ISER Working Paper Series

Youth employment and academic performance: Production functions and policy effects

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No. 2015-06
March 2015

INSTITUTE FOR SOCIAL & ECONOMIC RESEARCH

E·S·R·C ECONOMIC & SOCIAL RESEARCH COUNCIL

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Non-Technical Summary

Around 25% of 13-16 year-olds below the school leaving age in England take some formal paid employment during school term time. Having a job while still in full-time compulsory education may improve teenagers' and young adults' welfare by enabling them to consume more, and by giving them more bargaining power over what they consume and how they spend their time. It may also improve their future educational or labour market outcomes by improving their financial literacy or communication skills, or possibly by forcing them to think about the type of job they want in the longer term, and what they need to do to get there.

However, at the same time, having a job reduces the time available for other activities, so is likely to crowd out the amount of time spent studying, or if the student is more tired, its quality. As the student has an income, it may also enable take-up of risky behaviours (e.g. alcohol, smoking and cannabis consumption). As such, whatever the direct human capital benefits of having a job while in school, the overall effect is likely to be to reduce academic performance. This matters in the longer term because the qualifications people leave school with substantially determine their subsequent education and adult labour market opportunities.

In this paper we show that longer hours of employment at ages 14 and 15 increases take-up of risky behaviours, and reduces both the amount of study undertaken at home and outside of lessons, and students' reports that their schoolwork is important. (Having a low-skilled part-time job does not raise students' motivation for schoolwork as a means to widening their future occupational options, rather reduces motivation either through general tiredness or shifting preferences towards the activities their employment and earnings open up). This occurs to a much greater extent among girls than boys. The only time use where boys' employment resulted in greater crowd-out was sporting participation, which we show is less important for academic performance.

Overall, we find no effect of in-school employment at age 14 or 15 on GCSE performance (age-16 exams, at the end of compulsory education) for boys, but a significant negative effect of employment at age 15 for girls. For this group, an additional hour of paid employment per week reduces GCSE performance by approximately 1 grade in one subject (4.3% of a standard deviation in the total point score). About 25% of this effect can be accounted for by the study time crowded out. Those in work at age 15 on average work 6 hours per week, meaning that having a job is likely to reduce their subsequent educational and labour market opportunities substantially. This effect will be particularly severe for students near the cut-off for progression into post-compulsory education (5 A*-C grades including English and Maths).

Youth employment and academic performance: Production functions and policy effects*

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March 11, 2015

Abstract

This paper proposes an approach to identifying the education production function with endogenous inputs, and applies it in the context of part-time employment decisions by UK teenagers in compulsory education. We identify simultaneously the effect of part-time employment and latent endogenous inputs including study effort, at different points in time, and compare the reduced-form effect of having a job while at school with the production function parameter. Part-time employment is shown to reduce academic performance among girls but not boys. We present evidence that this is due to employment crowding out a wider range of productive activities among girls than boys.

Keywords: Labour supply; human capital; education production function; child development

JEL classifications: C35, I21, J22, J24

*This work was carried out during PhD studies supported by an Economic and Social Research Council '1+3' studentship in Economics [reference number ES/I025499/1], with supervision and advice from Emilia Del Bono and Stephen Pudney, and postdoctoral research supported by the Economic and Social Research Council Research Centre on Micro-Social Change. Thanks to Pedro Carneiro and Thomas Crossley for their advice as my PhD examiners, to seminar participants at the ZEW Summer Workshop in microeconometrics and programme evaluation, Mannheim, July 2014. All errors are my own. This work is based on data from the Longitudinal Study of Young People in England (Secure Data Service Access), produced by the Department for Education and National Centre for Social Research, and supplied through the Secure Data Service at the UK Data Archive. This work also uses local labour market statistics produced by the Office for National Statistics.

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1 Introduction

Having a job while still in education may improve teenagers' and young adults' welfare by affording them additional consumption. It potentially improves their stock of cognitive and non-cognitive human capital, in the form of financial literacy, communication skills, and lower discount rates (Oettinger, 1999; Light, 2001), but may detract from human capital by crowding out time devoted to productive 'investment' activities (Ruhm, 1997). In-school employment is therefore expected to reduce academic performance. The qualifications obtained from formal education substantially determine subsequent education and adult labour market opportunities, so in-school employment may restrict the young adult's trajectory of human capital accumulation over a much longer period (Dustmann and van Soest, 2007). This matters to many individuals. Around 25% of 13-16 year-olds below the school leaving age in England take some formal paid employment during school term time. In the US, the figure is approximately 60% of 14-15 year-olds (Buscha et al., 2008; Bureau of Labor Statistics, 2000), with 92% of the National Longitudinal Study of Youth (NLSY) 1997 cohort having worked at some point during High School (Hotz et al., 2002).

In this paper we evaluate the effect of in-school employment on educational outcomes at the end of compulsory schooling. We use data from the Longitudinal Study of Young People in England (LSYPE), which followed a cohort of teenagers aged 13-14 in 2004 through to their entry into the labour market and Further or Higher Education. We make three significant contributions. Firstly, the longitudinal structure enables us to identify how the effect of in-school employment varies by age, or equivalently, time-to-exams. We show that in-school employment is only costly to academic performance among girls, and when taken in the year prior to final examinations. We find no evidence that employment at earlier stages is detrimental to academic performance, except by acting as a gateway to later employment. Secondly, using OLS estimation, we obtain a robust ranking for the absolute productivity of a range of investment activities across a series of assumptions. Once this range of activities (plus a factor representing the child's attitude towards school) is controlled for, we find no significant effect of labour supply on school performance. Thirdly, we implement a model exploiting the causal pathway from in-school labour supply, via the student's time constraint and budget constraint, to other positive or negative 'investment' activities; study time, active leisure, social life and risky behaviours; as a means to identify both the direct effect of in-school labour supply, and the parameter on these endogenous inputs in the education production function. In the majority of cases, we find the effect of in-school labour supply on these activities, at at least one point in time, to be either small or imprecisely estimated, meaning that estimates of the production function parameter are only weakly identified. Nevertheless, the largest effects on the three most productive or damaging activities at age 15 (according to our OLS rankings) are found for girls. This suggests that distinct time-use and behavioural effects of in-school employment provide a mechanism for the gender differential in its net effect.

Our results are presented in two parts. First we evaluate the reduced-form effect of employment at age 14 and age 15 on grades at age 16. In these specifications, the child's other activities are not held constant. Here we obtain the "policy effect": the overall impact of an exogenous change in a specific input to the production function - in-school employment - on measured performance. This includes the effects of unobserved changes in study time, active leisure, social life and risky behaviours which may also arise from this increase in labour supply. Several strategies have been used to identify the net effect of part-time employment on academic outcomes, including OLS regression in a contemporaneous (Lillydahl, 1990; Montmarquette et al., 2007) or cumulative specification (Ruhm, 1997; Payne, 2004), individual fixed effects or differences-in-differences (Oettinger, 1999; Sabia, 2009; Buscha et al., 2008), and instrumental variables (Stinbrickner and Stinebrickner, 2003; Häkkinen, 2006). Our approach is most similar to that of Tyler (2003), Rothstein (2007) and Kalenkoski and Pabilonia (2010) who use state or county unemployment rates, local wage rates and state laws on teen employment as instruments for employment among US high school or college students in a cross-sectional framework. Tyler (2003) and Kalenkoski and Pabilonia (2010) both show large negative effects of in-school employment on college performance. In Rothstein (2007) the effect appears to be negligible. We too use indicators of local labour market opportunities, but also month of birth as a determinant of whether restrictions on teenage employment will bind on the teenager at the time when vacancies arise. We model selection into employment at age 14 and age 15, and hours of employment in each time period enter the second stage equation (for academic performance at age 16) as separate regressors. The preceding literature is either silent on gender differences in outcomes resulting from in-school employment (focusing on males only or using a pooled sample), or finds only small differences. Our instrumental variables regressions show no effect of employment at age 14 for either boys or girls, holding age 15 employment constant. However, while no effect of age 15 employment is found for boys, an additional hour of employment per week at age 15 is shown to reduce age 16 educational performance by around 4.3% of a standard deviation for girls.

Since the policy effect includes the indirect effects of changes to other inputs made by optimising individuals, it will likely differ from the "production function parameter", or direct human capital cost or benefit of in-school employment. For example, De Fraja et al. (2010) and Datar and Mason (2008) show that students and parents respectively treat school inputs as substitutes for their own, in which case policy effects of increased school quality are expected to understate such interventions' effects in the education production function. (Browning and Heinesen, 2014, discuss the conditions under which this will apply in greater detail).

In the second part of our analysis we evaluate the production function parameter for in-school employment under a series of assumptions and holding constant latent variable representations of up to four additional activities; study, active leisure, social life, and risky behaviours. We focus on adolescent self-investments and abstract from the role of parental investments. We argue that the latter bestow little marginal benefit to the development of human capital by the child's mid-teens (Del Boca et al., 2012), but we proxy for the differences in initial conditions that parental investments create by controlling for a rich set of parental and household characteristics.

We first present a series of OLS specifications. We start from a cumulative model, dependent on inputs at age 14 and age 15 and on family background controls, then estimate augmented versions controlling successively for prior educational performance, school fixed-effects, and a latent representation of the child's attitude towards schoolwork. Following the approach of Fiorini and Keane (2014) (who used exhaustive time use data and focus on the cognitive ability of 4-7 year-olds) we obtain a ranking of the productivity of these activities that is preserved across these specifications. We also show that the relative productivity of later (age 15) investments increases as progressively more attempts are made to control for unobserved heterogeneity. The parameter on in-school employment is found always to be close to zero.

Next, we estimate a system of simultaneous equations in which, at each point in time, hours of employment are again determined by exogenous variation in our instrumental variables representing labour market opportunities, but one additional latent input is either crowded out or facilitated by exogenous variation in labour supply. Both labour supply and the latent input at both points in time (age 14 and age 15) then enter the production function of the educational outcome measured at age 16. We thus observe the 'direct effect' of labour supply, and that which is mediated via the additional input.

Identification of the production function parameter on each endogenous input rests on cohort members' behaviour being causally and significantly dependent on their labour supply. We do not impose this in the econometric specification, but test this statement and interpret subsequent parameters appropriately. The lack of crowd-out of study at home and outside of lessons among boys means we learn little about the productivity of this key investment among males, though this provides an intuitive explanation for the small net effect of labour supply for this group. For girls, we show that labour supply at age 15 results in significant crowd-out of contemporaneous study time at home and outside of lessons, and as with boys, crowd-out of positive attitudes to schoolwork during lessons. This means we can identify the production function parameter on each of these inputs. We find a significant positive and quantitatively large effect of age 15 attitude for boys (those who care about their schoolwork more, do better) and a smaller, insignificant effect for girls, for whom an increase in the amount of study done outside school lessons (at the margin driven by changes in labour supply) appears relatively more important.

2 Data and institutional background

2.1 LSYPE data

We use data from the first three waves of the Longitudinal Study of Young People in England (LSYPE). This sample is drawn from a single academic cohort of teenagers in England, interviewed annually from 2004, at age 13-14, through to the end of compulsory schooling and their entry into the labour market or Further or Higher Education. The data enable us to control for a rich set of individual and household variables and the child's prior educational performance.

Term time employment is captured by the questions "Do you ever do any work in a spare-time paid job, even if it is only for an hour or two now and then? (Please don't include jobs you only do during the school holidays or voluntary work)", and for those answering 'yes', "How many hours on average do you usually work in this job (or jobs) during a term time week? Please include any hours you work at the weekend during term-time". We do not observe the type of employment undertaken, but as this question explicitly relates to school term time, the crowding out of study time or other extra-curricular activities is always a salient concern. The measures of our 'investment' factors are defined in Table 4 (page 18).

2.2 Employment of children in England

The rules governing the employment of children in England are set by the Department for Education (see guidelines in DCSF, 2009). Children aged at least 13 but less than the school leaving age may undertake 'light' work, deemed as not being harmful to their health, safety or development.[1] There are age-specific restrictions on the types and hours of work children may do. Those under 16 cannot work 'mainly or solely' for the sale of alcohol, for example. Those in compulsory education may work only 12 hours per week in term time, including a maximum of 2 hours on a weekday or Sunday; 8 hours on a Saturday (5 hours if under 15 years); one hour before school on a weekday; and none during school hours or after 7pm on a school night.

2.3 The exam system in England

Our measure of academic performance at age 16, the end of compulsory schooling, is the 'GCSE and equivalent total point score', standardized by subtracting the population mean and dividing by the population standard deviation. The majority of students obtain GCSE (General Certificate of Secondary Education) qualifications in around 10 subjects, of which at least English, Maths and Science (covering topics in all of Chemistry, Physics and Biology) were compulsory. Students are graded from A*-G, plus U ("unclassified"), and usually require five GCSEs at grade A*-C, including English and Maths to continue into Further Education. Around 60% achieve this threshold. GCSEs and equivalent grades obtained from General National Vocational Qualifications (GNVQs) in non-academic subjects contribute to a student's overall point score.[2] To account for each student's trajectory of academic outcomes over time, we also control for performance in 'National Tests' in English, Maths and Science at age 11 and age 14. Here, students are awarded a 'level' which is converted into a point score. We use students' average point score standardized by the mean and standard deviation. These qualifications and examinations are criterion-based, measuring students' performance against a fixed standard rather than relative to their peers. There is no rationing of the top grades.

All GCSE subjects were assessed with 'final exams' sat at age 16. Most GCSEs also had some form of continuous assessment in the form of 'modular exams' sat periodically over the preceding two years, or 'coursework' written outside school time and marked by the student's teacher.

[1] Full-time education is compulsory until the last Friday in June of the academic year when the child turns 16.

[2] The point score system is explained here: `http://www.education.gov.uk/schools/performance/secondary_11/PointsScoreAllocation2011.pdf`, p.3

Coursework contributed up to 40% of the total mark. GNVQs were based predominantly or exclusively on coursework. Continuous assessment is perceived to benefit girls relative to boys (Gipps and Murphy, 1994). The widening of the gender gap in GCSE performance after 1988, when English schools switched to this system from the entirely exam based O-Level qualifications, has been partly attributed to this change (Machin and McNally, 2005; Stobart et al., 1992). One might also expect the effect of in-school employment to be worse under continuous assessment than final exams. In the latter case, high ability students may mitigate their loss of learning over the preceding two years with a single intense period of revision (Schmidt, 1983). Strong performance under continuous assessment entails consistent input over an extended period, which may be difficult to reconcile with a job. As such, our results may differ significantly from those obtained for O-level qualifications by Dustmann and van Soest (2007). They found a small adverse effect on the exam performance of girls and none for boys. The current change in GCSE structure to final exam assessment and very limited coursework, occuring in stages from September 2013 to June 2017, may enable students to gain human capital and experience while mitigating the detrimental effect on measured academic performance.[3]

2.4 Descriptive statistics

Table 1 shows descriptive statistics relating to family background, employment and earnings at ages 14 and 15. Those in employment are positively selected on age 14 prior educational performance, and go on to perform better at the end of compulsory schooling. Those in employment also on average come from higher income households and are less likely to have a lone parent. These differences are statistically significant at the 1% level for both boys and girls at every point in time. While girls are positively selected on parental education, boys are marginally negatively selected. Overall however the table suggests that positive selection driven by social networks or 'soft skills' outweighs any negative selection driven by household financial constraints.

The propensity to work rises more markedly among girls, who start from a lower base. Conditional on working, girls work longer hours than boys, but receive lower earnings and hourly wages. Since girls have superior prior educational performance and are more positively selected

[3]See `http://www.bbc.co.uk/news/education-23756128` (accessed 4-3-2014) for a summary of changes to the exam system in England.

Table 1: Descriptive statistics by gender.

	Wave 1 (age 14)		Wave 2 (age 15)	
	Boys	Girls	Boys	Girls
Employed (%)	24.9%	18.9%	28.3%	27.1%
Mean age 16 exam score[1]	281.13 (3.04)	308.25 (2.67)	283.62 (3.11)	309.51 (2.82)
Observations	7116	7250	6258	6303

By employment status	Wave 1 (age 14)				Wave 2 (age 15)			
	Boys		Girls		Boys		Girls	
Employed:	Yes	No	Yes	No	Yes	No	Yes	No
Mean hours employment[2]	4.14 (0.10)	.	4.24 (0.11)	.	5.16 (0.13)	.	5.38 (0.10)	.
Mean earnings[2]	£14.52 (0.41)	.	£14.24 (0.39)	.	£20.58 (0.52)	.	£18.90 (0.33)	.
Family background: 'Permanent' income percentile	0.584 (0.007)	0.534 (0.005)	0.589 (0.009)	0.537 (0.004)	0.584 (0.007)	0.519 (0.005)	0.595 (0.007)	0.518 (0.005)
Higher Educated parent	17.0%	17.6%	18.7%	16.6%	16.1%	17.3%	19.0%	15.7%
Lone Parent	18.1%	23.7%	20.6%	23.2%	17.0%	24.0%	18.3%	24.4%
Educational performance: Standardized age 14 exam score[3]	0.097*** (0.032)	-0.101 (0.034)	0.293*** (0.034)	0.019 (0.030)	0.096*** (0.033)	-0.090 (0.036)	0.302*** (0.031)	-0.009 (0.018)
Mean age 16 exam score[1]	365.37*** (4.17)	342.04 (2.61)	409.87*** (4.34)	379.75 (2.41)	366.42*** (4.26)	342.89 (2.89)	414.65*** (3.73)	376.89 (2.83)

Notes: Standard errors in parentheses. Population means and proportions calculated using final probability weights. Standard errors clustered by school. [1]: GCSE total point score. [2]: Hours of employment and earnings are per week. [3]: Key Stage 3 Average Point Score, standardized by subtracting mean and dividing by standard deviation. ***: p-value for difference in mean educational performance between those in and out of employment <0.01.

