

September 21, 2007

Dr. Loeb:

My coauthors and I would like to submit the enclosed paper, "Measuring School Characteristics: A Group-Based Modeling Approach," to PAA Session 702: School and Teacher Quality—Levels and Distribution. Please note that future drafts of this paper will incorporate a substantive example, modeling the relationship between social background, school characteristic trajectories, and a variety of educational outcomes. We intend to present results from this example, along with the results contained herein, at the conference this spring.

Sincerely,

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Measuring Primary and Secondary School Characteristics: A Group-Based Modeling Approach*

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Measuring Primary and Secondary School Characteristics: A Group-Based Modeling Approach

Abstract

In this paper we introduce a new way to evaluate the educational resources that young people encounter as they make their way from kindergarten to high school graduation. Using recent methodological advances in group-based modeling and a unique data set, we empirically test for and identify a series of categorically distinct “school quality” trajectories. The results show that these trajectories vary significantly in terms of their shape and slope, their prevalence within the sampled population, and in the sociodemographic makeup of their constituent members. We conclude by offering some initial thoughts on how this approach can be used to assess dependencies between school characteristics, educational outcomes, and occupational attainment across the life-course.

Measuring Primary and Secondary School Characteristics: A Group-Based Modeling Approach

The extent to which schools' resources affect individuals' positioning within the social hierarchy is a question that continues to attract the attention of academics, policymakers, and educators. In the past four decades, researchers have attempted to model the relationship between a broad range of indices—including pupil-teacher ratio, length of school year, per pupil expenditures, and teachers' education and experience—and an even broader assortment of outcomes (Altonji and Dunn 1996; Behrman and Birdsall 1983; Betts 1995; Card and Krueger 1996; Coleman et al. 1966; Entwisle and Hayduk 1988; Greenwald et al. 1996; Grogger 1996a; Hanushek 1989; Heckman et al. 1996; Johnson and Stafford 1973; Lloyd et al. 2003; Rose and Betts 2004; Ross and Mirowsky 1999).

While this line of analysis has produced an impressive body of work, we suggest that much of the existing research has failed to sufficiently account for the cumulative nature of schooling. If we start from the premise that the importance of school characteristics varies by non-trivial amounts depending on the age and grade level of the student (Entwisle and Hayduk 1988), then it would seem inadequate to observe school characteristics at only one or two points in time—as is typical in the “school effects” literature. This problem is further exacerbated if schools themselves change—in the resources they make available to their students, in their enrollment and attendance, and in the size, experience, and composition of their teaching staff—over the course of a given student's career. The primary contribution of this paper is to empirically test for the presence of distinct “school quality” trajectories, to describe the shape and prevalence of these trajectories, and to determine whether some background characteristic or

some set of background characteristics distinguish individuals in one trajectory from those in another.¹

We draw extensively on group-based modeling techniques (Jones and Nagin 2007; Jones et al. 2001; Loughran and Nagin 2006; Nagin 1999a; Nagin 2005; Nagin and Land 1993; Nagin et al. 2003; Nagin and Tremblay 2005; Nagin and Tremblay 1999) to propose a new way of conceptualizing youths' exposure to different types of schooling resources and environments. Rather than simply observing school characteristics at a particular moment in time, or taking the average over a fixed period, the group-based approach uses a finite mixture modeling strategy to assign respondents to a limited number of "developmental trajectories" or "latent longitudinal strata" on the basis of continuities and differences in the primary and secondary schools they attended (Haviland and Nagin 2005). In addition to identifying categorically similar trajectories, the methodology provides the statistical capacity to test the precision with which youth are assigned to different trajectory groups; to compute group membership probabilities as a function of time-invariant covariates; and to relate one's trajectory group to distal outcomes like post-secondary enrollment and occupational attainment.

The remainder of this paper is organized into five sections. In the section that follows we present a brief summary of research on school effects, focusing in particular on common conceptual limitations and opportunities for elaboration. We then go on to describe our data set. In the third and fourth sections we introduce the group-based modeling technique, discuss its statistical foundation, and show how it can be used to model school quality trajectories. We intend for this demonstration to serve as a technical precursor to future analyses, which use the trajectory assignments produced herein to model the effect of school characteristics on

¹ Here and throughout our definition of the term "school quality" is extremely narrow. We refer only to the financial resources and personnel that schools have at their disposal.

individuals' educational and occupational attainments. We conclude by offering some initial remarks on what these models might look like.

A brief overview of research on school effects

Questions concerning the efficacy of school resources can hardly be considered new. Since the release of the influential "Coleman Report" (Coleman et al. 1966) social scientists have sought to link school quality to a variety of outcomes, including achievement on standardized tests (Hanushek 1986), labor market experiences and lifetime earnings (Card and Krueger 1992; Grogger 1996b; Heckman et al. 1996), and educational and occupational attainment (Betts 1995; Greenwald et al. 1996; Griffin and Alexander 1978; Kerckhoff et al. 1982; Sander 1993). The results of these efforts have been surprisingly unsuccessful (Hanushek 1997). Academic performance has been shown to be independent of school attributes and resources (Hanushek 1986; 1989). Similar conclusions have been reached with respect to earnings (Betts 1995; Grogger 1996a) and employment (Dearden et al. 2002). Even in those cases where the empirical evidence suggests that additional resources do have a predictable effect on labor market prospects, the effect size has often been modest (Card and Krueger 1996; Grogger 1996b; Heckman et al. 1996; Hedges et al. 1994). While it is certainly possible that these findings reflect an underlying reality about the influence of school resources, we feel that it would be premature to draw such a firm conclusion. Three questions, in our view, are deserving of further consideration.

