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Abstract

Educational expectations measure a youth's plans for further educational attainment and have been dubbed the "strategic center" of a model of educational and occupational outcomes. Research on educational expectations has been invigorated of late with increasing interest in decision-making theories in sociology and economics. In this paper, we compare long-standing theories in the status attainment literature about the static nature of expectations with ideas drawn from Bayesian learning theory about the importance of experiential learning in educational expectations. In this comparison, we focus on race-ethnic differences in the formation and effects of educational expectations, another long-standing but problematic finding in the literature on educational expectations. Contrary to early status attainment research, we find relatively little support for a static latent construct driving students' reports of educational expectations. However, we also find there is minimal updating of expectations based on rather large changes in grade point average. These processes do not vary by race-ethnic group in a correctly specified model with appropriate academic achievement measures and errors in variables. We conclude that educational decision models cannot be monolithic in their conceptualization of the decision-making process, a fact that invites the continued development of appropriate and rigorous social psychological models of the education process.

INTRODUCTION

Beginning with Sewell, Haller, and Portes (1968), the educational expectations of youth have enjoyed sustained interest in the sociological literature as the "strategic center" of social psychological models of status attainment (Haller and Portes 1973:68). Interest in educational expectations has surged of late as sociologists, economists, and psychologists seek to understand decision-making processes related to individual outcomes. This surging interest in economics and sociology traces to accumulating evidence of violations of many of the basic assumptions of a strict, neo-classical rational choice model and persisting social class inequalities vis-à-vis educational attainment in many contexts. Calls for revised decision-making models—largely based on Bayesian theory—mark both the economic and sociological literatures (Manski 1993, 2004; Breen 1999; Morgan 2005). Yet, the literature in both sociology and economics has little to say about the way students really formulate and revise educational expectations over time, largely resorting to inferred caricatures of these processes rather than modeling educational expectation formation and revision directly.

In this paper, we aim to better understand how adolescent students make decisions about their education. Specifically, we compare long-standing but untested status attainment theory about static educational expectations with more recent assertions in sociology and economics based on Bayesian learning theory positing the importance of experiential learning and revision in educational expectations. We model this process by race-ethnic groups for which distinct differences in the relationship between expectations and education have been observed for some time. We focus on educational expectations in adolescence for a number of reasons. Educational expectations are used widely in research in sociology, and detailed, repeated panel measures are available in national studies from adolescence forward. Recent research assesses the role of expectations in college attendance and finds very small changes in expectations after a student enrolls in post-secondary school though a rather large effect of educational expectations in high school on expectations during post-secondary schooling (Alexander, Bozick, and Entwisle 2008).[1] Thus, it makes sense to begin with the formation and revision of expectations in early adolescence forward. We begin with a discussion of educational expectations before turning to more recent work on educational decision-making. We then provide an exposition of dynamic structural models of expectation revision in the context of accumulating information about academic achievement and of the effect of expectations on years of educational attainment.

BACKGROUND

Situating Educational Expectations in Sociological Research

Two notable and related assumptions of an older body of research on educational expectations persist today: (1) the assumption that educational expectations depend upon a static construct of achievement motivation or the like, and (2) evidence of statistically significant race-ethnic differences in expectations formation and in the effect of expectations on educational attainments. Both are central to any inquiry into the formation and revision of educational expectations, so we address them in turn.

Initial research on educational expectations uses survey data for samples of white males only and finds educational expectations mediate the effects of social background characteristics on later educational attainments. Perhaps not surprisingly, subsequent research finds the original status attainment model and its social-psychological variants do not describe the attainment processes for Blacks and women as well as for white males (Blau and Duncan 1967; Sewell 1971). In particular, early findings indicate that whites' educational expectations depend more on socioeconomic status than Blacks' and that expectations exert a smaller and sometimes insignificant effect on Blacks' educational attainment (Kerckhoff and Campbell 1976, 1977; Portes and Wilson 1976).[2] Evidence from that early body of work also suggests further racial differences in expectations formation. Hout and Morgan (1976), for example, find that grades have a stronger effect on educational expectations among Black males than other race-sex groups.

Early and substantial evidence of Black-white differences in the effect of educational expectations has been attributed to various sources including, most importantly, racial discrimination. Ultimately, this evidence sparked a shift away from the idea of socialized expectations offered by the Wisconsin school to an arguably more structural "allocation" model emphasizing the importance of available opportunities and individuals' perceptions of their opportunity structure (Kerckhoff 1976). Not surprisingly, research employing an allocation model found direct and indirect evidence of the importance of individuals' perceptions of opportunity structures and of discrimination for educational outcomes (Kerckhoff and Campbell 1977). However, differences between the socialization and allocation perspectives are more a matter of nomenclature than of substance in many respects. Both perspectives draw on the notion that an individual's subjective perceptions are socially conditioned and differ by her or his position in a social hierarchy. While the socialization perspective highlights the family and school milieu, the allocation perspective highlights the civic milieu and its racial politics. Both the socialization and allocation perspectives, however, emphasize individuals' psychological states of mind and how such subjective states affect their (ultimate) social position. Both perspectives also model expectations as static and unyielding internal states, thus unaffected by changes in social, civic, and academic statuses and environments. Therefore, questions remain not only about the social-psychological dynamics of educational expectations but about the extent of race-ethnic differences in the formation and effects of educational expectations as well as.

Linking Educational Expectations and Decision-Making Theory

An increasing interest in the micro-foundations of educational inequalities and individual decision-making models has led to a recent, concomitant increase in interest in educational expectations since the 1990s. This interest stems from developments in both economics and sociology. Many economists are beginning to abandon core assumptions of neo-classical rational choice models such as revealed preferences in favor of more direct measures of behavior and intentions. This movement stems in large part from work in psychology and game theory aimed at understanding the nuances of decision-making processes (von Neumann and sMorgenstern 1949; Kahneman and Tversky 1979). Despite the flexibility of neo-classical rational choice models (e.g., Becker 1993), evidence contrary to basic assumptions of the theory and continued calls for consideration of other theoretical models mark an important shift in economic thinking. Manski (1993, 2004) presents an early argument for the importance of educational expectations for understanding the micro-foundations of educational inequalities and, along with his colleagues, has begun developing probabilistic measures of expected economic returns to education (Dominitz and Manski 1994). Manski argues, "I have concluded that econometric analysis of decision making with partial information cannot prosper on choice data alone. However, combination of choice data with other data should mitigate the credibility problem and improve our ability to predict behavior. The data I have in mind are self-reports of expectations elicited…[as] subjective probabilities," (2004:1330).

Changes are afoot in sociology as well. As some economists have moved away from a neo-classical rational choice model and its entailed assumptions, sociologists have become increasingly interested in rational choice models and in decision-making and learning theory such as Bayesian theory.[3] Goldthorpe (1996) provides an early exposition of the matter. He argues that persisting and stable social status differentials in educational attainment in stratification research require more refined micro-level theory than can be found in broader theories of class dynamics. In this vein, Goldthorpe asserts the vantage point of methodological individualism and rational action provides sound epistemological footing from which to construct a micro-theory of persistent social status inequality. Starting from work by Boudon (1974) and others, Goldthorpe ultimately argues that student and parent evaluations of costs, benefits, and chances of success at different junctures in the educational system underlie the persistence and stability of class differentials (1996:491). This is the case because of class differences in risk thresholds and inequalities in educational resources (1996:495,496). He concludes that greater attention must be paid to how educational decisions are made and, in particular, how information informing these decisions is processed (1996:497).

Several sociologists have heeded Goldthorpe's call to develop micro-level decision models (e.g., Breen 1999; Breen and Garcia-Penalosa 2002). Morgan (2004, 2005) presents a useful and recent discussion of educational expectations. Similar to earlier work, Morgan also calls for a micro-level model of educational decision-making and endorses Bayesian learning theory as a useful starting point. This theory suggests that individuals update prior beliefs or expectations based on pertinent information. In his work, Morgan briefly explores the extent to which youth update their educational expectations over time. He estimates autoregressive correlations among educational expectations measures net of various social background measures, 10^{th} grade test scores, and expectations of significant others, a model illustrated in Figure 1. Though he does not estimate a formal model of updating in educational expectations, he argues such auto-regressions are "the signature of an underlying dynamic process" (2004:36). Morgan finds evidence of declining correlations between expectations measures across time for at least whites and Black females. He also suggests the smaller correlation between a residualized measure of expectations in the first period and the same measure in the last period indicates expectation revision. However, his work is not clear on the matter since it does not explicitly model updating in expectations. The residualized correlations he observes do not necessarily stem from an underlying dynamic process. In fact, these correlations and their pattern could be due to any number of sources such as measurement error, an underlying static construct, omitted variables, and more—none of which is tested. Instead, Morgan suggests observed race-ethnic differences in the effect of expectations on educational attainment depend on "additional belief-based effects for Blacks that operate outside of traditional status socialization models" (p. 69). He goes on to develop a theoretical model of educational commitments and attainments, leaving the questions of experiential learning in educational expectations and race-ethnic differences in the formation and effects of expectations unanswered.

Insert Figure 1 here.

Evaluating the Evidence on Learning in Educational Decision-Making

Recent work in sociology and economics on decision and learning models like Morgan (2004, 2005) provide a powerful impetus for examining how we think about educational decision-making. It moves us away from the notion that educational expectations are indicators of a stable latent construct associated with status attainment research and, to a lesser extent, allocation models.[4] However, evidence elsewhere clearly suggests caution should be exercised in freely applying Bayesian learning models to educational decision-making. Indeed, Goldthorpe's own theoretical exposition on the matter emphasizes the importance of ability handicaps and adaptation strategies determined by social background and the likely difficult task of altering the perception of potential educational success at least partially generating such handicaps and strategies. Therefore, ideas about the stability of educational expectations across the educational career may not be completely off the mark.

Survey evidence clearly supports this possibility. Correll (2001) assesses gender differences in students' academic self-assessments and choice of college major in a sample of high school students from the 1990s. In those analyses, male students are more likely to assess their math ability at higher levels than female students with similar math test scores and grades. However, this relationship flips with verbal ability. In that case, female students assess their verbal ability at higher levels than do male students with similar verbal test scores and grades. Students may not update subjective assessments and expectations in the face of new information based on socially structured, in this case gendered, notions about aptitude and the like.

One also finds evidence of inertia in academic self-concept and expectations in research on socioeconomic or class differences in educational attainments. Gabay-Egozi, Shavit, and Yaish (2009) assess curricular choices for a sample of Israeli students drawn from four high schools in Tel Aviv. They find socioeconomically disadvantaged and female students are more likely to complete curricula that the authors suggest minimize these students' risk of academic failure. From the authors' perspective, lower socioeconomic status students hedge their bets and opt to take courses in "easier" subjects such as the social sciences rather than courses in presumably more difficult subjects such as math. In contrast, higher socioeconomic status students are more likely to take the majority of their courses in difficult subjects.

