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## Bounds on the Return to Education in Australia using Ability Bias

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# Bounds on the Return to Education in Australia using Ability Bias\*

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## Abstract

We estimate the average return to education and the ability bias applying a parametric model of intra-household correlation suggested by Card (1999, 2001) to the Household, Income and Labour Dynamics in Australia survey. Using the subsample of dual-earner households, we obtain an average return to education of 5.5% and an ability bias of 19%. Our paper is also the first to provide informative inference results on ability bias.

We extrapolate the ability bias estimate from dual-earner households to the whole sample. Using Manski's (1989) nonparametric no-assumptions bounds to partially identify the ability bias for the whole sample, we find that ability bias lies between 9% and 63%. This implies an average return to education of between 3.0% and 7.4% for the whole sample. Our estimates are conservative and compare well to other estimates of the average return to education which typically lie to the right of that interval.

**Keywords:** ability bias, return to education, inference, partial identification, Australia.

**JEL classification:** I21, I28, J24.

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# 1 Introduction

Unobserved ability biases the ordinary least squares (OLS) estimator of the average return to education upwards. Instrumental variables (IV) estimation ideally circumvents this problem but typically yields point estimates with large standard errors (see, for example, Angrist and Krueger (1991, 1999)). As a consequence, estimates of ability bias are also imprecisely measured because the large standard errors feed through.

For Australia, Leigh and Ryan (2008), using different natural experiments, obtain point estimates for ability bias, depending on the instrumental variable technique employed, of 9% and 38% but do not calculate standard errors. Using their inference results for OLS and instrumental variable (IV) estimates, we apply the delta method to calculate standard errors of 27% and 26% for the two ability bias estimates. Miller, Mulvey, and Martin (2006) estimate the average return to education for a sample of identical twins. While their focus is not on ability bias, we combine their OLS and IV results to calculate the ability bias to be 70% with a standard error of 17%. Although the standard error is tight compared to Leigh and Ryan, it only applies to a small subsample of the population (identical twins). We argue that extrapolation to the rest of the sample (non-twins) yields uninformative results.<sup>1</sup>

Our paper makes three contributions to the literature on the return to education and ability bias for Australia. First, we apply a parametric model of intra-household correlation suggested by Card (1999, 2001) to wave 9 of the Household, Income and Labour Dynamics in Australia (HILDA) survey. For the subsample of dual-earner households we estimate an average return to education of 5.5% which is measured with a relatively small standard error.

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<sup>1</sup>Two previous studies that also focus on Australian twins are Miller, Mulvey, and Martin (1995) and Miller, Mulvey, and Martin (1997). A recent paper by Klein and Vella (2009), by using conditional second moments rather than using instrumental variables, estimates an average return to education of 10%.

Second, our paper is the first to compute standard errors on ability bias. We show that the return to education obtained from the intra-household model implies a point estimate for ability bias of 19% with a standard error of 14%, which is considerably tighter than the implied standard errors of Leigh and Ryan (2008) and smaller than those implied by Miller, Mulvey, and Martin (2006). Third, using the ability bias estimates, we extrapolate the average return to education from the subsample of dual-earners to the whole sample. We do so under the weakest possible set of additional assumptions. The estimates from the model of intra-household correlation are all based on the subsample of dual-earner households. The idea behind this approach is that the unobserved characteristics that cause bias in the estimation of the average return to education can disappear *partially* within a household.<sup>2</sup> In order to extrapolate the average return to education from dual-earner households to the whole population under the weakest set of additional assumptions we apply Manski's (1989) work on nonparametric partial identification. We partially identify and estimate the ability bias for the whole sample to lie between 9% and 63%. This implies a range for the average return to education of between 3.0% and 7.4% for the whole sample. This range on the average return to education is informative: previous estimates in the literature that apply to the population at large fall to the right of that range.

The paper proceeds as follows: section 2 summarises the data, section 3 provides the OLS estimates, section 4 presents the parametric model of intra-household correlation, section 5 estimates the ability bias and standard errors and provides a nonparametric extension, and section 6 concludes.