The first relates to the way researchers measure school resources. Despite considerable disagreement over the appropriate unit of analysis (e.g., the classroom, the school, the district, or the state), scholars have been remarkably consistent in one important respect: they generally observe school characteristics at a single time point, usually early during the primary years or

when students enter high school. In his exhaustive survey of the school effects literature, for example, Hanushek (1997) reviewed nearly 400 estimates of the impact of school resources on student outcomes—all of which pertained to elementary school characteristics or characteristics at the secondary level, but never both.² The validity of this technique is unclear. If the resources available to schools and their students remain stable over time and across institutional boundaries, then a single measurement should suffice. If, however, education is better understood as a cumulative process, where resources vary from one school year to the next, then ignoring the duration and sequencing of students' exposure to educational resources seems inappropriate. In this paper we describe a more dynamic measurement approach, which permits indicators of school quality to fluctuate over time.

The second question deals with the mechanisms through which school characteristics confer benefits to students. Although much has been written about the impact school quality has on years of schooling and on the rate of return to schooling (Card and Krueger 1992; Card and Krueger 1996; Heckman et al. 1996; Johnson and Stafford 1973), we are not aware of any empirical studies that relate school quality to the *type* of education students receive. It seems reasonable to expect that instructional resources and learning environments shape, at least in part, students' course taking patterns; a set of decisions that have known consequences for college enrollment (Gamoran and Mare 1989; Oakes et al. 1992; Rosenbaum 1980) and subsequent labor market outcomes (Rose and Betts 2004). After identifying the most appropriate way to conceptualize and measure school resources, future drafts of this paper will investigate this possibility (1) by examining the role school quality plays in determining curricular track; (2)

² Just over one-quarter of the studies Hanushek (1997) considered employed a value-added approach, where the specified model included information about prior achievement to “ameliorate any problems arising from missing data about past school and family factors” (p. 147). While this class of studies is clearly an improvement over other approaches, we hesitate to call it a substitute for directly observing school data for each year between kindergarten and high school graduation.

by measuring the extent to which school quality influences post-secondary enrollment and attainment net of course taking; and (3) by estimating the effect of school quality on occupational attainment across the life course, controlling for track and post-secondary attainment.

Our third and final question concerns causal heterogeneity. With the exception of research on black-white differences in returns to school quality (e.g., Morgenstern 1973; Rizzuto and Wachtel 1980; Akin and Garfinkel 1980), very few studies have investigated the ways in which the impact of the attributes and characteristics of elementary and secondary schools might be heterogeneous across groups of students (Griffin and Alexander 1978). Instead, the bulk of the school effects literature concentrates on the average returns to various school inputs (Namboodiri et al. 1993). We imagine, in contrast, a number of ways in which school effects may vary across groups of students. For example, the impact of pupil-teacher ratios may vary across students at different points in the IQ distribution; the impact of school financial resources may vary by student socioeconomic background; and the consequences of the attributes of schools on labor market outcomes may be different for people in rural areas than they are for their urban counterparts. In subsequent versions of this paper we intend to integrate the group-based modeling technique, described at length below, into the potential outcome approach to estimate causal effects and to understand how these effects differ across groups of students.

Constructing our data set and measures

We analyze data from the Wisconsin Longitudinal Study (WLS), a long-term study of a random sample of 10,317 men and women who graduated from Wisconsin high schools in 1957. The WLS includes detailed information about social background, youthful aspirations, schooling experiences, military service, labor market experiences, family characteristics and events, social

participation, psychological characteristics, retirement, and health. Survey data were collected from the original respondents by mail and/or telephone in 1957, 1964, 1975, 1993, and 2005 and from a randomly selected sibling in 1977, 1994, and 2004. Retention across survey waves has been remarkably high, with more than three quarters of living respondents participating in the most recent round of surveys.

To supplement the limited amount of school-characteristic data already on offer in WLS, we collected archival data from annual district reports filed with the Wisconsin Department of Public Instruction at the conclusion of every academic year. These data are housed at the Wisconsin State Historical Society, and can be obtained for all years in which the WLS cohort was enrolled in primary and secondary schools (e.g., 1945-1957). For each year our records include information (separately by level of schooling) on the number of pupils and number of teachers; the duration of the school year; the number and type of school facilities available; teachers' salaries; expenditures on instruction; enrollment by grade and gender; number of graduates in 1957, by gender; teachers' experience; and teachers' education. It should be noted that because the vast majority of Wisconsin school districts were comprised of one elementary school, one middle school, and one high school, these district-level data are largely synonymous with schoolhouse data.³

Two variables in the WLS allowed us to link the district data to members of the cohort: a question from the 2005 telephone survey that asked respondents to provide the name and location of the elementary school they attended the longest; and high school district identifiers

³ Of the district records that we collected for the 1945 school year, for instance, 91.8 percent contained only a single elementary school. The exceptions include large urban districts like Madison and Milwaukee, which encompassed a number of neighborhood schools and satellite communities.

from the original 1957 survey.⁴ Using this information to match individuals to multiple years of district data required us to make strong assumptions about students' geographic mobility. Only knowing the district in which respondents attended elementary school the longest, for example, forced us to treat all individuals as if they remained in a single district for the entirety of their primary years. Similar compromises were necessary for the high school years (e.g., 1954-1957), where the only information available to us was respondents' location during their senior year.

In an effort to validate this procedure, we compared the location of respondents' high schools and primary schools with their place of birth. Because the WLS does not offer information pertaining to childhood migratory experiences, this comparison was meant to provide a crude assessment of respondents' geographic mobility. Not surprisingly, a substantial proportion of respondents (58.9 percent) attended primary school in the city in which they were born. More importantly for our purposes, 49.9 percent completed their senior year of high school in their city of birth, and 84.8 percent reported going to elementary school in the same city as their high school.⁵ While obviously an imperfect assessment of mobility, the latter two findings provide some reassurance as to the extent of inter-district migration.

