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The "Window Problem" in Studies of Children's Attainments: A Methodological Exploration

Barbara WOLFE, Robert HAVEMAN, Donna GINTHER, and Chong Bum AN

Numerous statistical studies of the determinants of children's attainments measure the circumstances or events occurring over the childhood period by observations of these variables for a single year or a short duration during childhood. These variables are accepted as proxies for information over the entire childhood period. We explore the reliability of estimated results from studies that use such "window" variables. Because window variables describing intermittent events and discontinuous periods of more persistent characteristics may fail to correspond to variables describing the entire childhood experience, the basic question concerns the extent to which such limited duration information is consistent with that measured over the entire childhood period. We first present an omitted variables model that describes the nature of the "window" problem, and which allows us to measure the consistency of window variables to their longer-duration counterparts. We then use the distinctions revealed by this model to empirically study the potential problems associated with the use of window variables. We use 21 years of data on a sample of 1,705 children from the Michigan Panel Study of Income Dynamics in reduced form models of the determinants of children's schooling and fertility outcomes. We develop four tests of the reliability of estimates using varying window lengths relative to full information on the childhood experience. These include omitted variable likelihood ratio tests, tests of goodness of fit, a sign and significance comparison, and a comparison of the magnitude of the simulated changes using window variables versus those of longer duration.

We conclude that single-year and limited duration window variables serve as weak proxies for information describing the entire childhood experience, and often lead to inferences of effects that may be misleading; we draw the implications of this finding for future data collection and research.

KEY WORDS: Childhood attainments; Duration; Window variables.

1. INTRODUCTION

Numerous studies since the early 1980s have used longitudinal microdata on families and their children to estimate life-cycle models in which family circumstances and events during childhood are presumed to affect children's attainments when they are young adults. The primary data sets used are the University of Michigan Panel Study of Income Dynamics (PSID) and the National Longitudinal Survey of Youth (NLSY). The attainments analyzed include schooling, fertility behavior (especially teen nonmarital births), welfare recipiency, and labor market success. Hypotheses drawn from economics, sociology, and developmental psychology concerning the potential effect on children's later success or failure of various circumstances or events experienced while growing up have been tested. These circumstances or events include parental education, income, family structure, welfare recipiency, parental divorce, and geographic move.

Ideally, child- and family-specific longitudinal information on an extensive set of circumstances and events spanning the entire childhood period would be available for testing these hypotheses. However, many of the published studies have used longitudinal data that do not contain such long-duration information. Two reasons account for the use of more restrictive information. First, some of the prominent longitudinal data sets used for these analyses (e.g., the NLSY), do not begin collecting information on individuals until they are at least 14 years old; hence measures of events and circumstances during preadolescent years are unavailable. In other cases, researchers who study outcomes later in life (e.g., attainments among 20 to 30 year olds) accommodate to the limited duration of longitudinal data by selecting a sample of older individuals, thus trading off information on preadolescent circumstances for information on outcomes during adult years. Because of either data limitations or researcher choice, information on family, school, and neighborhood variables measured during a brief observation "window"—often a single year, typically when the child is age 14—has been used to proxy for more complete information spanning the entire childhood period.

Among the post-1980 studies that use information on a truncated period (often a single year) of observation during children's adolescent years in analyzing the influence of family events and circumstances on children's attainments are those by Antel (1988), Astone and McLanahan (1991), Brooks-Gunn, Duncan, Klebanov, and Sealand (1993), Case and Katz (1991), Corcoran, Gordon, Laren, and Solon (1992), Crane (1991), Datcher (1982), Duncan, Hill, and Hoffman (1988), Duncan and Hoffman (1990a and 1990b), Greenberg and Wolf (1982), Hauser and Sewell (1986), Hayward, Grady, and Billy (1992), Hogan and Kita-

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gawa (1985), Krein (1986), Lundberg and Plotnick (1990), Manski, Sandefur, McLanahan, and Powers (1992), Mare (1980), Mayer (1991), McLanahan (1985), McLanahan and Bumpass (1988), Ribar (1991), Sandefur, McLanahan, and Wojtkiewicz (1992), and Sewell, Hauser, and Wolf (1980). The statistical methods used in these studies include ordinary least squares multiple regression, maximum likelihood estimation, sequential or simultaneous equations models (e.g., bivariate probit models), and nonparametric estimation techniques. Haveman and Wolfe (1995) review and critique this extensive body of research.

The reliability of studies of children's attainments that use circumstance or event variables based on window observations is questionable. The primary issue is the extent to which information measured during a brief window of time *corresponds* to that measured over a longer period. This is of special concern when relevant time periods extend for several years so that discrete events can occur multiple times or particular circumstances can persist for various durations. The question is: Can a variable based on a short observation window reliably capture events that might occur intermittently or with a low frequency throughout the childhood years (e.g., parental separations), or circumstances during childhood that are complex, fluid, and of varying durations (e.g., family welfare receipt)?

Because variables describing childhood events or circumstances measured during a brief window contain less information (or at best equal information) relative to variables measured over a longer period, statistical measures of the effect on children's attainment of such events and circumstances may be affected. A second question, then, is: How accurate are estimates of effects based on variables constructed from window information relative to estimates based on variables that contain long-duration childhood information? The correspondence of window and long-duration variables, and the accuracy of estimates of effects based on window variables, have also been studied by Cherlin and Horiuchi (1980) and, more recently, by Martinson and Wu (1992).

In this article, we provide evidence on these correspondence and accuracy issues. Section 2 presents linear and probit models that reveal the essence of the window problem. These models demonstrate the conditions under which the use of window variables will yield biased and inconsistent estimates of the effects of family circumstances and events during childhood on children's attainments when they are young adults. We also classify the extent to which window variables are reliable proxies for, or correspond to, those that more fully describe the childhood experience. Our focus is both on family events that are intermittent (such as the divorce or separation of parents) and on family circumstances, such as income, that are more akin to continuous variables. Section 3 describes our data and variables, and Section 4 measures the correspondence of window variables to their long-duration counterparts. Section 5 provides our estimates of the extent to which window variables yield biased estimates of the effects of childhood events and circumstances on three measures of children's attainments: two education outcomes and one childbearing outcome. Section 6 concludes.