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<sup>2</sup>A similar motivation is behind the twin-study estimators of Ashenfelter and Krueger (1994) and Ashenfelter and Rouse (1998), where unobserved heterogeneity is removed *completely* when comparing sets of identical twins. However, instead of restricting ourselves to the small subsample of twins we focus our estimation on the larger subsample of dual-earner households.

## 2 Data

We use wave 9 of the Household, Income and Labour Dynamics in Australia (HILDA) survey that was released in December 2010. HILDA is an annual household-based panel data set that started in 2001. We use the panel dimension of HILDA only to construct a person's education level as accurately as possible. For the wage regressions we use the most recent earnings and work hours information from the 2010 interviews. Like Leigh and Ryan (2008), we define our whole sample as the set of people with positive earnings who have an Australian school degree and are aged between 25 and 64 years. This *whole sample* is denoted  $\Omega$ . To estimate a model of intra-household earnings correlations, we need to split the whole sample  $\Omega$  into two subsamples: Dual-earner households and nondual-earner households. More formally, the set of all individuals in  $\Omega$  with exactly one other person in the same household who is also in  $\Omega$  constitute all individuals in dual-earner households. The complement of that set in  $\Omega$  is the set of nondual-earner households. By far the most households in the set of nondual-earner households are single-earner households, few are triple-earner households.

HILDA contains several measures of a person's earnings: annual income (pre and post tax), weekly earnings, and hourly wages. We focus solely on the hourly wage as dependent variable for two reasons. First, hourly wages are the best proxy for a person's current earnings potential. Second, hourly wages are not biased due to unobserved selection along the intensive and extensive margins. Because the estimation is based on dual-earner households, if we use annual income instead of hourly wages, we could potentially observe households in which one partner works full-time and reports high annual earnings while the other partner works part-time with low annual earnings. The model of intra-household earnings correlation would attribute that earnings gap to differences in unobserved ability rather than the likely result

of joint household optimization regarding time-allocation. Using hourly wages avoids this misinterpretation.

Table 1 presents summary statistics for the whole sample of working individuals aged 25–64 as well as the subsamples of dual-earner households and nondual-earner households. All standard errors here and throughout this paper are robust to the sample design and take into account the stratified nature of the HILDA survey.

[Table 1 about here.]

The table shows that the average person in the whole sample is almost 42 years old and has 12.67 years of education (just past a completed high-school degree). The fraction of females equals 48%, the fraction of full-time workers (working at least 35 hours per week) is 74%, and 59% of the whole sample are married. The average hourly log-wage equals 3.24.

The subsample of dual-earner households is very similar in its characteristics to the whole sample. We will return to this fact when we discuss the estimation results from the model of intra-household correlation. Not surprisingly, one notable discrepancy occurs for the fraction of married individuals. It is 25 percentage points higher in the subsample of dual-earner households, which, of course, results from construction. The hourly log-wage for dual-earners is not significantly different to that of the whole sample. By implication, the remaining subsample of nondual-earners resembles the whole sample and the subsample of dual-earners.

### 3 Baseline: Ordinary Least Squares Estimation of Returns to Education

The starting point for our estimations is the following standard empirical specification of the human capital earnings function:

$$y_j = \mu + s_j\beta + x_j'\gamma + u_j, \quad (3.1)$$

where  $y_j$  is the hourly log-wage of person  $j$ ,  $s_j$  is a person's total years of education, and the vector  $x_j$  includes age and demographic observables. It is standard to interpret the coefficient  $\beta$  as the average marginal return to education in the population (we will refer to  $\beta$  simply as the average return to education). Table 2 reports the estimates of the coefficients  $\mu$ ,  $\beta$ , and  $\gamma$  and their standard errors for the whole sample  $\Omega$ .

[Table 2 about here.]

Table 2 shows that each additional year of education increases the wage by 8.1%–8.4%. The different regressions in the columns show that parameters are reasonably stable. The coefficient estimate for age fluctuates between 3.3% and 4.0%. There exists a significant earnings penalty for women: The most conservative estimate is that women earn 10% less than men. The hourly wage of full-time workers exceeds that of part-time workers by about 7.8%. The return to being married equals at least 11.2% while the interaction between being female and being married is not significant. We do not include the interaction term in the rest of our analysis.