Once respondents were matched to primary and secondary districts, we computed a number of frequently cited measures of school quality. These time-varying variables, which represent the focal point of our analysis, include indicators of classroom characteristics (percent

⁴ The actual 2005 survey question was phrased somewhat differently depending on whether the respondent attended elementary school in a city or rural area, a difference that had implications for how we matched respondents' to the district-level data. Most respondents attended elementary school in a city or township, and were thus asked to provide the name of that municipality. Respondents who attended elementary school in a rural area, however, were told to name the county in which the school was located. Because Wisconsin counties were often comprised of multiple school districts, we were forced to allocate these individuals to their most likely elementary school district using a probabilistic assignment rule. First, we determined the enrollment in each district as a percentage of the total county enrollment. Next, we assigned each respondent a random number between 1 and 100. We were able to use these two numbers—the percentage of the total county enrollment that a district accounted for and the random number—to allocate respondents. For example, if District A made up 34 percent of the total county enrollment and District B made up the remainder, we assigned respondents with random numbers between 1 and 34 to District A and individuals with random numbers between 35 and 100 to District B.

⁵ An even larger share, 93.3 percent, attended elementary school and high school in the same Wisconsin county.

of teachers with 4 or more years of schooling beyond the 12th grade, percent of teachers with 5 or more years of teaching experience, and pupil-teacher ratio) and financial resources and outlays (per pupil expenditures, which we present in constant 2000 dollars). In very rare instances, we applied logical edits and imputation procedures to handle implausible or missing values. In the next section we describe how we applied these variables within a group-based modeling framework.

Measuring school quality as a group-based trajectory

The primary emphasis and primary contribution in this draft is the estimation of group-based trajectory models. Below, we briefly outline group-based modeling techniques as they will be used to identify categories of school quality trajectories and assign individuals to specific groups. Let $Y_i = \{y_{i1}, y_{i2}, y_{i3}, \dots, y_{iT}\}$ represent the longitudinal sequence of measurements of some attribute of individual i over T time periods (e.g., pupil-teacher ratio or per pupil expenditures as measured across the years in which WLS respondents were enrolled), and let $P(Y_i)$ represent the probability of observing Y_i . Group-based trajectory models assume that there are J underlying trajectory groups in the population such that

$$P(Y_i) = \sum_{j=1}^J \pi_j P^j(Y_i), \quad (1)$$

where $P^j(Y_i)$ is the probability of observing longitudinal sequence Y_i given membership in group j and π_j is the probability of group j (Jones et al. 2001; Nagin 1999b). The model assumes that the random variables y_{it} , $t=1,2,3,\dots,T$, are independent conditional on membership in group j . Thus

$$P^j(Y^i) = \prod_{t=1}^T p^{jt}(y_{it}). \quad (2)$$

The values of π_j , $j=1,2,3,\dots,J$, are estimated by a multinomial logit function:

$$p_j = e^{q_j} / \sum_{j=1}^J e^{q_j}, \quad (3)$$

where π_l is normalized to zero (Jones et al. 2001). The functional form of $p^{jt}(y_{it})$ in Equation 2 is determined by whether y_{it} is a continuous variable or a binary variable. When y_{it} is a continuous variable, as is the case throughout our analysis, $p^{jt}(y_{it})$ is assumed to follow a censored normal distribution, in part to allow for the possibility of clustering at the minimum and maximum (Jones et al. 2001; Kim and Lee 2006; Nagin 1999b; Nagin 2005).

The link between time and the variable in question is modeled as a polynomial relationship; the software that estimates these models allows for up to fourth-order polynomials. For example, when y_{it} is continuous, the linkage between time (or year, in our case) and the variable in question is established via latent variable y_{it}^{*j} such that:

$$y_{it}^{*j} = b_0^j + b_1^j Year_{it} + b_2^j Year_{it}^2 + b_3^j Year_{it}^3 + e_{it}, \quad (4)$$

where disturbance ε_{it} is assumed to be distributed normally with a mean of zero and constant standard deviation σ (Jones et al. 2001; Nagin 1999b; Nagin 2005).

After the model has been fit, the parameter estimates can be used to compute an individual's posterior probability of group membership, denoted $\hat{P}(j | Y_i)$. The posterior probability records the likelihood that an individual i , with the observed sequence of school characteristics measurements Y , belongs to a given trajectory group j . In this respect, the posterior probability provides a criterion for assigning individuals to their most likely trajectory group. As described in considerable detail in Nagin (2005), the appropriate formula is:

$$\hat{P}(j | Y_i) = \frac{\hat{P}(Y_i | j) \hat{p}_j}{\sum_j \hat{P}(Y_i | j) \hat{p}_j}, \quad (5)$$

where $\hat{P}(Y_i | j)$ and \hat{p}_j are calculated according to Equation 2 and 3, respectively.

Models are estimated through maximum likelihood, where the maximization is performed using a general quasi-Newton procedure (Dennis et al. 1981; Dennis and Mei 1979). Throughout our analysis we relied upon the Bayesian Information Criterion (BIC) for model selection (e.g., to determine the preferred number of trajectory groups). See Jones, Nagin, and Roeder (2001) and Jones and Nagin (2007) for more information about model estimation. We estimated our group-based trajectory models using the SAS procedure PROC TRAJ.

Preliminary results from our group-based models

In this section we present preliminary results from our group-based models and then go on to describe the characteristics of the individuals assigned to each trajectory group. In all of our models the sample began with the randomly selected subset of WLS respondents who were asked to provide the name and location of their Wisconsin elementary school ($n = 3,520$). We subsequently dropped cases ($n = 413$) where the individual attended private or parochial schools during both their primary and secondary years; unfortunately, the district reports that we collected provide no information about the resources and characteristics of these schools. We then eliminated an additional 22 individuals because they attended public elementary and/or high schools for which no district-level data were available.⁶ The resulting sample includes 3,085 individuals and is broadly representative of white men and women with at least a public high school diploma.⁷

⁶ In a supplementary analysis we compared these individuals to those in our final sample. In terms of social background (father's occupational status and parents' years of schooling), family composition (number of siblings and family structure), and geographic characteristics (farm versus non-farm), the two groups were statistically indistinguishable from one another. Results from this analysis are available upon request.