There are any number of reasons why individuals like those studied by Correll (2001) and Gabay-Egozi et al. (2009) may not follow updating rules hypothesized in Bayesian and other learning models. Experimental evidence from research in decision theory suggests individual decision-makers may not act on evidence disconfirming their beliefs because they tend to overlook such information (Einhorn and Hogarth 1988). For example, a female student may ignore high levels of math achievement as anomalous because such information does not confirm her previous notions about her academic self. Indeed, other evidence from the decision-making literature suggests a "primacy effect" wherein individuals weigh information from early periods more heavily in making their decisions (Varey and Kahneman 1992). Tversky and Kahneman (1983, 1986) provide laboratory evidence suggesting individuals do not necessarily understand how new information may revise their beliefs due to strongly held dispositions such as guilt or optimism.

Neuroscience research generally corroborates survey and experiment-based evidence in psychology on the relative inertia of subjective expectations and beliefs. Neuro-social science is a growth industry that has generated several key findings over the past 30 years about the architecture and biochemistry of the brain related to the basic mechanics of human behavior. Based on evidence mainly from experiments using fMRI technology to trace blood flow in the brain (Edelman 1987; Bargh and Chartrand 1999), neuroscientists now largely believe the brain is a selective system that operates under directives of efficiency and automation. While higher executive cognitive functions like language and long-term planning are important capabilities of the human brain, automatic and subconscious processes encompass the bulk of the brain's activity. So-called "controlled" processes similar to those outlined in Bayesian learning models wherein individuals logically and consistently update their beliefs or expectations based on available information occur only in the context of special circumstances where individuals experience unexpected or challenging events or strong visceral emotions. In fact, it takes considerable effort to override automatic processes in the brain—the individual must recognize these automatic processes and then deliberately work to correct them (Gilbert 2002). The automaticity of information processing in the brain undergirds a general pattern-matching process wherein individuals automatically process new information via extant categories the brain uses to maintain efficiency (Leboeuf 2002; Medin and Bazerman 1999). Mullainathan (2002) suggests that when updating beliefs in response to new information does occur, it occurs in a disjointed manner. In summary, revision of beliefs and expectations likely occurs only in light of the accumulation of considerable evidence, based on existing categories, and in an inconsistent and sometimes unrelated manner.

Here is the problem then: While the sociological literature on education is beginning to seriously engage behavioral decision-making theories, most models leave the behavioral mechanism posited by the theory implicit and fail to directly model how individuals process information. This falls into the arguably undesirable practice of using observed outcomes to infer social psychological processes—a practice Manski (2004) refers to as "the credibility problem." Moreover, proponents of decision-making theories that assert frictionless learning and belief revision do not adequately address the evidence from experimental, survey, and fMRI studies that suggest the decision-making models championed by these theories do not hold in day-to-day experience. Still, such reservations about up-and-coming learning models seem flimsy when there has been no definitive test of counterpoint status attainment models that assert a static internal state of mind is the fountainhead of educational expectations.

Aside from the tension between status attainment and learning models of educational expectations, there is also a well-established body of assumptions and findings about race-ethnic differences in the formation and consequences of educational expectations. In our judgment, these findings are questionable because almost all of them rely on naïve analytic treatments of survey responses. That is, they ignore the possibility that observed differences in statistical estimates may be an artifact of differences in the reliability and validity of data. Early status attainment models clearly illustrate the necessity of modeling errors in variables though no recent research on expectations makes such considerations (Bielby, Hauser, and Featherman 1977; Hauser, Tsai, and Sewell 1983; Ganzeboom, Treiman, and Ultee 1991). With all of these issues in mind, we pursue three research questions here: (1) Are educational expectations static over time or do adolescent students revise expectations in the face of pertinent information? (2) Are there race-ethnic differences in this process?; and (3) If adolescents do update their educational expectations over time, to what extent does this occur, and what information affects changes in expectations?

DATA AND METHODS

Data

This analysis uses a sample from the National Education Longitudinal Study 1988 (NELS88). The NELS88 is a national probability sample of 1000 schools and 25,000 eighth-graders attending those schools in 1988. Data were collected in four waves, following students from the eighth grade in 1988 until 2000 when students were 26 or 27 years of age. The study includes surveys of students, principals, teachers, and parents as well as high school and post-secondary transcripts. Students were assessed in all years of the study; parents were surveyed in the first wave in 1988 when students were in the 8^{th} grade and in 1992 when students were typically high school seniors. The four-panel sample consists of 12,144 individuals. We limit the sample to Blacks, Latinos, and whites who participated in all four panels of the study. The former condition is necessary since we are interested in the extent to which the processes in question differ between historically disadvantaged race-ethnic minority groups and the majority group; the latter condition is necessary in order to maintain multiple measures of educational expectations and academic achievement and to obtain a measure of educational attainment at age 26 when the study concluded. We estimate models separately by race-ethnic group, imposing equality constraints on coefficients across groups as necessary. We do not consider gender differences among race-ethnic groups here due to a lack of statistical power. We further limit the sample to high school graduates in our main analyses. We invoke this criterion in order to ensure that students who have already made key decisions about educational attainment prior to later measures of educational expectations and academic achievement are not included in the sample.[5] These restrictions leave an analytic sample of 6669 whites, 759 Blacks, and 1073 Latinos. Observations with missing data on educational attainment at age 26 and any measure of educational expectations used here are dropped from the sample since the latter is the explanatory variable of greatest interest and the former is the ultimate outcome of interest. We impute missing data in other variables.[6]

We consider a number of exogenous demographic and social background measures in our models. We include a dummy measure of gender indicating whether the student is female. We also include two dummy variables for the immigrant status of the student and his/her parents. These dummy measures denote if the student was born outside the U.S. or if either parent was born outside the U.S. We include multiple measures of social background characteristics as well. In all instances except family income, we use both a student and parent report of each of the social background characteristics, mostly from the 1988 surveys. Social background variables with a student and parent measure include years of each parent's education and the occupational education of each parent.[7] We opt to use occupational education given evidence of its importance relative to other features of occupational standing in the determination of educational attainment (Hauser and Warren 1997). Parents not working in the civilian labor force are assigned the average level of occupational education for fathers or mothers within a race-ethnic group, and dummy variables indicating missingness on these variables are included in the model (Allison 2001). For family income, we include two parent reports obtained in 1988 and 1992 on the argument that the two measures together characterize the non-transitory income of the household. In addition to multiple measures of the aforementioned social background characteristics, we also use a single student report of whether the family is intact when the student is age 16. Parents were not interviewed when most students were age 16 in the study, and, therefore, we are only able to use a student report for this measure. We also include a 1988 parent report of the total number of siblings up to six or more siblings. We prefer a parent's report of the number of siblings because their version of the question is more comprehensive than the version asked of students.

The key endogenous variable in the analysis is educational expectations.

Educational expectations are elicited at multiple waves of the study with the question: “What is the highest level of education you ever expect to complete?” Respondents choose among 10 categorical options in ascending order. To facilitate comparison with Morgan (2004, 2005), we recode the original categorical variable to years of education. Though not the probabilistic estimates advocated by Bayesian theory, this measure of educational expectations still represents the subjective educational intentions and plans of youth. This measure also provides a longitudinal measure of a youth’s educational intentions and allows us to explicitly estimate a structural updating model. We include three measures of educational expectations taken in 1988, 1990, and 1992 when students were typically in the 8th, 10th, and 12th grades, respectively.

We specifically test whether educational expectations are revised over time based on new information about grade point average and test scores. Three grade point average measures are taken from self-reports and transcript records for the middle school grades (6th through 8th) and for early and later high school grades (9th through 10th and 11th through 12th). The middle school grade point measure is taken from student self-reports. Students were asked in the 8th grade to report whether they received mostly A’s, B’s, C’s, D’s, or F’s in a given subject during middle school. We convert these reports to a four-point scale and average across subjects. The high school grade point measures for grades 9th-10th and 11th-12th are taken from high school transcripts and constructed in a similar manner. Finally, we use math and reading test scores in the 8th, 10th, and 12th grades to construct test score percentile rank measures.[8]

The ultimate dependent variable in the analysis is years of educational attainment in 2000, when respondents are about 26 years of age. This measure is derived from secondary and post-secondary transcripts obtained as part of NELS88 in the third and fourth waves of the study. Descriptive statistics including proportion missing are shown for all model variables by race-ethnicity in Tables 1 and 2.

Model Estimation

To answer our research questions, we estimate a series of dynamic structural models spanning five periods: childhood, 8th grade, 10th grade, 12th grade, and young adulthood (age 26). We model absolute levels of expectations, grades, and percentile test score rank at three periods—8th, 10th, and 12th grades—rather than the relative change from period to period. We prefer absolute measures over relative change measures given the well-known difficulties of estimating measurement error for relative change measures (Blau and Duncan 1967). Thus, the dynamic models can be understood not as a test of the effects of a given magnitude of change in grades or test achievement on change in educational expectations but in terms of the counterfactual: If we were to change a student's achievement in a given period holding all other measures constant, would that student subsequently revise her or his expectations?

We estimate variants of two structural models that we explain in detail below: (1) a model of the educational attainment process with a static construct of educational expectation but a dynamic process in grades and test scores across periods and (2) a model of the educational attainment process with a dynamic process in expectations, grades, and test scores within *and/or* across periods. The first model we refer to as the static expectations model; the second model we refer to as the dynamic updating in expectations model.[9]

Structural models are technically composed of two parts: A structural model describing relationships among exogenous and endogenous variables and a measurement model describing how these variables are measured and errors in those measures. All models are identified in part by covariance and cross-equation restrictions described in the text below. Based on indices of model fit, we constrain structural effects of demographic and social background characteristics on expectations, grades, and test scores as well as structural errors in these latter measures to equality across race-ethnic groups in all models.[10] We also constrain factor loadings in the measurement model to equality across race-ethnic groups in order to achieve comparability in the scale of structural estimates across these groups.

The structure of the static expectations model is illustrated schematically in Figure 2.[11] This model speaks directly to early status attainment research asserting individuals form a latent mental frame or construct that persists over time and influences important education and labor market decisions. In this model, demographic and social background variables affect a static construct, “Educational Expectations.” This construct determines educational expectation in each of three periods: 8th, 10th, and 12th grades. Social background variables also affect initial measures of grades and test achievement in the 8th grade period. The model is block recursive between grades and test scores; prior measures of these variables affect the same measures in the next period. Structural disturbances of grades and test scores within a period are allowed to covary with each other as well as with the structural disturbance of the static construct "Educational Expectations." Unlike the dynamic updating in expectations model, the static expectations model allows for measurement error in all three expectations measures. This is because these three measures are determined by a single latent factor "Educational Expectations." Turning to the final outcome in the static expectations model, we allow "Educational Expectations" as well as 12th grade measures of grade point average and test achievement to affect years of educational attainment at age 26. Based on evidence of model fit, we also allow measures of father's education and family income to directly affect educational attainment in young adulthood.

Insert Figure 2 here.

We next estimate a dynamic updating in expectations model, which can be further distinguished by variations in inter- and/or intra-period updating in educational expectations based on grade and test achievement. The inter- and intra-period updating models are represented schematically in Figures 3 and 4. Inter- and intra-period updating in expectations is shown separately in each of these figures for clarity, but we simultaneously estimate both types of updating effects in some models (see Table 3).

The dynamic updating in expectations models explicitly specify expectation revision mechanisms posited in Bayesian learning models.

Insert Figure 3 here.

Insert Figure 4 here.

