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Do Dads matter? Or is it just their money that matters? Unpicking the effects of separation on educational outcomes.

Ian Walker
University of Warwick and Institute for Fiscal Studies

and

Yu Zhu
University of Kent and Centre for the Economics of Education

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Abstract

The widely held view that separation has adverse effects on children has been the basis of important policy interventions. While a small number of analyses have been concerned with selection into divorce, no studies have attempted to separate out the effects of one parent (mostly the father) leaving, from the effects of that parent's money leaving, on the outcomes for the child. This paper is concerned with early school leaving and educational attainment and their relationship to parental separation, and parental incomes.

While we find that parental separation has strong effects on these outcomes this result seems not to be robust to adding additional control variables. In particular, we find that when we include income our results then indicate that father’s departure appears to be unimportant for early school leaving and academic achievement, while

income is significant. This suggests that income may have been an important unobservable, that is correlated with separation and the outcome variables, in earlier research. Indeed, this finding also seems to be true in our instrumental variables analysis – although the effect of income is slightly weakened.

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Corresponding author: Ian Walker, Dept. of Economics, University of Warwick, Coventry, CV7 7AL, UK.
Tel +44/0 2476 523054 Fax +44/0 2476 523032 Email i.walker@warwick.ac.uk

1. Introduction

It is widely thought that parental separation has adverse effects on children – social researchers have uncovered correlations between separation and many aspects of children's behaviours including early school leaving, low achievement, behavioural disorders, crime, and poor health[1]. The falling cost of separation has resulted in large increases in separation rates in many countries in recent years. Consequently, many policy initiatives have been designed to foster reconciliation of fragile partnerships so as to reduce the separation rates of parents or, at least, reduce the impact of separation of parents on their children[2]. In some countries, tax policy is used to favour marriage which then implies higher separation costs than for cohabitation[3], and in most countries there is a system of child support that raises the costs of separation to the non-custodial parent[4] and lowers it for the custodial parent.

However, relatively few studies have attempted to identify the causal impact of separation. Causality becomes questionable if there are omitted variables that are likely to be important for the outcomes and are correlated with separation. In particular, income has typically been omitted from previous analyses and yet there are large negative income effects for the children that are associated with separation and there is considerable evidence that income does affect outcomes for children[5]. Yet, few studies have attempted to separate out the effects of one parent leaving (mostly the father) on the outcomes for the child(ren), from the effects of that parent's money leaving. That is, existing research fails to control adequately for income on outcomes. We are concerned that when fathers leave, not only does their time and influence go, but so too does their money. Child support (CS) is the policy instrument that can offset any income effects so we also consider the effects of CS on outcomes. Thus,

[1] See Amato and Keith (1991) who concluded that children with divorced parents, compared with children with continuously married parents, score significantly lower on measures of academic achievement, conduct, psychological adjustment, self-concept, and social relations. Amato (2001) updated this analysis. Haveman and Wolfe (1995) identify divorce as a major contributing factor in their review of the determinants of child outcomes.

[2] In the UK attempts to implement compulsory mediation have not been successful. Mediation was a key element of the Family Law Act of 1996 and pilot project results showed that only 7% had attended voluntary mediation. In those pilot areas where mediation was compulsory there was widespread use of exceptions granted to people fearing violence from former spouses.

[3] See Feenberg and Rosen (1995).

[4] See Cancian *et al* (2003) for US evidence and González (2005) for evidence from across 16 countries.

[5] See Dahl and Lochner (2005) for example.

this paper is concerned with educational outcomes at age 16, and their relationship to parental separation, parental incomes, child support, and parental repartnership.

Since child support is an important mechanism for ameliorating the loss in income associated with separation it is of interest to try to unpick the way in which separation affects children[6]. If policy towards the children of separated parents is to be effective we need to know the extent to which the living standards of children should protected in the face of separation of their parents, whether parents should be discouraged from separating, say through the use of fiscal incentives[7], and even whether couples who are likely to separate in the future should be discouraged from becoming parents?

Our empirical work here is based on a large panel dataset[8]. The results suggest that living in a non-intact family has a large negative correlation with the risks of leaving school at the age of 16 and of low educational attainment. These findings are robust with respect to the successive addition of regressors that control for youth's own characteristics and the characteristics of the responsible parent. However, when we add total net family income to the specification we find that living in a non-intact household has substantially smaller coefficients and they are no longer statistically significant. These estimates imply that at least part of the effect of separation found in previous studies can be accounted for by the omission of income.

The educational outcomes that we observe occur only once per child and therefore we cannot use fixed effect estimation methods even though the dataset is a panel. Moreover, the dataset is too small to reliably exploit sibling difference based estimation methods. However, we do produce estimates based on matching by pre-separation observables in an attempt to control for selection on observables. Moreover, we attempt to control for selection by unobservables into separation (and into repartnership) by exploiting the relationship history information in the data.

[6] Amato (2005) speculates as to why child outcomes are affected by separation.

[7] In Walker and Zhu (2006a) we show that CS is an important disincentive to separate. Most parental separations are instigated by mothers and we interpret the lower rates of separation associated with higher levels of CS as better behaviour by fathers within marriage to reduce the probability of being ejected from the household.

[8] In future work we intend to exploit the additional information about the BHPS adults own experience of separation when they were young. Similarly, we intend to revisit the cohort studies to investigate the role of both income and separation.