Comparing our point estimates to Leigh and Ryan (2008), we find returns to education have not increased over time. Using the 2003 wave of Hilda, Leigh and Ryan report an OLS estimate of 8.0% (controlling for the full vector of covariates) compared to our 8.1%.

## 4 A Parametric Model of Intra-household Correlation

OLS estimates of  $\beta$  in equation (3.1) are biased upward due to omitted variable bias. The error term can be decomposed as  $u_j = \alpha_j + \varepsilon_j$  where  $\alpha_j$  is now a person's unobserved ability and  $\varepsilon_j$  is a random error term. If ability is correlated with schooling,  $s_j$ , then the coefficient estimate  $\hat{\beta}$  of  $\beta$  not only captures the direct effect of education on earnings but also the indirect effect through its correlation with ability.

As an alternative estimation strategy to OLS and instrumental variables estimation we present a parametric model of intra-household correlation, suggested first by Card (1999, 2001). The idea behind this approach is that the unobserved characteristics that cause bias in the estimation of the average return to education can disappear *partially* within a household. A similar idea motivates the twin-study estimators, where unobserved heterogeneity is removed *completely* when comparing sets of identical twins. However, instead of restricting ourselves to the small subsample of twins we focus our estimation on the larger subsample of dual-earner households. We address the potential bias due to sample selection below. For now, our objective is to estimate the average return to education and the ability bias for that well-defined subsample of dual-earners.

Consider the following version of the human capital earnings function for household  $i$ :

$$y_{ij} = \alpha_{ij} + s_{ij}\beta_j,$$

where  $j \in 1, 2$  and  $y_{ij}$  represents the hourly log-wage of person  $j$  in household  $i$ . To reduce notational clutter we now drop the subscript  $i$ . The complete model is given in the next three



equations (we omit the covariates  $x_j$  for brevity; they are included in all estimations below):

$$y_j = \alpha_j + s_j\beta_j, \quad (4.1)$$

with:

$$\alpha_j = \bar{\alpha}_j + \lambda_{j1}(s_1 - \bar{s}_1) + \lambda_{j2}(s_2 - \bar{s}_2) + \nu_j \quad (4.2)$$

$$\beta_j = \bar{\beta} + \psi_{j1}(s_1 - \bar{s}_1) + \psi_{j2}(s_2 - \bar{s}_2) + \eta_j, \quad (4.3)$$

where  $\bar{\alpha}_j$  and  $\bar{s}_j$  are within household averages and  $\bar{\beta}$  is the average return to education for the subsample. Our objective is to estimate  $\bar{\beta}$ . The above equations model the relationship between education and ability parametrically. Card (1999, 2001) presents a partial equilibrium model of optimal schooling choice that results in equations (4.1) through (4.3).

Equation (4.1) says that the hourly log-wage of household member  $j$  is determined linearly by ability  $\alpha_j$  and education  $s_j$ . Equation (4.2) expresses ability as a function of the education of both household members. If, for example,  $j = 1$  then  $\lambda_{j1}$  is the partial correlation of ability with own education while  $\lambda_{j2}$  is the partial correlation with the partner's education. The term  $\nu_j$  is a pure random error. Equation (4.3) specifies the individual return to education which is based on the average return to education  $\bar{\beta}$  and is modelled as a person-specific slope term. Like the ability term it is a function of the education of both household members. The term  $\eta_j$  is a pure random error.

