

# **Academic Performance and Early School Leaving: Before and After National Examinations\***

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## **ABSTRACT**

A general international observation is that adolescents from disadvantaged families are more likely to leave school at age 16. In this paper we extend the literature on school-leaving decisions by using a new and extensive panel data set from New Zealand; and by examining the effect of family income, and personal and environmental characteristics since childhood on both academic performance and subsequent schooling choices. We also examine self-selection issues related to participation in national examinations and early school leaving. Results obtained from single equations and joint estimation, allowing for possible endogeneity of academic performance, reveal the importance of the role of academic performance in models of demand for education. Several factors that are at work for a long time, such as household income at different points in time, influence the school-leaving decision through academic performance. These results point to the role that stimulating academic performance may play in breaking cycles of disadvantage. We further show that results are not affected by sample selection.

JEL classifications: I21, J13, J24, J18

Key Words: Demand for Education, Endogeneity of Academic Performance, Family Resources

## **I. Introduction**

Early school leaving in many cases closes pathways to further education. In countries such as the U.K., Australia and New Zealand, and in many states of the U.S., where education is compulsory up to the age of sixteen, schooling choices at sixteen have lifetime economic impacts. A general observation is that adolescents from disadvantaged families are more likely to leave school at the time it ceases to be compulsory, and they are less likely to participate in university education.<sup>1</sup>

In this study, we extend the literature on the decision of school leaving by examining the link between academic performance and the choice to leave school. Our analysis uses a new panel data set from New Zealand that includes several variables usually not available in typical longitudinal data sets. These variables include childhood and adolescent family income, childhood IQ scores, and nationally comparable academic performance results at age 15. Our analyses include both single-equation and joint estimations, which allow for non-zero correlation between the unobserved terms in the academic performance and school-leaving equations. The results consistently show the importance of academic performance in school-leaving choices. This result is robust over alternative specifications.

Demand for post-compulsory education as a personal choice has been addressed by Willis and Rosen (1979), who estimate participation in university studies, and by Rice (1987), who estimates secondary school leaving in Britain. The question of the effect of parental resources on the academic performance of children and adolescents has received recent attention by, for example, Blau (1999), Feinstein and Symons (1999), and Ermisch and Francesconi (2001). This study extends this literature by estimating models of school leaving and academic performance, which incorporate potential endogeneity of academic performance, and the impact of family resources and a child's personal characteristics. The study allows personal and family resources

throughout childhood to influence academic performance, which in turn can influence early school-leaving choices.

The Christchurch Health and Development Study (CHDS) data set used in this paper has several features making it particularly suitable for this type of study.<sup>2</sup> First, it allows us to control for important longitudinal personal and household conditions starting from birth. The available information includes annual parental income decile from early childhood to teenage years, the child's IQ at age 8, and a measure of academic performance at age 15, which is standardized through the use of a national set of examinations. This latter measure, in particular, distinguishes this data set favorably from many other data sets. In addition, the large number and detail of available variables substantially reduce the 'unexplained' part of estimations due to unobserved heterogeneity. This is achieved by controlling for the factors that are related to personal academic ability and parental resources. The ability to distinguish between early childhood and teenage household income conditions is of interest in examining the effects of parental income at different points in time on academic performance and early school-leaving choices.

The primary and secondary educational systems in New Zealand are in many respects similar to the U.S. system and the systems in other English-speaking countries. In New Zealand, education, which starts with a kindergarten-equivalent year at age 5, continues for 12 years beyond the initial kindergarten year. Those who are at school in grades 10 and 12 are expected to take nationally administered examinations. Education is compulsory in New Zealand up to the age of 16. School Certificate Exams at the end of grade 10 are taken when students are 15 or 16 years old depending on their birth month. These nationally administered exams are based on the same set of questions and grading for all participants. This is a great advantage as the use of such a measure of academic performance eliminates problems with the potential inconsistency in

comparing grades across schools in lower and higher income decile localities. The School Certificate results thus provide nationally comparable academic performance results (Grade Point Average (GPA) results) at around age 15 and prior to the potential school leaving at age 16. In contrast, for example, SAT scores (Scholastic Aptitude Tests) for College Entrance Examinations in the U.S. are given at the end of high school and could not be used in models of early school leaving.<sup>3</sup>

This nationally comparable measurement of academic performance allows us to shed new empirical light on its effect on school leaving. School leaving entails important policy implications. In addition, it is useful to have information on childhood scholastic ability for the same children as reflected by IQ scores at age eight in models of academic performance at age 15 to control for this important personal indicator of ability. In addition, there are several positive features of the CHDS data set, such as the extensive set of variables, including separate measures of permanent family income for early childhood and later years, and its representative nature of the population in an English speaking country. These features provide an opportunity to study the links between school leaving of teenagers, their academic performance and family resources.

The plan of the paper is as follows. Section II provides a brief discussion of the data set and the characteristics of the sample. The analytical framework and econometric models are presented in Section III, followed by a discussion of our results in Section IV. The analyses include single-equation and joint estimations of school leaving and academic performance. Concluding remarks are presented in Section V.

## **II. Data and Characteristics of the Sample**

The Christchurch Health and Development longitudinal Study (CHDS) includes extensive

economic and academic information on a cohort born in Christchurch in 1977. This cohort is followed throughout their childhood and adolescence, providing information on their transition from school to further education, training and work.

Christchurch is the third largest city in New Zealand, an English speaking country. Christchurch has income and educational characteristics that resemble New Zealand national averages, but a higher proportion of the population (91.8%) is from an English-speaking background, compared to the 80.1% at the national level. The population of Christchurch and its surrounding areas is under half a million, and the other ethnic groups in the population include Maori, Pacific Island and other Asian and European ethnic groups. Among the advantages of this data set is the extensive amount of information on the cohort's academic and home environments, academic performance and ability, and socio-economic background. In addition, while the data set follows a cohort and is localized by nature, it provides a rather rare and special opportunity in providing a natural control of general environmental, social, and political conditions for the entire sample. This characteristic of the data set is important for examining the impact of variables, such as family resources, on teenage academic performance and schooling choices.

The sample analyzed in this study utilizes information from the survey years between birth in 1977 to age 16 of the cohort, selecting respondents for whom data on all variables of interest were available.<sup>4</sup> Columns 1 and 2 in Table 1 present mean characteristics of individuals in the sample and of those who continued with post-compulsory education. These characteristics include the individual's academic performance as reflected by the average School Certificate grade obtained; IQ score at age 8 (which is unknown to the individual); and the household income decile between ages 11 and 14, and in early childhood between ages 1 and 5. In addition, the data set includes school, neighborhood and peer factors, such as the proportion of the

student's class continuing to post-compulsory levels (at age 16) or association with peer groups with deviant behavior (measured on a 1 to 10 scale reflecting problems with the law, substance abuse, etc.). The latter is expected to serve as a proxy for the student's interest in deviant behavior.<sup>5</sup>

**[ Table 1 about here ]**

The IQ variable is the total score at age 8 based on the Wechsler Intelligence Scale for Children (WISC) which tests the cognitive performance of children. It is an international test performed by qualified psychologists. The scores range from 70 to 145. We expect that childhood cognitive tests reflect both innate ability and investments by parents in their children up to that time. It is useful to have this information in the models to predict future academic performance.<sup>6</sup>

As column 1 of Table 1 on the full sample shows, about half of the sample (50.5 per cent) was female. The characteristics of the sample on academic performance and economic conditions reflect the expected national averages, such as the average IQ score of 102.8 and the average school certificate grade of 1.06 (measured on a scale of 0 to 3), which is equivalent to a C, the average national grade for these exams. Home ownership by parents was 88.6 per cent. The average proportion of family income from benefits was 13.9 per cent. In the sample, the ethnicity of 7.4 per cent was indigenous Maori and 2.8 per cent had Pacific Island ethnicity.

In relation to parental education, 49.8 per cent of the mothers and 47.5 per cent of the fathers of the respondents had no school qualifications (that is, less than the year 10 School Certificate), and 20.6 per cent of mothers and 19.5 per cent of fathers had tertiary (university or other post high school) qualifications.

