effects allowed for estimation of between-family variance only in the intercept. To model the between-family (L2) variability in the effects of birth order on children's intelligence, we next specified the birth order coefficients as randomly varying at L2. At L1, this model can be expressed as:

$$y_{ij} = \beta_{0j} + \sum_{k=1}^{K-1} \beta_{j(k)} d_{ij(k)} \tag{4}$$

Here as in the previous model, β_{0j} is the intercept term varying between families. In this model, we also specified the $\beta_{j(k)}$ coefficients to vary randomly at L2, between families. In the L2 model, this variability is represented by:

$$\beta_{j(k)} = \gamma_{10(k)} + u_{1j(k)} \tag{4a}$$

where $\gamma_{10(k)}$ is the estimate of the mean difference between the first child and a child with birth order = (k + 1*)*, and $u_{1j(k)}$ is each family's deviation from that mean effect of birth order = (k +1). As can be seen from Equation 4, the r_{ij} residual term is not included in this model, because the use of random coefficients for dummy-coded birth order perfectly accounts for all within-family variance in the birth order effect. The birth order dummy variable coefficients (in addition to their fixed portion) are specified as random between families (L2), meaning that they can vary in their magnitudes between individual families. This allows each birth order dummy variable to perfectly account for the difference between the first, comparison, child and the focal child, leaving no within-family variance to be expressed in an r_{ij} term. When the expanded equations for the intercept (from Equation 3a) and coefficients for dummy variables (Equation 4a) are combined, the resulting full model is given by:

$$y_{ij} = \gamma_{00} + u_{0j} + \sum_{k=1}^{K-1}[(\gamma_{10(k)} + u_{1j(k)})d_{ij(k)}] \qquad (4b)$$

When this model is fit to the data, the fixed population mean of the intercept and each coefficient is estimated (the γ_{00} and $\beta_{(k)}$ terms), as well as the variances and covariances of the coefficients specified as random at L2. In this case, intercept and birth order coefficients were specified as random, so the between-family variance in each of them is estimated, as are their covariances. In the 7-8 (13-14) year old samples, this resulted in 4 (3) additional L2 variance estimates for each of the birth order dummy variable coefficients, and 10 (6) covariance estimates of the dummy variable coefficients with the random intercept terms and each other. The between-family variance estimates in birth order effects are particularly useful. Highly variable effects have different implications for understanding family influences than do highly stable ones.

Modeling Effects of Control Variables. After estimating the birth order effect as varying across families, we wished to investigate the relationship of birth-order effects to various between-family control variables. Models employing between-family controls would provide the strongest test of the idea that the birth order effect is a strictly within-family phenomenon, as one would not expect the introduction of variables varying between families to affect within-family influences on child intelligence. Although we initially attempted to use our model of random birth order effects (Equation 4b) as a baseline model for the introduction of control variables, adding control variables to this model caused widespread difficulties in estimation. Analyses would either not converge, or yielded nonsensical parameter estimates, such as negative variances. We needed a robust baseline model for the introduction of control variables, which led us to return to the model of fixed birth order effects (Equation 3b) as a framework for investigation of the effects of control variables. From a statistical perspective, this choice is justifiable on the grounds that, as will be reported later, the model of random birth order effects did not fit our data significantly better than the model with fixed birth order effects.

Model Partialling EFS from Intercept. In the first model employing control variables, we introduced Eventual Family Size (EFS) to encapsulate between-family influences that might impact each child's intelligence. EFS was used to predict each family's PIAT intercept score, that is the score of each family's first born child on the applicable PIAT subtest. This model takes a step toward controlling for any between-family (L2) factors that may be associated with a reduction of each child's intelligence and an increase in the average number of children in a given family.

The L1 equation for model 5 appears the same as the model in Equation 3 at the outset:

$$y_{ij} = \beta_{0j} + \sum_{k=1}^{K-1} \beta_{(k)} d_{ij(k)} + r_{ij} \qquad (5)$$

The difference lies in the fact that the intercept, allowed to vary randomly in Equation 3a, is now predicted by the between-family factor of EFS, and expressed as follows at L2:

$$\beta_{0j} = \gamma_{00} + \gamma_{01} EFS_j + u_{0j} \qquad (5a)$$

where γ_{00} is the fixed predicted value of the intercept when EFS = 0, γ_{01} is the estimate of the fixed effect of EFS on intercepts across families, and u_{0j} is family *j*'s deviation from the predicted intercept yielded by this model. Combining Equations 5 and 5a yields the full model:

$$y_{ij} = \gamma_{00} + \gamma_{01} EFS_j + \sum_{k=1}^{K-1} \beta_{1j} d_{ij(k)} + (u_{0j} + r_{ij}) \tag{5b}$$

Terms have been rearranged so that between and within-family deviations come last, in parentheses.

When this model is fit to the data, one more parameter than in the baseline model (Equation 3) is estimated. This new parameter is the EFS coefficient, γ_{01}, which represents effects on intercepts associated with factors that might influence how many children a mother will ultimately have.