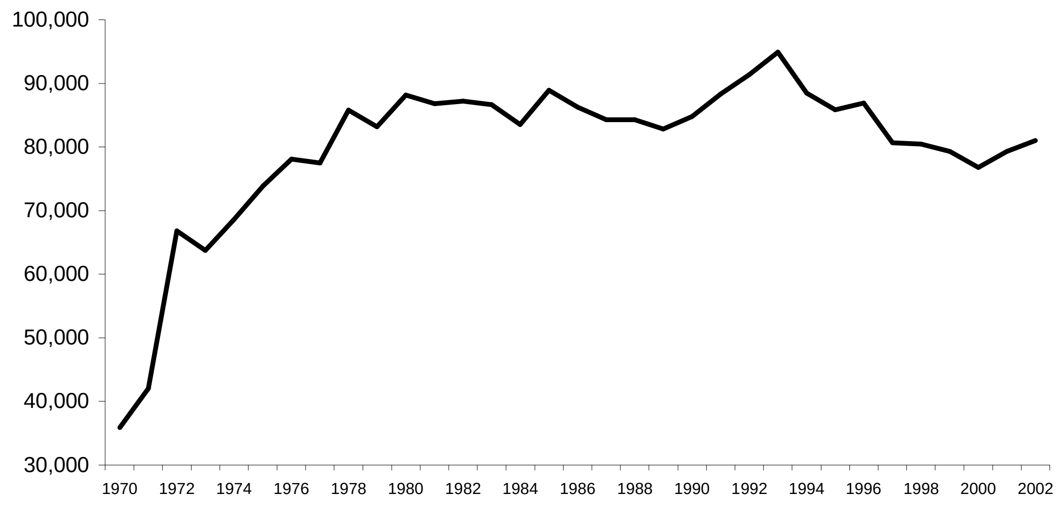
We also attempt to control for the endogeneity of parental incomes using instrumental variables exploiting the information on parental birth order[9]. While we find that parental separation has strong effects on child well-being in the pooled cross-sectional data, and this result seems to be robust to adding additional control variables, it does not carry over to our instrumental variables analysis. This suggests that there are important unobservables that are correlated with separation and our outcome variables as well as observable income.

We confine ourselves to educational outcomes in our analysis here. An analysis of subjective well-being is contained in Walker and Zhu (2006b).

2. Literature

The number of divorces of couples grew dramatically in many countries from the 1970's. Figure 1 shows the number of (married) couples with children (aged 0-16) in the UK who divorced each year from 1970. The divorce rate for parents with dependent children, as a percentage of existing marriages with dependent children is now approximately 2.5% p.a. in the UK (2001). Many studies examine the correlations between separation and outcomes for children[10] although few consider the issue of causality[11].

Figure 1 Number of Parents Divorcing (Child aged 0-16)



[9] See Booth and Kee (2005) for evidence that supports an effect of birth order on income.

[10] See, for example, Kiernan (forthcoming).

[11] See, however, Ní Bhrolcháin (2001) and Elliott and Richards (1991).

Despite the wealth of evidence an important limitation of most of the literature is that divorce is correlated with the unobservable determinants of child outcomes and this fact results in the adverse effects of separation being exaggerated in correlation studies. Gruber (2004) takes a novel approach. He uses 40 years of census data to capture the variation in divorce regulations across US states and over time and finds that unilateral divorce regulations have significantly increased the odds of an adult being divorced (by about 12%) and of a child living with a divorced parent (15% more likely to be living with a divorced mother and 11% more likely to be living with a divorced father, relative to the old laws). He then assesses the impact of easier divorce regimes on the higher education of children by comparing the adult circumstances of children who grew up in states where unilateral divorce was available, versus children who grew up in states where it was not available. He finds that children who grew up under laxer divorce laws were less likely to go to college and more likely to live in lower income households. His findings indicate that increased exposure to unilateral divorce regimes worsens child outcomes, but only up to about eight years after the change in laws. After that, there is little additional harm from continuing exposure to the laxer laws. Gruber suggests that this implies that unilateral divorce rules may have only a short-run impact on the divorce rate. Finally, Gruber notes that making divorce easier may not only increase the odds that a child grows up in a divorced household but may also change the bargaining power within intact households. For example, one parent in a two-parent household may now feel more able to shift family spending away from child investment towards private consumption. Gruber’s estimates are clearly the effects of divorce law changes and not divorce *per se*.

Piketty (2003) is in the same vein and shows that, controlling for observable parental characteristics, children with divorced or separated parents tend to perform less well at school than children living with their two parents. He pursues two identification strategies to address the potential selection problem. First, he notes that children whose parents eventually separate do as badly in school as children whose parents have already separated. Secondly he, like Gruber, exploits the large increase in separation rates following the 1975 divorce law reform, together with the regional variations in divorce rates. He argues that his results imply that it is parental conflict, rather than separation, that is bad for children, and that the degree of conflict intensity between couples has been fairly stable over time.

Sanz de Galdeano and Vuri (2004) employ a difference-in-differences methodology that relies on comparing teenager's outcomes before and after divorce with those who did not experience divorce, to control for family specific effects. They conclude that parental divorce does not adversely affect teenagers' cognitive development, as had been suggested by cross-sectional evidence. However, this study only considers the impact up to two years after separation and does not consider the impact of repartnership.

Finally, Bjorklund and Sundstrom (2002) use a sibling difference approach in a very large Swedish dataset to show that selection accounts for the observed cross-section correlation. Sibling differences are, however, problematic in this context since it seems likely that there are important peer effects between siblings arising from divorce. Our overall reading of the recent literature is that a substantial part of the observed correlation between separation and outcomes for children can be accounted for by selection.