⁷ In future analyses we plan to incorporate information regarding district graduation rates in order to make adjustments for censoring at 12 years of schooling.

We relied on the BIC to determine the appropriate number of trajectories (Raftery 1995). The PROC TRAJ software calculates the BIC as the value of the model's maximized likelihood minus one-half the number of parameters in the model multiplied by the log of the sample size (Nagin 2005). In this respect, the statistic extracts a penalty for adding additional parameters (e.g., trajectories or higher-order terms), and thus tends to favor more parsimonious model specifications. To calibrate the improvement in fit between a model with j trajectories and a model with $j + 1$ trajectories, we treated twice the change in the BIC or $2(\text{BIC}_{j+1} - \text{BIC}_j)$ as an approximation of the Bayes factor (D'Unger et al. 1998; Kass and Raftery 1995; Kass and Wasserman 1995; Raftery 1995). According to Raftery's (1995) revision of Jeffrey's (1961) scale of evidence, a Bayes factor of more than 20 represents "strong evidence" that model M_{j+1} is preferable to model M_j . As illustrated in Table 1, we added groups iteratively until further improvement in model fit (e.g., strong evidence) could not be achieved. Our preferred models are shown in bold.

Figure 1 plots trajectories of per pupil expenditures from kindergarten through 12th grade. We obtained the best fit using a two-group model, in which 60.3 percent of respondents were classified as receiving consistently low expenditures (group 1) and the remaining 39.7 percent were grouped into the consistently high expenditure trajectory (group 2). Both trajectories employ a third-order polynomial. Note that the point estimates for each trajectory—and the accompanying group-specific means, graphed in grey—appear to be parallel throughout the entire period.⁸ We formally tested this hypothesis using a Wald test (Jones and Nagin 2007; Wald 1943). The procedure showed that the intercepts for the two trajectories were significantly different from one another, but coefficients on the higher-order terms were not—a result that is

⁸ The group-specific means represent weighted averages based on actual per pupil expenditures in group members' districts. The weights are a function of each member's probability of belonging to the group in question. See Nagin and Tremblay (2005) for a more detailed discussion.

consistent with the notion of parallel trajectories. This finding offers evidence that a conventional, single-measurement approach to modeling per pupil expenditures (e.g., taking data from one year) is sufficient. That is, at any point from kindergarten to high school graduation the same basic pattern holds: one segment of the population attends schools with more financial resources.

The same pattern does not hold for teachers' educational background. Figure 2 displays our preferred three-group model of teachers' schooling trajectories. Each of the three trajectories—labeled low schooling, medium schooling, and high schooling—was specified to follow a cubic function of year. The form of the expected trajectories and the observed means reveal appreciably large between-group differences at the primary level, which attenuate almost completely when students transition to high school. It is not surprising, then, that Wald tests easily rejected the hypothesis of equivalent higher-order coefficients ($\alpha = .01$), indicating that the trajectories are not parallel. What does this mean in terms of analyzing teachers' schooling? Importantly, it suggests that the way we measure teachers' education shades our interpretation of potential inequities. A measurement obtained during the high school years produces a different picture than a measurement taken during elementary school, and a different picture still than an approach that considers the entire duration. A student in group 1 has had a different set of school resources than a student in group 4, even though the two students' teachers look quite similar with respect to experience if measured at a single point in time in high school

One can draw a similar conclusion from Figures 3 and 4. The former summarizes teachers' experience trajectories from our preferred five-group model and the latter graphs trajectories for a four-group model of pupil-teacher ratio.⁹ Although both figures include groups that run parallel to one another throughout the entire period, they also contain trajectories that

⁹ For the sake of graphical clarity, we have omitted the group-specific means in Figures 3 and 4.

converge as students move from grade school to graduation, as well as groups that bifurcate over time. Consider the trajectories for individuals in groups 1 and 4 in Figure 3, for example. Comprising just over one-sixth of the sampled population (16.8 percent), group 1 consists of respondents whose primary and secondary schools had uniformly low levels of experienced teachers (between 52 and 66 percent). For members of group 4, on the other hand, the share of experienced teachers diminished steadily over time, falling from a maximum of 91 percent in the second grade to a level in high school that was commensurate with group 1. The fact that these trajectories take different routes to the same destination indicates, again, that the choice of measurement technique and time horizon can influence how we portray youths' exposure to school resources.

Individual-level characteristics of group members

In the foregoing analysis we identified and described distinct school characteristic trajectories. Interesting questions about the members of these trajectories, however, remain unanswered. Do individuals in different trajectories differ with respect to socioeconomic background? Does family structure and urban-rural status influence the likelihood of belonging to one trajectory versus another? The best way to answer these questions—at least at the bivariate level—is to use the maximum posterior probabilities calculated in Equation 5 to sort WLS respondents into their most likely trajectory group. These assignments, in turn, permit us to cross-classify trajectory group membership with a number of individual, familial, and geographic characteristics. Note that this procedure is not immune to misclassification (Roeder et al. 1999). Individuals whose posterior probability places them on the margins of two or more groups, for example, are

assigned to their most likely trajectory despite the presence of significant uncertainty.¹⁰ In order to alleviate this concern we weighted each case according to its posterior probability of group membership. For a more detailed discussion of this weighting technique see Nagin (2005: 91-92).