In dynamic updating models, each expectations measure is a self-representing measure with a single indicator of educational expectations in a period, similar to the treatment of measures of grades and test scores in the static expectations model, and is based on the student's report.[12] Measures of expectations, grades, and test scores in the second period, the 8th grade, are determined by childhood demographic and social background measures in the updating model. We also now use the same block recursive structure in the relationships between expectations, grades, and test scores as we estimate in the static expectations model between grades and test scores alone (see Figure 3). That is, we allow the expectations, grades, and test achievement measures in a given period to affect expectations, grades, and test achievement measures in the subsequent period. We refer to the paths from grades and test scores in the prior period to expectations in the subsequent period as inter-period updating in expectations.

We sometimes allow grades and test scores *within* a period to affect educational expectations in that same period as well (see Figure 4). This is because of the timing of expectations, grades, and test measures within a period. Expectations are measured toward the end of the period while grade measures in particular span the entire period in question. An argument can be made that test achievement at the end of a given period similarly contains information about test achievement throughout the period. Therefore, this more immediate information about academic achievement may be more relevant for the revision of expectations than information about academic achievement in the previous period. We refer to paths from grades and test scores to expectations within a period as intra-period updating.

Intra-period updating estimates are identified because we do not allow expectations in a period to simultaneously affect grades and test scores in that same period. Free paths from expectations to grades and test achievement within a period would also make little sense because expectations are ascertained toward the end of each period. While the 10th and 12th grade measures of grade point average for a given period primarily contain information exogenous to the expectations measure, they do contain some information concurrent with and, to some extent, even after the expectations measure. Moreover, the 8th grade measure of grade achievement is completely endogenous to the 8th grade measure of educational expectations, since it is based on a student report obtained at the same time as the student report of educational expectations. Coefficients for the 10th and 12th grades should be interpreted as the upper bound of updating in expectations based on grades; the intra-period updating in expectations coefficient in the 8th grade period is simply a symmetric partial correlation. We initially estimate a model with both inter- and intra-period updating effects. We then test alternate specifications of intra- and inter-period updating of expectations, which we discuss in detail in the findings section (see Table 3).

Measures of educational expectations, grades, and test achievement in the 12^{th} grade affect years of attained education at age 26 in the dynamic updating models. As in the static expectations model, we allow father's education and family income to affect years of attained education directly. All other demographic and social background variables only affect educational attainment indirectly in dynamic updating models.

For the structural models just described, we test the robustness of model fit and estimates to different assumptions about measurement.[13] We initially estimate a basic measurement model of reliability in test scores in the 8^{th}, 10^{th}, and 12^{th} grades for each of the structural models, an approach that mimics much of the previous literature on the formation and effects of educational expectations using reduced-form models. In this scenario, we model only student reports of their social background characteristics and do not allow for any measurement error in demographic and social background characteristics or grades in the static expectations model nor in demographic and social background characteristics, expectations, or grades in the dynamic updating in expectations models. We then extend the measurement model for structural models in a second variation in which we introduce a parent report of the student's social background characteristics into the model. We allow for errors in both student and parent reports of social background characteristics and correlate within-person (reporter) errors across measures of mother's and father's education and occupation. The final measurement model introduces errors into self-representing grade and expectation measures. Measurement errors in self-representing measures of expectations and grades are weakly identified compared to errors in social background characteristics and test achievement for which we have two reports in each period. Measurement error in expectations and grades is statistically identified because we assume social background characteristics only affect measures of expectations, grades, and test scores in the 8^{th} grade directly, because there are no lagged effects between grades 8 and 12, and because expectations, grades, and test achievement in the 12^{th} grade only affect education at 26 years directly. However, we also introduce equality constraints in errors in grades across periods as well as within race-ethnic group and equality constraints in errors in expectations across groups in order to stabilize model estimates. Estimates based on these constraints are consistent with estimates from a model with errors in expectations and grades freely estimated across and within race-ethnic groups, improve model fit considerably, and produce in-range estimates of correlations among structural errors. Our results also remain consistent across structural models with and without errors in self-representing measures of expectations and grades, as we demonstrate below.

FINDINGS

Is There Revision and Learning in Early Educational Expectations Over Time?

We begin by assessing the fit of the static expectations models with differing measurement assumptions relative to analogous specifications of intra- and inter-period updating in expectations models. We use these comparisons to determine whether students actually revise their educational expectations as Bayesian learning theory suggests or whether students' expectations are based on a static construct, as the status attainment literature asserts. Looking down Table 3, we see fit statistics for the static expectations model and different specifications for dynamic updating in expectations by the three measurement scenarios described above.[14] Initially, the static expectations model fits the data better than the updating model with no errors in variables aside from test scores as well as in a model with a social background measurement model (compare χ^2 and BIC in models 1.a and 2.a and models 1.b and 2.b). On this evidence alone, we would clearly accept previous assertions in the literature about a static expectations construct formed early and persisting through adolescence regardless of variations in academic performance. However, there is a key distinction between the static expectations model and the updating models. While the dynamic updating models do not always specify measurement error in self-representing expectations measures, errors in expectations measures are naturally built into a model asserting a static expectation factor. If one did not build this feature into a model of dynamic updating in expectations, one would erroneously assume individuals' expectations are based on a static latent construct; no updating model without error in expectations fits the data as well as a static expectations model. Looking at model fit statistics for each structural model that includes the full measurement model with errors in expectations and grades, the findings reverse (compare models 1.c and 2.c). Any dynamic updating model fits the data much better than a static expectations factor model once errors in expectations are considered in both models (also, see the fit of models 3.c and 4.c). This provides strong and clear evidence that expectations are not determined exclusively by a persisting mental construct. Previous status attainment research is incorrect insofar as it assumes that a static factor drives individual expectations. The errors in expectations measures may not be identified well in the current analysis for reasons discussed above, but it would be a severe oversight to omit them completely from the analysis, an oversight that would lead to incorrect conclusions about the nature of educational expectations.

Given that there is strong evidence of some updating in expectations over time, the next question is whether this occurs within and/or across periods. Again, fit statistics for different updating models provide important information for answering the question. Looking once more down Table 3, we first model inter and intra-period updating in expectations together, a model that fits much better overall than a static expectations model once we consider a full measurement model (Model 2.c). We also specify inter and intra-period updating alone with various measurement models (Models 3 and 4). We see that a structural model specifying intra-period updating alone fits the data best in each measurement scenario of various inter and intra-period updating models. However, the better fit of the intra-period updating model declines relative to the inter-period updating model as we expand the measurement model to include errors in expectations in particular.[15] In inter and intra-period updating models with a full measurement model, the intra-period updating model is strongly preferred over the inter-period model but by a much smaller margin than in models with a less elaborate measurement specification.

In the remainder of our discussion of our findings, we present fit statistics and estimates from both a model with only inter-period updating and a model with only intra-period updating to better understand the updating process in expectations over time and the effect of expectations on educational attainment. It is useful to note why we continue to consider the inter-period updating model even though the intra-period updating model fits better. The intra-period updating model conflates information about grades and expectations to some extent in the 10th and 12th grade periods, and the grades and expectations measures are completely endogenous in the 8th grade period. It is not appropriate to mechanically choose the best fitting model according to the Bayesian Information Criterion (BIC) statistic because it is not clear to what extent the observed advantage in fit of the intra-period updating model is predicated upon this endogeneity. Moreover, though estimates differ somewhat across the two updating models, the general story remains the same.

We next simplify the structure of the inter- and intra-period dynamic updating models, an exercise that clarifies the paths by which students may update their educational expectations over time. Table 4 shows fit statistics for a series of models testing basic assumptions about the specified structure between expectations, grades, and test achievement measures in three periods for all three race-ethnic groups. In each test, we simply constrain structural paths of interest to zero and compare model fit to the appropriate baseline model. The first row of each panel simply replicates the fit statistic for the preferred model for the inter-period updating model (Model 3.c) and the intra-period updating model (Model 4.c) from Table 3.

Briefly, substantial and clear improvements in fit are apparent for all structural constraints across both the inter-period updating and the intra-period updating models except in one case—constraining updating in expectations by grades to zero. First, expectations do not influence measures of academic achievement in any real way despite their effect on attained years of education. Moreover, there is no updating in expectations based on test achievement in either the inter-period updating model or the intra-period updating model. These results are the first evidence we have of the relative independence of educational expectations from other measures of educational achievement. It is not the case that adolescent students form a static expectation for their educational attainment, but neither is it the case that expectations influence or are influenced by measures of academic achievement, particularly test achievement. The evidence for updating in expectations by grades is less clear. In the inter-period updating model, constraining the path from grades in the previous period to expectations in the subsequent period leads to a modest improvement in fit. In the intra-period updating model, constraining this same path to zero leads to a small decrease in the BIC statistic, indicating no real difference in fit between an intra-period updating model with and without updating in expectations by grades. A modest case could be made that expectations are not updated by grades either, based on little to no improvement in fit when we constrain the effect of grades in the prior period on expectations in the next period. Were it not for the statistically significant and consistent effect of educational expectations on attained education, one might conclude educational expectations have little bearing on educational achievement. For the sake of argument and given the modest changes in fit, we maintain that a student's educational expectations are updated by grades and explore the magnitude of this effect across and within periods in the two updating models below.

Do Adolescent Students Revise Educational Expectations Differently Across Race-Ethnic Groups?

To better understand race-ethnic differences in updating in expectations over time and the effect of expectations on education, we test for race-ethnic group equality constraints among these parameters in both the inter-period updating and intra-period updating models. This portion of the analysis speaks to a large literature in sociology addressing race-ethnic differences in the formation and effects of educational expectations. These models and accompanying fit statistics are shown in Table 5. We begin by restricting the parameters representing the effect of expectations in one period on expectations in the next period in Model 2. Constraining these two parameters to equality across Blacks, Latinos, and whites leads to a considerable improvement in BIC, and, in fact, the increase in χ^2 between the two models is not statistically significant (χ^2 = 5.04 with 4 *df*). Models 3 and 4 in Panel A and Models 3, 4, and 5 in Panel B constrain the effect of GPA on expectations. Excepting the contrast between Model 3 and Model 1 in Panel B, none of these constraints yields a statistically significant decrement in fit.

Constraining the path from 8th grade GPA to 8th grade expectations in Model B3 does lead to poorer fit, but the decline in fit is still small enough to represent modest evidence (in terms of BIC). It remains uncertain whether the decrement in fit is an artifact of the confounded measures of 8th grade GPA and expectations.[16] Turning to Model 5 in Panel A, there is no evidence of race-ethnic differences in the effect of expectations on educational attainment at age 26. Constraining this same path in the intra-period updating model (Panel B) leads to a similarly large improvement in fit. The final model in Panel A, Model 6, constrains all the effects between expectations, grades, test achievement, and educational attainment to equality across the three race-ethnic groups. This specification leads to a considerable improvement in BIC and suggests that there are no substantial no race-ethnic differences in any of these relationships. The story is the same for the intra-period updating model.