2. THE WINDOW PROBLEM

Parameter estimates based on variables that reflect circumstances prevailing (or events occurring) during a constrained interval of an observation period will be biased and inconsistent estimates of true underlying relationships, relative to variables that reflect circumstances or events over the entire period. We demonstrate this proposition by constructing a model in which dummy variables measure the occurrence of a circumstance or event in a single year during childhood.

Let the true measure of a childhood circumstance, such as living in a poor family, be the proportion of the childhood years during which a child experiences this condition:

$$x_i = \frac{1}{n}\sum_{t=1}^{n} x_{it},$$

where n is the number of years during the childhood period and x_{it} is a dummy variable reflecting the occurrence of an event or the presence of a circumstance in year t during the childhood period; it is a one-period observation. Thus $x_i = 1$ is a maximum value if a circumstance is experienced (or an event occurs) in each year of the childhood period; $x_i = 0$ is a minimum value if a circumstance is never experienced (or an event never occurs) during the observation period.

In the linear case, the true model is given by (1), where y_i is the ith child's outcome (measured when the child is a young adult) and $\boldsymbol{\beta}$ is a vector of parameters. The error term is assumed to be normally distributed with zero mean and variance equal to σ_ε^2.

$$\begin{aligned} y_i &= \boldsymbol{\beta}' x_i + \varepsilon_i \\ \varepsilon &\sim N(0, \sigma_\varepsilon^2). \end{aligned} \tag{1}$$

A particular 1-year window observation, x_T, is often used as a proxy for the entire childhood experience, x_i. Let z_i be the absolute value of the difference between the entire childhood experience x_i and the window variable x_{Ti}:

$$z_i = |(x_i - x_{Ti})|$$

If the event occurs (or the circumstance is experienced) in each year of childhood outside of the window *and* in the window period, then $z_i = 0$. Similarly, if the event never occurs or the circumstance is never experienced, then $z_i = 0$. In these cases, the 1-year window observation correctly characterizes the occurrence of an event or the experiencing of a circumstance; however, it omits information on the duration of the occurrence or experience.

But if the event never occurs (or the circumstance is never experienced) during the observation period outside of the window but does occur (or is experienced) in the window period, then the absolute value of z_i takes on maximum value $z_i = \max(z_i = (n-1)/n$. (The same result holds if the event occurs or the circumstance is experienced in each year of the observation period outside of the window and does not occur or is not experienced in the window period.) In such cases, the 1-year window observation provides information that is totally different from that observed during the remainder of childhood, and x_{Ti} provides an erroneous measure of x_i, the true measure of an event's occurrence or a circumstance experienced during the childhood period. The characterization of the occurrence or experience is in error, and moreover no information on the duration of the event or circumstance is provided.

If the event occurs (or the circumstance is experienced) during some years of the observation period outside of the window but does not occur (or is not experienced) in the window period (or, conversely, the event does occur or the circumstance is experienced in the window period), then z_i will lie between zero and $\max(z_i)$. In these cases, the window observation is also an inaccurate measure of x_i, omitting information on the frequency with which an event occurs or the duration in which a circumstance is experienced, and perhaps mischaracterizing whether or not an event occurred or a circumstance is experienced.

With these definitions, we can rewrite the true model fit over all individuals as

$$Y = \boldsymbol{\beta}'(Z + X_T) + \varepsilon. \tag{2}$$

Researchers who use a window variable run the following regression:

$$Y = \boldsymbol{\beta}^{*\prime} X_T + U.$$

The estimated coefficient $\boldsymbol{\beta}^*$ is a biased and inconsistent estimate of the true parameter $\boldsymbol{\beta}$ when the covariance of X_T and Z is nonzero:

$$\hat{\boldsymbol{\beta}}^* = (X_T' X_T)^{-1} X_T' Y,$$

$$\hat{\boldsymbol{\beta}}^* = (X_T' X_T)^{-1} X_T' (Z\boldsymbol{\beta} + X_T \boldsymbol{\beta} + \varepsilon),$$

$$E(\hat{\boldsymbol{\beta}}^*) = \boldsymbol{\beta} + E((X_T' X_T)^{-1} X_T' Z \boldsymbol{\beta}),$$

and

$$\text{plim}(\hat{\boldsymbol{\beta}}^* - \boldsymbol{\beta}) = \text{plim}((X_T' X_T)^{-1} X_T' Z \boldsymbol{\beta}) \neq 0.$$

When the covariance is nonzero, the best a window variable can do is to correctly describe whether or not an event occurred or a circumstance was experienced during the childhood period; however, information on the duration of the occurrence or the experience will be omitted. Hence when the values of x_{it} for the nonwindow years are not randomly assigned, X_T and Z_i will covary, and using X_T will lead to bias; that is, there is an omitted variables problem. However, should the values of x_{it} for the nonwindow years be random—assigned, say, by flipping a coin—using X_T would yield an unbiased estimate of the true coefficient. The information for the nonwindow years would simply be noise, and using all of the information provided by these observations would lead to unnecessarily large standard errors but no bias; the problem here would be an errors-in-variables problem.

Similar to the linear model, coefficients estimated using window variables in limited dependent variable models will also be biased and inconsistent when the covariance of Z_i and X_T is nonzero. As there is no closed-form solution for estimated coefficients in probit models, we show the approximate effects of using a window variable, following Kiefer and Skoog (1984) and Yatchew and Griliches (1985).