Table 2: Employment transition probabilities and sequences

Transition probabilities

Boys	W2 No	W2 Yes	**Girls**	W2 No	W2 Yes
W1			W1		
No	0.854	0.146	No	0.845	0.155
Yes	0.370	0.630	Yes	0.384	0.616

Employment sequences (percent)

Sequence:	00	10	01	11
Boys	62.1	9.0	12.6	16.2
Girls	65.1	7.3	15.1	12.3

Notes: Transition probabilities are probability of being in employment in future wave, conditional on status in current wave, using unweighted data. W1 = Wave 1, W2 = Wave 2. First digit in **sequences** refers to employment at age 14, second to age 15. e.g. 00 = Never worked. 11 = Always worked. Longitudinal probability weights are applied.

into employment by the measures discussed above, this is unlikely to be driven by differential selection. Instead, these observations are consistent with boys and girls being active in distinct labour markets with different demand-side factors and human capital implications (Kooreman, 2009; Erdogan et al., 2012).[4] For this reason we estimate our models separately by sex.

[4]See Howieson et al. (2006) for a survey of employment types among schoolchildren in Scotland, where the

The left-hand side of Table 2 shows transition probabilities, or the proportion of sample members in employment at age 15 conditional on their initial age 14 employment status. The figures suggest some persistence in employment. Around 62% of those in employment in one year are still in employment the following year, which is more than double the population employment rate. Around 15% of the larger group of those *not* in employment in one year have entered employment by the following year, or half of the population employment rate. The right-hand side of Table 2 shows the proportion of sample members undertaking each sequence of employment decisions over the two years. 36% of students have a job at some point, and 22% undergo a transition between these two years. Thus, we have the data to identify distinct effects of employment at different points in the educational process.

3 Theoretical and empirical models

We motivate our empirical specification by presenting a theoretical model of selection into employment and the effect of employment on academic performance. This model shows firstly that it is necessary to allow for distinct effects of employment at different points in the education process; secondly that employment will crowd out time devoted to study, which has a human capital payoff; and hence thirdly that the net causal effect (policy effect) of employment will capture both the direct human capital effect and the opportunity cost in terms of reduced investment in other activities, and so is likely to differ from the 'production function parameter'.

We assume an individual who aims to maximise his expected utility within each time period $t = 1...T$. Here $t = 1$ is the first time period in which the child is able to take in-school employment. Utility is a function of independent consumption ($w_t L_t$, where w_t is his hourly wage and L_t his hours of employment) and leisure ($(1 - L_t - S_t)$, where S_t is time devoted to study) in the current period; and expected educational performance in period T, at the end of compulsory education ($E[Y_T]$, where Y_T is a stochastic function of the individual's human capital). A vector of socio-economic characteristics which we assume to be time-invariant ($\mathbf{X}$) are expected to affect individuals' relative preferences over these elements.

We assume that the utility function is separable into the present ($f_t(.)$) and future ($g(.)$) oriented

legal situation and institutional background is very similar to England.

components, such that the individual's maximisation problem can be written, for $t = 1...T$:

$$\max_{L_t, S_t} U_t = f_t(\mathbf{L}, \mathbf{S}, \mathbf{X}) + E[g(Y_T(\mathbf{L}, \mathbf{S}, \mathbf{X}, \boldsymbol{\epsilon}, \upsilon_T))] \tag{1}$$

The vectors $\mathbf{L}$ and $\mathbf{S}$ include current and all lagged or time varying values of the variable. We assume that for each t, $f_t(.)$ is a concave function in current consumption and leisure, which are complements. The individual has a baseline human capital endowment μ_0, which is a reduced form function of individual and household characteristics: $\mu_0 = \mu_0(\mathbf{X})$. Human capital evolves each period as a function of further investments in study and labour supply, as well as household circumstances, according to the function $h_t(.)$ and a multiplicative error term $\epsilon_t \sim ln.\mathcal{N}(0, \sigma_t^{\epsilon})$ with a log-normal distribution such that $E[ln.\epsilon_t] = 0$:

$$\mu_t = \mu_{t-1}.h_t(L_t, S_t, \mathbf{X}).\epsilon_t \tag{2}$$

We assume there is a positive human capital effect to study at all times, so $\frac{\partial h_t}{\partial S_t} > 0$. We offer no prior about the marginal human capital product of labour supply ($\frac{\partial h_t}{\partial L_t}$). Final human capital at the end of compulsory education can then be written:

$$\mu_T = \mu_0(\mathbf{X}).\prod_{t=1}^{T}[h_t(L_t, S_t, \mathbf{X}).\epsilon_t] \tag{3}$$

Educational performance is the function $k(.)$ of final human capital and a multiplicative error term $\upsilon_T \sim ln.\mathcal{N}(0, \sigma^{\upsilon})$, with a log-normal distribution such that $E[ln.\upsilon_T] = 0$:

$$Y_T = k(\mu_T.\upsilon_T) \tag{4}$$

We assume that the overall effect of diminishing human capital returns to $\mathbf{L}$ and $\mathbf{S}$ and diminishing marginal utility of GCSE performance is to ensure the function-of-functions $g(Y(.))$ is concave in $\mathbf{L}$ and $\mathbf{S}$. With $g(Y(.))$ concave and the evolution of human capital over time uncertain, this model predicts that the individual will underinvest in study relative to the case where the human capital outcome is deterministic. This uncertainty becomes progressively smaller as t approaches T, as the outcomes of the random draws ϵ_t in earlier periods become known. See Appendix A.1.1 (page 39) for a graphical illustration of this prediction.

Assuming that $k(.) = ln(.)$ and $h_t(.) = e^{m(L_t, S_t, \mathbf{X})}$, with $m(.)$ and $\mu(\mathbf{X})$ as linear functions, the education production function for performance at the end of compulsory education can be written and estimated in the following form. This follows Cunha and Heckman's (2007, 2009) approach to the "technology" of human capital formation in making it explicit that the *timing* of both employment and study matter for academic performance, not just their total amounts. This is a "cumulative model":

$$Y_T = \sum_{t=1}^{T}[\pi_t^L L_t + \pi_t^S S_t + ln.\epsilon_t] + \boldsymbol{\beta}\mathbf{X} + ln.v_T \tag{5}$$

The error terms ϵ_t and v_T are log-normally distributed so the composite error term in equation (5) ($\sum_{t=1}^{T}[ln.\epsilon_t] + ln.v_T$) is normally distributed with mean zero.

There are three barriers to obtaining unbiased estimates of the production function parameters π_t^L and π_t^S. Firstly, study is not observed. To address this, we use a vector of latent variable representations of study and three other activities expected to affect academic performance, in place of each S_t in equation (5). Secondly, even assuming that the correct vector of inputs is observed perfectly, we would expect some unobservable characteristic entering $\sum_{t=1}^{T}[ln.\epsilon_t] + ln.v_T$, to positively determine selection into both employment and study. This means that $E[\sum_{t=1}^{T}[ln.\epsilon_t] + ln.v_T|\mathbf{L}, \mathbf{S}, \mathbf{X}] \neq 0$, and we will obtain positively biased estimates of π_t^L and π_t^S. In section 5 we estimate equation (5) using OLS with different assumptions under which this bias is eliminated. Thirdly, in practice there may be measurement error in teenagers' hours of work and other investment activities, which will attenuate the OLS coefficient on these variables (Tyler, 2003). In section 5 we address these problems by estimating an education production function using instrumental variables methods and repeated measures of endogenous inputs, and discuss the associated identification issues.

Policymakers will also be interested in the partial or policy effect of employment on academic performance, including its indirect effects via inputs crowded out or facilitated by employment. The policy effect is equal to ϕ_t^L in the reduced form specification shown in equation (6):

$$Y_T = \sum_{t=1}^{T}[\phi_t^L L_t] + \boldsymbol{\psi}\mathbf{X} + \zeta \tag{6}$$

In equation (6), ϕ_t^L may be biased by the omission of exogenous unobserved characteristics ('ability' or 'motivation'). We adopt an instrumental variables strategy to control for these. We thus obtain the overall effect of an exogenous change in employment caused by changes in labour market opportunities ($\mathbf{Z}$) which, conditional on other observed characteristics ($\mathbf{X}$), are orthogonal to educational performance. This instrumental variables specification is shown in equation (7):[5]

$$E[Y_t|\mathbf{Z},\mathbf{X}] = \sum_{t=1}^{T}[\phi_t^L E[L_t|\mathbf{Z},\mathbf{X}]] + \boldsymbol{\psi}\mathbf{X} \tag{7}$$

In equation (7), the policy effect ϕ_t^L is still distinct from the production function parameter π_t^L, due to the omission of the time varying endogenous input, study. Our model predicts a strictly negative tradeoff between employment and study. The proof of this prediction is shown in Appendix A.1.2 (page 41). Provided that the production function parameter on study, π_t^S is non-negative, the 'partial effect' of employment will always represent a lower bound of the production function parameter ($\phi_t^L \leq \pi_t^L$). This prediction continues to hold if the specification is relaxed to permit employment and study to have cross-effects in production, i.e. to become complements (in which case the crowd-out will be relatively small) or substitutes. In Browning and Heinesen (2014), the direction of the behavioural response to an exogenous change in one input depends on whether they are substitutes or complements as well as the cost of the activity to the individual. In our model, the inputs are mutually exclusive time inputs, and the crowd-out is driven by the individual's preference for the third time-use category, leisure.

3.1 Instrumental variables

We use Full Information Maximum Likelihood (FIML) to estimate the policy effects represented in equation (7) and the production function represented in equation (5) adapted to account for endogenous inputs. These entail first-stage tobit equations for hours of employment per week, and a final-stage linear regression for GCSE performance. Estimating the production function requires a measurement model for the latent factors and an intermediate-stage linear regression

[5] We expect there to be dynamic state dependence in teenage employment. This means that lagged employment will determine current employment: It is easier to keep a job than to obtain one. We present evidence to this effect in Appendix A.3 (page 46). To account for this, we attempted to model employment at each $t > 1$ as a function of all time-invariant and time-varying individual characteristics which determined employment in current and previous waves. Importantly, we observe cohort members in the first full school year in which they are permitted to take paid employment, so we observe the initial condition: there is no unobserved selection into employment from an earlier period (Hotz et al., 2002). However, although the local youth unemployment rate is time varying, at a one-year interval the rates are highly collinear, leading to large and opposite-signed coefficients on successive waves' unemployment rates in the employment hours equation. The use of three common instruments for two endogenous variables also results in the predicted hours of employment (the second stage regressors of interest) being very highly correlated. Instead, therefore, we use only the contemporaneous unemployment rate, alongside IMD and month of birth, for each wave's hours of employment. The second-stage results do not change in a statistically or quantitatively significant way as a result of this.

equation determining each factor as a function of labour supply. The system is identified through instrumental variable exclusion restrictions in the later stage equations. Specifically, we exclude (i) the child's month-of-birth within the academic cohort, (ii) the index of multiple deprivation (IMD) measured in 2004 and (iii) the age 18-24 claimant count unemployment rate in the month of interview. Month of birth is set equal to 1 for September births (the oldest in the academic cohort) and 12 for August births (the youngest in the academic cohort). IMD is standardized with mean zero and variance of one. The unemployment rate is a decimal.

Two conditions must be met for the use of instrumental variables to be valid. The *relevance* condition requires that conditional on other explanatory variables, the instruments have a sufficiently strong direct effect on the endogenous explanatory variable. The *exogeneity* condition requires that the instruments are conditionally mean independent from the second-stage dependent variable. In other words, the instruments must have no direct effect on the second-stage dependent variable, except through the endogenous explanatory variable.

3.1.1 Month of birth

Month of birth will directly affect teenagers' working hours because those born earlier in the academic year will be allowed to work longer hours or in specific job types earlier than their younger peers. This means they are better placed to fill suitable vacancies which arise in the autumn as older cohorts leave for university. In our empirical specification, we also include dummy variables for the month-of-interview and for interview in or after the month of the child's birthday in all equations. This means that spurious variation in employment generated by being interviewed later in the fieldwork schedule will not contribute to identifying the causal effect of employment on academic performance.

It is well established that those born earlier in the school year retain an advantage in educational outcomes (Crawford et al., 2013 and references therein). There are four potential mechanisms through which this effect could be causal: (i) Age-at-test: those born earlier in the school year are older when taking a test on a common date; (ii) Age of starting school: those born later in the school year are younger on a common school entry date, and so less ready to learn; (iii) length-of-schooling: if those born later in the school year also start school later in a common academic year, they will have received less schooling by the time of a test; and (iv) relative age: institutional practices such as sorting into 'sets' or 'tracks' by observed performance at a given time will compound these initial differences as those born earlier in the school year are more likely to reach the higher tracks.

Crawford et al's (2013) analysis suggests that age-at-test is the dominant mechanism. Using data on English schoolchildren one to three cohorts behind our LSYPE sample they find that the performance gap between the oldest and youngest pupils in each cohort becomes progressively smaller with age as the relative age gap between September and August birthdays shrinks.[6] These converging performance measures mean it is insufficient to control for prior performance at only one point in time. In this paper we shall control for the trajectory of academic performance through absolute performance at both ages 11 and 14, and assume that this leaves no residual direct effect of month of birth on academic performance.

3.1.2 Local microeconomic conditions

We use the 2004 Index of Multiple Deprivation (IMD) of the teenager's area of residence as a very localised proxy for area characteristics determining his or her employment opportunities. The IMD measures the prevalence of deprivation within Lower Super Output Areas (LSOAs), which contain 400-1200 households and have an average area of 1.45 square miles or 3.75 square km (Office of the Deputy Prime Minister, 2004). The index is calculated from a combination of aggregated individual or household-level indicators of deprivation and area characteristics in seven domains: income; employment; health; education, skills and training; barriers to housing and services; crime; and the living environment. All of these elements are expected to be correlated with youth labour market opportunities. Of greatest relevance in driving this relationship are (i) the overall unemployment rate, and (ii) the average road distance to a post office and supermarket or convenience store. The latter are suitable potential employers and may also be clustered close to other shops and businesses.

The local authority district (LAD) age 18-24 unemployment rate is a more direct measure of labour market opportunities over a wider geographic area. LADs have an average population of 164,000 and area of 155 square miles or 401 square km (about 1.6 times the population but one-eighth the average area of a US county). Kalenkoski and Pabilonia (2010) and Rothstein (2007)

[6] e.g. In June of school year 11, when most cohort members are 16, a cohort member born on 1st September has lived 6.3% longer than one born on 31st August, compared with 7.3% in school year 9 (age 14) and 9.3% in school year 6 (age 11). For the performance measure "meeting the expected standard" (an absolute measure), they show (Crawford et al., 2013, figures 3.1-3.2, pp.20-21) 26, 13, 7.8, and 6.4 percentage point gaps between August and September birthdays at ages 7, 11, 14 and 16 respectively.

used either the state or county adult unemployment rate. By using two levels of geography we accommodate an expected decline in the relative importance of the very localized opportunities as teenagers get older, while the age restriction in our unemployment measure should increase precision since we expect there to be differentiation between youth and adult labour market opportunities.[7]

We condition on individual household circumstances, specifically including parental income, employment, health, education and qualification levels. These are the household-level counterparts to the aggregated measures used to calculate the local unemployment rate and the IMD. Conditional on these, and the child's prior educational performance, we assume the area-level labour market conditions have no residual direct effect on the student's educational performance, except via the teenager's hours of labour supply. We also assume that while the effect of labour supply on educational performance or other activities may be heterogeneous, these instruments are uncorrelated with the 'quality' of employment, and that in estimation we identify the *average* treatment effect or production function parameter.