Table 2 provides the resulting cross-classification. We expressed social background, family structure, and geographic characteristics in terms of father's occupational status (measured using Duncan's socioeconomic index or SEI) in 1957, mother's and father's years of schooling completed, whether the respondent lived on a farm in 1957, whether the respondent's family was intact, and the size of the respondent's sibship. Comparing the profiles of each of the groups within the four types of trajectory models, at least two patterns are apparent. First, groups can be distinguished according to members' urban-rural status. Members of the low and medium-declining pupil-teacher ratio trajectories, for example, are significantly more likely live on farms than members in either of the other two groups—a finding that is not surprising given the sparse enrollments in many of Wisconsin's rural school districts. Second, group membership is a correlate of social background. For instance, individuals in the high teachers' experience trajectory tend to come from households with well-educated and well-paid parents. This is a departure from the low experience group, where having a father with a lower status job is more typical. In fact, the 11 point gap between the two trajectories in terms of father's SEI represents a difference of more than one-half of a standard deviation.

These patterns provide evidence that respondents are not distributed randomly to the trajectory groups we identified above. Urban-rural status and socioeconomic background each influence the trajectory of educational resources that student experience from kindergarten

¹⁰ A series of model accuracy diagnostics, which we do not report here, indicate that our models sort individuals into specific groups with a sufficiently high degree of certainty. The results from these diagnostics are available upon request.

through 12th grade. Although it remains (for now) to be seen whether trajectories of school characteristics independently influence educational or post-schooling outcomes, it seems very likely that trajectories of school characteristics serve as an important mechanism through which educational advantage and disadvantage are reproduced across generations.

Concluding remarks and future directions

In this paper we introduced a new way to evaluate the educational resources that young people encounter as they make their way from kindergarten to high school graduation. Using a group-based modeling strategy and a unique data set, we empirically tested for and identified a series of categorically distinct school quality trajectories. We showed that these trajectories vary substantially in terms of their shape and slope, their prevalence within the sampled population, and in the sociodemographic makeup of their constituent members.

What have we gained by using this technique over more conventional approaches? First, the group-based method allows for a more dynamic measurement of the duration and sequencing of youths' exposure to different educational resources and environments. Although this mode of thinking is well-established within the life-course literature (Elder 1985; Elder 1998; George 1999; Moen et al. 1992), and is becoming increasingly common in the study of delinquent and criminal behavior (D'Unger et al. 1998; Laub et al. 1998; Sampson and Laub 1995), childhood poverty (Wagmiller et al. 2006), and health and obesity (Mustillo et al. 2003), to our knowledge the present analysis is the first to use trajectories to conceptualize the way students' experience different school characteristics and attributes.

Second, and perhaps just as importantly, we have established key empirical parameters for future investigations. The trajectories that we derived in the previous section can be used to assess the dependency between school characteristics and an assortment of subsequent outcomes,

including course-taking patterns, college enrollment and completion, and occupational attainment across the life-course. It is worth noting that such investigations are not confined to standard regression estimators. Following the inferential strategy set forth by Haviland and colleagues (Haviland and Nagin 2005; Haviland and Nagin 2007; Haviland et al. 2006), we intend to incorporate the group-based modeling technique into the potential outcome, counterfactual approach to causal analysis. We expect that this methodology—which builds on the posterior probabilities and trajectories estimated above—will yield new insights into the presence and extent of school effects, the mechanisms through which these effects operate, and the members of the population for whom they are the most relevant.

Table 1. Bayesian Information Criterion (BIC) and Approximate Bayes Factors (2 x ΔBIC)

Model, BIC, Approximate Bayes Factor	Number of groups					
	1	2	3	4	5	6
Per pupil expenditures						
BIC	-202360.5	-198338.4	-198358.5	—	—	—
2(ΔBIC)		8044.2	-40.2	—	—	—
Teachers' education						
BIC	-1888.47	8170.43	10747.73	10747.06	—	—
2(ΔBIC)		20117.8	5154.6	-1.34	—	—
Teachers experience						
BIC	12184.04	16324.32	17655.84	18212.67	18795.63	18780.56
2(ΔBIC)		8280.56	2663.04	1113.66	1165.92	-30.14
Pupil-teacher ratio						
BIC	-80579.81	-77521.58	-76032.34	-75108.54	-75099.55	—
2(ΔBIC)		6116.46	2978.48	1847.6	17.98	—