The literature on the causal effects of parental *earnings* or *incomes* on educational outcomes for their children is not extensive. Random assignment experiments are potentially informative but uncommon. Blanden and Gregg (2004) review US and UK evidence on the effectiveness of policy experiments which largely focus on improving short term family finances. These include initiatives such as the Moving to Opportunity (MTO) experiments in the US which provide financial support associated with higher housing costs from moving to more affluent areas. MTO programs are associated with noticeable improvements in child behavior and test scores but whether these are caused by the financial gain or the environment, school and peer-group changes is unclear[12]. In the UK, the pilots of Educational Maintenance Allowances (EMA's) provided a sizeable means tested cash benefit conditional on participation in education and paid, depending on pilot scheme, either to the parents or directly to the child (UK Department for Education and Skill, 2002). Enrollments increased by up to 6% in families eligible for full subsidies. However,

[12] Note that new work on MTO by Sanbonmatsu *et al* (2004) suggests that MTO-driven neighbourhood effects on academic achievement were not significant.

this transfer was conditional on staying in school and so does not tell us about the effects of unconditional variations in income. In the absence of informative experimental evidence, instruments have been used to identify income effects. Shea (2000) uses union status (and occupation) as an instrument for parental income and therefore assumes that unionized fathers are not more ‘able’ parents than nonunion fathers with similar observable skills, while Meyer (1997) uses variation in family income caused by state welfare rules, income sources and income before and after the education period of the child, as well as changes in income inequality. While strong identification assumptions are used in both these studies, they both find that unanticipated changes in parental long-run income have modest and sometimes negligible effects on the human capital of the children[13]. Using UK data, Blanden and Gregg (2004) find the correlation between family income and children’s educational attainment has actually risen between the 1970 birth cohort data and the later British Household Panel Survey data containing children reaching 16 in the late 1990’s. They estimate the causal effect of family income in ordered probit models of educational attainment (from no qualifications up to degree level) based on sibling differences in the panel data. They also provide estimates of the probability of staying-on at school past the minimum age of 16. Throughout income is assumed to be exogenous.

Recent evidence suggests that income has a strong role to play in outcomes for children. Dahl and Lochner (2005), Plug and Vijverberg (2003, 2005), Chevalier *et al* (2005) and Harmon *et al* (2005). suggest that income does have a causal impact on educational outcomes for children. However, none of these studies allow for an effect of separation. Similarly, many studies consider the impact of separation but not income[14]. Indeed, to our knowledge, there are no studies that attempt to control for income as well as separation. This is an important omission because separation is usually accompanied by large reductions in the child’s equivalent income. Indeed, it is the purpose of child support payments to counter this.

[13] Acemoglu and Pishke (2001) use similar arguments to Meyer (1997) and exploit changes in the family income distribution between the 1970’s and 1990’s. They find a 10 percent increase in family income is associated with a 1.4% increase in the probability of attending a four year college.

[14] See, for a recent example, Francesconi *et al* (2005).

3. Data

Our data comes from the British Household Panel Survey (BHPS) which is a nationally representative sample of some 5,500 households recruited in 1991, with around 10,000 original sample members (OSMs). These OSMs and their children, who also become sample members after reaching 16, are interviewed each year, together with all adult members of their families, even if the OSMs split off from their original households to form new families and/or relocate to other areas (of the UK). This sampling design ensures that the sample remains representative of the UK population over time. The core questionnaire of BHPS collects information on household organisation, housing, employment, education, health and incomes in all waves. In wave 2, BHPS also collected lifetime histories of marriage, cohabitation, and fertility and employment transitions, which allow us to construct spells in progress of the current relationship for all couples in our sample, despite the fact that we are unable to observe the partnerships from the time of their formation.

On average, 2% of partnerships with dependent children separate each year. Table 1 reports summary statistics by family types, where non-intact families are further divided into lone-mother and repartnered-mother households.

We concentrate on educational outcomes at the age of 16 and we have 1496 unique youths aged 16 in our sample, of which 71.5% are in intact families, 17.8% in lone-mother families, and 10.7% in repartnered families[15]. It is worth noting that there is not much difference in terms of household net income between intact and remarried families, which both average 50 log points higher than lone-mother families. Almost 40% of repartnered mothers households contain step-children, almost all of which are the mothers natural children with the new partner.

Intact parents have children with much lower early school leaving rates than lone mother households but repartnership seems to restore most of the difference. However the much lower rate of achievement for children with lone mothers relative to intact parents is even lower with repartnered mothers.

[15] Families headed by custodial fathers constitute only a very small proportion of all non-intact families (less than 5%), and hence are dropped out of our sample.