The true model of y_i^* (a latent variable measuring the utility of a particular outcome, say, graduating from high school) is

$$y_i^* = \boldsymbol{\beta}' x_i + \varepsilon_i$$

$$\varepsilon \sim N(0, \sigma_\varepsilon^2), \tag{3}$$

where y_i^* is not observed. We observe y_i, whether or not an individual graduates from high school:

$$y_\imath = \begin{cases} 1 & \text{if } y_i^* > 0 \\ 0 & \text{if } y_i^* \leq 0. \end{cases}$$

Assuming that y_i is a Bernoulli variable with

$$\Pr(Y_1 = 1) = \Phi(\boldsymbol{\beta}' X_i) = F_\imath,$$

the normed log-likelihood is

$$L(\boldsymbol{\beta}) = \frac{1}{m} \sum_{i=1}^{m} y_i \ln F_i + (1 - y_i) \ln(1 - F_i).$$

Following Kiefer and Skoog (1984), we can approximate the local bias of using window variables in place of full childhood experience variables in a probit model:

$$\hat{\Delta} = (X_T \Omega X_T)^{-1} X_T \Omega Z \boldsymbol{\beta},$$

where Ω_i is a diagonal matrix with the $\imath$th element equal to

$$\Omega_i = y_i \, \frac{\partial^2 \ln F_i}{\partial \boldsymbol{\beta} \partial \boldsymbol{\beta}'} + (1 - y_i) \, \frac{\partial^2 \ln F_i}{\partial \boldsymbol{\beta} \partial \boldsymbol{\beta}'} \, .$$

Similar to the linear case, when information is omitted by the window variable, parameter estimates based on limited dependent variable models fit over window variables are likely to be biased and inconsistent.

For any observation, three possible cases relating the window variable x_{Ti} and z_i (our indicator of the discrepancy between the entire childhood experience x_i and the window variable) can be distinguished:

- x_{Ti} correctly characterizes whether an event occurred or a circumstance was experienced but omits information on the frequency of the occurrence or the duration of the experience. In this case, $z_i = 0$.
- x_{Ti} perhaps mischaracterizes the occurrence of an event or the experiencing of a circumstance and omits information on the frequency of the occurrence or the duration of the experience; $0 < z_i < \max(z_i)$.
- x_{Ti} both mischaracterizes whether or not an event has occurred or a circumstance was experienced and omits information on the frequency of the occurrence or the duration of the experience. Here $z_i = \max(z_i) = (n-1)/n$.

In each case, the window variable omits relevant frequency or duration information, and using it in estimation

Table 1. Correspondence of Entire Childhood (Age 6–15) and Window (Age 14) Measures

	Proportion of observations			
	$z_i = 0$	$0 < z_i < max(z_i)$	$z_i = max(z_i)$	
	x_{Ti} correctly characterizes occurrence or experience but omits duration/frequency information	x_{Ti} may or may not correctly characterize occurrence or experience but omits duration/frequency information	x_{Ti} both incorrectly characterizes occurrence and experience and omits duration/frequency information	Correlation between age 14 and age 6–15 variables*
Living in SMSA				
Age 14 = 1	.642	.077	.001	.95
Age 14 = 0	.220	.060	.000	
Mother worked				
Age 14 = 1	.250	.375	.007	.73
Age 14 = 0	.128	.233	.006	
Changed location				
Age 14 = 1	.000	.107	.024	.44
Age 14 = 0	.333	.536	.000	
Parents separated				
Age 14 = 1	.000	.005	.018	.31
Age 14 = 0	.777	.201	.000	
Living with one parent				
Age 14 = 1	.162	.164	.015	.87
Age 14 = 0	.590	.069	.000	
Receiving welfare benefits				
Age 14 = 1	.029	.094	.009	.75
Age 14 = 0	.713	.153	.001	
Family head is disabled				
Age 14 = 1	.045	.124	.016	.73
Age 14 = 0	.608	.205	.001	

* The correlation between average income reported over age 6-15 and age 14 is .88.

will yield biased and inconsistent estimates of true relationships as long as the covariance of x_{Ti} and z_i is nonzero in the sample. The first three column headings of Table 1 summarize these cases.

3. DATA AND VARIABLES

In measuring the reliability of estimates of the determinants of children's attainments based on use of window variables as proxies for the entire childhood experience, we use data from a sample of children from the Michigan Panel Study of Income Dynamics (PSID). Our sample consists of the 1,705 children who were age 0 to 6 in the first year of the PSID (1968) and were still in the survey in 1988. For each child, detailed annual information on family *background,* including race, parental education, one or two parents present in the household, geographic location, and number of siblings; *economic resources,* including family income, income source, and adult labor supply; *events,* including parental separation, remarriage, and geographic moves; and *neighborhood* characteristics are recorded and made specific to the child's age. The outcomes that we study include a continuous variable (years of education) and two limited variables (teen nonmarital birth = 1 and high school graduation = 1). For the first of these we use only those who have attained age 24 by the last (or 21st) year in which they are observed, so as to have a reliable measure of completed schooling; only females are included in the teen nonmarital birth estimates, whereas the entire sample is included in the high school graduation estimates.

All of the variables except the neighborhood characteristics are available in the PSID. The neighborhood variables (percentage of families in the neighborhood headed by a female and percentage of youths age 16–19 in the neighborhood who are high school dropouts) are merged onto the PSID data by matching small area (typically, Census tract) data from the 1970 and 1980 U.S. Census to where the child resided each year. The annual values of the neighborhood variable are linear weighted averages of the 1970 and 1980 values. All monetary variables are in constant 1976 dollars.