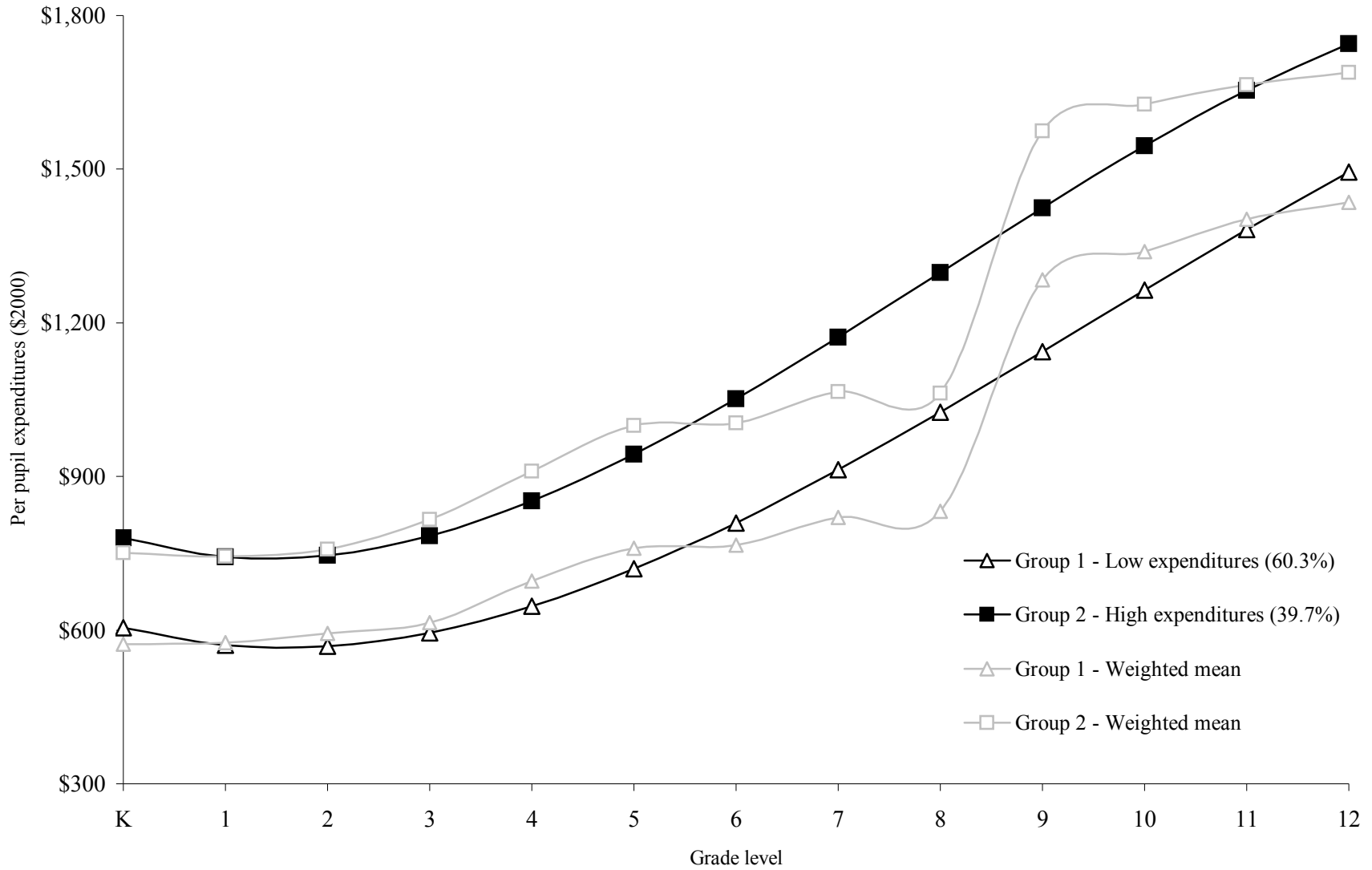
Note: As described in Nagin (2005), the PROC TRAJ estimation software computes BIC as $\log(L) - 0.5k \log(N)$, where L is the value of the model's maximized likelihood, N is the sample size, and k is the number of parameters. All models were specified to follow a cubic form. We used Raftery's (1995) revision of Jeffrey's (1961) scale to determine the preferred number of groups j , in which an approximate Bayes factor of more than 20 offers "strong evidence" that model M_{j+1} is preferable to model M_j . Groups were added iteratively until further improvement (e.g., strong evidence) could not be achieved. Preferred models are shown in bold.

Table 2. School quality trajectory group profiles, by select sociodemographic characteristics (N = 3,085)

School quality indicator and trajectory group	Background characteristics						
	Mean occupational status (SEI), father	Mean years of schooling, father	Mean years of schooling, mother	Proportion in two-parent household	Mean number of siblings	Proportion living on a farm	Average family income (logged \$1957)
<i>Per pupil expenditures</i>							
Group 1: Low expenditures	29.03	9.35	10.32	0.91	3.49	0.27	8.38
Group 2: High expenditures	36.16	10.25	10.61	0.90	2.91	0.09	8.63
<i>Teachers' education</i>							
Group 1: Low schooling	23.75	9.06	10.11	0.91	3.81	0.42	8.19
Group 2: Medium schooling	34.26	9.95	10.49	0.91	3.10	0.14	8.57
Group 3: High schooling	29.12	9.29	10.52	0.89	3.42	0.25	8.35
<i>Teachers' experience</i>							
Group 1: Low experience	26.52	9.17	10.18	0.92	3.52	0.32	8.30
Group 2: Medium experience	25.30	8.82	9.96	0.91	3.95	0.42	8.19
Group 3: Medium-declining experience	26.89	9.16	10.26	0.91	3.62	0.32	8.31
Group 4: High-declining experience	32.37	9.82	10.57	0.89	3.27	0.18	8.51
Group 5: High experience	37.54	10.33	10.67	0.90	2.84	0.05	8.68
<i>Pupil-teacher ratio</i>							
Group 1: Low pupil-teacher ratio	29.41	9.57	10.06	0.92	3.66	0.29	8.36
Group 2: Medium-declining pupil-teacher ratio	26.14	9.17	10.29	0.89	3.65	0.32	8.25
Group 3: Medium pupil-teacher ratio	33.74	9.90	10.58	0.91	3.11	0.16	8.56
Group 4: High-declining pupil-teacher raio	34.59	9.83	10.57	0.89	2.87	0.12	8.58
Entire sample (s.d.)	31.93 (21.10)	9.73 (3.32)	10.45 (2.82)	0.90 (0.29)	3.26 (2.56)	0.20 (0.38)	8.49 (0.67)