Card (1999), by re-arranging and taking linear projections, shows that equations (4.1) through (4.3) can be summarised in the set of reduced form equations:

$$y_1 = c_1 + \tau_{11}s_1 + \tau_{12}s_2 + e_1 \quad (4.4)$$

$$y_2 = c_2 + \tau_{21}s_1 + \tau_{22}s_2 + e_2, \quad (4.5)$$

with

$$\begin{aligned}\tau_{11} &= \bar{\beta} + \lambda_{11} + \psi_{11}\bar{s}_1 & \tau_{12} &= \lambda_{12} + \psi_{12}\bar{s}_1 \\ \tau_{21} &= \lambda_{21} + \psi_{21}\bar{s}_2 & \tau_{22} &= \bar{\beta} + \lambda_{22} + \psi_{22}\bar{s}_2.\end{aligned}$$

Equations (4.4) and (4.5) can be estimated simultaneously in a system of seemingly unrelated regressions yielding consistent estimates for  $\tau_{11}$ ,  $\tau_{12}$ ,  $\tau_{21}$ , and  $\tau_{22}$ . Without any further assumptions we cannot, however, back out an estimator for the average return to education,  $\bar{\beta}$ . The parameter is not identified.

To proceed, we impose a weak symmetry assumption on the parameters of equations (4.2) and (4.3). We assume that  $\lambda_{11} = \lambda_{22}$  and  $\lambda_{12} = \lambda_{21}$ . The first equality says that own education affects person 1's ability in the same way that own education affects ability for person 2. The second equality says that cross-education affects person 1's ability in the same way that cross-education affects ability for person 2.<sup>3</sup> We also assume that  $\psi_{11} = \psi_{22}$  and  $\psi_{12} = \psi_{21}$  with a similar interpretation to the one just given.

Furthermore, the data support the hypothesis that  $E[s_{i1}] = E[s_{i2}]$ , i.e., expected value of education of person 1 is the same as the expected value of education for person 2 (shown below). Together with the symmetry assumptions this implies that  $\tau_{11} = \tau_{22}$  and  $\tau_{12} = \tau_{21}$ . Below we affirm these last two equations through hypothesis testing. This provides empirical support for the symmetry assumptions.

Subtracting equation (4.5) from equation (4.4) we obtain

$$y_1 - y_2 = (c_1 - c_2) + (\tau_{11} - \tau_{21})s_1 + (\tau_{12} - \tau_{22})s_2 + (e_1 - e_2),$$

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<sup>3</sup>Hertz (2003), in an empirical application for South Africa, also assumes symmetry.

which under symmetry reduces to

$$\begin{aligned} y_1 - y_2 &= (c_1 - c_2) + [\bar{\beta} + (\lambda_{11} - \lambda_{12}) + (\psi_{11} - \psi_{12})\bar{s}_1] \cdot (s_1 - s_2) + (e_1 - e_2) \\ &= (c_1 - c_2) + \theta \cdot (s_1 - s_2) + (e_1 - e_2), \end{aligned} \tag{4.6}$$

where  $\theta := \bar{\beta} + (\lambda_{11} - \lambda_{12}) + (\psi_{11} - \psi_{12})\bar{s}_1$ . Regressing intra-household differences of  $y$  on intra-household differences of  $s$  therefore yields an estimator of  $\theta$ . Mechanically, if  $\lambda_{11} = \lambda_{12}$  and  $\psi_{11} = \psi_{12}$  then the OLS estimator  $\hat{\theta}$  from the regression of  $(y_1 - y_2)$  on  $(s_1 - s_2)$  and a constant term would be a consistent estimator of  $\bar{\beta}$ , the average return to education.

Yet, the assumption that  $\lambda_{11} = \lambda_{12}$  and  $\psi_{11} = \psi_{12}$  is not one we are willing to make. The parameter  $\lambda_{11}$  measures the correlation between own ability and own education while the parameter  $\lambda_{12}$  measures the correlation between own ability and the partner's education. There is no a priori reason to assume that those would be identical. It may be reasonable to instead assume that  $\lambda_{11} \geq \lambda_{12}$ . This is the case where own education has a stronger correlation with own ability than the partner's education. A similar argument holds for the relationship between  $\psi_{11}$  and  $\psi_{12}$ .