Our finding of no race-ethnic differences in the formation and effects of educational expectations runs counter to the bulk of the literature on the topic. This counter-finding invites the question: what features of our data and/or model specification can account for this finding specifically? In supplementary analyses available upon request, we estimate reduced-form models and simple structural models that suggest appropriate controls for socioeconomic background and prior academic achievement as well as modeling measurement error in expectations can explain the race-ethnic difference in the formation and effects of expectations. Thus, such differences are really a matter of correctly specifying the model. An absence of statistically significant race-ethnic differences in the dynamic updating and effects of educational expectations follows other race-ethnic similarities in our models. Recall from our description of model estimation that we have already constrained the effect of student's social background on initial measures of expectations, grades, and test scores in the 8^{th} grade to equality as well as the structural disturbances for measures of expectations, grade, test scores, and educational attainment at age 26 based on large improvements in BIC. This means that race-ethnic groups are indistinguishable in the socioeconomic determinants of educational expectations, revision of educational expectations over time based on information about academic achievement, *and* in the effects of educational expectations on later educational attainment. We observe a single exception to this overarching pattern of race-ethnic similarities in the formation and revision of educational expectations and their effects on years of attained education—the effect of 12^{th} grade GPA on attained education for Latinos. We found very strong evidence that this coefficient was smaller for Latinos than for the other two race-ethnic groups and, as a result, estimate it freely for Latinos in all remaining models.

Quantifying Updating in Educational Expectations over Time

Having established the basic structure of the relationships among educational expectations, grade point average, and test scores over time and the absence of race-ethnic differences in these relationships, we next determine the extent to which students update their expectations in the face of new information about their grade point average.

To put this task in the form of a question: How much do students really update their educational expectations? To answer this question, we show unstandardized coefficients from a model with only inter-period updating in expectations in Table 6. Panel A of the table shows estimates from the inter-period model that does not consider errors in measures of expectations or GPA while Panel B shows estimates from the same model with errors in expectations and GPA. Comparison across the two panels illustrates the extent to which model results are sensitive to our identification strategy for errors in expectations and grades. Table 6 should be read from left to right, with row variables affected by column variables. Column variables are numbered by the order they appear in the rows. Looking across the second row of Panel A, we see the first entry in that row is the effect of 8^{th} grade expectations on 10^{th} grade expectations. The same pattern applies throughout the table.

In the following discussion, we focus on estimates in Panel B from a dynamic inter-period updating model that specifies measurement errors in expectations and grades. These patterns of results are also apparent in the model in Panel A that ignores errors in these variables.[17] Turning our attention back to Panel B, the effect of 12^{th} grade expectations on educational attainment at age 26 is significant and indicates an additional year of expected education at the conclusion of high school leads to about 0.4 years of additional education at age 26. Expectations clearly matter, and the size of the effect is clearly sensitive to measurement error (compare estimates across the two panels of Table 6). Second, auto-regressions of expectations in Panel B show strong persistence in expectations over time, especially between the 8th and 10th grades. There is less persistence in expectations from the 10th to the 12th grades, but it remains remarkably high. On this evidence alone, one might conclude there is little updating in expectations over time. As expected, estimates of the effects of grade point average in one period on expectations in the following period are statistically significant but show little updating. For example, a unit increase in 8th grade GPA leads to a 0.314 increase in years of expected education in the 10th grade. This effect is quite small in practical terms as a student would have to increase his GPA, say, from a C average to a B average – a considerable feat – before he would revise his expectations upward by 0.3 years of education. This effect is even smaller in the following period. A unit increase in 10th grade GPA leads to a 0.07 increase in expected years of education in the 12th grade – an effect of marginal statistical significance. This is as we would expect given the survey, experiment, and fMRI evidence of the relative persistence of expectations over time in the face of new information. However, the decline in updating over time suggests there is some validity in Bayesian learning models. In sum, we can only accept a very qualified variant of Bayesian learning in the inter-period updating model: There is only very slight revision of expectations in light of grade achievement, and this revision declines to nearly nil by the conclusion of high school.

This story largely holds in models of intra-period updating in expectations without and with errors in expectations and grade point average. Estimates from these models are presented in Table 7. These models suggest larger amounts of updating in expectations within a period though updating remains small in practical terms. There are a number of reasons one might have reservations about the larger updating effects we observe in the intra-period updating model, the first and foremost being the endogeneity of expectations and the within-period GPA measures. The 8th grade GPA measure is especially prone to this problem since it is reported by the student in the same interview where the student reports her 8th grade educational expectations. Thus, we limit ourselves to estimates from high school where endogeneity of expectations and grade point average is less of a concern. These effects still indicate only a modest change in expectations for a rather large change in grades. Again, a student must essentially move from, say, a C average to a B average before she will update her expectations by just over 0.8 years of expected education. Similar to the inter-period updating model, the updating coefficients decline over time, also suggesting students' educational expectations become even more stable as they complete high school. However, the decline in updating coefficients over time is much smaller in the intra-period model.

DISCUSSION AND CONCLUSION

In this paper we evaluate various theories about the formation and effects of expectations in adolescence and race-ethnic differences in this process. We contribute to the literature in three key ways. First, the educational expectations literature has long suggested individuals formulate a static latent expectations construct. However, we find relatively weak evidence of a static latent construct driving reported expectations, regardless of the hypothesized source of such a construct. Second, the educational expectations literature has also long suggested educational expectations are constituted and operate in different ways for Black and white youth, and considerable effort has been spent trying to explain these apparent differences. Morgan (2004, 2005) specifically hypothesizes that observed race-ethnic differences in the effect of expectations on educational attainment depend on "additional belief-based effects for Blacks that operate outside of traditional status socialization models," (p. 69). The findings here provide a clearer explanation for race-ethnic differences in the effects of expectations on educational attainment: Appropriate measures of observables and measurement error in educational expectations. While ideas about the structural determinants of educational attainment stemming from early observations of race-ethnic differences vis-à-vis educational expectations are an important facet of the literature—especially those related to racial discrimination, it remains the case that these differences do not hold in a properly specified model with measurement error, a fact carrying serious implications for work in this area.

This brings us to the third contribution of the paper: Dynamic structural models of educational expectations formation and revision. Others have advocated for Bayesian learning theory as a means to understand how individuals update their beliefs and expectations but have provided inadequate tests of that theory. Expositions of this theory usually suggest there is little to no friction in updating one's subjective beliefs, though evidence to the contrary exists across a wide array of literatures. For example, we know that gendered norms about math and verbal ability as well as perceptions about the chances of success shaped by one's socioeconomic status each create substantial drag in the process of revising one's beliefs. Our analyses show adolescent youth do not easily revise their educational expectations based on relevant information about their academic achievement. In fact, students must achieve extremely large increases in academic performance before updating their educational expectations by at most 0.8 years. A more conservative model suggests a much smaller effect of academic achievement on expectations, as little as 0.3 additional years of expected education for every unit increase in grade point average. Our results align with those from prior survey, experimental, and neurological research. Indeed, strict learning models asserting frictionless updating of expectations or strict static expectations models asserting an unchanging, underlying mental construct driving expectations both turn out to be less than helpful caricatures of the actual process.

The findings here highlight the need to develop appropriate and rigorous social psychological models of the education process that can better illuminate inequalities by observed status characteristics. Given the popularity and the maturity of the literature on educational expectations in sociological research generally, it is unfortunate that measures and models of subjective educational expectations and decision-making are not better developed in the sociological literature. Sociologists are particularly well-poised to make important contributions to educational expectations and decision-making research because of a long-standing emphasis in the discipline on social influences, inter-personal interaction, and subjective measures. The latter is a unique characteristic of sociology relative to economics, which more often relies on observed behavior and outcomes to infer subjective decision-making processes. Subjective facets of any process can be difficult to measure and are sometimes measured badly, but efforts still should be made to address the inferential gap between behavioral processes and observed outcomes by developing reliable, well-understood subjective measures of future expectations and beliefs. Notably, little has been done in the way of validating educational expectations measures despite their long-standing popularity in sociological research. For example, we find that expectations are not consistent with a static mental construct as early status attainment research supposes. This is an important structural feature of educational expectations that to our knowledge has not been made explicit before, even though it has serious implications for understanding and modeling students' educational decision-making.

Research on educational expectations has mostly evolved independent of research drawing on Goldthorpe's (1996) theory of educational decision-making though these concepts are potentially linked. For example, Gabay-Egozi and colleagues (2009) test aspects of Goldthorpe's theoretical model, specifically the effects of measures of relative risk, subjective utility of various school curricula, and subjective perceptions of academic failure in those curricula on students' intended curricular choices. It is not clear to what extent traditional educational expectations measures are related to these newly developed measures, but it is highly likely subjective utility and failure perceptions are folded into educational expectations measures. Future research should explore the structure of adolescents' educational expectations measures through additional structural modeling as well as experimental studies alone *and* along with other, related work on educational decision-making using concepts of relative risk aversion, subjective utility, and subjective failure expectations.

Also, research on strong shocks – major changes in information or perception – and subsequent expectation revision would be useful. We find that there is little updating in educational expectations under the usual changes in grade and test achievement. However, we would expect, based on the neuroscience literature, that substantively significant updating in expectations would occur in the presence of sharp and drastic changes in information and/or perceptions of future academic success and attainments. It is not clear, however, the extent to which such revisions are transitory or not. This would further refine our conclusions here and provide useful details as to the exact mechanics of educational decision-making processes under normative and non-normative circumstances.

Finally, our observation of relative inertia in adolescents' expectations points to a clear need for research on conceptions and expectations of educational attainment among younger students. Work should be undertaken to determine when in the early educational career conceptions and expectations are formed and ossify and their relationship with more objective facets of the educational career such as academic achievement. Work in economics, for example, has begun to develop models of cognitive and non-cognitive resources across the educational career with a special emphasis on how these resources develop (Cunha and Heckman 2008). The emphasis in this work on the development of early educational resources is extremely useful, but it omits important connections between subjective and objective components of the educational career. The omission of these connections engenders monolithic, largely theoretical decision-making models like those we test in this paper that do not adequately capture complex decision-making processes. If we do not understand the interconnections between the subjective expectations and beliefs about educational attainments and objective measures of educational resources and attainments, we are consequently but unnecessarily forced to rely on *a priori* caricatures of the decision-making process. The so-called "strategic center" remains a fruitful area of research for all these reasons.

NOTES

1. In fact, Alexander et al. (2008) are overly and unnecessarily dismissive of research "riveted on the high school years," (p. 391). They suggest their findings indicate that a student's formative conditions and experiences decline to insignificance as students age and as later conditions and experiences in the post-secondary career take precedence. This is simply not true. It ignores not only their own evidence on the effect of expected education at the end of high school relative to the effect of expected education in post-secondary school, but important evidence of the long-term factors partly generating the conditions and experiences of young adults and how differences in individual experiences and conditions potentially build on each other over time. Early status attainment research and recent research in economics drawing on the psychology of human development clearly demonstrate the importance of early life conditions for later educational outcomes. Cunha and Heckman (2008), for example, estimate 50 percent of lifetime inequality in earnings is determined by factors set by age 18.

2. We address race-ethnic differences in the effect of educational expectations on educational attainments, that is, differences in slopes. We do not address the question of race-ethnic mean differences, a wholly separate issue highlighted by Mickelson (1990), Kao and Tienda (1998), and others. We define "effect" here as the procedural relationships between educational expectations and other measures of interest.