From the PSID, we can measure a number of family circumstances and events at each of the child's ages from 6–15 (the entire childhood period), and also over various subperiods within the entire period. We start childhood at age 6, because our data allow us to measure every child's age 6 characteristic but not those at younger ages. Family background variables, such as race and parent's schooling, are assumed to measure family circumstances from age 0–5. The circumstances and events that serve as independent variables and that may vary in window length include:

- percentage of years living in an urban area (SMSA)
- percentage of years mother worked
- average annual number of geographic moves
- average annual number of parental separations

Table 2. Likelihood Ratio Tests of Hypothesis that Models Estimated with Age 14 Window Variables (Age 6–15 Variables) Are Not Subject to Omitted Variables Bias

	Ln likelihood	Degrees of freedom
Teen out-of-wedlock birth		
A. Model based on age 6–15 variables	−282.95	17
B. Model based on age 14 window variables	−286.21	17
C. Model based on age 14 window variables and age 6–15 variables	−280.46	25
Test statistic		
Test of B vs. C*	11.52	
High school graduation		
A. Model based on age 6–15 variables	−618.91	19
B. Model based on age 14 window variables	−633.80	19
C. Model based on age 14 window variables and age 6–15 variables	−616.02	27
Test statistic		
Test of B vs. C*	35.57	
Years of Education		
A. Model based on age 6–15 variables	−1373.6	19
B. Model based on age 14 window variables	−1391.3	19
C. Model based on age 14 window variables and age 6–15 variables	−1371.1	27
Test statistic		
Test of B vs. C*	40.37	

Critical values: .25 = 10.22; .10 = 13.36; .05 = 15.51.
* Test is of the null hypothesis that adding age 6-15 variables to models estimated with age 14 variables provides *no* significant information; that the latter models are not subject to omitted variables bias.

- percentage of years living with one parent
- average ratio of family income to the poverty line (needs)
- percentage of years family received welfare (AFDC) benefits
- percentage of years the family head is disabled.

With the exception of the ratio of family income to the poverty line, the single-year window measure of these variables is dichotomous. Both the geographic moves and the parental separations variables measure *events;* the family income variable should be considered a *circumstance.* The remaining variables can be thought of as either a series of events occurring during the childhood period or as a circumstance experienced during childhood.

To evaluate the effects of using increasing amounts of information in our estimation, we measure these variables with increasing window lengths, from a single year (age 14), to age 6–8, age 12–15, age 9–15, and (using all the information available in the data) age 6–15. All variables are scaled by the length of the window (i.e., averaged over the length of each specific window), to compare coefficients across models. We use estimated coefficients on the age 12–15 and age 9–15 variables as well as the full period (age 6–15) as the basis for evaluating the extent of bias incurred using a window variable measured over a limited number of years; we also use estimated coefficients on the age 6–8 variables to evaluate the validity of using a window year late in childhood (age 14) to represent years early in childhood (age 6–8).

Table 3. Results of Likelihood Ratio Tests of Hypotheses that Models Estimated with Age 14 Window Variables (Various Multiyear Variables) Are Not Subject to Omitted Variables Bias

	Ho: Adding age 14 variables to model including multiyear variables provides no significant information (A vs. C)			Ho: Adding multiyear variables to model including age 14 variables provides no significant information (B vs. C)		
	Teen birth	High school grad	Years of education	Teen birth	High school grad	Years of education
Age 12–15	6.16	7.31	14.09	14.77	25.05	18.15
Age 9–15	3.61	7.55	7.29	6.56	28.63	13.51
Age 6–8	25.04	21.51	10.19	32.71	25.67	20.75

Critical values: .25 = 10.22; .10 = 13.36; .05 = 15.51.

4. THE CORRESPONDENCE OF WINDOW MEASURES TO LONG-DURATION MEASURES

To what extent do the age 14 variables (x_{Ti})—and variables measured over subperiods during childhood—correspond to, and accurately proxy for, measures of the entire childhood experience (x_i)? Table 1 shows the relative frequency of observations in each of three categories of z_i (the difference between the full childhood experience and the variable for a particular window measurement) for both observations with a value of 1 at age 14 and with a value zero at age 14. The proportions are shown for the seven dichotomous variables describing circumstances and events during the childhood years. (The continuous measure of family income relative to needs is not included.) The last column reports the correlation between the age 14 and age 6–15 variables.

The *sum* of the relative frequencies in the pair of cells in the first column of each matrix indicates the extent to which the age 14 window variable corresponds to, or is an accurate proxy for, the entire childhood experience; however, even in this case, information on duration or frequency is omitted (see Sec. 2). This sum ranges from 33% (geographic moves) to 86% (percentage of years in SMSA) over the seven variables.

For both events and circumstances that are rare and those that are persistent, the window variable may be a reliable proxy of the entire childhood experience (though omitting duration or frequency information). For example, nearly 78% of our observations experienced parental separation (a relatively rare event) neither at age 14 nor in any other year of childhood; the window variable correctly characterizes the experiencing of this event for these observations. Similarly, 86% of the children living in (or not living in) an SMSA at age 14 experienced the corresponding age 14 location characteristics in every other year of the childhood period; the window variable accurately characterizes this rather persistent circumstance for these observations. However, for those circumstances that may change often during childhood years (e.g., mother's working), or events that are relatively common (e.g., geographic moves), the age 14 window variables correspond to those describing the entire childhood experience for a relatively small proportion of the observations. (The sums of the column 1 proportions are 38% and 33% for these two variables.)

The last column reports the simple correlation coefficients between the age 14 value and the age 6–15 value; the age 14 variable can only take on a value of zero or 1, whereas the age 6–15 variables can take on values from zero to 1 (in intervals of .1). For variables that measure circumstances that tend to be persistent, the correlation coefficient is relatively high and conveys much the same information as does our classification of the z_i indicator. For example, the years in an SMSA variable has a correlation coefficient of .95. Similarly, for those variables in which the proportion of observations in the middle column of each matrix is relatively high (above, say, .25), the correlation coefficient lies toward the middle of the zero–1 range; from .44 to .87 for our variables. However, in the case of rare events (e.g., parental separations), the correlation coefficient is low, reflecting the high proportion of zeros (78%) for both the age 14 and age 6–15 variables. For dummy variables in which a high percentage of observations are zero, and hence have no variation, the correlation coefficient reveals less about the degree of correspondence between the window and full childhood experiences than does the information in the matrix.