Model Partialling EFS from Intercept and Birth Order Coefficients. Removing EFS from the intercept controlled for the effect of EFS on between family differences in level of intelligence of children, but not differences between children of different birth orders. To remove EFS from these difference scores, we introduced into the L2 equation the cross-level interaction of EFS with each of the dummy-coded birth-order variables. Due to our use of dummy variables representing birth order, EFS values were not centered. This technique removed the effect of between-family factors encapsulated in EFS from between-family variation in birth-order coefficients. The cross-level interaction terms represent the interaction of a family-level variable (i.e. EFS) with a child-level variable (i.e. dummy-coded birth order). This technique offered the additional advantage that we could investigate whether between-family differences encapsulated in EFS predicted the expression of the within-family birth order effect. In this model, non-random variation in birth order was predicted with EFS, via the cross-level interactions (c.f. Bryk & Raudenbush, 2002). The cross-level interaction terms, represented in Equation 6 below describing the birth order coefficients, constitute the change in this model from the previous one:

$$\beta_{j(k)} = \gamma_{10(k)} + \gamma_{11(k)} EFS_j \qquad (6)$$

where the new $\gamma_{11(k)}$ terms refer to the effect of EFS on each birth order coefficient, $\beta_{j(k)}$. Note the absence of error terms for the birth order coefficients represented in Equation 6. As previously noted, this is a result of using the model represented by Equation 3b as a basis for the introduction of L2 control variables. When this new model for the birth order terms is combined with the model for intercepts from Equation 5a, the full model is expressed as:

$$y_{ij} = \gamma_{00} + \gamma_{01} EFS_j + \sum_{k=1}^{K-1} [(\gamma_{10(k)} + \gamma_{11(k)} EFS_j) d_{ij(k)}] + (u_{0j} + r_{ij}) \qquad (6a)$$

When this model is fit to data, as many new parameters as there are dummy variables (*K-1*) are estimated, one for each of the new $\gamma_{11(k)}$ terms. This model is designed to remove the effects of EFS from both components of the dummy variable contrasts used to test the effects of birth order.

Model Partialling MIQ and EFS from Intercept; Also partialling EFS from Birth Order. Finally, because it is known that mother's intelligence is positively correlated with children's intelligence and is also related to family size, we included MIQ as a predictor of intercept in the next model, resulting in the following L2 model:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}EFS_j + \gamma_{02}MIQ_j + u_{0j} \qquad (7)$$

where γ_{02} represents the mean effect in the population of mother's intelligence on the intercept. Combining the models for the intercept (Equation 7) and birth order effects (Equation 6b) in expanded form, the final model is shown in Equation 7a:

$$y_{ij} = \gamma_{00} + \gamma_{01}EFS_j + \gamma_{02}MIQ_j + \sum_{k=1}^{K-1}[(\gamma_{10(k)} + \gamma_{11(k)}EFS_j)d_{ij(k)}] + (u_{0j} + r_{ij}) \qquad (7a)$$

When this model is fit to the data, one additional parameter beyond that from the previous model is estimated. This additional parameter is γ_{02}, the effect of MIQ on the intercept. The following parameters are estimated: (a) the mean and variance of the intercepts, γ_{00} and *var*(u_{0j}); (b) the fixed coefficients, $\gamma_{01}EFS$ for the effect of EFS on the intercept, $\gamma_{02}MIQ$ for the effect of MIQ on the intercept, $\beta_{(k)}$ for the dummy variables representing birth order, and $\gamma_{11(k)}EFS$ for the effect of EFS on each of the birth order coefficients; and (c) the level-1 residual variance, *var*(r_{ij}).

Testing Model Fit

In addition to the parameter estimates produced in the results for each model, a deviance statistic is obtained that can be used to conduct χ^2 difference tests between nested models. A model is nested within another if its parameters are a subset of the parameters of another model.

For instance, our variance partitioning model is nested within a model estimating the effect of birth order as a fixed variable. The variance partitioning model is nested within the more complex model, in that fitting the model without estimating the effect of birth order is equivalent to fitting a model with birth order, specifying that each of the birth order coefficients should be zero. One would expect that as our models become more complex, they will better explain the data. This suggests that as we move through the sequence of models, model fit as measured by χ^2 difference tests should improve.

Results

The series of models described in the previous section was applied to data from each of the two samples of children described earlier (age 7-8; age 13-14). For each sample, three different PIAT subtests were used as outcome variables (Math, Reading Recognition, and Reading Comprehension). Thus, the entire series of models was applied six times, once for each outcome variable in each age sample. Because results were so highly consistent across age sample, we focus on results from the larger, 7-8 year old sample, and note discrepancies between samples when they occur. Results are listed separately for each sample, and results from a given model are listed for both samples in the same table. For quick orientation, Table 2 provides a summary of our models and their purpose.

--Insert Table 2 about here—

Traditional Regression Model. Regressing the PIAT Math, Reading Recognition, and Reading Comprehension scores on dummy-coded birth order in a traditional regression analysis yielded significant effects for all dummy variables on all outcome variables. We include this traditional model only to show how easily the use of an inappropriate model for birth order effects can lead to the apparent conclusion (drawn in many previous investigations) that birth order does indeed have a negative effect on intelligence. Table 3 shows that compared to the intercept (β_{00}), which due to our dummy coding of birth order was equal to the predicted PIAT subtest score of the first-born child, subsequent children's PIAT subtest scores were lower, on average (as indicated by the successively larger, negative, β's). In parentheses below each parameter estimate is the estimate of the standard error. An approximate significance test can be conducted by dividing the parameter estimate by its standard error. If the result is 2 or greater in absolute value, the parameter estimate is significantly different from zero, at $p \sim .05$. In this model, all parameter estimates were significant.

--Insert Table 3 about here—

Unconditional, or Multilevel Variance-partitioning Model. To determine how much of the variance in subtest scores was due to between-family factors, and how much was due to within-family factors, a multilevel variance partitioning model was next fit to the three subtest scores in both samples, and its results summarized in Table 4.

--Insert Table 4 about here—

The intercept values (γ_{00}) in Table 4 show that collapsed across all children in our sample, average PIAT subtests scores were close to 100. Importantly, the results in the right-most two columns in Table 4 show significant variance in scores due to both between-family, L2 (*var (u))* and within-family, L1 (*var* (*r*)) factors. This indicates that while there were within-family influences on PIAT subtest performance (shown by the significant within-family variance in scores), there were simultaneously between-family influences (shown by significant between-family variance in scores) on all outcome measures. As our argument is that much of the supposed birth order effect is really a function of factors varying between families, this evidence of significant between-family variance supported continued investigation.