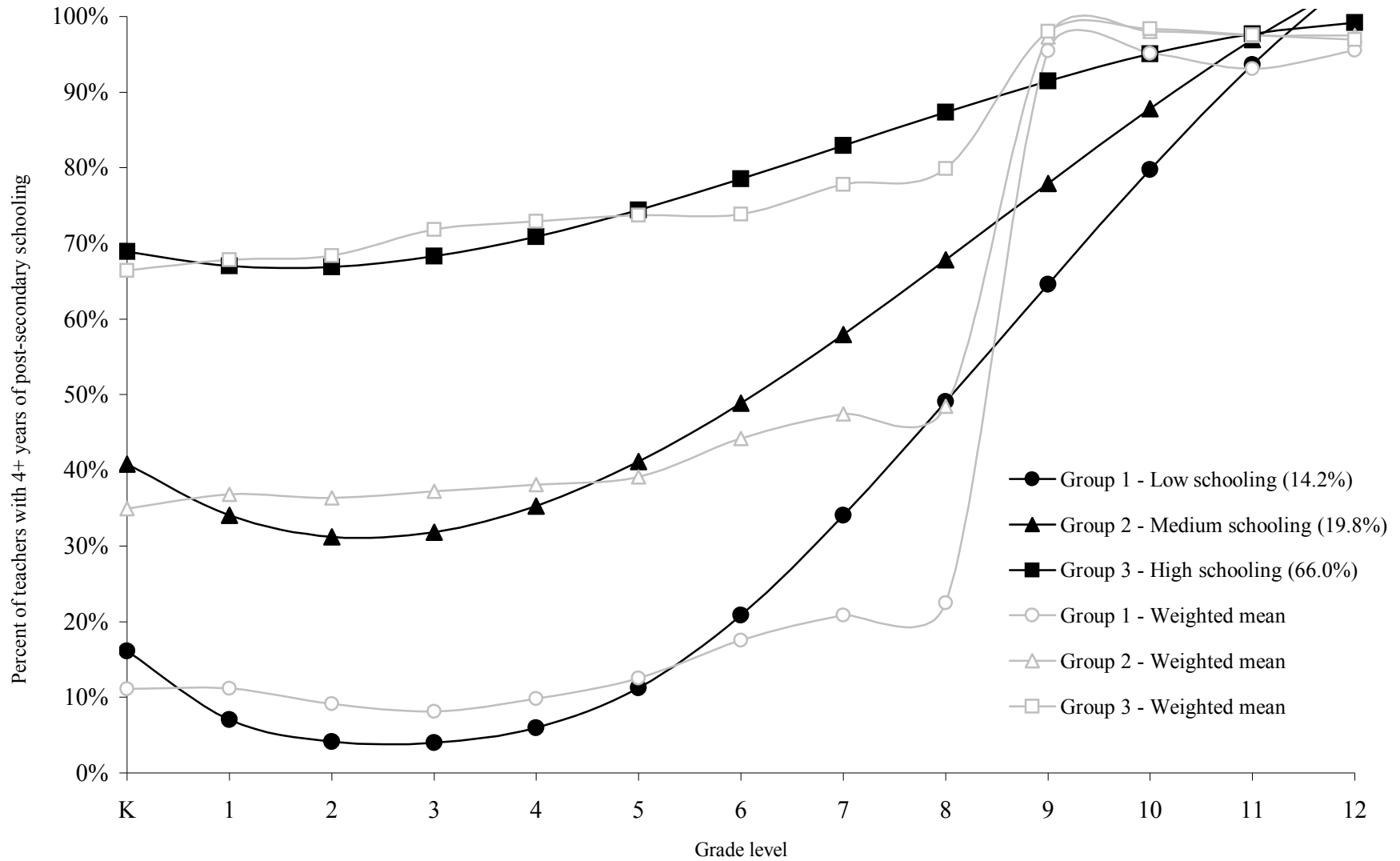
Note : In total, there were 354 cases where family income was missing in the 1957 graduate survey; 30 cases where father's occupational status was missing; 6 cases where there was no information on number of siblings; and 2 cases where respondents' did not provide a valid answer with respect to their parents' marital status. Rather than dropping these individuals, we used hot-deck imputation methods to impute missing values. All of the cross-tabulations employ weights based on the posterior probability of group membership (as per Equation 5). See Nagin (2005: 91-92) for further discussion of this weighting technique.

Figure 1. Trajectories of per pupil expenditures



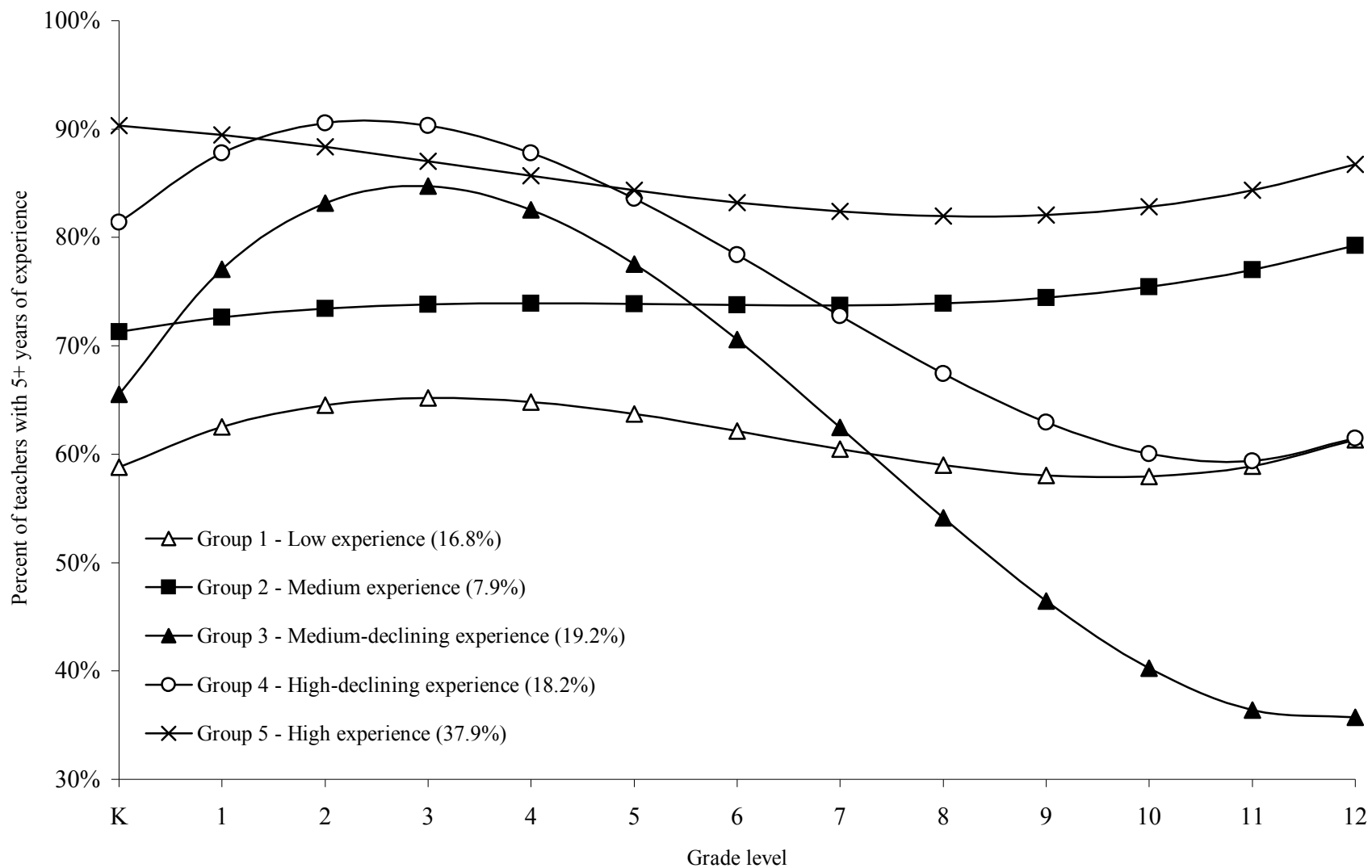
Source: Wisconsin Longitudinal Study (WLS); Wisconsin State Department of Public Instruction, Annual School District Reports, 1945-1957

