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Matthew Effects for Whom?

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Abstract

Which children are most at risk of experiencing a Matthew effect in reading? We investigated this question using population-based methodology. First, we identified children entering kindergarten on socio-demographic factors (i.e., gender, race/ethnicity, and socioeconomic status) well known to index the relative risks and resources available to them as beginning readers. Second, we fitted growth curve models to the kindergarten—3rd grade reading scores of these children as they participated in the Early Childhood Longitudinal Study–Kindergarten Class (ECLS-K) study. Third, we compared the children's relative reading achievement (as measured in standard deviation units from the sample's overall mean across the study's time points) of those children most and least at risk for learning disabilities. We found that those population subgroups most at risk for learning disabilities fall further behind typical readers over time. By contrast, those least at risk for learning disabilities do not move further ahead. We conclude that a one-sided Matthew effect exists and, moreover, it exists for those children at greatest risk for learning disabilities.

The "Matthew effect" is a pattern of increasing advantage or disadvantage following initial advantage or disadvantage. The term comes from the Gospel according to Matthew: "For unto one that hath shall be given, and he shall have abundance: but from him that hath not shall be taken away even that which he hath" (XXV: 29, New Analytical). In reading, the Matthew effect refers to the notion that "over time, better readers get even better, and poorer readers become relatively poorer" (Bast & Reitsma, 1998, p. 1373).

A specific developmental cycle, termed the Matthew effects model (Bast & Reitsma, 1998; Stanovich, 2000), is thought to result in the fan spread effect. Children in homes and schools fostering rapid development of reading skills—the reading rich—should begin to enjoy reading from a very young age, and thus practice it more frequently. Frequent reading practice then fuels further skill development (e.g., Cunningham & Stanovich, 1997; Guthrie, Schafer, & Huang, 2001). These children should spiral upward as increasingly competent and motivated readers. Hence, the "rich get richer."

Children experiencing consistent difficulty acquiring reading skills—the reading poor—should follow a different trajectory. Their reading difficulties should lead them to develop more negative attitudes towards reading (e.g., Lepola, Salonen, & Vauras, 2000) and practice it far less (Anderson et al., 1988; Scarborough & Parker, 2003). Over time, the

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"poor get poorer" because of this increasing avoidance of reading practice (Cunningham & Stanovich; Senechal, LeFevre, Hudson, & Lawson, 1996; Stanovich, 1986). Children with learning disabilities should be especially likely to experience this poor get poorer effect. Indeed, Stanovich (1986) uses the model to explain why children with learning disabilities can display increasingly generalized cognitive, motivational, and behavioral deficits (Scarborough & Parker; Stanovich).

Which groups of children are likely to experience the hypothesized Matthew effect in reading? We investigate this question using population-based methodology. First, we categorized children on the basis of their socioeconomic status (SES), gender, and race/ ethnicity. Second, we then used these factors to predict the intercepts and slopes in growth curve models of the children's reading achievement from kindergarten through third grade. Third, we used the resulting estimated coefficients to calculate beginning and ending reading scores for all possible subgroups of children categorized by their SES, gender, and race/ ethnicity. After standardizing the resulting scores using the standard deviations of reading proficiency in kindergarten and third grade (separately), we examined which, if any, of these population subgroups experience Matthew effects in reading.

This methodology is not designed to focus on the detailed mechanisms by which Matthew effects may occur. Instead, we simply ask *whether* any of the population subgroups whose exogenous characteristics should predispose them to low or high reading performance indeed do experience a Matthew effect. Epidemiologically, the answer to this question is important in order to identify those population subgroups that are most at risk of experiencing the model's increasingly generalized cognitive, motivational, and behavioral deficits. Identifying which young children are likely to lag increasingly behind in becoming readers should help researchers, practitioners, and policy-makers more effectively target early intervention services (McCoach et al., 2006; Parrila et al., 2005). Theoretically, and as detailed below, previous investigations of the Matthew effect has yielded inconsistent findings. Consequently, a necessary first step in evaluating the validity of Stanovich's (1986) theoretical model is to determine whether and for whom the predicted Matthew effect in fact occurs.