Models Estimating Simple Effects of Birth Order. We next fit multilevel models estimating the effect of birth order on each subtest. Results for the first such model, a model estimating only the fixed component of birth order effects (birth order effects were not specified to vary randomly), showed that for all PIAT subtest scores, the size of birth order coefficients ($\beta_1 ... \beta_4$) was somewhat reduced relative to the effects found in the traditional regression model (Table 5). This trend is most obvious comparing equivalent β's in Table 3 to Table 5, and consistent with our hypotheses.

--Insert Table 5 about here--

As noted above, χ^2 -difference tests can be conducted to test if one nested model fits the data better than another. As can be see in Table 6, models in both age samples estimating the simple effects of birth order proved to be a better fit to the data than the previous variance partitioning models. This was true for all PIAT subtests. The χ^2-difference tests for other models reported in Table 6 will be referenced below.

--Insert Table 6 about here--

Next, a multilevel model of random birth order effects was applied to the outcome measures. Birth order effects, as represented by the coefficients for the dummy variables, were specified as varying randomly between families, so that between-family variance in the effects of birth order on PIAT scores could be estimated. Results in Table 7 show that while the estimates of the mean effects ($\gamma_{00}, \beta_1, \beta_2, \beta_3, \beta_4$) of birth order remained similar to those of the previous model of fixed birth order effects, there was a large amount of between-family variance in those effects. Take as an example the birth order coefficient β_1 for the PIAT math subtest. This coefficient had an estimated mean of –1.27, and a L2 variance estimate (β_1 / β_1) of 167.3. The square root of this variance estimate yields a standard deviation of 13. That is, the model estimates that, across families, the difference in PIAT Math scores between first-born and second-born children had a mean of –1.27 with a *SD* = 13. Assuming these differences to be normally distributed, approximately 95% of these differences would lie within two standard deviations of the mean, or within the interval of –27 and +25 points. Similar patterns for other coefficients in Table 7 suggest considerable variation across families with respect to differences among children of different birth orders. In spite of the apparently large variance estimates for the random effects of birth order, this model did not offer significantly better fit to the data than the previous model of fixed birth order effects (see Table 6). As was the case with the model of fixed birth order effects, however, χ^2 -difference tests showed that it fit better than the variance-partitioning model (Table 6) for all PIAT outcome measures for all but one case. This case was the PIAT math test for the 13-14 year old sample, where we had model estimation difficulties (see note in Table 7). In addition to the lack of improvement in fit over the fixed effects model, this model of random birth order effects did not prove computationally robust when control variables were added. When either EFS or MIQ was added to the model of random birth order effects, the analyses either failed to converge on a solution, or gave results (such as negative variances) that were impossible. For this reason, subsequent models use the more robust model specified in Equation 3 as a foundation to investigate the effects of EFS and MIQ on birth order (see Nezlek, 2001; p. 781 for a discussion of when to specify variables as fixed or random).

--Insert Table 7 about here--—

Models Controlling Between-Family Influences on Intelligence. We next fit models that included family-level (L2) control variables. Because the control variables chosen (EFS and MIQ) varied between families (i.e. were constant within-family), an analysis of their influences provided the best test of the idea that birth order effects are due to between, not within-family influences on intelligence. If the outcome measure is a function of within-family factors, adding between-family factors to the model as control variables should not affect the influence of these factors. Alternatively, if including control variables that vary only between families affects the relationship between birth order and intelligence, this supports our hypothesis that the birth order effect is (partially or completely) caused by the between-family factors that both affect child intelligence, and that also covary with birth order.

The results of the first control model fit to children's PIAT subtest scores supported this latter perspective. As shown in Table 8, our model partialling EFS from the intercept term showed that across subtest scores and age samples, EFS (γ_{01}) had a negative impact on the level of the intercept (γ_{00}) in each model. More specifically, the more children a mother had by the time she reached her mid thirties, the less intelligent her first-born tended to be. More relevant, however, is that this control model strongly reduced the effect of birth order as represented by the dummy-variable coefficients on all PIAT subtest scores in the 7-8 year old sample. The effect of EFS (γ_{01}) ranged in size from –1.3 to -.8, which was small, but still enough to render many of the $\beta_1 ... \beta_4$ birth order coefficients non-significant. Indeed, across subtest scores in the 7-8 year old sample, 9 of 12 comparisons testing birth order effects were non-significant. In the 13-14 year old sample, 6 of the 9 birth-order comparisons were non-significant.

This finding supports a reconceptualization of birth order effects. It suggests that birth order appears important as a predictor of intelligence only because it covaries with true environmental influences on cognitive ability. Evidently, environmental influences encapsulated in EFS influence both the number of children a mother has, and these children's intelligence. Table 6 shows the results of χ^2 -difference tests comparing the model including EFS as predictor of intercepts to a model without EFS across PIAT subtests. Across all subtests, in both samples, the model that incorporated EFS as a predictor of intercepts had significantly better fit than the previous model.

--Insert Table 8 about here--

The next model using control variables included EFS as a predictor of both intercept (γ_{00}) and birth order coefficients ($\beta_1, \beta_2, \beta_3, \beta_4$). Using this model, we examined the influence of between-family EFS on within-family birth order effects. To predict birth order effects using EFS, interactions of EFS with each of the birth order dummy variables ($\gamma_1, \gamma_2, \gamma_3, \gamma_4$ in Table 9) were included in the model. Again, if birth order effects were due primarily to within-family influences, as previously assumed, partialling the between-family variable of EFS from each birth order should *not* result in a substantial reduction of the size of the birth order effect.