3. The Bayesian theorem is formally expressed as follows. Consider two random events, A and B, in the following equation:

$$P(A|B) = [P(B|A)P(A)]/P(B),$$

where P(A|B) is the conditional probability of A given B, what is known as the posterior probability; B(B|A) is the conditional probability of B given A, P(B) is the probability of B, and P(A) is the probability of A. The equation states P(A) (or the prior) is multiplied by some factor (P(B|A)/P(B)). This factor is sometimes referred to as the normalized likelihood. Equation 1 simply asserts the posterior probability of A is updated by some factor, the normalized likelihood. More in-depth explanations of Bayesian inference can be found in Greene (2008).

4. While status attainment models explicitly posit educational expectations are a socialized and stable construct, allocation models assert they are a function of the opportunity structure. These expectations could change as the opportunity structure changes, but nowhere in the literature is this made explicit to our knowledge.

5. We ran supplementary analyses including high school dropouts in our sample and find no real difference between those findings and the findings presented here. Those findings are available upon request.

6. Imputation models include all variables considered here as well as additional measures such as family composition. We assume non-monotone missing patterns in the data and use a Monte Carlo Markov chain model to impute the data. Race-ethnic groups are imputed separately, and we drop observations with missing data on educational attainment and expectations measures after imputing (von Hippel 2007). Imputed responses remain unedited (Horton, Lipsitz, and Parzen 2003).

7. Occupational education is defined as the percentage of persons in an occupation who have completed at least one year of college. That is, the status of each parent is characterized by the level of education that is typical of their occupation as well as by their actual level of educational attainment.

8. Arguably, these test measures may not provide information about students' test achievement known to students since these test scores are not expressly reported to them. However, the NELS88 test scores ostensibly capture general test achievement, achievement that likely transfers across different tests and that is well known to the student. Other available test measures in the NELS88 tied more directly to educational outcomes such as the SAT or ACT only apply to students intending to enter a post-secondary institution requiring such a test and are often taken only once towards the end of high school. Because such tests only apply to a select group of students for a unitary purpose, may be taken only at one point in time, and are highly correlated with general test achievement, we use the test score percentile rank measures from the NELS88.

9. See the appendix for equations describing estimated models.

10. In supplementary analyses, we estimate models with variable structural errors across race-ethnic groups. Those results are similar to those presented here and support the conclusions we draw.

11. Please note that certain features are omitted from this and other schematic figures for the sake of simplicity. For example, covariances among structural disturbances are omitted from figures. The reader should refer to the main text and the appendix for full details of the models in Figures 2, 3, and 4.

12. Latent variables for expectations and grades only have one indicator and, thus, are self-representing. In contrast, latent endogenous variables representing "test achievement" in any given period are indicated by two observed measures of test achievement—reading and math. We normalize the metrics of observed test achievement measures by constraining the factor loading for reading to one for each period.

13. It may be difficult to intuit measurement error in subjective measures such as

educational expectations, but a large literature in survey methodology underscores the importance of errors in such measures. Tourangeau, Rips, and Rasinski (2000) provide a useful explication. Measurement error in expectations is best understood as variation in cognitive processes such that a respondent provides different answers to the same question between occasions in the absence of true change.

14. We assess fit using chi-square and Bayesian Information Criterion (BIC) statistics. See Raftery (1995) for a detailed discussion of the BIC statistic. In the present analysis, a more negative BIC statistic indicates a better fitting model. A decrease in the BIC statistic of 10 or more is very strong evidence of better model fit.

15. In supplementary analyses, we estimated models with errors only in grades and not errors in expectations that support this assertion.

16. We estimate a variant of the model with race-ethnic equality in all expectations, grades, and test score effects for the intra-period updating model, Model 7 of panel B, freeing the path from 8th grade GPA to 8th grade expectations across race-ethnic groups and find it does not significantly improve fit over the version of Model 7 constraining all structural paths to equality across race-ethnic groups.

17. The main difference between estimates in the two panels is downward bias in the estimates of the auto-regression of expectations in period t on expectations in period $t-1$ as well as downward bias in the effects of expectations and grades on educational attainment at age 26. Once we account for measurement errors in expectations, these auto-regression coefficients increase substantially, while the effects of updating in expectations decline. Interestingly, the effect of 12th grade test achievement on educational attainment at age 26 is upwardly biased in models that do not account for measurement error in expectations and grades while the effect of 12th grade expectations and GPA are downwardly biased in the same models. This suggests that test achievement effects based on psychometrically derived instruments are upwardly biased in models that crudely measure expectations and GPA in comparison.

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Table 1. Proportion Missing by Race-Ethnicity for Model Variables, NELS88

Variable	White	Black	Latino
Female?	0.00	0.00	0.00
Immigrant Parent?	0.06	0.11	0.14
Immigrant Student?	0.07	0.11	0.16
Intact Family by Age 16? - Student	0.01	0.02	0.01
Father's Years Education - Student	0.11	0.24	0.19
Mother's Years Education - Student	0.09	0.11	0.15
Father's Occupational Status - Student	0.07	0.23	0.14
Mother's Occupational Status - Student	0.04	0.06	0.07
No. Siblings - Parent	0.05	0.08	0.11
Father's Education - Parent	0.17	0.13	0.13
Mother's Education - Parent	0.07	0.48	0.26
Father's Occupation - Parent	0.18	0.51	0.30
Mother's Occupation - Parent	0.13	0.21	0.27
Family Income - Parent, 8th	0.04	0.08	0.10
Family Income - Parent, 12th	0.13	0.10	0.22
Educational Expectations, 8th	0.00	0.00	0.00
Educational Expectations, 10th	0.00	0.00	0.00
Educational Expectations, 12th	0.00	0.00	0.00

Continued on the next page…

Table 1. Continued….Proportion Missing by Race-Ethnicity for Model Variables, NELS88

Variable	White	Black	Latino
GPA, 9th - 10th	0.02	0.05	0.04
GPA, 6th - 8th	0.01	0.01	0.00
GPA, 11th-12th	0.29	0.35	0.33
Reading Test Achievement, 8th	0.03	0.03	0.04
Math Test Achievement, 8th	0.03	0.02	0.03
Reading Test Achievement, 10th	0.03	0.05	0.06
Math Test Achievement, 10th	0.03	0.06	0.06
Reading Test Achievement, 12th	0.18	0.20	0.22
Math Test Achievement, 12th	0.18	0.20	0.22
Educational Attainment in Years	0.00	0.00	0.00
	N=6669	N=759	N=1073

Table 2. Descriptive Statistics by Race-Ethnicity, NELS88

Variable	White	Black	Latino
Female?	0.50	0.53	0.53
	(.499)	(.492)	(.497)
Immigrant Parent?	0.05	0.07	0.57
	(.222)	(.268)	(.498)
Immigrant Student?	0.02	0.03	0.16
	(.136)	(.185)	(.347)
Intact Family by Age 16? - Student	0.65	0.36	0.61
	(.464)	(.491)	(.480)
Father's Years Education - Student	13.99	13.30	13.07
	(2.638)	(2.350)	(2.385)
Mother's Years Education - Student	13.92	13.20	12.65
	(2.373)	(2.351)	(2.133)
Student Doesn't Know Father's Education	0.11	0.24	0.19
	(.309)	(.390)	(.374)
Student Doesn't Know Mother's Education	0.09	0.11	0.16
	(.278)	(.306)	(.346)
Father's Occupational Status - Student	0.13	-0.39	-0.17
	(1.197)	(1.144)	(1.091)
Mother's Occupational Status - Student	0.24	-0.07	-0.23
	(1.022)	(1.034)	(.938)
Student Doesn't Know Father's Occupation	0.05	0.14	0.10
	(.201)	(.343)	(.295)
Student Doesn't Know Mother's Occupation	0.03	0.04	0.07
	(.158)	(.221)	(.240)
Father Not in the Regular Labor Force - Student	0.02	0.02	0.01
	(.124)	(.182)	(.128)
Mother Not in the Regular Labor Force - Student	0.17	0.12	0.24
	(.384)	(.322)	(.438)
Number of Siblings - Parent	2.11	2.64	2.60
	(1.445)	(1.804)	(1.654)
Father's Education - Parent	13.88	13.29	11.64
	(2.588)	(2.084)	(2.701)
Mother's Education - Parent	13.23	12.93	11.42
	(2.077)	(1.955)	(2.434)
Partner's Education Not Applicable	0.13	0.35	0.13
	(.324)	(.467)	(.326)
Father's Occupation - Parent	0.33	-0.14	-0.19
	(1.195)	(1.179)	(1.083)

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Table 2. Continued….Descriptive Statistics by Race-Ethnicity, NELS88

Variable	White	Black	Latino
Mother's Occupation - Parent	0.45	0.09	-0.16
	(1.076)	(1.184)	(1.066)
Father Not in the Regular Labor Force - Parent	0.01	0.01	0.01
	(.112)	(.125)	(.105)
Mother Not in the Regular Labor Force - Parent	0.04	0.03	0.03
	(.197)	(.168)	(.187)
Family Income - Parent, 8th	76.44	44.54	46.20
	(58.548)	(35.154)	(33.675)
Logged Family Income - Parent, 8th	6.98	6.95	6.95
	(.052)	(.033)	(.032)
Family Income - Parent, 12th	75.75	42.53	42.87
	(56.445)	(36.512)	(33.759)
Logged Family Income - Parent, 12th	6.98	6.95	6.95
	(.051)	(.034)	(.032)
Educational Expectations, 8th	15.80	15.75	15.52
	(1.758)	(1.701)	(1.916)
Educational Expectations, 10th	15.76	15.76	15.38
	(1.886)	(1.918)	(2.008)
Educational Expectations, 12th	15.87	15.81	15.63
	(1.863)	(1.879)	(1.910)
GPA, 6th - 8th	3.05	2.81	2.85
	(.688)	(.678)	(.686)
GPA, 9th-10th	2.43	1.87	2.02
	(.836)	(.792)	(.823)
GPA, 11th-12th	2.41	1.88	2.00
	(.831)	(.765)	(.795)
Reading Test Achievement, 8th	53.38	47.19	47.61
	(9.772)	(9.157)	(9.061)
Math Test Achievement, 8th	53.45	46.42	47.36
	(9.902)	(8.517)	(8.793)
Reading Test Achievement, 10th	53.04	47.52	48.12
	(9.422)	(9.228)	(9.103)
Math Test Achievement, 10th	53.21	46.01	47.35
	(9.422)	(8.987)	(8.872)
Reading Test Achievement,12th	52.96	46.99	47.75
	(9.109)	(9.162)	(9.081)

Continued on the next page….