In general, Table 1 shows that those who continued in post-compulsory education had mean characteristics which were different from the full sample. These differences included a higher average School Certificate grade, a higher average IQ score at age 8, a higher family income decile, their parents' education levels were higher, and they went to a school with a higher proportion of the class continuing to the post-compulsory 11<sup>th</sup> grade. These characteristics are consistent with the hypothesis that individuals sort themselves into different choices based on their academic ability, the expected returns to their choice, family income constraints, and influences from the school and peer environment. Students from the lower income deciles are more likely to leave school early and less likely to participate in higher studies.

### **III. Analytical Framework**

This paper models school leaving as a function of academic achievement, family resources and personal characteristics. Academic achievement is a function of ability, personal characteristics and family resources, which includes many of the same factors that explain school leaving. In addition, some of the same unobservable individual or household characteristics may influence both academic performance and school leaving. This indicates the necessity of allowing for potential endogeneity of academic performance in the school-leaving model, through joint estimation of the equations for school leaving and academic performance.

In this section, we briefly discuss the previous literature on school leaving and academic performance. The existing literature has traditionally assumed that academic performance is exogenous in schooling choice models. In this paper we extend the literature by estimating models of academic performance at age 15 and school-leaving choices at age 16. Single-equation estimations are described in III.1 and III.2, and joint reduced-form and joint estimations, allowing for the potential endogeneity of academic performance, are described in III.3.

### III.1 School Leaving

The theoretical modeling framework, which is widely adopted in the economic literature on participation in post-compulsory education, focuses on individual choice for long-term investment in human capital (for example, Becker, 1993; Schultz, 1961).<sup>7</sup>

The decision to participate in higher education and training is intrinsically related to a number of factors. For example, investment in higher education is expected to result in higher returns for those with greater academic ability and a taste for lifetime labor force participation. In addition, household financial constraints would influence the cost of obtaining education. Moreover, the family socio-economic background can affect the demand for post-compulsory and higher education through tastes and the costs of obtaining information.

Willis and Rosen (1979) and Rice (1987) describe an extended framework for analyzing participation in higher education. Willis and Rosen's analysis utilized structural models and focused on self-selection. Rice's application utilized reduced-form models of participation and emphasized the effect of financial constraints on school-leaving choices. In this framework, educational choices for the  $i$ th individual and the  $j$ th level of education are determined by:

$$V_{ij} = V \{E_j(S_i), X_i, u_i\}, \quad j=0,1. \quad (1)$$

where  $V_{ij}$  is the utility of net expected present value of life-time earnings at each level of educational attainment  $j$  ( $E_j$ ), as influenced by individual talents and abilities ( $S_i$ ); observable personal and environmental characteristics ( $X_i$ ), which determine the individual's tastes, expectations and the financial constraints facing the household; and  $u_i$  is the unobservable component. Estimation of the probability of enrolment at post-compulsory education (Pr PCE) is based on these expected net present values:

$$\Pr \text{PCE}_i = \Pr [ (V_{i1} - V_{i0}) = G(S_i, X_i, u_i) > 0 ] \quad (2)$$

where vectors of observables  $S_i$  and  $X_i$  lead to participation in post-compulsory education if net benefits  $V_{i1} - V_{i0}$  are positive. Assuming that the net benefits conditional on  $S_i$  and  $X_i$  are normally distributed and that  $G(\cdot)$  is a linear function of  $S_i$  and  $X_i$ :

$$V_{i1} - V_{i0} \sim N ( S_i'\beta + X_i'\gamma, \sigma^2 ) \quad (3)$$

with parameters  $\beta$ ,  $\gamma$  and  $\sigma^2$  constant across the population. Then  $\Pr \text{PCE}_i$  would follow the standard normal cumulative density function and equation (2) can be estimated via Probit analysis.

The dependent variable in the school-leaving equation in this paper is binary, indicating whether or not the respondent had left school at the post-compulsory age of 16. A probit model is therefore chosen to analyze school leaving:

$$\Phi^{-1}(\Pr D_i) = \alpha_d + X_{di}'\gamma_d + A_i\delta_d \quad (4)$$

where  $\Phi^{-1}$  is the inverse of the standard normal cumulative distribution function;  $\Pr D_i$  is the probability that the respondent leaves school at age 16, as opposed to enrolment in the 11<sup>th</sup> grade (also called the Sixth Form);  $A_i$  represents academic performance for individual  $i$ ; and  $X_{di}$  represents personal, family and environmental characteristics. The full list of variables and their definitions is provided in Table A1 in Appendix A.

In this paper we are specifically interested in examining the effect of academic performance on schooling choices. Therefore, we replaced the more general specification of  $S_i$  in equation (3) with variable  $A_i$  in equation (4).  $S_i$  stands for the potential to learn, whereas  $A_i$  is an observable

measure of academic performance (in this case, the grade point average in a set of School Certificate national examinations at age 15).  $A_i$  is broader than  $S_i$  and reflects personal effort and family resources in addition to the potential to learn.  $S_i$  is expected to influence academic performance  $A_i$  directly. A possible measure for  $S_i$  could be IQ.<sup>8</sup>

### **III.2 Academic Performance**

The academic performance of children and adolescents has recently received interest in the literature in models that link parental resources to children's academic performance. Examples are Blau (1999), Borjas (1995), Case and Katz (1991), Duncan *et al.* (1998) and Montgomery (1991) for the U.S.; Feinstein and Symons (1999) and Ermisch and Francesconi (2001) for the U.K.; and Miller and Volker (1989), Prior and Beggs (1989) for Australia. Academic achievement is also shown to explain labor market success as reflected by earnings (Boissiere, Knight and Sabot, 1985; Rumberger and Lamb, 2003; and Maani, 2004, for New Zealand).

The recent literature on educational attainment has emphasized the significance of parental investments in human capital since childhood. Therefore, even if teenagers have a significant input into the decision of when to terminate secondary schooling, they are constrained in their choice by academic performance and human capital investments throughout childhood (Ermisch and Francesconi, 2001).

Models of *children's* academic performance are usually based on a production function, where parents are the producers.<sup>9</sup> The academic performance of teenagers at age 15 and their school-leaving choices at age 16 are likely to be influenced by some of the same factors, such as the adolescent's personal ability, and human capital investments by parents throughout the adolescent's childhood. Looking at academic performance in isolation this can be modeled as:

$$A_i = f(S_i, X_i, v_i) \quad (5)$$

where  $A_i$  is an observable academic performance measure of individual  $i$  (representing ability, effort, and parental investments);  $S_i$  represents personal talents and abilities;  $X_i$  is a vector of personal and parental resources, and environment; and  $v_i$  represents the effect of unobserved factors, such as motivation or traumatic events prior to exams.

As noted earlier, academic performance in this study is measured by the average score in the National School Certificate Examinations, which are taken at the end of the 10<sup>th</sup> grade at age 15 or 16, in at least 5 subjects.<sup>10</sup> If a student fails these examinations they would need to repeat the year. The grade D for a fail in each subject is translated into a value of 0, a grade C into 1, a grade B into 2 and a grade A into 3. The average score (GPA) over all subjects is considered to be a continuous variable, as constructed by averaging the numeric values of the score over all subjects taken in the certificate. Thus the minimum GPA score is 0 and the maximum score is 3, from which follows that the GPA score is censored. That is, the academic performance of the most and the least capable students (below and above a certain academic performance level) cannot be accurately measured or ranked. The equation for latent academic performance  $A_i^*$  looks as follows:

$$A_i^* = \alpha_a + X_{ai}'\gamma_a + \varepsilon_{ai} \quad (6):$$

$$A_i = A_i^* \text{ if } 0 < A_i^* < 3 \quad (7)$$

$$A_i = 0 \text{ if } A_i^* \leq 0 \quad (8)$$

$$A_i = 3 \text{ if } A_i^* \geq 3 \quad (9)$$

To account for the censored dependent variable, assuming  $\varepsilon_{ai}$  is normally distributed with mean zero and variance  $\sigma_1^2$ , a standard Tobit specification can be used to estimate equation 5. In our data set, truncation is most prevalent at the lower end.