5. EFFECTS OF THE CHILDHOOD EXPERIENCE ON ATTAINMENTS: ESTIMATES USING WINDOW AND LONG-DURATION MEASURES

Given these results on the correspondence of the dichotomous window variables to long-duration childhood variables, we next conduct a series of tests of the reliability of estimates of the effects on attainments from using window variables relative to long-duration childhood experience variables. Our tests are based on estimates of several reduced-form models relating family background and circumstance/event variables to each of three outcomes observed during young adult ages: two limited dependent variable outcomes (high school graduation and teen out-of-wedlock birth) and a continuous variable (the number of years of schooling attained). Each model includes an identical set of family background and demographic variables, and each also includes the eight family circumstance/event variables that can be measured over various periods during the entire age 6–15 childhood period. The specification of the models follows those of An, Haveman, and Wolfe (1993), Haveman and Wolfe (1994), and Haveman, Wolfe, and Spaulding (1991). The estimated models are shown in Appendix A. Definitions of the variables, along with their means and standard deviations, are provided in Appendix B.

Using these models, we undertake four tests of the reliability of estimates based on window variables relative to those based on their long-duration counterparts:

- Test 1: Omitted variables likelihood ratio tests of the null hypotheses that adding information from the age 6–15 period to a specification including the age 14 window variable does not significantly improve the fit of the estimated model.
- Test 2: Tests of the goodness of fit of the age 14 and longer-duration specifications.
- Test 3: A sign-and-significance test in which the estimated coefficients on the family circumstances/event variables measured using the age 14 window are compared to the estimated coefficients on longer-duration childhood variables.
- Test 4: A comparison of the magnitude of the effects of simulated changes of those window and longer-duration variables that conform in terms of sign and statistical significance.

5.1 Test 1: Likelihood Ratio Tests

Table 2 presents the results of log-likelihood tests indicating the presence or absence of omitted variable bias in models that include the age 14 information but exclude the

Table 4. Comparability of Age 14 Window and Age 6–15 Coefficients and Statistical Significance

	Teen birth	High school graduation	Years of education
Percentage of years in SMSA	0	0	NC
Percentage of years mother worked	0	+	0
Average annual number of geographic moves	NC	−	−
Average annual number of parental separations	NC	NC	NC
Percentage of years living with one parent	+	−	NC
Average ratio of family income to needs	−	NC	+
Percentage of years receiving welfare benefits	0	0	0
Percentage of years family head is disabled	NC	−	−

NOTE: NC = Estimates from the two models are not statistically significant at the .1 level, but have opposite signs.
− = Coefficients both negative and significant at the .1 level.
+ = Coefficients both positive and significant at the .1 level.
0 = Neither coefficient significant at the .1 level.

age 6–15 information. The reported test (B versus C) is of the null hypothesis that adding age 6–15 variables to a model that includes age 14 variables provides no significant additional information. If age 14 information is a good proxy for the entire age 6–15 period, then we should expect the data to accept this hypothesis. For both of the education outcomes, the test statistic is significant at the .05 level; for the teen out-of-wedlock birth outcome, it is not significant at this level. In general, adding information contained in the age 6–15 variables to models containing the age 14 variables appears to provide significant information. We conclude that models of children's attainment using only age 14 information to measure the effect of family circumstances and events on children's attainments tend to be subject to omitted variable bias.

Table 3 shows analogous omitted variable tests for the addition of variables, including information from various subperiods during age 6–15 relative to models that include the age 14 variables, and the reverse comparison in which age 14 variables are added to models that include the various subperiod variables. The first two rows of results are for shorter subperiod variables surrounding the age 14 variable—in particular, age 12–15 and age 9–15. The third row compares models estimated with age 6–8 variables to those estimated with age 14 variables.

The comparisons in the first two rows of Table 3 are similar to those reported in Table 2. At a 10% confidence level, models using age 14 variables alone relative to those using multiyear variables surrounding age 14 appear to be subject to omitted variable bias; the null hypothesis for this test (B versus C, shown in the last three columns) is rejected for all three outcomes using the age 12–15 measure and for two of the three outcomes using the age 9–15 measure.

The null hypothesis for the test in which age 14 information is added to models including multiperiod variables surrounding age 14 (A versus C, shown in the first three columns) is accepted for five of six models (the two limited dependent variable models and the continuous education model when the age 14 variable is added to the model that includes age 9–15 information); in those cases, the age 14 variables fail to add significant information.

The comparisons in the third row of Table 3 indicate that adding age 14 variables to models containing early childhood (age 6–8) variables and adding early childhood variables to models that include age 14 variables both yield significant additional information. In five of the six cases, the null hypothesis is rejected.

*Table 5. Simulated Effects on Outcomes of a One Standard Deviation Increase in Those Family Circumstances/Events Variables with Comparable Signs and Significance**

	Simulated probability		Percent change from base		Absolute change from base	
	Age 14	Age 6–15	Age 14	Age 6–15	Age 14	Age 6–15
Teen out-of-wedlock birth (base probability = .079)						
Percentage of years living with one parent	.121	.098	+52.4	+23.3	+.042	+.019
Average ratio of family income to needs	.041	.047	−48.1	−41.0	−.038	−.033
High school graduation (base probability = .877)						
Average annual number of geographic moves	.853	.836	−2.5	−4.6	−.022	−.040
Percentage of years family head is disabled	.852	.848	−2.6	−3.3	−.023	−.029
Percentage of years mother worked	.890	.893	+1.7	+1.8	+.015	+.016
Percentage of years living with one parent	.860	.858	−1.8	−2.2	−.016	−.019
Years of education (base years of education = 13.2)						
Average ratio of family income to needs	13.5	13.7	+2.2	+3.3	+.3	+.4
Average annual number of geographic moves	13.1	13.0	−1.1	−1.6	−.1	−.2
Percentage of years family head is disabled	13.1	13.1	−1.1	−1.4	−.2	−.2

* Variables that are same-signed in both age 14 and age 6-15 estimates and are significant at the .1 level in both cases.