Under the assumption that  $\lambda_{11} \geq \lambda_{12}$  and  $\psi_{11} \geq \psi_{12}$  the parameter  $\theta$  is an upper bound on  $\bar{\beta}$  and thus, the OLS estimator  $\hat{\theta}$  from the regression of  $(y_1 - y_2)$  on  $(s_1 - s_2)$  and a constant term has the following probability limit:

$$\begin{aligned} \text{plim } \hat{\theta} &= \bar{\beta} + (\lambda_{11} - \lambda_{12}) + (\psi_{11} - \psi_{12})\bar{s}_1 \\ &\geq \bar{\beta}. \end{aligned}$$

We therefore interpret the OLS estimate  $\hat{\theta}$  as a conservative parametric upper bound estimate of the average return to education. (This implies that all estimates and upper bounds on ability bias below are biased against us.)

Table 3 contains all results for the intra-household estimation. Recall that the sample is restricted to the subset of dual-earners. Column (1) reports mean education of person 1 in the dual-earner household, column (2) reports mean education of person 2. Together with the standard errors, both columns show that we cannot reject the hypothesis that  $E[s_{i1}] = E[s_{i2}]$ . We conclude that mean education is identical for both partners.

Columns (3) and (4) give the results of the reduced form estimation of equations (4.4) and (4.5). For the reduced form parameters on own education we find estimates  $\hat{\tau}_{11} = 0.065$  and  $\hat{\tau}_{22} = 0.064$  which, together with their standard errors, implies that we cannot reject the null hypothesis that  $\tau_{11} = \tau_{22}$ . Likewise, for the reduced form parameters on the partner's education we obtain estimates  $\hat{\tau}_{12} = 0.008$  and  $\hat{\tau}_{21} = 0.009$  again implying (after consideration of the standard errors) that we cannot reject the null hypothesis  $\tau_{12} = \tau_{21}$ .

The combined finding that  $E[s_{i1}] = E[s_{i2}]$ ,  $\tau_{11} = \tau_{22}$ , and  $\tau_{12} = \tau_{21}$  is a necessary condition for—and at the same time it is the strongest support that can be provided by the reduced form equations (4.4) and (4.5) in favor of—symmetry (defined earlier as  $\lambda_{11} = \lambda_{22}$  and  $\lambda_{12} = \lambda_{21}$ ).

[Table 3 about here.]

Column (5) presents the results of an OLS regression of hourly log-wages on education for the subsample of dual-earners. The biased estimate of the average return to education equals 6.8% which is 1.3 percentage points lower than the comparable OLS estimate in Table 2 for the whole sample. The difference in the estimate is due to sample selection. Persons in households where both partners work earn a lower average return to education compared to nondual-earner households.

Column (6) shows the estimation results of equation (4.6). The dependent and indepen-

dent variables are in intra-household differences. For the coefficient on education this results in the unbiased estimate of the average return to education. For the other parameter estimates we simply estimate the coefficient on the differenced covariates. The estimated average return to education,  $\bar{\beta}$  equals 5.5% which is considerably below the OLS estimate of 6.8% for that sample.

## 5 Estimating Upper Bounds on the Ability Bias

### 5.1 Estimates of the Parametric Model

Leigh and Ryan (2008) estimate ability bias as the deviation of the (inconsistent) OLS estimator from the (consistent) IV estimator as a percentage of the OLS estimator. The idea behind this definition is that the OLS estimator converges in probability to a biased measure or the “true” average return to education while the IV estimator converges to the “truth”. This implies the following formal definition of ability bias for our study:

$$A := 1 - \frac{\text{plim}(\hat{\theta})}{\text{plim}(\hat{\beta}_{OLS})}.$$

This definition is informative about how far (in percent) the probability limit of the OLS estimator is away from the “true” average return to education as measured by  $\theta$ . Using the results from section 4 we can readily estimate the ability bias via the analogy principle (see Goldberger (1968)) as

$$\hat{A} := 1 - \frac{\hat{\theta}}{\hat{\beta}_{OLS}} = 0.19.$$

An ability bias of 19% is not negligible. It falls between the two point estimates of 9% and 38% reported by Leigh and Ryan (2008).