### **III.3 Joint Estimations**

We expect academic performance to affect school leaving at age sixteen (in equation 4) directly. However, the assumption of exogeneity may be incorrect. Academic performance measures a mixture of academic ability, resources and effort. Therefore, when using academic performance to explain school leaving, the possibility of endogeneity should be investigated, since the school-leaving decision and academic performance could be determined by similar unobserved factors such as motivation.

Not allowing for this endogeneity could result in assigning a causal relation between the two variables due to spurious correlation.<sup>11</sup> The direction of the bias of the coefficient on academic performance depends on the cause for the spurious correlation. For example, if unobserved motivation affects school leaving negatively and the examination results positively, it would result in a negative correlation between school leaving and the average examination results. This effect would hold even after controlling for other contributing factors, resulting in a downwards bias of the coefficient on the average grade. However, if for example, an unobserved interest in learning a trade rather than further academic learning would induce a student to leave school at age sixteen for an apprenticeship or training that will lead to a job in the trades, a positive error term would be expected. To be accepted into a good apprenticeship program or to obtain a good job with training, may still require good examination results, encouraging effort for higher examination grades (also a positive effect on the error term). Not allowing for this positive correlation would bias the coefficient on academic performance upwards. Alternatively, a positive correlation could arise if a student experienced an unobserved traumatic or distracting event prior to exams, or the examination in certain subjects was unexpectedly difficult, which could affect academic performance for some students negatively, but not change their school-

leaving decision, resulting in a positive correlation between the two error terms. The issue of correlation is further discussed in the results section.

To allow for endogeneity a joint model of academic performance and school leaving is estimated. However, we also estimate equations (4) and (6) separately to enable comparison with other studies which do not use joint estimation. The robustness of these single-equation results is explored by allowing for the potential endogeneity of academic performance in the school-leaving equation.

First, the joint (structural) model is specified by re-writing equations (4) and (6) as a set of two equations, estimated simultaneously (see for example Maddala, 1983):

$$A_i^* = \alpha_a + X_{ai}'\gamma_a + \varepsilon_{ai} \quad (10)$$

$$D_i^* = \alpha_d + X_{di}'\gamma_d + A_i\delta_d + \varepsilon_{di} \quad (11)$$

where  $D_i^*$  is the latent school leaving tendency. Equation (10) is estimated by Tobit and equation (11) by Probit. Error terms  $\varepsilon_{ai}$  and  $\varepsilon_{di}$  have a bivariate normal distribution, with zero means, variances  $\sigma_1^2$  and 1, and correlation  $\rho$ .<sup>12</sup> We are especially interested in whether the value and direction of  $\delta_d$  changes or diminishes in importance once endogeneity and a non-zero error correlation across the two equations are incorporated.<sup>13</sup>

Our system of equations (10) and (11) is based on the assumption that school leaving is not expected to affect academic performance directly. This assumption is supported by the sequence of the two events, where academic performance is measured about one year before the school-leaving decision. By having only one of the observed dependent variables on the right hand side, the assumption ensures that equations (10) and (11) are logically consistent (Maddala, 1983). However, if this assumption does not hold and academic performance is affected by the school-

leaving decision, the logical choice is to have academic performance depend on latent school leaving, given that the actual school leaving has not occurred yet. The effect of school leaving on academic performance depends on the reason for school leaving. It could be positive for someone who wants to enter a trade or negative for someone with poor motivation. The effect of leaving out this direct effect on the structural coefficients is ambiguous. However, it should be noted that the joint reduced form (to be discussed below as the second alternative) implicitly accounts for this direct effect.

A challenge in identifying the system of equations in this framework is that most of the factors expected to influence academic performance are also expected to influence the school-leaving choice. However, in this data set, the IQ score measured at age 8 provides an exclusion restriction for equation (11). Theoretically speaking, it is reasonable to assume that the later observed academic performance (known by the student and others involved) is a better approximation of personal talent, ability and effort and thus a more appropriate predictor of school-leaving choices than IQ. Therefore, once the more recent academic performance measure is included in the model, it would be unlikely for the childhood IQ to exert an additional and independent effect on school leaving at age 16. That is, the observed academic performance ( $A_i$ ) incorporates the effect of academic ability, as measured by childhood IQ, and it also contains additional information beyond ability, such as effort. This assumption is empirically verified in the results section. Excluding IQ helps to identify the system in addition to the non-linear transformation of latent academic performance to observed academic performance, which is censored at 0 and 3.

A second alternative for a joint model is the following reduced-form version, which is slightly different from the model specified in equations 10 and 11:

$$A_i^* = \alpha_a + X_{ai}' \gamma_a + \varepsilon_{ai} \quad (12)$$

$$D_i^* = \alpha_d + X_{di}' \gamma_d + A_i^* \delta_d + \varepsilon_{di} \quad (13)$$

This specification assumes that the *latent* rather than the *actual* academic performance influences school leaving directly (see for example Stern, 1989; Cai and Kalb, 2005). Rewriting this so that all endogenous variables only appear on the left hand side, leads to the following reduced form equations:

$$A_i^* = \alpha_a' + X_i' \gamma_a' + \varepsilon_{ai}' \quad (14)$$

$$D_i^* = \alpha_d' + X_i' \gamma_d' + \varepsilon_{di}' \quad (15)$$

where  $X_i$  consists of all variables in  $X_{di}$  and  $X_{ai}$ . The above equations can be estimated by Tobit and Probit like before.<sup>14</sup>

The two alternative methods to include the direct effect of academic performance on school leaving (which is of special interest in this study) allow us to examine whether the predicted effects of individual characteristics change with the specification.<sup>15</sup>

### III.4 Income Variables Included in the Model

The measures of parental income we have included reflect permanent rather than current income, providing a measure of long-term parental resources (see Blau, 1999, for U.S. evidence). In addition, the data allow us to distinguish between parental income effects during early childhood and adolescent years on later academic performance and school-leaving choices. We use data on income decile, as a measure which is more universally recognizable and relevant to policy by reflecting information on income and relative deprivation. In addition, combining information on income deciles for different years is more straightforward than combining information on

absolute levels of income.<sup>16</sup> The two income measures are correlated, but the correlation is only 0.55. Thus, each measure provides some independent information on the financial history of the household.

## **IV. Results**

All models in the following subsections are estimated on a sample for which information on all variables in any of the models is available. The first two subsections describe the single-equation results and Section IV.3 discusses the joint results.

### **IV.1 School Leaving at Age 16**

Results for the school-leaving (dropout) equation in the last three columns of Table 2 show that academic performance has a significant effect on the early school-leaving decision. Based on the estimated coefficients in Table 2, marginal effects have also been calculated.<sup>17</sup> For example, a policy that could improve the academic performance of students by one point of a grade would reduce the probability of leaving school at age 16 significantly by 4.3 percentage points on average across the sample. This is a substantial decrease, given the mean predicted dropout rate of 6.2 per cent. At a practical level, policies aimed at improving academic performance may be multifaceted, among which educators would emphasize assistance with homework or the provision of a place for children from disadvantaged families to do their homework. The estimates further show that, keeping other factors constant, females were much less likely to drop out of school, which may be related to fewer women going into employment in a trade or apprenticeship. Once academic performance and peer and school effects are included in the dropout model, few other variables are significant.

**[ Table 2 about here ]**

Similar to the finding by Duncan *et al.* (1998), early income deciles have a greater effect on school leaving than later income deciles. With the inclusion of variables on academic performance, the proportion of family income from benefits, and school and peer effects from age 15; the income decile for adolescent years has no additional direct effect on school leaving. However, early childhood income shows a nearly significant direct effect on school leaving of about 0.1 percentage point for one decile increase. The effect is opposite to expectations and is discussed further in the next section. The finding is consistent with the hypothesis that conditional on academic performance, children from wealthier families, who do not know what they want to do and who do not like school, may be given more leeway or options to drop (temporarily) out of school.