5.2 Test 2: Goodness-of-Fit Tests

A second important criterion in assessing estimated models concerns the "fit" of the estimated relationships to the underlying data (see Hauser, Tsai, and Sewell 1983). We applied the Akaike information criterion (AIC) for goodness-of-fit tests to both the age 14 and age 6–15 models for both of the two limited dependent variable outcomes. The AIC is used in cases where competing models are not nested; smaller values dominate larger values (see Amemiya 1981). The values for the age 14 and age 6–15 teen birth model were 302.8 and 299.6; the values for the high school graduation model were 653.2 and 636.6. In both cases, the estimates based on the age 6–15 variables dominate those based on the age 14 variables.

The ability of the models to correctly identify individual outcomes observed in the data is another test of model fit. We find that in all of the outcomes, the models with age 6–15 variables correctly predict a larger proportion of the outcomes than do the models with only age 14 variables. (Results of the "correct predictions" tests are not shown.) With but one exception, these AIC and correct predictions test results hold in comparing the age 14 to the age 9–15 and age 12–15 models.

5.3 Test 3: Sign-and-Significance Comparison

The primary comparison is between the estimated coefficients on the age 14 window variables and the coefficients on variables measured over the entire age 6–15 period. Hence there are eight comparisons for each of the teen birth and education models, one for each of the eight independent variables that may vary in window length (see Table 4). We conclude that the age 14 window and the age 6–15 variables do *not* convey the same information regarding "effects" if *either* the two coefficients have different signs *or* the coefficients have the same sign but only one of them is statistically significant at the .1 level. In 16 of the 24 pairwise comparisons shown in the table, the age 14 variables are judged to yield comparable information on effects to that of the age 6–15 variables. In 8 cases, conformance does not exist. In 7 of the 16 cases in which comparability is observed, neither coefficient has statistical significance at the .1 level or less. In only 9 of the 16 conforming cases do both the age 14 and the age 6–15 variables have statistical significance at the .1 level; 7 of these 9 same-signed and significant comparisons are in the education estimates. In all eight of the nonconformance cases, the two coefficients have different signs, but neither coefficient is statistically significant at the .1 level.

To the extent there is a pattern to the conformance, it appears that those variables measuring relatively rare events, such as parental separations, are less likely to be in conformance than those variables where the occurrence is more persistent or where the independent variable is continuous.

5.4 Test 4: Magnitude of Simulated Effect Test

This comparison concerns the implications for policy of the results from the 24 age 14 versus age 6–15 pairwise comparisons. For those nine pairwise comparisons in which the coefficients on the window and entire childhood period variables have the same sign *and* are statistically significant at the .1 level, we compare the magnitude of the effect on the dependent variable of equivalent, one-standard-deviation simulated changes in the independent variables. The results are presented in Table 5. For example, the first row indicates that increasing by one standard deviation the age 14 variable measuring the effect of the number of years living with one parent would increase the probability of a teen nonmarital birth by .042, from .079 to .121, or by more than 50%; an equivalent increase of the same variable recorded over age 6–15 would increase the probability of a teen nonmarital birth by .019, or by less than 25%.

How different are these simulated changes in the dependent variable? If we view simulated changes in which the ratio of the two *percentage* changes from the base is more than 1.5 (in absolute terms) as conveying different information on effects, then four of the nine same-signed and significant cases indicate different quantitative effects. Alternatively, if we view cases in which the two *absolute* changes from the base differ from each other by more than an order of magnitude of less than one-half or twice or more as conveying dissimilar information on effects, then three of the nine same-signed and significant cases indicate dissimilar quantitative effects.

6. CONCLUSION

This exploration has yielded rather discouraging results regarding both the correspondence of single-year window observations to longer-duration measures of the childhood experience and the reliability of empirical estimates of effects of variables on attainments when window variables are used. We conclude that in general, single-year "window" variables serve as weak proxies for multiyear information recorded over childhood years. They are particularly weak measures of unique events such as parental separations.

Hence we conclude that those estimates in the published literature based on one-year window observations should be interpreted with caution. By relying on observed circumstances and events in but a single snapshot, many of these studies appear to provide biased and misleading estimates of the effects of a child's environment over a longer (or for a different) period. They are likely to be less biased for variables measuring continuous or persistent variables than for those measuring rare or unique events.

These results also highlight a basic issue of data collection in the social sciences. Our results suggest a high priority for the collection of longitudinal information on individuals and families extending over the entire childhood period. Because of the cost and timing constraints imposed by such efforts, an alternative might be to compile retrospective information on parental situations at various points during childhood from respondents who are older children. However, although the costs of the latter strategy are lower, this approach is less capable of accurately capturing correctly timed information on important aspects of parental circumstances and events.

APPENDIX A: ESTIMATES OF THE EFFECTS OF FAMILY BACKGROUND, CIRCUMSTANCES, AND EVENTS ON HIGH SCHOOL GRADUATION, TEEN OUT-OF-WEDLOCK BIRTH, AND YEARS OF EDUCATION: VARYING PERIODS OF CIRCUMSTANCES/EVENTS OBSERVATION