Results shown in Table 9 indicate that fitting this second control model to children's PIAT performance measures again yielded consistent results across subtests. In models for each of the subtests, the inclusion of EFS as a predictor of the birth order effects eliminated the negative effect of birth order on intelligence. Across age samples, only 1 of 21 comparisons testing the effect of birth order was significant, and as in the previous control model, this single significant coefficient showed that birth order had a *positive* impact on PIAT math scores, which is opposite to the expected direction (i.e. β_3 for the PIAT Math subtest in Table 8, 7-8 year old sample). All members of a single family have the same EFS value, and obtaining these effects after controlling for a variable varying only between families again suggests that birth order effects are caused by the covariation of birth order with more proximal influences on intellectual ability that vary between families.

--Insert Table 9 about here—

When EFS is entered into the model with birth order, the unique contribution of each to the outcome can be assessed. These analyses show that EFS influences the outcome measure above and beyond the influence of birth order. Further, including cross-level interaction terms to model the influence of EFS on the birth order effects renders the effect of birth order on intelligence trivial and non-significant. An examination of the EFS x Birth Order interaction terms ($\gamma_1 ... \gamma_4$) across outcome measure shows that EFS significantly moderated the effects of a number of the separate birth order coefficients on PIAT subtest scores. Interestingly, when compared to the previous model, which used EFS only as a predictor of intercept value, χ^2-difference tests indicated that only one of the six model fit difference tests conducted in our samples showed significantly better fit when EFS was added as a predictor of the birth order coefficients. Although the fit of the other models showed a trend of improving as well, it was not by a significant amount (see Table 6). It appears that the birth order effect is so tenuous that it can be wiped out even by adding terms to the model that do not result in significant improvements in fit.

In our final model examining the effect of birth order on PIAT subtests, MIQ was additionally partialled from the intercept term. Although the use in previous models of EFS alone showed that the birth order effect is explained by between-family influences, the theoretical relevance to our outcome measure of MIQ led us to add it as well. Our results supported the idea that more intelligent mothers have more intelligent children, and further showed that adding MIQ as a predictor of intercept resulted in significantly better model fit, across outcome measures (Table 6).

As shown in Table 10, across models fit to each PIAT subtest score, the effect of MIQ on the intelligence of the first-born child was positive. As in the previous model, the negative simple effects of birth order observed in earlier models that did not use control variables were completely absent. The two (of the 21 total) birth order coefficients that did show significant estimates were both *positive* (i.e. β_3 for PIAT Math, and β_1 for Reading Recognition, both in the 7-8 year old sample), which would suggest that being a later-born child improves, rather than worsens, PIAT performance after EFS and MIQ are partialled out. Also as before, there was sporadic evidence that EFS predicts the birth order effect (the γ_3 coefficient for Math in the 7-8 year old sample).

--Insert Table 10 about here—

Discussion

We begin our discussion by summarizing the logic of our design and reviewing our conclusions within the context of that logic. Next, we broaden our conclusions to discuss future directions for research on family structure and intelligence.

If IQ/achievement score means decline across birth order, the cause of those declines may lie with variables that differentiate children from one another within families, or with variables that differentiate families from each other. Researchers have consistently interpreted the data using within-family models to explain the declines. We argue that this interpretation is empirically unjustified. In this study, we have controlled for age and for the cross-sectional confound with two design innovations, and with a unique analytic strategy. First, we used within-family data, which virtually all birth order theorists have recognized as having critical advantages. Second, we compared siblings to one another at fixed ages (as opposed to the usual approach of using a fixed time). The ages we chose span the cross-over period suggested by Zajonc and Mullalay (1998) as occurring somewhere around age 12. Our analytic approach used multilevel modeling, which explicitly partitioned the variability in our PIAT measures into within-family variance and between-family variance.

The NLSY data could not speak more clearly and conclusively within the context of this particular design and analytic strategy. Without controls, the usual negative and consistent birth order pattern was observed. However, when we controlled for variables reflecting only between-family variance, it took only one well-chosen between-family control variable (mother's eventual family size) for that strong pattern to completely disappear, into non-significance. Adding a second control variable (mother's IQ) to the multilevel model caused the birth order-IQ relationship to dampen even further. This result suggests that the cause of supposed birth order effects lies between, not within families. This finding obtained in two age groups (ages 7/8 and ages 13/14), and was observed in data that originated as a national probability sample. (We note, however, that it was the mothers who were randomly sampled through a sample of U.S. households in 1979 to reflect the whole U.S. population of adolescents in that year; further, attrition, non-response, and selection for child-bearing are additional threats to the external validity of this sample).

This study is fundamentally different from previous work, but supports a conclusion for which there is mounting evidence. In addition to its multilevel modeling approach, it uses a unique age-snapshot sampling technique. For instance, in past research, Rodgers et al. (2000) used scores based on a time-matching design, rather than an age-matching design (actually, they averaged scores over a two year period at two different points in time, and then also analyzed age-restricted subsets of each of those fixed-time periods). Their logic was based on the presumption that if past patterns in cross-sectional data did actually originate primarily within the family, then those patterns should be approximately the same using within-family and between-family data. They reviewed a number of within-family data sources showing that this was not the case, and analyzed an overlapping but different subset of the NLSY data used in the current study to show that the birth-order PIAT pattern was flat within families. Armor (2001) and Rodgers, Cleveland, van den Oord, and Rowe (2001) extended this result by additionally considering both Peabody Picture Vocabulary (PPVT) and Digit Span patterns. These findings are consistent with ours. The sources of the often-found birth order-IQ relationship appear to lie outside the family.