Table 2. Continued….Descriptive Statistics by Race-Ethnicity, NELS88

Variable	White	Black	Latino
Reading Test Achievement, 12th	53.20	45.65	47.75
	(9.315)	(8.911)	(8.868)
Educational Attainment in Years at Age 26	13.93	13.05	12.97
	(2.348)	(2.156)	(1.947)
	N=6669	N=759	N=1073

Table 3. Fit Statistics for Group Models, NELS88

Model	Description	DF	$\chi 2$	BIC
1.a	Basic Static Expectations Model	374	751.01	-2633
1.b	Basic Static Expectations Model with Social Background Measurement Model	1119	3749.98	-6375
1.c	Basic Static Expectations Model with Full Measurement Model	1116	3442.35	-6655
2.a	Inter and Intra-Period Updating Model	569	2760.29	-2388
2.b	Inter and Intra-Period Updating Model with Social Background Measurement Model	1095	4258.50	-5649
2.c	Inter and Intra-Period Updating Model with Full Measurement Model	1089	3172.16	-6681
3.a	Inter-period Updating Model	581	2811.40	-2445
3.b	Inter-period Updating Model with Social Background Measurement Model	1107	4306.78	-5709
3.c	Inter-period Updating Model with Full Measurement Model	1101	3232.13	-6730
4.a	Intra-period Updating Model	577	2671.92	-2549
4.b	Intra-period Updating Model with Social Background Measurement Model	1103	4172.08	-5808
4.c	Intra-period Updating Model with Full Measurement Model	1097	3159.89	-6766

Table 4. Updating Models with Structural Constraints, Fit Statistics

Panel A: Inter-Period Updating Model		**DF**	**χ^2**	**BIC**
1	Inter-Period Updating Model with Full Measurement Model	1101	3232.13	-6730
2	Model 1 + No Expectations Effects on Grades	1105	3122.95	-6875
3	Model 1 + No Expectations Effects on Test	1105	3246.80	-6751
4	Model 1 + No Test Effects on Grades	1105	3172.70	-6825
5	Model 1 + No Grade Effects on Test	1105	3221.25	-6777
6	Model 1 + No Updating in Expectations by Test	1105	3239.03	-6759
7	Model 1 + No Updating in Expectations by Grades	1105	3259.41	-6739
8	Model 2-6 Together	1121	3195.35	-6947

Panel B: Intra-Period Updating Model		**DF**	**χ^2**	**BIC**
1	Intra-Period Updating Model with Full Measurement Model	1097	3159.89	-6766
2	Model 1 + No Expectations Effects on Grades	1101	3077.97	-6884
3	Model 1 + No Expectations Effects on Test	1101	3177.54	-6784
4	Model 1 + No Test Effects on Grades	1101	3158.17	-6804
5	Model 1 + No Grade Effects on Test	1101	3156.24	-6806
6	Model 1 + No Updating in Expectations by Test	1103	3167.43	-6812
7	Model 1 + No Updating in Expectations by Grades	1103	3219.13	-6761
8	Model 2-6 Together	1119	3125.54	-6999

Table 5. Updating Models with Group Equality Constraints, Fit Statistics

Panel A: Inter-Period Updating Model		**DF**	**$\chi 2$**	**BIC**
1	Inter-Period Updating Model with Full Measurement Model and Select Structural Constraints	1121	3195.35	-6947
2	Model 1 + Race-Ethnic Equality in Persistence in Expectations	1125	3200.39	-6979
3	Model 1 + Race-Ethnic Equality in Updating in 10th Gr Expectations by Grades	1123	3197.96	-6963
4	Model 1 + Race-Ethnic Equality in Updating in 12th Gr Expectations by Grades	1123	3198.98	-6962
5	Model 1 + Race-Ethnic Equality in the Effect of 12th Gr Expectations on Education	1123	3196.03	-6965
6	Model 1 + Race-Ethnic Equality in all Expectations, Grades, and Test Score Effects	1142	3240.02	-7093
Panel B: Intra-Period Updating Model		**DF**	**$\chi 2$**	**BIC**
1	Intra-Period Updating Model with Full Measurement Model and Select Structural Constraints	1119	3125.54	-6999
2	Model 1 + Race-Ethnic Equality in Persistence in Expectations	1123	3134.75	-7026
3	Model 1 + Race-Ethnic Equality in Updating in 8th Gr Expectations by Grades	1121	3151.71	-6991
4	Model 1 + Race-Ethnic Equality in Updating in 10th Gr Expectations by Grades	1121	3128.36	-7014
5	Model 1 + Race-Ethnic Equality in Updating in 12th Gr Expectations by Grades	1121	3128.76	-7014
6	Model 1 + Race-Ethnic Equality in the Effect of 12th Gr Expectations on Education	1121	3127.27	-7015
7	Model 1 + Race-Ethnic Equality in all Expectations, Grades, and Test Score Effects	1142	3207.63	-7125

Note: Select structural constraints include no effect of expectations on grades and test scores, no effect of grades on test and vice versa, and no updating in expectations by test scores.

Table 6. Unstandardized Structural Coefficients for Pooled Inter-Period Updating Model

Panel A: Inter-Period Updating Model with Social Background Measurement Model

	1	2	3	4	5	6	7	8	9
Expectations 8th Grade (1)									
Expectations 10th Grade (2)	0.473***			0.700***					
	(.010)			(.026)					
Expectations 12th Grade (3)		0.496***			0.487***				
		(.009)			(.021)				
Grades 8th Grade (4)									
Grades 10th Grade (5)				0.767***					
				(.010)					
Grades 12th Grade (6)					0.796***				
					(.006)				
Test 8th Grade (7)									
Test 10th Grade (8)							0.971***		
							(.012)		
Test 12th Grade (9)								0.770***	
								(.012)	
Years of Education (10)			0.210***			0.906***			0.513***
			(.012)			(.030)			(.041)

Panel B: Inter-Period Updating Model with Full Measurement Model

	1	2	3	4	5	6	7	8	9
Expectations 8th Grade (1)									
Expectations 10th Grade (2)	0.974***			0.314***					
	(.036)			(.092)					
Expectations 12th Grade (3)		0.900***			0.067				
		(.020)			(.035)				
Grades 8th Grade (4)									
Grades 10th Grade (5)				1.402***					
				(.036)					
Grades 12th Grade (6)					0.893***				
					(.009)				
Test 8th Grade (7)									
Test 10th Grade (8)							0.984***		
							(.012)		
Test 12th Grade (9)								0.775***	
								(.012)	
Years of Education (10)			0.383***			1.106***			0.166***
			(.024)			(.047)			(.047)

Note: * p<0.05, ** p<0.01, *** p<0.001

Table 7. Unstandardized Structural Coefficients for Pooled Intra-Period Updating Model

Panel A: Intra-Period Updating Model with Social Background Measurement Model

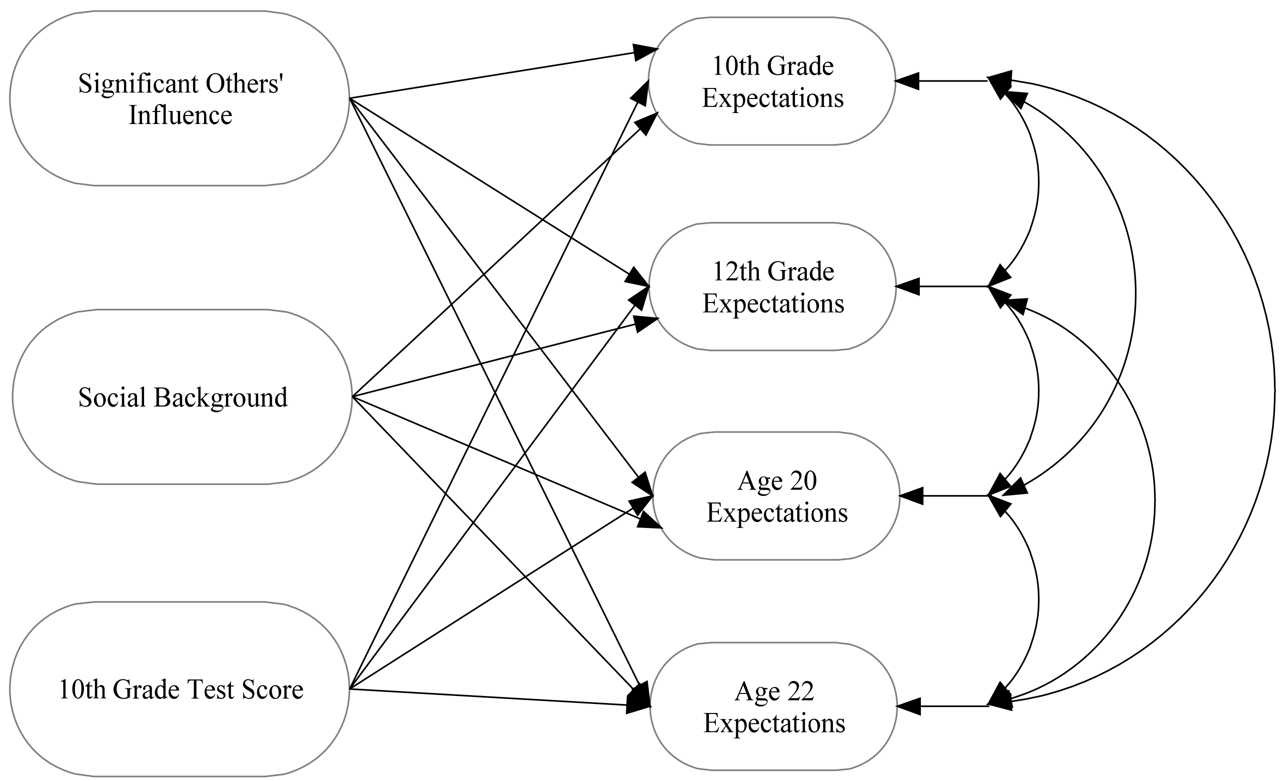
	1	2	3	4	5	6	7	8	9
Expectations 8th Grade (1)				0.805***					
				(.025)					
Expectations 10th Grade (2)	0.479***				0.740 ***				
	(.010)				(.024)				
Expectations 12th Grade (3)		0.516***				0.534***			
		(.009)				(.024)			
Grades 8th Grade (4)									
Grades 10th Grade (5)				0.771***					
				(.010)					
Grades 12th Grade (6)					0.796***				
					(.006)				
Test 8th Grade (7)									
Test 10th Grade (8)							0.974***		
							(.013)		
Test 12th Grade (9)								0.768***	
								(.012)	
Years of Education (10)			0.210***			0.907***			0.514 ***
			(.012)			(.030)			(.040)

Panel B: Intra-Period Updating Model with Full Measurement Model

	1	2	3	4	5	6	7	8	9
Expectations 8th Grade (1)				1.604 ***					
				(.066)					
Expectations 10th Grade (2)	0.807***				0.831***				
	(.020)				(.050)				
Expectations 12th Grade (3)		0.804***				0.303***			
		(.019)				(.043)			
Grades 8th Grade (4)									
Grades 10th Grade (5)				1.392***					
				(.034)					
Grades 12th Grade (6)					0.886***				
					(.009)				
Test 8th Grade (7)									
Test 10th Grade (8)							0.985***		
							(.012)		
Test 12th Grade (9)								0.775***	
								(.012)	
Years of Education (10)			0.362***			1.076***			0.206 ***
			(.022)			(.045)			(.046)

Note: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Figure 1. Morgan's (2004, 2005) Model of Serial Correlations