	(Probit) High school graduation		*(Probit) Teen out-of-wedlock birth*		*(Ordinary least squares) Years of education*	
Variable	*Coefficient*	*|T statistic|*	*Coefficient*	*|T statistic|*	*Coefficient*	*|T statistic|*
Constant	1.23	(4.95)	−1.24	(3.09)	11.9	(34.0)
Non−time-varying variables						
Black = 1	.19	(1.33)	.27	(1.47)	.08	(.37)
Female = 1	−.05	(.43)			−.31	(2.08)
Black × female	.42	(2.61)			.83	(3.83)
Religion	.08	(.53)	−.34	(1.55)	.45	(2.04)
Mother's education	.35	(3.63)	−.65	(4.28)	.44	(3.36)
Father's education	.43	(3.74)	−.02	(.14)	.79	(5.17)
One or no parents in 1968	.05	(.42)	−.15	(.80)	.25	(1.13)
Number of siblings	−.06	(2.21)	.08	(2.07)	−.11	(2.83)
Percentage of families in neighborhood headed by a female	−.81E−4	(.02)	.25E−2	(.39)	−.18E−2	(.26)
Percentage of young adults in neighborhood (ages 18–25) who are high school dropouts	−.16E−1	(3.52)	.81E−2	(1.07)	−.86E−2	(1.24)
Time-varying variables						
Average annual number of parental separations						
Age 14	−.66E−1	(.26)	−.29	(.72)	−.29	(.80)
Age 6–15	.19	(.21)	3.92	(3.15)	.22	(.16)
Age 9–15	.13	(.18)	2.99	(3.05)	.74	(.68)
Age 12–15	−.13	(.22)	1.41	(1.67)	−.04	(.05)
Age 6–8	−.41E−1	(.09)	.56	(.89)	−.45	(.69)
Average annual number of geographic moves						
Age 14	−.36	(3.36)	−.17E−2	(.01)	−.42	(2.40)
Age 6–15	−1.19	(5.28)	.47	(1.30)	−1.34	(4.09)
Age 9–15	−.82	(3.90)	.29	(.89)	−1.06	(3.43)
Age 12–15	−.66	(3.75)	−.09	(.30)	−.82	(2.95)
Age 6–8	−.78	(5.39)	.44	(1.90)	−.82	(3.70)
Percentage of years head of family is disabled						
Age 14	−.33	(3.37)	.40E−2	(.03)	−.36	(2.38)
Age 6–15	−.59	(4.24)	−.08	(.38)	−.61	(2.92)
Age 9–15	−.57	(4.40)	−.08	(.40)	−.56	(2.84)
Age 12–15	−.48	(4.02)	−.11	(−.57)	−.55	(2.86)
Age 6–8	−.39	(3.16)	.01	(.07)	−.52	(2.71)
Percentage of years mother worked						
Age 14	.18	(2.14)	.05	(.35)	.11	(.90)
Age 6–15	.28	(2.25)	.11	(.59)	.03	(.21)
Age 9–15	.22	(1.93)	.16	(.93)	.05	(.31)
Age 12–15	.24	(2.35)	.24	(1.47)	.04	(.30)
Age 6–8	.16	(1.55)	.04	(.31)	−.07	(.53)
Percentage of years family received welfare						
Age 14	−.18	(1.46)	−.12	(.67)	.03	(.02)
Age 6–15	−.08	(.40)	−.08	(.31)	.04	(.15)
Age 9–15	−.15	(.85)	−.17	(.68)	−.01	(.04)
Age 12–15	−.15	(.94)	−.07	(.30)	−.02	(.07)
Age 6–8	−.09	(.59)	.26	(1.14)	−.07	(.29)
Percentage of years lived with one parent						
Age 14	−.18	(1.69)	.65	(4.28)	.04	(.25)
Age 6–15	−.26	(1.69)	.39	(1.74)	−.05	(.18)
Age 9–15	−.20	(1.46)	.52	(2.72)	.03	(.12)
Age 12–15	−.17	(1.37)	.58	(3.40)	.22	(1.19)
Age 6–8	−.25	(1.62)	.12E−1	(.06)	−.20E−3	(0)
Average ratio of family income to needs						
Age 14	−.22E−03	(.01)	−.13	(2.00)	.13	(4.00)

APPENDIX A: CONTINUED

Variable	(Probit) High school graduation Coefficient	|T statistic|	(Probit) Teen out-of-wedlock birth Coefficient	|T statistic|	(Ordinary least squares) Years of education Coefficient	|T statistic|
Average ratio of family income to needs—Continued						
Age 6–15	.29E−1	(.70)	−.19	(2.00)	.27	(5.68)
Age 9–15	.22E−1	(.62)	−.17	(1.93)	.25	(5.61)
Age 12–15	.11E−1	(.38)	−.18	(2.27)	.22	(5.40)
Age 6–8	.66E−1	(1.33)	−.15	(1.61)	.24	(4.92)
Percentage of years living in urban area (SMSA)						
Age 14	−.05	(.52)	.12	(.69)	.03	(.24)
Age 6–15	−.12	(1.04)	.16	(.93)	−.04	(.27)
Age 9–15	−.06	(.61)	.14	(.84)	−.31E−2	(.02)
Age 12–15	−.04	(.36)	.12	(.72)	.01	(.09)
Age 6–8	−.18	(1.61)	.25	(1.53)	−.07	(.48)
	Log-Likelihood		R^2			
Age 14	−633.80	−286.21	.276			
Age 6–15	−618.91	−282.95	.309			
Age 9–15	−626.52	−281.66	.301			
Age 12–15	−628.31	−283.54	.297			
Age 6–8	−624.70	−294.73	.295			
N	1,705	873	765			

NOTE: The coefficients for the non–time-varying variables are from models with time-varying variables measured over age 6–15.

APPENDIX B: MEANS AND STANDARD DEVIATIONS OF VARIABLES USED IN ESTIMATED EQUATIONS (NOT WEIGHTED)

Variable	High school graduation mean (Standard deviation)	Teen out-of-wedlock birth mean (Standard deviation)	Years of education mean (Standard deviation)
Non–time-varying variables			
Race (African-American = 1)	.46	.49	.46
	(.50)	(.50)	(.50)
Female = 1	.51		.54
	(.50)		(.50)
Religion (any religion = 1)	.92	.93	.94
	(.27)	(.26)	(.25)
Head foreign born	.02	.02	.02
	(.14)	(.13)	(.15)
Father high school graduate = 1	.42	.41	.40
	(.49)	(.49)	(.49)
Mother high school graduate = 1	.52	.50	.52
	(.50)	(.50)	(.50)
One or no parent in 1968 (hence no education variable is available for one or both parents)	.22	.21	.23
	(.41)	(.41)	(.42)
Number of siblings	2.52	2.61	2.73
	(1.61)	(1.65)	(1.70)
Percentage of families in neighborhood headed by a female	19.28	19.68	18.64
	(13.12)	(13.20)	(12.41)
Percentage of young adults (age 18–25) in neighborhood who are high school dropouts	16.45	16.67	17.20
	(9.50)	(9.45)	(9.69)
Average annual number of parental separations (Parents of child separated or divorced in that year = 1 divided by number of years in age group)			
Average annual number of parental separations, age 6–8	.03	.03	.03
	(.09)	(.10)	(.10)
Average annual number of parental separations, age 9–15	.02	.03	.02
	(.06)	(.06)	(.06)