Prior Studies of the Existence of Matthew Effects

Controversy exists as to whether a Matthew effect truly occurs in reading (e.g., Bast & Reitsma, 1997, 1998; Leppanen, Niemi, Aunola, & Nurmi, 2004; Parrila, Aunola, Leskinen, Nurmi, & Kirby, 2005; Scarborough & Parker, 2003; Shaywitz et al., 1995; Stanovich, 2000). For such an effect to exist, two phenomena should be evident. First, skill differences between good and poor readers should remain stable (i.e., "rich" readers remain rich while "poor" readers remain poor). Ample empirical evidence exists for this phenomenon (e.g., Anderson, Wilson, & Fielding, 1988; Baker, Decker, & DeFries, 1984; Jordan, Kaplan, & Hanich, 2002; Juel, 1988; McGee, Williams, Share, Anderson, & Silva, 1986; Scarborough, 1998; Shaywitz et al., 1995; but also see Phillips, Norris, Osmond, & Maynard, 2002). For example, Smith (1998) reported that, of children with the highest and lowest preschool assessment scores, 93% and 71%, respectively, were reading above or below grade level in the third grade. Juel found that 87% and 88%, respectively, of average-to-good and poor readers in first grade remained average-to-good or poor readers in fourth grade. Such stability led Juel to conclude that poor readers in her sample appeared “doomed” (p. 444).

Second, skills differences between good and poor readers should increase over time (i.e., rich readers become richer while poor readers become poorer). This increasing gap is sometimes referred to as the fan spread effect. Much of the controversy is due to inconsistent evidence for the fan spread effect (e.g., Leppanen et al., 2004). For example, whereas Bast and Reistma (1998) reported that the gap in word recognition skills between good and poor readers widened over time, neither Aarnoutse and van Leeuwe (2000) nor Baker et al. (1984) nor McCoach, O’Connell, Reis, and Levitt (2006) observed this to occur. Instead, poor readers have often narrowed the reading achievement gap (e.g., Aarnoutse & van Leeuwe; Catts, Hogan, & Fey, 2003; Jordan et al., 2002; Parrila et al., 2005; Phillips et al., 2002; Shaywitz et al., 1995). This was the case in the only study to date to investigate the Matthew effect using a sample of children with learning disabilities. Scarborough and Parker (2003) tracked a small sample (i.e., $N = 57$) of children with and without learning disabilities from grade 2 to grade 8. Their analyses yielded a correlation of −.77 between the children’s beginning reading scores and their reading growth. Given their and others findings, Scarborough and Parker (2003) concluded that the Matthew effect remains “elusive, despite the plausibility and wide-spread acceptance of that well-reasoned hypothesis (p. 65).”

Matthew Effects for Whom?

To date, almost all previous studies have sought to test for a Matthew effect simply by identifying rich and poor readers as those with high and low reading test scores, respectively, at or near the beginning of their school careers, and then comparing these scores to those from a later time point (e.g., Bast & Reitsma, 1998; Shaywitz et al., 1995). Whereas this approach is intuitively appealing, it is also problematic. Important epidemiological (e.g., gender) or etiological (e.g., SES) information about a child’s background characteristics is lost when they are classified simply as good or poor readers. Methodologically, children’s performance (both at school entry and later) is at least partially due to chance elements and measurement error, as well as to circumstances that are subject to change. Nor does this traditional approach explicitly account for the differing resources available to children from more or less advantaged families. For example, consider two children with the same initial low score in kindergarten. One may have a cognitive deficit in phonological processing but receive a great deal of supplemental assistance over time from his highly educated and well-to-do parents. In contrast, the other child may have no such cognitive deficit, but receive no assistance from his poorly-educated and poverty-stricken parents. Which, if either, of these two children should be classified as a poor reader in a test of Matthew effects?

There are additional factors that should influence the Matthew effect’s occurrence. These factors should be therefore be accounted for. One set of influences is made up of exogenous child- and family-level factors that help shape the context within which a young child’s reading growth occurs. Examples include the child’s gender, the family’s social class background, household structure, and race/ethnicity (e.g., D'Angiulli, Siegel, & Hertzman, 2004; McCoach et al., 2006; Neuman & Celano, 2001).