Some researchers have argued that the within-family processes really are there, but are hidden by age confounds (e.g., Zajonc, Markus, & Markus, 1979; Zajonc & Mullalay, 1997). Rodgers et al. (2000) addressed this issue by looking at patterns on both sides of the age cross-over identified by Zajonc & Mullalay. Although this design eliminated time confounds as a source of bias, it still did not address concerns regarding the differential ages of the siblings compared to one another within the families (e.g. Zajonc, 2001). The design in the current study explicitly addresses this concern, by age matching rather than time matching. Its findings offer compelling confirmation that birth order does not affect intelligence. Of course, age matching creates some potential threats to internal validity as well, caused by period effects, for example. But when results from both age matching and time matching designs converge on the same conclusion, these threats are less plausible. It is well-known to demographers and developmental researchers that age, cohort, and period effects are confounded in such a way that only two of those have independent influences (e.g., Schaie, 1965). Implicitly, then, cohort confounds are accounted for by combining results from the two studies.

What direction should researchers take from here? First, we should accept that previous claims of a consistent and/or potent birth order effect on IQ/achievement in cross-sectional studies were misattributions. When we look inside families at a fixed time period to find these patterns, they are typically absent (Rodgers et al., 2000). When we looked inside ages in the current study, these patterns initially appeared to be there, consistent with past research findings. However, we showed that these patterns actually originated in the differences between families, and not through processes operating within the family. Obviously, new studies with similar designs – especially those based on within-family data – need to be run to determine whether these results replicate. So far, there is considerable consistency across the several within-family studies reviewed in the introduction to this paper. Second, if birth order/IQ patterns are really artifactual, and if the causal factors at work are located outside the family, then new emphasis on the study of family size effects could be fruitful. Family size is a between-family variable (at least if it is measured at a given point in time, but not necessarily if it is measured at a given age; this is the reason that we used EFS – mother's eventual family size – rather than current family size as one of our between-family control variables). Third, researchers might go beyond the simple concept of EFS as encapsulating diffuse between-family influences, and look at specific factors that differentiate families from each other.

Our data suggest that instead of constructing environments that differentially influence intellectual development across children, parents and families support intellectual development similarly for all children within a given family. Rather than being due to differences in birth order, the substantial differences among children in intellectual ability and achievement at a given age or at a given time period (age-adjusted) more likely derive from differences *between* families. Parental IQ (passed on through both genetic and environmental mechanisms), parental education, SES differences, neighborhood effects, and school effects are all examples of between-family influences that are likely contenders to explain substantial variance in childhood and adolescent IQ/achievement. In the context of research on birth order effects on intelligence, these are all confounds. Birth order is confounded with some of these true between-family influences on intelligence, and the current study suggests that such confounds are responsible for its apparent effects.

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Table 1

Number of Children per Birth Order by Sample.

	Age	
	7-8	13-14
First Born:	1517	1140
Second Born:	1076	583
Third Born:	510	180
Fourth Born:	155	56
Fifth Born:	48	10
Sixth Born:	12	5
Seventh Born:	4	0
Total N:	3322	1974

Table 2

Overview of Models

Model Name:	Investigative Function:	Important Parameters:
Unconditional, or Multilevel Variance Partitioning Model	How much of the variance in the outcome measure is due to between-family (L2) and how much is due to within-family (L1) influences?	Overall Mean (γ_{00}) Between-family Variance (*u*) Within-family Variance (*r*)
Model with Birth Order Effects as Fixed	What is the estimate of any birth order effects in a MLM framework?	Intercept (γ_{00}) Coefficients for Dummy-Coded Birth Order ($\beta_1 ... \beta_{K-1}$)
Model with Birth Order Effects as Random	How much variance is there in the birth order effect at L2, between families?	Intercept (γ_{00}) Coefficients for Dummy-Coded Birth Order ($\beta_1 ... \beta_{K-1}$) Between-family variance of birth order coefficients ($\text{var}\,\beta_1 ... \text{var}\,\beta_{K-1}$)
Model partialling EFS from	Does the effect of birth order	Intercept (γ_{00})

intercept	remain significant when between-family influences on child intelligence are partialled out of each family's intercept?	EFS Effect on intercept (γ_{01}) Coefficients for Dummy-Coded Birth Order ($\beta_1 ... \beta_{K-1}$)
Model partialling EFS from intercept and birth order coefficients	Does the effect of birth order remain significant when between-family influences on child intelligence are partialled out of both each family's intercept and birth order coefficients?	Intercept (γ_{00}) EFS Effect on intercept (γ_{01}) Coefficients for Dummy-Coded Birth Order ($\beta_1 ... \beta_{K-1}$) EFS Effects on Birth Order ($\gamma_1 ... \gamma_{K-1}$)
Model partialling EFS and MIQ from intercept, and EFS from birth order coefficients	Same as above	Intercept value (γ_{00}) EFS (γ_{01}) and MIQ (γ_{02}) Effects on the intercept. Coefficients for Dummy-Coded Birth Order ($\beta_1 ... \beta_{K-1}$) EFS Effects on Birth Order ($\gamma_1 ... \gamma_{K-1}$)

Table 3

Traditional Regression Model ($y_i = \beta_0 + \sum_{k=1}^{K-1} \beta_k d_{i(k)} + r_i$*).*

7-8 Year Old Sample

PIAT Subtest (Sample Size)	Intercept	Birth Order Coefficients				
	β_0	β_1	β_2	β_3	β_4	Var. (*e*)
Math	100.92	-1.39	-2.76	-3.74	-6.81	131.39
(3036)	(.31)	(.48)	(.61)	(1.01)	(1.72)	(3.37)
Reading Comp.	105.67	-1.69	-4.47	-5.56	-6.87	126.39
(2712)	(.32)	(.49)	(.64)	(1.05)	(1.83)	(3.43)
Reading Recog.	105.23	-2.19	-5.22	-6.80	-9.10	150.98
(3029)	(.33)	(.51)	(.66)	(1.10)	(1.84)	(3.88)