APPENDIX B: CONTINUED

Variable	*High school graduation mean (Standard deviation)*	*Teen out-of-wedlock birth mean (Standard deviation)*	*Years of education mean (Standard deviation)*
Average annual number of parental separations, age 12–15	.02 (.07)	.02 (.07)	.02 (.07)
Average annual number of parental separations, age 6–15	.02 (.05)	.03 (.05)	.03 (.05)
Parents separated at age 14 = 1	.02 (.15)	.02 (.15)	.02 (.16)
Average annual number of geographic moves (Change in household location of the family in that year = 1 divided by number of years in age group			
Average annual number of geographic moves, age 6–8	.19 (.26)	.17 (.25)	.17 (.25)
Average annual number of geographic moves, age 9–15	.15 (.19)	.14 (.18)	.14 (.18)
Average annual number of geographic moves, age 12–15	.14 (.22)	.13 (.21)	.12 (.20)
Average annual number of geographic moves, age 6–15	.16 (.18)	.15 (.17)	.15 (.17)
Changed location at age 14	.13 (.34)	.13 (.33)	.12 (.32)
Percentage of years family head is disabled (Head disabled in that year = 1 divided by number of years in age group)			
Percentage of years family head is disabled, age 6–8	.14 (.31)	.16 (.32)	.17 (.32)
Percentage of years family head is disabled, age 9–15	.17 (.30)	.19 (.33)	.19 (.31)
Percentage of years family head is disabled, age 12–15	.18 (.32)	.20 (.33)	.19 (.33)
Percentage of years family head is disabled, age 6–15	.16 (.28)	.18 (.29)	.16 (.27)
Family head is disabled at age 14	.19 (.39)	.20 (.40)	.19 (.40)
Percentage of years mother worked (Mother worked outside the home in that year = 1 divided by number of years in age group)			
Percentage of years mother worked, age 6–8	.51 (.43)	.50 (.43)	.51 (.43)
Percentage of years mother worked, age 9–15	.60 (.39)	.60 (.39)	.56 (.39)
Percentage of years mother worked, age 12–15	.63 (.41)	.62 (.42)	.58 (.42)
Percentage of years mother worked, age 6–15	.57 (.36)	.57 (.37)	.54 (.37)
Mother worked at age 14	.63 (.48)	.63 (.48)	.58 (.49)
Percentage of years family receiving welfare benefits (Family receiving welfare in that year = 1 divided by number of years in age group)			
Percentage of years receiving welfare benefits, age 6–8	.12 (.29)	.12 (.28)	.11 (.28)
Percentage of years receiving welfare benefits, age 9–15	.14 (.28)	.14 (.29)	.15 (.29)
Percentage of years receiving welfare benefits, age 12–15	.13 (.29)	.14 (.30)	.15 (.31)
Percentage of years receiving welfare benefits, age 6–15	.13 (.27)	.13 (.27)	.14 (.27)
Receiving welfare benefits, age 14	.13 (.34)	.14 (.35)	.16 (.37)

APPENDIX B: CONTINUED

Variable	High school graduation mean (Standard deviation)	Teen out-of-wedlock birth mean (Standard deviation)	Years of education mean (Standard deviation)
Percentage of years living with one parent (Living with one parent in that year = 1 divided by number of years in age group)			
Percentage of years living with one parent, age 6–8	.24	.23	.24
	(.41)	(.40)	(.40)
Percentage of years living with one parent, age 9–15	.30	.30	.29
	(.42)	(.42)	(.41)
Percentage of years living with one parent, age 12–15	.31	.31	.30
	(.44)	(.44)	(.44)
Percentage of years living with one parent, age 6–15	.28	.28	.27
	(.40)	(.39)	(.39)
Living with one parent, age 14	.34	.35	.34
	(.47)	(.48)	(.47)
Average ratio of family income to needs (Average over specified ages of the ratio of family income to the matched poverty line)			
Average ratio of family income to needs, age 6–8	2.05	2.05	1.91
	(1.50)	(1.57)	(1.52)
Average ratio of family income to needs, age 9–15	2.46	2.48	2.39
	(1.90)	(2.00)	(1.72)
Average ratio of family income to needs, age 12–15	2.61	2.63	2.52
	(2.17)	(2.33)	(1.89)
Average ratio of family income to needs, age 6–15	2.34	2.35	2.24
	(1.74)	(1.82)	(1.61)
Income to needs ratio, age 14	2.67	2.70	2.57
	(2.71)	(3.15)	(2.17)
Percentage of years in SMSA (Living in SMSA in that year = 1 divided by number of years in age group)			
Percentage of years in SMSA, age 6–8	.73	.72	.71
	(.43)	(.44)	(.44)
Percentage of years in SMSA, age 9–15	.72	.71	.72
	(.43)	(.44)	(.43)
Percentage of years in SMSA, age 12–15	.72	.71	.72
	(.44)	(.44)	(.44)
Percentage of years in SMSA, age 6–15	.72	.72	.72
	(.42)	(.43)	(.43)
Living in SMSA, age 14	.72	.71	.72
	(.45)	(.45)	(.45)

NOTE: Sample sizes are 1,705 (the full sample) for high school graduation; 873 (all females in the sample) for teen out-of-wedlock birth; 765 (all those age 24 or older as of the last year of data included [1988]) for completed years of education.

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