## **IV.2 Academic Performance**

The results of the single equation for academic performance in the first three columns of Table 2 show that both early childhood and adolescent parental income deciles are important (and highly significant) in explaining academic performance. This may explain the counterintuitive effect of income on school leaving. The raw correlation between school leaving and the average income deciles is negative. The relationship only becomes positive after controlling for several other characteristics. Income may work through academic performance rather than directly affect the school-leaving decision. The effect of moving up one decile in the recent income measure (averaged over the time when the respondent was aged between 11 and 14) is estimated to be equivalent to 0.054 of a grade in the exams. In addition to this effect, moving up one early childhood income decile explains an additional effect of about 0.035 of a grade.<sup>18</sup> Therefore, keeping other factors constant, together the predicted effect of the income decile variables is 0.089 of a grade difference for 1 decile increase. Over ten deciles, this could be close to the

difference between a C and a D average grade, for example. The results found here are consistent with the effect of poverty (Duncan *et al.*, 1998), the positive effect of income in many U.S. studies (Haveman and Wolfe, 1995), and Gregg and Machin's (1998) finding on the effect of financial difficulties in early or late childhood. However, the finding by Duncan *et al.* (1998), that only early childhood parental income is significant in explaining the years of completed schooling and high school completion, is not repeated here for academic performance. The results are further consistent with recent results for the U.K. regarding the importance of resources throughout childhood in determining children's academic performance (Feinstein and Symons, 1999; Ermisch and Francesconi, 2001).

Our results are in contrast to Blau's (1999) study examining the effect of parental current and permanent income for early childhood development. Blau finds that 'family background and other family and child characteristics often have larger effects on child development, ... than does income ...' (p. 273). One of the differences between his study and our study is that the average age at which the child development scores are measured in his study is 5.7 years, compared to 15 to 16 years in our study.<sup>19</sup>

As the results in Table 2 show, childhood scholastic performance, as reflected by the IQ test score at age eight, is also important. Each additional unit of the IQ score is associated with an increase of 0.027 of a grade. This is a large effect considering the range of IQ scores. The mean IQ score was 102.8 with a standard deviation of 14.8. This highlights the importance of the respondent's childhood scholastic ability in predicting academic performance in later years. Comparing this effect to the combined effect of the two income decile variables, we see that one income decile is equivalent to slightly more than 3 IQ units. To the extent that these childhood scholastic performance results may reflect early childhood parental investments in children's

learning, the separate effect of income in the household during childhood is of interest.

### **IV.3 Joint Estimates**

In the joint model based on equations 10 and 11, the direct effect of academic performance on school-leaving choices becomes more important, its coefficient increasing from  $-0.7107$  to  $-1.3091$  (see Tables 2 and 3). Thus, joint estimation strengthens the earlier finding on academic performance, showing that the earlier results concerning the importance of academic performance in school-leaving choices are robust. In addition, the effects of family income and other significant variables on academic performance are robust across the single-equation and joint estimations.

**[ Table 3 about here ]**

A second result of interest is that error correlation across the two equations is positive, indicating that after controlling for all the characteristics in the model, the unobserved heterogeneity is no longer negatively correlated. Where there are few variables of relevance available for inclusion in the model, the expectation is that the effects of unobserved ability or motivation and effort would introduce a negative component to the error correlation. This expectation is based on similar unobserved factors having a positive effect on the average academic performance score and a negative effect on the dropout probability. This is precisely what happens when the direct effect of academic performance is excluded from the school-leaving equation as can be seen in Table 4. The reduced-form joint model results in a significantly negative error correlation ( $\rho = -0.223$ ). This is the outcome we would expect if the error terms contained important unobserved characteristics related to the schooling decision, such as ability, motivation or effort.<sup>20</sup> This is further support for the earlier finding regarding the importance of including academic performance as a factor which directly influences schooling choices by young adults.

The positive correlation between the error terms in the model based on equations 10 and 11 could be explained by a few factors as discussed in Section III.1. First, it is consistent with some school leavers moving into training programs for which high academic scores may be required. Estimating the model with a slightly altered specification, redefining school leavers as those who are no longer in school or in a training or apprenticeship program, supports the apprenticeship effect hypothesis, as the error correlation decreases to  $\rho = 0.39$  in this specification (a decrease of about 25% from  $\rho = 0.51$ ). The effects of other characteristics remain similar to the results presented in Table 3. Additionally, the error terms may contain unobserved traumatic effects. For example, students who had performed unexpectedly poorly in their exams due to an exogenous (and unobserved) incident such as an accident, illness, or emotional trauma before the exams could have had lower than expected exam grades (a negative error term in equation 10). However, due to long-term choices they would have been likely to continue with their post-compulsory education regardless of their low exam score, resulting in a lower than expected dropout rate (a negative error term in equation 11).

The results for the joint model without the explicit direct effect of academic performance, as described in equations 14 to 16, are shown in Table 4. For comparison, the direct effect of academic performance can be derived from these reduced-form results using early childhood ability as reflected by the IQ score at age eight to identify the system. Calculating the direct effect of  $A_i$  from the transformed parameters in Table 4, using the formulas in (16), we find a coefficient of -0.84, which lies in between the direct effect found in the single-equation and the previous joint model. This is consistent with the expectation that the negative error correlation in the reduced-form model is caused by the large negative value of the direct effect of academic performance, as can be derived from the relationships between the old and transformed parameters in (16). That is, the true correlation in the underlying structural model is positive as in

the other specification of the joint model.

**[ Table 4 about here ]**

In the joint model, the coefficient of early childhood family income decile in the reduced-form school-leaving equation is no longer significant at the 5 per cent level, and the effect of more recent income is negative although insignificant. This shows that the negative effect of income on school leaving is through academic performance, but not directly.<sup>21</sup> This result is consistent with the hypothesis that conditional on a specific level of academic performance, higher family income could provide an alternative to going to school. However, this effect is no longer statistically significant in the joint estimation.

Comparing the results for the academic performance model on other aspects, the reduced-form joint model is similar to the first joint model. The reduced-form school-leaving component of the model, however, provides greater differences in results, compared to the first joint specification. To make a proper comparison of the implications of the two models, marginal effects are presented in Tables 2 to 4 for the exogenous variables. The marginal effects allow for direct and indirect effects of characteristics. In summary, the marginal effects show that the effect of IQ is understated, and the effect of living in a rural area is overstated in the single equation school-leaving model, because the indirect influences through academic performance are not recognized.<sup>22</sup>

These results consistently support the theory that parental resources and personal ability influence academic performance, which in turn determines schooling choices. The joint estimations further show that the effect of academic performance on school-leaving choices is robust across different model specifications. We also examined the sensitivity of the coefficients in Table 3 to an alternative specification of the joint model with IQ included in the school-leaving equation (11)

(see the discussion in Section III.3 on page 14). This alternative version is in principle identified through the non-linear transformation of the latent academic performance variable. The coefficients of interest, such as income decile, early income decile and IQ at age 8 (in the academic-performance equation) are robust to this change in specification (exhibiting only minor changes in the coefficients and marginal effects). Thus, the conclusions are not sensitive to the alternative specification. The IQ coefficient in the school-leaving equation is found to be small and insignificant (0.006 with a t-value of 0.53 and a likelihood ratio test statistic of only 0.26), when academic performance is also present in the school-leaving equation. Thus, the null hypothesis of the IQ parameter being zero could not be rejected at any sensible significance level. This test confirms that IQ (which is unknown to the child, their parents or teachers) is strongly correlated with academic performance at age 15, but beyond the effect through academic performance, it does not have an independent effect on school leaving. This confirms its choice as an instrument.

We also tested whether there was evidence of selection bias in the academic performance equation due to students leaving school before the exam. The results, reported in Maani and Kalb (2003), indicate that selection bias is not an issue.

Finally, the results highlight the need for joint estimation to assess the role of different variables properly when the endogenous academic performance measure is included as well. It also shows that academic performance explains more than childhood IQ and family resources on their own, and seems to have a direct effect on the school-leaving decision.