13-14 Year Old Sample

Math	98.15	-1.39	-3.89	-5.05		175.38
(1757)	(.41)	(.71)	(1.13)	(1.92)		(5.91)
Reading Comp.	96.77	-2.32	-6.22	-8.87		165.62
(1744)	(.40)	(.70)	(1.10)	(1.85)		(5.61)
Reading Recog.	102.14	-2.51	-6.97	-9.46		247.26
(1757)	(.49)	(.85)	(1.35)	(2.25)		(8.34)

Note: The blank spaces for the coefficients of birth order terms for the 13-14 year olds in this and all further tables are a result of our choice to maximize result reliability by analyzing birth order 1-5 in the 7-8 year old sample and birth order 1-4 in the 13-14 year old sample. Table 1 shows the numbers of children of each birth order available in each sample.

Table 4

Variance Partitioning Model ($y_{ij} = \gamma_{00} + (u_{0j} + r_{ij})$)

7-8 Year Olds

PIAT Subtest (Sample Size)	Overall Mean	L2 Between Family Variance	L1 Within Family Variance
	γ_{00}	Var (u)	Var (r)
Math (3036)	99.87 (.23)	50.75 (4.4)	81.65 (3.81)
Reading Comp. (2712)	104.09 (.24)	46.02 (4.69)	83.73 (4.27)
Reading Recog. (3029)	103.40 (.25)	70.19 (5.08)	86.10 (4.06)

13-14 Year Olds

Math (1757)	97.32 (.34)	63.62 (8.20)	112.33 (7.50)
Reading Comp. (1744)	95.41 (.33)	65.09 (7.89)	104.62 (7.05)
Reading Recog. (1757)	100.73 (.41)	96.61 (11.65)	155.39 (10.42)

Table 5

Model Estimating Birth Order Coefficients as Fixed ($y_{ij} = \gamma_{00} + \sum_{k=1}^{K-1} \beta_{(k)} d_{ij(k)} + (u_{0j} + r_{ij})$)

7-8 Year Olds

PIAT Subtest (Sample Size)	Mean Intercept	Fixed Birth Order Coefficients				L2 Intercept Variance	L1 Within Family Variance
	γ_{00}	β_1	β_2	β_3	β_4	Var (u)	Var (r)
Math (3036)	100.77 (.30)	-1.31 (.43)	-2.11 (.56)	-3.22 (.94)	-4.84 (1.59)	48.45 (4.33)	82.30 (3.83)
Reading Comp. (2712)	105.47 (.31)	-1.62 (.45)	-4.15 (.60)	-5.23 (.99)	-6.21 (1.73)	43.62 (4.57)	82.60 (4.20)
Reading Recog. (3029)	105.03 (.32)	-2.16 (.45)	-4.59 (.59)	-5.78 (.98)	-6.86 (1.66)	65.58 (4.93)	85.55 (4.03)

13-14 Year Old Sample

Math (1757)	98.02 (.41)	-1.23 (.65)	-3.31 (1.04)	-3.78 (1.79)		61.50 (8.15)	112.77 (7.51)
Reading Comp.	96.71 (.40)	-2.46 (.63)	-5.40 (1.01)	-7.97 (1.70)		62.75 (7.68)	102.16 (6.88)

(1744)							
Reading	102.07	-2.50	-6.18	-6.93		91.09	155.27
Recog.	(.48)	(.77)	(1.24)	(2.09)		(11.44)	(10.38)
(1757)							

Table 6

Table of χ^2 Difference Tests

7-8 Year Old Sample

χ^2_{diff} (*df* change)	Math	Reading Recognition	Reading Comprehension
Birth Order (BO) Fixed *vs.* Variance Partitioning Basic Model	28* (4)	87* (4)	70* (4)
BO Random *vs.* BO Fixed	11**(15)	11**(15)	6 (15)
BO Random vs. Variance Partitioning Basic Model	40* (17)	76* (17)	75* (17)
EFS as Predictor of Intercept *vs.* BO fixed	13203* (1)	13323* (1)	11748* (1)
EFS as Predictor of Intercept and BO *vs.* Previous Model	13* (4)	7 (4)	5 (4)
EFS & MIQ as Predictors of Intercept and EFS as predictor of BO *vs.* Previous Model	597* (1)	532* (1)	425* (1)

13-14 Year Old Sample

Birth Order (BO) Fixed *vs.* Variance	14* (3)	35* (3)	70* (4)

Partitioning Basic Model			
BO Random *vs.* BO Fixed	237*** (4)	12 (10)	24* (10)
BO Random *vs.* Variance Partitioning Basic Model	223*** (7)	46* (13)	75* (13)
EFS as Predictor of Intercept *vs.* BO fixed	7645* (1)	8098* (1)	11748* (1)
EFS as Predictor of Intercept and BO *vs.* Previous Model	5 (3)	2 (3)	5 (4)
EFS & MIQ as Predictors of Intercept and EFS as predictor of BO *vs.* Previous Model	376* (1)	353* (1)	425* (1)

*= model fit *improved* p<.05

** = fit did not change significantly, but change was in wrong direction.

***= model fit *worsened* significantly, p<.05

Table 7

Model of Random Birth Order Coefficients ($y_{ij} = \gamma_{00} + u_{0j} + \sum_{k=1}^{K-1}[(\gamma_{10(k)} + u_{1j(k)})d_{ij(k)}]$)