We combine their information on point estimates, sample sizes, and standard errors and apply the delta method to compute standard errors and one-sided confidence intervals for

the implied ability bias. It turns out that both point estimates reported by Leigh and Ryan are measured quite imprecisely. The main contribution of our paper is to provide tight and informative standard errors for the ability bias estimate.

Table 4 shows that Leigh and Ryan’s point estimate of 9% comes with a standard error three times that size (column (5)). Based on these numbers, we construct one-sided 95% confidence intervals. We restrict the confidence intervals to one side because we assume that the correlation between education and ability is (weakly) positive resulting in an ability bias that at the very least equals zero. The number reported in column (6) therefore is the 95% quantile of the distribution of  $\hat{A}$  as given by its asymptotic approximation. We interpret that number as the conservative upper bound on the ability bias. The table shows that the conservative upper bound on Leigh and Ryan’s point estimate of 9% is 54%. Their point estimate of 38% has a standard error of 0.258 which translates to a conservative upper bound on the ability bias of 80%.

Miller, Mulvey, and Martin (2006) estimate the return to education for a sample of identical twins. Comparing their OLS estimate to the IV estimate, we are able to compute the ability bias which we find to be 70%.<sup>4</sup> Again, we apply the delta method to calculate the standard errors. At 0.168, the standard error is comparably tight, however the conservative upper bound estimate equals 98%. While Miller, Mulvey, and Martin’s twin study estimates have high internal validity, extrapolation to the rest of the sample will not be informative: Short of imposing restrictive additional assumptions, if the conservative upper bound on ability bias equals 98% for the twin-sample, the upper bound for the rest of the sample cannot be lower (see subsection 5.2 below). But then, the most conservative estimate, even in the

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<sup>4</sup>We report Miller, Mulvey, and Martin’s OLS and IV estimates for identical twins from their Table 3. Their IV estimate results from a regression of between-identical-twins-differences in earnings on differences in education and other covariates and therefore is close in spirit to our intra-household estimation.

absence of estimating anything, is always 100%.

[Table 4 about here.]

In contrast, our point estimate of 19% is relatively accurately measured with a standard error of 0.142 and an implied conservative upper bound of 42%.

Why is ability bias in the other studies measured so imprecisely? The ability bias is constructed as the ratio of two coefficient estimates and as such it inherits their variances. Our estimation procedure has the advantage that the two coefficient estimates,  $\hat{\beta}_{OLS}$  and  $\hat{\theta}$ , have comparably tight standard errors. Leigh and Ryan calculate the ability bias using instrumental variables estimates as a benchmark to compare the OLS estimator to. Their instruments are “experimental” in the sense that they exploit month of birth and school leaving legislation as exogenous sources of variation. Such estimators, while theoretically valid, are typically plagued by wide standard errors which leads to imprecise inference (see Bound et al. (1995) for a case in point). In their estimations, the IV estimators typically have standard errors that are six to seven times—in one instance more than 22 times—larger than the standard errors of the OLS estimator. The result is that point estimates of ability bias are also measured imprecisely.

## 5.2 Nonparametric Extension to Whole Sample

The estimation results of subsection 5.1 apply only to the subsample of dual-earners. That subsample, while covering a significantly larger proportion of the whole sample than subsamples based on twins, still only counts for about 46% of the whole sample (54% are nondual-earners). Our aim is to calculate an average return to education that applies to the whole sample.

A straightforward way to do so is to simply apply the estimated ability bias of dual-earners to the rest of the sample. Doing so, we obtain an estimated average return to education of 6.6% for the whole sample (19% below the OLS estimate of 8.1%), well below existing estimates in the literature. This approach would be justified under the assumption that both subsamples, dual-earners and nondual-earners, are subject to the same ability bias. This assumption may be too strong. We could weaken it by assuming that the subsample of nondual-earners has an ability bias at least as large as the subsample of dual-earners. Under that assumption the estimate of 6.6% for the average return to education is a conservative upper bound for the whole sample.