3.2 Additional controls

We control for prior educational performance at age 11 and 14, household income, home ownership, receipt of disability benefits, parents' employment status, education and socio-economic class, household structure and non-resident siblings, child's ethnicity, special educational needs (SEN) classification, urban-rural classification, and living in Greater London. Consistent with equation (7), we treat all covariates as time invariant. Several are in fact time-varying (specifically parents' employment status, ill-health, education, and socio-economic classification; housing tenure; lone-parent family indicator; and resident and non-resident siblings), but any changes affect very few households, meaning they are almost perfectly collinear between waves. We use the wave 1 observation of each covariate, to best account for initial conditions and avoid endogeneity issues. Parental income is elicited using different questions in each wave of the LSYPE,

[7] We explored several other indicators of labour market opportunities. The job density (number of jobs per 100 people in the labour force), and sex-specific or overall unemployment rates for either the youth (aged 18-24) or the adult (age 16-64) age-group are available at the Local Authority District level (LAD). All of these are strongly collinear with the total youth unemployment rate and so contribute little identifying variation when used in addition. The 'adult' measures are felt to be less representative of the opportunities for schoolchildren, while the sex-specific rate for females is particularly sensitive to changes in labour force participation. We also constructed a noisy indicator of the proportion of 16-29 year-olds in each LSOA who are unemployed. However, the measurement error in this indicator (caused by the claimant count for each age-group - 16-17, 18-24 and 25-29 - being rounded to the nearest 5) and resulting attenuation bias contributed to weak identification.

so we construct a measure of the household's relative 'permanent' income over the first three waves.

The LSYPE sample is clustered within schools. Academic performance is a function of school quality. However, we cannot use school fixed effects in our instrumental variables specifications. Because hours of employment are non-negative, we estimate a first-stage tobit regression. This is a nonlinear model (kinked at $L_{it} = 0$), and we never observe the within-school mean of latent desired employment. Moreover, since the majority of students in each school are resident in the same LAD, our measure of local youth unemployment will only vary within schools as a result of pupils crossing LAD boundaries to attend school. These students are likely to differ systematically from their peers. For example, their parents will not have accepted the default school offer for their place of residence, so are likely to place a high value on (a particular kind of) education. We therefore assume that conditional on other individual and household characteristics (including the student's trajectory of academic performance at age 11 and 14), there is no residual correlation of school quality with individuals' employment opportunities, motivation or academic performance. This assumption is supported by Table 7. This shows that adding school fixed effects to the OLS production function specifications moderates the parameters on most latent input activities only slightly (with the change never being statistically significant, and has no detectable effect on the parameter on Work Hours.[8]

4 Policy effects

4.1 The effect of employment on academic performance

Estimates of the empirical counterpart to the 'policy effect' equations (6) and (7) are shown in Table 3. To be consistent with our production function models, we assume that $T = 2$. Results for boys show insignificant positive and negative coefficients on employment at ages 14 (wave 1) and 15 (wave 2) respectively, in both the OLS and instrumental variables specifications. For girls, the OLS and instrumental variables estimates produce significantly different results at age 15. The instrumental variables results show a trivial insignificant negative effect at age 14 but a very large negative effect at age 15, equivalent to 4.3% of a standard deviation in the total

[8]We also estimated our instrumental variable specifications including the 2004 school mean GCSE performance (for the cohort two years above our sample) in all the equations as a proxy for school quality. The results were not statistically or quantitatively different from those obtained here.

point score per hour of employment per week.

Table 3: 'Policy effects' of employment on GCSE performance

	Boys				Girls			
	Instrumental variables			OLS	Instrumental variables			OLS
	W1 Work Hours	W2 Work Hours	Standardized GCSE score	Standardized GCSE score	W1 Work Hours	W2 Work Hours	Standardized GCSE score	Standardized GCSE score
W2 Work Hours	.	.	-0.012	-0.004	.	.	-0.043**	-0.007**
	.	.	(0.012)	(0.004)	.	.	(0.021)	(0.003)
W1 Work Hours	.	.	0.012	0.001	.	.	-0.004	-0.007
	.	.	(0.015)	(0.005)	.	.	(0.022)	(0.005)
W2 Age 18-24 LAD	.	-14.027	.	.	.	-43.195***	.	.
unemployment rate	.	(10.687)	.	.	.	(10.846)	.	.
W1 Age 18-24 LAD	-4.984	.	.	.	-19.094	.	.	.
unemployment rate	(9.441)	.	.	.	(11.858)	.	.	.
IMD	-0.905***	-1.230***	.	.	-0.976***	-0.678***	.	.
(standardized)	(0.201)	(0.271)	.	.	(0.227)	(0.251)	.	.
Month of	-0.069	-0.034	.	.	-0.158***	-0.095*	.	.
birth	(0.050)	(0.055)	.	.	(0.060)	(0.050)	.	.
Age 14 ave' point score	.	0.071	0.783***	0.783***	.	-0.553	0.717***	0.722***
(standardized)	.	(0.402)	(0.027)	(0.027)	.	(0.356)	(0.026)	(0.026)
Age 11 ave' point score	0.266	-0.011	-0.049**	-0.048**	0.552***	1.479***	0.014	0.001
(standardized)	(0.187)	(0.415)	(0.024)	(0.024)	(0.201)	(0.380)	(0.025)	(0.024)
Joint significance of	28.07	32.21	.	.	37.32	27.95	.	.
instruments: χ^2_{t+2} (p-value)	(0.000)	(0.000)	.	.	(0.000)	(0.000)	.	.
Observations			5125				5072	

Notes: Joint significance statistics and p-values are Wald test statistics. Standard errors, clustered by school, in parentheses. Longitudinal weights applied. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. GCSE (age 16), age 14 and age 11 average point scores, and index of multiple deprivation are standardized by substracting the mean and dividing by standard deviation. Month-of-birth within academic year: Sept (oldest in year) = 1, Aug (youngest in year) = 12. **Additional controls**: Parent's socio-economic status, parents' employment, resident and non-resident siblings, lone parent family, child's special educational needs (SEN) classification, urban-rural classification, child's ethnicity, timing of interview.

4.2 The effect of the instrumental variables on employment

Being born later in the academic year significantly reduces hours of employment only for girls. For this group, those born in August are predicted to work 1.7 hours less per week in wave 1, and 1 hour less per week in wave 2, than their September-born peers. The effects of this instrument are consistent with turning age 14 expanding employment opportunities more than turning 15; and also with boys' employment being concentrated in informal positions (such as newspaper delivery) where age restrictions are not binding, while girls' employment is concentrated in formally regulated roles such as serving in shops (Howieson et al., 2006) or with positions of responsibility such as babysitting (Kooreman, 2009). The coefficient on IMD is negative and statistically significant at the 1% level in all cases . A one standard deviation increase in IMD reduces predicted employment among boys by 54 and 74 minutes per week, and girls by 59 and 42 minutes, in waves 1 and 2. The coefficient on the local youth unemployment rate is statistically significant only for girls in wave 2. At this point a 1 percentage point increase in age 18-24 unemployment reduces girls' predicted employment by 26 minutes (i.e. 0.43 hours) per week. More generally, for both boys and girls the effect of the unemployment rate is over twice as large in wave 2 than wave 1, and at any time over twice as large for girls than boys. This is consistent with the relevant 'travel-to-work area' becoming larger in size as teenagers become older and more independent, and with boys' opportunities being restricted to a more localized level. This means that, on average, each hour of employment by girls is likely to entail a greater travelling time than faced by boys. This will exacerbate the crowd-out of study time by employment for girls relative to boys and may therefore partly explain the gender difference in our estimated policy effect of in-school employment.

Finally it is worth noting that, once the additional characteristics are controlled for, girls remain strongly positively selected into employment by prior educational performance, while for boys there is no longer a statistically significant relationship.

5 Production function parameters

In this section, we estimate the education production function. This means we obtain estimates of the effect of part-time employment and four other investment activities on academic performance, holding the other investments constant. We also provide insight into the mechanisms through which the partial effect of part-time employment estimated above occurs, by showing how an exogenous increase in employment crowds out other investment activities.

5.1 Latent inputs

We propose four latent inputs to the education production function: 'Study', 'Active Leisure', 'Social Life' and 'Risky behaviour'. We also use a latent variable representation of the teenager's 'Attitude' to education, which is motivated in section 5.2 below. We have measures for all of these inputs at time of interview in waves 1 and 2 of the LSYPE.[9] These relate to strength of agreement with a statement ("strongly disagree" to "strongly agree"), frequency of or "ever" engaging in certain activities, or participation "in the last four weeks". Where appropriate, measures have been recoded such that a higher value corresponds to greater participation or a more positive attitude.

[9]Questions on employment, risky behaviours, attitude, and selected measures of study are available at wave 3 of the LSYPE, though crucially not homework time or any of our measures for social life or active leisure. In addition, a significant minority (18.5%) of students in wave 3 are interviewed after their final GCSE exams, for whom answers recording current activities cannot be inputs to the production function, and indeed may be

Table 4: Factor loadings and cut points in ordered logit measurement models.

Factor loadings:

Attitude		Study		Active Leisure		Social Life		Risky Behaviour	
Work hard	1	Not truant	1	Play sport	1	Nightclub	1	Smoke	1
Worth it	0.832	Homework	1.453	School sport	0.687	Pub or bar	0.700	Alcohol	0.594
	(0.020)		(0.080)		(0.025)		(0.046)		(0.022)
Work waste	0.954	Outside	2.500	Sport in gen	0.903	Concert	0.336	Cannabis	1.347
	(0.025)		(0.251)		(0.027)		(0.018)		(0.074)
Interest	1.228	Study club	2.563	School clubs	0.329	Arcade	0.647		
	(0.027)		(0.249)		(0.015)		(0.046)		
				Play music	0.186	Friends out	0.442		
					(-0.257)		(0.027)		

Cut Points:

Attitude		Study		Active Leisure		Social Life		Risky Behaviour	
Work hard		Not truant		Play sport		Nightclub		Smoke	
1	-5.028	1	-1.511	1	-0.257	1	1.303	1	3.422
2	-2.048			School sport					
3	-1.992			1	0.250				
4	-1.898			2	0.917				
5	1.404			3	3.020	Pub or bar		Alcohol	
6	1.467			4	4.684	1	2.222	1	0.126
Worth it		Homework		Sport in gen				2	0.882
1	-3.888	1	-2.101	1	-3.683			3	0.927
2	-2.996	2	-1.376	2	-2.596			4	0.971
3	0.197	3	0.002	3	-2.010	Concert		5	1.578
4	0.053	4	1.183	4	-0.699	1	0.045	6	2.118
5	0.078	5	2.530	5	-0.695			7	3.260
6	0.103			6	-0.691			8	5.797
Work waste		Outside		7	1.136				
1	-4.642	1	0.497	School clubs		Arcade		Cannabis	
2	-3.07	2	1.620	1	0.553	1	2.014	1	4.418
3	0.584	3	3.827	2	1.059				
4	0.641	4	6.028	3	3.068				
5	0.685			4	4.946				
6	0.740								
Interest		Study club		Play music		Friends out			
1	-5.148	1	1.099	1	1.437	1	-1.390		
2	-2.134	2	2.054			2	0.246		
3	-2.013	3	4.056			3	0.255		
4	-1.854	4	5.626			4	1.509		
5	-1.710								
6	2.953								

Variance:

Attitude	2.414	Effort	0.263	Active Leisure	4.454	Social Life	2.489	Risky	7.032

Notes: Standard errors, clustered by individual, in parentheses. Measures are defined as follows. **Attitude:** 'Work hard': "I work as hard as I can in school". 'Worth it': "School work is worth doing". 'Work waste': "The work I do in lessons is a waste of time" (recoded). 'Interest': "The work I do in lessons is interesting to me". **Study**: 'Not truant': Student has not truanted in last 12 months (dummy variable). 'Homework': Estimate of hours per week spent doing homework, based on reported time spent on a computer doing schoolwork, nights per week doing so, and nights per week doing any homework. (Categories are zero, 1 to under 2 hours, 2 to under 4, 4 to under 6, 6 to under 10, and 10 or more). 'Outside': Works towards exams with teachers outside of lessons (frequency on 5-point scale). 'Study club': Attends school study clubs (frequency on 5-point scale). **Active Leisure**: 'Play sport': Played any kind of sport in the last four weeks (dummy). 'School sport': Frequency of using school sports facilities (5-point scale). 'Sport in gen': Frequency of doing sport (5-point scale). 'School clubs': Frequency of participation in school clubs or societies. (5-point scale). 'Play music': Played a musical instrument in the last four weeks. **Social Life**: 'Nightclub': Gone to a party, dance, nightclub or disco in the last four weeks. 'Pub or bar': Gone to a pub or bar in the last four weeks. 'Concert': Gone to a cinema, theatre or concert in the last four weeks. 'Arcade': Gone to an amusement arcade in the last four weeks. 'Friends out': How many times gone out with friends in last seven days. **Risky behaviours**: 'Smoke': Whether cohort member "ever smokes" (dummy variable). 'Alcohol': Frequency of alcohol consumption (6-point scale). 'Cannabis': Whether cohort member "ever tried cannabis" (dummy variable). 'Don't know' is coded as the within-wave mean, creating up to three extra categories for the following measures: Work hard (3^{rd}, 4^{th}, 6^{th} categories), Worth it (4^{rd}-6^{th}), Work waste (4^{th}-6^{th}), Interest (3^{rd}-5^{th}) , Sport in gen' (5^{th}-6^{th}), Friends out (3^{rd}), Alcohol (3^{rd}, 4^{th}, 6^{th}).

Table 4 defines the measures and shows the factor loadings and ordered logit cut points for each latent input. The factor loading for the first measure is always constrained to one. The variance of each factor is shown in the bottom section. The measurement models are estimated using the pooled sample of both sexes and both waves. This ensures that a given change in the principal component of the factor corresponds to an equivalent change in absolute activity levels across groups and over time. This means that the level, crowd-out by employment, and

dependent on GCSE performance.

Table 5: Interpretations of a one standard deviation change in each latent factor

Input	Measure	Interpretation	Baseline
Attitude			
	A 1 s.d. change on average is equivalent to all of:		
	Work hard	33.4 p.pt more likely to 'strongly agree' that "I always work hard in school"	26.1% strongly agree
	Worth it	29.2 p.pt more likely to 'strongly agree' that "School work is worth doing".	47.3% strongly agree
	Work waste	35.4 p.pt more likely to 'strongly disagree' that "The work I do in lessons is a waste of time".	36.6% strongly disagree
	Interest	21.4 p.pt more likely to 'strongly agree' that "The work I do in lessons is interesting to me".	12.7% strongly agree
Study			
	A 1 s.d. change on average is equivalent to all of:		
	Not truant	6.4 p.pt less likely to have truanted in the last year.	19.2% answer yes.
	Homework	1 hour additional homework per week.	Median response: ≥ 4, < 6 hours p.w.
	Outside	1 extra visit to work with teacher outside lessons per week.	Median: Never; $75^{th}\%^{ile}$: < 1 p.w.
	Study club	1 extra visit to school study clubs per week.	Median: Never; $75^{th}\%^{ile}$: < 1 p.w.
Active Leisure			
	A 1 s.d. change on average is equivalent to all of:		
	Play sport	33.4 p.pt more likely to have played any kind of sport in the last four weeks.	53.9% answer yes.
	School sport	1.5 additional occasions to use school sport facilities each week.	Median: Never; $75^{th}\%^{ile}$: 1-2 p.w.
	Sport in gen	Move from "hardly ever" participate in sport to once per week *or* move from once per week to several but not "most" days per week.	$25^{th}\%^{ile}$: 1 p.w.; Median: > 1 p.w.; $75^{th}\%^{ile}$: "Most days"
	School clubs	0.5 additional occasions to participate in other school clubs each week.	Median: Never; $75^{th}\%^{ile}$: 1-2 p.w.
	Play music	6.8 p.pt more likely to have played a musical instrument in the last four weeks.	19.9% answer yes.
Social Life			
	A 1 s.d. change on average is equivalent to all of:		
	Nightclub	35.5 p.pt more likely to have gone to a party, dance, nightclub or disco in last four weeks.	28.8% mention.
	Pub or bar	14.9 p.pt more likely to have gone to a pub or bar in the last four weeks.	13.8% mention.
	Concert	13.0 p.pt more likely to have gone to a cinema, theatre or concert in the last four weeks.	49.0% mention.
	Arcade	15.3 p.pt more likely to have gone to an amusement arcade in the last four weeks.	15.5% mention.
	Friends out	1 additional trip out with friends in last week.	Median: 1-2 p.w.; $75^{th}\%^{ile}$: 3-5 p.w.
Risky Behaviours			
	A 1 s.d. change on average is equivalent to all of:		
	Smoke	29.8 p.pt more likely to "ever smoke".	14.0% answer yes
	Alcohol	34.7 p.pt more likely to ever consume alcohol. (Conditional on some consumption: More than double frequency: bi-monthly to monthly/ monthly to 2-3 times per month/2-3 per month to 1-2 per week).	52.2% never consume alcohol $75^{th}\%^{ile}$: once every 2 months; $90^{th}\%^{ile}$: 2-3 p.m.
	Cannabis	28.8 p.pt more likely to have "ever tried cannabis".	13.3% answer yes

Abbreviations: "p.pt" = "percentage point". "p.w" = "'per week". "p.m" = "per month". "$\%^{ile}$" = "percentile". **Note:** Changes expressed as percentage point change in unconditional probability that condition is met due to a uniform one standard deviation change in the latent input across the entire pooled sample population, from the levels observed in the data.

productivity of each factor is expressed in a common unit. An interpretation of the change in activity or attitude associated with a one standard deviation increase in each factor is given in Table 5. In Appendix A.2 (page 43) we describe the distribution of the inputs between waves and sexes, to show that although significant differences exist, there is substantial overlap, so the adjustments described in Table 5 would represent a plausible and relevant change in all cases.