7-8 Year Old Sample

	PIAT Math	PIAT Reading Recognition*	PIAT Reading Comprehension
	n = 3036	n = 3029	n = 2712
Fixed Effects			
γ_{00}	100.77 (.29)	105.04 (.32)	105.47 (.31)
β_1	-1.27 (.43)	-2.24 (.46)	-1.62 (.46)
β_2	-2.02 (.53)	-4.73 (.60)	-4.17 (.59)
β_3	-3.29 (1.02)	-5.70 (.90)	-5.25 (.94)
β_4	-5.26 (1.62)	-3.90 (.36)	-5.33 (1.40)
Random Effects			
L2 Variance Estimates:			
$\gamma_{00} / \gamma_{00}$	128.67 (4.84)	151.67 (5.69)	127.17 (5.04)
β_1 / β_1	167.30 (10.96)	183.16 (11.94)	172.54 (12.28)
β_2 / β_2	145.10 (14.86)	178.08 (17.71)	158.42 (17.55)
β_3 / β_3	166.44 (32.13)	176.15 (29.61)	132.85 (30.36)
β_4 / β_4	137.53 (58.18)	61.34 (9.97)	205.68 (80.73)

L2 Covariance Estimates:

β_1 / γ_{00}	-81.21 (6.46)	-89.75 (7.21)	-85.25 (7.09)
β_2 / γ_{00}	-75.68 (8.42)	-86.22 (10.00)	-81.34 (9.63)
β_2 / β_1	79.01 (11.21)	84.57 (13.06)	84.68 (13.05)
β_3 / γ_{00}	-70.25 (17.00)	-100.03 (15.81)	-69.11 (16.41)
β_3 / β_1	48.24 (24.23)	87.68 (21.68)	67.42 (23.35)
β_3 / β_2	66.62 (20.94)	105.00 (20.47)	74.99 (21.00)
β_4 / γ_{00}	-59.40 (30.63)	-33.21 (5.94)	-119.37 (39.60)
β_4 / β_1	95.65 (36.69)	78.25 (8.52)	93.99 (49.61)
β_4 / β_2	13.98 (37.05)	88.22 (10.14)	142.01 (42.20)
β_4 / β_3	45.82 (37.84)	36.00 (10.69)	46.74 (44.75)

13-14 Year Old Sample

	PIAT Math**	PIAT Reading Recognition	PIAT Reading Comprehension
	n = 1757	n = 1757	n = 1744
Fixed Effects			
γ_{00}	97.94 (.38)	102.09 (.48)	96.74 (.39)
β_1	-.93 (.65)	-2.46 (.76)	-2.42 (.62)
β_2	-2.99 (1.41)	-6.81 (1.23)	-5.99 (.97)

β_3	-3.47 (1.93)	-6.99 (1.9)	-9.48 (1.42)
Random Effects			
L2 Variance Estimates:			
$\gamma_{00} / \gamma_{00}$	163.93 (6.96)	248.51 (10.91)	165.64 (7.28)
β_1 / β_1	154.67 (^^^)	308.82 (26.11)	201.53 (17.15)
β_2 / β_2	266.93 (^^^)	237.36 (38.08)	130.49 (20.61)
β_3 / β_3	128.54 (^^^)	239.66 (77.59)	145.73 (39.71)
L2 Covariance Estimates:			
β_1 / γ_{00}	**	-159.02 (15.37)	-103.18 (10.16)
β_2 / γ_{00}	**	-111.58 (22.91)	-53.88 (13.65)
β_2 / β_1	**	62.20 (33.44)	18.29 (20.45)
β_3 / γ_{00}	**	-138.66 (42.81)	-95.50 (22.51)
β_3 / β_1	**	112.76 (54.08)	89.40 (29.31)
β_3 / β_2	**	105.43 (54.24)	-28.42 (25.53)

*To achieve convergence, the convergence criterion for this model was adjusted to 0.01 from the default of .001.

**This model constrained the L2 variance of birth order effects such that while the between family variance in each birth order effect was separately estimated, all off-diagonal elements of the L2 matrix (i.e. birth order covariances) were set to zero. It failed to converge when birth order variances and covariances were estimated without constraints.

^^^LISREL did not report S.E. estimates for these values.

Table 8

EFS as a Predictor of Random Intercepts for 7-8 Year-Olds

$$(y_{ij} = \gamma_{00} + \gamma_{01} EFS_j + \sum_{k=1}^{K-1} \beta_{1j} d_{ij(k)} + (u_{0j} + r_{ij}))$$

PIAT Subtest (Sample Size)	Intercept with EFS partialled	EFS effect on intercept	Birth Order Coefficients				L2 Variance of Intercepts	L1 Within Family Variance
	γ_{00}	γ_{01}	β_1	β_2	β_3	β_4	Var (u)	Var (r)
Math	103.57	-1.15	-.53	.53	-1.27	-2.10	50.00	80.13
(1316)	(.91)	(.32)	(.65)	(.90)	(1.4)	(2.37)	(6.42)	(5.55)
Reading Comp.	107.32	-.80	-1.40	-3.58	-2.64	-3.68	42.53	78.86
(1181)	(.91)	(.33)	(.68)	(.96)	(1.5)	(2.66)	(6.57)	(5.98)
Reading	107.98	-1.27	-1.16	-2.55	-2.15	-3.34	69.21	86.40
Recog.	(.99)	(.35)	(.69)	(.97)	(1.48)	(2.48)	(7.59)	(6.04)
(1316)								

13-14 Year Old Sample

Math	102.60	-1.53	-.72	-.012	-2.62		65.62	113.56
(795)	(1.31)	(.44)	(1.0)	(1.53)	(2.82)		(12.22)	(11.10)
Reading Comp.	99.57	-1.06	-2.53	-2.68	-5.17		73.37	89.46
(782)	(1.27)	(.43)	(.93)	(1.41)	(2.57)		(10.93)	(9.01)