Another set of factors is the language and literacy-related actions of a child or his or her parents or caregivers during the preschool period, as well as the language and literacy-related resources available to each. Examples of such actions and resources include whether and to what extent the child (a) engages in shared storybook reading or visits the library, (b) accesses books in his or her home, (c) converses with an adult, who uses a relatively complex vocabulary, and (d) interacts with parents or caregivers who provide instruction in concepts about print and letter knowledge (e.g., Neuman, 1999; Snow, Barnes, Chandler, Goodman, & Hemphill 1991; Weigel, Martin, & Bennett, 2005). These variables affect the child's emergent literacy skills, such as phonological processing ability, knowledge of print principles, emergent writing, oral vocabulary, and letter name and sound knowledge (e.g., Dickinson, McCabe, Anastasopoulos, Peisner-Feinberg, & Poe, 2003; Whitehurst & Lonigan, 2002).

A third set of influences is the reading-related actions undertaken by the child and his or her teachers, parents, and caregivers through the school years, as well as the reading-related resources available to the child. These variables include the curriculum and how a teacher chooses to deliver it, the child's peer group, the parental assistance with reading provided to the child, and, again, the child's own interest and reading efforts inside and outside school (e.g., Cunningham & Stanovich, 1997; Guthrie, Wigfield, Metsala, & Cox, 1999).

Consequently, testing for a Matthew effect is determined in part by which of these sets of diverse factors are included in the estimated model. Related to this choice is the conceptualization of which groups of children are considered likely to be reading rich and poor. This conceptualization is critical when attempting to test for fan spread.

Here, we defined rich and poor readers by exogenous child- and family-level background variables indexing the biological, social, and economic resources available to each child and his or her family. Thus, we ask, "Matthew effects for whom?" This approach has both substantive and methodological advantages. First, it allows us to identify groups of children that, over subsequent years, will likely average stronger or weaker literacy-related abilities, interests, actions, and inputs (via parents, child-care workers, peers, and teachers). Such higher- versus lower-level flows of reading-related resources, activities, and instruction seem a particularly appropriate conceptualization of a child's reading-related "wealth."

Second, using exogenous child and family background variables allows us to better track the growth trajectories of children most at risk for learning disabilities. Epidemiological research repeatedly finds that children from certain population groups (i.e., boys, minorities, and those from low-income households) are much more likely to be identified as disabled (e.g., Delgado & Scott, 2006; Donovan & Cross, 2002; Kavale, 1988; Klinger, Artiles, & Barletta, 2006). For example, Katusic, Colligan, Barbaresi, Schaid, and Jacobsen (2001) found that boys were two to three times more likely to be reading disabled than girls, regardless of whether a regression-, discrepancy, or low-achievement identification method was used. Artiles, Rueda, Salazar, and Higareda (2005) reported that children who were

English Language Learners (ELL) were 3.5 times more likely to be placed in special education by 12th grade than children who were language proficient. Stanton-Chapman, Chapman, and Scott (2001) reported that low maternal education was the strongest child-level predictor of school-identified disability. Moreover, interactions between these gender, race, and social class factors may further increase a child's likelihood of having a disability. For example, whereas only about 7% of White mothers of school-age children have less than a high school diploma, the comparable rates for Black or Hispanic mothers are about 20% and 50%, respectively (NCES, 2002). Artiles et al. also reported that ELL children from low-income homes were 1.4 times more likely to be identified as learning disabled than ELL children from middle-to-high income homes. By incorporating child- and family-level variables into our statistical model, we are able to more precisely test whether those children most at risk for learning disabilities experience the hypothesized poor get poorer effect.

Third, our approach has the advantage that it can be empirically implemented by recently developed techniques of growth curve modeling (Goldstein, 1995; Raudenbush & Bryk 2002; Singer & Willett 2003). Such models have a number of properties that are particularly useful in testing for the fan spread effect. In particular, they remove the artifact of regression toward the mean (Bast & Reitsma 1997; Campbell & Kenny 1999; Shaywitz et al. 1995). Further, the estimated coefficients from growth curve models allow one to compute average reading starting values and growth trajectories for population subgroups defined by their background characteristics. These estimated coefficients and growth trajectories then reveal which groups of children are becoming stronger or weaker readers relative to typical children over time, empirically answering the question, Matthew effects for whom?