Table 1: Summary Statistics by Family Types

Family Type	Intact Families	Lone Mothers	Repartnered Mothers	Total
% cohabiting	0.6	-	28.8	3.5
Log total income	5.93	5.39	5.91	5.84
% boys	48.9	53.4	55.0	50.3
% only child	15.1	23.7	16.3	16.8
No. of kids<16	0.96	0.98	1.29	1.00
Youth's age	15.8	15.9	15.9	15.9
% step siblings	1.1	1.1	38.8	5.1
% new siblings	0.2	0.0	36.9	4.1
% mother non-white	6.2	11.7	3.8	7.0
% owning house	81.3	56.8	65.6	75.3
Age of mother	43.1	39.7	39.5	42.1
Age mother left school	17.3	17.2	17.2	17.3
% Leaving School at 16	19.0	27.8	26.3	21.3
% with 5+ GCSEs	58.3	45.1	41.9	54.2
Obs	1070	266	160	1496
%	71.5	17.8	10.7	100.0

4. Results

We pursue three strategies to allow for the potential endogeneity of non-intactness (and income). First we explore sibling differences in the spirit of Sanz de Galdeano and Vuri (2004) but feel that, while our estimates of the impact of intactness are suggestive, our samples are too small to support parametric multivariate analysis and so we are unable to decompose the effect of separation into an income and a parental presence effect. Secondly, we examine how sensitive our multivariate parametric results on the levels data are to including additional control variables[16]. We find that the crucial control variable is income: non-intactness has large and precise coefficients until household income controls are added, whereupon the sizes of the coefficients are, at least, halved and become insignificant. Thirdly, we use propensity score matching and find that, once we match we find no effects of separation on the separated and a negative effect on the untreated – significantly so in the case of achievement for boys and early leaving for girls. Finally, we use instrumental variable estimation and find that there are no causal effects of non-intactness.

[16] See Rhum (2003) who uses this idea in the context of the effects of maternal care.

4.1 Non-parametric sibling differences

Sibling comparisons are always problematic. Samples are likely to be small and this is true here as Table 2 shows. Here, to identify the effect of separation we require that BOTH siblings be observed at age 16 in the sample and the elder is 16 prior to parental separation and the younger is 16 post-separation (column 3 in Table 2). Moreover we need to compare this affected group with control groups where both children were 16 before any separation occurred (column 2) and/or where both were 16 after separation occurred (column 4). Indeed, in this case we restrict our attention to comparisons between children who are step-siblings. That is, both children are natural children of the mother but the eldest was the child of the first partnership which is no longer intact, while the second is the child of the new partnership. For completeness we also present the data for those mothers who repartner between the point where the youngest child reaches 16 and when the older child reaches 16 (column 5) to capture a repartnership effect.

To reveal the effects of changes in circumstances we take the difference in the sibling differences between columns 3 and 2. Thus, becoming separated *reduces* the probability of leaving at 16 by 0.105 (ie -0.034-0.071) but this is not significant; and is reduced by an insignificant 0.005 (ie -0.034+0.029). Similarly, the effect of becoming repartnered is revealed by the difference between the sibling differences amongst the repartnered group (column 5) and those that remain separated (column 4). The effect on the probability of leaving post 16 of repartnering is -0.074 (ie -0.048-0.026), while the effect on the achievement of 5+ GCSE's is 0.280 which is significant.

However, such sibling comparsons only capture the effects of a treatment, in this case separation or repartnership) if it is the case that only one child is affected and not the other. For example, if parents (and step-parents) take compensating actions to spread the costs and benefits across all siblings (and step-siblings) then these differences will underestimate the true effect of the change. Moreover, even if this were not a problem, these sibling differences do not help us to unpick the transmission mechanism whereby separation (or repartnership) affects children.

Table 2: Sibling Differences in Outcomes

	All youths	Intact to Intact	Intact to non-intact	Non-intact to non-intact	Non-intact to intact
	1	2	3	4	5
Actual School Leaving at 16					
Elder sibling	0.196	0.159	0.310	0.279	0.286
Younger sibling	0.249	0.230	0.276	0.305	0.238
Difference	**0.053**	**0.071**	-0.034	0.026	-0.048
Std error of mean difference	0.018	0.021	0.105	0.042	0.109
5+ Good GCSE Grades					
Elder sibling	0.539	0.610	0.552	0.390	0.190
Younger sibling	0.527	0.572	0.517	0.396	0.476
Difference	-0.012	-0.029	-0.034	0.006	**0.286**
Std error of mean difference	0.021	0.026	0.093	0.041	0.140
N	683	479	29	154	21

4.2 Parametric analyses

Table 3 presents estimates for actual early school leaving. Column 1 is the raw correlation – the effect of non-intactness (when the child is 16) on the probability of staying on post 16. Column 2 adds repartnership, and column 3 adds log current net household (from all sources) when the child is 16. Column 4 adds controls for the child's characteristics including gender, while column 5 adds characteristics of the mother and time effects. Estimates for the pooled sample appear at the top of the sample, followed by those for boys and girls separately. Having a lone mother as a parent at 16 seems to have a large effect but simply adding household income is enough to drive that apparent effect to zero. Repartnership seems not to make any significant difference. The effect of income is large but is cut by about one-third when we add maternal characteristics and this becomes significant at only the 10% level when maternal controls are included. Relative to girls, boys seem to be only half as sensitive to separation but are about twice as sensitive to income.

Table 4 presents corresponding the results for educational attainment – the probability of attaining 5+ GCSEs good passes. As in Table 3 separation and repartnership seems not to matter once income is included. Again, boys seem more sensitive to income and less to lone motherhood than girls but these differences are not as pronounced as in Table 3. The scale of the income effects are broadly the same across these two outcomes.