Reading	105.96	-1.40	-1.66	-4.38	-1.76		93.19	138.59
Recog.	(1.50)	(.51)	(1.12)	(1.73)	(3.15)		(15.73)	(13.72)
(789)								

Table 9

EFS as Predictor of Random Intercepts with Cross-Level Interaction Terms

$$(y_{ij} = \gamma_{00} + \gamma_{01} EFS_j + \sum_{k=1}^{K-1} [(\gamma_{10(k)} + \gamma_{11(k)} EFS_j) d_{ij(k)}] + (u_{0j} + r_{ij}))$$

7-8 Year Old Sample

PIAT Test (Sample Size)	Intercept with EFS partialled	EFS effect on intercept	Birth Order Coefficients with EFS partialled from each one.				Effects of EFS on Birth Order Coefficients				L2 Variance of Intercepts	L1 Within Family Variance
	γ_{00}	γ_0	β_1	β_2	β_3	β_4	γ_1	γ_2	γ_3	γ_4	Var (u)	Var (r)
Math	102.88	-.87	.88	-.25	17.46	-17.68	-.87	-.53	.12	-4.16	49.48	79.34
(1316)	(1.14)	(.43)	(1.75)	(3.11)	(6.14)	(10.51)	(.43)	(.60)	(.86)	(1.34)	(6.35)	(5.49)
Reading	106.09	-.28	1.48	-.42	2.97	-14.65	-1.10	-1.05	-1.50	1.40	42.14	78.68
Comp.	(1.16)	(.44)	(1.82)	(3.35)	(6.90)	(10.61)	(.64)	(.94)	(1.52)	(1.71)	(6.54)	(5.97)
(1181)												

Reading	106.29	-.57	3.00	1.18	2.58	-10.06	-1.55	-1.25	-1.38	.60	69.67	85.35
Recog.	(1.21)	(.45)	(1.85)	(3.33)	(6.54)	(10.99)	(.63)	(.92)	(1.42)	(1.79)	(7.56)	(5.97)
(1316)												

13-14 Year Old Sample

Math	102.93	-1.65	.57	-9.88	4.43		-.41	2.57	-1.51		69.40	109.41
(795)	(1.55)	(.55)	(2.80)	(4.83)	(18.21)		(.90)	(1.24)	(4.04)		(12.11)	(10.71)
Reading	98.80	-.76	-.22	-.09	-12.15		-.79	-.77	1.39		73.40	89.18
Comp.	(1.48)	(.52)	(2.63)	(4.49)	(16.79)		(.84)	(1.16)	(3.72)		(10.91)	(8.98)
(782)												
Reading	105.57	-1.25	.20	-4.60	-27.05		-.62	-.003	5.55		95.58	136.16
Recog.	(1.76)	(.62)	(3.17)	(5.49)	(20.49)		(1.01)	(1.41)	(4.54)		(15.67)	(13.51)
(789)												

Table 10

EFS & MIQ as Predictors of Random Intercepts with EFS Cross Level Interactions

$$(y_{ij} = \gamma_{00} + \gamma_{01} EFS_j + \gamma_{02} MIQ_j + \sum_{k=1}^{K-1} [(\gamma_{10(k)} + \gamma_{11(k)} EFS_j) d_{ij(k)}] + (u_{0j} + r_{ij}))$$

7-8 Year Old Sample

PIAT Test (Sample Size)	Random Intercept with EFS partialled	EFS effect on intercept	MIQ effect on intercept	Birth Order Coefficients with EFS partialled from each one.				Effects of EFS on Birth Order				L2 Between Family Variance	L1 Within Family Variance
	γ_{00}	γ_{01}	γ_{02}	β_1	β_2	β_3	β_4	γ_1	γ_2	γ_3	γ_4	Var. (u)	Var.(r)
Math	94.74	-.22	.17	2.22	.12	15.41	-16.64	-.89	.13	-3.64	2.28	26.89	80.59
(1263)	(1.20)	(.41)	(.01)	(1.71)	(3.03)	(5.9)	(10.61)	(.60)	(.85)	(1.29)	(1.70)	(5.45)	(5.51)
Reading	99.59	.14	.14	2.65	.53	1.92	-14.88	-1.34	-1.25	-1.11	1.58	27.50	80.70
Comp.	(1.26)	(.43)	(.01)	(1.81)	(3.30)	(6.84)	(11.04)	(.64)	(.92)	(1.50)	(1.74)	(6.03)	(6.07)
(1139)													

Reading	98.84	-.06	.16	4.11	1.18	1.23	-8.76	-1.76	-1.14	-.92	.57	50.04	87.59
Recog.	(1.33)	(.44)	(.01)	(1.84)	(3.33)	(6.49)	(11.50)	(.63)	(.92)	(1.40)	(1.82)	(6.93)	(6.15)
(1263)													

13-14 Year Old Sample

Math	94.44	-1.23	.23	.15	-8.67	.37		-.18	2.50	-.57		37.20	108.93
(765)	(1.59)	(.52)	(.02)	(2.66)	(4.64)	(17.36)		(.85)	(1.21)	(3.85)		(10.32)	(10.39)
Reading	90.34	-.38	.23	-.20	-.54	-17.32		-.68	-.42	2.55		38.33	90.08
Comp.	(1.50)	(.49)	(.02)	(2.48)	(4.32)	(16.04)		(.79)	(1.13)	(3.56)		(9.13)	(8.84)
(752)													
Reading	97.52	-.81	.22	.17	-4.02	-28.80		-.57	-.02	5.85		61.59	136.05
Recog.	(1.85)	(.59)	(.02)	(3.06)	(5.36)	(19.81)		(.98)	(1.40)	(4.40)		(13.92)	(13.30)
(759)													