Method

Design of the Study

We tested for Matthew effects using a model that included both child- and family-level variables, as well as endogenous reading achievement outcomes as children progressed from the fall of kindergarten to the spring of third grade. In particular, we tested whether the reading trajectories of subgroups of children defined by their gender, race/ethnicity, and their parents' SES have the Matthew effects property. That is, we asked: do those most at risk for learning disabilities (i.e., boys, Blacks and Hispanics, and those arriving at school from low-income households) begin on average near the low end of the reading skills distribution and move further below the mean over time, while those least at risk for learning disabilities (e.g., girls, Asians, and those arriving from high-income families) begin near the top of the distribution and increase their advantage over time? The answer to this question offers more than a simple "yes/no" test of whether children who began near the bottom or top of a particular reading skill measure's distribution end up, respectively, further below or above the mean later on. Instead, it identifies which, if any, population groups of children defined by demographic variables that index the reading-related resources available to them begin school as poor or rich readers and then experience systematic tendencies to grow poorer or richer.

As noted above, we focused on risk factors such as gender, race/ethnicity, and social class because many previous studies have found these to be important predictors of reading actions, resources, and skills growth, as well as reading disabilities (Kavale, 1988; McCoach et al., 2006). For example, ethnographic (e.g., Lareau, 2003; Neuman & Celano, 2001), survey (e.g., Dickinson, McCabe, & Anastasopoulos, 2002), and quasi-experimental research (e.g., Downhower & Beagle, 1998) all indicate that young children living in socio-economically poor communities are particularly likely to begin school as poor readers because they often lack access to books and other print materials. Further, less well-educated parents, caregivers, and child-care workers spend less time teaching knowledge of letters and letter-sound correspondence. They are also less likely to transmit the oral language skills (e.g., grammatical-syntactic coding and vocabulary knowledge) that are useful for the transition to school (Farkas & Beron, 2004; Hart & Risley, 1995; Heath, 1982; Whitehurst & Lonigan, 2002). McCoach et al. (2006) recently reported that children from low-income families scored, on average, 6.2 point lower on a measure of reading proficiency than children from high-income families across their first two years of school. Racial and ethnic differences are also evident in the growth of children's reading skills (e.g., Landgren, Kjellman, & Gillberg, 2003; Sanchez, Bledsoe, Sumabat, & Ye, 2004), although, for some children, differences in the quality of education may at least partially explain these achievement discrepancies (e.g., Beron & Farkas 2004; Fryer & Levitt, 2004; Manly, Jacobs, Touradji, Small, & Stern, 2002). Gender also appears to moderate the effect of early reading struggles on children's reading motivation and skill (e.g., Lepola, 2004; Riordan, 2002).

The ECLS-K Data

We estimated the model using the Early Childhood Longitudinal Study—Kindergarten Class (ECLS-K), a large, representative national sample of U.S. children who entered kindergarten in 1998 and whose reading progress is still being followed (Rathbun & West, 2004; Rock & Pollack, 2002; West, Denton, & Reaney, 2000). These data are collected and made available through the U. S. Department of Education's National Center for Education Statistics (NCES). The database is a multi-stage cluster sample of elementary schools, classes within these schools, and children within these classes. Schools were selected from geographic areas consisting of counties or groups of counties from which 1,280 public and private schools offering kindergarten programs were originally selected. A target sample of 24 children from each public school and 12 children from each private school was drawn, with Asian/Pacific Islander children oversampled. We analyzed data from 10,587 children across five time points (i.e., the fall and spring of kindergarten and first grade, and from the spring of third grade).

Reading Test—The ECLS-K's Reading Test was developed through a multi-step panel review process (see Rock & Pollack, 2002, for details). Items were included in the Test's final form if they displayed (a) acceptable item-level statistics, (b) good fit with maximum likelihood item response theory (IRT) parameters, and (c) no differential item functioning across gender or race (NCES, 2004). The Test includes subtests of three main types of reading skills. The first skill category is Basic Skills, including familiarity with print and recognition of letters and phonemes. The second is Vocabulary. The third is Reading Comprehension. Measures of reading comprehension were based on a National Assessment of Educational Progress framework involving four types of reading comprehension skills:

(a) initial understanding; (b) developing interpretation; (c) personal reflection and response; and (d) demonstrating a critical stance (Rock & Pollack). Sample items from the ECLS-K direct child assessment may not be reproduced here due to copyright protections.

Utilizing one-to-one administered adaptive testing, children were given a test whose coverage of these domains varied according to their grade and skill level (Rock & Pollack, 2002). Most of the Reading Test's items utilize a multiple-choice format. A few are open-ended questions or call for a constructed response. The Reading Test's content emphasis changes over time as children's grow as readers. For first graders, 40%, 10%, and 50% of the measure's testing time is devoted to assessing basic skills, vocabulary, and comprehension, respectively. For third graders, these percentages change to 15%, 10%, and 75%, respectively.