Table 3: Probit for Actual School Leaving at 16

	(1)	(2)	(3)	(4)	(5)
ALL					
Non-intact	0.273***	0.291***	0.064	0.059	0.034
	(0.079)	(0.093)	(0.100)	(0.101)	(0.108)
Mother		-0.047	0.191	0.120	0.021
Repartnered		(0.135)	(0.140)	(0.161)	(0.172)
Log income			-0.385***	-0.394***	-0.286***
			(0.053)	(0.053)	(0.057)
Boy				0.207***	0.237***
				(0.076)	(0.080)
Youth Characteristics				Yes	Yes
Family characteristics					Yes
Wave dummies					Yes
Region dummies					Yes
N	1496	1496	1464	1464	1464
χ^2(d.f.)	12.07 (1)	12.20 (2)	62.22 (3)	72.49 (7)	171.73
					(27)
Log likelihood	-769.26	-769.20	-716.40	-711.43	-644.32
BOYS					
Non-intact	0.185*	0.215*	-0.035	-0.027	-0.001
	(0.107)	(0.127)	(0.135)	(0.136)	(0.148)
Mother		-0.082	0.175	0.072	-0.139
Repartnered		(0.182)	(0.192)	(0.226)	(0.245)
Log income			-0.513***	-0.518***	-0.464***
			(0.081)	(0.081)	(0.088)
Youth Characteristics				Yes	Yes
Family characteristics					Yes
Wave dummies					Yes
Region dummies					Yes
N	753	753	743	743	743
χ^2(d.f.)	2.96 (1)	3.17 (2)	42.67 (3)	46.81 (6)	119.66
					(26)
Log likelihood	-411.50	-411.39	-379.96	-379.06	-332.58
GIRLS					
Non-intact	0.364***	0.366***	0.159	0.171	0.127
	(0.116)	(0.137)	(0.150)	(0.151)	(0.167)
Mother		-0.007	0.228	0.181	0.079
Repartnered		(0.200)	(0.208)	(0.232)	(0.249)
Log income			-0.271***	-0.273***	-0.134*
			(0.071)	(0.071)	(0.079)
Youth Characteristics				Yes	Yes
Family characteristics					Yes
Wave dummies					Yes
Region dummies					Yes
N	743	743	721	721	721
χ^2(d.f.)	9.86 (1)	9.87 (2)	21.75 (3)	24.07 (6)	89.14 (26)
Log likelihood	-354.69	-354.69	-329.41	-328.81	-292.77

Note: Robust s.e's in brackets. *: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level. Youth characteristics include youth being an only child, number of children, and the presence of any step siblings. Family characteristics include the presence of new child (of the natural mother and the step father), whether family owns house, mother's age, years of education and being non-white.

Table 4: Probit for Passing 5 GCSEs

	(1)	(2)	(3)	(4)	(5)
ALL					
Non-intact	-0.364***	-0.333***	-0.058	-0.034	-0.012
	(0.072)	(0.086)	(0.095)	(0.095)	(0.100)
Mother		-0.082	-0.380***	-0.417***	-0.271*
Repartnered		(0.126)	(0.133)	(0.150)	(0.159)
Log income			0.410***	0.420***	0.271***
			(0.056)	(0.056)	(0.054)
Boy				-0.237***	-0.247***
				(0.067)	(0.070)
Youth Characteristics				Yes	Yes
Family characteristics					Yes
Wave dummies					Yes
Region dummies					Yes
N	1496	1496	1464	1464	1464
χ^2(d.f.)	25.36 (1)	25.76 (2)	77.96 (3)	98.95 (7)	226.82 (27)
Log likelihood	-1018.89	-1018.68	-959.94	-950.86	-880.64
BOYS					
Non-intact	-0.318***	-0.294**	0.003	0.003	0.038
	(0.100)	(0.119)	(0.130)	(0.130)	(0.137)
Mother		-0.064	-0.366**	-0.284	-0.162
Repartnered		(0.172)	(0.184)	(0.208)	(0.222)
Log income			0.511***	0.513***	0.343***
			(0.085)	(0.084)	(0.080)
Youth Characteristics				Yes	Yes
Family characteristics					Yes
Wave dummies					Yes
Region dummies					Yes
N	753	753	743	743	743
χ^2(d.f.)	10.14 (1)	10.28 (2)	45.50 (3)	53.98 (6)	118.33 (26)
Log likelihood	-516.84	-516.77	-484.78	-482.11	-445.85
GIRLS					
Non-intact	-0.396***	-0.360***	-0.082	-0.078	-0.090
	(0.105)	(0.125)	(0.140)	(0.140)	(0.148)
Mother		-0.099	-0.418**	-0.562***	-0.397*
Repartnered		(0.186)	(0.194)	(0.215)	(0.238)
Log income			0.341***	0.344***	0.207***
			(0.074)	(0.074)	(0.075)
Youth Characteristics				Yes	Yes
Family characteristics					Yes
Wave dummies					Yes
Region dummies					Yes
N	743	743	721	721	657
χ^2(d.f.)	14.23 (1)	14.50 (2)	35.28 (3)	39.41 (6)	118.21 (26)
Log likelihood	-497.30	-497.16	-467.21	-465.41	-420.76

Note: Robust s.e's in brackets. *: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level. Youth characteristics include youth being an only child, number of children, and the presence of any step siblings. Family characteristics include the presence of new child (of the natural mother and the step father), whether family owns house, mother's age, years of education and being non-white.

Table 5 converts the results from the last columns in Tables 3 and 4 into marginal effects and we break out some of the maternal and child characteristics. Younger mothers are associated with worse outcomes even controlling for maternal education, and more educated mothers generate better outcomes. If the child has a step-sibling then there is a much larger chance of leaving early, even though repartnership itself does not matter. This effect is much larger for boys.