#### **IV.4 Test for Sample Selection**

The results in the previous section are based on those who had not left school before the exam. Since we can only observe the average score for those who did not drop out before the exam and

who took the exams, we need to allow for sample selection in the observed exam results. For the students who had left school before the exams, no measure of academic performance is available, but fortunately information on all other factors is available. We estimate the probability of having observable examination scores (by not having left school prior to exams) with a Probit model

$$\Phi^{-1}(\text{Pr PBE}_i) = Z_i' \gamma_Z \quad (17)$$

where  $\text{Pr PBE}_i$  is the probability of dropping out before the exams,  $Z_i$  are the explanatory variables and  $\gamma_Z$  are the parameters to be estimated.

Since academic performance is estimated by a Tobit, the usual Heckman adjustment for sample selection does not apply. However, we can estimate equations (17) and (6) jointly through maximum likelihood and test for their independence. In the sample selection Probit, a dummy variable on birth month (=1 if birth was during the first semester of the year) was included for identification. Birth month can be used for identification because 5-year olds who start school in the first semester take the first kindergarten equivalent year only once, but those who are born in the second semester usually have a full kindergarten year in the following year. The latter group could therefore reach age 16 and leave school before the national examinations at the end of the 10<sup>th</sup> grade. The results showed that those who were born in the second semester were indeed more likely to have left before the exams.

The error correlation coefficient across the two equations in the joint estimation failed the test of significance (estimated at  $-0.138$  with a  $z$ -value of  $-0.42$ ). In addition, joint estimation resulted in minor changes in the other parameters and the log likelihood value.<sup>23</sup> Different specifications, that is including or excluding birth month, gave consistent results of the independence of the two equations, indicating that the two equations were independent.<sup>24</sup>

Given these results, which indicate that sample selection bias is not an issue, we estimate equation (6) for everyone who had examination results without correcting for sample selection.<sup>25</sup> The estimated parameters from the academic performance Tobit are used to predict the average grade for everyone in the sample. We find that those who had dropped out before the national exams were expected to perform poorly and significantly below those who did take the national exams (see Table 5). The predictions in the first row, for example, show that those who took the national exams had a predicted average grade equivalent to a C (mean =1.1599) compared to a predicted average grade of D (mean=0.2635) for those who did not. This expectation of poor performance is completely due to a difference in observed characteristics between the two groups.

[ Table 5 about here ]

## **V. Conclusion**

This study has provided empirical evidence on the effect of personal characteristics and family resources since childhood on the academic performance of teenagers and their choices regarding leaving secondary school or continuing with post-compulsory education at age 16. The school-leaving choice is an important decision since it generally determines further higher education options and has lifetime income effects.

The study shows that the school-leaving decisions at age 16 are influenced by factors that are at work over a long period of time. This means policies aimed at retaining students at school should target children from a young age onwards. Personal ability, household income constraints and socio-economic background are all influential in school-retention choices. They exert an influence through factors such as academic performance, parental income, and school and peer

effects.

The results further show consistently the importance of including academic performance as an explanatory variable in models of demand for education. For example, the estimates from the single equation predict that policies that can improve the academic performance of students by one point of a grade would improve the student's probability of school retention at age 16 significantly by 4.3 percentage points. That is, the average probability of school leaving would be reduced from 6.2 per cent to 1.9 per cent. This indicates that if academic performance could be targeted in policies, for example, through providing assistance with homework or study for children from disadvantaged families, this could improve school retention.

Examining the determinants of academic performance at age 15, it is shown that it is not only influenced by parental income and resources, as reflected by the recent income decile, but also by early childhood income resources. The estimated coefficient of the latter is about two thirds of the coefficient size of the more recent income decile variable. This result, in addition to the effect of the mother's school qualifications and childhood IQ, highlights the long-term nature of the early school-leaving decision process, the outcome of which is observed at age 16. This result is consistent with recent results for the U.K. regarding the importance of early childhood resources in determining children's academic performance (Feinstein and Symons, 1999; Ermisch and Francesconi, 2001). This result is further consistent with results on the direct effect of early childhood resources on the probability of school leaving in the U.S. (Duncan *et al.*, 1998). This clearly points to the need for long-term solutions to improve school retention of children from disadvantaged families.

A feature of this paper has been to compare single-equation estimations of academic performance and school leaving to joint estimations of academic performance and school leaving. Jointly

estimated models extend the literature by acknowledging the potential endogeneity of academic performance in the school-leaving equation, through allowing for non-zero error correlation in the error terms. We find that the results of interest are robust across the various estimation methods, and they support the relevance of including measures of academic performance in models of school leaving. There is a direct effect from academic performance on school leaving in addition to the simultaneous effect of other observable and unobservable characteristics. One variable for which the differently specified models have different implications is childhood IQ. The results indicate that accounting for the indirect effect of IQ through academic performance is important to properly assess the importance of IQ in a model that includes academic performance as an explanatory variable.

In conclusion, the results are consistent with the hypothesis that students sort themselves into schooling choices at age 16, based on the expected returns to these choices, their tastes, and information available to them through their family, school and peer networks. In the school-leaving choice, the student's academic performance is an important channel through which personal ability and economic factors exert their influence. With regard to the economic factors, the influence seems to be through academic performance rather than directly.

To the extent that the academic performance of students can be influenced throughout their education years, these results point to the role that childhood and teenage academic performance can play in breaking cycles of disadvantage.

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**Table 1: Characteristics of the Sample**

Characteristics	Mean (Standard Deviation)	
	Full Sample	Continued with Post-compulsory Education
<b>Personal Characteristics</b>		
Female (%)	50.5%	52.6%
Maori Ethnicity (%)	7.4%	5.7%
Pacific Island Ethnicity (%)	2.8%	2.3%
IQ (tested at 8 years of age)	102.8 (14.88)	105.8 (13.63)
<b>Education</b>		
Average School Certificate Grade Point Average (age 15 and 10 <sup>th</sup> grade, where Fail=0, C=1, B=2, A=3)	1.061 (0.86)	1.26 (0.80)
Mother without Qualifications (<10 <sup>th</sup> grade)	49.8%	43.6%
Mother with a Tertiary Qualification	20.6%	24.6%
Father without Qualifications (< 10 <sup>th</sup> grade)	47.5%	41.3%
Father with a Tertiary Qualification	19.8%	23.2%
Total Dropout rate from school at Age 16	15.5%	---
Dropout rate from school before Exams	8.8%	---
<b>Family and Social Environment</b>		
Adolescent Average Income Decile: Ages 11-14 (10 is the most affluent decile)	5.53 (2.54)	5.92 (2.48)
Early Childhood Average Income Decile: Ages 1-5	5.82 (2.40)	6.13 (2.33)
Own their Home (%)	88.6%	92.1%
Number of Siblings	1.48 (0.94)	1.47 (0.89)
Rural Location (%)	15.9%	16.0%
Proportion of Family Income from Benefits	0.139	0.106
Regional Unemployment Rate	10.6%	10.6%
Proportion of Respondent's class continue at Age 16	0.836 (0.162)	0.864 (0.116)
Average Class Size	28.8 (4.20)	28.9 (4.15)
Association with Deviant Peers age 15 (10 is the highest association)	2.30 (2.45)	1.91 (2.14)
<b>Sample Size:</b>	<b>713</b>	<b>561</b>

**Table 2: Academic Performance and School Leaving, Single Equations**

(Equation (10): Ave\_Grade (National Exam Grade at age 15))

(Equation (11): Dropout: 1=Left School at Age 16; 0=Enrolled in School at Age 16)