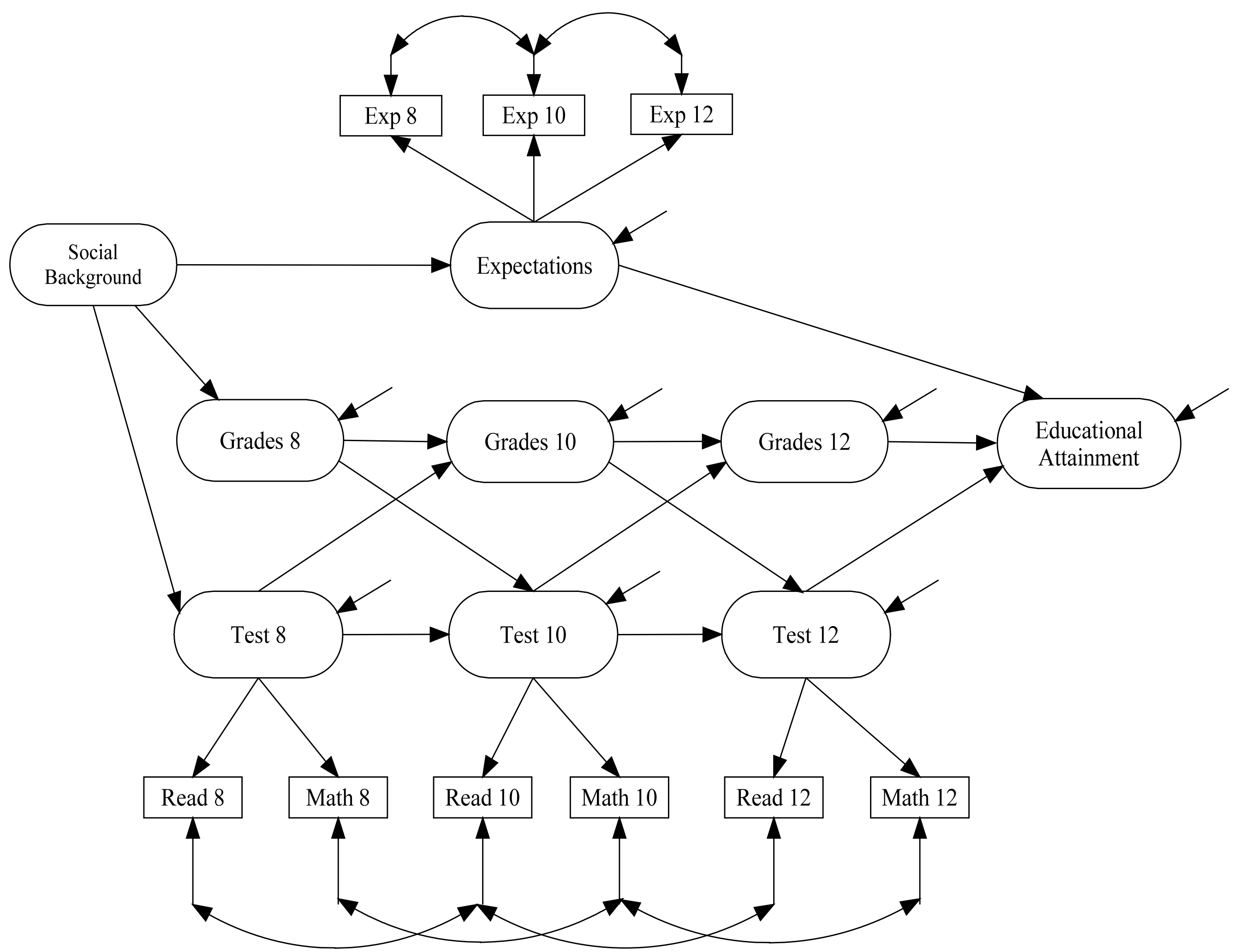


Figure 2. Schematic Model of Static Expectations

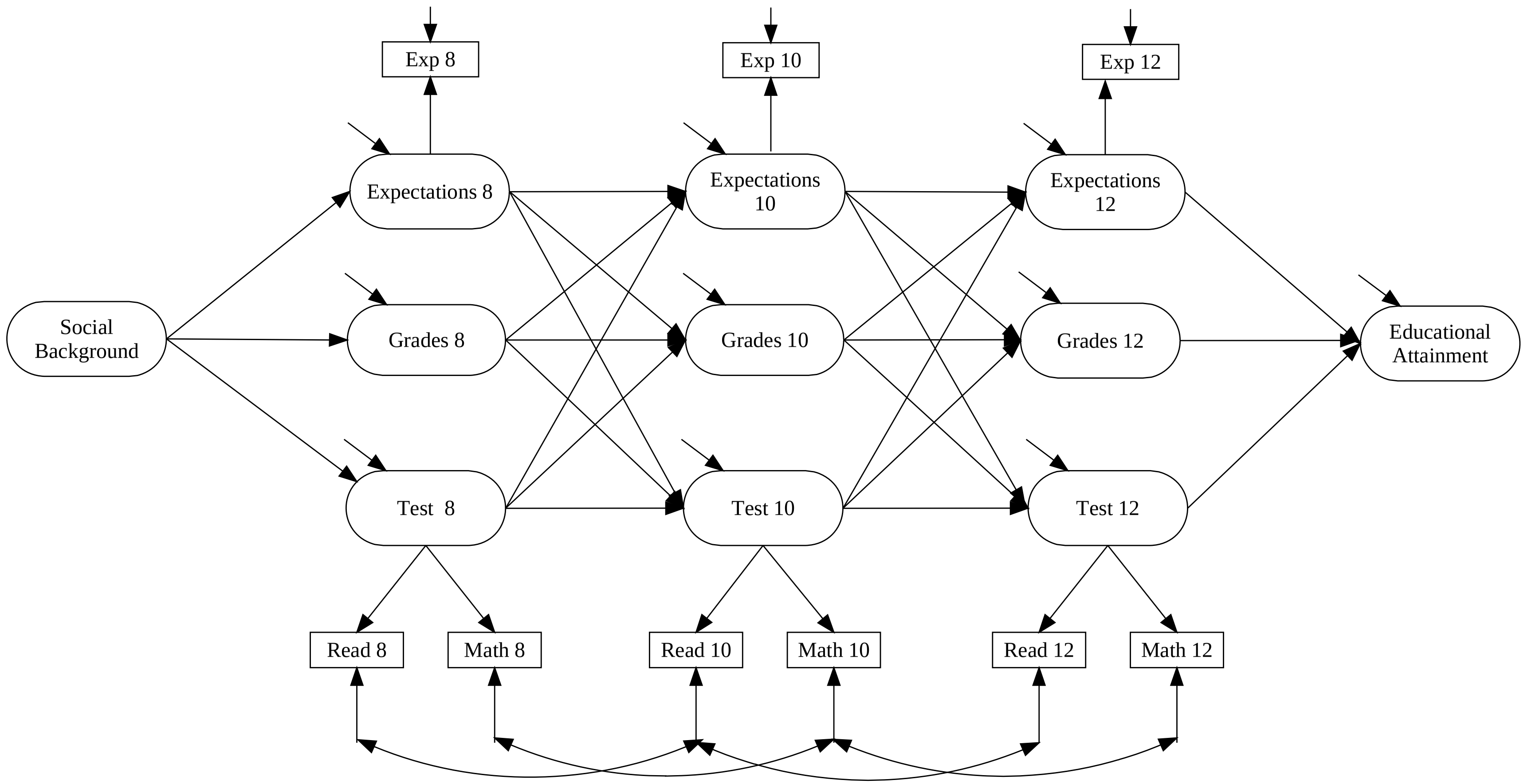


Figure 3. Schematic Model of Dynamic Inter-Period Updating in Educational Expectations