Table 5: Marginal effects corresponding to Col 5 of previous tables

	Left school at 16 = 1			Attained 5+ GCSEs = 1		
	All	Boys	Girls	All	Boys	Girls
Non-intact	0.009	-0.002	0.029	-0.005	0.016	-0.035
	(0.027)	(0.039)	(0.040)	(0.040)	(0.055)	(0.057)
Mother Repartnered	0.005	-0.035	0.018	-0.108	-0.064	-0.156
	(0.044)	(0.059)	(0.060)	(0.063)	(0.088)	(0.094)
Log income	**-0.072**	**-0.123**	-0.030	**0.107**	**0.137**	**0.080**
	(0.014)	(0.024)	(0.018)	(0.021)	(0.032)	(0.029)
Youth Boy	**0.060**	-	-	**-0.097**	-	-
	(0.020)			(0.027)		
Youth only child	-0.018	-0.006	-0.019	-0.010	0.013	-0.021
	(0.028)	(0.044)	(0.035)	(0.040)	(0.057)	(0.057)
Number of children	**-0.024**	-0.032	-0.020	0.002	0.015	-0.002
	(0.011)	(0.017)	(0.015)	(0.015)	(0.022)	(0.022)
Step brother/ Sister	**0.306**	**0.468**	**0.277**	-0.114	-0.269	-0.030
	(0.138)	(0.168)	(0.168)	(0.117)	(0.157)	(0.151)
New brother/ sister	-0.136	-0.170	-0.121	0.155	0.211	0.198
	(0.041)	(0.042)	(0.040)	(0.124)	(0.194)	(0.138)
Mother non-white	**-0.150**	**-0.185**	**-0.114**	-0.018	-0.003	-0.071
	(0.020)	(0.024)	(0.030)	(0.064)	(0.082)	(0.115)
Owns House	**-0.109**	-0.047	**-0.161**	**0.193**	**0.219**	**0.165**
	(0.028)	(0.039)	(0.041)	(0.035)	(0.050)	(0.050)
Mother age	**-0.010**	**-0.018**	-0.004	**0.013**	**0.016**	**0.012**
	(0.003)	(0.004)	(0.003)	(0.003)	(0.005)	(0.005)
Mother age left school	**-0.022**	**-0.024**	**-0.019**	**0.031**	**0.025**	**0.038**
	(0.005)	(0.007)	(0.005)	(0.006)	(0.008)	(0.080)
N	1464	743	721	1464	743	721
χ^2(d.f.)	171.73	119.66	89.14	226.82	118.33	118.21
	(27)	(26)	(26)	(27)	(26)	(26)
Log likelihood	-644.32	-332.58	-292.77	-880.64	-445.85	-420.76

Notes: Robust s.e's in brackets. Other regressors include wave and region dummies. Bold figures indicate statistical significance at the 5% level.

4.3 Extensions

The specifications presented in the previous subsection assumed that only current (net household) income matters. In fact, there is considerable evidence in the literature that suggests that permanent income matters most. Thus, in this section we construct a specification that allows us to identify the effect of transitory income (when the child is 16) from the effect of permanent income as perceived earlier in the child's life. Thus, we assume that the relevant income for determining outcomes for children is the log of the weighted sum of both parents incomes - $\log\left(y^m + \beta y^f\right)$ so that β>1 implies that more long run weight is attached to maternal income. If y^f / y^m is small then we can approximate this log weighted sum by $\log y^m + \beta\left(y^f / y^m\right)$. Thus we estimate a log paternal income equation and we estimate a log of the ratio of paternal to maternal incomes and include the prediction of the former, evaluated when the child was 16, and the exponential of the prediction of the latter, again evaluated when the child was 16, into our specification. To capture the effects of shocks to household income we compute the difference between log household income, when the child is 16, and subtract the predicted paternal income (if he is still in the household) by exponentiating his permanent income equation, and the predicted maternal income, by including his permanent income prediction into the log ratio of incomes equation and solving.

4.4 Matching

A possible concern with the analysis above is that separated and intact households are quite different in their observable characteristics so that linear unweighted regression methods suffers from a lack of common support.

Thus, in Table 8, we present propensity score matching estimates of the impact of parental separation. Here the treatment group (non-intact families) and the control group (intact families) are matched on the mothers' and fathers' ages (in columns 1 and 3) and (in columns 2 and 4) to the ages and estimated residual (evaluated in wave 2) from a regression of GHQ12 (a reliable measure of mental well-being) on mother's age, mother's job satisfaction, financial surprises, and contemporary measures of youth's gender and age, whether only child, number of dependent children in the household, whether house owner, and mother's education and ethnicity[17]. We have excluded any non-intact families who separated before wave 1 (which means all families in the matching analysis were intact at the beginning of the sample period).

The school leaving results show no significant effects on the treated suggesting that the unmatched results were heavily contaminated by selection on observables. In the last panel we show the treatment effects on GCSE passes. These are always similarly statistically insignificant for the treated while there is typically a stronger, albeit still insignificant, negative effect on the untreated[18] suggesting that separation would be damaging for those that we would not expect to separate. This provides strong support for the results in Piketty (2003) and Bjorklund and Sunndstrom (2002).