Explanatory Variables	Average_Grade (TOBIT)			Dropout (PROBIT)		
	Coefficient	z-value	Marginal Effects <sup>a</sup>	Coefficient	z- value	Marginal Effects <sup>a</sup>
<b>Direct Effect:</b>						
Ave_Grade				-0.7107 ***	-4.14	-4.3134
<b>Personal Characteristics</b>						
Female	0.1845 **	2.97	0.1639	-0.6975 **	-2.76	-6.4335
Maori	0.1054	0.94	0.0942	0.3278	1.00	3.5328
Pacific Islander	-0.1099	-0.63	-0.0968	-0.2421	-0.47	-1.9633
IQ at age 8	0.0299	14.12	0.0266			
Mother_No_Qualifications	-0.1404 **	-2.18	-0.1255	0.2184	0.92	1.9844
Mother Tert_Qualifications	0.1172	1.57	0.1052	-0.1920	-0.51	-1.6328
Father_No_Qualifications	-0.0376	-0.60	-0.0334	0.1497	0.65	1.3823
Father_Tert_Qualifications	0.1351	1.71	0.1215	0.0595	0.16	0.5623
Income_Decile(ages 11-14)	0.0610 ***	4.06	0.0544	0.0107	0.17	0.0991
Early_Income Decile(ages1-5)	0.0393 **	2.75	0.0350	0.0865	1.72	0.7390
Number of Siblings	0.0056	0.18	0.0050	0.2431 **	2.18	2.5686
Parents Own Home	-0.1198	-1.12	-0.1069	-0.4465	-1.48	-5.0218
Rural	0.1610	1.50	0.1439	0.9643 **	2.56	12.7844
Prop Family Income Benefits <sup>b</sup>	0.2009	1.78	0.0018	0.6586	1.87	0.0610
Local_Unemployment	0.1413	1.42	0.1267	0.6383	1.77	8.2868
Proportion Students Continue <sup>b</sup>	0.6090 **	2.46	0.0054	-0.6072	-0.70	-0.0558
Class Size	0.0063	0.91	0.0056	0.0356	1.27	0.3352
Deviant Peers	-0.0628 ***	-5.13	-0.0555	0.1003 **	2.58	0.9787
Constant	-4.6538 ***	-4.05	1.2068	-9.1961 *	-2.27	6.2054
Variance of error term				0.6327	0.0198 (std. error)	
Number of observations =	598	LR chi <sup>2</sup> (19) = 395.06		598	LR chi <sup>2</sup> (18)= 74.6	
Left-censored: right censored	56 at 0: 10 at 3					
Pseudo R <sup>2</sup> =	0.254			0.269		
Log likelihood =	-578.943	Prob > chi <sup>2</sup> = 0.0000		-101.476	Prob > chi <sup>2</sup> = 0.0000	

Note: \*\*\* Significant at .001; \*\* Significant at .01; \* Significant at .05

a: The marginal effects are calculated for each individual and averaged across the sample. For dummy variables the effect of going from a value of 0 to a value of 1 is calculated. The row with the constant term contains the average predicted value across the sample.

b: The marginal effect is approximated by increasing the value of the variable with 0.01 instead of 1.

**Table 3: Academic Performance and School Leaving, Joint Estimation**

(Equation (10): Ave\_Grade (National Exam Grade at age 15))

(Equation (11): Dropout: 1=Left School at Age 16; 0=Enrolled in School at Age 16)

Explanatory Variables	Average_Grade (TOBIT)			Dropout (PROBIT)		
	Coefficient	z-value	Marginal Effects <sup>a</sup>	Coefficient	z-value	Marginal Effects <sup>a</sup>
<b>Direct Effects:</b>						
Ave_Grade				-1.3091***	-6.21	----
<b>Personal Characteristics</b>						
Female	0.1454 **	2.35	0.1312	-0.4074	-1.67	-5.4996
Maori	0.1483	1.37	0.1345	0.3636	1.22	2.1351
Pacific Islander	-0.1257	-0.74	-0.1125	-0.3917	-0.79	-2.1505
IQ at age 8	0.0288 ***	13.39	0.0260			-0.2936 <sup>b</sup>
Mother_No_Qualifications	-0.1370 *	-2.17	-0.1243	0.0439	0.20	1.8385
Mother Tert_Qualifications	0.1135	1.53	0.1033	0.0382	0.11	-0.7911
Father_No_Qualifications	-0.0346	-0.56	-0.0312	0.0638	0.31	0.9723
Father Tert_Qualifications	0.1384	1.77	0.1263	0.3853	0.11	-1.0259
Income_Decile(ages 11-14)	0.0575 ***	3.88	0.0520	0.0516	0.88	-0.1019
Early_Income Decile(ages1-5)	0.0397 **	2.85	0.0359	0.1047 *	2.28	0.6157
Number of Siblings	0.0157	0.51	0.0141	0.2218 *	2.14	2.2492
Parents Own Home	-0.1443	-1.39	-0.1307	-0.3200	-1.12	-1.6745
Rural	0.1730	1.63	0.1568	0.8544 **	2.46	8.4641
Prop Family Income Benefits <sup>c</sup>	0.2593 *	2.33	0.0023	0.7634 **	2.36	0.0458
Local_Unemployment	0.1385	1.41	0.1258	0.4480	1.36	3.4060
Proportion Students Continue <sup>c</sup>	0.5465 **	2.23	0.0049	-0.0276	-0.03	-0.0575
Class Size	0.0082	1.20	0.0074	0.0324	1.28	0.2291
Deviant Peers	-0.0567 ***	-4.66	-0.0509	0.0717 *	1.96	1.3910
Constant	-4.4540 ***	-3.90	1.2418	-7.0996 *	-1.90	5.6594
Variance of error term	0.6315 ***	31.90	P=0.000			
Rho	0.5170***	3.76	P=0.000			
Number of observations =	598		Wald chi2(18) =	436.09		
Log likelihood =	-676.051		Prob > chi <sup>2</sup> =	0.0000		

Note: \*\*\* Significant at .001; \*\* Significant at .01; \* Significant at .05

a: The marginal effects are calculated for each individual and averaged across the sample. For more detail, see footnote 23. The row with the constant term contains the average predicted value.

b: This effect works only indirectly through academic performance.

c: The marginal effect is approximated by increasing the value of the variable with 0.01 instead of 1.

**Table 4: Reduced-Form Estimations**

Equation (14): Ave\_Grade (National Exam Grade at age 15))

Equation (15): Dropout: 1=Left School at Age 16; 0=Enrolled in School at Age 16)

Explanatory Variables	Average Grade (TOBIT)			Dropout (PROBIT)		
	Coefficient	z-value	Marginal Effects <sup>a</sup>	Coefficient	z-value	Marginal Effects <sup>a</sup>
<b>Personal Characteristics</b>						
Female	0.2077 ***	3.28	0.1833	-0.7848 ***	-3.21	-7.6856
Maori	0.0898	0.80	0.0796	0.2820	0.88	3.1444
Pacific Islander	-0.1110	-0.63	-0.0970	-0.1556	-0.31	-1.3779
IQ at age 8	0.0301 ***	14.18	0.0266	-0.0253 **	-2.96	-0.2388
Mother_No_Qualifications	-0.1441 *	-2.23	-0.1280	0.2540	1.11	2.4212
Mother Tert_Qualifications	0.1224	1.63	0.1091	-0.2612	-0.73	-2.2526
Father_No_Qualifications	-0.0366	-0.58	-0.0323	0.1067	0.48	1.0374
Father Tert_Qualifications	0.1303	1.65	0.1163	-0.0299	-0.09	-0.2845
Income_Decile (ages 11-14)	0.0627 ***	4.16	0.0555	-0.0287	-0.48	-0.2712
Early_Income_Decile(ages1-5)	0.0394 **	2.76	0.0349	0.0581	1.18	0.5855
Number of Siblings	0.0018	0.06	0.0016	0.2051 *	1.87	2.2408
Parents Own Home	-0.0922	-0.86	-0.0816	-0.4056	-1.41	-4.7598
Rural	0.1524	1.41	0.1352	0.7715 *	2.19	10.1932
Prop Family Income Benefits <sup>b</sup>	0.1847	1.64	0.0016	0.3894	1.14	0.0382
Local_Unemployment	0.1316	1.32	0.1171	0.5255	1.53	6.8708
Proportion Students Continue <sup>b</sup>	0.6389 **	2.57	0.0056	-0.9312	-1.11	-0.0892
Class Size	0.0054	0.77	0.0048	0.0297	1.09	0.2993
Deviant Peers	-0.0644 ***	-5.25	-0.0565	0.1202 **	3.16	1.2535
Constant	-4.6301 ***	-4.02	1.1918	-5.1013	-1.27	6.2548
Variance of the error term:	0.6349	Std. Error=.0201				
Rho	-0.2230	2.28	P= 0.022			
Number of observations =	598	LR chi <sup>2</sup> (19) = 529.16				
Log likelihood =	-683.040	Prob > chi <sup>2</sup> = 0.0000				

Note: \*\*\* Significant at .001; \*\* Significant at .01; \* Significant at .05

a: The marginal effects are calculated for each individual and averaged across the sample. For more detail, see footnote 23. The row with the constant term contains the average predicted value.

b: The marginal effect is approximated by increasing the value of the variable with 0.01 instead of 1.