The Reading Test displays very good psychometric properties. The ECLS-K data provide an overall Item-response Theory (IRT) scale score. This score serves as a composite summary measure of each child's reading proficiency at each time point. The reliabilities of the IRT theta scores (the appropriate measure of internal consistency) on the full reading test range from .93 to .97 (NCES, 2000). First graders' Reading Test scores correlated .85 or above with the Kaufman Test of Educational Achievement reading test (NCES, 2002); third graders' scores correlated .83 with the Woodcock-McGrew-Werder Mini-Battery of Achievement (NCES, 2005).

Child and Family Characteristics—Child-level variables include the child's gender, race/ethnicity (a set of dummy-coded variables comparing White children with Black children, Hispanic children of all races, Asian children, and children categorized as belonging to "other" races), and a standardized composite measure of the child's family SES. The SES variable, provided by NCES, reflects an average of household income, parent's education, and parents' occupational prestige scores for each child.

Data Analysis

We used multilevel linear growth curve modeling to analyze the development of children's reading skills over time (Raudenbush & Bryk, 2002; Singer & Willett, 2003). We specified a reading growth model as follows (see Raudenbush & Bryk, 2002). Level 1 equation:

$$\mathrm{Reading}_{it}=b_{0i}+b_{1i}t+e_{it}. \quad (1)$$

The intercept and slope regression coefficients from the first stage were written as a function of exogenous background characteristics:

$$b_{0i}=c_0+c_1X_{1i}+\ldots..+c_kX_{ki}+u_i \quad (2)$$

$$b_{1i}=d_0+d_1X_{1i}+\ldots..+d_kX_{ki}+v_i. \quad (3)$$

Thus, the estimated reading test score for person *i* at time *t* is an additive function of the intercept and a set of child and family background growth terms. Children's race/ethnicity and family SES are used to estimate both their initial (fall kindergarten) test scores as well as their rate of test score gain over time. The “c” coefficients show the effects of exogenous background characteristics on starting values, while the “d” coefficients show the effects of background on test score growth trajectories. This model therefore allows us to simultaneously identify the “rich and poor” (those students with high and low estimated intercepts, respectively) and those who “get richer and poorer” (those with steep growth curves and those with flatter curves, respectively). . After estimating the coefficients in this model, we will use the results to calculate predicted scores for those population subgroups that begin and end their reading performance trajectories at either the low or high end of the reading score distributions. Since social class (SES) is positively associated with the student’s rate of reading growth, these groups comprise all combinations of gender and race/ ethnicity, with SES in either the bottom or top quintile.

Results

Table 1 displays the mean scores for the measures and descriptive statistics for the background variables. We describe the exogenous background variables first. The sample was 62% White, 13.5% African-American, 13.2% Hispanic, 5.3% Asian, and 6% Other ethnicity (this included Native Americans and mixed race children). With family SES coded into quintiles, the average score was 3.30. (This was above 3.0 because of a slight excess of missing cases below the mean of the variable.) The sample was 50% male.

The ECLS-K researchers computed a continuous IRT-scaled composite reading score for each child at each survey wave. As shown in Table 1, when kindergarten began, the mean of this composite was 22.9, with a standard deviation of 8.6. By the spring of third grade both the mean and standard deviation had increased substantially, to 109.4, and 19.5, respectively. These beginning and ending means and standard deviations can be used to compute, for poor and rich readers, whether their difference from the mean has or has not increased over time.

Table 2 shows the fitted growth curve coefficients for the composite reading score. The first column shows a simple regression with just a constant term and slope; the second column shows how these vary as a function of a child’s characteristics. As expected, for the beginning score (y-intercept of the fitted growth curves), males performed lower than females and SES had a strong positive effect. Hispanics and Other Ethnicities performed lower than Whites; Asians performed higher.

For the reading growth slope, males’ reading skills grew more slowly than females. SES continued to have a significant positive effect on skills growth. Reading skill grew much more slowly for African-Americans than for Whites. Hispanics, Asians and Other Ethnicities grew significantly but only modestly slower than Whites.