If, however, our aim is to extrapolate from the subsample of dual-earners to the whole sample under the *weakest* set of assumptions, we could follow Manski's (1989) nonparametric no-assumptions bounds. We take the ability bias estimate of 19% for the subsample of dual-earners as given, and recognise that the (unobserved) ability bias for the subsample of nondual-earners must fall between 0 and 100%. For the whole sample altogether this implies a range for the ability bias of 9% to 63% (the weighted average for the two subsamples). With an ability bias in that range, the average return to education for the whole sample has to fall in between 3.0% and 7.4%—well below existing estimates for the average return to education that apply to the population at large. This partial identification result is obtained under the weakest possible set of assumptions—given the parametric estimate for the subsample of dual-earners.

## 6 Conclusion

Our whole sample comprises all people with positive earnings who have an Australian school degree and are aged between 25 and 64 years. For that group we estimate an average return



to education of 8.1% via OLS. We know this estimate is upwards biased due to omitted ability. Using IV estimators that are based on natural experiments is one way to solve this problem. While such estimators can converge to the correct probability limits, they often are plagued by large variances. As a result, the implied estimate of ability bias is measured imprecisely.

We solve the problem by splitting the whole sample into two: dual-earners and nondual-earners. For the subsample of dual-earners we apply a parametric model of intra-household correlation to back up an estimate of the average return to education. Using OLS, we estimate an average return to education of 6.8% for the subsample of dual-earners. When we use OLS on intra-household differences we obtain an estimate of 5.5% which we show to be a conservative estimate of the average return to education. The implied ability bias equals 19% and is relatively precisely measured. Strictly speaking, however, it applies only to the subsample of dual-earners which comprises about 46% of the whole sample.

In order to estimate an average return to education for the whole sample, we apply Manski's (1989) nonparametric partial identification method which enables us to derive lower and upper bounds on the ability bias for the whole sample and, by implication, the average return to education. We estimate a range for the ability bias of 9% to 63% which implies an average return to education for the whole sample in between 3.0% and 7.4%—well below existing estimates for the average return to education that apply to the population at large. The estimates for the whole sample are obtained using the weakest possible set of assumptions (given the estimates from the model of intra-household correlation).

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Table 1. —Means and Standard Errors of Whole Sample and Subsamples

	Whole sample		Subsample			
			Dual-earner		Nondual-earner	
Hourly log-wage	3.24	(0.012)	3.28	(0.014)	3.22	(0.018)
Education	12.67	(0.046)	12.76	(0.066)	12.61	(0.063)
Age	41.95	(0.235)	42.53	(0.345)	41.50	(0.301)
Age squared	1,869	(20.609)	1,903	(29.876)	1,842	(26.379)
Female	0.48	(0.007)	0.50	(0.002)	0.46	(0.013)
Full-time	0.74	(0.007)	0.71	(0.009)	0.77	(0.010)
Married	0.59	(0.113)	0.84	(0.011)	0.39	(0.014)
Married $\times$ full-time	0.28	(0.006)	0.42	(0.006)	0.16	(0.009)
N	4,666		2,168		2,498	

Note.—Whole sample: Individuals with positive hourly log-wages, Australian school degree, non-full-time students, age 25–64. Subsamples: dual-earner households and nondual-earner households as explained in text. Full-time work: at least 35 hours per week. Robust standard errors in parentheses.

Table 2. —Ordinary Least Squares Estimates of Average Return to Education

	(1)	(2)	(3)	(4)	(5)
Constant	1.324* (0.2654)	1.364* (0.2622)	1.311* (0.2703)	1.424* (0.2519)	1.423* (0.2499)
Education	0.083* (0.0044)	0.084* (0.0044)	0.083* (0.0044)	0.081* (0.0042)	0.081* (0.0042)
Age	0.039* (0.0139)	0.039* (0.0137)	0.040* (0.0136)	0.033* (0.0124)	0.033* (0.0124)
Age squared	0.000* (0.0002)	0.000* (0.0002)	0.000* (0.0002)	0.000* (0.0002)	0.000* (0.0002)
Female		-0.140* (0.0197)	-0.117* (0.0186)	-0.108* (0.0178)	-0.100* (0.0335)
Full-time			0.066* (0.0290)	0.080* (0.0304)	0.078* (0.0324)
Married				0.112* (0.0256)	0.119* (0.0251)
Female × full-time					-0.014 (0.0428)

Note.—Dependent variable: hourly log-wage. Sample: Individuals with positive hourly log-wages, Australian school degree, non-full-time students, age 25–64. Full-time work: at least 35 hours per week. Robust standard errors in parentheses. The symbol \* denotes significance at the 5% level.  $N = 4,666$ .