**Table 5: Predicted Average Grade for Full Sample, based on Tobit Regressions**

	<b>Mean</b>	<b>Standard Deviation</b>	<b>Minimum</b>	<b>Maximum</b>
Group 1:				
Did not drop out before, and took exams (n=629):	1.1599	.6151	0	3
Group 2:				
Did not drop out before Exams, but Did Not take exams (n=21):	.3453	.3796	0	1.5379
Group 3:				
Dropped out before exams, and Did Not take exams (n=60)	.2635	.3782	0	1.3986

Note: Estimations for the full sample, based on estimates for all those who took the national level School Certificate Exams at the end of the 10<sup>th</sup> grade.

## APPENDIX A

**Table A1: Definition of Variables**

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School leaving at age 16 (Dropout)	Binary dependent variable: 1 for individuals who did not enroll beyond the post-compulsory level (age 16, usually at the 11 <sup>th</sup> grade (Sixth Form); 0 for those who continued.
Average School Certificate Grade at Age 15 (Ave_Grade)	The average value of all School Certificate (10 <sup>th</sup> grade, age 15) national level Examination Grades over all subjects taken with weightings of 3 for an A, 2 for a B, 1 for a C and 0 for a fail (D).
(Female)	Binary=0 for a male; 1 for a female.
(Maori)	Binary=1 if ethnicity Maori.
Pacific Islander (Pacific Islander)	Binary=1 if ethnicity Pacific Islander.
Mother without Qualifications (Mother_NO_Qualifications)	Binary=1 if child's mother does not have formal educational qualifications (10 <sup>th</sup> grade School Certificate or higher).
Mother with Tertiary Qualifications (Mother_Tert_Qualifications)	Binary=1 if a child's mother has a university or other tertiary qualification.
Father without Qualifications (Father_NO_Qualifications)	Binary=1 if a child's father does not have formal educational qualifications (10 <sup>th</sup> grade or higher).
Father with Tertiary Qualifications (Father_Tert_Qualifications)	Binary=1 if child's father has a university or other tertiary qualification.
Average Income Decile (Income_Decile (ages 11-14))	Average income decile of the family when the child was between ages 11 and 14: 1 is consistently poor; 10 is consistently affluent.
Early Childhood Average Income Decile (Early_Income_Decile (ages 1-5))	Average income decile of the family when the child was between ages 1 and 5: 1 is consistently poor; 10 is consistently affluent.
Parents Own their Own Home (Parents Own Home)	Binary=1 if parents own their own home and the child is living at home at 15 years of age.

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**Table A1: continued**

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Rural Lifestyle (Rural)	Binary=1 if a child was not living in a main urban centre at 15 years of age.
Proportion of Family Income from Benefits (Prop Family Income Benefits)	The proportion (between 0 and 1) of the family's income derived from social welfare benefits.
Registered Unemployment (Local_Unemployment)	Regional unemployment rate by gender in which each individual was living at 15 years of age. There were 8 regions and the corresponding levels of unemployment ranged between 5.9 and 12.1 per cent.
Total Intelligence Quotient (IQ at age 8)	The child's measured total IQ score, testing cognitive performance at 8 years of age (revised Wechsler Intelligence Scale for Children).
Proportion of Students Continuing (Proportion Students Continue)	Proportion of an individual's 10 <sup>th</sup> grade (Fifth Form) class within the data set continuing onto the 11 <sup>th</sup> grade. The relevant individual is excluded from the calculation.
Class Size (Class Size)	Average class size in secondary school
Affiliation with Deviant Peers (Deviant Peers)	Affiliation with deviant peers at age 15 based upon self-reported use of tobacco, alcohol, illicit drugs, other illegal behavior, etc. by friends: 0 to 10, with 10 being the most deviant affiliations.

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## APPENDIX B

### The Log Likelihood Function for Joint Estimation of Academic Performance and School Leaving

Starting from the joint model in equations (10) and (11) in Section III.3, equations (7) to (9), which denote the corresponding observed values for academic performance, and

$$D = \begin{cases} 1 & (= \text{dropped out}) \quad \text{if } D^* > 0 \\ 0 & (= \text{not dropped out}) \quad \text{if } D^* \leq 0 \end{cases}$$

for school leaving, the log likelihood function to estimate all parameters can be derived.

First define:

$$P_{i,mn} = \Pr(A = m, D = n) \text{ for observation } i, \text{ for } m=0 \text{ or } 3 \text{ and } n=0,1.$$

$$P_{i,2n} = \Pr(A = A^*, D = n) \text{ for observation } i, \text{ for } 0 \leq A^* \leq 3 \text{ and } n=0,1.$$

$$d_{i,mn} = \begin{cases} 1 & \text{if } A = m \quad \text{and} \quad D = n \\ 0 & \text{otherwise} \end{cases}, \text{ for } A = 0, 3 \text{ and } D = 0, 1.$$

$$d_{i,2n} = \begin{cases} 1 & \text{if } 0 < A < 3 \quad \text{and} \quad D = n \\ 0 & \text{otherwise} \end{cases}, \text{ for } 0 < A < 3 \text{ and } D = 0, 1.$$

The log-likelihood function to be maximized for the sample is then

$$ll = \sum_{i=1}^N \sum_{m=0,2,3} \sum_{n=0}^1 d_{i,mn} \log P_{i,mn}.$$

The exact terms  $P_{i,mn}$  are defined as follows for the different values of  $m$  and  $n$ :

$$P_{i,00} = \Pr(A_i^* \leq 0 \text{ and } D_i^* \leq 0) = \Phi_2(-(\alpha_a + X_{ai}'\gamma_a)/\sigma_1, -(\alpha_d + X_{di}'\gamma_d), \rho)$$

where  $\Phi_2$  is the bivariate standard normal cumulative distribution.

$$P_{i,01} = \Pr(A_i^* \leq 0 \text{ and } D_i^* > 0) = \Phi_2(-(\alpha_a + X_{ai}'\gamma_a)/\sigma_1, (\alpha_d + X_{di}'\gamma_d), -\rho)$$

$$P_{i,20} = \Pr(A_i^* = A_i \text{ and } D_i^* \leq 0) =$$

$$\Phi\left(\frac{-(\alpha_d + X_{di}'\gamma_d + A_i\delta_d) - \rho(A_i - (\alpha_a + X_{ai}'\gamma_a))/\sigma_1}{\sqrt{1-\rho^2}}\right)\phi((A_i - (\alpha_a + X_{ai}'\gamma_a))/\sigma_1)$$

where  $\Phi$  is the univariate normal cumulative distribution and  $\phi$  is the univariate normal density function.

$$P_{i,21} = \Pr(A_i^* = A_i \text{ and } D_i^* > 0) = \Phi \left( \frac{(\alpha_d + X_{di}'\gamma_d + A_i\delta_d) - \rho(A_i - (\alpha_a + X_{ai}'\gamma_a))/\sigma_1}{\sqrt{1-\rho^2}} \right) \phi((A_i - (\alpha_a + X_{ai}'\gamma_a))/\sigma_1)$$

$$P_{i,30} = \Pr(A_i^* > 3 \text{ and } D_i^* \leq 0) = \Phi_2((\alpha_a + X_{ai}'\gamma_a - 3)/\sigma_1, -(\alpha_d + X_{di}'\gamma_d + 3\delta_d), -\rho)$$

$$P_{i,31} = \Pr(A_i^* > 3 \text{ and } D_i^* > 0) = \Phi_2((\alpha_a + X_{ai}'\gamma_a - 3)/\sigma_1, (\alpha_d + X_{di}'\gamma_d + 3\delta_d), \rho)$$

Similar expressions can be derived for the log likelihood function based on equations (14) and (15).