In our descriptive statistics (Table 6) and subsequent output (Tables 7-9) each factor is constrained to have mean zero and standard deviation 1, and is treated as observed (the measurement model is not estimated simultaneously). We assume there to be no heterogeneity in the 'quality' of each factor and that the measurement error in these inputs is uncorrelated with the exogenous component of labour supply. Table 6 shows no statistically significant differences in the attitude to schoolwork or the actual study effort undertaken by those with and without a job, but that those in employment are significantly more active in leisure and social activities, and risky behaviours. In section 5.3 we evaluate the extent to which these relationships are causal, and the effect of these inputs on educational performance.

Table 6: Descriptive statistics: latent variables by employment status and gender.

	Wave 1				Wave 2			
	Boys		Girls		Boys		Girls	
Employed:	Yes	No	Yes	No	Yes	No	Yes	No
Attitude	0.103	0.044	0.098	0.126	-0.029	-0.281	-0.170	-0.151
	(0.032)	(0.016)	(0.032)	(0.016)	(0.025)	(0.019)	(0.026)	(0.019)
Study	-0.140	-0.178	-0.126	-0.124	-0.062	-0.074	0.042	0.015
	(0.028)	(0.022)	(0.029)	(0.019)	(0.030)	(0.024)	(0.028)	(0.022)
Active Leisure	0.488***	0.330	-0.026***	-0.302	0.414***	0.226	-0.205***	-0.488
	(0.026)	(0.019)	(0.033)	(0.021)	(0.026)	(0.020)	(0.029)	(0.026)
Social Life	0.154***	-0.090	0.310***	0.018	0.321***	0.033	0.463***	0.122
	(0.030)	(0.018)	(0.031)	(0.018)	(0.028)	(0.018)	(0.028)	(0.019)
Risky Behaviours	0.053***	-0.170	0.080***	-0.099	0.464***	0.237	0.597***	0.328
	(0.025)	0.016	(0.035)	(0.016)	(0.029)	(0.020)	(0.036)	(0.023)

Notes: Latent inputs all have mean zero and standard deviation of 1 in the pooled sample of both sexes and both waves. Standard errors in parentheses. Population means calculated using final probability weights. Standard errors clustered by school. ***: p-value for difference in mean latent input between those in and out of employment <0.01.

As Fiorini and Keane (2014) note, it is difficult to obtain a sufficient number of valid instruments for a wide array of activities. Even if the order condition is met (meaning there are more instrumental variable exclusion restrictions than endogenous variables), the rank condition for identification requires that each endogenous variable is conditionally correlated with at least one instrument (Nichols, 2007). Moreover, the assumptions underlying instrumental variables estimation are not necessarily less restrictive than OLS. Fiorini and Keane (2014) choose not to adopt an instrumental variables approach. Instead they obtain a ranking of factor productivities that is robust to the assumptions of a series of OLS regression models. We first follow this approach by adapting the production function (equation 5) to include all our latent inputs, and estimate it by OLS using several assumptions under which the production function parameters are unbiased.

To be specific, our analysis relates to n individuals i at times $t = 1...T$. In our empirical application we assume that $T = 2$. Each sampled individual at time t is characterised by:

- Q dimensions of 'true' activities $\mathbf{s}_{it} = (s^1_{it}...s^Q_{it})$. Each is measured by the discrete indicators

S^q_{ijt}, $j = 1..J^q$.

- Desired hours of employment l_{it}, with actual hours of employment $L_{it} \geq 0$.
- A vector of time-invariant socio-economic characteristics, $\mathbf{X}_i$.
- A vector of instruments which determine selection into employment, $\mathbf{Z}_{it}$.
- A continuous measure of educational performance in the initial (Y_{i1}) and final (Y_{iT}) periods.

We assume an ordinal quasi-linear structure for measurement of the activities:

$$\tilde{S}^q_{ijt} = \alpha^q_{jt} + \lambda^q_{jt} s^q_{it} + \epsilon^q_{ijt} \quad for \quad j = 1..J \tag{8}$$

$$S^q_{ijt} = p \quad iff \quad W^q_{jp-1t} \leq \tilde{S}^q_{ijt} < W^q_{jpt} \quad for \quad p = 1...P^q_j \tag{9}$$

Here, λ^q_{jt} is the factor loading relating the observed indicator j to factor s^q_{it}. W^qs are threshold parameters. P^q_j is the number of response categories for indicator S^q_{ij}, and ϵ^q_{ijt} is the logistically distributed random response error. This means the observable indicator S^q_{ij} is linked to its unobserved continuous form $\tilde{S}^q_{ij}$ by an ordered logit function.[10]

5.2 OLS estimates of the production function

We first estimate the standard cumulative model ("CU" adopting the notation of Fiorini and Keane, 2014), which can be written as follows:

$$Y_{iT} = \sum_{t=1}^{T} [\pi^L_t L_{it} + \sum_{q=1}^{Q} [\pi^q_t s^q_{it}] + ln.\epsilon_{it}] + \boldsymbol{\beta}_0 \mathbf{X}_{i0} + ln.v_{iT} \tag{10}$$

The production function parameters estimated here are unbiased provided that any omitted inputs (including the individual's unobserved ability or initial human capital endowment) and the measurement error in the test score are conditionally uncorrelated with the included inputs (Todd and Wolpin, 2003).

Secondly, we estimate a "cumulative value-added" model (CV). This means we add the measure

[10] The model and notation outlined here follows closely the structure used for a model of disability status and benefit receipt by Hancock et al. (2013).

of prior educational performance Y_{i1} as a control variable:

$$Y_{iT} = \sum_{t=1}^{T}[\pi_t^L L_{it} + \sum_{q=1}^{Q}[\pi_t^q s_{it}^q] + ln.\epsilon_{it}] + \boldsymbol{\beta}_0 \mathbf{X}_{i0} + \delta Y_{i1} + ln.v_{iT} \tag{11}$$

This specification will reduce the component of the bias in equation (10) that is driven by the correlation of unobserved inputs with the measurement error in the relationship translating human capital to educational performance at time T, if this measurement error is serially correlated. Todd and Wolpin (2003) show that the assumptions for consistency in this specification are somewhat more demanding: The input coefficients and effect of baseline human capital must be geometrically declining with distance from the achievement measure all at the same rate, and the serial correlation of the measurement error in test scores must exactly match this rate of decline. We must also assume that individuals do not increase their unobserved effort in response to poor realized educational performance at time $t = 1$.

Next, we add fixed effects for each school m (CV-FE). This will eliminate the bias caused by any unobserved factor that is constant across pupils within the same school, which we refer to as 'school quality' (Υ) for brevity:

$$Y_{iT} = \sum_{t=1}^{T}[\pi_t^L L_{it} + \sum_{q=1}^{Q}[\pi_t^q s_{it}^q] + ln.\epsilon_{it}] + \boldsymbol{\beta}_0 \mathbf{X}_{i0} + \delta Y_{i1} + \Upsilon_m + ln.v_{iT} \tag{12}$$

This specification is unbiased provided that $E[\sum_{t=1}^{T}[ln.\epsilon_t] + ln.v_T|\mathbf{L}, \mathbf{s}, \mathbf{X}_0, Y_1, \Upsilon] = 0$. Notwithstanding the assumptions attached to the value-added specification, this assumption will fail if there exists any residual within-school heterogeneity which determines selection into both employment and study. In our final OLS production function specification, we propose this is captured by a one-dimensional latent variable; the teenager's 'Attitude' to study, a_{it}. Attitude is measured by the discrete indicators A_{ikt}, $k = 1...K$ assuming an ordinal quasi-linear structure for measurement, as shown in Table 4 and in equations (8-4.9), *mutatis mutandis.* The OLS production function specification (CV-FE-Att) is now written:

$$Y_{iT} = \sum_{t=1}^{T}[\pi_t^L L_{it} + \sum_{q=1}^{Q}[\pi_t^q s_{it}^q] + \pi_t^a a_{it} + ln.\epsilon_{it}] + \boldsymbol{\beta}_0 \mathbf{X}_{i0} + \delta Y_{i1} + \Upsilon_m + ln.v_{iT} \tag{13}$$

The results for the specifications in equations (10-13) are presented in Table 7. The coefficients on employment in both waves are not statistically different from zero in any case. For boys there are also no statistically significant differences among the coefficients on labour supply, though for girls, adopting a value-added specification causes the sign of the parameter on wave 2 employment to change from positive to negative. Comparing these results with the instrumental variable 'policy effect' coefficients in Table 3 shows that the wave 2 production function parameter (under any of the OLS specifications) is less negative than the policy effect for both boys and girls, but this difference is only statistically significant and quantitatively important for girls. This suggests that the true productivity of the inputs crowded out by employment is greater for girls than for boys.

Turning to the parameters on the latent inputs, the most interesting results are apparent for Study. The large positive effect on academic performance is very similar for boys and girls. The parameter on Study at both points in time gets closer to zero as progressively more controls for the selection bias are added, but the relative importance of Study at wave 2 compared with wave 1 becomes larger. This is expected as the additional controls absorb more unobserved heterogeneity in the initial conditions. The magnitude of the effect is plausible. In the final (CV-FE-Att) specification, a one-standard deviation increase in Study at wave 2; equivalent to one hour more homework, one extra visit to a school study club and one to work with a teacher outside a lesson per week, and a 6.4 percentage point reduction in the probability of truanting over the school year; improves school performance by 6% of a standard deviation.

Regarding the other inputs, the coefficients on Active Leisure suggest that participation in these activities is beneficial for academic performance, but the significant moderation of the parameters when moving from left to right in the table shows that positive selection has a particularly large role here, and especially for girls. There appears no clear effect of Social Life for boys, with tentative evidence of a negative effect for girls in wave 2. As expected, a positive Attitude is strongly associated with age 16 educational performance. There are unambiguously large damaging effects of Risky Behaviours in wave 2.

Table 7 shows a consistent ranking for the effect of a standard deviation change in each input across the specifications. The largest effect in absolute value is of Risky Behaviours (which has a significant negative effect), Study, then Active Leisure, and Social Life (also negative). (Attitude, if treated as an input, rather than a measure of unobserved heterogeneity, takes second place for girls and third for boys).

Table 7: OLS Production Function parameters

	Boys				Girls			
	CU	CV	CV-FE	CV-FE-Att	CU	CV	CV-FE	CV-FE-Att
Work Hours W2	-0.005 (0.004)	-0.001 (0.003)	-0.002 (0.003)	-0.002 (0.003)	0.001 (0.004)	-0.005 (0.003)	-0.005 (0.003)	-0.005 (0.003)
work Hours W1	0.004 (0.005)	0.003 (0.004)	0.002 (0.004)	0.003 (0.004)	-0.002 (0.006)	-0.004 (0.004)	-0.001 (0.004)	-0.002 (0.004)
Study W2	0.178*** (0.017)	0.106*** (0.011)	0.079*** (0.010)	0.058*** (0.010)	0.140*** (0.016)	0.082*** (0.012)	0.068*** (0.010)	0.057*** (0.010)
Study W1	0.088*** (0.016)	0.032*** (0.012)	0.024** (0.010)	0.012 (0.010)	0.056*** (0.015)	0.023** (0.012)	0.012 (0.010)	0.003 (0.010)
Active Leisure W2	0.086*** (0.018)	0.068*** (0.013)	0.055*** (0.012)	0.053*** (0.012)	0.092*** (0.018)	0.053*** (0.013)	0.044*** (0.011)	0.040*** (0.011)
Active Leisure W1	0.017 (0.018)	-0.021 (0.014)	-0.011 (0.012)	-0.014 (0.012)	0.058*** (0.017)	-0.017 (0.013)	-0.004 (0.012)	-0.006 (0.012)
Social Life W2	-0.011 (0.014)	-0.007 (0.010)	-0.009 (0.009)	-0.008 (0.009)	-0.010 (0.014)	-0.016 (0.011)	-0.024** (0.010)	-0.021** (0.010)
Social Life W1	-0.039*** (0.014)	-0.001 (0.011)	-0.003 (0.009)	-0.001 (0.009)	-0.007 (0.014)	0.004 (0.010)	0.013 (0.009)	0.015 (0.009)
Risky Behaviours W2	-0.073*** (0.019)	-0.106*** (0.014)	-0.099*** (0.012)	-0.081*** (0.012)	-0.100*** (0.017)	-0.102*** (0.014)	-0.109*** (0.013)	-0.096*** (0.013)
Risky Behaviours W1	0.008 (0.018)	-0.001 (0.014)	-0.007 (0.012)	-0.004 (0.012)	-0.002 (0.017)	-0.004 (0.014)	-0.012 (0.013)	-0.011 (0.013)
Attitude W2	. .	. .	. .	0.075*** (0.010)	. .	. .	. .	0.044*** (0.011)
Attitude W1	. .	. .	. .	0.024** (0.010)	. .	. .	. .	0.016 (0.011)
Lagged Test Score Y_{i1}	. .	0.714*** (0.013)	0.720*** (0.013)	0.711*** (0.013)	. .	0.691*** (0.015)	0.683*** (0.014)	0.679*** (0.014)
Family Background ($\mathbf{X}_{i0}$)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School Fixed Effects (Υ_m)	No	No	Yes	Yes	No	No	Yes	Yes
Observations	5020				4977			

Notes: Standard errors in parentheses. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$. Longitudinal weights applied. **Family background controls**: Parent's socio-economic status, parents' employment, resident and non-resident siblings, lone parent family, child's special educational needs (SEN) classification , child's ethnicity.

5.3 Instrumental variables models exploiting tradeoffs in activities

If we permit the input choices to be endogenous to an additional dimension of unobserved heterogeneity or any component of the baseline human capital endowment not controlled for by prior educational achievement, then the OLS results above are biased. The standard approach is then to obtain an exogenous source of variation in inputs using instrumental variables. De Fraja et al. (2010) make the foremost contribution using this method, estimating a production function with three endogenous inputs; child, parent and school effort. They motivate the child's birth weight, father's social class, and school size as instruments for the respective inputs, which are determined simultaneously by the three optimizing agents.

There are theoretically viable candidates for instruments for each of the inputs assessed in the present paper. Financial incentives targeting students' self investments have been shown to raise investments in study time. Freyer (2010) shows these to be more effective than targeting *outcomes*, because individuals may not know what investments are effective, or as shown in our theoretical model here, may be deterred by uncertainty about outcomes or the long time horizon. Other papers propose sources of exogenous variation in the opportunity cost of study or value of leisure, such as the weather (Kalenkoski and Pabilonia, 2014) or major football (soccer) tournaments during the exam period (Burgess et al., 2011). Cross-sectional variation in opportunities for structured social activities or entertainment may determine selection into Social Life, Active Leisure and Risky Behaviours. Barron et al. (2000) used variables such as the size of high school and 'library books per student' for this purpose. The LSYPE collects reports on whether such facilities or clubs are available, but only 12% and 8% of sample members respectively report they are not. With information on social networks, current or lagged peer-group behaviour could also be used (Lundborg, 2006; Clark and Loheac, 2007) though if these signals are observable, parents' school choices may be endogenous.

We do not have the data to pursue exogenous variation in all the endogenous inputs simultaneously. However, as motivated in our theoretical model, with individuals behaving optimally we predict a strictly negative tradeoff of employment with study time (section 3 and Appendix A.1.2). Therefore we propose a structure in which exogenous variation in employment determines the child's contemporaneous level of Study, but Study does not affect employment. Both labour supply and Study then enter the production function. To identify the production function parameter on Study we require that the principal component of our latent Study indicator is strictly decreasing in labour supply. We do not impose this relationship as a restriction in the econometric framework. Instead we test whether it is borne out empirically, and interpret the coefficients obtained on Study in the appropriate light.

In our $T = 2$ case we have four instrumental variables: Month of birth, IMD, and the unemployment rate at $t = 1$ and $t = 2$. Month of birth, IMD and the time-specific unemployment rate all identify the direct effect of employment on educational performance, and the effect of employment on the contemporaneous Study level. Exogenous variation in employment identifies the effect of Study on educational performance. The product of the latter two effects can be interpreted as the indirect effect of employment, or the portion of the overall effect that is mediated by changes in Study. Hence, the model contains employment and a single endogenous latent factor, both measured at two points in time. We describe this as a 'single-factor multiple-wave' specification. A model with multiple factors would be underidentified.