Figure 2. Trajectories of teachers' education



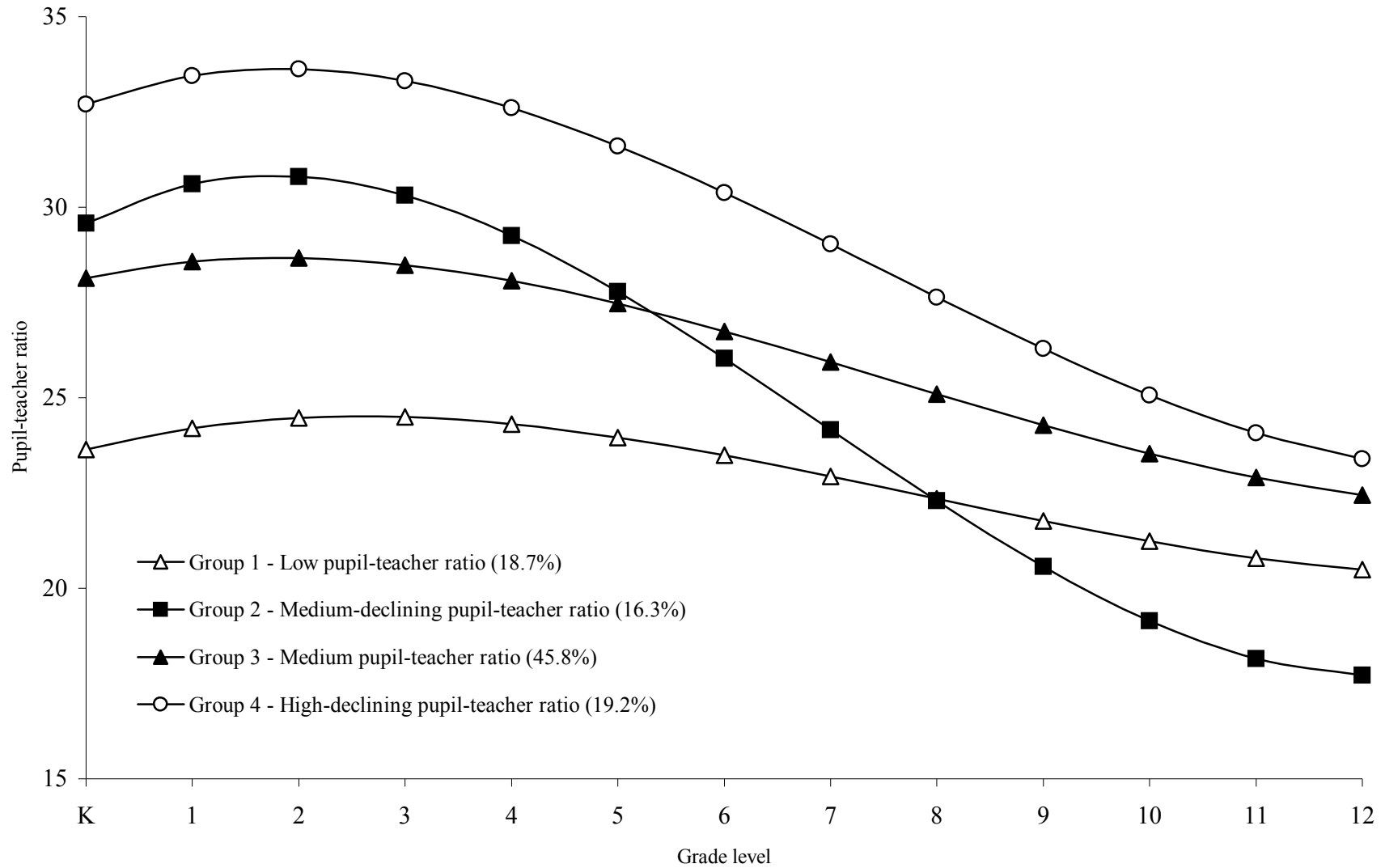
Source: Wisconsin Longitudinal Study (WLS); Wisconsin State Department of Public Instruction, Annual School District Reports, 1945-1957

Figure 3. Trajectories of teachers' experience



Source: Wisconsin Longitudinal Study (WLS); Wisconsin State Department of Public Instruction, Annual School District Reports, 1945-1957

Figure 4. Trajectories of pupil-teacher ratio



Source: Wisconsin Longitudinal Study (WLS); Wisconsin State Department of Public Instruction, Annual School District Reports, 1945-1957

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