Table 3. —Estimation Results: Model of Intra-household Correlation

Dependent variable:	Education		Hourly log-wage			
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	12.787* (0.0773)	12.734* (0.0759)	1.321* (0.2947)	1.676* (0.2825)	1.571* (0.2046)	-0.013 (0.0211)
Own education			0.065* (0.0087)	0.064* (0.0069)	0.068* (0.0052)	0.055* (0.0087)
Age			0.049* (0.0138)	0.030* (0.0126)	0.039* (0.0093)	0.001 (0.0051)
Age squared			-0.001* (0.0002)	0.000* (0.0002)	0.000* (0.0001)	0.008 (0.0132)
Full-time			0.036 (0.0438)	0.015 (0.0443)	0.024 (0.0348)	0.073* (0.0367)
Married			0.001 (0.0431)	0.057 (0.0424)	0.031 (0.0353)	0.294 (0.2681)
Female			-0.098* (0.0330)	-0.099* (0.0356)	-0.100* (0.0215)	-0.059 (0.0305)
Partner's education			0.008 (0.0091)	0.009 (0.0062)		

Note.—Sample: Dual-earners from whole sample (see Table 1 for definition of whole sample). Full-time work: at least 35 hours per week. Columns (1) and (2) present the average education for persons 1 and 2 in the household. Columns (3) and (4) report the estimates of equations (4.4) and (4.5). Column (5) shows the OLS estimates for the sample and column (6) gives the estimates of equation (4.6) where all variables are intra-household differences. Robust standard errors in parentheses. The symbol \* denotes significance at the 5% level.  $N = 2,168$ .

Table 4. —Ability Bias across Different Studies

Instrument used	Sample size	Parameter estimates		Ability bias		
		OLS	IV	Point estimate	Upper bound	
(1)	(2)	(3)	(4)	(5)	(6)	
Leigh and Ryan (2008)	Leaving age $\times$ birthyear	7,211	0.130 (0.0050)	0.118 (0.0350)	0.09 (0.271)	0.54
	Birthmonth $\times$ birthyear	998	0.128 (0.0130)	0.079 (0.0320)	0.38 (0.258)	0.80
Miller, Mulvey, and Martin (2006)	Identical twins	OLS: 1,518 IV: 759	0.060 (0.0050)	0.018 (0.0085)	0.70 (0.168)	0.98
<b>This paper (2011)</b>	<b>Dual-earners</b>	<b>2,168</b>	<b>0.068</b> <b>(0.0052)</b>	<b>0.055</b> <b>(0.0087)</b>	<b>0.19</b> <b>(0.142)</b>	<b>0.42</b>

Note.—OLS and IV estimates for Leigh and Ryan are from their Table 5 (IV: leaving age  $\times$  birthyear) and Table 3 (IV: birthmonth  $\times$  birthyear). OLS and IV estimates for Miller, Mulvey, and Martin are from their Table 3 (Remark: Miller, Mulvey, and Martin refer to what we call an IV estimate as an OLS estimate. It results, in any case, from a regression of between-identical-twins-differences in earnings on differences in education and other covariates. This, of course, has the interpretation of an IV estimator in which the instrument is the difference in education from the other twin. Our estimation for dual-earners exploits the same idea.) Ability bias defined as  $\hat{A} := 1 - \hat{\theta} / \hat{\beta}_{OLS}$ . Standard errors in parentheses. Standard errors for ability bias in column (5) are calculated using the delta-method. Upper bound in column (6) is the finite endpoint of the left-sided 95%-confidence interval.