We apply this structure to the other latent inputs. We expect the earnings from labour supply to facilitate ('crowd in') Social Life and Risky Behaviours to a greater extent than the time constraint will cause crowd-out. For Active Leisure we expect the time constraint to cause crowd-out to a greater extent than consumption complementarities or increasing budget would increase participation. We also test for the endogeneity of Attitude (a_{it}) to labour supply by treating it like the remaining inputs. We have no expected sign: employment may reduce motivation through general tiredness, or increase it through exposure to the disadvantages of jobs requiring few qualifications (Dustmann and van Soest, 2007).

To be explicit, desired hours of employment are determined by a linear labour supply function of $\mathbf{X}_i$, $\mathbf{Z}_{it}$ and prior educational performance:[11]

$$l_{it} = \boldsymbol{\theta}_t^l \mathbf{X}_i + \boldsymbol{\gamma}_t^l \mathbf{Z}_{it} + \delta_t^l Y_{i1} + \xi_{it}^l \tag{14}$$

Hours of employment equal zero if desired hours are negative, and desired hours otherwise:

$$\begin{aligned} L_{it} = l_{it} \quad iff \quad l_{it} \geq 0 \\ L_{it} = 0 \quad iff \quad l_{it} < 0 \end{aligned} \tag{15}$$

Each endogenous input s_{it}^q (including Attitude) is determined by a linear function of socio-economic characteristics, which will have determined parental and self-investments and the child's preferences, but also by hours of employment:

$$s_{it}^q = \boldsymbol{\theta}_t^q \mathbf{X}_i + \gamma_t^q L_{it} + \delta_t^q Y_{i1} + \xi_{it}^q \tag{16}$$

In equations (14) and (16), $\boldsymbol{\theta}$s represent vectors of coefficients, and γ_t^q the crowd-out (or crowd-in) of factor s_{it}^q by hours of employment. The residual ξs capture other unobservable factors.

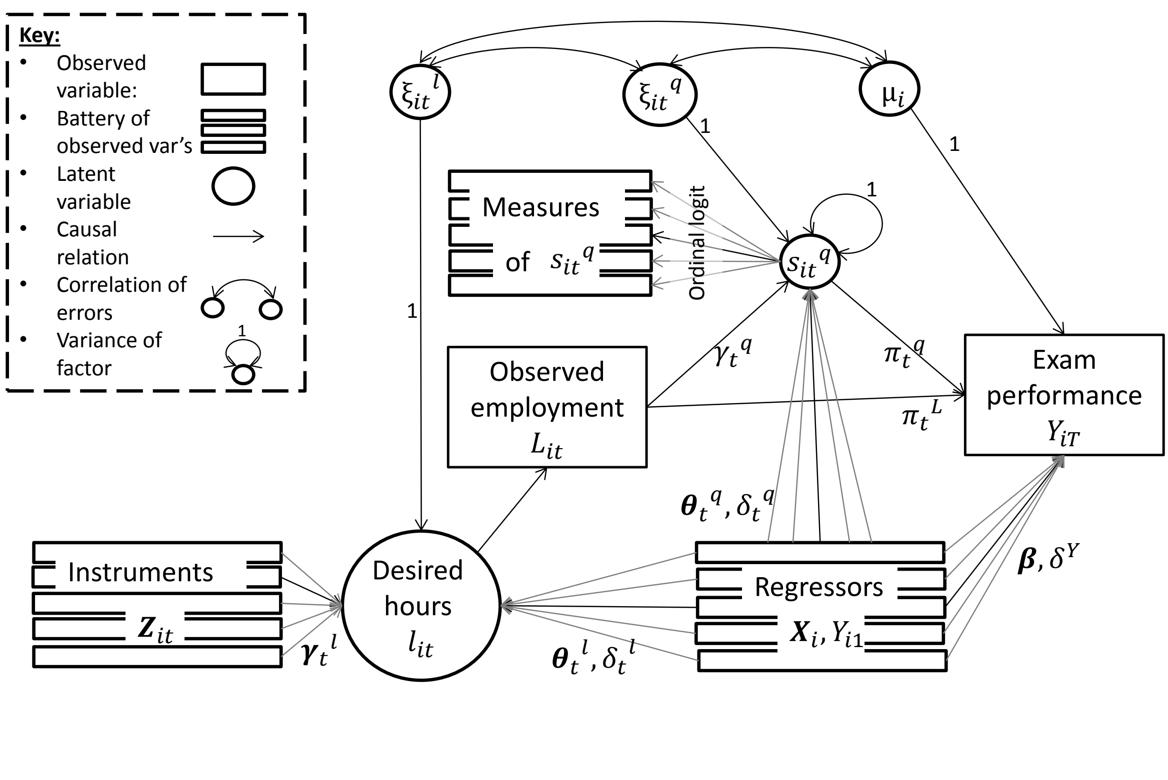
[11] Specifically, age 11 and 14 performance enter equations for dependent variables measured at $t = 2$. Only age 11 performance is included for dependent variables measured at $t = 1$, because for the majority of students, the examinations determining the age 14 score occurred after the wave 1 interview.

Academic performance is modelled by the following linear regression specification:

$$Y_{iT} = \sum_{t=1}^{T}[\pi_t^L L_{it} + \pi_t^q s_{it}^q] + \boldsymbol{\beta}\mathbf{X}_i + \delta^Y Y_{i1} + u_i \tag{17}$$

Here, $\boldsymbol{\beta}$s and πs are (vectors of) production function parameters. u_i is a composite stochastic disturbance term ($u_i = \sum_{t=1}^{T}[ln.\epsilon_{it}] + ln.v_{iT}$). The residuals u_i, ξ_{it}^l and ξ_{it}^q are assumed to be positively correlated, so equations (14-15), (16) and (17) are estimated jointly, such that we can treat u_i as independent of the exogenous variation in $\mathbf{L}_i$ and $\mathbf{s}_i^q$ caused by variation in $\mathbf{Z}_i$. As a normalization restriction, the variance of each latent factor across both waves is set equal to one. We assume this structure to be 'invariant', in that neither the deterministic or stochastic components of the relationship between the inputs and outcome is affected by the fact of 'treatment', or employment (Heckman and Pinto, 2013). This general structure can be represented visually in Figure 1, for the single factor, single time-period ($T = 1$ and $Q = 1$) case. For simplicity this diagram omits the individual measurement error terms for each observed regressor, measure and instrument.

Figure 1: Path diagram



5.3.1 Estimates of tradeoffs in investments

Table 8 shows estimates of γ_t^q (from equation 16) when the system represented in equations (14-17) and for $t = 1, 2$ is estimated jointly. This represents the contemporaneous crowd-out (or crowd-in) of each factor (s_{it}^q) by employment in each time period. (To interpret these coefficients within the complete system, note that the coefficients for Study can be seen in the 2nd and 4th (boys), 7th and 9th (girls) columns of Table A2, page 48, which shows coefficients on the key variables for all five equations in each system.

The results show that Attitude is endogenous to hours of employment. An additional hour per week crowds out Attitude in wave 2 by 3% and 6% of a standard deviation in wave 2, and 2.2% (albeit insignficant) and 3% of a standard deviation in wave 1 for boys and girls and respectively. This means that the effects of general tiredness, or a shift in preferences towards the other activities opened up by employment and earnings, outweigh any positive effect on motivation for education-oriented human capital through making the role of education in widening future job options more salient (Dustmann and van Soest, 2007). For Study we observe a strong negative effect for girls in wave 2 (3.6% of a standard deviation per hour) and a smaller one for boys in wave 1 (2.4%). The greater degree of study crowd-out for girls in wave 2 may be explained partly by differences in travelling time, and partly by their relative lack of previous experience in combining employment with other activities (55% of girls working in wave 2 had not previously worked, compared with 44% of boys - see Table 2). Elsewhere coefficients are close to zero and statistically insignificant. These coefficients mean that, for example, increasing employment in wave 2 makes girls *do less* and *care less about* schoolwork. Boys become less motivated, but do not significantly reduce the *amount* of Study they do. Considering the remaining inputs, Table 8 shows crowd-out of Active Leisure only among boys (significant in both waves), and a significantly stronger crowd-in of Risky Behaviours among girls than boys, particularly in wave 2 (with a moderate effect for both boys and girls in wave 1).

Relating these parameters to our ranking of investment activities, we note that (considering both wave 2 alone and averaging across waves 1 and 2), the absolute effect of labour supply on the investment activity is significantly greater for girls than boys with respect to the first (Risky Behaviours), second and third (Attitude and Study for girls and vice-versa for boys) most productive activities, and is greater for boys only for the fourth (Active Leisure). This supports the gender differential in the net effect of labour supply being driven by employment having a larger effect on the more productive or damaging behaviours and time uses for girls.

Table 8: Contemporaneous effect of a one hour exogenous increase in employment hours on each latent factor (measured in standard deviations)

		Attitude		Study		Active Leisure		Social Life		Risky Behaviours	
		Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls
Wave 2											
	Work Hours	-0.025**	-0.057***	-0.007	-0.036***	-0.038***	-0.018	0.007	0.008	0.009	0.029**
		(0.012)	(0.012)	(0.012)	(0.013)	(0.011)	(0.015)	(0.009)	(0.012)	(0.009)	(0.012)
Wave 1											
	Work Hours	-0.023	-0.030**	-0.024**	-0.016	-0.027**	-0.016	-0.005	0.012	0.021*	0.022*
		(0.015)	(0.015)	(0.012)	(0.022)	(0.013)	(0.011)	(0.012)	(0.014)	(0.011)	(0.013)
	Observations	5022	4982	5125	5072	5125	5072	5124	5070	5021	4979

Notes: *: $p < 0.1$, **: $p < 0.05$, * * *: $p < 0.01$. Standard errors, clustered by school, in parentheses. All coefficients from single-factor-2-wave models. First stage equation for hours of employment not shown. Effect of hours of employment is identified by exclusion of labour market variables from second stage. (Local unemployment and IMD in all cases, month of birth in all cases except Active Leisure, as age-within cohort is direct determinant of participation in sporting activities). Additional regressors as in Tables A2-A3

5.3.2 Estimates of production function parameters

The rank condition for identification of each production function parameter π_t^q in equation (17) requires that $\gamma_t^q \neq 0$. The only specifications in which γ_t^q is statistically different from zero and of the expected sign at the 10% level or less for both $t = 1, 2$ are for Risky Behaviour by girls and Active Leisure by boys. Wave 2 Attitude (both boys and girls), Study and Social Life (girls only) all also significantly change with employment at the 5% level or less. These production function parameters would therefore be identified in a contemporaneous ($t = 2$ only) specification. In the cumulative single-factor multiple-wave specification, these parameters are sensitive to the wave 2 observations' collinearity with the underidentified wave 1 observation.

In Table 9 we show the estimated production function parameters π_t^L and π_t^q for each q, in cumulative ($T = 2$ with $t = 1, 2$) and contemporaneous ($T = 2$ with $t = 2$ inputs only) specifications, and a reduced form version accounting for wave 1 inputs only ($T = 2$ but $t = 1$ inputs only). In the top section, the 'policy effect' estimates for labour supply (ϕ_t^L) from the corresponding specifications are shown for ease for comparison. For each of our latent inputs, only coefficients in **bold** are identified by the criteria described above.

Considering first the specifications in which all parameters are identified in the cumulative specification, the coefficients on Active Leisure for boys are positive and moderate in size in

Table 9: Single-factor instrumental variable production function parameters

	Boys			Girls		
	Cumulative (Both waves)	Contemporaneous (Wave 2 only)	'Reduced form' (Wave 1 only)	Cumulative (Both waves)	Contemporaneous (Wave 2 only)	'Reduced form' (Wave 1 only)
Work Hours only (Policy effect)						
Work Hours W2	-0.012	-0.012	.	-0.043**	-0.051***	.
	(0.012)	(0.009)	.	(0.021)	(0.016)	.
Work Hours W1	0.012	.	0.002	-0.004	.	-0.042**
	(0.015)	.	(0.014)	(0.022)	.	(0.016)
Observations	*5125*	*5125*	*5125*	*5072*	*5072*	*5072*
Attitude						
Work Hours W2	0.000	0.000	.	-0.031	-0.033	.
	(0.013)	(0.011)	.	(0.027)	(0.022)	.
Work Hours W1	0.009	.	0.002	-0.000	.	-0.037*
	(0.015)	.	(0.014)	(0.024)	.	(0.019)
Attitude W2	**0.556*** **	**0.494*** **	.	**0.164**	**0.203**	.
	(0.128)	**(0.108)**	.	**(0.305)**	**(0.240)**	.
Attitude W1	-0.189	.	-0.030	**0.049**	.	**0.043**
	(0.129)	.	(0.080)	**(0.352)**	.	**(0.243)**
Observations	*5022*	*5096*	*5132*	*4982*	*5048*	*5064*
Study						
Work Hours W2	-0.007	-0.009	.	-0.032*	-0.040**	.
	(0.011)	(0.009)	.	(0.020)	(0.017)	.
Work Hours W1	-0.000	.	0.003	-0.006	.	-0.037**
	(0.016)	.	(0.014)	(0.022)	.	(0.017)
Study W2	0.405	0.132	.	**0.274**	**0.245**	.
	(0.323)	(0.463)	.	**(0.219)**	**(0.210)**	.
Study W1	**-0.408**	.	0.078	0.117	.	**0.193**
	(0.263)	.	(0.247)	(0.461)	.	**(0.443)**
Observations	*5125*	*5152*	*5187*	*5072*	*5095*	*5117*
Active Leisure						
Work Hours W2	-0.008	0.001	.	-0.033	-0.043***	.
	(0.019)	(0.019)	.	(0.023)	(0.017)	.
Work Hours W1	0.021	.	0.008	-0.012	.	-0.041**
	(0.020)	.	(0.020)	(0.025)	.	(0.017)
Active Leisure W2	**-0.017**	**0.111**	.	0.352*	0.308	.
	(0.323)	**(0.285)**	.	(0.208)	(0.201)	.
Active Leisure W1	**0.233**	.	0.005	0.003	.	0.132
	(0.377)	.	(0.330)	(0.296)	.	(0.435)
Observations	*5125*	*5152*	*5187*	*5072*	*5095*	*5117*
Social Life						
Work Hours W2	-0.015	-0.014	.	-0.039*	-0.044**	.
	(0.012)	(0.010)	.	(0.021)	(0.017)	.
Work Hours W1	0.012	.	0.000	-0.008	.	-0.043***
	(0.014)	.	(0.013)	(0.022)	.	(0.016)
Social Life W2	0.308	0.281	.	-0.046	**0.058**	.
	(0.214)	(0.226)	.	(0.348)	**(0.172)**	.
Social Life W1	-0.047	.	-0.118	0.143	.	0.064
	(0.130)	.	(0.149)	(0.398)	.	(0.157)
Observations	*5124*	*5151*	*5187*	*5070*	*5093*	*5117*
Risky Behaviours						
Work Hours W2	-0.005	-0.022	.	-0.046**	-0.049**	.
	(0.011)	(0.016)	.	(0.021)	(0.020)	.
Work Hours W1	-0.004	.	-0.001	0.008	.	-0.028
	(0.017)	.	(0.015)	(0.021)	.	(0.017)
Risky Behaviours W2	-0.342**	**0.286**	.	**0.170**	**0.045**	.
	(0.156)	**(0.309)**	.	**(0.120)**	**(0.254)**	.
Risky Behaviours W1	**0.594**	.	0.143	**-0.385*** **	.	**-0.271**
	(0.242)	.	(0.255)	**(0.136)**	.	**(0.171)**
Observations	*5021*	*5095*	*5132*	*4979*	*5046*	*5063*

Notes: Bold: Coefficient on latent factor identified in that effect of exogenous change in hours of employment on contemporaneous latent factor is statistically significant at the 10% level or less (For cumulative specification see Table 8). W1/W2: Wave 1/Wave 2. Standard errors in parentheses. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$. Longitudinal weights applied. **Additional covariates**: Parent's socio-economic status, parents' employment, child's prior educational performance, resident and non-resident siblings, lone parent family, child's special educational needs (SEN) classification , child's ethnicity.

wave 1 and close to zero in wave 2, but never statistically significant. More interestingly, from the bottom section of Table 9 we learn that early (wave 1) take-up of Risky Behaviours significantly reduces educational performance among girls (the coefficient is negative and significant at the 0.1% level in the cumulative, and narrowly insignificant at the 10% level in reduced form specifications) but that conditional or unconditional on this, later take-up matters significantly less. This stands in contrast to our expectation that activities undertaken closer to the time of examination will have a larger effect on educational performance. We suggest that this is due to self-financed early initiation into these relatively minor risky behaviours acting as a gateway - with a lag - to participation in more serious behaviours or a lifestyle proving more disruptive to educational investments. (For boys, we note the positive and significant coefficient on wave 1 Risky Behaviours, and negative and significant - though not identified - coefficient in wave 2. However, since neither of these interpretations are replicated in the contemporaneous or reduced form specifications; coefficients in both these are positive but statistically indistinguishable from zero; we are reluctant to draw inference on the role of Risky Behaviours in the production function for boys).