Table 3 displays predicted beginning and ending Z-scores for population subgroups, based on the growth curve coefficient estimates. These scores are computed for gender x race subgroups with SES at either the lowest or highest quintile – the subgroups with the lowest and highest average beginning and ending scores. Importantly, these are calculated using the reading score means and standard deviations computed *separately* for kindergarten and third graders. The table indicates that, in the fall of kindergarten, the lowest performing groups were those in the lowest quintile of SES. Among these, the very lowest were Hispanic, "other ethnic" group including American Indian) and Black males. These children performed .83 - .66 standard deviations below the kindergarten mean. By contrast, the highest performing groups were those with SES in the highest quintile. Among these children, the very highest ranked subgroups were Asian females and males. These children performed 1.16 – 1.01 standard deviations above the mean.

By the spring of third grade, all subgroups were reading at a much higher level. However, relative to one another, it was still generally the case that those in the lowest quintile of SES performed below the mean while those in the highest quintile performed above the mean. Yet a number of groups changed their relative ranking. Which groups moved up and which moved down?

Black males in the lowest SES quintile lagged further behind their peers in reading growth. Between the beginning of kindergarten and the end of third grade their average reading *Z*-score declined from −0.66 to −1.12. This is an increase of 0.5 of a standard deviation in the distance that this group's reading skill fell below that of typical readers. A similar result is observed for "other ethnic group" males, whose relative reading performance fell from −0.83 to −1.18. For Black females, reading performance fell from −0.63 to −0.93, a decline of 0.3 standard deviation. "Other ethnic group" females fell from −0.77 to −1.08, also a decline of about 0.3 standard deviations. Thus, the relative reading performance of these four groups of at-risk readers exhibited fan spread. Their relative reading performance became worse over time.

We observe no comparable increases in relative position among those children least likely to be learning disabled. Indeed, those groups of children who were the greatest distance above the mean when school began (i.e., Asian females and males) had their relative positions eroded by approximately 0.5 of a standard deviation by the spring of third grade. Furthermore, the largest group of high performing children (i.e., high SES White females) showed little change in their relative position. Thus, we observed no fan spread for resource-rich, low risk population subgroups. Insofar as literacy acquisition is concerned, a "one-sided Matthew effect" exists—the poor grow poorer, but the rich do not grow richer.

Discussion

The existence of a Matthew effect in reading is controversial (e.g., Bast & Reitsma, 1997, 1998; McCoach et al., 2006; Parrila et al., 2005; Shaywitz et al., 1995; Scarborough & Parker, 2003; Stanovich, 2000). Much of the controversy is due to inconsistent evidence for the fan spread effect (e.g., Aarnoutse & van Leeuwe, 2000; Bast & Reitsma, 1998; Shaywitz et al., Scarborough & Parker). Previous studies have tested for the fan spread effect by comparing children's performance on a reading measure near the beginning of their school careers to scores from a later point (e.g., Bast & Reitsma, 1998; Shaywitz et al., 1995). The methodological and substantive limitations of this approach may be contributing to the mixed evidence for a Matthew effect.

Instead of using initial test performance to select rich and poor readers, we tested for fan spread by defining rich and poor readers using exogenous child- and family-level characteristics indexing the relative magnitude of reading-related risks and inputs that a child is likely to experience during the preschool and early elementary school years. We did so for two reasons. First, the relative magnitudes of these risks and inputs are a particularly appropriate conceptualization of a child's reading-related "wealth." Thus, we were able to more fully account for the diverse sets of factors thought to influence the Matthew effect model's predicted growth trajectories. Second, using these exogenous characteristics also allowed us to determine whether the Matthew effect exists for those most at risk for learning disabilities.

We used growth curve modeling to test for fan spread. This approach removes the artifact of regression toward the mean. It also allowed us to compute average reading growth trajectories for specific population subgroups defined by the aforementioned exogenous background characteristics. These epidemiological analyses revealed which groups of children became richer or poorer readers relative to typical readers over time. As such, the analyses empirically answered the question, Matthew effects for whom? Despite our use of standard scores (see, e.g., Stanovich, 2000), we investigated this question in a way that was *not* methodologically tautological. That is, it was perfectly possible for our analyses to yield any of the following conclusions: (a) any, some, or none of the initially lowest-performing groups moved further from the mean over time (measured in standard deviation units separately at the beginning and ending time periods); and (b) any, some, or none of the initially highest-performing groups moved further from the mean over time.