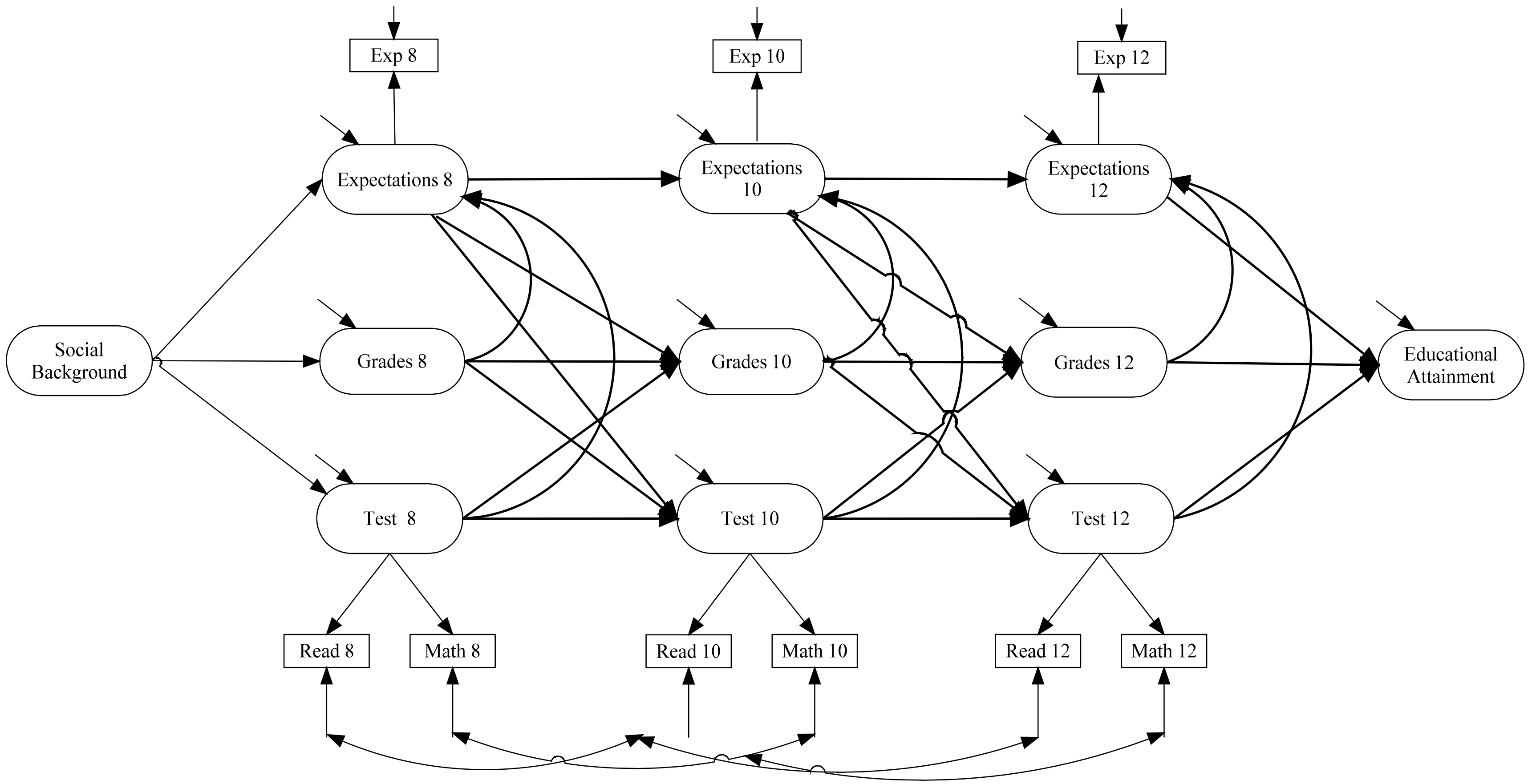


Figure 4. Schematic Model of Intra-Period Updating in Educational Expectations

APPENDIX

EXTENDED SPECIFICATION OF STRUCTURAL AND MEASUREMENT MODELS OF EDUCATIONAL EXPECTATIONS AND ATTAINMENT

We estimate a five-period model of expectations formation and educational attainment spanning childhood to young adulthood. We begin here by specifying an inter-period dynamic updating model with no measurement error similar to that described in the text and then modify equations describing this model to specify an intra-period updating model and a static expectations model. In the inter-period updating model, $\boldsymbol{\xi}^{\mathbf{k}}_{\mathbf{t=1}}$ is a K by 1 vector of exogenous students' childhood social background characteristics at $t = 1$; $\boldsymbol{\eta}^{\mathbf{j}}_{\mathbf{t}}$ is a J by 1 vector of latent variables representing students' expectations, grades, test scores, and educational attainment in adolescence and young adulthood at $t = 2,3,\ldots,5$. Periods $t = 2,3,\ldots,5$ correspond to 8th grade, 10th grade, 12th grade, and young adulthood, respectively. In the structural model, $\boldsymbol{\beta}^{\mathbf{j}}_{\mathbf{t}}$ is a J by J matrix describing the relationships among these latent endogenous variables, and $\boldsymbol{\Gamma}^{\mathbf{jk}}_{\mathbf{t}}$ is a J by K matrix describing the effects of exogenous childhood social background characteristics on students' educational expectations, grades, test scores, and educational attainment. The matrixes $\boldsymbol{\Phi}_{\mathbf{t=1}}$ and $\boldsymbol{\Psi}_{\mathbf{t}}$ are period-specific variance-covariance matrices for $\boldsymbol{\xi}^{\mathbf{k}}_{\mathbf{t=1}}$ and $\boldsymbol{\eta}^{\mathbf{j}}_{\mathbf{t}}$. The structural model for inter-period updating in expectations at period $t = 2$ is given by:

$$\eta^j_{t=2} = \Sigma\gamma^{jk}_{t=1}\xi^k_{t=1} + \zeta^j_{t=2}, \quad (1)$$

where j is limited to the students' educational expectations, grades, and test scores at $t = 2$ in the 8th grade. The ζ^j_t are random disturbances in the structural equations. We estimate off-diagonal elements of $\mathbf{\Psi_t}$ to induce cross-equation covariances among the ζ^j_t at t = 2,3,4 when the analogous element of $\boldsymbol{\beta}^{\mathbf{j}}_{\mathbf{t}}$ is not estimated. The structural model for t = 3,4 for inter-period updating in expectations is the same in these two periods:

$$\eta^j_t = \Sigma\beta^j_{t-1}\eta^j_{t-1} + \zeta^j_t \quad (2)$$

where once again j is limited to educational expectations, grades, and test scores and we include off-diagonal terms in $\mathbf{\Psi_t}$ when the analogous elements of $\boldsymbol{\beta}^{\mathbf{j}}_{\mathbf{t}}$ are not estimated. Note that exogenous childhood social background characteristics $\boldsymbol{\xi}^{\mathbf{k}}_{\mathbf{t}}$ do not directly determine expectations, grades, or test scores at t = 3,4. Rather, a measure of any η^j_t at t = 3,4 is directly determined by all measures η^j at t-1. Equation (2) describes a block recursive structure among measures of expectations, grades, and test scores from the 8th to the 12th grades in the inter-period updating model. In the final period t = 5, we model educational attainment at young adulthood as:

$$\eta^j_{t=5} = \Sigma\gamma^{jk}_{t=1}\xi^k_{t=1} + \Sigma\beta^j_{t=4}\eta^j_{t=4} + \zeta^j_{t=5} \quad (3)$$

where j at $t = 4$ is limited to educational expectations, grades, and test scores and where k at $t = 1$ is a subset of k exogenous childhood social background measures that directly determine educational attainment in young adulthood. In equation (3), we only allow the elements of $\boldsymbol{\xi}^{\mathbf{k}}_{\mathbf{t}}$ for father's education and family income to directly determine educational attainment in young adulthood.

In the measurement model, $\boldsymbol{\Lambda}^{\mathbf{y}}_{\mathbf{t}}$ is a p by J matrix of coefficients derived from the regression of the vector $\mathbf{y_t}$ on the vector $\boldsymbol{\eta}^{\mathbf{j}}_{\mathbf{t}}$. Analogously, $\boldsymbol{\Lambda}^{\mathbf{x}}_{\mathbf{t}}$ is a q by K matrix of coefficients derived from the regression of $\mathbf{x_t}$ on $\boldsymbol{\xi}^{\mathbf{k}}_{\mathbf{t}}$. Initially, our measurement model describing observed social background, expectations, grades, and educational attainment is quite sparse, with only one indicator per construct and no errors in variables. However, we observe a math and a reading test score for each period $t = 2,3,4$ that we model as products of a latent endogenous element $\boldsymbol{\eta}^{\mathbf{j}}_{\mathbf{t}}$. Thus, the measurement model consists of

$$y_t = \lambda^y_t \eta^j_t + \varepsilon_t \qquad (4)$$

for test scores,

$$y_t = \lambda^y_t \eta^j_t \qquad (5)$$

for other endogenous variables, and

$$x_{t=1} = \lambda^x_{t=1} \xi^k_{t=1} \qquad (6)$$

for the exogenous demographic and social background variables. In equation (4) an observed reading test measure y and an observed math test measure y at time $t = 2,3,4$ are both determined by $\boldsymbol{\eta}^{\mathbf{j}}_{\mathbf{t}}$ and a random measurement error, ε^j_t. The variance-covariance matrix of the ε^j_t is denoted by $\boldsymbol{\Theta}^{\varepsilon}$ with elements θ^{ε}. We permit off-diagonal entries (correlations) between errors in each indicator of academic achievement across adjacent periods. For example, the error in math achievement in the 8th grade may be correlated with the error in math achievement in the 10th grade. We normalize test achievement indicators by constraining the loading for reading achievement (λ^y_t) to one for each period t = 2,3,4. For the other endogenous variables, y_t, the model of equation (5) does not include error terms, so each $\lambda^y_t = 1$. The vector $\boldsymbol{\Lambda}^x_t$ is also composed of self-representing elements measured without error in the initial, naive measurement model (equation 6), and all $\lambda^x_t = 1$. The system of equations described by (1)-(6) is estimated separately for Blacks, Latinos, and whites, but we constrain $\boldsymbol{\Lambda}^y_t$ in equation (4) to equality among the three groups in order to establish a common metric for test achievement in the structural model with naïve measurement of all other exogenous and endogenous variables.

The inter-period model described above can be modified to include or alternatively estimate intra-period updating in educational expectations. This is achieved by freeing elements of $\boldsymbol{\beta}^j_t$ while constraining corresponding elements of $\boldsymbol{\Psi}_t$. We re-write equations (1) and (2) to describe expectation formation in a period based on inter- *and* intra-period updating:

$$\eta^j_{t=2} = \Sigma\gamma^{jk}_{t=1}\xi^k_{t=1} + \Sigma\beta^j_{t=2}\eta^j_{t=2} + \zeta^j_{t=2} \qquad (7)$$

$$\eta^j_{t=3,4} = \Sigma\beta^j_t\eta^j_t + \Sigma\beta^j_{t-1}\eta^j_{t-1} + \zeta^j_t \qquad (8).$$

In equation (7), educational expectations at $t = 2$ in the 8th grade are determined by exogenous social background characteristics at $t = 1$, the $\beta^{j}_{t=2}$, and a disturbance ζ^{j}_{t}. The $\beta^{j}_{t=2}$ are limited to effects of 8th grade GPA and 8th grade test achievement on expectations. Since these elements of $\boldsymbol{\beta}^{\mathbf{j}}_{\mathbf{t}}$ are now free, we constrain corresponding elements of $\boldsymbol{\Psi}_{\mathbf{t}}$ to zero. Equation (8) omits effects of the exogenous variables but permits inter-period updating (β^{j}_{t-1}). Thus, at $t = 3,4$ we retain a block recursive structure for inter-period measures of expectations, grades, and test scores, and allow intra-period effects from grade and tested achievement to educational expectations.

We also estimate a static expectations model. Once again, we can modify the equations used to describe a model with inter-period updating in educational expectations to describe the static expectations model. We re-write equation (1) as:

$$\eta^{edexp} = \Sigma\gamma^{k}_{t=1}\xi^{k}_{t=1} + \zeta^{j} \qquad (9).$$

Note that we have removed the subscript t to indicate the static nature of this construct over time and that we refer to the η specifically as "edexp" to underscore that equation (9) only applies to educational expectations in the static expectations model. The structure remains as before in equation (2) for grades and test achievement. The measurement model for the static expectation construct changes much more significantly. Now, we have:

$$y_t = \lambda^{y}{}_{t}\eta^{edexp} + \varepsilon_t \qquad (10)$$

for $t = 2, 3, 4$, where the y_t are no longer single, self-representing measures but three measures of one latent educational expectation construct that happen to have been taken across three periods. While the ε_t term is limited to test achievement in the original equation in (4) for dynamic updating models, we now include this measurement disturbance for observed expectations measures. Recall that all variations of the static expectations model include this feature—errors in expectation measures.

We also estimate three different measurement models for each of the structural models described above. These measurement models vary specifications of equations (4) to (6). The first is exactly as specified in equations (4) to (6) and (10): We initially model measurement error only in test achievement in all structural models and measurement error in a static expectation construct. In the second variant we estimate:

$$x_{t=1} = \lambda^{x}{}_{t=1}\xi^{k}{}_{t=1} + \delta_{t=1} \qquad (11).$$

That is, all observed x_t are determined by the $\xi^{k}{}_{t}$ as before but now we include two reports x_t for certain $\xi^{k}{}_{t}$, allowing us to specify a measurement error, $\delta_{t=1}$ for each of the x_t. The variance-covariance matrix of the measurement errors in exogenous variables is given by $\Theta^{\delta}{}_{t=1}$ with elements $\theta^{\delta}{}_{t=1}$. We use two observed indicators of each parent's education and occupational status, as well as family income. We also allow for some error terms $\delta_{t=1}$ to covary across measurement equations, as described in the main text.

In the third variation of the measurement model, we specify error in all observed self-representing measures of the endogenous variables except educational attainment in young adulthood (where a random error of measurement would not be identified). Recall that we initially estimated

$$y_t = \lambda^{yj}{}_t \eta^j{}_t + \varepsilon_t \qquad (12)$$

only for observed test achievement measures in the dynamic updating models and for test achievement and expectations in the static expectations model. We now relax this restriction and estimate equation (12) for all observed expectations, grades, and test measures, even self-representing measures of expectations and grades where they occur. The error variances, $\theta^{\varepsilon}{}_t$, are identified for expectation and grade measures by constraining social background effects on endogenous measures at $t = 3,4$ to zero, by specifying no two-period lagged effects of expectations, grades, or academic achievement, and by constraining the effects of expectations and grades at $t = 2,3$ on educational attainment to zero. Furthermore, we impose within-group, cross-period and cross-group, within-period equality constraints on the $\theta^{\varepsilon}{}_t$ terms for expectations and grades in order to stabilize estimates. These constraints are described in detail in the main text.

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