The second and third sections of Table 9 are informative about the relative importance of Attitude and Study at each age and for boys and girls. Age 15 (wave 2) Study is a quantitatively important determinant of educational performance among girls. Both the cumulative and contemporaneous specifications show that a one standard deviation increase in Study (approximately 1 hour more homework per week, one extra visit to a teacher outside of lessons, and 1 extra session at a school study club) leads to approximately 0.25 standard deviation increase in GCSE performance, or one grade in 6 GCSE subjects, though this effect is not statistically significant. Evidence on the role of Study at age 14 (wave 1) is more tentative. In the cumulative specification the parameter is weakly identified. Though the parameter estimated in the reduced form specification is well identified, it is smaller and statistically indistinguishable from zero, suggesting that this coefficient is absorbing the effects of the omitted wave 2 Study with which it is positively correlated.

All the estimated parameters on girls' Attitude are well identified and stable between specifications. A standard deviation increase in Attitude is marginally less productive than a standard deviation change in Study measured at the same time, but similarly statistically insignificant.

For boys, the parameter on Study at age 15 is not identified in either specification, and on age

14 Study is either not identified or insignificant. However, while we obtain no evidence on age 14 Attitude, the parameter on age 15 Attitude in both the cumulative and contemporaneous specifications for boys is statistically significant and approximately twice as large in magnitude to that on Study for girls.

In other words, we learn that having a job makes girls do less, and care less about, their schoolwork, and both of these inputs appear to have a quantitatively large positive effect on school performance, albeit statistically imprecise. For boys, this exercise yields no evidence on how much Study contributes to educational performance. As with girls, a positive Attitude to schoolwork among boys is crowded out by having a job, but unlike girls, such an Attitude has a significant positive effect in the education production function. This gender distinction is consistent with girls facing a lower nonpecuniary cost of effort in their education (Goldin et al., 2006). Over a range of academic or vocational subjects, as captured by our performance measure, this is unlikely to reflect an advantage in cognitive ability (Spelke, 2005), rather a difference in non-cognitive skills, such as attentiveness and self-discipline, even in the absence of enthusiasm (Buchmann et al., 2008; Jacob, 2002).

Finally, we note that while the moderation in the production function parameter on wave 2 labour supply for girls, compared with the instrumental variables policy effect, is never statistically significant, for Attitude and Study especially, the difference is quantitatively important: Approximately 25% of the negative 'policy effect' of in-school labour supply is accounted for by the marginal reduction in Attitude or Study induced by this labour supply. The still-substantial residual negative policy effect will partly be due to omitted *types* of inputs (we can control for only one additional endogenous input in each specification), but also largely due to omitted *timing* of inputs. For example, study during regular term-time (which we observe measures for) may be a poor predictor of intensive revision close to high-stakes exams, which may be highly productive but we do not observe. If labour supply is highly autocorrelated and later crowds out unobserved revision time the estimated effect of labour supply will be downward biased.

6 Summary and conclusions

A large proportion of teenagers and young adults in the UK and North America take some formal paid employment while still in full-time education. In this paper we first evaluated the net effect of teenage employment on performance in high stakes qualifications by English pupils in compulsory education. We estimated OLS and instrumental variables cumulative specifications for age 16 academic performance, that identify the net effects of part-time employment at different points in time, including indirect effects caused by unobserved changes in other activities which may result from changes in labour supply. We identified a significant negative effect of the labour supply of girls at age 15 only. For them, an additional hour of employment reduces academic performance by 4.3% of a standard deviation of our chosen measure. This effect is quantitatively large, and sufficient to substantially narrow subsequent educational opportunities.

We then sought to understand the mechanism behind this effect by controlling for additional endogenous inputs, first in a series of OLS specifications, and then assuming a causal structure for the tradeoff in time-use between employment and study and other potentially productive or damaging activities. We provide evidence which supports the gender differential in the net effect of in-school employment being due to these tradeoffs being larger for the most productive activities among girls than boys. However, even when study time at home and outside of lessons is accounted for in this way, the estimated production function parameter on girls' labour supply at age 15 remains large in magnitude, suggesting that employment is crowding out important unobserved inputs closer in time to the final high-stakes exams.

We noted that our sample faced a system of continuous assessment over a two-year period, contributing to a significant minority of the overall marks in most GCSE subjects, with the remainder determined by final exams sat at the end of compulsory schooling. It is possible that the ongoing move from continuous assessment to final-exam-only assessment of GCSEs from 2013-2017 will reduce the penalty to having a job by reducing the relative importance of long-term inputs of study in favour of intensive revision shortly before these high-stakes exams. A comparison of our results with those obtained from the 'Our Futures' or 'LSYPE2' dataset, following a cohort of students aged 13-14 in 2013, will enable future research to evaluate the effect of assessment structure on the impact of part-time work and long-term study.

In policy terms, our results suggest that any step to reduce the hours of part-time employment among schoolchildren in the final two years of compulsory education, through enforcement or revision of the current permitted hours, would improve the age-16 academic performance of girls but not boys. While there is dynamic state dependence in employment; it is easier to keep a job than obtain one (see Appendix A.3, page 46); we do not make a case for raising the age at which children are allowed to take a job: the micro benefit of not having a job at age 14 making it harder to get a job at age 15 (when the damage to academic performance is done) will not translate into a macro benefit if the entire cohort faces the same initial restriction. Moreover, although we find no negative effects on age 16 academic performance of having a job at age 14, this work does not address dynamic questions, such as whether earlier employment experience either increases students' ability to accommodate this without crowding out other productive activities, or instead influences their preferences to initiate a poorer trajectory of investment activities.

It should be borne in mind that those taking part-time employment are on average somewhat positively selected, and that the crowding out of study observed here actually moderates the significant gender gap by which girls outperform boys at age 16 in the UK. There may also be a role for prior employment experience in improving subsequent employment opportunities beyond compulsory education. Nevertheless, we have found no evidence for a positive role for in-school employment in producing the education-oriented human capital captured by our exam performance measure. Insofar as in-school employment induces early initiation into risky behaviours and a reduction in students' valuation of education-oriented human capital, and that these effects may be expected to persist, we have also shown evidence for an additional mechanism, beyond age 16 exam scores, through which subsequent human capital accumulation may be restricted.

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A Appendix

A.1 Graphical illustrations of model predictions

A.1.1 Uncertainty leads to underinvestment in Study

In section 3 we stated that the theoretical model predicts that uncertainty in the evolution of human capital and in GCSE performance will lead to underinvestment in study, compared to the case with no uncertainty. Figure A1 shows a graphical illustration of this prediction, which is an application of Jensen's inequality.

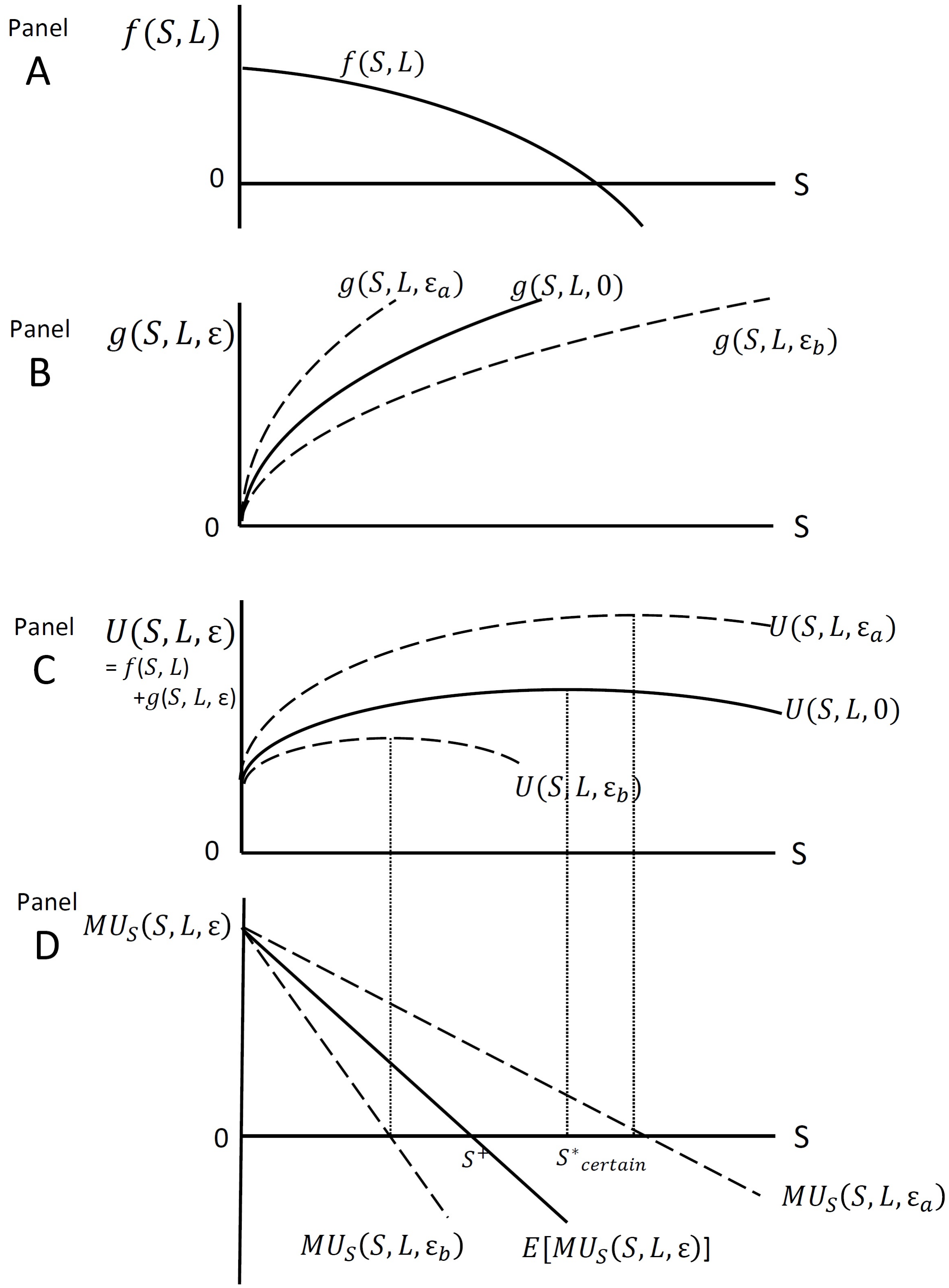
Panel A shows the deterministic relationship between the present-orientated component of utility $f(S, L)$ and study (S). This has its peak at $S = 0$. Because consumption and leisure are complements $f(S, L)$ is decreasing in S at an accelerating rate.

Panel B shows the relationship between the future-orientated component of utility $g(S, L, \epsilon)$ and study (S). Its expected value $g(S, L, 0)$ is illustrated by the middle line. The upper and lower lines $g(S, L, \epsilon_a)$ and $g(S, L, \epsilon_b)$ show the utility from two possible realizations (labelled ϵ_b and ϵ_b) of the vector of shocks to human capital $(\boldsymbol{\epsilon})$ and GCSE performance conditional on human capital $(\mathbf{v})$, which occur with equal probability.

Panel C shows the sum of the graphs in panels A and B. The point $S^*_{certain}$ shows the optimal choice of study for the case with no uncertainty. At this point $U(E[g(.)])$ is at its maximum and $MU(E[g(.)]) = 0$. Panel D plots the net marginal utility of study for the expected realization of g, labelled $MU(E[g(.)])$, and the expected net marginal utility of study, labelled $E[MU(g(.))]$. The latter is the mean of the functions $MU(g(S, L, \boldsymbol{\epsilon}_a))$ and $MU(g(S, L, \boldsymbol{\epsilon}_b))$.

It can be seen that expected marginal utility $E[MU(g(.))]$ is always below the marginal utility of the expected outcome $MU(g(S, L, 0))$, and $E[MU(g(.))] = 0$ at a lower Study (S^+) than $MU(g(S, L, 0)) = 0$ (at $S^*_{certain}$). This means the individual will underinvest in Study relative to the case with no uncertainty. As the random draws ϵ_1 and ϵ_2 become known, the overall variance of the residual uncertainty becomes smaller. Uncertainty is reduced still further if the ϵ_ts and v are positively serially correlated, and the individual can update his prior about the likely sign and magnitude of the shock to human capital.

Figure A1: Uncertainty leads to underinvestment in Study



A.1.2 Strictly negative tradeoff of employment and study

This appendix shows that in our model, the effect of employment on study time must be negative. Hence, the coefficient on employment when study is omitted from a regression model will represent a lower bound of the human capital effect of employment on academic performance. Treating labour supply as fixed the first order condition for the choice of study time is:

$$\frac{\partial E[g(\mathbf{S},\mathbf{L})]}{\partial S_t} + \frac{\partial f_t(\mathbf{S},\mathbf{L})}{\partial S_t} = 0 = [.] \tag{A1}$$

Using implicit differentiation, the partial derivative of study with respect to labour supply that maintains this optimal position is as follows:

$$\frac{\partial S_t}{\partial L_t} = -\frac{[\frac{\partial [.]}{\partial L_t}]}{[\frac{\partial [.]}{\partial S_t}]} = -\frac{[\frac{\partial^2 E[g(\mathbf{S},\mathbf{L})]}{\partial S_t \partial L_t}] + [\frac{\partial^2 f_t(\mathbf{S},\mathbf{L})}{\partial S_t \partial L_t}]}{[\frac{\partial^2 E[g(\mathbf{S},\mathbf{L})]}{\partial S_t^2}] + [\frac{\partial^2 f_t(\mathbf{S},\mathbf{L})}{\partial S_t^2}]} \tag{A2}$$

We now show that for an interior solution both the denominator and numerator of this expression must be strictly negative, meaning the partial derivative itself is negative.

Figure A2 plots the marginal utility (MU) of study for the present- and future-orientated components of utility ($f(\mathbf{S},\mathbf{L})$ and $E[g(\mathbf{S},\mathbf{L})]$), holding labour supply constant. The expected MU of study in the future-orientated component is always positive ($\frac{\partial E[g(S)]}{\partial S} > 0$), but decreasing in study ($\frac{\partial^2 E[g(S)]}{\partial S^2} < 0$). The expected MU of study in the present-orientated component is always negative ($\frac{\partial f(S)}{\partial S} < 0$) but decreasing in study ($\frac{\partial^2 f(S)}{\partial S^2} < 0$). For an interior solution it must be the case that at $S = 0$, $\frac{\partial E[g(S)]}{\partial S} > -\frac{\partial f(S)}{\partial S}$, and therefore in the ($S$, MU_S) space the function $\frac{\partial E[g(S)]}{\partial S}$ must cut $\frac{\partial f(S)}{\partial S}$ from above at the optimal point. Hence, $[\frac{\partial^2 E[g(\mathbf{S},\mathbf{L})]}{\partial S_t^2}] + [\frac{\partial^2 f_t(\mathbf{S},\mathbf{L})}{\partial S_t^2}]$, the denominator in equation A2, is less than zero.

Figure A3 plots the MU of study for the present- and future-orientated components of utility over a range for labour supply. The expected MU of study in the future-orientated component is always positive ($\frac{\partial E[g(S)]}{\partial S} > 0$) but may be increasing, constant or decreasing in L depending on whether study and labour supply are complements in production. The expected MU of study in the present-orientated component is always negative ($\frac{\partial f(S)}{\partial S} < 0$), and because consumption and leisure are complements, decreasing in labour supply ($\frac{\partial^2 f(S)}{\partial S \partial L} < 0$). For an interior solution it must be the case that at $L = 0$, $\frac{\partial E[g(S)]}{\partial S} > -\frac{\partial f(S)}{\partial S}$, so again in the (L, MU_S) space, the function $\frac{\partial E[g(S)]}{\partial S}$ must cut $\frac{\partial f(S)}{\partial S}$ from above at the optimal point. Hence, $[\frac{\partial^2 E[g(\mathbf{S},\mathbf{L})]}{\partial S_t \partial L_t}] + [\frac{\partial^2 f_t(\mathbf{S},\mathbf{L})}{\partial S_t \partial L_t}]$, the numerator in equation A2, is less than zero. Hence, $\frac{\partial S_t}{\partial L_t}$, the negative of the ratio of two negative expressions, is itself negative.