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## Notes

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<sup>1</sup> In addition, the experience of countries such as Australia and New Zealand, which abolished university fees to increase access throughout the 1970s to the 1980s, has shown that the socio-economic background of students is highly stable over time. For example, in Australia 10 years after the abolition of university fees, the socio-economic background of tertiary students had not changed, mainly representing children from fathers with a white-collar occupation and higher income levels (for example, Williams, 1987; and Anderson and Vervoon, 1983).

<sup>2</sup> Further information and other research using this data set can be found in Fergusson, Horwood and Lloyd (1991), and Fergusson and Lynskey (1993).

<sup>3</sup> After the year 2002, the School Certificate examination grades (also called the National Certificate of Educational Achievement (NCEA) examination) will include a significant internal assessment component provided at the school level. Therefore, the current data provide a good opportunity to use nationally comparable School Certificate results before these changes take effect.

<sup>4</sup> The original cohort of individuals in the survey consisted of 1265 individuals. The sample used in this study contains 713 observations to analyze the dropout before exams, and 598 observations for the joint estimations of School Certificate Examination at age 15 and school leaving at age 16. The smaller sample used for age 16 is partly due to minor attrition over time, and partly due to missing values on variables of importance to this part of the study, such as average score, parental income, and school factors. Analysis indicates that the selected sample is slightly less likely to drop out of secondary school than the full sample (the probability is 0.0034 lower). A study for the New Zealand Treasury (Maloney, 1999) showed that attrition was related

to some initial characteristics such as ethnicity and having a single parent. Nevertheless, comparisons with later Census data at both local and national levels show that the CHDS is still fairly representative of the population of children born around 1977.

<sup>5</sup> See Table A1 in Appendix A for a full list of variable descriptions.

<sup>6</sup> The IQ variable is correlated with both reading and mathematics scores at ages 8 and 9, but we found that the IQ score was consistently a better predictor of later academic performance than the other two measures. This possibly reflects the measurement of a broader set of skills.

<sup>7</sup> A detailed review of the empirical literature on participation in post-compulsory and higher education is provided in Maani (1996a, 1996b, and 1997).

<sup>8</sup> Studies of schooling choices, such as high-school completion, or college attendance and completion, have included high-school test scores either as a proxy for ability,  $S_i$ , or as a control variable of earlier measures of learning,  $A_i$ . That literature provides strong support for the link between academic performance and later schooling choices. See for example, Evans and Schwab (1995), and Fuller, Manski and Wise (1982). In that literature, academic performance is generally treated as exogenous. Both studies rightly recognize the potential endogeneity of test scores, but leave its treatment to future studies. Light and Strayer (2000) allow for non-zero correlation of error terms across a set of equations of quality of college attended and subsequent college graduation. They find that allowing for endogeneity predicts higher college drop out rates for students with low ability scores due to unobservable characteristics.

<sup>9</sup> Ding and Lehrer (2004) examine approaches and assumptions relating to ability heterogeneity in estimating production functions of academic performance. They note various problems with implicit assumptions regarding the nature of omitted ability in standard methods. A general conceptual model of current academic performance allows for the full history of influencing variables, where the effect of inputs on academic performance can vary over time (see for example, Hanushek (1979), Todd and Wolpin (2003) or Ding and Lehrer (2004)). The data used here does not include equivalent information to the School Certificate exam results for more than one time period. Instead, our model includes childhood IQ to control for ability, which is not generally available in other studies. We further include average family income over two extended time periods, which is consistent with the approach in the studies named above.

<sup>10</sup> With new terminology implemented in 2002 in New Zealand, the years of study from age 5 to 18 are termed Year 1 to Year 13, but in this paper, we are referring to the North-American equivalent years of kindergarten to the 12<sup>th</sup> grade.

<sup>11</sup> A possible argument against potential endogeneity is that the academic performance results are measured one year prior to the school-leaving decision captured in equation 11. This means the two variables could be seen as two separate outcomes where the earlier one could influence the later decision on school leaving, but where the unobservable factors are not the same.

<sup>12</sup> The variance in the Probit equation cannot be identified and is usually set to 1. This approach has been followed here as well.

<sup>13</sup> The derivation of the joint likelihood function to be maximized for this joint model is available in Appendix B.

<sup>14</sup> The parameters in the reduced-form model are related to the old parameters in the following way:  $\alpha_a' = \alpha_a$ ,  $\alpha_d' = \alpha_a \delta_d + \alpha_d$ ,  $\gamma_a' = \gamma_a$ ,  $\gamma_d' = \gamma_a \delta_d + \gamma_d$ ,  $\varepsilon_a' = \varepsilon_a$ , and  $\varepsilon_d' = \varepsilon_a \delta_d + \varepsilon_d$ .

The transformed error terms are still normally distributed with means zero and transformed covariance matrix parameters. Exclusion restrictions are required to identify the original parameters.

<sup>15</sup> As an alternative estimation approach, we applied a two-stage approach, similar to the two-step approach described in Stern (1989) and Maddala (1983: p. 246). The two-stage method is essentially an instrumental variable method, where all exogenous variables are used as instruments to estimate each equation in the system separately (see for example, Greene, 1993). Using this approach we also found results for the school-leaving equation that were similar to the joint estimation approach reported in the paper, indicating an increase in the effect of academic performance on school leaving when allowing for the endogeneity of academic performance (compared to the effect when assuming academic performance is exogenous). The two-stage estimation method produces consistent parameter estimates, but is not efficient because the potential correlation between the error terms in the structural equations is not taken into account. Therefore we have focused on the method reported in the paper.

<sup>16</sup> In the results section, we provide corresponding dollar values on the income effects.

<sup>17</sup> The marginal effects of the exogenous variables for the joint models are approximated by using a simulation approach. We draw 8000 times from the joint error distribution for each person in the sample and calculate school leaving and average score for each draw based on the individual's characteristics. The calculated values are averaged over the draws to obtain the expected value of the average score and school-leaving probability for each person, which is then averaged over the sample. For dummy variables, we set the value of one of the variables to 0 and compare the outcome to the calculation with the same variable set to 1. We can then compute the marginal effect of this characteristic by taking the difference in predicted outcomes. For continuous variables, we increase the value of one characteristic with one unit for all individuals and recalculate the predicted outcome. The marginal effect for this particular characteristic is calculated as the difference between this predicted outcome and the predicted outcome at the observed value.

<sup>18</sup> For the teenage years, family income decile 1 corresponds with an average nominal weekly family income of around \$300, and decile 10 corresponds with \$1635. For early childhood, family income decile 1 corresponds with around \$105, and decile 10 with \$410 per week.

<sup>19</sup> Blau (1999) has examined the question of endogeneity of parental income and scores of childhood development. He notes that unobservable characteristics that are correlated with parental income may also explain child development. Applying different methods, especially fixed effects reflecting genetic or motivation factors (referred to as 'grandparent' effects, based on the characteristics of the child's maternal aunt) resulted in significantly larger permanent

income effects on child development, but small and insignificant current income effects. Blau concluded that while the results were somewhat speculative, the evidence suggested that the estimated effects of permanent income are, if anything, biased downward in OLS estimations (p. 270).

<sup>20</sup> The estimated error correlation becomes larger negative, when important variables (such as IQ) are left out of the academic performance equation, which supports this conclusion.

<sup>21</sup> As noted earlier, the raw correlation between school leaving and the average income deciles is negative. The relationship only becomes positive after controlling for several other characteristics.

<sup>22</sup> IQ was not included in the final version of the single-equation model presented here. However, in an alternative specification where IQ was included, the effect of IQ was insignificant and the calculated marginal effect was much smaller (-0.13 percentage points) than in the joint models.

<sup>23</sup> In order to test for the robustness of this result further, we also used the usual two-step Heckman adjustment estimating equation (6) through OLS rather than Tobit, given that most observations on academic performance are not censored. The earlier results were fully confirmed by this exercise.

<sup>24</sup> These results are available from the authors.

<sup>25</sup> The Tobit had a number of significant coefficients, especially the income variables, IQ, gender, mother's qualifications, and peer variables (the results are available from the authors).