We consistently observed significant effects when we estimated growth curve models to predict proficiency on the composite reading test. We found that males began kindergarten with lower reading skills than females, and their skills grew more slowly than those of females. Family SES background was strongly and positively associated with both a child's beginning reading skills and his or her subsequent rate of reading growth. Hispanic children entered school with significantly fewer reading skills than White children; Asians entered with significantly greater reading skills than Whites. The reading skills of Blacks, Hispanics, and Asians also grew more slowly than those of White children. Among these, it was the Black students who experienced the greatest increase in their gap with White children.

When we combined the child- and family-level variables to define population subgroups, we observed a fan spread effect in the composite reading scores of four groups of low-performing children: Blacks and "other ethnic group" (including American Indian) males and females. Between the fall of kindergarten and the spring of third grade, their distance below average children's reading level increased by 0.5 – 0.3 of a standard deviation. This seems a straight-forward case of poor readers growing poorer.

In contrast, Asian females and males from families in the highest quintile of the SES distribution typically entered school as the highest-performing readers. In the fall of kindergarten, their composite reading scores averaged 1.16 and 1.01 standard deviations above the mean, respectively. However, these children did not grow to become increasingly more skilled than typical readers of the same age. Instead, by the spring of third grade, their average reading score had declined to about 0.6 standard deviations above the overall average. Other high performing groups also failed to become increasingly more skilled readers. For example, White female children from the top quintile of SES families increased their average reading score from only 0.62 to 0.68 standard deviation above the mean.

Thus, we found that the reading rich do not become richer. Put another way, those children who entered school at relatively lower risk for having learning disabilities (e.g., high SES Asian and White females) did not become comparatively better. Other studies (e.g., Leppanen et al., 2004; McCoach et al., 2006; Phillips et al., 2004) report such an effect. Yet, and unlike these other studies, we did not find that poorly skilled readers begin to catch up with their peers. Instead we found evidence for a one-sided Matthew effect. That is, relative to typical readers of the same age, children who entered school at relatively higher risk for having learning disabilities (e.g., low SES Black males) became comparatively poorer readers over time. The difference between our and others' findings may be due to our larger sample and our use of gender, race/ethnicity, and SES to index a child's reading growth. These factors exert strong effects (e.g., McCoach et al., 2006). At the very least, results from our study and others suggest that Stanovich's (1986) Matthew effects model may not produce uniform influences on rich and poor readers' progress in becoming literate.

Limitations

Our study has at least three limitations. First, our data are limited to kindergarten through third grade. Thus, we do not know to what extent these Matthew effects continue as children move beyond the primary grades. Second, we did not directly test the specific developmental model thought to cause the Matthew effect. For example, we did not test whether children at risk for learning disabilities also became less motivated to engage in reading or practiced it less frequently than their peers (Chapman, Tunmer, & Prochnow, 2000; Stanovich, 1986). However, this study was not designed to empirically evaluate the Matthew effects model's inter-related, reciprocally causative mechanics. We rather attempted to test which population subgroups were more or less likely to experience the model's predicted fan spread effect. From our standpoint, a necessary first step in evaluating the validity of Stanovich's (1986) theoretical model is to resolve whether and for whom the predicted Matthew effect in fact occurs. Thus, and although our results indicate that a fan spread effect does occur for children from those population subgroups most at risk for later being identified learning disabled, the causal mechanisms underlying this fan spread, as well as interventions capable of reducing or eliminating it, still require further study.

Third, we entered only a small set of exogenous variables into the growth curve models. We did so because previous research has indicated that differences in gender, race/ethnicity, and SES would be particularly powerful indicators of a child's risk status (McCoach et al., 2006). This indeed proved to be the case. That is to say, children of different gender, race/ethnicity, and SES groups, on average, performed differently on this study's measure of reading proficency. However, this is not the same as saying that a child's gender, race/ethnicity, or SES should be construed as a lasting marker of his or her status as a good or poor reader. Any given subgroup in our sample included both good and poor readers. As in any such analyses, "risk" is a probabilistic rather than a deterministic function.