Figure A2: Showing that $[\frac{\partial^2 E[g(\mathbf{S},\mathbf{L})]}{\partial S_t^2}] + [\frac{\partial^2 f_t(\mathbf{S},\mathbf{L})}{\partial S_t^2}] < 0$

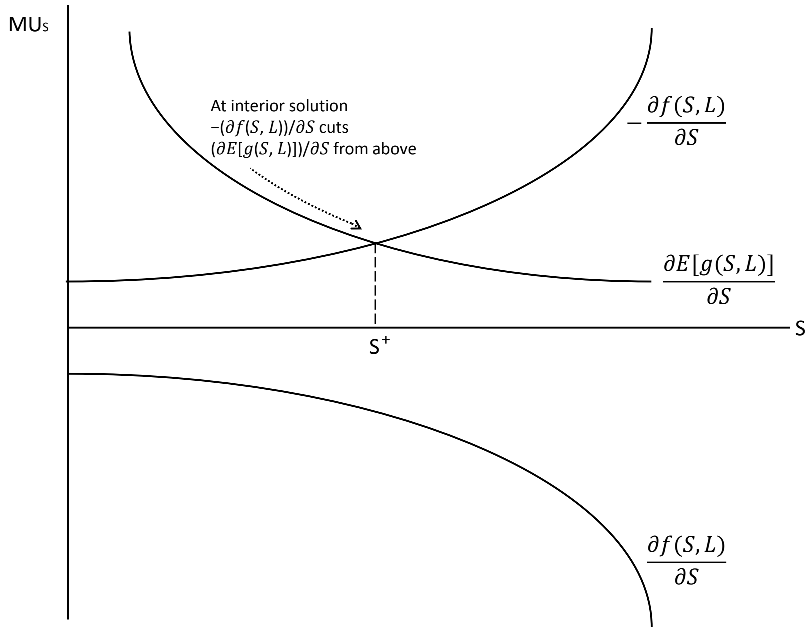
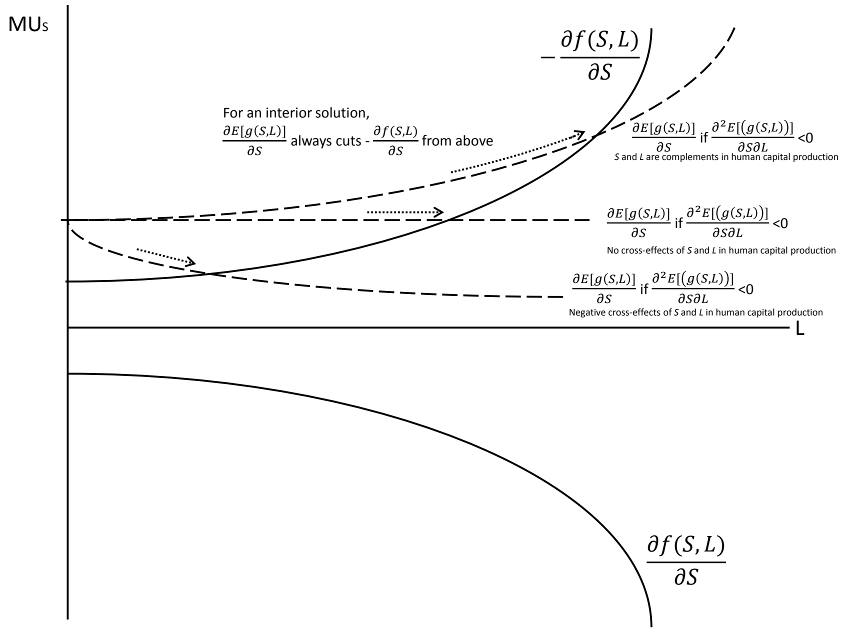


Figure A3: Showing that $[\frac{\partial^2 E[g(\mathbf{S},\mathbf{L})]}{\partial S_t \partial L_t}] + [\frac{\partial^2 f_t(\mathbf{S},\mathbf{L})}{\partial S_t \partial L_t}] < 0$



A.2 Distribution of latent inputs

Recall that the measurement model (equations 8-4.9, shown in Table 4) was estimated using the pooled sample of both waves and sexes. This ensures that a standard deviation change in each factor represents a common unit in terms of absolute activity levels, the interpretations of which are provided in Table 5. In turn, this means that the parameters representing the crowd-out or facilitation of each activity by employment, and their production function parameters, are directly comparable between waves and sexes.

Figures A4-A8 show the distribution of the principal component of each latent factor by wave and sex. Each histogram has 12 bins, and the four histograms within each figure share a common scale on both axes. The similarity or overlap between groups mean that the proposed changes in activity levels will represent a relevant and plausible adjustment for each group.

The distributions are most similar for Study (Figure A4) and Attitude (Figure A8), though in the former case girls are slightly more concentrated in the middle and less at the bottom of the distributed, and in the latter case, marginally more prevalent at the top. Differences are more apparent for Social Life; girls are slightly more frequent at the foot of the distribution, but also have a mass point at one standard deviation above the mean; and Active Leisure, where the distribution for boys is always to the right of that for girls (the modal density being just over one standard deviation higher), though there is considerable overlap between the sexes. Risky behaviours are highly postively skewed, though in a very similar way for boys and girls. For all groups the modal density is at no risky behaviours.

Figure A4: Distribution of principal component of Study by wave and sex

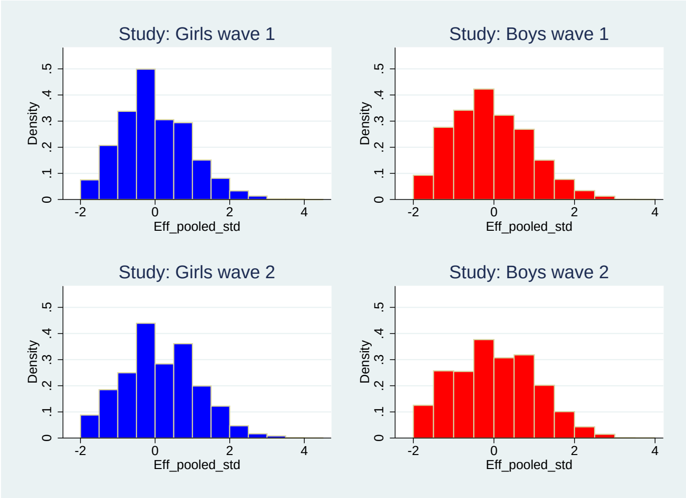


Figure A5: Distribution of principal component of Active Leisure by wave and sex

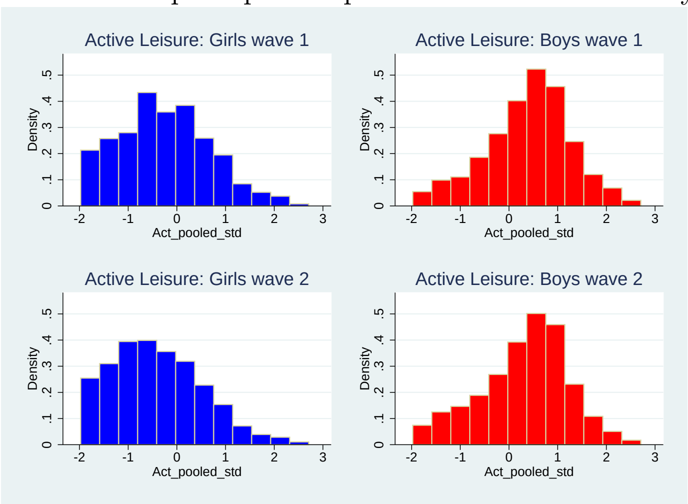


Figure A6: Distribution of principal component of Social Life by wave and sex

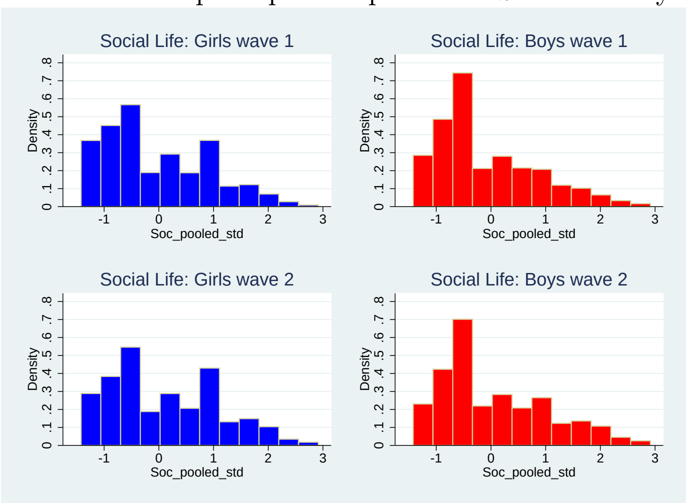


Figure A7: Distribution of principal component of Risky Behaviours by wave and sex

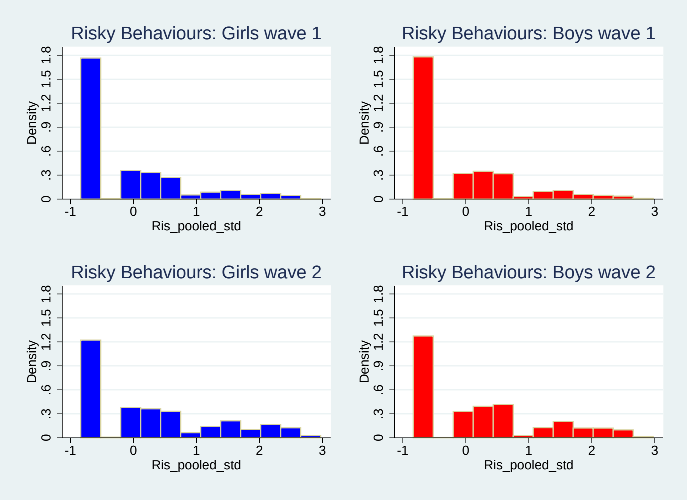
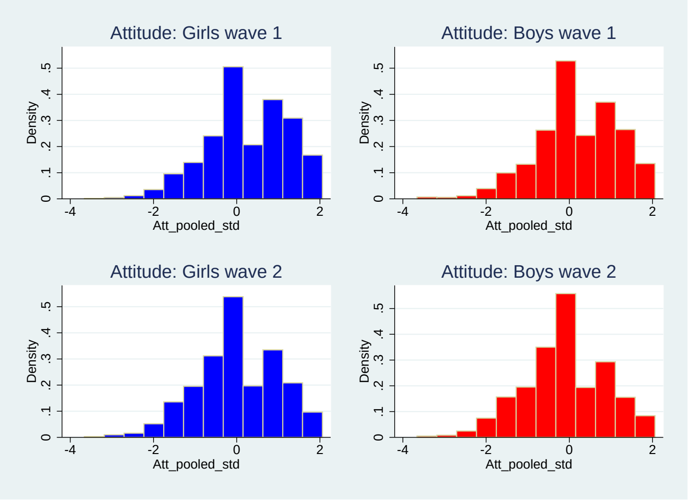


Figure A8: Distribution of principal component of Attitude by wave and sex



A.3 Employment as a gateway to future employment

Table A1 shows the state dependence of current employment in waves 2 and 3 of the LSYPE on employment in the previous wave, or equivalently academic year. We show random-effects linear regression coefficients for hours of employment per week. These results show strong positive state dependence in employment. The best linear prediction is that each hour of employment per week in one year adds about 0.4 hours per week in the following year.

Table A1: State dependence in hours of employment

	Boys		Girls	
	No initial conditions	Wooldridge treatment	No initial conditions	Wooldridge treatment
Lagged Work Hours	0.400***	0.398***	0.365***	0.360***
	(0.027)	(0.027)	(0.024)	(0.024)
IMD (standardized)	-0.173***	-0.152***	-0.144***	-0.120***
	(0.042)	(0.043)	(0.046)	(0.046)
Month of birth	-0.053***	-0.053***	-0.055***	-0.055***
	(0.014)	(0.014)	(0.013)	(0.013)
Contemporaneous: LAD age	-6.872***	20.843**	-4.642**	27.777***
18-24 unemployment rate	(1.836)	(8.180)	(1.905)	(9.710)
Mean over time: LAD age	.	-30.609***	.	-35.735***
18-24 unemployment rate	.	(8.578)	.	(10.270)
Individuals	4772	4772	4695	4695
Observations	9359	9359	9261	9261

Notes: Longitudinal weights applied. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. Index of multiple deprivation are standardized by substracting the mean and dividing by standard deviation. Month-of-birth within academic year: Sept (oldest in year) = 1, Aug (youngest in year) = 12. **Additional controls**: Parent's income, parent's socio-economic status, parents' employment (plus time-varying mean), parent receives disability benefit (plus time-varying mean), housing situation (plus time-varying mean), child's prior educational performance, resident and non-resident siblings, lone parent family, child's special educational needs (SEN) classification, urban-rural classification, child's ethnicity, timing of interview.

In the main body of this paper, a static specification, accounting for employment at only one point in time, would ignore this dynamic dependence. The coefficient on hours of employment in wave 1 could not be interpreted as the direct causal effect of labour supply at that time, for example, because we would not hold constant the hours of employment undertaken in wave 2. Not only is this highly correlated, but, Table A1 shows, it is also causally dependent on employment at wave 1. In addition, in confirming the strong serial correlation in employment, these results give credence to our interpretation that the large negative coefficient on wave 2 employment for girls in our instrumental variables specifications is biased by the effects of activities crowded out by employment in close proximity to final high-stakes examinations.

These results are presented using specifications both with and without the Wooldridge (2005) treatment of initial conditions, which entails including the mean of time-varying regressors in the specification. This makes no difference to the inference relating to the state dependence of employment. This is to be expected, since the first wave of the LSYPE corresponds to the first full school year in which teenagers may enter the labour market. Hence, we observe the initial condition. However, the high serial correlation of the local youth unemployment rate over the short period considered here leads to large and opposite-signed coefficients on the time-specific level and on the mean. The effect of the mean dominates, being larger in magnitude and negative. In the main body of this paper, for clarity about the source of identifying variation in employment, we control only for the contemporaneous level of the unemployment rate.

A.4 Complete estimation output

Table A2: Complete estimation output: Production function parameters with single time-varying endogenous latent input: 'Study'