Table 8 Propensity Score Matching estimates of impact of parental separation

	BOYS		GIRLS	
	Mother and Fathers age at Wave 1	Mother and Fathers age at Wave 1 and GHQ12 residual at Wave 2	Mother and Fathers age at Wave 1	Mother and Fathers age at Wave 1 and GHQ12 residual at Wave 2
School leaving at 16				
Unmatched	0.046 (0.067)		0.100 (0.066)	
ATT	0.011 (0.069)	-0.023 (0.084)	0.077 (0.097)	0.070 (0.096)
ATU	-0.009 (0.068)	0.063 (0.093)	0.169 (0.107)	0.214 (0.127)
5+ GCSEs				
Unmatched	-0.071 (0.080)		-0.006 (0.088)	
ATT	-0.023 (0.096)	-0.018 (0.107)	-0.006 (0.097)	0.004 (0.103)
ATU	-0.016 (0.100)	-0.043 (0.110)	-0.071 (0.100)	-0.131 (0.132)
N	552	552	560	560

Notes: Standard error in parentheses bootstrapped with 200 repetitions. The treatment group (non-intact families) and the control group (intact families) are matched on mother and father's age at Wave1, plus mother and father's GHQ12 residual at Wave2, as well as contemporary measures of youth's gender and whether only child, number of children in the household, whether owns house, and mother's age, and education. Bold figures indicate statistical significance at the 5% level.

[17] We match on the residual to insulate ourselves from the potential effect of the long run level of GHQ on the outcomes for the children.

[18] Note that there is high correlation between early school leaving intentions and actual GCSE passes (the correlation coefficient in a bivariate probit model is estimated to be around -0.6). For those who intended to leave at 16, just over 10% managed to achieve the 5 good pass grades in their GCSE's taken at age 15 or 16, comparing to nearly 60% for those who intended to stay on.

4.3 Instrumental Variable Estimates

Many authors have emphasised the importance of marital status endogeneity[19]. Here, we use the sample of youths whose parents stayed together at wave 1 and, since we want to use instruments which are only observed in wave 13 (in particular, birth order index) we require that BOTH parents be observed at wave 13. The sample size is approximately halved. We consider the following variables to be potentially endogenous: log income, and non-intact[20]. We use a variety of specifications. We begin by endogenising income assuming that separation is exogenous. We then endogenise income but assume that income is exogenous. Finally we endogenise both variables. Our core instruments are: mother's and father's birth order index, number of siblings, dummy for only child, age at wave 1, and age of grandparents to exploit the discontinuity in grandparental education arising from the raising of the school leaving age reform that took place in 1947. In addition we include an interaction between parents birth orders and their grandparents ages when the parents were born, which is observed for all adults in wave 13. We do this on the grounds that there is considerable evidence that early motherhood is associated with separation and this may transmit to the grandchildren who are themselves more likely to separate[21].

Overall, there is some support in Table 9 for the idea that the earlier results are generated largely by selection by unobservables. In all cases our specification easily passes the overidentification tests yet none of the estimated intactness coefficients are significant. For boys, income seems to matter for leaving and for 5+ GCSEs. For girls, income seems not to matter for leaving and there is a large estimated effect on achievement but this is only significant at the 10% level.

[19] See Lundberg (2005).

[20] Here we have excluded the 115 mothers who have repartnered because of their small sample size. Our attempts to endogenise mother's education suggested that this made no difference to our estimates and we report only estimates where this is assumed to be exogenous.

[21] We also use an extended specification which includes additionally nineteen wave 1 characteristics: cohabiting, number of former marriages, age relationship started, log duration of relationship spell, same race, same religion, partner non-religious, youngest child under 5, number of dependent children, parents with different education levels, 5 dummies for age differences between parents, mother in employment, mother unemployed, father in employment, father unemployed. These results are very similar and are available on request.

Table 9 IV Estimated Second Stages

Endogenous variables	BOYS (N=324) Only income	Only intact	Both income and intact	GIRLS (N=321) Only income	Only intact	Both income and intact
Leaving School at 16						
Log income	**-0.371**	**-0.130**	**-0.325**	-0.166	-0.051	-0.174
	(0.149)	(0.065)	(0.154)	(0.157)	(0.040)	(0.161)
Non-intact	-0.151	0.331	0.228	0.070	0.178	0.180
	(0.129)	(0.394)	(0.416)	(0.131)	(0.269)	(0.290)
Maternal education	-0.004	**-0.020**	-0.007	-0.008	**-0.011**	-0.008
	(0.011)	(0.008)	(0.012)	(0.006)	(0.005)	(0.006)
R-squared	0.3602	0.3689	0.3414	0.1901	0.2141	0.1809
Hansen J stat	17.540	16.352	13.563	8.503	9.050	8.372
Chi-sq (df)	(13)	(13)	(12)	(13)	(13)	(12)
P-value	0.1758	0.2306	0.3295	0.8093	0.7692	0.7554
5+ GCSEs						
Log income	**0.616**	**0.163**	**0.552**	0.460	**0.204**	0.439
	(0.228)	(0.076)	(0.230)	(0.236)	(0.079)	(0.233)
Non-intact	0.227	-0.498	-0.293	0.162	0.427	0.424
	(0.183)	(0.486)	(0.537)	(0.203)	(0.438)	(0.502)
Maternal education	-0.010	0.019	-0.006	0.012	0.018	0.012
	(0.017)	(0.011)	(0.017)	(0.010)	(0.008)	(0.010)
R-squared	0.6123	0.6510	0.6077	0.7014	0.7186	0.7005
Hansen J stat	5.508	9.877	4.503	8.017	9.956	8.332
Chi-sq (df)	(13)	(13)	(12)	(13)	(13)	(12)
P-value	0.9623	0.7039	0.9726	0.8425	0.6976	0.7587

Note: Robust s.e's in brackets. First stage results reported in the Appendix. The IV sample includes both repartnered and lone mothers. Excluding repartnered mothers will give estimates of very similar magnitude and level of statistical significance (indeed log income will become significant at the 5% level in the girls GCSE equations). However, this will reduce the number of non-intact families by a third. Bold figures indicate statistical significance at the 5% level.