Contributions to the Extant Literature

Our findings contrast with those of others as to whether a Matthew effect exists (e.g., Aarnoutse & van Leeuwe, 2000; Catts, Hogan, & Fey, 2003; Jordan et al., 2002; Leppanen et al., 2004; McCoach et al., 2006; Parrila et al., 2005; Phillips et al., 2002; Shaywitz et al., 1995). For example, Shaywitz et al. used both growth modeling and statistical control for exogenous variables, but still did not find evidence for fan spread between rich and poor readers. Several factors may account for differences in our and others' findings. First, our dataset was much larger (i.e., 10,587 children) than all others to date. For example, Scarborough and Parker's (2003) null finding was based on a small sample of 57 children with and without reading disabilities. Thus, our sample provided ample statistical power to detect effects. Second, in our analyses, reading achievement intercepts and slopes were allowed to be a function of the child's or family's background variables. Third, in testing for Matthew effects for particular groups of children, we included SES. This factor strongly affects children's reading growth during preschool and elementary school, and likely captures some of the causal forces underlying the Matthew effect model on children's reading development (e.g., Shaywitz et al.; Stanovich, 1986), and yet has not been typically incorporated into other investigators' analyses (e.g., Leppanen et al., 2004; Parrila et al., 2005).

Our findings help identify which population subgroups are likely to lag increasingly behind in becoming readers. Put another way, our findings starkly illustrate the power of a small set of background variables (i.e., gender, race, and socioeconomic class) to explain the relative reading progress—or lack of progress—of large groups of children in the United States. Evidence for these patterns remained after the use of rigorous statistical techniques. Evidence of fan spread cannot easily be discounted as either a result of other, confounding variables, or as a statistical artifact. We conclude that a one-sided Matthew effect exists, and it exists for those most at risk for later being identified as learning disabled. The implications for such a finding seem clear. Practitioners, researchers, and policy-makers working to "leave no child behind" should consider focusing their efforts on providing intensive and high-quality early interventions to at risk children. Without the benefit of such efforts, those groups of children who arrive in kindergarten already at risk for being poor readers will only fall increasingly behind their peers.

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Table 1

Descriptive Statistics

	M	*SD*	*Min*	*Max*
Composite Reading	22.908	8.597	10.08	69.66
Fall K				
Spring K	32.257	10.433	10.85	70.80
Fall 1st	39.737	12.775	12.69	86.63
Spring 1st	57.089	13.260	14.77	88.95
Spring 3rd	109.440	19.454	42.36	148.95
White	0.618	0.486	0.00	1.00
Black	0.135	0.342	0.00	1.00
Hispanic	0.132	0.338	0.00	1.00
Asian	0.053	0.225	0.00	1.00
Other Ethnicity	0.060	0.238	0.00	1.00
SES Quintile	3.304	1.328	1.00	5.00
Gender (Male=1)	0.502	0.500	0.00	1.00

Note: SD = standard deviation; Min = minimum; Max = maximum.

Table 2

Growth Curve Estimates for Composite Reading Score

	Composite Reading	
	Level 1	**Level 2**
Intercept	15.58***	10.17 ***
Male		−1.37 ***
SES		1.88 ***
Black		−0.09
Hispanic		−1.14 ***
Asian		3.36 ***
Other Ethnicity		−0.83 *
Slope	2.15***	1.99 ***
Male		−0.05 ***
SES		0.07 ***
Black		−0.25 ***
Hispanic		−0.06 ***
Asian		−0.07 ***
Other Ethnicity		−0.17 ***
Tau	0.082	−0.039

Note:

* $p < .05$.

** $p < .01$.

*** $p < .001$

Table 3

Standardized Beginning and Ending Scores on Composite Reading IRT Scale for Population Subgroups

	Composite Reading Score	
	Beginning	**Ending**
White Male, SES 1	−0.48	−0.77
Black Male SES 1	−0.66	−1.12
Hispanic Male, SES 1	−0.80	−0.77
Asian Male, SES 1	−0.40	−0.20
Other Male, SES 1	−0.83	−1.18
White Female, SES 1	−0.46	−0.46
Black Female, SES 1	−0.63	−0.93
Hispanic Female, SES 1	−0.65	−0.43
Asian Female, SES 1	−0.37	−0.42
Other Female, SES 1	−0.77	−1.08
White Male, SES 5	0.47	0.52
Black Male, SES 5	−0.04	−0.15
Hispanic Male, SES 5	0.23	0.28
Asian Male, SES 5	1.01	0.58
Other Male, SES 5	0.73	0.47
White Female, SES 5	0.62	0.68
Black Female, SES 5	0.33	0.06
Hispanic Female, SES 5	0.38	0.49
Asian Female, SES 5	1.16	0.67
Other Female, SES 5	0.58	0.39

Note: SES reported in quintiles, with 1 = lowest & 5 = highest