Study	Boys					Girls				
	W1 Work Hours	W1 Study	W2 Work Hours	W2 Study	GCSE point score	W1 Work Hours	W1 Study	W2 Work Hours	W2 Study	GCSE point score
W2 Work Hours	.	.	.	-0.007	-0.007	.	.	.	-0.036***	-0.032*
	.	.	.	(0.012)	(0.011)	.	.	.	(0.013)	(0.020)
W1 Work Hours	.	-0.024**	.	.	-0.000	.	-0.016	.	.	-0.006
	.	(0.012)	.	.	(0.016)	.	(0.022)	.	.	(0.022)
W2 Study	.	.	.	.	0.405	.	.	.	.	0.274
	.	.	.	.	(0.323)	.	.	.	.	(0.219)
W1 Study	.	.	.	.	-0.408	.	.	.	.	0.117
	.	.	.	.	(0.263)	.	.	.	.	(0.461)
W2 Age 18-24 LAD unemployment rate	.	.	-15.094	.	.	.	.	-46.462***	.	.
	.	.	(10.824)	.	.	.	.	(10.591)	.	.
W1 Age 18-24 LAD unemployment rate	-6.354	.	.	.	.	-20.020*	.	.	.	.
	(9.445)	.	.	.	.	(11.768)	.	.	.	.
IMD (standardized)	-0.860***	.	-1.197***	.	.	-0.969***	.	-0.620**	.	.
	(0.202)	.	(0.274)	.	.	(0.227)	.	(0.252)	.	.
Month of birth	-0.081	.	-0.042	.	.	-0.160***	.	-0.096*	.	.
	(0.049)	.	(0.055)	.	.	(0.060)	.	(0.050)	.	.
Age 14 ave' point score (standardized)	.	.	-0.000	0.189***	0.679***	.	.	-0.669*	0.191***	0.642***
	.	.	(0.404)	(0.035)	(0.065)	.	.	(0.360)	(0.033)	(0.052)
Age 11 ave' point score (standardized)	0.280	0.084***	0.052	-0.035	0.021	0.550***	0.088***	1.587***	-0.019	0.027
	(0.188)	(0.021)	(0.419)	(0.034)	(0.040)	(0.201)	(0.020)	(0.382)	(0.031)	(0.045)
'Permanent' income percentile	-0.218	0.101	-0.335	-0.001	-0.018	-0.080	-0.194**	-0.654	-0.041	0.162
	(0.884)	(0.087)	(0.996)	(0.090)	(0.073)	(0.981)	(0.089)	(0.998)	(0.093)	(0.120)
Parent receives incapacity benefit	-1.400***	-0.015	-0.846	-0.060	-0.002	-0.007	0.010	-1.538**	0.003	-0.042
	(0.492)	(0.047)	(0.542)	(0.048)	(0.038)	(0.614)	(0.051)	(0.629)	(0.052)	(0.033)
Home owner (mortgage or outright)	0.220	-0.033	0.444	-0.015	0.105***	-0.888**	-0.048	0.346	0.011	0.114***
	(0.425)	(0.043)	(0.491)	(0.042)	(0.033)	(0.449)	(0.040)	(0.485)	(0.043)	(0.038)
Parent in PT employment only	0.709	0.048	1.301	-0.051	0.076	0.341	-0.132*	0.067	0.027	0.140*
	(0.742)	(0.075)	(0.900)	(0.082)	(0.061)	(0.883)	(0.074)	(0.852)	(0.072)	(0.083)
Parent in FT employment	0.180	-0.018	1.820*	-0.040	0.010	0.549	-0.085	-0.034	-0.014	0.074
	(0.722)	(0.073)	(0.946)	(0.081)	(0.055)	(0.837)	(0.067)	(0.824)	(0.068)	(0.069)
Parents' education										
Degree	-0.323	0.045	-1.794**	0.060	0.131**	0.192	0.014	1.432*	0.002	0.046
	(0.674)	(0.068)	(0.843)	(0.071)	(0.057)	(0.804)	(0.063)	(0.789)	(0.067)	(0.048)
A-Levels	0.423	0.010	-0.287	0.090	0.026	-0.183	0.047	1.912***	0.078	0.001
	(0.579)	(0.058)	(0.757)	(0.061)	(0.054)	(0.689)	(0.056)	(0.727)	(0.057)	(0.057)
GCSEs	0.373	-0.011	0.101	0.049	0.018	0.460	-0.033	2.201***	0.016	0.009
	(0.565)	(0.056)	(0.735)	(0.059)	(0.049)	(0.668)	(0.052)	(0.706)	(0.057)	(0.045)
Other	1.907	-0.013	2.821**	-0.037	-0.001	-0.172	-0.131	0.332	-0.038	-0.002
	(1.268)	(0.132)	(1.356)	(0.111)	(0.101)	(1.501)	(0.113)	(1.676)	(0.140)	(0.099)
Non-resident siblings	0.008	-0.009	0.041	-0.003	-0.023**	-0.026	-0.024*	0.163	-0.020	-0.028
	(0.128)	(0.014)	(0.151)	(0.013)	(0.010)	(0.162)	(0.014)	(0.150)	(0.015)	(0.018)
Resident children	0.644***	0.002	0.634***	0.006	-0.005	0.658***	0.044***	0.847***	0.029*	0.022
	(0.136)	(0.015)	(0.159)	(0.016)	(0.011)	(0.153)	(0.015)	(0.175)	(0.016)	(0.026)
Lone parent	-0.654	-0.096**	0.208	-0.124**	-0.173***	0.388	-0.100**	-0.240	-0.053	-0.072
	(0.416)	(0.046)	(0.569)	(0.048)	(0.044)	(0.456)	(0.043)	(0.465)	(0.045)	(0.063)
Socio-economic class':										
NSSEC 4 (self-employed)	-0.277	0.023	0.991*	-0.021	0.053	0.223	-0.017	-0.215	-0.014	-0.021
	(0.530)	(0.061)	(0.600)	(0.064)	(0.045)	(0.652)	(0.063)	(0.671)	(0.056)	(0.048)
NSSEC 1-2	-0.715*	0.065	-0.159	0.041	0.061*	-0.501	0.072*	-0.735*	0.036	-0.024
	(0.374)	(0.040)	(0.456)	(0.043)	(0.034)	(0.427)	(0.039)	(0.394)	(0.041)	(0.047)
NSSEC 3	-1.198**	0.061	-1.654**	-0.042	0.090*	-1.459**	0.026	-0.508	0.050	-0.030
	(0.586)	(0.061)	(0.649)	(0.063)	(0.054)	(0.700)	(0.056)	(0.663)	(0.060)	(0.046)
NSSEC8 (Long-term unemployed)	-0.427	-0.037	-0.159	-0.139**	0.013	-1.050	-0.085	-1.057	-0.010	-0.002
	(0.618)	(0.063)	(0.743)	(0.069)	(0.057)	(0.785)	(0.059)	(0.717)	(0.063)	(0.058)
Observations			5125					5072		

Continued on next page

Notes: Standard errors, clustered by school, in parentheses. Longitudinal weights applied. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. GCSE (age 16), age 14 and age 11 average point scores, and index of multiple deprivation are standardized by substracting the mean and dividing by standard deviation. Month-of-birth within academic year: Sept (oldest in year) = 1, Aug (youngest in year) = 12.

Table A3: Complete estimation output: Production function parameters with single time-varying endogenous latent input: 'Study' (continued)

Study	Boys					Girls				
	W1 Work Hours	W1 Study	W2 Work Hours	W2 Study	GCSE point score	W1 Work Hours	W1 Study	W2 Work Hours	W2 Study	GCSE point score
Youth's ethnicity Mixed race	-3.064***	0.024	-2.539**	0.121	0.056	-0.668	0.103	-0.353	0.011	0.017
	(0.872)	(0.087)	(1.070)	(0.088)	(0.072)	(0.751)	(0.078)	(0.773)	(0.078)	(0.069)
Indian	-3.470***	0.387***	-4.671***	0.346***	0.204**	-5.642***	0.462***	-7.484***	0.496***	0.023
	(0.734)	(0.072)	(1.050)	(0.062)	(0.087)	(1.127)	(0.068)	(1.016)	(0.060)	(0.285)
Pakistani	-6.439***	0.555***	-6.549***	0.416***	0.198*	-9.461***	0.387***	-10.858***	0.481***	0.031
	(1.032)	(0.075)	(1.095)	(0.082)	(0.112)	(1.887)	(0.074)	(2.301)	(0.083)	(0.252)
Bangladeshi	-6.808***	0.206*	-9.417***	0.377***	0.149	-9.024***	0.351***	-12.290***	0.451***	0.162
	(1.339)	(0.116)	(1.683)	(0.091)	(0.132)	(1.987)	(0.118)	(2.938)	(0.114)	(0.236)
Black Caribbean	-1.509	0.317***	-2.537*	0.477***	0.114	-1.471	0.181*	-1.994	0.328***	0.070
	(1.743)	(0.103)	(1.490)	(0.110)	(0.126)	(1.243)	(0.096)	(1.247)	(0.111)	(0.143)
Black African	-3.664***	0.424***	-3.592**	0.473***	0.183	-2.747*	0.702***	-2.800*	0.629***	0.069
	(1.367)	(0.142)	(1.585)	(0.135)	(0.147)	(1.430)	(0.110)	(1.515)	(0.132)	(0.409)
Other	-0.829	0.418***	-3.348**	0.290**	0.302**	-2.802**	0.216**	-2.608	0.060	0.346***
	(1.281)	(0.145)	(1.483)	(0.124)	(0.120)	(1.409)	(0.099)	(1.925)	(0.111)	(0.128)
Special Ed' Needs	-0.164	-0.216***	-0.648	-0.243***	-0.236***	-0.715	-0.207***	-0.708	-0.187***	-0.161
	(0.424)	(0.046)	(0.524)	(0.046)	(0.064)	(0.636)	(0.057)	(0.650)	(0.062)	(0.121)
Town or Village	-0.046	0.029	1.317***	0.019	0.046	1.390***	0.019	2.605***	-0.039	0.046
	(0.360)	(0.043)	(0.449)	(0.043)	(0.035)	(0.433)	(0.044)	(0.403)	(0.045)	(0.035)
Hamlet or Isolated	0.620	0.027	1.854**	0.103	0.028	1.095	-0.013	3.876***	0.057	0.089
	(0.713)	(0.075)	(0.848)	(0.072)	(0.065)	(0.843)	(0.085)	(0.710)	(0.084)	(0.061)
Not Greater London	1.878***	-0.208***	1.625**	-0.298***	-0.039	2.511***	-0.223***	2.871***	-0.172***	0.081
	(0.602)	(0.063)	(0.766)	(0.054)	(0.079)	(0.645)	(0.067)	(0.713)	(0.064)	(0.135)
W1 Time of interview: February	-0.764	0.020	.	.	0.041	-1.183	-0.119	.	.	-0.051
	(0.665)	(0.097)	.	.	(0.085)	(0.925)	(0.082)	.	.	(0.090)
March	-0.455	-0.117	.	.	-0.038	-0.390	-0.154*	.	.	-0.019
	(0.652)	(0.097)	.	.	(0.090)	(0.924)	(0.079)	.	.	(0.099)
April	-0.455	-0.117	.	.	-0.038	-0.390	-0.154*	.	.	-0.019
	(0.652)	(0.097)	.	.	(0.090)	(0.924)	(0.079)	.	.	(0.099)
May	0.122	-0.157	.	.	0.029	0.024	-0.302***	.	.	-0.029
	(0.705)	(0.099)	.	.	(0.098)	(0.923)	(0.083)	.	.	(0.157)
June-July	0.968	-0.071	.	.	-0.088	0.594	-0.121	.	.	-0.033
	(0.900)	(0.106)	.	.	(0.098)	(1.238)	(0.103)	.	.	(0.095)
After birthday	0.216	-0.026	.	.	0.032	-0.265	-0.004	.	.	0.031
	(0.424)	(0.033)	.	.	(0.033)	(0.486)	(0.034)	.	.	(0.031)
W2 Time of interview: February	.	.	-1.203	-0.072	0.043	.	.	-2.762*	-0.192	0.108
	.	.	(1.203)	(0.100)	(0.079)	.	.	(1.524)	(0.132)	(0.100)
March	.	.	-1.475	-0.055	-0.008	.	.	-1.296	-0.157	0.026
	.	.	(1.034)	(0.075)	(0.065)	.	.	(1.352)	(0.105)	(0.085)
April	.	.	-1.153	-0.111	0.027	.	.	-0.753	-0.091	0.019
	.	.	(1.023)	(0.077)	(0.069)	.	.	(1.321)	(0.104)	(0.079)
May	.	.	-1.467	-0.094	0.037	.	.	-0.829	-0.059	0.028
	.	.	(1.043)	(0.077)	(0.067)	.	.	(1.323)	(0.103)	(0.079)
June-July	.	.	-0.627	-0.170**	0.054	.	.	-0.836	-0.064	0.023
	.	.	(1.072)	(0.078)	(0.080)	.	.	(1.331)	(0.106)	(0.078)
After birthday	.	.	0.378	-0.001	-0.060*	.	.	-0.494	0.013	-0.052
	.	.	(0.532)	(0.036)	(0.033)	.	.	(0.457)	(0.039)	(0.035)
Observations			5125					5072		

Notes: Joint significance statistics and p-values are Wald test statistics. Standard errors, clustered by school, in parentheses. Longitudinal weights applied. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. GCSE (age 16), age 14 and age 11 average point scores, and index of multiple deprivation are standardized by substracting the mean and dividing by standard deviation. Month-of-birth within academic year: Sept (oldest in year) = 1, Aug (youngest in year) = 12.

Table A4: Complete estimation output: State dependence in hours of employment

	Boys		Girls	
	No initial conditions	Wooldridge treatment	No initial conditions	Wooldridge treatment
Lagged Work Hours	0.400***	0.398***	0.365***	0.360***
	(0.027)	(0.027)	(0.024)	(0.024)
IMD (standardized)	-0.173***	-0.152***	-0.144***	-0.120***
	(0.042)	(0.043)	(0.046)	(0.046)
Month of birth	-0.053***	-0.053***	-0.055***	-0.055***
	(0.014)	(0.014)	(0.013)	(0.013)
Contemporaneous: LAD age	-6.872***	20.843**	-4.642**	27.777***
18-24 unemployment rate	(1.836)	(8.180)	(1.905)	(9.710)
Mean over time: LAD age	.	-30.609***	.	-35.735***
18-24 unemployment rate	.	(8.578)	.	(10.270)
'Permanent' income percentile	-0.176	-0.198	-0.057	-0.059
	(0.198)	(0.200)	(0.212)	(0.220)
Age 14 ave' point score	-0.137	-0.139	-0.092	-0.094
(standardized)	(0.087)	(0.087)	(0.080)	(0.080)
Age 11 ave' point score	0.045	0.048	0.171**	0.174**
(standardized)	(0.078)	(0.078)	(0.075)	(0.075)
Parent receives incapacity benefit	0.021	0.105	-0.140	0.338
	(0.107)	(0.455)	(0.108)	(0.428)
Mean over time: Parent receives	.	-0.070	.	-0.525
incapacity benefit	.	(0.474)	.	(0.461)
Home owner (mortgage/outright)	0.015	0.021	-0.010	0.022
	(0.099)	(0.288)	(0.095)	(0.343)
Mean over time: Home owner	.	-0.014		-0.031
(morgage or outright)	.	(0.309)	.	(0.359)
Parent in FT employment	0.419**	0.064	0.105	0.039
	(0.167)	(0.291)	(0.148)	(0.258)
Mean over time: Parent in FT	.	0.588	.	0.077
employment	.	(0.360)	.	(0.315)
Parent in PT employment only	0.214	-0.214	-0.202	-0.268
	(0.171)	(0.294)	(0.152)	(0.278)
Mean over time: Parent in PT	.	0.706**	.	0.097
employment only	.	(0.360)	.	(0.327)
Parents' Education:				
Degree	-0.271**	-0.297**	0.132	0.134
	(0.132)	(0.132)	(0.131)	(0.131)
A-Levels	-0.052	-0.078	0.351***	0.352***
	(0.115)	(0.115)	(0.109)	(0.110)
GCSEs	0.082	0.054	0.388***	0.387***
	(0.112)	(0.111)	(0.093)	(0.094)
Other	0.332	0.301	0.001	0.001
	(0.307)	(0.308)	(0.222)	(0.224)
Non-resident siblings	0.058*	0.057*	-0.006	-0.008
	(0.030)	(0.030)	(0.028)	(0.028)
Resident children	0.126***	0.127***	0.090***	0.091***
	(0.031)	(0.031)	(0.029)	(0.029)
Lone parent	0.029	0.039	0.057	0.047
	(0.108)	(0.112)	(0.095)	(0.096)
Socio-economic class':				
NSSEC 4 (self	0.286*	0.282*	0.188	0.185
employed)	(0.154)	(0.154)	(0.168)	(0.169)
NSSEC1-2	0.081	0.091	-0.157	-0.159
	(0.104)	(0.104)	(0.097)	(0.097)
Individuals	4772	4772	4695	4695
Observations	9359	9359	9261	9261

Continued on next page

Notes: Longitudinal weights applied. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. Index of multiple deprivation are standardized by substracting the mean and dividing by standard deviation. Month-of-birth within academic year: Sept (oldest in year) = 1, Aug (youngest in year) = 12.

Table A5: Complete estimation output: State dependence in hours of employment (continued)

	Boys		Girls	
	No initial conditions	Wooldridge treatment	No initial conditions	Wooldridge treatment
NSSEC 3	-0.141 (0.136)	-0.139 (0.136)	0.162 (0.168)	0.163 (0.169)
NSSEC 8 (Long-term unemployed	0.168 (0.164)	0.302 (0.185)	-0.066 (0.133)	-0.049 (0.141)
Youth's ethnicity: Mixed race	-0.211 (0.148)	-0.205 (0.148)	-0.267* (0.146)	-0.272* (0.146)
Indian	-0.717*** (0.084)	-0.719*** (0.084)	-1.011*** (0.082)	-1.005*** (0.083)
Pakistani	-0.785*** (0.125)	-0.790*** (0.126)	-0.982*** (0.093)	-0.986*** (0.094)
Bangladeshi	-0.628*** (0.152)	-0.616*** (0.154)	-0.664*** (0.121)	-0.660*** (0.122)
Black African	-0.468*** (0.145)	-0.467*** (0.144)	-0.524*** (0.149)	-0.510*** (0.148)
Black African	-0.546*** (0.163)	-0.514*** (0.163)	-0.500*** (0.177)	-0.489*** (0.177)
Other	-0.490*** (0.156)	-0.485*** (0.158)	-0.585*** (0.192)	-0.577*** (0.192)
Special Ed' Needs	-0.212** (0.099)	-0.210** (0.099)	-0.206* (0.112)	-0.195* (0.113)
Town or Village	0.459*** (0.118)	0.440*** (0.117)	0.880*** (0.131)	0.870*** (0.131)
Hamlet or Isolated	0.722** (0.289)	0.705** (0.289)	1.168*** (0.258)	1.150*** (0.259)
Not Greater London	0.177** (0.079)	0.142* (0.080)	0.318*** (0.085)	0.277*** (0.084)
Time of interview: February	-0.226 (0.303)	-0.416 (0.307)	0.104 (0.375)	-0.094 (0.377)
March	-0.440 (0.299)	-0.542* (0.299)	-0.130 (0.374)	-0.236 (0.375)
April	-0.315 (0.299)	-0.355 (0.298)	-0.001 (0.380)	-0.041 (0.380)
May	-0.419 (0.298)	-0.419 (0.298)	-0.186 (0.378)	-0.185 (0.378)
June-July	-0.241 (0.305)	-0.244 (0.304)	-0.095 (0.380)	-0.090 (0.380)
After birthday	-0.056 (0.110)	-0.056 (0.110)	0.023 (0.101)	0.025 (0.101)
Individuals	4772	4772	4695	4695
Observations	9359	9359	9261	9261

Notes: Longitudinal weights applied. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. Index of multiple deprivation are standardized by substracting the mean and dividing by standard deviation. Month-of-birth within academic year: Sept (oldest in year) = 1, Aug (youngest in year) = 12.