5. Conclusions

A preliminary inspection of the raw data would suggest that parental separation has strong effects on children's education levels and achievements. Our least squares results suggest that parental separation has strong effects on children's education but this result seems not to be robust to adding additional control variables – in particular these results are not robust to including income. The sibling difference data suggests that only the effect of separation on academic achievement is likely to be causal – but this does not control for income differences associated with separation. Moreover, the result carries over to our matching modelling suggesting that there are important unobservables associated with separation for the separated that account for the apparent correlation.

Overall, our IV estimates suggest that there is some support for the idea that the simple results are generated largely by selection by unobservables. None of the estimated intactness coefficients are significant. For boys, income seems to matter for school leaving and for achieving 5+ GCSEs. For girls, income seems not to matter for school leaving and matters only marginally significantly so for achievement. In both cases it is hard to find evidence that the presence of fathers matters.

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Appendix

Table A2 First Stage IV Results

Endogenous variables	BOYS (N=324) Only income	Only Non-ntact	Both income and non-intact		GIRLS (N=321) Only income	Only intact	Both income and non-intact	
Log income	-	**-0.132**	-	-	-	**-0.114**	-	-
		(0.034)				(0.031)		
Non-intact	**-0.573**	-	-	-	**-0.637**	-	-	-
	(0.113)				(0.158)			
Mother's education	**0.057**	**0.009**	**0.055**	0.002	**0.027**	**0.008**	**0.024**	0.005
	(0.009)	(0.005)	(0.010)	(0.004)	(0.010)	(0.004)	(0.010)	(0.004)
Father's birth index	-0.011	-0.031	0.008	-0.032	-0.008	-0.029	0.011	-0.031
	(0.075)	(0.032)	(0.078)	(0.034)	(0.072)	(0.035)	(0.073)	(0.036)
Father's no. of sibs	**-0.041**	-0.006	**-0.040**	-0.001	-0.010	0.003	-0.013	0.005
	(0.017)	(0.007)	(0.018)	(0.007)	(0.018)	(0.006)	(0.018)	(0.006)
Father only child	-0.128	0.047	-0.168	0.070	-0.147	0.038	-0.185	0.059
	(0.094)	(0.044)	(0.103)	(0.050)	(0.089)	(0.038)	(0.094)	(0.040)
Father's age at W1	-0.012	-0.001	-0.013	0.001	**-0.008**	-0.007	-0.004	**-0.006**
	(0.013)	(0.006)	(0.014)	(0.006)	(0.005)	(0.002)	(0.006)	(0.003)
Mother's birth index	-0.381	0.185	-0.527	0.254	-0.186	0.148	-0.302	0.182
	(0.345)	(0.217)	(0.359)	(0.227)	(0.357)	(0.184)	(0.402)	(0.203)
Mother's no. of sibs	-0.030	0.020	**-0.045**	**0.026**	0.013	**0.016**	-0.003	**0.016**
	(0.018)	(0.011)	(0.019)	(0.011)	(0.015)	(0.007)	(0.021)	(0.008)
Mother only child	-0.216	-0.027	-0.217	0.001	-0.106	-0.033	-0.091	-0.022
	(0.134)	(0.037)	(0.137)	(0.035)	(0.136)	(0.030)	(0.139)	(0.029)
Mother's age at W1	**0.206**	0.016	**0.213**	-0.012	0.042	-0.037	0.071	-0.045
	(0.105)	(0.055)	(0.100)	(0.054)	(0.132)	(0.050)	(0.128)	(0.048)
Grandfather RoSLA	0.034	0.143	-0.052	0.150	0.045	0.025	0.031	0.022
	(0.134)	(0.094)	(0.149)	(0.101)	(0.146)	(0.066)	(0.152)	(0.069)
Grandmother RoSLA	-0.046	-0.096	-0.009	-0.097	**-0.297**	-0.051	**-0.285**	-0.019
	(0.136)	(0.080)	(0.144)	(0.085)	(0.127)	(0.063)	(0.126)	(0.062)
Grandfather age when	0.003	0.013	-0.004	0.013	0.011	**0.019**	-0.001	**0.019**
mum born	(0.020)	(0.008)	(0.021)	(0.009)	(0.017)	(0.009)	(0.018)	(0.009)
Grandmother age	-0.005	-0.012	0.002	-0.013	-0.022	-0.016	-0.013	-0.015
when mum born	(0.022)	(0.011)	(0.024)	(0.012)	(0.023)	(0.009)	(0.024)	(0.009)
Grandfather age *	0.006	-0.011	0.013	-0.012	-0.000	-0.013	0.008	-0.014
mum's birth index	(0.018)	(0.007)	(0.018)	(0.008)	(0.015)	(0.008)	(0.016)	(0.008)
Grandmother age *	0.005	0.005	0.002	0.005	0.005	0.010	-0.001	0.010
mum's birth index	(0.020)	(0.009)	(0.020)	(0.010)	(0.020)	(0.009)	(0.022)	(0.009)
Shea's Partial R^2	0.0756	0.0585	0.0699	0.0560	0.0513	0.0787	0.0504	0.0787

Note: Shea Partial R^2 for the instrumented variables reported in the last row. Bold figures indicate statistical significance at the 5% level.